Overheating risk reduction in UK dwellings.

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Mousa Alrasheed

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Cardiff University
School of Engineering

Summary

Rising global temperatures are driving more frequent heatwaves in the UK, increasing overheating risk in the housing stock and compromising the health and comfort of occupants, particularly the elderly. Given the diversity and scale of the stock, assessing individual buildings for overheating risk is impractical. Instead, representative archetypes provide a scalable approach to capturing key dwelling variations, enabling large-scale investigations that are essential for understanding overheating patterns and developing effective mitigation strategies.

However, the influence of methodological choices on archetype representativeness remains under-explored. To address this, a minimum segmentation frequency (MSF) approach was introduced to preserve feature diversity. A sensitivity analysis was conducted on archetype representativeness to investigate the influence of different MSF levels, variable counts and clustering metrics. Results showed that lower MSF values improved representativeness, and the choice of clustering metric impacted the optimal number of archetypes. The Davies-Bouldin index consistently identified more representative archetypes than the Calinski-Harabasz and Silhouette indices.

Subsequently, a framework for archetype development was established, integrating geographical and temporal scales, computational cost and research focus to balance representativeness and simulation feasibility. Using the framework, building archetypes derived from English Housing Survey (EHS) data were developed to analyse overheating risk across regions and dwelling types.

The developed archetypes were evaluated through dynamic thermal simulations, revealing consistent overheating patterns that align with observed overheating trends, demonstrating both the cooling potential of a passive measure (e.g., external shutters) and the overheating severity for different typologies. Simulated internal temperatures reflected monitoring studies, reinforcing their reliability. A Random Forest model demonstrated that the data variation within the developed archetypes is sufficient to reliably identify key drivers of overheating. The model demonstrated strong predictive performance, with R^2 values ranging from 0.79 to 1 for living rooms and 0.79 to 0.96 for bedrooms across both baseline and 2050 climate scenarios. The findings confirm the utility of the archetypes, derived from the suggested framework, for large-scale overheating assessments, providing a foundation for future research, policy and adaptive cooling strategies in a changing climate.

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Publications

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- Alrasheed, M. and Mourshed, M. (2024). Building stock modelling using k-prototype: A framework for representative archetype development. Energy & Buildings, 311:114111

Nomenclature

ACH	Air changes per hour
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BREDEM	Building Research Establishment Domestic Energy Model
CCC	Climate Change Committee
CH	Calinski-Harabasz index
CIBSE	Chartered Institution of Building Services Engineers
CO_2	Carbon dioxide
COVID-19	Coronavirus Disease 2019
CREEM	Canadian Residential Energy End-use Model
DB	Davies-Bouldin index
DSY	Design Summer Year
EFUS	Energy Follow Up Survey
EHS	English Housing Survey
EU	European Union
GHG	Greenhouse gas
HVAC	Heating, Ventilation and Air Conditioning
IDF	Input data file
IPCC	The Intergovernmental Panel on Climate Change
IOTR	Indoor-outdoor temperature ratio
k	Number of clusters
LPS	Large panel system
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MSF	Minimum segmentation frequency
$MtCO_2e$	Megatonnes of CO_2 equivalent
PAF	Postcode address file
PCM	Phase change material

PHPP	Passive House Planning Package
R^2	Coefficient of determination
RF	Random Forest
SAP	Standard Assessment Procedure
SILH	Silhouette index
SLR	Systematic literature review
SPSS	Statistical Package for Social Sciences
TWh/year	Terawatt-hours per year
TM	Technical Memorandum
UHI	Urban heat island
UKDCM	UK Domestic Carbon Model
u-values	Thermal transmittance values
VIF	Variance inflation factor
W	Watt
W/m^2K	Watts per meter squared kelvin
ZCH	Zero Carbon Hub

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Chapter 1 | Introduction

1.1 Overview

The scarcity of fossil fuels, stringent greenhouse gas (GHG) emission targets and anthropogenic climate change are all factors that contribute to the demand for passively cooled buildings (DEFRA, 2010). Buildings account for 36% of global energy consumption and 40% of carbon emissions (Langevin et al., 2020). The UK residential sector accounted for nearly 68 MtCO_2e of GHG emissions in 2020 (DBE, 2022). Peak summer temperatures in the UK could increase by 10°C by the 2080s compared to the 1990s reference climate (Zero Carbon Hub, 2015). Furthermore, temperatures exceeding 35°C are becoming more prevalent in the southeast, and several northern regions may experience temperatures exceeding 30°C at least once every decade by 2100 (Christidis et al., 2020). These rising outdoor temperatures will inevitably affect indoor environments, making overheating a growing concern.

Overheating refers to the occurrence of high internal temperatures that cause thermal discomfort, affecting occupants' health and productivity (Dodoo and Gustavsson, 2016). This phenomenon has already been observed in UK (Zero Carbon Hub, 2015; Beizaee et al., 2013; Lomas and Porritt, 2017; Pathan et al., 2017; Symonds et al., 2016) and dwellings (Brotas and Nicol, 2016) and is likely to increase due to global warming (Hamdy et al., 2017; DEFRA, 2010), which in turn will increase the cooling demand for maintaining thermal comfort. During the 2018 summer, a survey of 750 UK dwellings reported that 15% of living rooms and 19% of bedrooms experienced overheating, and the operative temperatures surpassed 26°C for more than 32 occupied hours in 69% of the bedrooms (EFUS, 2021a). Hence there is an urgent need for for passively cooled buildings to adapt to rising temperatures and increased cooling needs.

Overheating risks are projected to rise in the UK due to climate change, with external peak temperatures similar to heatwave patterns becoming hotter, more frequent and recurring (Mavrogianni et al., 2012; Gupta and Gregg, 2012; Porrit, 2012). The 2003 heatwave in southeast UK, with temperatures reaching 38.5°C (Johnson et al., 2005), surpassed the 1976 heatwave in the UK, with a peak temperature of 35.9°C in Cheltenham and 15 consecutive days surpassing 32°C in certain locations (Burt, 2004). In recent years, the UK has experienced several heatwaves that have surpassed previous records, demonstrating the ongoing trends of increasing temperatures. The external temperature in Glasgow in 2018 reached 31.9°C, while Felsham and Porthmadog recorded 35.6°C and 33°C respectively (McCarthy et al., 2019). Several heatwaves occurred in the UK during the summer of 2022, resulting in temperatures exceeding 40°C (Davie et al., 2023).

An overview of factors affecting overheating risks in dwellings, their impacts on occupants and potential solutions are presented in Figure 1.1 as a starting point for the contextual discussion. Dwelling characteristics and the design, together with climate and environmental features, affect overheating risks. The impacts on occupants range from sleep deprivation and reduced productivity to even death. Various solutions to overheating are found in the literature, ranging from solar shading to improving thermal properties of materials by adding more insulation.

Indoor overheating poses a significant health threat, especially to the elderly due to their considerable time at home and limited mobility (Lomas and Porritt, 2017; Porrit, 2012). During the 2003 heatwave across Europe, around 70,000 deaths (Robine et al., 2008) were reported, of which an approximate of 30,000 and 2091 were from Western Europe (Kosatsky, 2005) and the UK (Johnson et al., 2005) respectively. Consequently, public health stakeholders in the UK and Europe (World Health Organization, 2009) raised their concerns and called for preventative measures to reduce heat-related deaths. The shift to remote work since the COVID-19 pandemic has further intensified overheating risks, as increased indoor occupancy leads to higher internal heat gains. Thus, the demand for air conditioning increased during lockdown (Khosravi et al., 2023). It is urgent to reconsider the principles of housing design to reduce the increased risk of heat-related health complications.

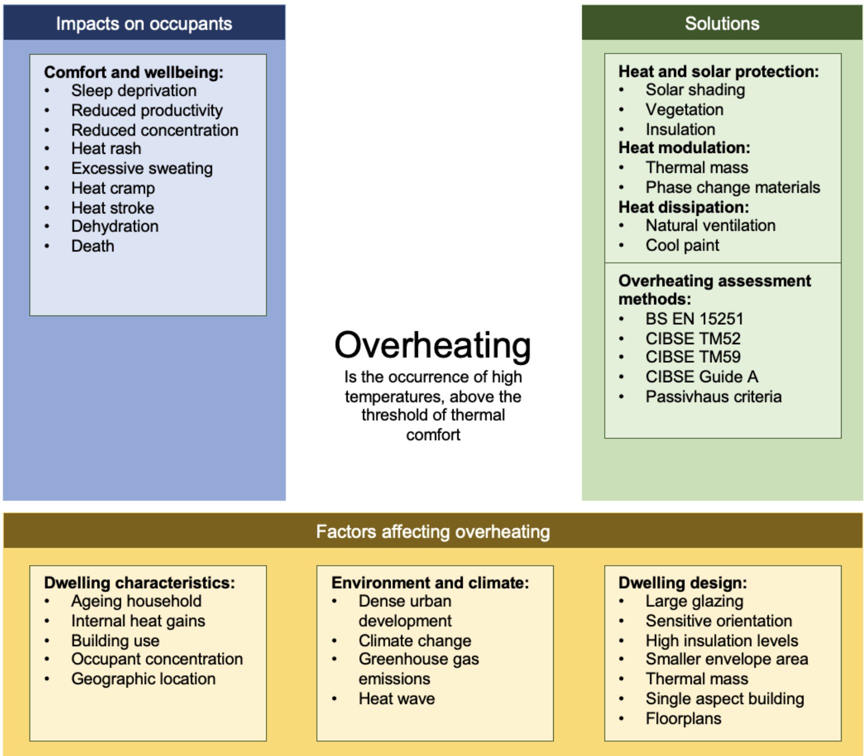


Figure 1.1: An overview of factors affecting overheating, its impacts on occupants and potential solutions to the problem.

1.2 Existing building stock and challenges

The UK housing stock is among the oldest in the world, and it is anticipated that most of the current dwellings will continue to be in use until the 2050s (Boardman, 2007). Given the UK's low rate of housing demolition (Tink, 2018), the current housing stock will likely remain for many years. In addition, the government's emphasis on enhancing insulation in both new and existing dwellings (Department for Energy Security and Net Zero and Department for Business, Energy & Industrial Strategy, 2021b) may result in a greater accumulation of indoor heat during the summer months as a result of increased air tightness (Davies and Oreszczyn, 2012). The UK's ambitions to reduce greenhouse gas emissions by 78% by 2035 and attain net-zero by 2050 may be undermined by the increased use of air conditioning to maintain thermal comfort indoors if passive cooling interventions are not implemented effectively (Department for Energy Security and Net Zero and Department for Business, Energy & Industrial Strategy, 2021c).

The severe temperatures experienced by buildings vary in intensity and duration, and are influenced by weather patterns documented in meteorological data (Smoyer-Tomic et al., 2003). Different regions could require different designs and building methods to control indoor heat efficiently. Choosing the appropriate materials and ensuring sufficient insulation are crucial factors that greatly impact a building's thermal inertia and capacity to control heat (Verbeke and Audenaert, 2018), influencing overheating risks (Mavrogianni et al., 2012). These building characteristics are important in determining the performance of dwellings under extreme temperatures.

Dwellings in northern UK, which typically experience colder weather conditions, frequently incorporate greater insulation and thicker walls (EHS, 2023) to provide strong thermal retention and prevent heat loss in winter. These dwellings often have cavity walls, which are more common in the northern regions compared to the southern regions (EHS, 2023). Design choices, such as building shape and window-to-wall ratios, impact heat gain, storage and dissipation within a dwelling. Greater window-to-wall ratios can result in elevated indoor temperatures (Gamero-Salinas et al., 2021), particularly if the windows are not adequately shaded. While dwellings in southern UK generally have a reduced wall surface area and increased window size (EHS, 2023), possibly strategically planned to optimise natural airflow and cooling. These regional variations have implications for overheating and passive cooling techniques. Although the thick walls and insulation of northern dwellings assist in heat retention during cold months, they may exacerbate overheating during warmer seasons. Southern dwellings, designed to promote airflow, may be more suitable for passive cooling, but they have difficulties owing to their larger windows, which may additionally increase solar heat gains.

Urban heat islands (UHI) are localised areas where buildings absorb heat from solar radiation and human activity during the day and release it at night (Eames et al., 2010). In dense urban environments, street canyons trap heat by limiting longwave radiation loss (Theeuwes et al., 2013), while urban noise often discourages natural ventilation as a cooling strategy (Lomas and Porritt, 2017). As a result, indoor temperatures in urban areas tend to be higher (Tam et al., 2015), increasing the risk of heat-related fatalities (Oikonomou et al., 2012). Importantly, roughly 24.2% of the UK housing stock is located in urban settings (EHS, 2023). These challenges underscore the need for targeted cooling strategies that consider local climate conditions.

Urban areas, such as London, have a higher prevalence of high-density housing, including flats and terraced houses (EHS, 2023), which are particularly susceptible to the UHI effect and often lack adequate natural ventilation. In contrast, rural regions predominantly feature detached and semi-detached houses with larger surrounding green spaces that can mitigate heat absorption. Additionally, rural dwellings tend to have larger floor spaces (EHS, 2023), which can improve the distribution of heat and potentially reduce the intensity of overheating in individual rooms. These discrepancies in urban density and dwelling typology emphasise the need for tailored heat mitigation strategies to the unique characteristics of different regions.

The UK housing stock is highly diverse, with regional differences in insulation levels, wall thickness, window sizes and dwelling forms (EHS, 2023), all of which influence how overheating develops across different areas. Given this variability, large-scale research is essential to support policymakers in developing targeted overheating mitigation strategies. While dynamic thermal modeling can assess how different dwelling types respond to climatic conditions, modelling each building individually is impractical due to the vast number of existing homes. Instead, building stock modeling offers a scalable solution by simulating representative archetypes based on extensive housing data, enabling more effective scenario analysis and policy interventions.

1.3 Building stock modelling

Building stock modelling plays a vital role in the development and testing of solutions and policies for improving energy efficiency (Röck et al., 2021; Reyna and Chester, 2017; Wang et al., 2018), reducing greenhouse gas emissions (Yamaguchi et al., 2022; Pittam et al., 2014; Stephan and Athanassiadis, 2017), adapting to climate change by reducing overheating risks (Gupta and Gregg, 2013; Gangolells and Casals, 2012), assessing the effects of building envelope modifications on indoor air quality (Taylor et al., 2014b) and optimising resource usage (Nutkiewicz and Jain, 2019; Mastrucci et al., 2014; Streicher et al., 2019) for a resilient built environment. The modelling process can be classified into two main approaches: the "one-to-one" method, which involves modelling every building within the study area, covering a broad spectrum of its diverse geometric and construction features, and the "archetype-based" method, which focuses on modelling only a representative subset of buildings. The former method has seen increased adoption in recent years, especially for smaller geographies with fewer buildings. This is primarily due to the declining cost of computation, and the advancement and increased availability of accessible building simulation tools (Wang and Zhai, 2016). However, their implementation remains challenging because "one-to-one" modelling requires significant efforts in terms of human and financial resources (Hu et al., 2020). On the other hand, in situations where many buildings need to be assessed using detailed and resource-intensive modelling approaches, developing building archetypes based on statistical analyses of a representative sample is a more feasible alternative to "one-to-one" modelling.

Each archetype embodies a range of characteristics of a particular segment of the building stock, which are often simulated to evaluate performance across a range of similar buildings while managing computational costs. Therefore, archetype-based stock modelling provides a pragmatic and time-efficient approach (Shahrestani et al., 2014; Cerezo Davila et al., 2016) while ensuring that the outcomes obtained adequately reflect the original larger set of buildings and are well-suited for their intended applications, spanning from district and urban energy and environmental modelling to national stock modelling.

Building archetypes are primarily developed through a three-step process involving data preprocessing, segmentation and clustering. First, the building stock dataset is analysed to identify relevant features that are significant in the study context, typically using statistical methods (Famuyibo et al., 2012). Significant features are sometimes transformed depending on the nature of their distribution and the presence of outliers to improve clustering effectiveness (Dong et al., 2023). Second, the selected subset is segmented into homogeneous groups typically based on geography and building characteristics such as age and type. Third, clustering methods are applied on each of the segregated subsets to further divide the sub-population into clusters of building archetypes with similar attributes. The level of segmentation and the selection of clustering technique depends on several factors such as the scope of the analysis, the availability and type of the variables required for modelling, and the computational complexity of the building model.

Ensuring that building archetypes adequately represent the diversity of the building stock is crucial for reliable simulation results. This concept, known as archetype representativeness, refers to the similarity in the distribution of relevant variables between the archetypes and the original building stock data, measured by comparing the total dwelling count across various variables.

1.4 Problem statement

The UK housing stock faces increasing risks of indoor overheating due to climate change, posing challenges to maintaining occupant comfort and reducing cooling energy use. Projections indicate a significant rise in peak summer temperatures by 2080, raising concerns about thermal discomfort and health, particularly in dwellings not designed for warmer climates. While energy efficiency improvements, such as increased insulation and airtightness, have been prioritised to meet carbon emission targets, they may also exacerbate overheating risks by trapping heat indoors during summer. Given the diversity in housing stock characteristics, including variations in construction type, insulation levels, and dwelling forms, overheating risks will not be uniform across all dwellings. Some dwellings, particularly those with high insulation and limited ventilation, may be more vulnerable than others.

Addressing this urgent challenge requires large-scale assessments through building stock modeling, which is essential for capturing the complexity and variability of the UK housing stock, assessing overheating risks at scale and informing effective mitigation strategies. Despite advancements in building stock modeling, the influence of methodological choices on archetype representativeness remains overlooked. Understanding this influence is crucial for developing more representative archetypes that better reflect the diversity of the housing stock and regional variations.

Traditional approaches to archetype development often rely on averaged dwelling characteristics, overlooking the diversity and regional differences in the housing stock, which can lead to oversimplified archetypes that lack representativeness. Large-scale overheating investigations in the UK have frequently used simplified archetypes, such as averaging floor area to define different archetypes, which potentially can misestimate overheating risks in certain dwellings and regions. Given that floor area influences air circulation, variations in dwelling size may influence overheating outcomes. Moving beyond these traditional methods requires adopting more refined methodologies that capture a wider range of dwelling features.

The current state-of-the-art lacks a comprehensive framework for developing representative building archetypes relevant to specific research contexts. The absence of an adaptable framework in this regard can lead to oversimplified archetypes, potentially reducing their usability and the accuracy of simulation results, due to low representativeness. While greater complexity in archetypes does not always lead to more accurate simulations, oversimplification might overlook significant details essential to the building stock. Conversely, overly detailed archetypes can introduce challenges without significantly improving prediction accuracy. The focus should be on achieving an desirable level of stock detail that effectively captures the essential characteristics needed to meet research objectives.

1.5 Research contributions

This research synthesises existing knowledge through a literature review on passive cooling measures and factors influencing indoor overheating. A comprehensive framework was established to describe the potential effectiveness of various passive cooling strategies, considering factors influencing overheating, including climate, material and building design, thereby providing valuable insights for future research and policy development.

A detailed sensitivity analysis of segmentation levels, clustering metrics and variable counts represents another contribution of this research. This investigation provides valuable insights into how different methodological choices influence the representativeness of building archetypes. The findings informed the creation of an archetype development framework.

A central contribution of this thesis is the introduction of the minimum segmentation frequency (MSF) and framework for archetype development that systematically integrates MSF selection. The MSF approach, a unique pre-clustering segmentation step, preserves the feature diversity inherent in the building stock at different levels. The framework guides the development of archetypes a desirable level of representativeness by strategically balancing granularity and scalability, capturing essential variations in the housing stock while remaining feasible for large-scale simulations.

The archetypes developed using the MSF approach within the framework were tested through dynamic thermal simulations, demonstrating their ability to replicate established overheating and cooling patterns across different UK regions and dwelling types. Their capacity to capture regional and typological variations in overheating risk makes them a reliable tool for assessing the thermal resilience of the housing stock under current and future climates. Additionally, the application of a Random Forest model to the archetype-derived dataset achieved high predictive accuracy across different typologies, highlighting the MSF-driven archetypes' ability to preserve and leverage the inherent diversity of the housing stock. These findings reinforce the applicability of the MSF approach in building stock modelling, demonstrating its potential for scenario testing, policy development and targeted mitigation strategies aimed at reducing overheating risks in dwellings.

1.6 Research questions

1. What are the primary determinants of overheating in the UK housing stock ?
2. Among various passive cooling measures, which appears most suitable for mitigating overheating risks across a range of influencing factors ?
3. How does methodological choices influence building archetype representativeness, and what recommendations can be made for developing representative archetypes ?
4. Can the developed archetypes, when used in dynamic thermal simulations, reflect typical patterns of overheating risk and the cooling potential of a passive measure such as external shutters ?

1.7 Aim and objectives

The aim of this study is to construct a framework for representative archetype development and assess the ability of the resulting archetypes to investigate overheating risk in the UK housing stock. The study is structured around several key objectives that address both the theoretical and practical aspects of overheating risk and building archetype development. The objectives are as follows:

1. Review existing literature on factors contributing to overheating risks and passive cooling strategies to reduce risks.
2. Investigate previous works on building archetype development.
3. Conduct sensitivity analysis to investigate changes in archetype representativeness.
4. Develop building archetypes from the English Housing Survey.
5. Investigate whether the data variation in developed archetypes provides sufficient accuracy through Random Forest, then analyse variation in degree hours across different scenarios.

1.8 Hypothesis

Archetypes developed using the proposed framework, informed by a pre-clustering segmentation approach termed the minimum segmentation frequency, can replicate established overheating patterns, such as regional and dwelling type variations, and reflect the cooling impact of a passive measure, such as external shutters. This validation supports their applicability for large-scale overheating assessments and informs future studies on archetype-based thermal risk analysis.

1.9 Thesis flow and outline

This thesis contains seven chapters, starting with an introduction that sets the background and outlines the research problem, followed by a comprehensive literature review and a detailed methodology. Subsequent chapters discuss the results from various investigations. Figure 1.2 illustrates the context, research questions, objectives and corresponding findings, with references to specific chapters where each finding is discussed. The relationships between each research objective and research question are also highlighted, providing a clear overview of the structured approach taken throughout the study. The chapters are summarised as follows:

- Chapter 1 introduces the background and importance of the research, highlighting the increasing risks of indoor overheating due to climate change, the rising demand for passively cooled buildings, the challenges of overheating in the UK housing stock and the need for building archetypes for stock modelling. The chapter also provides the research questions, aims, objectives and hypothesis.

- Chapter 2 presents the literature review on the influencing factors of indoor overheating and suitable passive cooling measures to reduce overheating risks. This is followed by previous works on archetype development to inform the methodology adopted for creating archetypes for the subsequent overheating simulation.

- Chapter 3 describes the methodology adopted to develop building archetypes for overheating simulations. It covers the data preparation, variable selection, segmentation and clustering processes to create archetypes for the study. The characterisation of the developed archetypes follows this, providing the thermal zoning approach, constructional and architectural characteristics, and weather files to create them.

- Chapter 4 demonstrates a sensitivity analysis of archetype representativeness considering segmentation level, clustering evaluation metric and variable count. The chapter discusses findings from the sensitivity analysis and leverages the results to inform a comprehensive framework for archetype development, considering overarching factors such as geographical and temporal scales, computational cost and research focus.

- Chapter 5 provides the methodological choices considered for developing the archetypes used for the overheating investigation. Moreover, the model validation results is provided for the overheating investigation by considering the ratio of the mean indoor temperature for the living room and bedroom to the mean external temperature.

- Chapter 6 presents the results and discussion of the dynamic thermal simulations conducted on the developed archetypes. The chapter concludes by contextualising these findings within broader literature on overheating mitigation and validating the archetype framework's utility for large-scale thermal resilience assessments.

- Chapter 7 concludes the research by revisiting each research question, providing justification for the study and highlighting its contributions to knowledge. The chapter also addresses the research limitations and proposes directions for future work.

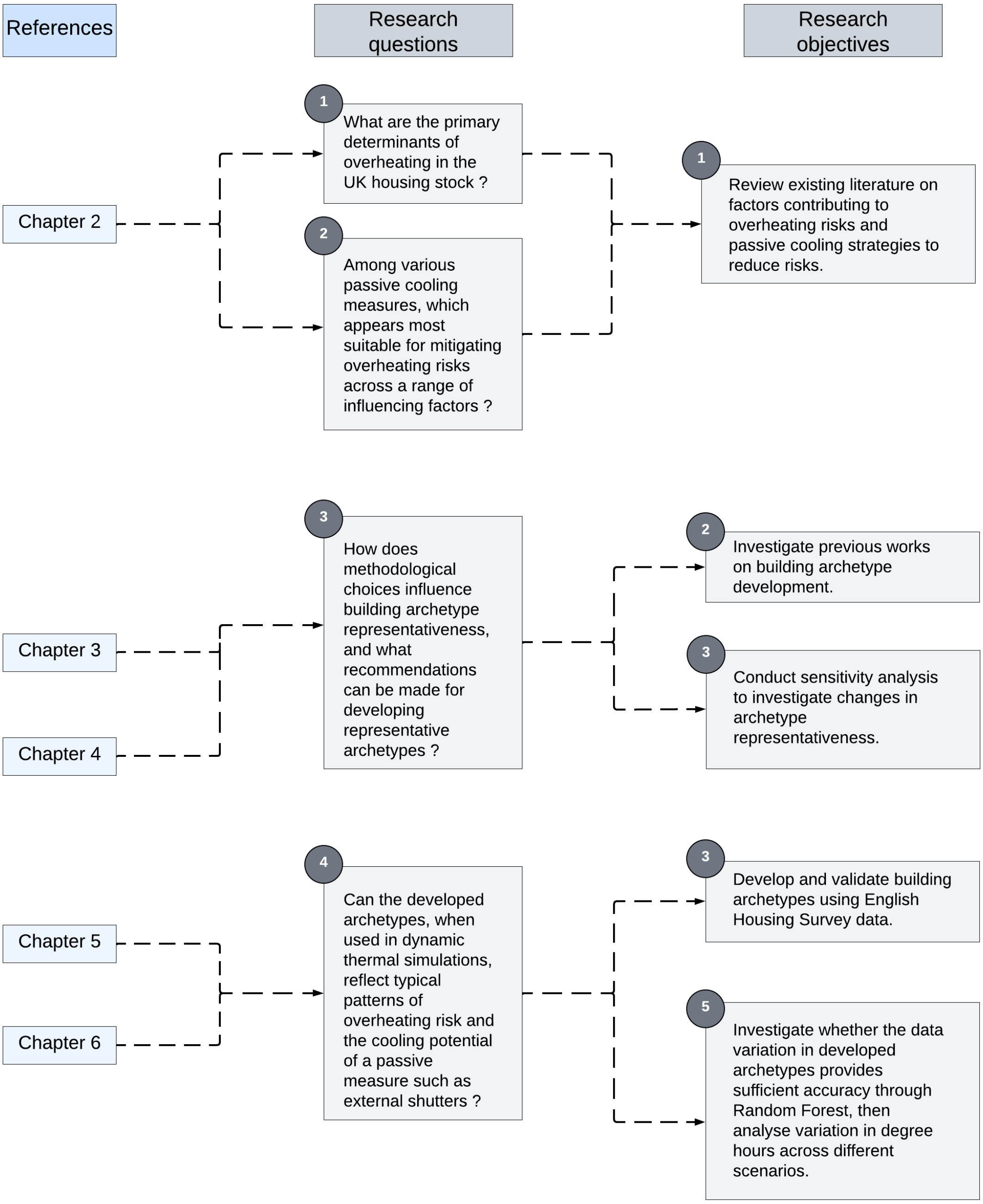


Figure 1.2: Schematic representation of thesis structure and flow.

Chapter 2 | Literature review

This chapter presents an in-depth review that establishes the theoretical framework required to achieve the research objectives of this thesis. It focuses on two primary themes: overheating and building stock modelling. It provides a comprehensive examination of the factors that influence overheating, including building design, climate and occupant behaviour. Additionally, strategies for preventing overheating are discussed. The chapter then covers studies that used building archetype models for large-scale investigations, with the aim of understanding the modelling methodologies used to develop building archetypes and test their applicability to be used for large-scale overheating analysis.

2.1 Background

Building regulations in the UK have increasingly prioritised energy efficiency following the oil crises of the 1970s, leading to stricter insulation standards by the 1990s to reduce energy consumption and carbon emissions. While these measures reduced winter heating demand, they have also increased overheating risk in some dwellings. This challenge is now exacerbated by a warming climate, making airtight, insulated dwellings increasingly difficult to keep cool without additional interventions.

Since 1960, the United Kingdom has experienced a consistent warming trend, with summer temperatures rising at approximately 0.28°C per decade and winter temperatures by 0.23°C per decade (Met Office, 2011). This pattern highlights the growing impact of climate change, which has not only increased average temperatures but has also led to more frequent and intense heatwaves. Consequently, global climate trends have exacerbated the challenge of indoor overheating, pushing temperatures beyond previously recorded limits. Historically, the UK had only moderate summer heat, but recent years have seen increasingly extreme weather events (Perry et al., 2022).

The link between climate change and indoor overheating has become increasingly evident since the late 20th century. The Intergovernmental Panel on Climate Change (IPCC) (Seneviratne et al., 2021) has repeatedly warned of more frequent extreme weather events, such as heatwaves, as global temperatures rise. The UK experienced record temperatures during the 2003 heatwave, reaching 38.5°C in Brogdale, Kent (Met Office, 2011). The 2018 summer was one of the warmest in UK history, comparable to 2006, 2003, and 1976, and ongoing climate change has increased the likelihood of similarly hot summers to an estimated 12% to 25% (Met Office, 2022). More recently, the external temperature reached 40.3°C Coningsby, Lincolnshire (Zachariah et al., 2022).

Heat-related deaths are projected to become more common as rising external temperatures, driven by climate change, continue to pose severe health risks, especially during heatwaves. Hajat et al. (2014) demonstrated that extreme heat is associated with increased mortality rates, a trend observed in multiple UK heatwaves. If current trends continue, the number of heat-related deaths in the UK could increase to 7,040 per year by 2050 (Arbuthnott and Hajat, 2017). Further analysis indicates that over the 35-year period from 1988 to 2022, approximately 51,670 deaths in the UK and 2,186 deaths in Wales were associated with the hottest days (Office for National Statistics, 2022).

Addressing the growing risk of overheating requires both immediate and long-term adaptation measures. Strategies such as retrofitting older buildings with improved ventilation and incorporating external shading are essential for reducing indoor temperatures. The introduction of new regulations, like the updated Part O of the Building Regulations (Department for Levelling Up, Housing and Communities, 2021), represents progress in minimising overheating risks in new constructions. However, the large number of existing dwellings to tackle remains a challenge. Policymakers and stakeholders must prioritise comprehensive, scalable solutions that ensure thermal comfort. To support these efforts, guidelines such as CIBSE TM52 (Chartered Institute of Building Services Engineers, 2013) and TM59 (Chartered Institution of Building Services Engineers, 2017) have been introduced to set thresholds for indoor thermal comfort and establish methodologies for assessing overheating risk.

2.2 Overheating assessment methods

Specialised evaluation methods, like CIBSE TM59 (CIBSE, 2017) and TM52 (CIBSE, 2013), are often used to evaluate overheating risks. Furthermore, they are referred to as adaptive assessment methods because they evaluate the ability of occupants to adjust to fluctuating temperatures, considering the outdoor climatic conditions. Conversely, CIBSE Guide A (Chartered Institution of Building Services Engineers, 2006) employs a static approach that uses fixed temperature thresholds to determine overheating, regardless of external weather conditions or building occupancy patterns. Consequently, it does not consider the occupants' ability to adapt.

CIBSE TM59 (CIBSE, 2017) offers an approach specifically for evaluating overheating risk in domestic buildings. It is based on two main criteria: 1) the number of hours during which the indoor operative temperature exceeds T_{max} by 1°C or more shall not be more than 3% of occupied hours; 2) the bedroom operative temperature should not exceed 26°C for more than 1% of the annual bedroom occupied hours.

The British Standard EN 15251 (BSI, 2007) establishes adaptive comfort temperatures for various categories of buildings and occupants, providing a degree of flexibility in temperature thresholds. Based on Equation 2.1, this standard divides deviations from the adaptive comfort temperature to the outdoor running mean temperature into three groups: high, normal and acceptable. Each group allows a different amount of deviation. A deviation of ±2K is permitted for sensitive groups, such as the elderly or infirm (high); for new constructions or renovations, the range is ±3K (normal); and for existing buildings, a deviation of ±4K is acceptable.

$$T_{\text{rm}}(^{\circ}C) = \frac{(T_{\text{od-1}} + 0.8T_{\text{od-2}} + 0.6T_{\text{od-3}} + 0.5T_{\text{od-4}} + 0.4T_{\text{od-5}} + 0.3T_{\text{od-6}} + 0.2T_{\text{od-7}})}{3.8} \tag{2.1}$$

- $T_{\text{od-1}}$ is the daily average of the external temperature for the day before.
- $T_{\text{od-2}}$ is the daily average of the external temperature for 2 days before.

CIBSE TM52 (CIBSE, 2013) applies thresholds from BS EN 15251 (BSI, 2007) to determine the maximum allowable temperatures for investigating overheating in buildings. This method defines overheating by evaluating the frequency of overheating occurrences, the intensity of this overheating and the daily temperature thresholds that are exceeded.

A comprehensive environmental design guide, CIBSE Guide A (CIBSE, 2006) includes benchmarks for thermal comfort and indoor air quality. The guide establishes specific temperature thresholds to identify overheated spaces. For example, living areas must not exceed 28°C for more than 1% of the year, and bedrooms must not exceed 26°C for more than 1% of the occupied hours of the year.

The industry-standard method for assessing dynamic thermal simulations is CIBSE TM59 (CIBSE, 2017), as required by Part O (Department for Levelling Up, Housing and Communities, 2021) of the building regulations. A comprehensive framework for evaluating overheating is provided by the integration of criteria from both CIBSE TM52 (Chartered Institute of Building Services Engineers, 2013) and Guide A (Chartered Institution of Building Services Engineers, 2006). From TM52, it employs the criterion that is based on the frequency of overheating occurrences. This criterion states that the number of hours during the summer season (May to September) in which the difference between the operative and maximum temperature (ΔT) exceeds 1°C should not exceed 3% of the occupied hours. It is important to note that the maximum temperature limits established by TM52 are influenced by the adaptive threshold limits of BS EN 15251 (BSI, 2007), which are delineated in Equations 2.2 and 2.3. Category I and Category II are applicable to occupants with normal expectations and vulnerable occupants, respectively. It incorporates the static temperature threshold for bedrooms from Guide A. The dynamic and static criteria specified in these standards must be met by a zone to be classified as not overheated, thus protecting against overheating-related risks.

$$T_{\text{max}}(^{\circ}C) = 0.33T_{\text{rm}} + 20.8 \tag{2.2}$$

$$T_{\text{max}}(^{\circ}C) = 0.33T_{\text{rm}} + 21.8 \tag{2.3}$$

2.3 Part O building regulations

Due to rising global temperatures, the housing stock is facing an increasing challenge in maintaining indoor thermal comfort without relying on mechanical ventilation to an excessive extent. This dependence can potentially increase energy consumption and carbon emissions, thereby emphasising the relevance of passive cooling strategies. In the past, building regulations primarily focused on heat retention. Nevertheless, the apparent consequences of climate change prompted enforcing regulations specifically designed to reduce temperature. In the UK, this issue is addressed through Part O of the Building Regulations (Department for Levelling Up, Housing and Communities, 2021), which sets requirements to manage and reduce indoor overheating.

Two methods can be employed to demonstrate compliance with Part O (Department for Levelling Up, Housing and Communities, 2021). The initial approach is the simplified technique, which offers a simple solution to the requirements. The second approach is the dynamic thermal modelling method, which is consistent with the principles outlined in CIBSE TM59 (CIBSE, 2017). This procedure provides a more comprehensive evaluation of a building's thermal performance.

The primary goal of Part O (Department for Levelling Up, Housing and Communities, 2021) is to promote the development of building designs that are naturally designed to reduce solar heat gain accumulation. This can be accomplished by optimising window placement, adopting shading devices and improving ventilation systems. Mechanical cooling solutions are considered the last option and are only implemented when other methods are insufficient to preserve thermal comfort.

2.4 Health effects

Overheating in residential buildings threatens the health and overall well-being of occupants. Elevated indoor temperatures have health consequences, including an increased risk of pre-existing health conditions and increased mortality rates. Excessive heat can cause significant distress, and in severe cases, it can lead to life-threatening conditions (Fanger, 1970). Armstrong et al. (2011) has demonstrated a relation between excessive mortality and unusually high temperatures. In a study of all fatalities in UK and Wales from 1998 to 2007, Brown et al. (2010) discovered an important relationship between temperature increases and the number of deaths. Similarly, Bull and Morton (1978) reported an increase in mortality rates when the ambient temperature exceeded 20°C.

High indoor temperatures can considerably disrupt sleep, crucial for maintaining optimal health and productivity (Okamoto-Mizuno and Mizuno, 2012). The body's ability to regulate its temperature is hindered by elevated bedroom temperatures, which leads to difficulties in maintaining sleep (Harding et al., 2019). Sleep deprivation, which has been linked to a variety of health issues and decreased productivity, may result from this disturbance.

Moreover, high indoor temperatures have a significant impact on vulnerable populations, resulting in an increase in health conditions and a rise in mortality rates. The prevalence of heat-related illnesses results in a substantial rise in hospital admissions during heat waves. During periods without heat waves, the range of admissions is 0.05% to 4.6%, while the spike in admissions ranges from 1% to 11% for each degree of temperature increase (Santamouris, 2020). A substantial social impact was experienced in Greater London during the 2003 heatwave. The number of excess fatalities increased by 44.7% among individuals aged 75-84 and by 33.3% across all age groups (McGregor et al., 2007).

2.5 Monitoring indoor temperature

The 2017 Energy Follow Up Survey (EFUS) (EFUS, 2021a) provides comprehensive data on indoor temperatures in 750 UK dwellings. Overheating was characterised by indoor temperatures that exceed the acceptable level of thermal comfort for more than 3% of the time the room is occupied. Overheating was found to be more prevalent in flats, with 30% of living rooms affected, as opposed to 12% in homes. There are substantial regional disparities, as 28% of households in London report experiencing excessive heat in their living rooms, while only 13% of homes in other regions report the same issue. The incidence of overheating was substantially higher in bedrooms than in living rooms. This finding is consistent with a previous meta-analysis of indoor temperatures in new builds, retrofits, and existing dwellings (Gupta et al., 2019), which showed that bedrooms had higher temperatures than living rooms. The adaptive thermal comfort requirements were exceeded in approximately 19% of UK dwellings' primary bedrooms. Furthermore, a substantial 69% of bedrooms were classified as overheated when the static overheating threshold of 26°C was considered. It is important to acknowledge that the investigation specifically focused on households experiencing fuel poverty, potentially affecting the recorded temperatures. These households may exhibit unique heating and cooling behaviours as a result of financial constraints.

Two of the most extensive monitoring studies on summertime temperatures within UK dwellings are by Beizaee et al. (2013) and Lomas and Kane (2013), which offer important insights into the prevalence of indoor overheating. During the cool summer of 2007, Beizaee et al. (2013) conducted face-to-face interviews in 207 homes across UK. They recorded temperatures and discovered that 72% of living rooms and bedrooms experienced temperatures below the Cat II lower threshold for more than 5% of the time. This is indicative of generally cool temperatures according to the BSEN15251 adaptive thermal comfort model (BSI, 2007). Nevertheless, modern dwellings were significantly warmer, and 21% of bedrooms exceeded 26°C for over 5% of the nighttime hours when using static criteria. Lomas and Kane (2013) monitored 268 Leicester dwellings during the summer of 2009. They found that, despite that the majority of rooms were deemed excessively cool by adaptive criteria, 15% of bedrooms experienced overheating for more than 30% of the summer when a fixed 26°C threshold was applied. These findings are consistent with the prior research conducted by Wright et al. (2005), which documented high temperatures exceeding 36°C in living rooms and bedrooms during the 2003 heatwave in London and Manchester.

The internal temperatures of 101 London dwellings were monitored by Mavrogianni et al. (2017) in August 2009, with a particular emphasis on the living and sleeping zones. As per the data, the average daytime temperature in living rooms was 23.1°C, with a peak temperature of 26.1°C. The average mean nighttime temperature in bedrooms increased slightly to 23.4°C, with the highest recorded temperature being 26.2°C. In addition, Pathan et al. (2017), which monitored temperatures in London, provided additional evidence of the overheating risk. The research presents the results of a monitoring investigation of overheating in 122 London dwellings during the summers of 2009 and 2010. The optimal indoor comfort temperature was determined by utilising the ambient temperature in the adaptive thermal comfort method for The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 55. More than 1% of the summertime occupied hours in 29% of all living rooms and 31% of all bedrooms monitored during 2009 fell outside the comfort zone recommended by the standard to achieve 90% acceptability. During the summer of 2010, 37% of the monitored living rooms and 49% of the monitored bedrooms were occupied for more than 1% of the time outside of this comfort zone.

McGill et al. (2016) conducted a meta-analysis of summertime temperatures in newly built dwellings across various regions. Their findings indicate that 57% of bedrooms and 75% of living rooms exceeded overheating thresholds, with indoor temperatures surpassing 25°C for more than 5% of annual occupied hours. Additionally, 30% of living rooms exceeded the adaptive comfort threshold, with temperatures remaining at least 1K above this limit for more than 3% of occupied hours. The widespread prevalence of overheating in both living rooms and bedrooms underscores the need for improvements in building standards and design practices to effectively mitigate overheating risks.

These studies collectively emphasise the significant risk of overheating in UK dwellings, encompassing both modern and old dwellings. The prevalence of overheating in both living rooms and bedrooms is significant, with the latter being at the greatest risk, as revealed by the EFUS (EFUS, 2021a) and extensive research by Beizaee et al. (2013), Lomas and Kane (2013), Mavrogianni et al. (2017) and Pathan et al. (2017). The results of McGill et al. (2016) further emphasise that the current building standards and design practices may not be sufficient to guarantee thermal comfort, particularly in new constructions. The consistent evidence of high temperatures disrupting sleep and exacerbating health issues underscores the urgent requirement for effective cooling strategies and building designs that counteract the effects of overheating.

2.6 Thermal zoning

Thermal zoning is the process of dividing a building into separate zones with individually controlled heating and cooling systems. This is essential for effectively managing energy consumption and guaranteeing the best possible thermal comfort for occupants. Establishing zoning simplicity is essential, mainly when conducting simulations that include numerous dwellings, as observed in national scale evaluations. The number of zones and the level of zoning complexity directly influence the amount of time required for simulating the building model. A literature review conducted by Shin and Haberl (2019) revealed that there are presently no explicit thermal zoning rules but rather general recommendations and considerations.

The Building Research Establishment Domestic Energy Model (BREDEM) (Dickson et al., 1996) provides a per-floor approach to zoning within the framework of UK building standards. Typically, one level is designated for the living room and another for the bedrooms. Several of the UK's commonly used housing stock models are derived from the BREDEM (Badiei, 2018), highlighting its essential role in national energy modelling methodologies. Conversely, the SAP (Standard Assessment Procedure) (Building Research Establishment, 2021) simplifies the thermal zoning by separating the living room from all other rooms and combining them into a single zone. Given the vast number of dwellings that are considered, these simplified zoning methods are suitable for large-scale studies.

Taylor et al. (2013) demonstrated that the computed annual energy demand was within a 10% difference when the built form was based on the actual dimensions, window frames were included and living rooms were separated. Heo et al. (2018) further underscored the importance of thermal zoning. The annual heating demand predictions were significantly underestimated by 17% and 26% when the number of thermal zones was reduced to one per floor and subsequently to a single zone for the entire dwelling.

A rectangular zoning method based on width-to-depth ratio was used by Swan et al. (2013) to simulate 16,952 Canadian dwellings. This method combined all habitable rooms within dwellings into a single thermal zone. The separate floors of the main area were not distinguished but instead merged into a single thermal zone. This approach has similarities to the one employed in the Canadian Residential Energy End-use Model (CREEM) (Farahbakhsh et al., 1998). Due to the insufficient geometrical details in the original datasets, a major obstacle in large-scale thermal modelling works, simplification was necessary.

Badiei (2018) investigated three different zoning strategies: a single zone strategy, a two-zone strategy with separate thermal zones for each floor of the dwellings (floor zoning) and a two-zone strategy with one thermal zone allocated to the living area and another to the rest of the dwelling, similar to SAP zoning (Building Research Establishment, 2021). The results indicated that the floor zoning approach was closest to the reference model in terms of space heating demand. Following an assessment of the internal temperatures and space heating demand estimates of the three zoning approaches, it was concluded that the floor zoning strategy is the most suitable for representing the dataset. Therefore, it is crucial to select appropriate zoning methods that achieve a balance between precision and computational practicality in energy modelling.

These studies underscore the importance of incorporating effective thermal zoning into building models to estimate indoor temperature and energy consumption adequately. The methodologies implemented in BREDEM (Dickson et al., 1996), SAP (Building Research Establishment, 2021), and the CHREM (Farahbakhsh et al., 1998), as well as the research conducted by Taylor et al. (2013) and Heo et al. (2018), demonstrate that simplified zoning techniques, such as the separation of living areas from other zones or the use of a floor-based zoning strategy, can achieve a satisfactory level of accuracy without necessitating many computational resources. Conducting practical and efficient national-level assessments would be advantageous by concentrating on critical areas within buildings, such as living rooms and main bedrooms, where controlling the temperature is the highest priority give higher occupancy rates in the spaces.

2.7 Overheating influencing factors

2.7.1 Occupancy

Occupant behavior significantly influence overheating risk in homes. While the primary focus often lies on building design and materials, how people use a space plays a crucial role in heat gain and indoor thermal comfort. Implementing strategies to manage occupancy-related heat generation is crucial for maintaining thermal comfort within the building. The number of occupants and their activities directly contribute to internal heat gain (Climate Change Committee, 2022), making enhanced management strategies essential to effectively control indoor temperatures and ensure comfort.

In addition to the number of occupants, occupancy factors that increase the risk of overheating include occupants' vulnerability, building use and thermal comfort perception. The elderly are most vulnerable to overheating (Lomas and Porritt, 2017) because of their lack of mobility, which could limit the use of passive cooling measures such as natural ventilation (Fletcher et al., 2017). Occupant behaviour influences overheating risks by altering the use of the adopted passive cooling measures and consequently their effectiveness (Porrit, 2012; Vellei et al., 2017; Petrou et al., 2019; Ozarisoy and Elsharkawy, 2019). Morgan et al. (2017) found that occupants who used programmed ventilation did not report overheating within 26 dwellings, whereas 46% of occupants did not understand or use programmatic controls, resulting in varying overheating levels amongst dwellings. Ridley et al. (2013) discovered that occupants' lack of operational knowledge of their louvres and exterior blinds contributed to increased solar heat gains during the summer. Baborska-Narożny et al. (2017) found a 70% variation in overheating levels across 18 monitored flats adopting different ventilation practices; the household with the lowest risk of overheating efficiently used mechanical ventilation. These findings inferred that occupants lack awareness of how systems and passive cooling measures could significantly contribute to increased overheating levels indoors. Petrou et al. (2019) showed that when the number of occupants was increased, the internal mean temperature was increased in the bedrooms but not in the living rooms. Possibly owing to the limited sample size, the findings for five and six occupants were not statistically significant.

Occupants must adopt passive cooling strategies to decrease the use of mechanical cooling and to abide by the UK's carbon emission targets for 2050 (Gupta and Gregg, 2020). Avoiding mitigation strategies may result in a drive to acquire mechanical cooling systems, as happened during the 2003 heatwave (Wright et al., 2005). According to Peacock et al. (2010), people in the UK may not be as willing to use air-conditioning units as in the US, but factors such as cheap operation and capital costs may encourage them. If UK occupants mimic US occupants' behaviours, 550,000 London residences would have air-conditioning units installed by 2030. This estimate is likely to increase beyond 2030 because of a warming climate.

Meinke et al. (2017) investigated occupants' cooling preferences; fewer participants kept air-conditioning as their first choice once informed about the associated energy use. This finding implies that some individuals may not be aware of the causes of climate change or, more precisely, how their use of mechanical cooling may contribute to global warming. Nonetheless, this finding should be considered carefully because of the small number of occupants (n = 5) who chose to save energy. Moreover, occupant perception of different passive cooling technologies was not considered. A more profound knowledge of adaptive behaviour and passive cooling efficiency, as suggested by Murtagh et al. (2019), can help society in mitigating the effects of climate change.

2.7.2 Internal heat gains

Internal heat gains are a critical factor contributing to overheating in residential buildings, originating from various sources as illustrated in Figure 2.1. Collectively, sources of internal heat gains contribute to the thermal environment within buildings. By understanding and quantifying these contributions, mitigation strategies can be developed to reduce overheating risks (Chen, 2019), such as improving building fabric and ventilation. These sources include:

- Occupant metabolic heat: Heat emitted by occupants through daily activities.
- Electrical appliances and lighting: Heat produced from every household equipments and lighting systems.
- Cooking: Heat generated during food preparation.
- Mechanical systems heat gain: Heat produced by systems such as HVAC units.

Previous research has demonstrated that internal heat gains influence overheating levels, with impacts being more pronounced in living rooms. This may be more common in flats where an open floor plan is more likely to be used, especially for the kitchen, dining and living areas. Peacock et al. (2010) established three distinct energy usage scenarios for appliances and cooking to analyse the effect of internal heat gains on overheating risk: scenario A (5682 kWh), scenario B (5064 kWh) and scenario C (5906 kWh). The research demonstrated that scenario C had more occupied overheating hours than scenarios A and B by 0.5% and 2.5%, respectively. The study highlights the effect of internal heat gains on internal temperatures, despite modest differences in electricity consumption, as a scenario with more tenants and greater electricity consumption may reveal a greater difference.

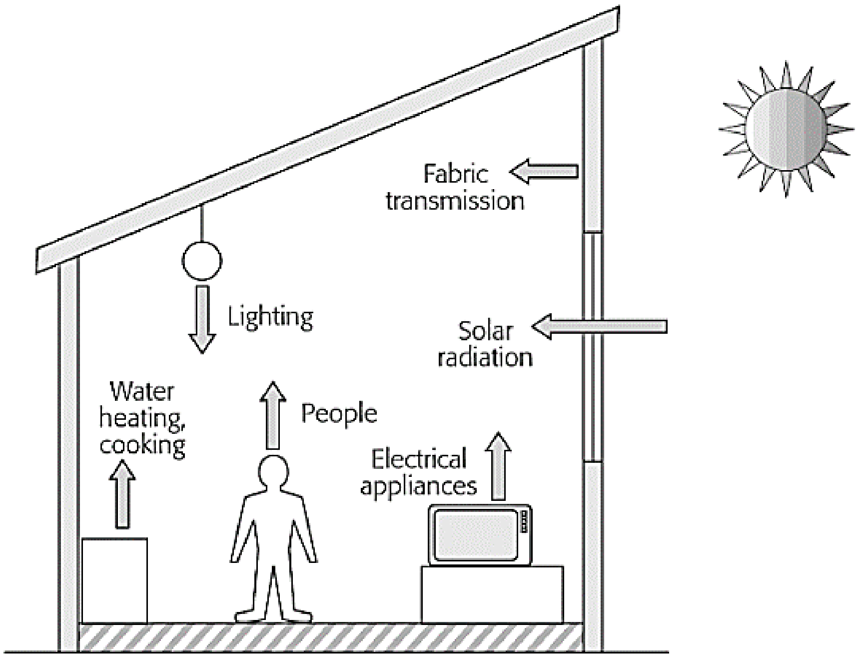


Figure 2.1: Sources of internal heat gains within a dwelling, from (Tamizharasan and Senthilkumar, 2018).

2.7.3 Construction

Different construction types play a crucial role in determining the thermal performance of buildings and their susceptibility to overheating. Older dwellings, particularly those built before the 1980s, often feature less insulation, making them less likely to overheat compared to newer, well-insulated constructions. These older buildings typically have solid walls that lack cavity insulation, which, while less energy-efficient in winter, can help dissipate heat more effectively in summer. However, the absence of solar shading (Gupta and Gregg, 2012; Vellei et al., 2017; Petrou et al., 2019; Baborska-Narożny et al., 2017; Hacker et al., 2005; Toledo et al., 2016), and the presence of excessive glazing area (Orme et al., 2003; Gupta and Gregg, 2012) could increase the risk of overheating. While dwellings constructed post-1980 often have the increased insulation standards aimed at improving energy efficiency for winter heating, which inadvertently exacerbate overheating risks in summer. Moreover, cavity insulated dwellings, which became more common in recent decades, tend to retain heat more than solid-walled dwellings, placing them at a higher risk of overheating.

Willand et al. (2016) estimated that an additional 15.84 kWh/day of cooling energy was required to keep the living room in a 6-star dwelling at the temperature of a 3-star dwelling, where the star rating reflects the energy efficiency of Australian dwellings. Similarly, Sajjadian et al. (2015) projected that the cooling load in a Passivhaus detached dwelling in London in the 2080s would be 14 times that in 2011, highlighting the need for effective summer cooling strategies.

Several studies have identified south glazing as an overheating factor in Passivhaus dwellings (McLeod et al., 2013; Ridley et al., 2013; Dan et al., 2016), where either solar shading (McLeod et al., 2013; Dan et al., 2016) or glazing ratio modification (McLeod et al., 2013) will be needed to minimise overheating risks. In addition, the Passivhaus overheating criteria could be modified to assess thermal comfort and account for occupants; occupants did not report thermal discomfort in overheated dwellings (Ridley et al., 2013; Dan et al., 2016). Post-occupancy resident training on building systems and efficient ventilation strategies (Fletcher et al., 2017) are also recommended to reduce overheating risks in Passivhaus dwellings.

The findings in Table 2.1 indicate that highly insulated dwellings, including Passivhaus dwellings, are susceptible to overheating, particularly in the absence of effective shading or ventilation strategies. This is especially relevant as Part L of the UK Building Regulations recommends high insulation standards for newly built dwellings to improve energy efficiency, which may unintentionally increase overheating risks if not complemented by appropriate passive cooling measures. The studies reviewed demonstrate how factors such as orientation and occupant behaviour influence overheating severity in insulated dwellings. Moreover, the findings highlight that highly insulated structures respond differently across regions, as variations in climate, solar exposure and ventilation potential affect their thermal performance. Therefore, understanding indoor thermal dynamics in highly insulated dwellings is essential for refining building regulation recommendations to ensure that energy efficiency improvements do not compromise thermal comfort.

Table 2.1: Findings on overheating in Passivhaus dwellings.

Reference	Dwelling type	Location	Methodology	Main findings
Hidalgo-Betanzos et al. (2015)	Detached	Spain	Monitoring	The dwelling passed the TM52 overheating criteria but not the Passivhaus criteria (11.4% over 25ºC).
McLeod et al. (2013)	End-terrace	UK	Modelling	Solar shading and the modification of glazing ratios effectively reduced overheating risks in the rooms with south-facing windows.
Ridley et al. (2013)	Detached	UK	Monitoring, Modelling	The dwelling overheated in the summer, but the occupants reported no thermal discomfort.
Sameni et al. (2015)	Flat	UK	Monitoring	Regression analysis indicated that occupancy is the most influential factor in reducing overheating risks.
Fletcher et al. (2017)	End-terrace	UK	Monitoring	Overheating occurred during the cold months and night-time.
Mlakar and Štrancar (2011)	Detached	Slovenia	Modelling	Solar shading and natural ventilation provided thermal comfort in a hot and humid climate.
Ridley et al. (2014)	Detached	UK	Monitoring	Each dwelling's susceptibility to overheating risk was influenced by its south oriented windows.

Reference	Dwelling type	Location	Methodology	Main findings
Colclough et al. (2018)	Semi-detached	UK	Monitoring	Post-occupancy engagement is determined to be the key to understanding the thermal behaviour of highly insulated dwellings and improving occupant behaviour.
Mitchell and Natarajan (2019)	Flats and houses*	UK	Monitoring	Fewer bedrooms passed the Passivhaus overheating criteria when applied at room level and not building level.
Figueiredo et al. (2016)	Detached	Portugal	Monitoring, Modelling	Passivhaus construction is found to be feasible in the southern European climate, but different parts of the region could need different passive solutions to overcome overheating.
Sage-Lauck and Sailor (2014)	Semi-detached	USA	Monitoring	Phase change material (PCM) in semi-detached flats reduced overheating hours from 400 to 200 h.
Dan et al. (2016)	End-terrace	Romania	Monitoring, Modelling	The occupants were unconcerned despite their dwelling failing the overheating criteria.

2.7.4 Design

The section delves into how the geometrical layout of interior and exterior surfaces plays a critical role in residential overheating. It explores various architectural elements and dwelling orientations that impact thermal comfort, examining both empirical studies and theoretical perspectives. This section highlights how specific design choices, from floor plans to window orientations, influence heat accumulation and air circulation patterns, thereby affecting the overall thermal behavior of residential spaces.

2.7.4.1 Orientation

Indoor temperatures can be directly influenced by the direction of a building, which can considerably affect the amount of solar heat gain it receives. During the peak summer months, different orientations can expose different building sections to more intense and prolonged sunlight. Furthermore, the direction of the prevailing wind is a critical factor in natural ventilation, which can be used to cool internal zones. Cross-ventilation can be improved by orienting buildings to capitalise on the prevailing cool breezes, thereby minimising the risk of overheating. As a result, it is imperative to understand the implications of both wind direction and solar exposure to develop effective passive cooling strategies and reduce the risk of overheating.

Gupta and Gregg (2012) found that west-facing flats had more overheating hours than south-facing flats by 22%. Espinosa et al. (2019) found that reduced glazing on the southwest orientation reduces overheating risks significantly, meaning that the south and west windows of flats are extremely sensitive to overheating. Habitzreuter et al. (2020) showed that south-southwest oriented rooms were prone to overheating due to a lack of shading from nearby buildings. In addition, Dengel and Swainson (2012) discovered that southwest orientation posed a bigger risk of overheating in flats. Overall, the findings indicate that certain orientations make spaces more susceptible to overheating.

2.7.4.2 Dwelling type

Different dwelling types tend to have varying exposure levels to external heat gains due to differences in building surface areas. This results in distinct overheating risks for each type of dwelling. For instance, flats, with their compact designs and often limited natural ventilation, tend to be more susceptible to overheating compared to detached houses, which usually have wider exposing surfaces for heat dissipation. Similarly, the specific design elements of each dwelling type, such as window size and placement, insulation levels and construction materials, further influence their thermal performance.

Flats are the most sensitive dwelling type to overheating risks (Beizaee et al., 2013; Lomas and Kane, 2013; Hamdy et al., 2017; Baborska-Narożny et al., 2017; Firth et al., 2010; van Hooff et al., 2014), where the top floors are most vulnerable (Gupta and Gregg, 2020; Orme et al., 2003; Habitzreuter et al., 2020; Capon and Hacker, 2009; Mavrogianni et al., 2015; Quigley and Lomas, 2018). Petrou et al. (2019) showed that converted flats had the lowest internal temperature compared to other dwelling types. On the other hand, Taylor et al. (2018) found that converted flats had the highest internal temperature. Unlike other dwelling types, converted flats have had little research on their internal conditions; thus, more research may be required to confirm their internal conditions. Many studies in the UK have shown that detached dwellings are least likely to overheat (Beizaee et al., 2013; Lomas and Kane, 2013; Firth et al., 2010; Mavrogianni et al., 2017). In a Dutch context, however, Hamdy et al. (2017) found it to be at the highest risk of overheating, along with flats. The difference in conclusions could be due to the architectural arrangement of the dwellings investigated in Hamdy et al. (2017), where the detached dwelling had considerable glazing area. The semi-detached dwelling in Hamdy et al. (2017), reported to be the coolest, did not have as many windows on the sides as the detached dwelling.

2.7.4.3 Living room and bedroom

The internal temperatures and overheating risks in bedrooms and living rooms are influenced by the varying occupancy patterns of these spaces. Bedrooms are often used for rest and sleep, particularly during the night when external temperatures are lower. In contrast, living rooms are occupied throughout the day and evening, resulting in increased internal heat accumulation from activities such as cooking and the use of electronic devices, particularly if they are situated near kitchens. Their placement and function further exacerbate the susceptibility of living rooms to overheating in close proximity to sources of internal heat increases. As a result, distinct temperature thresholds are recommended for each room to manage these variations in heat exposure and usage.

The CIBSE has developed static (CIBSE, 2006) and adaptive (Chartered Institute of Building Services Engineers, 2013; CIBSE, 2017) overheating criteria for bedrooms and living rooms. A lower static threshold criterion makes bedrooms more vulnerable to overheating than living rooms (Beizaee et al., 2013; Lomas and Kane, 2013; McGill et al., 2016). Lomas and Kane (2013) found a statistically significant relationship between the dwelling age and the temperature difference between the bedrooms and living rooms. Beizaee et al. (2013) discovered that living room temperatures were higher than bedroom temperatures in flats and significantly higher than the internal temperature of living rooms in other dwelling types. They also determined dwelling age as an influencing factor on the temperature differences between living rooms and bedrooms. Mitchell and Natarajan (2019) found that 60% of the house bedrooms met the Passivhaus overheating criteria, while 83% of bedrooms in flats did. Petrou et al. (2019) showed that bedrooms were cooler than living rooms in bungalows, converted flats and purpose-built flats. Wright et al. (2005) found that during the 2003 heatwave, some flats in London had marginally cooler bedrooms than living rooms. However, their investigation in Manchester did not include flats and instead focused on detached and semi-detached dwellings, where bedrooms were consistently warmer.

2.7.5 Infiltration

Infiltration, which describes the unintended entry of external air into a building structure through gaps and cracks, substantially affects the quality of indoor air and the energy efficiency of buildings (Younes et al., 2011). Overheating risk can be exacerbated by increased heat absorption from the exterior during hot weather, which can be a consequence of higher infiltration rates. Alternatively, lowering infiltration rates may help maintain cooler indoor temperatures, but they can also impede natural ventilation, essential for removing internal heat gains. In order to accurately model the thermal behaviour of various types of dwellings, it is imperative to consider suitable air infiltration rates. Fan pressurisation tests are typically employed to quantify the air leakage rate at a set pressure difference, typically 50 Pascals (Pa).

By investigating 471 houses and 87 large panel system (LPS) units from the BRE database, Stephen (2000) examined the air leakage rates in the UK dwellings. The research demonstrated that older residences do not generally have higher air leakage rates, which challenges the notion that older buildings inherently have higher air leakge rates. Conversely, the disparities in infiltration rates were considerably more pronounced when different wall constructions were taken into account. Solid masonry, cavity masonry, timber-framed and LPS houses each exhibited unique characteristics in terms of air leakage, underscoring the substantial impact of construction type on infiltration.

2.8 Passive cooling strategies

Passive cooling has been recognised as a sustainable method for reducing cooling demand through heat transfer through conduction, convection and radiation (Al-Obaidi et al., 2014). There are three major types of passive cooling strategies: solar and heat protection, heat modulation and heat dissipation. Most passive cooling research is based on the Mediterranean climate, and recent warming trends suggest that the UK climate will resemble that of the Mediterranean in the future (Zero Carbon Hub, 2015). Therefore, findings from studies of the Mediterranean climate could be a useful predictor of what may occur in the UK in the future.

2.8.1 Heat and solar protection

Solar and heat protection reduces solar heat gains indoors which lowers overheating risks. It is possible to install protections that prevent solar heat gains from entering the building to prevent the temperature inside from rising.

2.8.1.1 Vegetation

Plants on building surfaces provide cooling via evapotranspiration, while their soil layers provide insulation. Dry green roofs have high thermal resistance, which is beneficial for lowering winter heat losses (Zinzi and Agnoli, 2012). Zinzi and Agnoli (2012) investigated green roof cooling in Barcelona, Palermo and Cairo. Barcelona, which receives far more rainfall than Cairo or Palermo during the summer, had the greatest reduction in discomfort hours above 26°C. Gagliano et al. (2014) found that green roofs reduced cooling loads by 80% in Sicily, Italy, for the summer months (June to September). It could be that a green roof may cool a bungalow faster than a two-storey dwelling.

According to Virk et al. (2014), insulated roofs decrease green roofs' cooling effectiveness. However, the research was conducted on a four-storey office building in London, not a dwelling. This finding would likely indicate green roofs' cooling potential if the same investigation was conducted in the domestic sector. Castleton et al. (2010) concluded that the cooling potential of green roofs could be optimised for the UK context by applying it to poorly insulated dwellings. Vegetation can be useful at the neighbourhood level by producing a cooling effect for the microclimate. Previous studies have shown that a decrease in the ambient temperature can be achieved if vegetation is applied at the neighbourhood level (Emmanuel and Loconsole, 2015; Laureti et al., 2018; Battista et al., 2019). New constructions can be subjected to a vegetation requirement, which will result in a sufficient number of dwellings with vegetation per neighbourhood, providing a cooling effect at the neighbourhood level as well as cooling non-vegetated dwellings.

2.8.2 Wall insulation

Increasing the insulation level may increase the risk of overheating (Hamdy et al., 2011; Fletcher et al., 2017; Willand et al., 2016), which could necessitate additional passive cooling measures. Tink (2018) found that internal wall insulation increases the risk of overheating in a semi-detached dwelling in Leicestershire. The authors claim the increased risk of overheating was low for that particular dwelling, location and time. This suggests that if future climate data had been used instead of 2015 temperature data, and a mid-terrace dwelling instead of a semi-detached dwelling was investigated in a different local setting, overheating hours may have been greater. Similarly, Porrit (2012) showed that the increase in overheating risk owing to internally inserted wall insulation was minimal, with the west-facing living room and east-facing bedroom having increased overheating hours. The family occupancy did not experience the increased overheating hours considering the different rooms and orientations. Mavrogianni et al. (2013) found that a dwelling with internally placed wall insulation had a slightly higher internal temperature than a dwelling with externally placed insulation. It can be deduced that internally placed wall insulation tends to slightly increase overheating risk compared to externally placed wall insulation.

2.8.3 Solar shading

External and internal solar shadings have different cooling potentials, with external shading being the better option in most contexts. Tillson et al. (2013) showed that external shadings outperformed dark and light internal shadings in preventing overheating; light-coloured roller and venetian blinds reduced the proportion of overheated housing stock by 27% and 18%, respectively. Porrit (2012) found that external shutters reduced degree hours over 26°C by 39% compared to internal blinds and curtains, which lowered degree hours by 20% and 15%, respectively. Although several studies have identified solar shading as an effective passive cooling strategy for reducing overheating (Dodoo and Gustavsson, 2016; Gupta and Gregg, 2012; Porrit, 2012; Kinnane et al., 2017; van Hooff et al., 2014; Mavrogianni et al., 2014; Psomas et al., 2016; Alders, 2017; Birchmore et al., 2017), its application in the UK may be limited due to the prevalence of outward window openings that external shadings could block (Grussa et al., 2019). In addition, solar shading reduces daylighting, which may affect occupants' productivity and wellbeing. Habitzreuter et al. (2020) found that external shading reduced overheating and daylighting by 74% and 30%, respectively. The effect of decreased daylighting reduces with increasing storeys, as the daylight factor increases. The average daylighting level was nearly the same for a low-rise flat without shading and a high-rise flat with shading. Baborska-Narożny et al. (2017) found that occupants preferred sufficient daylighting over solar heat gains when choosing solar shading. The findings highlight the importance of balancing cooling reduction and daylighting in solar shading design.

2.8.4 Heat modulation

Heat modulation reduces internal temperatures and minimises substantial temperature fluctuations by utilising a building's thermal mass. It differs from heat and sun protection in that it works when internal and external heat gains are present. In a warm climate, heat modulation may not be able to release stored heat and absorb additional heat, causing heat build-up.

2.8.4.1 Thermal mass

Thermal mass is the property of an indoor material to absorb and store heat over time; this lets the heat escape later and lowers cooling needs at peak times (Orme et al., 2003). Buildings with high thermal mass, such as those constructed from materials like bricks, concrete, and stone, exhibit slower thermal response times. This means they heat up and cool down more gradually compared to buildings with low thermal mass, effectively dampening indoor temperature swings (Peacock et al., 2010). The inherent ability of these materials to store and later release heat helps to shift the indoor heat peaks, thereby aiding in maintaining more constant indoor temperatures.

The integration of thermal mass into building design is increasingly recognized by regulators as a strategy to combat overheating, especially in lightweight constructions that are prone to higher temperature variability (McLeod et al., 2013). The effective use of thermal mass is particularly significant under varying climatic conditions. Research by Jimenez-Bescos (2017) indicated that thermal mass, combined with night ventilation, could significantly reduce overheating in buildings modeled with future climate scenarios, though the effectiveness was less pronounced with historical climate data from the 1970s.

2.8.4.2 Phase change material

Phase change materials (PCMs) are a subcategory of thermal mass that can cool buildings passively. Their cooling performance comes from their capacity to absorb and release heat based on their phase change point, which is determined by their latent heat of fusion. The material transitions from the solid to liquid phase when heat is absorbed. When the indoor temperature decreases at night, the heat absorbed during the day is released until the PCM reaches its melting point and reverts to its solid phase. Phase change material can be incorporated into numerous building components, offering diverse potential for arrangement and composition, which can be useful for different contexts. Phase change material-enhanced wallboards are favourable due to their practicality in being incorporated into the building fabric, lower cost and overall cooling performance (Saffari et al., 2017).

Auzeby et al. (2016) tested PCMs in mid-terrace dwellings in Aberdeen, Newcastle and Southampton using climate data from the 2030s, 2050s and 2080s. The adoption of PCMs reduced domestic overheating in the investigated cities; however, the well-insulated construction was in a greater need of PCMs than the poorly insulated construction. Sajjadian et al. (2015) used the 2020s, 2050s and 2080s climate data to assess PCM's cooling performance in a detached Passivhaus dwelling. Auzeby et al. (2016) and Sajjadian et al. (2015) found that the PCM's cooling efficiency is location and climate dependent, with the southern UK having the slightest decrease in overheating hours. They show that while PCM usage in dwellings may be beneficial until the 2050s, it cannot completely decrease overheating risks in the 2080s. As a result, when the external temperature rises, PCMs require additional passive cooling to maintain their cooling effectiveness. However, Auzeby et al. (2016) only looked at July, ignoring the heating season and the rest of the summer months, which may skew any conclusions based on a single summer month. Moreover, Sajjadian et al. (2015) investigated a Passivhaus dwelling, which has a different thermal environment than traditional dwellings. It may be inferred that different UK regions may require different PCM compositions and arrangements for optimal cooling performance.

The use of PCM has been investigated in other geographic regions. Fernandes and Costa (2009) modelled a standard family dwelling in Portugal to examine the cooling effectiveness of PCMs and showed that PCMs are least effective for southern Portugal. PCM performance varies across Mediterranean and American cities, according to Ascione et al. (2014) and Baniassadi et al. (2019) respectively, with lower performance in hotter cities.

2.8.5 Heat dissipation

The process of releasing excess heat from a building through heat sinks at lower temperatures is referred to as heat dissipation. The method of heat dissipation works in a manner similar to that of heat modulation in that it is effective when heat gains are present within the building for them to be dissipated via convective heat movement, that is, natural ventilation removing excess hot air.

2.8.5.1 Natural ventilation

The movement of air provided by natural ventilation enhances the transfer of heat between the interior and exterior of a building. Depending on the external temperature, it is often used in the evening to draw in fresh air from outside and push out warm air from within the dwelling. Air changes per hour (ACH) is a common way to indicate the air exchange rate between an enclosed internal space and its external environment. The amount of cooling achieved by natural ventilation is subject to variables such as the size of the windows and the ventilation strategy used. Different strategies must be adopted to optimise the use of natural ventilation for different constructions and climates. Shikder et al. (2012) investigated the effectiveness of natural ventilation in Birmingham, Edinburgh, London and Manchester. The authors discovered that London would require the most ACH to prevent overheating. This means more adaptation measures are needed in the south before the 2050s to maintain or improve thermal comfort. Weng (2017) in a follow-up study to Shikder et al. (2012) concluded that nighttime ventilation would be more effective than daytime ventilation in the 2080s. However, depending on the location, using natural ventilation may compromise security. Roetzel et al. (2010) claimed that the potential of window opening to dissipate heat gains could vary depending on its opening type and size. Different results may perhaps be observed for different opening types, with varying effectiveness of nighttime ventilation.

Peacock et al. (2010) adopted a window opening strategy in Edinburgh and London using the 2030s climate. Bedroom windows were left open throughout the night, ignoring noise pollution and security. Other windows in the dwelling were open if occupants were at home and closed at night; all windows were closed if occupants were not present. Edinburgh had nearly no degree hours above 28°C, while London was still at risk with 9.5%–11.5% of overheating hours considering different insulation levels and climates, reduced from 12% to 19%. This might imply that when the climate warms, the difference between the internal and external temperatures will be low, resulting in fewer heat exchanges. Improving the microclimate condition could be a solution to over- come such ineffectiveness. The study also revealed that natural ventilation is more effective for non-insulated dwellings.

2.8.5.2 Cool paint

Cool walls and roofs reflect significant amounts of solar heat gain owing to their albedo value, which decreases the temperature of the microclimate and surrounding interior thermal zone. As a result of its effective cooling in residential and urban settings (Garshasbi et al., 2020; Zhang et al., 2018; Laureti et al., 2018; Battista et al., 2019), cool roof solutions are becoming increasingly popular (Synnefa and Santamouris, 2012). Pisello and Cotana (2014) studied the performance of a cool roof on a residential building in Italy. In the summer and winter, the average operative temperature of the zone below the roof decreased daily by 2°C and 0.5°C, respectively. In July and January, peak temperatures were lowered by 4.7°C and 1.3°C, respectively. This study implies that cool roofs reduce summer cooling while causing modest winter heat losses. As the climate warms, extra passive cooling measures may be required alongside cool paint to reduce winter heat losses. The winter penalty can be minor in temperate zones, according to Gentle et al. (2011) and Barozzi and Pollastro (2016). Nonetheless, the winter penalty produced by cool materials is not well documented in the UK. A monitoring study by Zinzi and Fasano (2009) assessed the cooling potential of an innovative white paint with high solar reflectivity made from a milk and vinegar mixture. The adjacent thermal zone's temperature dropped significantly, proving that cool paints engineered to minimise cooling needs perform better than typical white paints on the market.

2.8.6 Combination of passive cooling measures

Previous subsections have explored how individual passive cooling measures perform in different contexts, such as the influence of construction types, layout, orientation, and room types on overheating risks. However, the combined effects of multiple passive cooling strategies can offer a more comprehensive approach to mitigating overheating. Combining strategies like nighttime ventilation, daytime shading, solar shading, and natural ventilation can enhance overall cooling performance and reduce the dependency on mechanical cooling systems.

Nighttime ventilation with daytime shading protects a solid-walled dwelling from overheating but may not prevent the increase in the internal temperature of dwellings with internal wall insulation (Mavrogianni et al., 2014; Lee and Steemers, 2017). Using solar shading and natural ventilation for a detached house in Germany, Banihashemi et al. (2017) obtained a significant cooling reduction. The combined use of solar shading and natural ventilation has also been of vital importance in preventing indoor temperatures from rising to critical levels in other European countries (Mlakar and Štrancar, 2011; Dan et al., 2016; Chvatal and Corvacho, 2009).

Findings on the combined usage of different passive cooling strategies are presented in Table 2.2. All studies adopted thermal simulation as their methodology, which could be due to time and cost constraints. Construction thermal properties, system design and operation, occupancy and weather are all factors that can affect modelling results. Referring to Adekunle and Nikolopoulou (2016) monitoring and modelling studies indicated that 67% and 22% of spaces were overheated, respectively. This suggests that modelling could underestimate indoor overheating levels and should be treated more carefully.

Ibrahim and Pelsmakers (2018) investigated two different combinations of passive cooling strategies; it is assumed that one is more occupant-dependent than the other owing to the existence of internal shadings. Both passive combinations significantly reduced overheating hours, indicating that adopting multiple passive cooling strategies may lessen the influence of occupancy on overheating risks. Furthermore, the effect of orientation on overheating risks may also be reduced. The reduction of overheating hours was almost identical for an elderly couple living in a west oriented dwelling to a family couple living in a north oriented dwelling (Porrit, 2012).

Combining multiple passive cooling strategies reduces overheating hours more effectively than employing a single passive strategy; however, its effectiveness reduces as the climate warms. Based on the strategies suggested from the findings, it is evident that building envelope modification and limitation of heat gains are most effective in reducing over- heating hours. Moreover, all the studies were conducted on traditional dwellings and not energy-efficient dwellings.

2.9 Effectiveness of passive cooling strategies

This section analyses the cooling effectiveness of passive strategies based on the influence of different overheating factors. Three scales, ‘high’, ‘medium’ and ‘low’

Table 2.2: Findings on the use of multiple passive cooling strategies. Dwelling features consist of the dwelling type, main orientation and occupancy

Reference	Passive cooling strategies	Dwelling features	Main findings
Capon and Hacker (2009)	Solar shading, cool wall, cool roof insulation and nighttime ventilation.	1. Flat, southwest (living room), northeast (bedroom), couple. 2. Semi-detached, southwest, family.	1. In the 2050s, the exceedance of occupied hours according to CIBSE Guide A overheating criteria was reduced from 67% and 41% to 26% and 8% for living rooms and bedrooms respectively in the flat. 2. Annual overheating hours for the semi-detached dwelling reduced from 83% and 53% to 2.2% and 1.1% in living rooms and bedrooms respectively.
Ibrahim and Pelsmakers (2018)	Combination 1: Nighttime ventilation, internal and external shading. Combination 2: Nighttime ventilation, improved glazing and external shading.	Detached, north and family.	Exceedance of Passivhaus overheating criteria reduced from 15% (2050s) and 22% (2080s) to 1% and 2%, 0% and 2% for combinations 1 and 2 respectively.
Porrit (2012)	Cool roof, cool wall, nighttime ventilation, window rules, curtain, internal wall insulation, loft insulation.	Mid- and end-terrace, all orientations and family + elderly.	Overheating risk was mitigated completely using a combination of measures together for both dwelling types.
Gupta and Du (2013)	Combination 1: Window rules, external shutter. Combination 2: Cool roof, cool wall, window rules and external shutter Combination 3: Cool roof, cool wall, thermal mass and external shading.	End-terrace, south and occupancy not specified.	Overheating hours above 26°C and 28°C in bedrooms and living rooms were reduced from 25.7% to 1.1%, 0.5% and 0% using combinations 1, 2, and 3, respectively (50th percentile 2080s climate data).
Gupta and Gregg (2012)	Combination 1: External wall insulation and roof insulation, low-e double glazing, cool wall, cool roof, exposed thermal mass and louvred shading. Combination 2: External wall insulation, low-e double glazing, cool wall, cool roof and louvred shading. Combination 3: Roof insulation, cool roof and louvred shading. Combination 4: External wall insulation, roof insulation, low-e double glazing, cool wall and cool roof.	Mid-terrace, flat, detached and semi-detached all west oriented, family and couple.	Combination 1 achieved the greatest reduction in overheating hours for the 2030s and 2050s climates. However, for the 2080s, no combination sufficiently reduced overheating hours.
Orme et al. (2003)	Thermal mass, nighttime ventilation, curtain and reduced internal heat gains.	Semi-detached, south and family.	The degree hours above 27°C decreased by 67.9%–79.7% across different bedrooms.

were used to express the cooling performance of passive strategies. For example, ‘high’ in ‘weather’ implies that the passive cooling measure’s cooling efficiency is highly influenced by the corresponding overheating factor, that is, its cooling efficiency decreases as the climate warms, and ‘low’ in ‘dwelling type’ suggests that the changes in cooling effectiveness of the passive measures are slightly influenced by different built forms. While ‘medium’, represents modest influences of the overheating factors on the passive strategies. The optimum passive interventions for a warming climate are solar shading and cool paint, according to Table 2.3. Furthermore, solar shading offers significant cooling performance in both traditional and energy-efficient dwellings. Cool paint appears to be the least affected by different dwelling types and changes in orientation. Thermal mass, PCM and natural ventilation all require air circulation for optimum cooling performance, which is dependent on occupant behaviour.

2.9.1 Vegetation

Vegetation is climate sensitive, and adequate rainfall as well as warm temperatures, are required for optimal performance (Zinzi and Agnoli, 2012; Ziogou et al., 2018). Furthermore, its cooling effectiveness appears to vary substantially with different orientations (van Hooff et al., 2014), most likely due to shadowing from surrounding structures. Previous studies did not adequately account for the effects of occupancy on vegetation’s cooling effectiveness. Occupants may water the plants or erect shading, which may affect the vegetation’s cooling performance. More research is therefore needed on the effects of human behaviour on the cooling performance of vegetation. Zinzi and Agnoli (2012) revealed that green roofs’ cooling effectiveness increases with more exposed surfaces, with a higher cooling potential for uninsulated dwellings.

2.9.2 Wall insulation

Occupant behaviour influences overheating risks in highly insulated dwellings owing to the variety of building operations, such as the use of solar shading and natural ventilation (Fletcher et al., 2017; Ridley et al., 2013; Morgan et al., 2017; Ridley et al., 2014; Sameni et al., 2015). Both van Hooff et al. (2014) and Porrit (2012) showed significant variation in the performance of wall insulation with respect to different orientations. Figueiredo et al. (2016) concluded that Passivhaus construction is a feasible concept in the Mediterranean climate, and Hidalgo-Betanzos et al. (2015) found that the investigated Passivhaus dwelling passed the TM52 (CIBSE, 2013) overheating criteria. Increasing insulation levels in UK dwellings can be a viable passive solution as the Mediterranean climate is now hotter than the temperate climate. Other passive strategies, like cool paint, may be needed to reduce overheating risks given greater insulation levels.

Table 2.3: Effectiveness of passive cooling strategies against overheating factors.

Overheating Factors	Vegetation	Wall insulation	Solar shading	Thermal mass	PCM
Occupancy	Lacks robust evidence	High (Hamdy et al., 2011; Ridley et al., 2013)	Medium (Ridley et al., 2014, 2013)	High (Kuczyński et al., 2021)	High (Fernandes and Costa, 2009)
Dwelling type	Medium (van Hooff et al., 2014; Zinzi and Agnoli, 2012)	Medium (Porrit, 2012)	High (Gupta and Gregg, 2012; Porrit, 2012)	Medium (van Hooff et al., 2014)	Medium (van Hooff et al., 2014)
Orientation	High (van Hooff et al., 2014)	High (Porrit, 2012)	Medium (Porrit, 2012)	High (van Hooff et al., 2014)	High (Berardi and Soudian, 2019)
Construction	High (Ziogou et al., 2018; van Hooff et al., 2014)	Medium (Willand et al., 2016; Hamdy et al., 2011)	Low (Porrit, 2012; Gupta and Gregg, 2012)	Medium (Morgan et al., 2017; Hacker et al., 2005)	Medium (Figueiredo et al., 2016)
Weather	Medium (Ziogou et al., 2018; Zinzi and Agnoli, 2012)	Medium (Figueiredo et al., 2016)	Low (Gupta and Gregg, 2012, 2013)	High (McLeod et al., 2013; Peacock et al., 2010)	High (Sajjadian et al., 2015; Sage-Lauck and Sailor, 2014)

Overheating Factors	Natural ventilation	Cool paint
Occupancy	High (Vellei et al., 2017; Petrou et al., 2019)	Low (Pisello et al., 2015)
Dwelling type	High (Porrit, 2012; van Hooff et al., 2014)	Medium (van Hooff et al., 2014; Porrit, 2012)
Orientation	High (Porrit, 2012; van Hooff et al., 2014)	Low (Porrit, 2012; van Hooff et al., 2014)
Construction	High (Peacock et al., 2010; van Hooff et al., 2014)	High (van Hooff et al., 2014; Porrit, 2012)
Weather	High (Panayiotou et al., 2010; Shikder et al., 2012)	Medium (Gupta and Gregg, 2012)

2.9.3 Solar shading

Despite its reliance on occupant behaviour (Ridley et al., 2014, 2013; Mavrogianni et al., 2014), Gupta and Gregg (2012) found external louvred shading to be the most effective passive strategy in the 2080s climate. Compared to terraced and detached dwellings, only flats had significant cooling variations in the cooling performance of solar shading (van Hooff et al., 2014), whereas Gupta and Gregg (2012) found lower cooling effectiveness for flats and mid-terrace dwellings. This could be due to higher storey flats having higher solar heat gains than other dwelling types and fewer exposed surfaces to provide solar shading for mid-terrace dwellings. Similarly, Porrit (2012) found that external shutters were more effective in reducing overheating hours than fixed shading. In addition, they showed significant differences in the cooling performance of solar shading (e.g. fixed shading and external shutter) between end-terrace and mid-terrace dwellings. van Hooff et al. (2014) used automated shading rather than fixed external shading, which could explain the similar cooling performance on the terraced and detached dwellings. In both well-insulated (Tink, 2018; McLeod et al., 2013; Ridley et al., 2013; Mlakar and Štrancar, 2011; van Hooff et al., 2014; Psomas et al., 2016) and traditional dwellings (Gupta and Gregg, 2012; Porrit, 2012; Tink, 2018), solar shading normally provides optimal cooling performance. However, overheating hours can vary greatly for different shading orientations as some are energy in-efficient (Habitzreuter et al., 2020) or difficult to shade (Gupta and Gregg, 2020; Kolokotroni et al., 2007; Gupta and Gregg, 2013; Mitchell and Natarajan, 2019).

2.9.4 Thermal mass

Heat dissipation and modulation strategies are often influenced by occupants' use of natural ventilation and external shading (Kuczyński et al., 2021). Sufficient air exchange is required to improve the cooling effectiveness of thermal mass. In addition, the use of nighttime ventilation to increase the cooling effectiveness of thermal mass will become less effective as the climate warms, as not enough air exchanges can occur with the outside environment because of the lower temperature difference; this will reduce thermal mass' cooling effectiveness as the external temperature increases (McLeod et al., 2013; Peacock et al., 2010; Jimenez-Bescos, 2017; Mulville and Stravoravdis, 2016). Moreover, previous studies have established the usefulness of thermal mass in well-insulated dwellings (McLeod et al., 2013; Hacker et al., 2005).

2.9.5 Phase change material

Ineffective ventilation strategies adopted by occupants can delay the solidification of PCM, affecting its cooling effectiveness (Guarino et al., 2017). The use of PCMs has been shown to be effective in well-insulated dwellings to reduce overheating risks (Sage-Lauck and Sailor, 2014; Auzeby et al., 2016; Figueiredo et al., 2016). Furthermore, south and west orientations allow for optimal solidification cycles and sharp temperature fluctuations, respectively (Berardi and Soudian, 2019). Information regarding the influence of different dwelling types on the cooling effectiveness of PCM was scarce. Therefore, it is assumed that the influence of different dwelling types on the cooling effectiveness of PCM would be similar to that of thermal mass due to their similar heat-modulating behaviours.

2.9.6 Natural ventilation

Several studies have found a significant association between occupant behaviour and using natural ventilation to decrease overheating risks (Vellei et al., 2017; Petrou et al., 2019; Morgan et al., 2017; Ridley et al., 2014; Baborska-Narożny et al., 2017; Toledo et al., 2016; Mavrogianni et al., 2017, 2014). van Hooff et al. (2014) found that the variation in the cooling effectiveness of natural ventilation for different orientations was modest for traditional dwellings and greater for insulated dwellings (Peacock et al., 2010; van Hooff et al., 2014). Porrit (2012) showed different cooling potentials achieved by natural ventilation for different orientations in traditional dwellings. It is worth noting that Porrit (2012) and van Hooff et al. (2014) employed different window opening strategies. Natural ventilation should be prioritised by occupants in highly insulated dwellings, given its reported importance.

2.9.7 Cool paint

The cooling efficiency of a cool roof may be enhanced by occupants adjusting the indoor environment's temperature with respect to the cool roof's cooling impact (Pisello et al., 2015); the cooling impact may be challenging to quantify precisely by occupants to adjust the indoor environment accordingly. Unlike cool walls, cool roofs are less sensitive to overheating in different orientations (Porrit, 2012). Furthermore, dwellings with minimal insulation (van Hooff et al., 2014; Zinzi and Agnoli, 2012) and more exposed surfaces (van Hooff et al., 2014) benefit the most from cool paint. However, it is worth noting that Gupta and Gregg (2012) evaluated a combination of cool walls and roofs, and van Hooff et al. (2014) did not specify whether cool roofs or walls were employed, simply that cool paint was applied to exterior surfaces (Porrit, 2012).

2.9.8 Summary

The framework in Table 2.3, describes the extent to which overheating factors influence the performance of passive cooling strategies, highlighting that their effectiveness is influenced by dwelling characteristics, ventilation potential, occupant behaviour and climate conditions. It highlights that the effectiveness of passive cooling strategies differs depending on various overheating-influencing factors, which impose constraints on their cooling performance. For instance, solar shading is more effective for detached dwellings with greater facade exposure, while thermal mass requires sufficient night ventilation, which may be restricted in airtight dwellings or those where window opening is limited due to noise or safety concerns. Additionally, natural ventilation can be further limited in elderly homes, where reduced occupant adaptability reduces the likelihood of effective window operation for heat dissipation. Similarly, its effectiveness decreases in warmer climates due to reduced indoor-outdoor temperature differentials. The framework highlights the need for a context-specific approach in selecting passive cooling measures, given how differing potential has been identified from previous works in different settings.

2.10 UK housing stock variation

Overheating risks in the UK housing stock are well documented, highlighting the urgent need for large-scale strategies to address widespread vulnerabilities. The stock is notably diverse in terms of construction type, insulation levels, dwelling age, and design features. For example, data from the English Housing Survey (EHS, 2023) indicate that cavity-insulated walls account for nearly 50% of dwellings, while solid uninsulated walls and other types comprise the remainder. Additionally, the age distribution spans multiple eras, from pre-1919 to post-1980 constructions, and building typologies range from predominantly two-storey dwellings to bungalows and taller structures such as multi-storey flats. This inherent diversity directly impacts thermal performance, making it essential to incorporate these numerical details into any effective overheating mitigation strategy.

Modelling millions of dwellings, each characterised by a wide range of features, makes detailed, building-by-building simulations impractical for national-scale analyses. While such granular modelling can yield valuable insights for localised assessments, the computational and data demands make it unsuitable for broader applications. An approach that groups dwellings based on shared characteristics is therefore essential to for large-scale policy implementation, allowing researchers to extract meaningful patterns and inform scalable interventions.

An archetype-based building stock modelling framework offers a promising solution to these challenges. This method allows for the assessment of overheating risks across a manageable number of representative dwellings by effectively capturing critical variations in key features, such as floor area distributions, construction types, insulation levels and other essential parameters. This can be helpful to support nationwide strategies to mitigate overheating risks across the UK's diverse housing stock.

2.11 Building archetype development

Building archetypes have become fundamental in building stock models, serving as representative buildings that address a wide range of research objectives, from mitigating overheating risks (Taylor et al., 2015; Rajput et al., 2022) to reducing greenhouse gas emissions (Yamaguchi et al., 2022; Pittam et al., 2014; Stephan and Athanassiadis, 2017). The characteristics of available data and specific study objectives influence the development of archetypes, emphasising the need for a systematic approach and a robust understanding of the complexities involved in their formulation.

2.11.1 Modelling principles

2.11.1.1 Bottom-up and top-down approaches

Different approaches are employed in developing building archetypes, broadly categorized into bottom-up and top-down methods. Bottom-up approaches rely on engineering models of identified archetypes, with results extrapolated to the entire building stock using weightings. Conversely, top-down approaches use statistical modelling techniques on aggregated stock data, focusing on identifying broad patterns without necessarily categorizing the building stock into specific archetypes.

Bottom-up models, as highlighted by Kavgic et al. (2010), are built from detailed data on various components, combined to estimate energy usage impacts. This method is particularly useful for identifying the most cost-effective CO_2e emission reduction strategies based on available technologies. These models require extensive empirical data, including details on building elements, thermal characteristics, and heating patterns. An example is CREEM (Farahbakhsh et al., 1998), which uses detailed house records to estimate energy consumption and assess the impact of retrofit and fuel-switching scenarios. Top-down models, on the other hand, work at an aggregated level, analysing historical time series of national energy consumption or CO_2e emissions to investigate the relationships between the energy sector and the economy. These models, such as econometric top-down models, lack detailed technological descriptions and focus more on macroeconomic trends.

2.11.1.2 Steady-state and dynamic models

Building physics-based models, a subset of bottom-up models, can be categorised by their underlying modelling principles: steady-state, quasi-steady-state and dynamic as follows:

- Steady-state models: These models assume that the building's thermal conditions remain constant over time, providing a simplified view of energy flows. They are less resource-intensive and can accommodate a larger number of archetypes, thus potentially increasing building stock representation. However, they do not capture the temporal variations in energy use and thermal behavior. Examples of steady-state models include the SAP (Building Research Establishment, 2021) used in the UK for regulatory compliance.
- Quasi-steady-state models: These models offer a compromise between steady-state and dynamic models by incorporating some temporal variations while maintaining a relatively simple computational structure. They provide more accurate results than steady-state models but with lower computational demands compared to fully dynamic models.
- Dynamic models: Dynamic energy models enable the investigation of detailed scenarios, capturing the temporal variations in energy use and indoor environmental conditions. These models consider factors such as weather changes, occupancy patterns, and thermal mass effects, offering a high level of detail and accuracy. However, they are often associated with high computational costs, which typically limit the number of archetypes to less than a hundred (Mavrogianni et al., 2012; Taylor et al., 2014a; Gupta and Gregg, 2012).

2.11.2 Segmentation and clustering

Segmentation and clustering are crucial steps in the process of developing representative building archetypes from large datasets. These techniques help to group buildings with similar characteristics, allowing for the creation of a manageable number of archetypes that accurately represent the diversity within the building stock.

Segmentation involves dividing the dataset into meaningful subsets based on specific criteria. This initial step is essential to ensure that the subsequent clustering process is more focused and effective. Segmentation can be based on various attributes such as building type, age, size or geographic location. By segmenting the dataset, we can ensure that the clustering algorithm operates on more homogeneous groups, improving the accuracy and relevance of the resulting clusters.

Clustering is the process of grouping similar instances within the segmented data into clusters. The selection of an appropriate clustering algorithm is a critical consideration, guided by both the research objectives and the nature of the dataset (Pistore et al., 2017). In the context of building archetype development, clustering helps identify groups of buildings that share similar characteristics, enabling the creation of archetypes that represent these groups. The choice of clustering technique depends on the specific requirements of the study, such as the nature of the data, the desired number of clusters and computational resources. Several clustering techniques have been deployed in past research on building archetype development:

- k-means: This is a partitional clustering technique that assigns each instance to exactly one of k mutually exclusive partitions. It is widely used due to its simplicity and efficiency. However, it is not well-suited for handling building data comprising both numerical and categorical variables (De Jaeger et al., 2020; Ali et al., 2019; Tardioli et al., 2018; Li et al., 2018; Borges et al., 2022; Ofetotse et al., 2021; Echlouchi et al., 2022).

- k-medoids: Similar to k-means, this technique also creates k partitions, but it is better at handling heterogeneous data. It is more robust to outliers compared to k-means but can be computationally intensive for large datasets (Tardioli et al., 2018; Murray et al., 2020; Li et al., 2018; Madbouly et al., 2022).

- Hierarchical: This method builds a hierarchy of clusters either through agglomerative (bottom-up) or divisive (top-down) approaches. It is useful for understanding the structure within the data and does not require the number of clusters to be specified in advance. However, it can be computationally expensive for large datasets (Tardioli et al., 2018; De Jaeger et al., 2020).

- *k*-prototype: This algorithm can simultaneously manage categorical and numerical data, making it one of the most effective methods for handling heterogeneous datasets such as building stocks. Despite its effectiveness, its application in developing building archetypes is relatively under-explored (Preud'homme et al., 2021).

Pre-clustering segmentation[1] or partitioning of the primary dataset has been found to capture the diversity of the building stock better than without Ali et al. (2019), thus enhancing the representativeness of resulting archetypes. Borges et al. (2022) used a deterministic method followed by *k*-means clustering to investigate the intricacies of Andorra's building stock. Similarly, Ali et al. (2019) first developed typologies through segmentation and subsequently employed *k*-means for clustering on the Irish building stock. However, the *k*-means algorithm, while effective in many cases, can fail to handle categorical variables and not account for aspects such as the total number of dwellings of each archetype. Tardioli et al. (2018) explored multiple clustering algorithms on segmented subsets but did not consider *k*-prototype clustering. Furthermore, Borges et al. (2022) and Tardioli et al. (2018) did not partition the segmented typologies into smaller datasets, which could have potentially enhanced the stock representativeness achieved through clustering.

Models with lower levels of disaggregation tend to generate results with diminished confidence, while models with higher disaggregation levels yield more precise outcomes, according to previous research conducted by Natarajan and Levermore (2007). For

[1]The terms segmentation and clustering are sometimes used synonymously in the literature as they both involve grouping of cases, but differences exist between them. In the context of archetype development, segmentation is an analysis-driven process that involves grouping cases into segments based on the scope and objectives of the study. Segmentation is usually applied on the primary dataset before clustering. On the other hand, clustering is a statistical technique that uses machine learning algorithms to group cases or data points into clusters based on their similarities. One of the key differences between segmentation and clustering is that segmentation is typically driven by human knowledge and expertise, while clustering is driven by machine learning algorithms.

instance, a model that only includes two "notional" dwellings significantly overestimated the anticipated carbon reductions. While models like DECarb (Natarajan and Levermore, 2007), UKDCM (Palmer et al., 2006) and BREHOMES (Shorrock and Dunster, 1997) have made significant advances in reducing dependence on average performance by generating heterogeneous building stock representations, they still fail to fully resolve this issue. The granularity of a model is a critical factor to consider; models with only one or two dwelling categories are overly simplistic, while an excessively detailed categorisation can result in insufficient supporting data for each category. One of the primary criticisms of models with minimal disaggregation is that they provide only broad or indicative results for relative differences when evaluating efficiency measures. Conversely, the need for more data to adequately support each detailed category presents a challenge for highly disaggregated models (Kavgic et al., 2010). Hence, it is essential to establish a suitable equilibrium in model granularity to ensure that energy and carbon performance assessments are both accurate and practical.

2.11.3 Archetype-based modelling

A key factor when determining the representation of a building stock is the number of archetypes, which ranges from two to several thousand previous works. Lechtenböhmer and Schüring (2011) used only two archetypes, one $120\,\mathrm{m}^2$ single/two family and one $1457\,\mathrm{m}^2$ large apartment building, to represent the European Union (EU) residential building stock. The authors acknowledged significant uncertainties arising from their choice of two archetypes. Nevertheless, the research offered approximate estimations of the potential, suitability and cost associated with upgrading the EU building stock. Portella (2012) developed a building stock model for France using 45 non-residential and 54 residential archetypes. The final energy demand was estimated at $435.5\,\mathrm{TWh/year}$ for the residential and $179.4\,\mathrm{TWh/year}$ for the non-residential sectors, which were 1.1-7.4% lower than the official statistics. Famuyibo et al. (2012) developed 13 archetypes to represent approximately 65% of the Irish housing stock, indicating that some studies might choose fewer archetypes even if they offer limited representation of the building stock.

Research by Molina et al. (2020) on the residential building stock of Chile demonstrated that a set of 496 archetypes represented the entire stock comprising 6.5 million dwellings while 90 of these archetypes represented 95% of the stock. The difference of

406 archetypes between the two thresholds indicated the presence of a large number of outlier archetypes. A χ^2 analysis in the same research revealed that the return on representativeness diminishes with increasing number of archetypes. The suitable number of archetypes was found to be dependent on the level of detail in the information sources and the desired outcomes or research questions. These findings highlight the variability in archetype selection, often influenced by different levels of segmentation, indicating the importance of methodological decisions in building stock modelling research, ensuring a balance between representation and manageability in modelling.

In larger, national-scale investigations, a broader range of archetypes is needed to account for the diversity in building characteristics and regional disparities, as highlighted in previous studies (Mata et al., 2013; Gendebien et al., 2014; Shorrock and Dunster, 1997). On the other hand, studies focused on a geographically limited, district-scale scope can achieve satisfactory representation of the building stock with fewer archetypes, owing to the more uniform set of characteristics in such areas (Streicher et al., 2019; De Jaeger et al., 2020; Echlouchi et al., 2022). However, it's important to note that even studies of the same geographic scale may require varying range of archetypes (Firth et al., 2010; Loucari et al., 2016), reflecting the diverse goals and subtleties of each research. While geographic scale often serves as a determinant for the number of archetypes, the distinct objectives of each study can further influence their selection, emphasising the complexities involved in archetype development.

The archetypes developed by Ballarini and Corrado (2017) utilised averaged values of building features based on heating systems and construction typologies. This approach can be helpful in contexts with limited data but may fail to account for the variability that exists in the building stock. A more granular approach, such as clustering each typology subset, could leverage the available data more effectively than average values, leading to archetypes that reflect stock diversity more closely. Using information theory and cluster analysis, the advanced approach from Geraldi and Ghisi (2022) attempts to overcome such limitations by incorporating real-world parameter variability into their archetypes. Nevertheless, the approach requires extensive computational resources and depends on subjective decision factors such as spatial configurations.

Overheating risk assessment for residential buildings could benefit from a data-driven approach that incorporates accurate weather data representative of local climatic conditions. Studies have demonstrated that weather files play a crucial role in determining relative overheating risks across dwelling types, underscoring the importance of using climatic data that reflects real-world variations. For instance, Taylor et al. (2014a) examined the influence of weather data on overheating assessments but relied on London-based building archetypes as a national proxy, which may not fully capture the diversity of dwelling characteristics across different contexts. Similarly, Mourkos et al. (2017) highlighted the significance of precise weather data selection, while Taylor et al. (2015) noted that using weather files from a single location could overlook climate variability, potentially affecting the accuracy of overheating predictions. Additionally, these studies did not explore how specific dwelling characteristics interact with climate-driven overheating risk, limiting their applicability to broader overheating assessments.

Symonds et al. (2017) simulated the indoor temperatures of 823 dwellings in different regions based on the English Housing Survey. While the dataset represents the national housing stock, concerns remain about the regional representativeness of the randomly selected subset. The methodology did not specifically target dwellings most susceptible to overheating but focused on cross-validating simulated indoor temperatures with monitored data. Additionally, the model struggled to predict maximum indoor temperatures during extreme weather, likely due to limited details on individual dwelling characteristics.

Using building archetypes, Wright and Venskunas (2022) investigated overheating risks across UK regions. However, they overlooked variations in dwelling size that influence heat gains and temperature regulation, assigning a fixed floor area to each dwelling type. The study also excluded older buildings with unique thermal properties, focusing solely on contemporary constructions. Their evaluation of solar shading and natural ventilation was limited to modern, average-sized dwellings, neglecting the potential differences in larger, older buildings with solid wall constructions, where design affects air circulation and heat retention. Investigating passive cooling strategies while accounting for the interactions between diverse building characteristics, rather than relying on average values, could provide a more detailed understanding of overheating risks.

Moreover, previous archetype-based overheating studies have often relied on simplified dwelling representations, which may not fully capture the range of characteristics influencing overheating risk. For instance, Mavrogianni et al. (2012) defined 15 archetypes based on dwelling type and age, with fixed average floor areas assigned to each typology. While this provides a structured approach to defining archetypes, it does not account for the variation in floor area within each dwelling type, which can influence air circulation and heat dissipation. Smaller dwellings may respond differently to overheating than larger ones, and findings based on averaged values may not always be applicable across all homes within a typology. Additionally, as floor area is often linked to window size, assuming fixed averages may overlook how differences in window-to-floor area ratios affect solar gains and ventilation potential.

Similarly, orientation assumptions vary across studies and may introduce limitations in representing real-world dwelling conditions. Mavrogianni et al. (2012) defined archetypes with four fixed orientations (N, E, S, W), but in reality, some dwellings may have intermediate orientations (e.g., SW, NW) or a combination of multiple orientations, which can influence solar exposure and overheating risk. Gupta and Gregg (2013) assigned a single west-facing orientation to all archetypes, based on its link with overheating, but this approach reduced variability in how different orientations influence thermal performance. Mulville and Stravoravdis (2016) similarly examined overheating using a single semi-detached archetype, considering only two main orientations (N/S and W/E), which may not fully capture how overheating risk varies across a wider range of orientations.

Beyond floor area and orientation, some studies also adopt simplified assumptions regarding thermal performance characteristics, such as U-values. The ARUP report (Bouhi et al., 2021) categorised archetypes based on average floor area per dwelling type, without distinguishing between different dwelling ages, despite that older and newer dwellings of the same typology may have different floor areas (EHS, 2023). Furthermore, the report considered fixed U-values for different wall types—such as cavity walls (insulated/uninsulated) and solid walls (insulated/uninsulated), which may not fully reflect variability in construction materials and thermal performance. Similarly, Peacock et al. (2010) examined overheating risk using three broad construction categories—timber frame (U=0.47 W/m²K), twin leaf masonry (U=0.37 W/m²K), and pre-1900 solid walls (U=1.6 W/m²K), but did not explore variations within each category due to differences in material properties or wall thickness. Orme et al. (2003) followed a similar approach, defining fixed average floor areas for different dwelling types, which may not capture the diversity in internal layouts and spatial configurations.

Given these variations in approach, there is scope to explore alternative methodologies for archetype development that allow for greater variation in dwelling characteristics. One approach is to incorporate a range of floor areas within each dwelling type rather than relying on averages, to better reflect how dwelling size influences overheating dynamics. Similarly, instead of applying fixed orientations across all archetypes, orientations could be assigned based on observed distributions in the housing stock, ensuring a more representative assessment of solar exposure effects. In addition, thermal transmittance values could be defined with a broader range of U-values to capture differences in construction quality and material properties rather than assigning a single value per wall type.

2.12 Summary

Building stock modelling has become an increasingly important tool for assessing energy performance and overheating risks in the residential sector. By simulating archetype dwellings that represent larger subsets of the housing stock, policymakers and researchers can evaluate a wide range of retrofit or design interventions at scale, which can be computationally infeasible on a dwelling-by-dwelling basis. This approach is especially relevant in contexts like the UK, where a diverse housing stock and ambitious climate targets intersect with growing concerns about summertime overheating. Yet, the effectiveness of building stock models largely depends on how well the chosen archetypes capture variations in building stock features.

Two key challenges emerge in current modelling efforts. The first is a lack of clarity on how specific methodological choices—such as which variables are included, how buildings are segmented and which clustering techniques are used, influence the overall representativeness of archetypes. Without guidance on these decisions, researchers risk creating archetype sets that overlook critical aspects of the housing stock. The second challenge is that existing archetype development methods often rely on broadly generalised or parametric models, which can overlook essential real-world variations such as main façade orientation, construction, window and floor areas for different dwelling types in each region.

Chapter 3 | Methodology

The previous chapter reviewed the risk of overheating associated with various construction types, geometries, occupancy patterns and weather conditions. The investigation highlighted the impact of these factors on overheating and discussed potential passive cooling strategies to mitigate these risks.

A systematic approach is helpful to develop building archetypes that can adequately reflect the varying characteristics of the building stock. The methodology employed to achieve this will be detailed in the subsequent sections. The steps taken to develop the archetypes are detailed in Section 3.1, involving the use of segmentation and clustering techniques to develop archetypes. The characterisation approach employed to define these archetypes is detailed in Section 3.2, which describes the geometry (e.g. varying floor areas), construction types, thermal zoning, material specifications, weather files and associated occupancy for the archetypes to conduct thermal simulations.

3.1 Archetype development

The proposed four-step methodology for developing building archetypes, illustrated with an example for better contextualisation, is shown in Figure 3.1. The process begins with the identification of variables frequently employed in previous research. Subsequent steps involve the identification, selection, cleaning, cross-referencing and transformation of pertinent datasets. Key variables are then identified via regression analysis and used to partition the primary dataset into frequency-based subsets. A clustering algorithm is subsequently applied to each subset to generate representative archetypes. A case number is assigned to each archetype through the algorithm to determine the distribution of each archetype within the EHS. These case numbers are then used to link the archetypes to their corresponding cases in the EHS. This allows for obtaining the total dwelling count each archetype represents. The innovation of this methodology resides in the incorporation of MSF during segmentation, procedures for data transformation and variable selection, and the adoption of a suitable clustering evaluation metric and variable count— collectively contributing to an enhanced representation. The involved steps are discussed in detail in the following sub-sections.

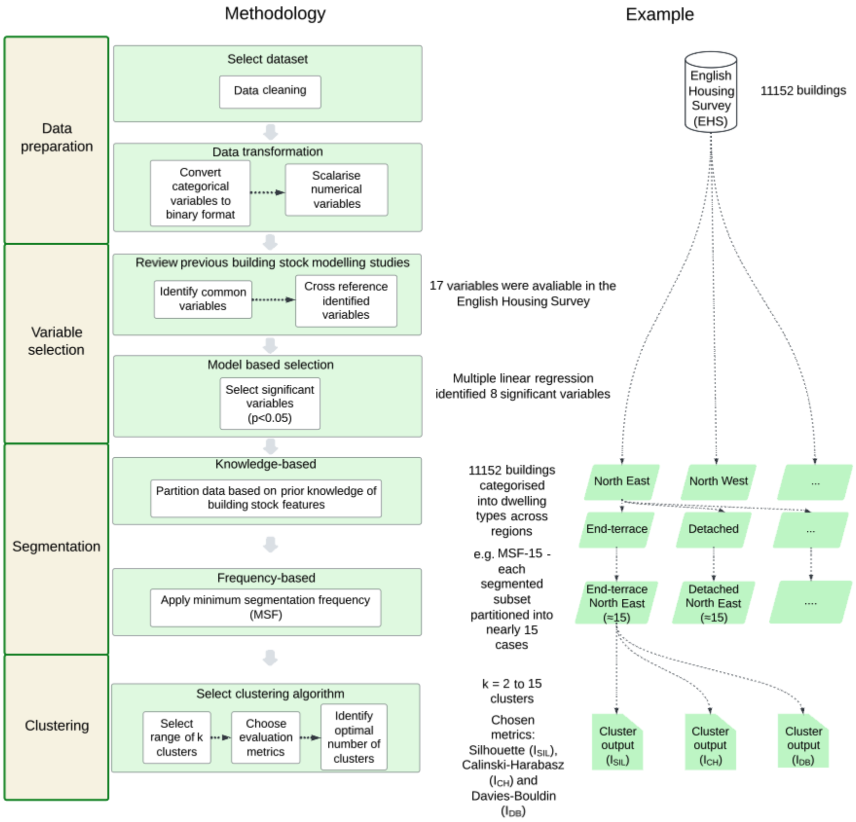


Figure 3.1: Overview of the methodology. Example application is given on the right to illustrate the progressive selection of variables and building count.

3.1.1 Data preparation

Primary datasets for archetype development usually consist of both numerical and categorical variables. For instance, geometric attributes such as floor area are numerical, whereas technical features such as heating systems and fuel types fall into the categorical category. The type of variable not only affects the selection of clustering algorithm and evaluation metrics but also impacts domain-specific modelling at the end of the clustering process. Data preparation and transformation are, therefore, important steps for archetype development.

The EHS (EHS, 2023) was selected as the primary dataset for this study due to various considerations: (a) the comprehensiveness and reliability of the dataset, (b) its status as one of the most extensively studied building stock and (c) the opportunity it offers for a more substantial contextualisation of research findings. The EHS is a national survey of the energy efficiency and condition of housing, and people's housing circumstances in the UK (DLUHC, 2017). The survey is commissioned by the Department for Levelling Up, Housing and Communities (DLUHC) and has been run since 1967. Data is collected through a household interview and a physical inspection of a sample of properties by a qualified professional. The independent categorical variables from the EHS were transformed into binary variables to satisfy the prerequisites for multiple linear regression (Sass et al., 2014; Li, 2016). Additionally, clustering outputs can be biased by skewed distributions and outliers (Olson and Delen, 2008), thus, scalarising data prior to clustering is essential to provide uniform weighting. Given its robust performance with various clustering methods (Tardioli et al., 2018), the Min-Max scalarisation was used to convert the floor area variable into a common scale ranging from 0 to 1 to improve the clustering performance.

3.1.2 Variable selection

Variables used in previous archetype development works are shown in Figure 3.2. Dwelling type and age emerged as the most frequently used variables. Some household characteristic variables such as household size (Paravantis and Santamouris, 2016) and tenure (Ofetotse et al., 2021), have seen comparatively limited utilisation. This might be attributed to the prevalent assumption of standardised occupancy profiles for dwelling archetypes, which consequently leads to excluding these variables from clustering algorithms. Variables such as ventilation systems (Ali et al., 2019) and the thickness of domestic hot water cylinders (Famuyibo et al., 2012), are rarely included, primarily because they are absent from most datasets. The omission of ventilation systems in analyses is often due to the limited variation in building stock. For instance, the majority of the UK homes rely on natural ventilation. Additionally, modelling challenges associated with ventilation (Cao, 2019), may also contribute to its exclusion. An important variable implemented is energy data (Paravantis and Santamouris, 2016; Ofetotse et al., 2021; Borges et al., 2022), which associates each dwelling type with its total energy consumption to establish a suitable benchmark.

A multiple linear regression model was used to examine the energy efficiency of the building stock. Energy efficiency rating (*sap12*) was chosen as the dependent variable to serve as a proxy indicator for the wide range of features that influence energy use

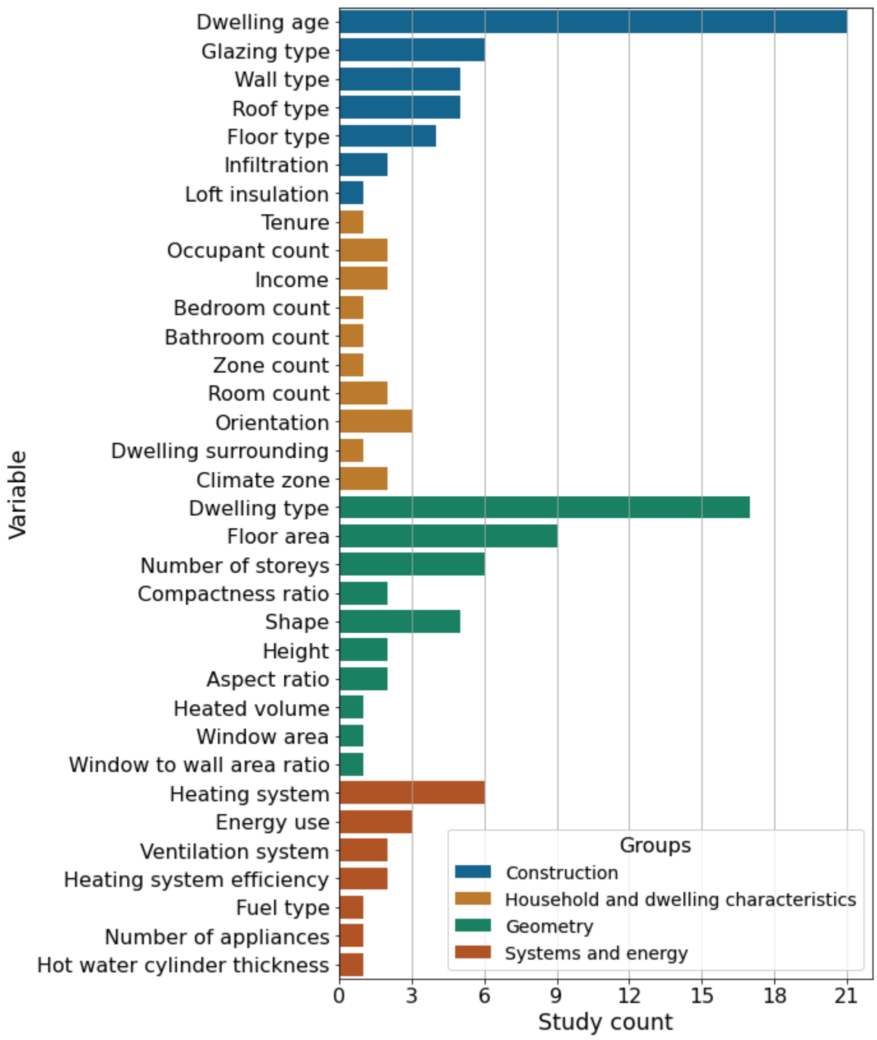


Figure 3.2: Variables used in previous building stock modelling works.

and indoor conditions across the building stock. Its relationship with the independent variables is demonstrated in Equation 3.1, where dependent and independent variables are on the y-axis and x-axis respectively. Independent variables were first identified by cross-referencing variables from the EHS dataset with those commonly used in previous works. The identified variables and their EHS symbols (in bracket) are: floor area (*floory*), loft insulation thickness (*loftins4*), number of storeys (*storeyx*), boiler system (*boiler*), fuel type (*fuelx*), system age (*sysage*), dwelling age (*dwage5x*), type of wall and insulation (*wallinsz*), dwelling type (*dwtypenx*), double glazing percentage (*dblglaz2*), heating system (*heat4x*), number of rooms (*nrooms1a*), number of bedrooms (*nbedsx*), income (*hhinc5x*), number of occupants (*hhsizex*), household age (*agehrp2x*) and tenure groups (*tenure2*). The coefficient of determination (R^2) was used to evaluate the regression model, executed using IBM SPSS Statistics (Version: 27.0.1.0). The

R^2 value of the regression model was 0.753, predicting roughly three-quarters of the variance in the building stock's energy efficiency ratings. This agrees with the results of earlier research, which found that dwelling geometry, heating system efficiency and wall U-value together account for 75% of the energy efficiency rating (Stone et al., 2014).

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \epsilon \tag{3.1}$$

where y is the dependent variable, $x_1 ... x_n$ are the independent variables β_0 is the constant term when all predictors are zero, $\beta_1 ... \beta_n$ are the regression coefficients of the independent variables and ϵ is the residual term.

Household-related variables such as *hhsizex* and *agehrp2x* achieved low regression coefficients, resulting in their exclusion from the final regression model, presented in Table 3.1. Only *heat4x* and *fuelx* were found to be insignificant, having $p-$values (Sig.) ≤ 0.05. Hence, it was decided to keep *fuelx* only since retaining it may act as a substitute for both variables *boiler* and *heat4x*. For example, if *fuelx* is gas, the associated *heat4x* will likely be central heating systems, while if *fuelx* is electric, the corresponding *heat4x* would be electrical heating systems. Hence, this approach allows for an optimised variable selection without compromising the representation of the building stock features. In addition, multicollinearity was investigated using variance inflation factors (VIFs) to verify the validity of the regression outputs. An average VIF score of 1.95 suggests a moderate level of multicollinearity between the variables, thereby indicating minimal influence of multicollinearity on the regression outputs (Shrestha, 2020).

3.1.3 Segmentation

Pre-clustering segmentation is an important step in ensuring representativeness of the resulting archetypes by avoiding imbalances in the distribution of variables. To achieve this, two segmentation approaches were implemented: knowledge- and frequency-based partitioning.

3.1.3.1 Knowledge-based

Knowledge-based segmentation groups buildings based on their inherent characteristics, such as dwelling type and region, to account for regional variations. In this study,

Table 3.1: Multiple linear regression estimates of influencing variables on the indoor environment.

Independent variables			Unstd. coefficients		Std. coefficients	t-statistics	Sig.
Symbol	**Name**	**Category**	β	**Std. error**	β		
β_0	Constant		67.462	.0342		197.137	.000
floory	Floor area		.023	.001	.119	17.041	$< .001$
dwtypenx	Dwelling type	End-terrace	1.778	.212	.054	8.404	$< .001$
		Mid-terrace	6.019	.197	.229	30.495	$< .001$
		Semi-detached	2.063	.173	.090	11.944	$< .001$
		Converted flat	9.115	.379	.166	24.046	$< .001$
		Low rise purpose built flat	8.444	.266	.317	31.794	$< .001$
		High rise purpose built flat	7.509	2.057	.104	3.651	$< .001$
dwage5x	Dwelling age	Pre-1919	-9.349	.225	-.366	-41.548	.000
		1919 to 1944	-8.527	.182	-.304	-46.961	.000
		1945 to 1964	-7.480	.152	-.303	-49.081	.000
		1965 to 1980	-5.891	.144	-.245	-40.776	.000
dblglaz2	Double glazing percentage	80% or more double glazed	3.192	.192	.089	16.592	$< .001$
heat4x	Heating system	Storage heater	1.327	.787	.027	1.687	.092
		Fixed room heater	-9.454	.822	-.136	-11.505	$< .001$
sysage	System age	Less than 3 years	1.343	.177	.058	7.573	$< .001$
		More than 12 years	.990	.159	.051	6.225	$< .001$
fuelx	Type of fuel	Not identified - communal system	1.427	1.245	.020	1.146	.252
		Oil fired system	-7.473	.268	-.147	-27.932	$< .001$
		Solid fuel	-5.805	.970	-.031	-5.987	$< .001$
		Electric	-7.952	.926	-.198	-8.587	$< .001$
boilerx	Boiler type	No boiler	-3.765	1.184	-.107	-3.179	.001
		Standard boiler (floor or wall)	-7.016	.230	-.199	-30.535	$< .001$
		Back boiler (to fire or stove)	-10.520	.513	-.111	-20.509	$< .001$
		Combination boiler	-4.030	.284	-.079	-14.166	$< .001$
		Condensing boiler	-.692	.134	-.029	-5.161	$< .001$
loftins4u	Loft insulation thickness	No roof above	-.617	.229	-.021	-2.697	.007
		None	-11.499	.332	-.178	-34.684	$< .001$
		Less than 100m	-3.166	.181	-.090	-17.451	$< .001$
		100 to 150mm	-1.673	.123	-.071	-13.607	$< .001$
storeyx	Number of storeys	1	-.878	.225	-.025	-3.906	$< .001$
		3	1.701	.153	.063	11.106	$< .001$
		4	4.011	.315	.070	12.731	$< .001$
		5	4.679	.509	.047	9.191	$< .001$
		6	8.285	2.022	.117	4.097	$< .001$
wallinsz	Type of wall and insulation	Cavity uninsulated	-5.198	.127	-.216	-40.779	.000
		Solid with insulation	1.799	.298	.031	6.040	$< .001$
		Solid uninsulated	-6.935	.178	-.298	-38.976	.000
		Other	3.973	.397	.050	10.006	$< .001$

the EHS data was segmented into 63 distinct typologies incorporating seven dwelling types (end-terrace, mid-terrace, semi-detached, detached, bungalow, converted flat, and purpose built flat) and nine regions (North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East, London, South East and South West).

3.1.3.2 Frequency-based

Variables in the segmented data from the previous step often have uneven distributions, with certain features being dominant. This bias can cause clustering algorithms to overlook less frequent but important features. For instance, given the prevalence of cavity insulated walls in the *wallinsz* variable, the clustering algorithm may only identify archetypes with cavity insulated walls and overlook wall types such as solid walls with insulation. Hence, "minimum segmentation frequency" (MSF) was introduced to retain feature diversity in the segmented data before clustering is applied. The approach divides the segmented data into smaller subsets, each containing a number of cases close to the specified MSF value. For example, MSF-15 represents the division of each of the 63 segments from the previous step into further subsets, each comprising approximately

15 cases. To examine the influence of MSF on the number and representativeness of the resultant archetypes, a sensitivity analysis was conducted. This involved repeating the frequency-based segmentation step eight times with different MSF values, ranging from 15 to 50, in increments of five.

3.1.4 Clustering

Clustering is a multivariate classification technique that groups objects into distinct clusters based on their intrinsic characteristics. Objects within the same cluster share comparable characteristics, reflecting a high level of within-cluster coherence while retaining unique distinctions between clusters.

Standard *k*-means and *k*-modes are clustering algorithms for numerical and categorical data respectively. They are not suitable for mixed data because they use different dissimilarity measurements (Huang, 1998). *k*-means uses the Euclidean distance, which measures the distance between two points in a numerical space. On the other hand, *k*-modes uses the Hamming distance, which is a measure of the difference between two binary vectors. Huang (1998) proposed *k*-prototype, which clusters mixed data types using *k*-means' Euclidean distance and *k*-mode's Hamming distance, the first and second expressions in Equation 3.2 respectively. The algorithm utilises the mean and mode of numerical and categorical variables respectively to minimise dissimilarity between cluster points. Clusters are formed randomly based on the predetermined number of clusters k, the algorithm is then iterated until each cluster's mean and mode values are adjusted and minimised based on the distance between cluster points.

$$d(x, y) = \sum_{i=1}^{p} ||x_i - y_i||^2 + \gamma \sum_{i=p+1}^{q} \delta(x_i, y_i) \tag{3.2}$$

where the first term represents the Euclidean distance between two numerical datapoints, the second term represents the Hamming distance between two categorical datapoints, and γ and δ are weighting factors to balance numerical and categorical distributions.

3.1.4.1 Cluster evaluation

The performance and efficacy of clustering techniques are determined using evaluation metrics, which quantifies the quality of cluster formations by assessing the cohesiveness of the groupings and how different they are from one another. Clustering evaluation metrics can be divided into two categories: internal and external. Internal metrics measure the quality of the clusters themselves, while external metrics measure the accuracy of the clustering algorithm against known ground truth labels. Internal metrics are commonly used for unsupervised clustering, where ground truth labels are not available. This research investigated the following three most commonly used metrics:

- **Davies-Bouldin index** (I_{DB}) quantifies cluster quality by balancing its compactness and separation, enabling the comparison of solutions and optimisation of cluster numbers (Liu et al., 2010), as defined in Equation 3.3. Separation measures the distance between clusters, and compactness measures data point proximity within clusters. Lower values of I_{DB} indicate well-separated, condensed clusters.

$$I_{\mathrm{DB}} = \frac{1}{k}\sum_{i=1}^{k} \max_{i \neq j} \left(\frac{s_i + s_j}{d_{ij}} \right) \tag{3.3}$$

  where k is the number of clusters, i and j represent cluster labels where s_i and s_j are cluster samples with respect to their centroids and d_{ij} denotes the distance between the centroids.

- **Silhouette index** (I_{SIL}), also known as Silhouette coefficient, describes the cohesiveness and separation of clusters by comparing the similarity of an object within its cluster to that of the objects in other clusters (Rousseeuw, 1987). Equation 3.4 is used to calculate I_{SIL}, which ranges from -1 to 1. $I_{\mathrm{SIL}} > 0.5$ signifies robust clustering (Rousseeuw, 1987) where higher values denote a more distinctive and compact cluster.

$$I_{\mathrm{SIL}} = \frac{1}{n}\sum_{i=1}^{n} \frac{b_i - a_i}{\max\{a_i, b_i\}} \tag{3.4}$$

  where a_i is the average distance between a data point i and all other data points in the same cluster and b_i is the smallest average distance between the data point i and all other data points in the other clusters. Therefore, a_i represents the the cohesiveness of the cluster containing the data point i and b_i denotes the extent of separation from the other clusters.

- **Calinski-Harabasz index** (I_{CH}) determines the optimal number of clusters by measuring the separability of clusters, and is calculated using Equations (3.5) to (3.7), dividing the total between-cluster dispersion (B_{k}) by the total within-cluster dispersion (V_{k}) (Caliński and Harabasz, 1974). A greater value of I_{CH} indicates that the clusters are more distinct from one another and more dense within themselves.

$$B_{\mathrm{k}} = \sum_{i=1}^{k} C_i ||m_i - m||^2 \tag{3.5}$$

$$W_{\mathrm{k}} = \sum_{i=1}^{k} \sum_{x \in C_i} ||x - m_i||^2 \tag{3.6}$$

$$I_{\mathrm{CH}} = \frac{V_{\mathrm{B}}}{V_{\mathrm{W}}} \times \frac{n-k}{k-1} \tag{3.7}$$

where k is the number of clusters, n is the total number of data points, C_i is the size of cluster i, m is the total mean of the dataset, m_i is the mean of cluster i, x is a data point in cluster i, V_{B} is the average between-cluster sum of squares and V_{W} is the average within-cluster sum of squares.

3.1.4.2 Determining the number of clusters

k-prototype clustering algorithm was implemented on the segmented subsets with the value of *k* ranging from 2 to 15. This range allowed a balanced examination of cluster possibilities while preserving computational feasibility. To determine the number of archetypes for each subset, optimal values of I_{SIL}, I_{CH} and I_{DB} were considered.

3.1.4.3 Post-processing of clustering outputs

The clustering algorithm assigns each case in the segmented subset to a specific cluster. The algorithm also identifies the centroid of each cluster. Where modelling is relatively straightforward and requires only the variables used in clustering, the centroid can act as the archetype, representing the cluster. In cases where modelling should ideally be based on real cases, the archetype is the closest case from the centroid. The matching of the centroid to a real case allows access to all variables in the original EHS dataset, not just the seven variables used in clustering. Corresponding dwelling count is then found by aggregating the rounded dwelling weight (*aagpd1920*) values of EHS cases sharing the same cluster number or ID. This step is repeated for all segmented subsets (63 in this research) to identify all archetypes in the EHS dataset.

Modelling the identified representative archetypes in appropriate simulation programs is the next step. Depending on the study objectives, more information than the variables utilised for clustering may be required for modelling individual cases. For example, floor area was used as a clustering variable in this study because of its importance in investigating energy and environmental performance of buildings. However, 3D geometric modelling for energy simulation requires the translation of floor area into building height, width and depth. Instead of making assumptions about the geometry parameters, i.e. width, depth and height, further EHS variables such as ground floor width (*Fdhmwid1*), depth (*Fdhmdep1*) and ceiling height (*cheight0*) can be used to effectively create the 3D geometry of the ground floor of the selected EHS case. Cross-linking the cluster number with the EHS ID (*serialanon*) thus affords the user to extend downstream simulation capabilities in terms of purpose and scope, which is one of the strengths of data-driven archetype identification.

Representative archetype development also offers the benefit of extending the analysis time horizon. For example, future energy and environmental performance under a changing climate can be evaluated using archetypes derived from the current building stock features. Assumptions about the evolution of the building stock such as the changes in heating systems from gas-fired boilers to heat pumps can be encapsulated in multiple scenarios with varying replacement rates, which can then be simulated to investigate the effects of their installation. Assuming that the core features of the current building stock remain unchanged, the representative archetypes can be suitable for assessing how existing buildings might perform under future warming conditions. However, the applicability of the archetypes may be limited in scenarios that involve changes to the core building stock features, i.e. the changes to the variables used for clustering. For instance, if a future scenario considers that a significant share of the new buildings by 2050 will be purpose-built flats with smaller floor area than the present, the characteristics of the building stock will change. In such cases, the baseline archetypes, which are based on the current data, serve as a starting point but may require adaptation or the development of new archetypes to reflect these changes.

3.1.4.4 Estimating representativeness

The representativeness of the building stock achieved by the archetypes was determined by comparing the total number of dwellings per variable between the clustering models and EHS using the mean absolute percentage error (MAPE). The MAPE of the variables was then averaged to indicate the clustering model's overall representativeness, where lower MAPE indicated greater representativeness. The MAPE equation is defined as:

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{3.8}$$

where n represents the total number of cases, and y_i and $\hat{y}_i$ are the total dwelling count for the variables of the EHS and clustering models respectively.

3.2 Defining archetype characteristics

Followed by the development of building archetypes, it is essential to characterise them and prepare each for simulation. This involves defining the thermal properties, thermal zoning, internal heat gains and external weather conditions of the archetypes. Once the optimal number of building archetypes was determined, four main steps were involved to prepare the archetypes for simulation, as illustrated in Figure 3.1. Firstly, using DesignBuilder, the initial average footprints of different dwelling types were constructed based on the English Housing Survey (EHS), followed by determining the average room dimensions for both the living room and the main bedroom. Secondly, a Python script was developed to define building features, where the EnergyPlus input data files (IDF)s generated from DesignBuilder were processed to create various archetypes with different characteristics based on the EHS data, i.e. varying floor areas and constructions. Thirdly, the IDFs were simulated using EnergyPlus to determine the indoor temperature of the living room and main bedroom of each archetype. Lastly, the indoor temperature was assessed using defined metrics to determine overheating, i.e. degree hours above temperature thresholds.

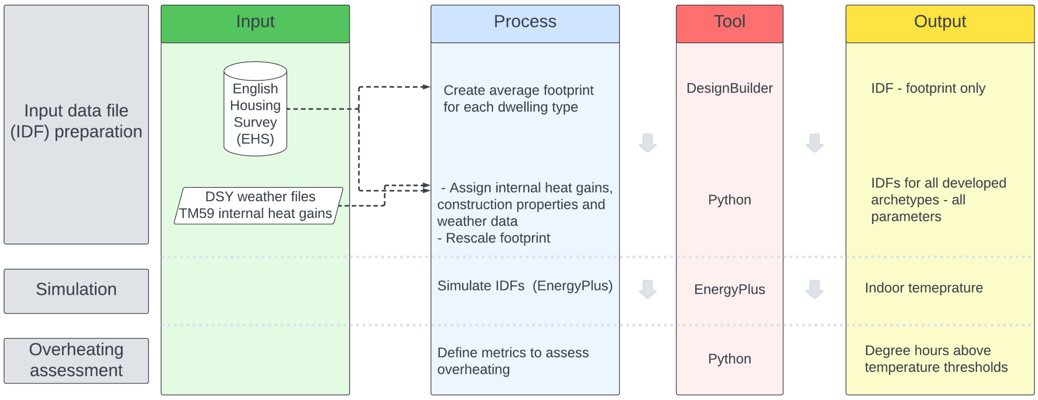


Figure 3.3: Flowchart outlining the overheating modelling process, including input data sources, processing steps, simulation tools and output metrics

3.2.1 Thermal zoning and geometry

Previous research on overheating has predominantly concentrated on main bedrooms and living rooms, due to their significant occupancy rates. These spaces are considered essential in overheating risk assessment due to their substantial contribution to occupant exposure to thermal discomfort, resulting from prolonged occupancy and associated internal heat gains.

This study incorporated a range of dwelling sizes, which required rescaling based on the EHS dimensions. While detailed internal layouts have been employed in previous studies, their suitability for diverse dwelling configurations is limited. To address this challenge, a simplified two-zone model, containing the living room and main bedroom on the ground floor living room and first floor respectively, was adopted. This approach results in a manageable yet representative assessment of overheating risks across varying dwelling sizes, focusing on the mostly occupied internal spaces.

Internal dimensions for approximately 50% of the dwellings were available from the EHS data, which enabled the computation of the average internal dimensions for living rooms and bedrooms for each dwelling type in each region. In combination with the footprint measurements (width and depth) that were available for all dwellings, the dimensions were rescaled using this data. This scaling method enabled a more precise representation of room sizes in the overheating model, even in the absence of detailed internal dimension data, by adjusting the internal space proportions based on the building footprint.

The window areas from the EHS were incorporated after the layout for the two thermal zones was established in the model. The SAP methodology was also adopted to recalculate the window areas of dwellings with extensions, taking into account the total area, age, and type of the dwelling. This recalibration was necessary to avoid inaccuracies in window size estimations for dwellings with extensions, which could have a substantial impact on indoor temperature predictions. This was due to the potential misallocation of window areas between the main and extended sections of the dwelling as the EHS variables provided total window areas for both sections combined without further specification.

3.2.2 Internal heat gains

Households of comparable size typically have similar appliance sets, indicating that equipment heat loads are relatively independent of floor area. This study maintains uniformity in analysing equipment loads across different dwellings using a uniform average wattage (W). This approach addresses the limitation of the EHS, which lacks specific data on the number and types of appliances in individual households. In addition, employing a uniform average wattage (W) value rather than a variable one is particularly advantageous given the study's primary focus on the impact of construction, geometry and weather on indoor temperature. This approach minimises the variation of internal heat gains, facilitating a more concentrated investigation of the key variables influencing thermal performance. For bedrooms, an 80 W load was assumed, active from 08:00 to 23:00. In the living room, a 450 W load was applied, with peak usage occurring between 18:00 and 22:00. For kitchens, a 300 W load was assigned, with peaks in the morning from 08:00 to 09:00 and in the evening from 18:00 to 20:00.

The relationship between lighting and floor area is more direct than appliances. Typically, more lighting would be required to achieve adequate illumination in larger spaces, leading to increased lighting energy consumption. Wattage per square meter (W/m²) was implemented to simulate internal heat gains from lighting precisely. This approach acknowledges that although the number and type of appliances in a household may stay mostly the same, the required lighting in dwellings could vary greatly depending on their size. Per CIBSE TM59 (Chartered Institution of Building Services Engineers, 2017), a value of 2 W/m² was chosen to account for lighting usage between 18:00 to 23:00.

Bedrooms were presumed to be occupied 24 hours a day, similar to TM59 (Chartered

Institution of Building Services Engineers, 2017). This assumption ensures that the heat accumulation in these rooms is consistently accounted for throughout the day and night, as at least one occupant is present. Additionally, a sensible heat gain of 75 W per occupant is considered to reflect the internal heat contribution from occupants. The heat gain profile for the living rooms and kitchens was aligned with typical usage patterns during the hottest periods of the day, occupied from 09:00 to 22:00.

3.2.3 Building fabric

The U-values for external walls varied from 0.35 to 2.1 W/m^{2}K, based on the age of the dwelling. These values were obtained from SAP tables (Building Research Establishment, 2021), which provide the U-values based on dwelling age and wall type. For older dwellings, i.e. pre-1919, higher U-values were adopted, which corresponded to thicker bricks with minimal or no insulation. The brick and insulation thicknesses were modified to reflect changes in U-values for different constructions. For instance, post-1980 dwellings were constructed with reduced U-values, suggesting that the walls were more adequately insulated, per contemporary building regulations. Internal partition walls were assumed to be constructed from brick, plastered on both sides, with a U-value of 1.450 W/m^{2}K for all constructions.

The ground floor was also modelled based on the dwelling age. Higher U-values were adopted for dwellings constructed pre-1980. The ground floor was constructed with cast concrete, floor screed and timber flooring, which lacked insulation, resulting in greater heat loss, with U-values around 1.35 W/m^{2}K. Conversely, it was assumed that insulation had been installed under the floor screed in dwellings constructed after 1980, which led to improved thermal performance and reduced U-values (0.25 W/m^{2}K). For internal floors, an uninsulated suspended wooden floor with a U-value of 1.657 W/m^{2}K was considered.

Loft insulation thickness was essential in determining the U-values of the roof structure, which varied from 0.16 to 2.1 W/m^{2}K based on the insulation level. The varying U-values resulted from different loft insulation thicknesses, as determined by the variable *loftins4* from the EHS (EHS, 2023). The roof structure consisted of clay tiles and roof screed, which, combined with the insulation thickness, determined the overall thermal performance of the roof.

Given the typical range of U-values for double glazing, which ranges from 2.0 to

3.1 W/m^{2}K, An average U-value of 2.55 W/m^{2}K was selected for the simulations. The EHS does not provide detailed information on the type of gas used between the panes or the thickness of the glass, making it difficult to accurately determine the U-value of glazing for each building archetype.

3.2.4 Infiltration

An approach to modelling infiltration is to apply a schedule that specifies the number of times the air in a closed space is replaced per hour (ACH). ACH is also used to describe the leakage rate, which is the frequency at which the internal air volume of a building is replaced by outside air within one hour, subject to specific testing conditions (del Ama Gonzalo et al., 2022). One of the most common approaches is to distribute the ACH value equally across all thermal zones.

The infiltration rates of dwellings are influenced by the type of wall construction, as evidenced by empirical data (Stephen, 2000). Dwellings with cavity walls were assigned 12 ACH at 50 Pa. This relatively low infiltration rate suggests that cavity walls offer better airtightness compared to other wall types. While dwellings with solid walls have a higher average ACH, approximately 15 ACH at 50 Pa. The increased air leakage associated with solid walls highlights their lower airtightness than cavity walls.

3.2.5 Weather file

The selection of appropriate weather files is essential for accurately evaluating overheating risk in the housing stock. This thesis adopts Design Summer Year (DSY) weather files to simulate overheating risks under current and future climate conditions. DSY files represent typical summer weather patterns likely to cause overheating in buildings. All simulations were conducted from 1 May to 30 September, aligning with the warmest months and the highest risk of overheating in the UK. For the baseline scenario, weather data from 1961-1990 was adopted to reflect current climatic conditions, chosen due to its representation of historical weather commonly used in building simulations. DSY files for the 2050 high-emission 50th percentile scenario were employed to project future climate scenarios. This scenario captures the potential impacts of climate change, including significant increases in average temperatures and the frequency of extreme heat events. Additionally, region-specific DSY files for different parts of the UK were used to account for regional climatic variations. The following cities were chosen for the climatic representativeness of their respective regions:

- **North East:** Newcastle
- **North West:** Manchester
- **Yorkshire and the Humber:** Leeds
- **East Midlands:** Leicester
- **West Midlands:** Birmingham
- **East:** Norwich
- **London:** London (Heathrow)
- **South East:** Bristol
- **South West:** Portsmouth

3.3 Overheating investigation

Following the development and characterisation of the archetypes, their thermal performance is simulated to provide indoor temperature profiles for additional analysis. Individual EnergyPlus input data file (IDF) files are prepared, incorporating variables such as building design, orientation and insulation. The EnergyPlus engine is then used to process these files and simulate different indoor temperatures. The simulation results allow for the evaluation of the frequency and intensity of high indoor temperatures and the efficacy of solar shading for different regions.

Threshold-based approaches for evaluating overheating risk in dwellings often rely solely on counting the number of hours that temperatures exceed a predetermined limit, neglecting the severity of each exceedance—thus, surpassing the threshold by 1°C is treated the same as exceeding it by 5°C, although the latter poses a greater risk to comfort. Furthermore, while adaptive comfort criteria can incorporate external temperatures, they may not be sufficiently refined for nighttime conditions in bedrooms, where overheating is especially problematic (Porrit, 2012). Consequently, to capture both the duration and magnitude of exceedances, employing a degree-hours metric provides a more nuanced basis for assessing thermal comfort and evaluating potential overheating.

3.3.1 Random Forest

Random Forest (RF) models were used to assess whether the developed archetypes capture sufficient variation in key building characteristics to reflect overheating patterns across different dwelling types and regions in the UK. The models were applied separately for each dwelling type within each English region to evaluate how well the dataset represents the diverse climatic and architectural conditions influencing overheating. The target variables—degree hours above 26°C (bedrooms) and 28°C (living rooms), were used to assess overheating severity. Model performance was evaluated using R^2 scores to determine whether the archetypes provide a robust basis for overheating risk prediction.

A composite variable, dwage5x_wallinsz, was developed by merging dwelling age (*dwage5x*), and wall type and insulation (*wallinsz*) into a single variable for the RF model. This approach was essential because the U-value of the external walls, was determined considering both the age of the dwelling and its insulation. If these variables were considered separately, the significance of one could potentially outweigh the other, leading to a skewed interpretation of their impact on overheating. The model effectively captures their combined influence by merging them.

3.3.2 Passive cooling effectiveness

Based on the literature review, external shutters were identified as the most effective passive cooling measure across various influencing factors. While cool paint also showed potential, it was excluded to avoid winter heat loss, given the study's focus on summer months. The current scope is centered on evaluating the cooling potential of passive strategies using archetype-based modelling, which necessitates a balance between practical applicability and computational feasibility. Assessing a single, well-established cooling intervention, such as external shutters, allows for a focused analysis of whether the developed archetypes can effectively capture cooling performance variations across different dwelling types and regions. This approach provides a baseline for understanding the interaction between overheating risk and passive cooling potential within the modelled housing stock, forming the foundation for future studies incorporating additional mitigation measures.

Using both baseline and future year weather data, the effectiveness of solar shading was investigated across different regions. External shutters were modelled in EnergyPlus with the following characteristics:

- **Blind-to-glass distance**: 0.0150 meters
- **Slat orientation**: Horizontal
- **Slat width**: 0.0250 meters
- **Slat separation**: 0.0188 meters
- **Slat thickness**: 0.0010 meters
- **Slat angle**: 45.0 degrees
- **Slat conductivity**: 0.900 W/m-K
- **Slat beam solar and visible transmittance**: 0.000
- **Slat beam solar and visible reflectance (both sides)**: 0.800
- **Slat diffuse solar and visible transmittance**: 0.000
- **Slat diffuse solar and visible reflectance (both sides)**: 0.800
- **Slat emissivity (both sides)**: 0.900
- **Blind opening multipliers (top, bottom and sides)**: 0.500

The external shutters were modelled to close when the internal temperature surpasses 22°C. This approach, which assumes no restrictions on window openings, was chosen to initiate shading in cases that could cause occupant discomfort. It is important to note that fully open windows were not considered in the simulations– limited window openings was assumed per SAP (Building Research Establishment, 2021).

The effectiveness of external shutters was investigated by considering the percentage reduction in degree hours exceeding 26°C and 28°C before and after their implementation on the archetypes. Additionally, the proportion of dwellings passing the TM59 overheating criteria in the baseline climate was compared to the 2050 climate scenario to determine whether shutters remain an effective mitigation strategy under future warming conditions. This approach provides a comparative analysis across different dwelling types and climates, highlighting both current and future cooling performance trends.

3.4 Model validation

It is imperative to validate the model employed to estimate the severity of indoor overheating with building archetypes to confirm the predictive accuracy of the outputs by comparing them to real-world data. An empirical approach was implemented to validate the overheating model by comparing the simulated results and the observed data from the 2017 Energy Follow Up Survey (EFUS). The following steps were followed for the validation process:

1. **Data extraction from EFUS:**
   - The mean indoor air temperatures for living rooms and bedrooms of end-terrace dwellings during the summer of 2018 were obtained from the EFUS 2017.
   - The mean external temperature for the same period was extracted that was included in the survey (from the Met Office).
2. **Normalisation of EFUS Data:**
   - The focus of the validation is on how the indoor temperature responds to external climatic conditions. By normalising the mean indoor temperature by the mean external temperature, these external factors are accounted for. This ratio, termed the indoor-outdoor temperature ratio (IOTR), is calculated as follows:

$$\text{IOTR (EFUS)} = \frac{\text{Mean indoor temperature (EFUS)}}{\text{Mean external temperature (EFUS)}}$$

3. **Model simulation:**
   - The housing stock model was used to simulate hourly indoor temperatures for end-terrace dwellings.

- The mean indoor temperature for living rooms and bedrooms was calculated.
- The mean external temperature from the weather file used for EnergyPlus simulation was also obtained.

4. **Normalisation of model output:**

   - Similarly, the mean indoor temperature from the EnergyPlus output was normalised by the mean external temperature from the adopted weather file.

$$\text{IOTR (EnergyPlus)} = \frac{\text{Mean indoor temperature (EnergyPlus)}}{\text{Mean external temperature (Weather file)}}$$

5. **Comparison and analysis:**

   - The normalised temperatures from the EFUS data and the model were compared. This comparison highlighted the model's accuracy in predicting indoor temperatures relative to external conditions.

3.5 Summary

This chapter outlines the development of representative building archetypes to investigate overheating risks in the UK housing stock. Using the English Housing Survey (EHS) dataset, the process begins with data preparation, followed by variable selection for clustering, ensuring that key parameters influencing overheating risk are appropriately considered. A clustering analysis is then conducted to determine the optimal number of archetypes using different evaluation metrics. Once the archetypes are established, they are characterised based on internal heat gains, geometry, orientation and weather conditions, with a Python script used to generate archetypes of different features. The chapter then describes the overheating assessment methods, detailing how overheating is quantified using simulated data to evaluate risk levels across the developed archetypes, followed by the validation steps to verify the simulated data.

Chapter 4 | Representativeness

4.1 Impact assessment of methodological parameters on archetype representativeness

This section presents a sensitivity analysis to explore the influence of different methodological parameters on archetype representativeness. By examining variations in segmentation levels, variable counts and evaluation metrics, this analysis aims to develop a methodological framework through sensitivity analysis, considering diverse research focuses, scales, temporal scopes and computational costs. This framework will subsequently be used to refine parameters for building archetype development specifically tailored to overheating investigations.

4.1.1 Segmentation level

A range of MSF values was investigated using the English Housing Survey, considering various metrics to identify the ideal number of archetypes. Figure 4.1 illustrates the sensitivity analysis of different segmentation levels, highlighting the trade-off between granularity and representativeness. Increasing the segmentation level (i.e., decreasing the MSF) increases the representativeness of the building stock features by partitioning the data into finer subsets, each subjected to clustering. However, this also results in a greater number of archetypes, which may increase computational costs for consequent simulations. Therefore, selecting an appropriate segmentation level is crucial, as it influences the number of resulting archetypes and their representativeness to different extents for each clustering evaluation metric.

4.1.2 Clustering evaluation metric

Different clustering evaluation metrics identified varying number of archetypes, each offering distinct levels of representativeness. Figure 4.1 illustrates the number of archetypes and their corresponding representativeness for different clustering evaluation metrics. Across varying levels of MSF, I_{SIL} consistently identified the fewest number of archetypes. This observation may suggest that I_{SIL} tends to identify more uniform clusters, potentially overlooking variations within the building stock, making it less suitable for a comprehensive stock analysis. On the other hand, I_{DB} detected the most archetypes, which can be preferable for studies requiring a thorough representation of building characteristics. While I_{CH} identified fewer archetypes than I_{DB}, it nonetheless demonstrated satisfactory representativeness, attempting to balance the number and representativeness of the archetypes. Thus, while each clustering evaluation metric has its intrinsic strengths and limitations, its strategic selection and application depend on the specific goals and granularity required in the research. By carefully choosing the evaluation metric, variable count and MSF, researchers can achieve their desirable archetype representativeness, whether they seek a broad overview or a detailed portrayal of the building stock.

4.1.3 Variable count

The sensitivity analysis also explored the influence of variable count on archetype representativeness. Five variable groupings were investigated, as illustrated in Figure 4.2. Across all metrics, a reduction in variable count typically resulted in higher representativeness, suggesting that using fewer clustering variables would result in a smaller number of building archetypes with higher representativeness. I_{SIL} showed the biggest reduction in MAPE with decreasing variable count, followed by I_{CH}, then I_{DB}. The difference in the MAPE between I_{DB} and I_{CH} was considerably smaller than the difference between I_{DB} and I_{SIL}. In addition, I_{CH} identified more archetypes than I_{DB} as the variable count decreased. These findings suggest that I_{DB} can be suitable for studies with a variety of variable counts or limited data availability, as it can achieve satisfactory representativeness with a relatively low variable count. Given that I_{DB} demonstrated better performance than I_{SIL} and I_{CH} in identifying archetypes across different variable counts and MSF, it was selected as the primary metric for further investigations. This decision enables a more focused exploration of how similar the distributions of variables in clustered outputs are to that of the EHS data.

The distribution of variables in the clustering outputs varied considerably for different segmentation levels. Figure 4.3 highlights the impact of segmentation level on the

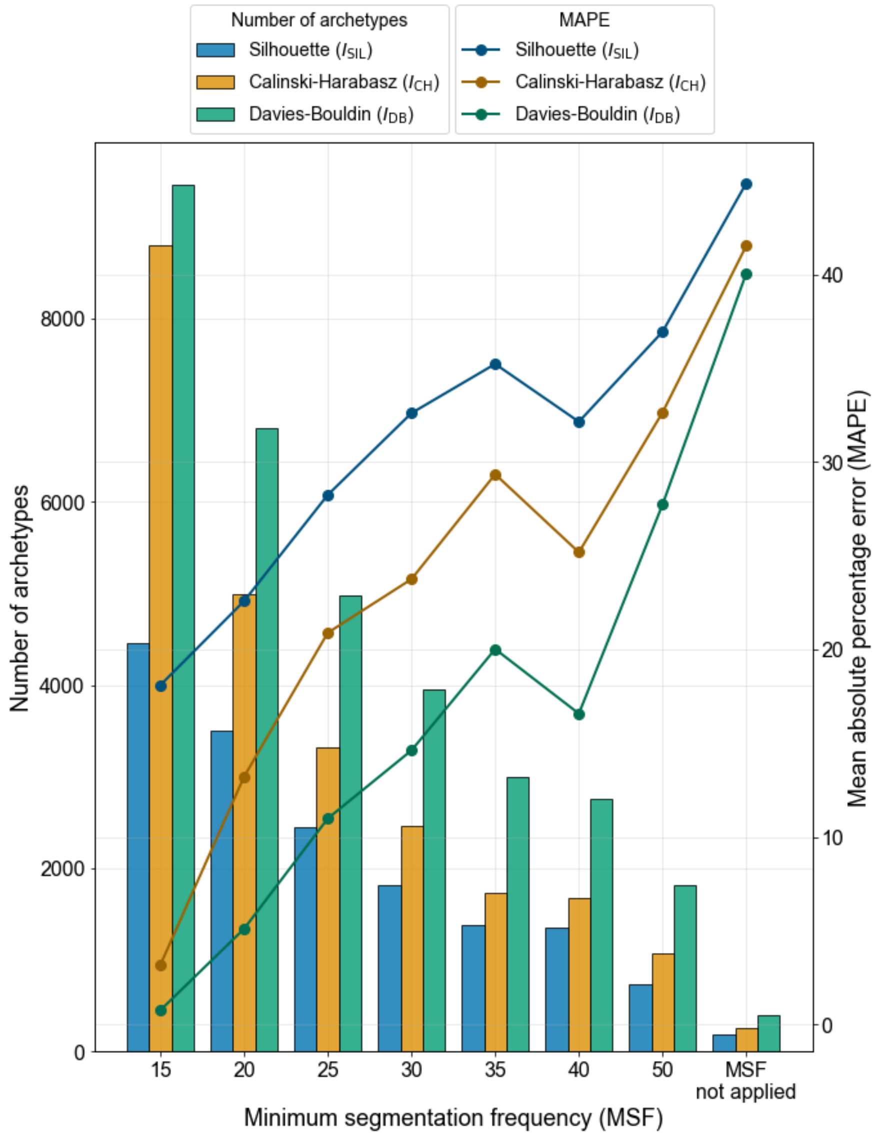
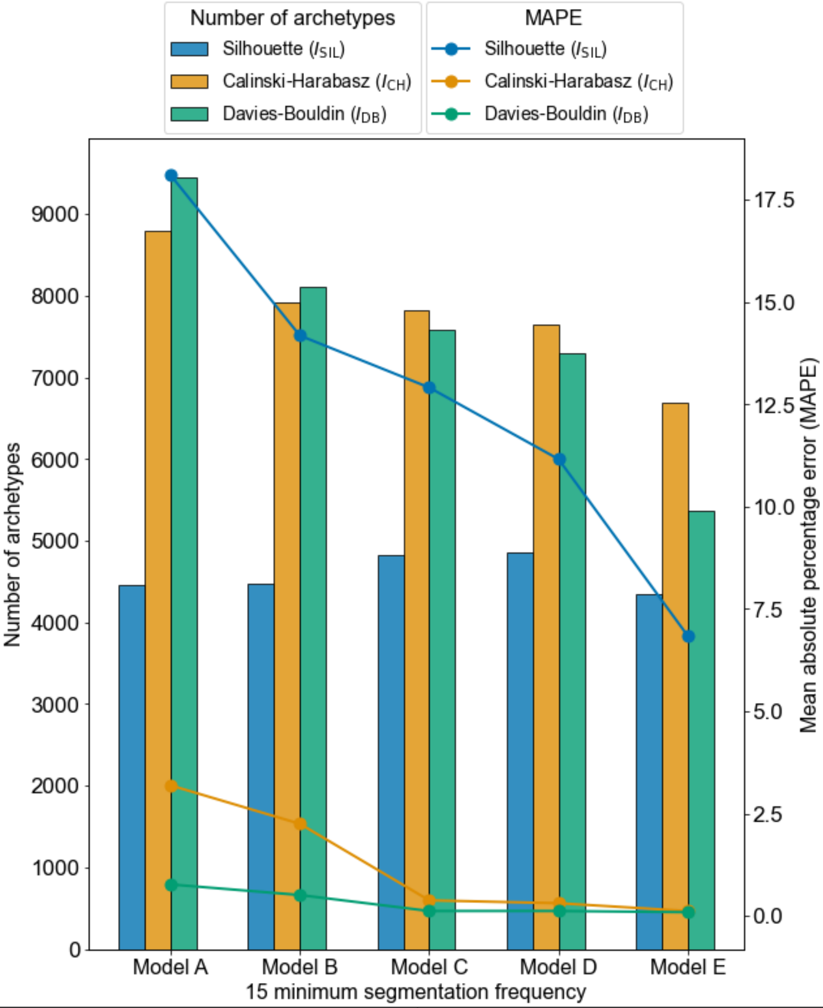


Figure 4.1: Impact of segmentation levels on representativeness and the number of resulting archetypes, evaluated using different clustering metrics. The bar plot represents the number of archetypes, while the line plot shows MAPE values, where lower MAPE indicates higher representativeness.

distribution of the categorical variables in the clustering outputs. Significant deviations can be observed between No-MSF and MSF-15 models. The No-MSF model consistently overestimated the share of the dominant feature at the expense of less-dominant ones. Hence, the resulting distribution was noticeably different from the distribution in the EHS. On the other hand, the distributions of all seven categorical variables in the MSF-15 outputs were almost similar to that of the distributions in the EHS. The No-MSF model overestimated the categories of *sysage*, *loftins4* and *wallinsz* by 22.5%, 14.5% and 12.5%, respectively. The model overestimated systems aged more than 12



Models	Variables
A	*floory, loftins4, storeyx, dblglaz2, wallinsz, fuelx, sysage*
B	*floory, loftins4, storeyx, dblglaz2, dwage5x, wallinsz*
C	*floory, loftins4, dblglaz2, dwage5x, wallinsz*
D	*floory, loftins4, dwage5x, wallinsz*
E	*floory, dwage5x, wallinsz*

Figure 4.2: Effect of variable count in on archetype representativeness considernig a range of variable count on one segmentation level, e.g. MSF-15. The analysis includes key housing characteristics such as floor area (floory), loft insulation thickness (loftins4), number of storeys (storeyx), double glazing percentage (dblglaz2), dwelling age (dwage5x), wall type and insulation (wallinsz), fuel type (fuelx) and system age (sysage). The bar plot represents the number of archetypes, while the line plot displays MAPE values, where lower MAPE indicates higher representativeness.

years, buildings with loft insulation thickness of 150mm or more and cavity insulated buildings. The tendency of the No-MSF model to overestimate building stock characteristics can have significant implications, especially if it is used to inform policy-making or strategic planning. For example, overestimating the prevalence of older systems (as indicated by *sysage*) could suggest that there are more inefficient systems than is the case, which could lead to the misallocation of resources for system replacements. Moreover, misrepresenting the number of buildings with substantial insulation could lead to policymakers believing that buildings are better insulated than they are, delaying essential energy efficiency measures.

The floor area distributions from the clustering outputs are shown in Figure 4.4, where the MSF-15 model's distribution was similar to that of the EHS, with an average difference of around 0.66%. In contrast, the No-MSF model's floor area distribution considerably deviated from the EHS. This model particularly underestimated the area of detached houses by approximately 45.5% and, conversely overestimated the area of other dwelling types, with converted flats being the most affected. The No-MSF model's limited ability to accurately represent the building stock's floor area could result in miscalculations of energy demands and efficiency, leading to inadequate or excessive provisions for heating, cooling and lighting. Within the EHS, detached dwellings showed significant variance in floor area distribution, potentially causing the clustering algorithm to focus on the most common sizes, overlooking larger dwellings. Furthermore, the limited sample size of converted flats may have constrained the algorithm's ability to effectively learn, possibly increasing its sensitivity to anomalies and skewing the overall representation. Therefore, adopting frequency-based segmentation, e.g. MSF-15, is essential to mitigate these discrepancies observed in the No-MSF model, and to provide a more accurate representation of the building stock's floor area distribution.

The MSF-15 model's ability to represent the building stock is further demonstrated by its close alignment with the EHS's distribution of dwelling types across different regions, as shown in Figure 4.5. For example, in London, the MSF-15 model's distribution of end- and mid-terrace dwellings differed from the EHS by less than 0.1%, while its distribution of purpose-built flats differed by approximately 0.43%. In contrast, the No-MSF model underrepresented London flats by 3.94% and incorrectly identified the South West region as having the most purpose-built flats. Misidentifying regions with predominant dwelling types can skew regional development plans, potentially causing overcrowding or under-utilisation, which may lead to ineffective housing and urban development strategies.

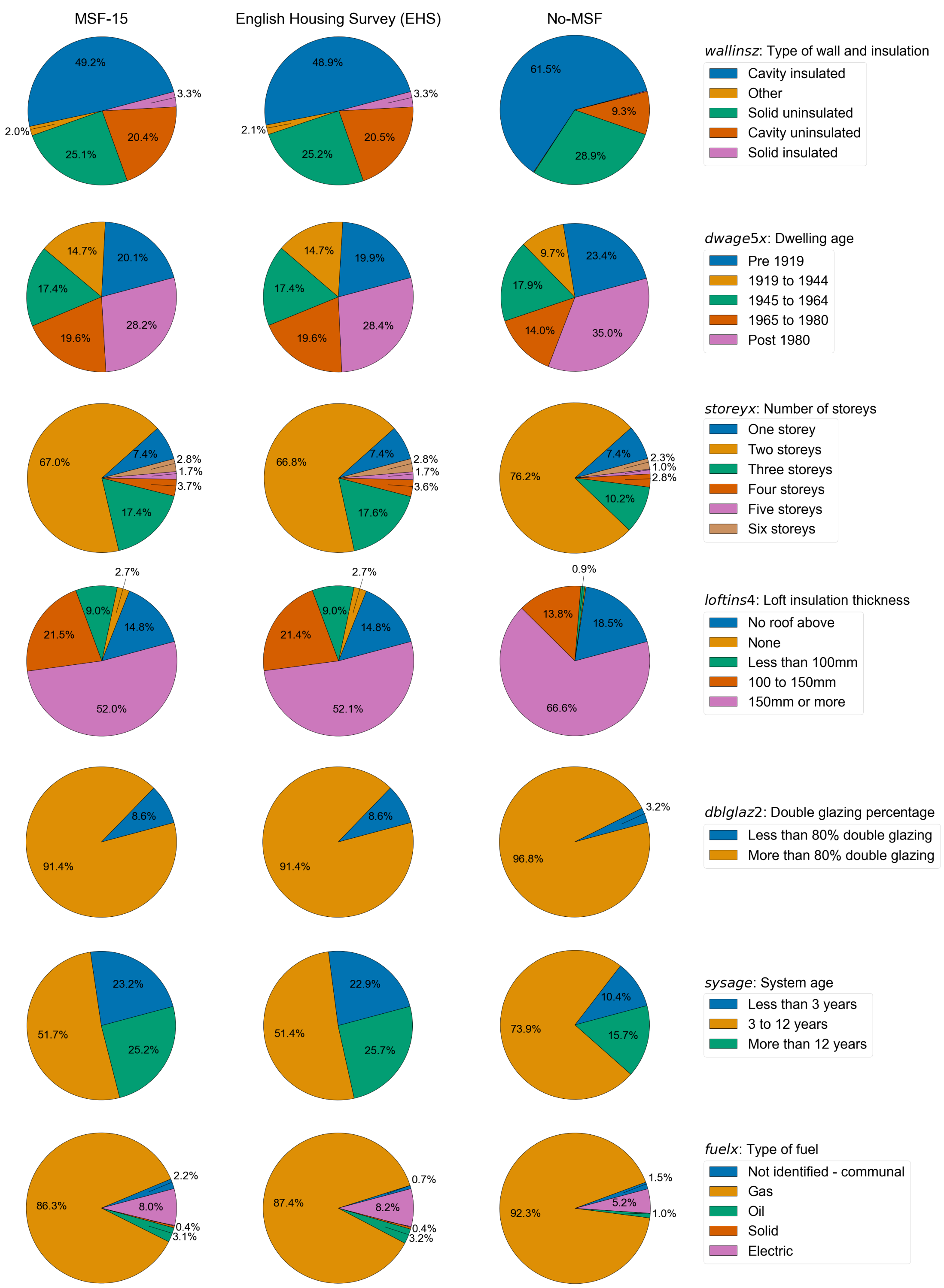


Figure 4.3: Comparison of the distribution of categorical variables in the clustering outputs and EHS.

4.2 Archetype development framework

Insights gained from the sensitivity analysis informed the development of a comprehensive framework for guiding the creation of building archetypes. The framework

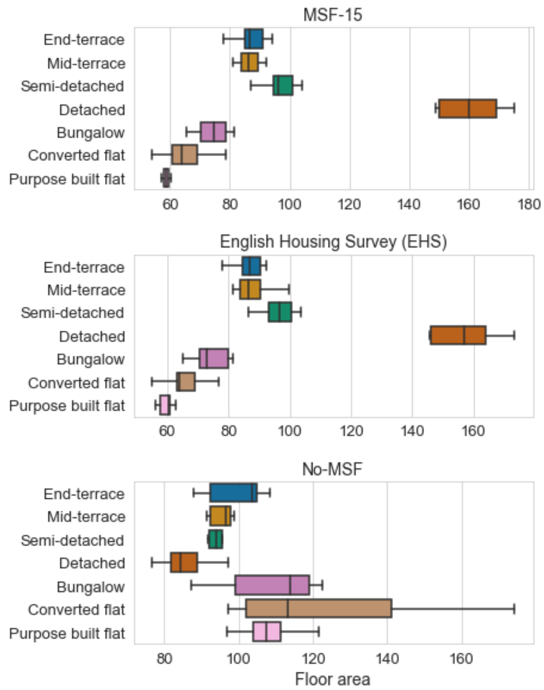


Figure 4.4: Floor area distribution of the clustering outputs and EHS.

allows the user to consider the interaction between influencing and decision factors during the archetype development process. As presented in Table 4.1, the framework comprises four influencing factors: geographical scale, research focus, temporal scale and computational cost. Given a set of influencing factors pertinent to the specific archetype development study, a user can choose the corresponding recommended values of the three decision factors: minimum segmentation frequency (MSF), evaluation metric and variable count.

Influencing factors are broadly categorised into features. The geographical scale is divided into district, city and national, based on stock homogeneity. Research focus is classed into specific and broad, depending on how broad the study objectives are. The specific research focus is linked with the investigation into specific characteristics of the building stock, typically within a single domain, e.g. energy efficiency and carbon emissions. Whereas the generic research focus is typically multi-domain and requires the modelling of interdependent factors, e.g. energy and environmental performance and the cost of retrofitting. Another way to differentiate between ‘specific’ and ‘broad’ research focus is to look at the number of dependent variables needed to identify significant variables for use in clustering using regression analysis. Specific research would normally require one dependent variable, whereas the broad focus might involve

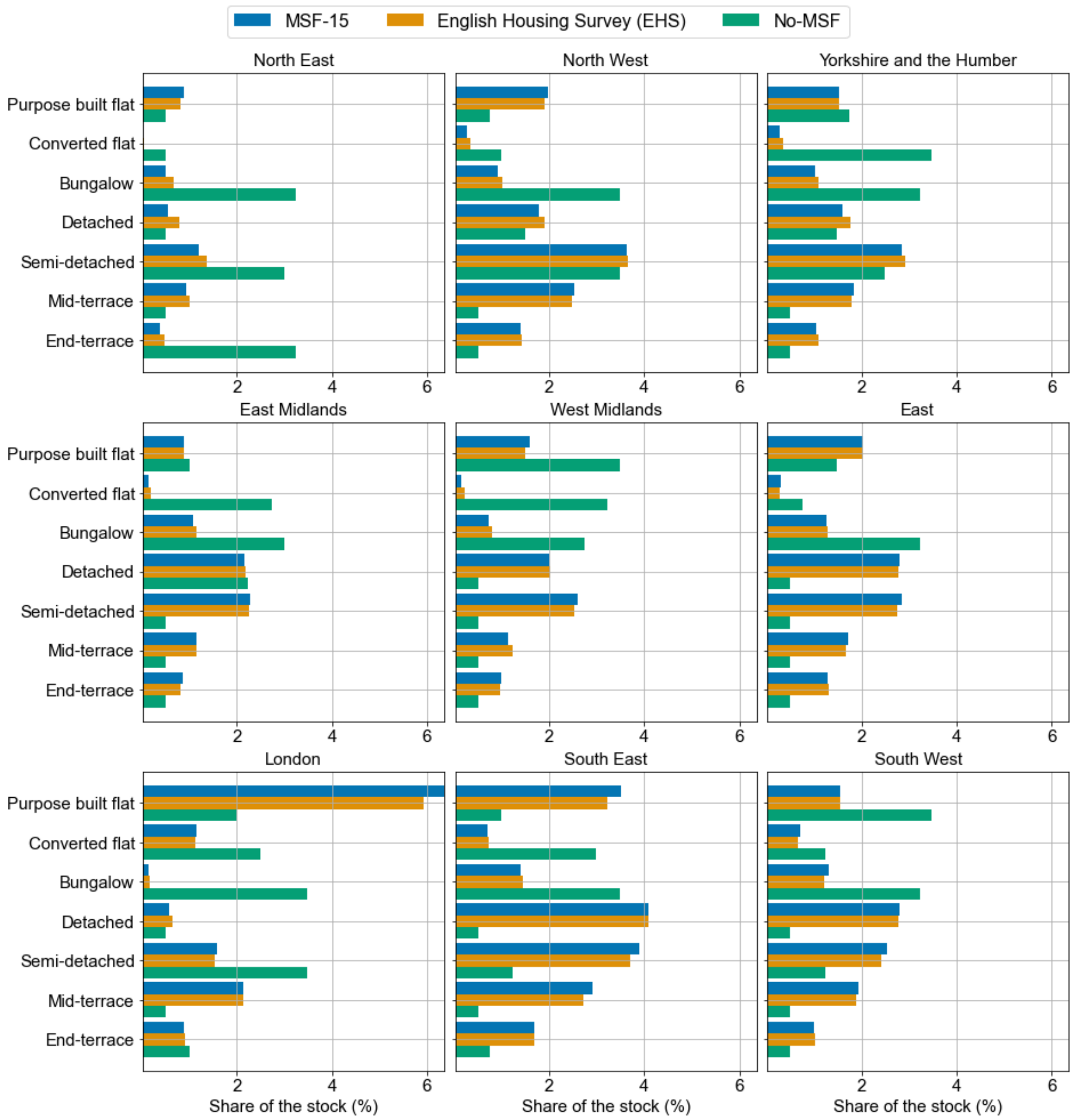


Figure 4.5: The distribution of dwelling types and regions between the clustering outputs and EHS.

multivariate regression analysis with two or more dependent variables. Temporal scales range between short- and long-term, referring to instantaneous to monthly and annual to decadal respectively. Computational cost depends on the detail and number of domains being modelled. Hence it is characterised by two features: low and high, with the assumption being that simplified or steady-state models are computationally less expensive than detailed and dynamic models to simulate the building archetypes.

Minimum segmentation frequency is inversely linked with segmentation level, i.e. the number of resulting data partitions from frequency-based segmentation. In this framework, MSF is divided into low, moderate and high with corresponding values of more than 40, between 25 and 40, and less than 25 respectively. There are three clustering evaluation metrics in the framework: Calinski-Harabasz (I_{CH}), Davies-Bouldin (I_{DB}) and Silhouette (I_{SIL}). Variable count refers to the number of variables selected for clustering. Even though the regression results may suggest a higher number of significant variables within the building stock data, the user may opt to use fewer variables to handle multicollinearity and reduce computation time during clustering. In the framework, low, moderate and high variable count refers to between 2 and 3, between 4 and 6, and more than 6 variables respectively.

Table 4.1: Framework for developing building archetypes considering different influencing factors.

Influencing factor	Feature	MSF[1]	Evaluation metric[2]	Variable count[3]
Geographical scale	District	High	I_{SIL} or I_{DB}	Low
	City	Low to moderate	I_{DB} or I_{CH}	Moderate to high
	National	Low	I_{DB} or I_{CH}	Moderate to high
Research focus	Specific	Moderate to high	I_{SIL} or I_{DB}	Low
	Broad	Moderate to high	I_{DB} or I_{CH}	Low to moderate
Temporal scale	Short-term	Low	I_{DB} or I_{CH}	Moderate to high
	Long-term	Moderate to high	I_{DB}	Low
Computational cost	Low (e.g. steady-state simulation)	Low	I_{DB} or I_{CH}	Moderate to high
	High (e.g. dynamic simulation)	Low to moderate	I_{DB}	Low to moderate

Notes:
[1]Minimum segmentation frequency (MSF): Low (MSF: <25), Moderate (MSF: 25-40), High (MSF: >40).
[2]Evaluation metric: I_{CH} (Calinski-Harabasz), I_{DB} (Davies-Bouldin), I_{SIL} (Silhouette).
[3]Variable count: Low (2-3), Moderate (4-6), High (>6).

4.2.1 Geographical scale

The methodological approach to archetype development is significantly influenced by the geographical context (Ali et al., 2019). Neighbourhoods and homogeneous districts are often characterised by limited data availability (Liu et al., 2010). In such cases, simplified models with few variables is generally more applicable than detailed models that require disaggregated data. A low segmentation level, i.e. high MSF, is often sufficient for neighbourhoods and districts due to the homogeneity in building characteristics such as age, materials, construction and usage. This reduced complexity avoids the unnecessary partitioning of data, as the buildings are likely homogeneous enough to be adequately represented with fewer archetypes. I_{SIL} can be ideal in these circumstances, as demonstrated in Figure 4.1, as the index consistently identified the fewest archetypes. However, if increased representativeness is desired within the scope of the available computational resources, I_{DB} can be employed to provide a more comprehensive portrayal of the building stock.

Conversely, the likelihood of the existence of high-quality data is higher for urban and national contexts, which supports the use of more complex modelling. Higher levels of segmentation, i.e. low MSF, can be adopted in such cases. In heterogeneous larger geographies, I_{CH} and I_{DB} indices are more applicable as they are better suited in identifying a broader range of representative archetypes, as shown in Figure 4.1. Representativeness is crucial in large-scale studies for accurately representing the variety of building characteristics found in heterogeneous building stocks, to ensure a detailed and encompassing view of the urban and national building landscapes.

4.2.2 Research focus

Research focus in building stock modelling varies from specific studies targeting a single domain to broader analyses considering multiple domains. The particular needs of the study, regardless of the geographical scale, often leads to the adoption of varying number of archetypes. For instance, a specific research on the effects of increasing cavity wall insulation on internal temperatures, a low to moderate segmentation level is often sufficient, particularly as the dataset tends to be uniform in insulation characteristics. The homogeneity of the data in this case facilitates the adoption of fewer variables. I_{SIL} is an ideal choice for evaluation metric because it results in fewer archetypes, as shown in Figure 4.1. However, for studies that target all types of wall insulation, I_{DB} may be more appropriate, as it can handle more variables and is capable of identifying archetypes with high representativeness.

Modelling complexity increases in studies with a broader research focus and multiple objectives. For instance, studies on indoor overheating due to climate change and corresponding energy demand requires the consideration of complex interactions between two interconnected domains: building thermal and energy systems. To effectively address this dual focus, the study would likely require a multivariate regression analysis to identify relevant clustering variables, using at least two dependent variables: indoor temperature and energy consumption. Hence, higher segmentation levels and more variables may be needed to adequately model the variations in building thermal characteristics, and energy and environmental systems to study their influence on indoor temperature and energy demand. When high segmentation levels are required, the choice between I_{CH} and I_{DB} can be guided by the variable count and availability of computational resources. I_{CH} appeared to be more effective for high variable counts, as shown in Figure 4.2, as it identifies fewer archetypes than I_{DB}, albeit at the expense of representativeness. However, in cases where computational cost is not a concern, I_{DB} is a better choice for enhanced representativeness.

4.2.3 Temporal consideration

Building stock modelling studies focusing on short-term analysis may require archetypes that comprehensively represent existing building characteristics. Hence, representative archetypes are essential for ensuring relevant analyses to inform effective decision-making and policy formulation. Figures 4.1-4.5 demonstrate how higher segmentation levels are well-suited to achieving high representativeness of variables such as "type of wall and insulation" (*wallinsz*), and are capable of adequately capturing different building typologies with a floor area variation closely resembling that of the original building stock, i.e. the EHS. Among all clustering evaluation metrics, I_{DB} is found to be particularly effective for such comprehensive analyses as it achieved the highest representativeness with a low variable count, as shown in Figure 4.2.

For long-term building stock analyses that anticipate changes in building characteristics, a low to moderate level of segmentation, and a low variable count are recommended to minimise computational costs and avoid the risk of archetypes becoming inconsistent or irrelevant over time. For instance, referring to Figure 4.3, it is observed that the No-MSF (i.e. no frequency-based segmentation) model tends to overestimate the prevalence of cavity-insulated dwellings within the existing building stock. However, this overestimation might be considered less-critical when projecting future (e.g. by 2050 or 2100) scenarios for indoor overheating assessment, given the anticipated rise in newly constructed dwellings featuring cavity wall insulation.

4.2.4 Computational cost

Simplified modelling such as steady-state simulations, due to their relatively lower computational demands (Gatt et al., 2020), are well-suited for building stock studies comprising a wide range of archetypes. Simplified models are often able to deal with diverse variables from multiple domains. A high level of segmentation is, therefore, recommended to account for the diversity of variables. I_{DB} is typically preferred in these scenarios for its ability to handle a variety of clustering variables with high representativeness, as shown in Figure 4.2. However, I_{CH} can also be used, especially when fewer archetypes are sufficient, offering flexibility in model design.

In contrast, detailed such as whole-building dynamic simulations are computationally expensive Hong et al. (2020), requiring careful considerations of the impact of the selected segmentation level on the number of resulting archetypes. While a larger number of archetypes can fully leverage the capabilities of dynamic simulations to provide detailed temporal insights, researchers often face limitations in computational power. This consideration becomes particularly crucial as the geographical scope increases and the building stock becomes more diverse. When less resources, both time and computation, are available to the user, adopting a moderate to lower segmentation level can be a practical approach to acquiring meaningful insights while dealing with resource constraints. This approach limits the dataset from being overly segmented, thereby reducing the number of archetypes needed for individual dynamic simulations. The combination of I_{DB} and low variable count can be advantageous for representative clustering, as demonstrated in Figure 4.2, especially when dynamic simulations are used as the analysis tool.

4.3 Summary

The summary has been as follows: This chapter investigates the methodological parameters that influence archetype representativeness, focusing on segmentation levels, clustering evaluation metrics and variable count. The analysis demonstrates that different clustering evaluation metrics yield varying levels of representativeness, with the Davies-Bouldin index identifying the highest number of archetypes with the greatest representativeness. Higher segmentation levels result in a greater number of archetypes, improving representativeness by capturing a broader range of building characteristics. While a reduced number of variables leads to fewer archetypes with sufficient representativeness, adopting many variables can increase complexity without major improvement of representativeness. Findings from the sensitivity analysis informed the development of an archetype framework, considering factors such as geographical and temporal scales, computational costs and research focus. The framework provides guidance on selecting appropriate parameters to develop representative archetypes tailored to different research contexts, aiming to balance complexity and practicality.

Chapter 5 | Archetype development

This chapter presents the development and validation of building archetypes used in this research. It outlines the process of creating the archetypes, detailing variable selection, segmentation and clustering evaluation metric. Following the development, a validation is conducted to ensure that the archetypes adequately reflect the characteristics of the UK housing stock to prepare for overheating simulations.

5.1 Developing archetypes for overheating analysis

A comprehensive framework for archetype development was introduced in Chapter 4. This framework provides a methodical approach to generating representative archetypes by simplifying the complex nature of many building features into manageable groups. While the previous chapter focused on identifying variables related to energy efficiency, the present investigation requires particular adjustments to the methodology in terms of choosing the variables, segmentation level and clustering evaluation metric to address the unique challenges associated with overheating risk assessment. This work demonstrates the flexibility of the archetype development framework by adjusting it to align with the specific context of overheating for different regions at the national level, highlighting the framework's adaptability for conducting context-specific evaluations for different research settings.

This investigation uses the virtual archetypes from clustering to identify the closest real-world equivalents within the English Housing Survey (EHS), particularly emphasising factors pertinent to overheating risks. Such selection prioritises important variables related to overheating for the clustering procedure, while also using additional data from secondary factors that were not included in the initial selection, i.e. any EHS variable not included in clustering.

The insufficient sample size of converted flats in the EHS limited the clustering algorithm's capability to represent these dwellings accurately. Furthermore, the methodology employed to represent the housing stock, which assumes typical internal arrangements like living spaces on the ground level and bedrooms on the first level, may not precisely represent the spatial arrangements of converted flats. The distinctive architectural designs and varying degrees of attachment to the surrounding surfaces in these flats make their inclusion more challenging, hence, converted flats were excluded from this study.

5.1.1 Variable selection

For the overheating assessment, the variables that were identified by multiple linear regression, such as loft insulation thickness (*loftins4*) and dwelling age (*dwage5x*), will be kept because they are important factors in both energy efficiency and indoor overheating. Nevertheless, particular variables such as fuel type (*fuelx*) and system age (*sysage*) will be omitted, given that they are more influential on energy performance than indoor temperature. The double glazing percentage (*dblglaz2*) has also been removed as a clustering variable, as the majority of buildings in the dataset are already double-glazed. Moreover, as the study considers both short- and long-term investigation, e.g. the baseline and 2050s climate scenario, it is likely that the housing stock will be fully double glazed by 2050. Retaining *dblglaz2* would increase the number of archetypes without yielding major benefits, only leading to higher computing costs for simulations. New variables, window size (*winsiz*), calculated from summing the window areas on each side from the EHS data, and orientation (*felorien*), have been included to more accurately represent overheating factors. These factors are essential for establishing archetypes that accurately represent the effects of solar heat gains, which directly influence indoor overheating. This approach aims to ensure that the chosen variables are relevant and assist in a more effective and concentrated investigation of overheating by reducing the number of variables and decreasing computational cost for simulations given a specific research focus.

5.1.2 Clustering evaluation metric

In Chapter 4, it was shown that the Davies-Bouldin index consistently identified more archetypes with a higher degree of representativeness than the Silhouette and Calinski-Harabasz indices. This makes the Davies-Bouldin index particularly useful for analysis requiring a thorough and detailed representation of the building stock, e.g. a national-scale investigation.

5.1.3 Segmentation level

It is important to acknowledge the anticipated variance in building constructions and geometries given the nationwide scope of this study. Higher segmentation levels are, therefore, ideal for capturing greater detail and potentially ensuring that the model appropriately represents the differences between various regions and building types.

The number of archetypes was effectively reduced from 9253 to 5561 by adopting MSF 17-20 for various dwelling types– this reduction is nearly half the original number of buildings. Despite this substantial reduction, the distribution of the clustering variables is consistent with the original data, as illustrated in Figure 5.1. Furthermore, the mean floor and window area of the reduced set of archetypes were 0.55% and 0.3% different from those of the EHS respectively. This balance between maintaining representativeness and reducing the number of archetypes demonstrates the effectiveness of using MSF levels within this range, such as MSF 17-20. This supports the validity of the approach for accurately modelling the diverse types of dwellings and their characteristics within the EHS dataset.

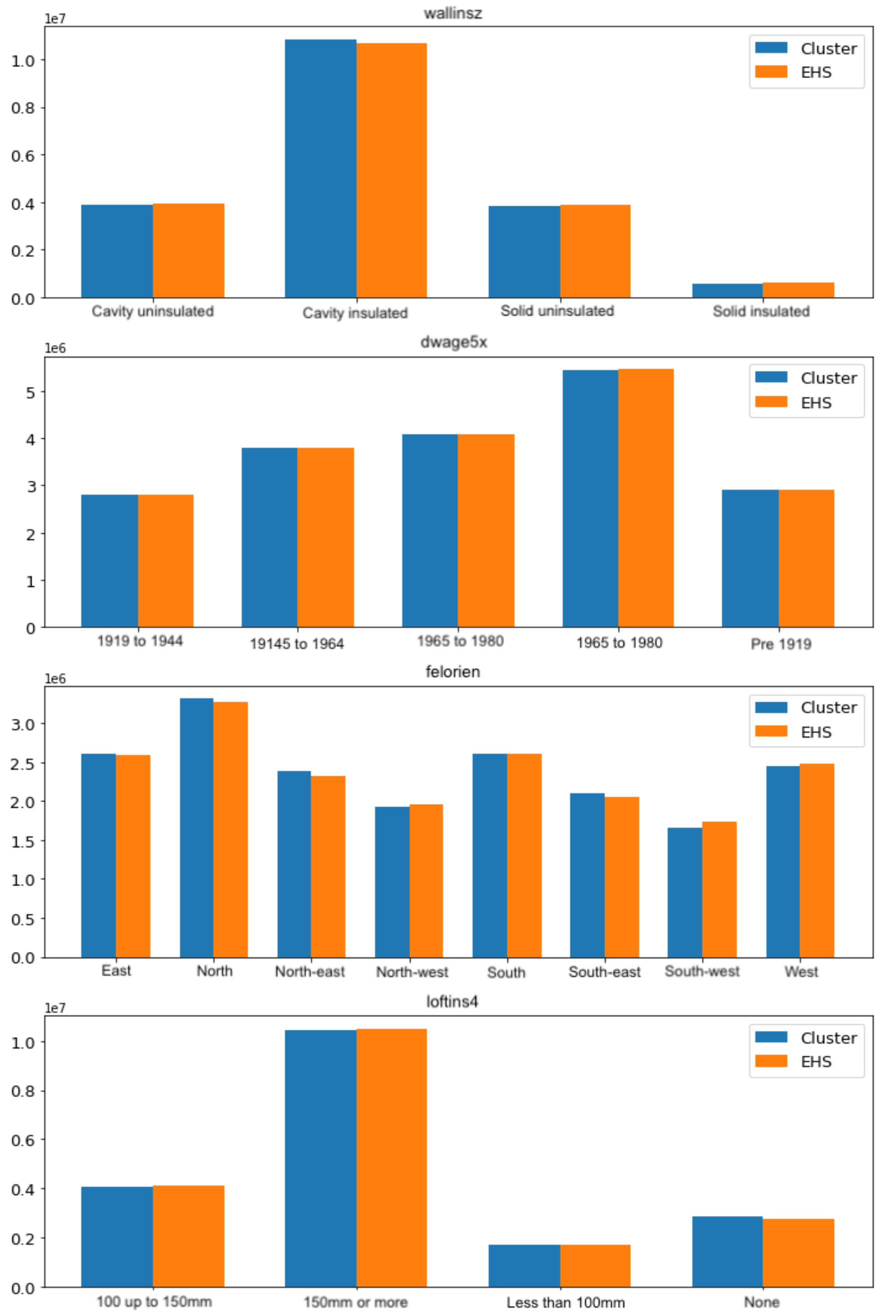


Figure 5.1: The distribution of clustering output to the EHS based on the dwelling counts of the clustering variables.

5.1.4 Understanding variations from the EHS

The EHS adopts a two-stage stratified sampling method, selecting geographic areas and sub-sampling households by tenure to create a representative sample of English households. While this approach reduces sampling errors and biases, systematic and random errors remain. For instance, households in newly developed areas not listed in the Postcode Address File (PAF) may be under-represented. Furthermore, households that choose not to participate might differ from respondents. Although the EHS uses stratification and weighting to address these issues, it cannot entirely eliminate these limitations.

Achieving representative archetypes is challenging due to the inherent limitations of the EHS sampling design, including potential biases and sampling frame constraints. Using clustering techniques to reduce the number of archetypes balances computational efficiency with representativeness. While this method may cause minor discrepancies in dwelling counts across variables, these differences are justifiable given the EHS's inherent limitations. The clustering approach effectively captures housing stock diversity while maintaining manageable archetype numbers, ensuring key variables influencing indoor overheating are well represented.

5.2 Validation results and analysis

A comparison of the housing stock model's outputs with empirical data from the EFUS (Department for Energy Security and Net Zero and Department for Business, Energy & Industrial Strategy, 2021a) is crucial for assessing the model's predictive capabilities. This is achieved by calculating the indoor-outdoor temperature ratio (IOTR), as explained in Section 3.4. By normalising indoor temperatures relative to external conditions across diverse dwelling types and regions, this study evaluates the model's capability to accurately represent the influence of external climate on indoor thermal environments. This investigation selects end-terrace archetypes to carry out the validation steps. The following analysis discusses the model's performance, identifying its strengths and weaknesses. Model assumptions, variations in building characteristics and occupant behaviour are also discussed to explain model outcomes. This evaluation validates the model's capabilities while pinpointing areas for improvement.

The EFUS dataset presents a limitation in providing only mean monthly temperatures for key indoor spaces, rather than hourly readings. By comparing the IOTR for June, July and August from the survey with corresponding simulated data from EnergyPlus, the aim is to ensure that the model has the capacity to adequately reproduce the impact of external climate on the indoor thermal environment within the typology of interest, i.e. end-terrace dwellings in each region.

A small discrepancy was observed when comparing the IOTR between the model and EFUS data. The model estimated the IOTR to be 0.73% higher for the living room (1.36 compared to 1.35) and 5.71% higher for the bedroom (1.44 compared to 1.36). While these differences indicate a modest overestimation of indoor temperatures, particularly in the bedroom, the model still performs well overall. The following section discusses potential explanations for these differences.

5.2.1 Addressing model discrepancies

The comparison between the building stock model's overheating predictions with empirical data from the EFUS revealed minor discrepancies in the IOTR for living rooms and bedrooms. The discrepancies observed may be explained by the following points:

- For the EnergyPlus model, more dwelling sizes were included, potentially consisting of smaller dwellings that could experience higher temperatures given less volume for air circulation. Differences may also be present in the construction data. For instance, some EFUS dwellings were at risk of fuel poverty, which may have a different distribution of dwelling ages, potentially with an over-representation of pre-1919 dwellings that typically have lower insulation levels and better natural ventilation. However, the focus of this study is solely on overheating during summer months, where the primary drivers are external climatic conditions, solar gains and ventilation behaviour, rather than heating-related influencing factors that are more relevant in winter. Given that EFUS represents the only large-scale, nationally representative indoor temperature survey of the UK housing stock, it remains a practical dataset for validation in this study. While some dwellings in EFUS may be at risk of fuel poverty, their proportion within the overall survey is relatively small, and the dataset still captures a broad range of dwelling characteristics.

- The EFUS (Department for Energy Security and Net Zero and Department for Business, Energy & Industrial Strategy, 2021a) shows that living rooms are frequently occupied during the day and evening. During weekdays, about 43% of households have an occupant indoors during the day, increasing to 60% on weekends. The survey shows that bedrooms are predominantly occupied during the nighttime— 94% of households reported an occupant within the dwelling during nighttime. During the day, however, bedrooms are less likely to be occupied, particularly on weekdays. In the EnergyPlus model, TM59 occupancies (Chartered Institution of Building Services Engineers, 2017) are adopted, which consider a worst case scenario for metabolic heat gains as it assumes constant bedroom occupancy, which potentially results in the model's slight overestimation of bedroom temperatures given a higher discrepancy (IOTR = 5.71%).

- Window opening may also contribute to the reported discrepancies between the EnergyPlus model and EFUS. Window opening behaviour can considerably influence indoor thermal performance, especially during summer. The EnergyPlus model adopted window opening rules per CIBSE TM59 (Chartered Institution of Building Services Engineers, 2017), which assumes fully opened windows when indoor temperatures exceeded 22°C during occupied periods in each room. An air change per hour (ACH) of 2 was adopted to account for potential limitations in window opening capabilities, similarly, this also assumes a worst case scenario as higher ACH are recommended per SAP (Building Research Establishment, 2021). The EFUS did not report window opening behaviours, but the adopted patterns may have been more effective in reducing internal temperatures than the model's assumed behaviour.

Chapter 6 | Discussion and results

This chapter presents the outcomes of the dynamic thermal simulations performed on the developed archetypes, analysing the mean indoor temperature, degree hours above critical thresholds and TM59 compliance (i.e., pass or fail for overheating risk) once shutter has been placed. The findings support the use of archetype-based modeling for capturing regional and dwelling-type variations in overheating risk.

6.1 Indoor temperature variation

An analysis of mean internal temperatures across various archetypes reveals variations in thermal performance when segmented by dwelling type and region, as show in Figure 6.1. For further insight, a detailed breakdown of the minimum and maximum temperature variations in baseline and future climate, along with the external temperature distributions for these regions, is provided in the Appendix A.2.

The analysis of regional variations in internal temperatures reveals higher temperatures in the South compared to northern regions. London recorded the highest internal temperatures, with living rooms averaging 23.93°C and bedrooms 23.59°C, reflecting findings from Beizaee et al. (2013) and Lomas and Kane (2013), which identify London as the region with the highest internal mean temperature. This can be due to the UHI effect, high-density housing and limited night-time cooling. In contrast, the North East and North West showed the lowest temperatures, with living rooms averaging 21.85°C and 21.84°C, and bedrooms 21.83°C and 21.82°C respectively, reflecting the influence of cooler external conditions and greater night-time cooling potential. Midland regions, such as the East Midlands and East, recorded intermediate temperatures, with living rooms around 22.20°C and bedrooms 21.94°C, reinforcing the broader trend of increased internal temperatures in the South due to higher external temperatures, increased solar radiation and the prevalence of better-insulated dwellings (EHS, 2023).

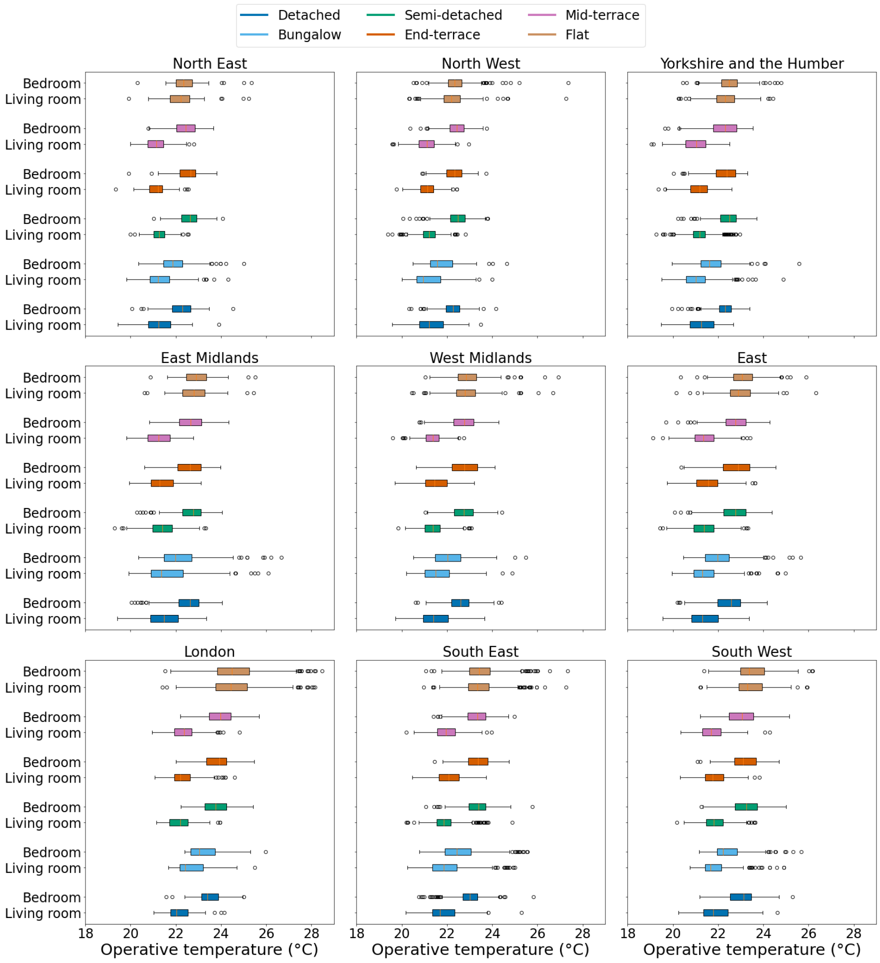


Figure 6.1: Daily mean temperature distribution in living rooms and bedrooms across regions and dwelling types in baseline climate.

Moreover, the mean internal temperature distribution reveals a pattern consistent with previous monitoring studies on the influence of dwelling age on internal thermal conditions. Pre-1919 dwellings recorded lower mean internal temperatures, with both bedrooms and living rooms maintaining cooler conditions compared to newly built constructions. Dwellings built after 1980 consistently show higher internal mean temperatures, particularly in bedrooms, where heat retention is more pronounced due to improved insulation and airtightness. These findings are in agreement with Beizaee et al. (2013) and Lomas and Kane (2013), who reported that older homes, particularly those constructed before 1919, tend to have lower internal temperatures as a result of increased heat loss through solid, uninsulated walls.

Similarly, distinct temperature patterns emerge across dwelling types, with flats recording the highest indoor temperatures, while bungalows and detached dwellings remain the coolest. Flats recorded the highest mean occupied temperatures, with living rooms averaging 23.78°C and bedrooms 23.12°C, consistent with Beizaee et al. (2013) and Lomas and Kane (2013), who identified flats as most prone to overheating. In contrast, bungalows had the lowest temperatures in bedrooms (21.52°C), likely benefiting from greater exposure to external airflow. Detached dwellings followed a similar trend, with living rooms at 22.04°C and bedrooms at 22.08°C, reinforcing findings that their larger external surface area facilitates heat dissipation. Mid-terrace dwellings averaged 22.19°C in living rooms and 22.23°C in bedrooms, while end-terraces recorded similar values of 22.19°C and 22.24°C, reflecting their shared walls' insulating effect while retaining better ventilation potential than flats. Although bungalows were not considered in Beizaee et al. (2013) and Lomas and Kane (2013), their inclusion in the EFUS (EFUS, 2021a) confirmed that bedrooms in bungalows tend to be the coolest. These findings confirm that flats face the greatest overheating risk, while detached dwellings and bungalows remain cooler, with terraced dwellings in between.

6.2 Overheating influencing variables

This section employs a Random Forest analysis on the archetype dataset to evaluate the influence of various building characteristics on overheating risk, quantified as degree hours above 26°C and 28°C in bedrooms and living rooms. The analysis explores whether the increased variation captured within the archetype data enables the RF model to reflect overheating influences. Model accuracy is subsequently assessed to establish whether the resulting patterns are reliable, and consistent with established trends.

The robustness of the results is reinforced by the strong performance of the Random Forest (RF) model. As shown in Figures 6.2 and 6.3, the high R^2 values across different dwelling types and regions demonstrate the model's ability to accurately predict the influence of various factors on degree hours in both bedrooms and living rooms under baseline and future climate conditions. The scatter plots, with points clustering closely near the diagonal, indicate consistent performance across both room types. This strong predictive accuracy can be attributed to the rich variation in the data provided by the comprehensive archetypes—variation that traditional parametric models, which often use less diverse data, may fail to capture. The following factors were considered:

- Thermal transmittance of building elements (*dwage5x_wallinsz*)
- Orientation of main facade (*felorien*)
- Household size (*hhsizex*)
- Terrain (*area3x*)
- Total window area (*winsiz*)
- Total floor area (*floory*)

In addition to the strong model accuracy identified, the patterns observed in the analysis (see Table A.2) are consistent with existing literature. In southern regions, where solar heat gains are higher, window area and orientation emerge as dominant factors. This effect is particularly evident in flats and detached homes, where larger window surfaces and direct sunlight exposure significantly increase overheating risk. In contrast, in northern regions, where solar gains are lower, the influence of window area and orientation is less, and the thermal transmittance of constructions is more influential. By 2050, these trends become even more pronounced: solar-driven overheating remains the primary concern in the South, while thermal transmittance becomes increasingly influential in the North.

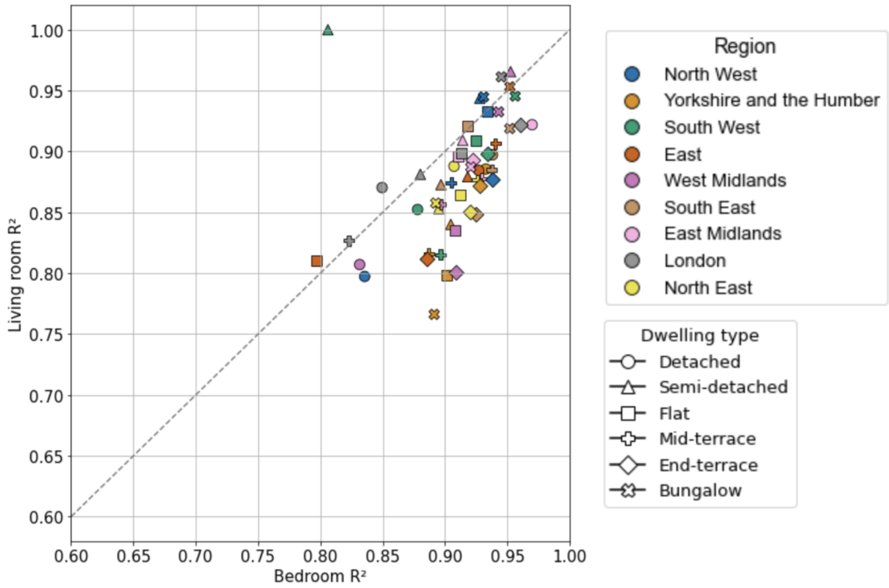


Figure 6.2: Relationship between bedroom and living room R^2 values for random forest model performance in the baseline climate, categorised by region and dwelling type.

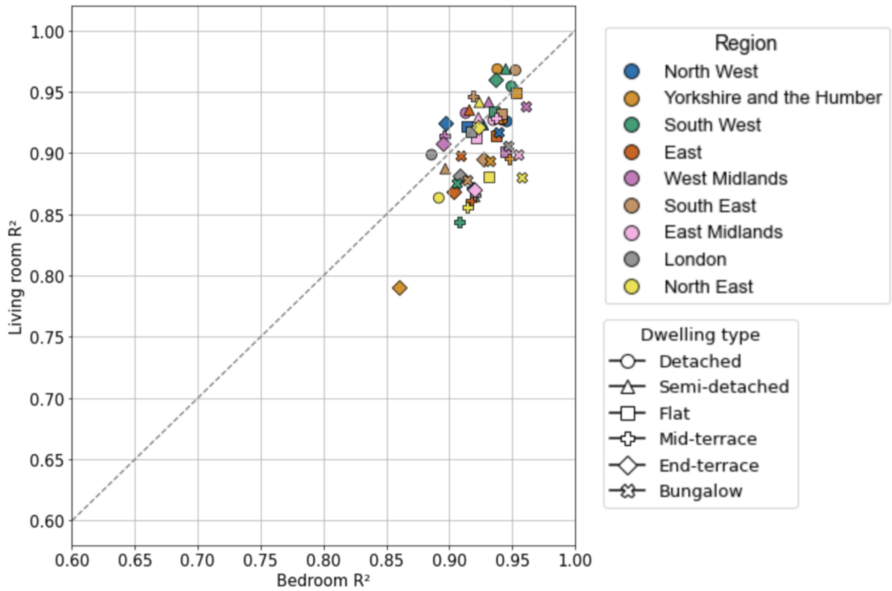


Figure 6.3: Relationship between bedroom and living room R^2 values for random forest model performance in the 2050 climate, categorised by region and dwelling type.

6.3 Regional analysis of overheating

The Random Forest models have effectively captured key influencing variables, as demonstrated by their predictive accuracy, while internal mean temperature patterns align with established trends across regions and dwelling types. Building on this foundation, the analysis now progresses to a regional analysis of overheating risk, quantified in terms of degree hours above 26°C in bedrooms and 28°C in living rooms, as shown in Figure 6.4.

London consistently recorded the highest overheating risk across all dwelling types and climate scenarios, with flats being the most affected dwelling type. In the baseline scenario, London's flats accumulate 870 degree hours above 26°C in bedrooms and 794 degree hours above 28°C in living rooms, which is higher than any other region. By 2050, these values increase considerably, reaching 2390.5 and 2459.1 degree hours respectively, indicating a near threefold increase. Other dwelling types in London, such as bungalows and mid-terrace homes, also record increases, with bungalows reaching 1582.8 bedroom degree hours and 1154.4 living room degree hours.

The South East and South West consistently show the next highest overheating risks, with overheating levels well above those seen in northern regions. In the baseline scenario, South East flats record 246.7 bedroom degree hours and 183.1 living room degree hours, while the South West follows closely with 228.5 bedroom degree hours and 106.5 living room degree hours. By 2050, overheating intensifies, with flats in the South East reaching 1563 bedroom degree hours and 1377.5 living room degree hours, while the South West reaches 1951 bedroom degree hours and 1712.3 living room degree hours. These trends indicate that southern England will face extreme overheating conditions, second only to London. The higher temperatures in these regions are mostly driven by increased solar radiation exposure compared northern areas, making overheating mitigation strategies essential for future developments.

Northern regions show considerably lower degree hours in both the baseline and projected climate scenario. In the baseline climate, bedroom degree hours for flats in the North East are 93.1, while the North West records an even lower 51.6, both substantially lower than values seen in the South. Living room overheating risks follow a similar pattern, with the North East at 85.7 degree hours and the North West at just 0.4. However, despite these lower starting values, the 2050 projections reveal a sharp percentage increase in overheating. In the North East, flats increase to 409.9 bedroom degree hours and 342.1 living room degree hours, while the North West reaches 411.2 bedroom degree hours and 211.1 living room degree hours. Although the absolute values remain lower than in the South, these three- to fivefold increases demonstrate that climate change will intensify overheating risks across the entire country, even in traditionally cooler northern regions.

Among all dwelling types, flats are the most vulnerable to overheating in every region and scenario. In London, flats reach 2390.5 bedroom degree hours and 2459.1 living room degree hours by 2050, making them the most heat-stressed dwellings in the UK. This trend is consistent across other regions, with flats in the South East reaching 1563.0 bedroom degree hours and 1377.5 living room degree hours, while those in the South West rise to 1951.0 bedroom degree hours and 1712.3 living room degree hours. Even in the North East and North West, where overheating is less severe, flats still record the highest overheating levels, highlighting their structural disadvantages. In contrast, detached dwellings tend to perform better, benefiting from larger surface areas for heat dissipation and improved cross-ventilation, making them less prone to extreme overheating.

The findings of Fosas et al. (2018) and Mulville and Stravoravdis (2016) indicate that higher insulation levels and improved fabric energy efficiency can lead to increased overheating risk in some dwellings. The increased overheating risk in well-insulated homes is evident in the current analysis, where post-1980 dwellings consistently recorded the highest degree-hour accumulations across both baseline and future scenarios. Post-1980 dwellings averaged approximately 107.7 degree hours above 28°C in living rooms and 160.5 degree hours above 26°C in bedrooms, higher than the values for older constructions. By 2050, these figures increase to around 701.9 degree hours in living rooms and 969.9 degree hours in bedrooms, while dwellings built before 1919 or between 1919 and 1980 maintain considerably lower degree hours.

Thermal simulations conducted using the archetype-based modeling framework have demonstrated their robustness in capturing both present and projected overheating trends across the UK housing stock. The findings further reinforce the reliability of this approach in assessing overheating risks under current and future climate conditions, with strong alignment between simulated outputs and prior empirical and modeling studies. This consistency underscores the framework's capacity to provide meaningful insights into regional and dwelling-type variations, making it a valuable tool for large-scale overheating assessments.

Figure 6.4: Average degree hours for bedrooms and living rooms in current and future climate.

6.4 Passive cooling performance

A further check on the archetype-based simulations involves evaluating the effectiveness of external shutters as a passive cooling strategy by comparing the number of archetypes that fail the overheating criteria before and after shutter installation. The observed reduction in dwelling failures provides a quantitative measure of the cooling impact, demonstrating that the application of external shutters can markedly decrease the percentage of units exceeding the TM59 threshold.

In regions with higher solar heat gains, such as London, the South East, and the South West, external shutters exhibit more pronounced cooling performance, actively reducing overheating levels. For example, in South West flats, the baseline degree hours decrease from 228.5 to 98.1 (around 57.1% reduction), and under the 2050 scenario, it drop from 1951.0 to 796.8 degree hours (a 59.2% reduction). This demonstrates that shutters can significantly counteract the effects of intense solar exposure in these areas. However, despite these substantial reductions, the cooling effect of shutters alone is insufficient to completely eliminate overheating risk, suggesting that additional measures will be necessary in regions with extreme solar gains. In contrast, northern regions, where baseline overheating is lower, experience relatively smaller reductions in degree hours.

To note, in the base scenario, the application of shutters led to a reduction in overheating failures in almost 27% of the buildings, allowing more dwellings to pass the TM59 criteria. However, by 2050, as the climate warms, this benefit diminished significantly, with shutters only reducing failures in about 10% of the buildings. Despite still providing some cooling potential, fewer dwellings were able to meet TM59 requirements, even with shutters are used. The overall overheating failure rate also increased sharply, rising by over 65% compared to the base scenario without shutters.

Across all scenarios, flats consistently recorded the most degree hours, both prior to and following the installation of shutters. This trend is observed in all regions, where flats continue to exceed TM59 thresholds in 2050 despite the application of shutters. In contrast, detached dwellings show consistently lower degree hours. These findings align with patterns observed in previous studies, where flats tend to face greater thermal discomfort due to their design characteristics, while detached homes experience more favorable conditions given more exposing surfaces.

The findings of this study reinforce the validity of the archetype-based modeling framework in capturing key patterns in passive cooling potential of external shutters. Wright and Venskunas (2022) demonstrates that shading provides notable cooling benefits, particularly in detached dwellings, where lower overheating risks are observed in London and other southern regions. Furthermore, regional variations in shading effectiveness are evident, as similar performance trends emerge across different climatic conditions. The analysis further indicates that while shading remains a significant passive cooling measure under future climate scenarios, its efficacy is particularly pronounced in buildings with larger exposed surfaces, e.g. detached dwellings. These findings align with Porritt et al. (2013), who highlight the reduced effectiveness of shading in flats and terraced dwellings due to installation constraints. Collectively, these results demonstrate that the archetype-based methodology reliably reflects the primary drivers of overheating risk and mitigation across diverse dwelling types.

6.5 Summary

The archetype-based approach derived from the proposed framework has proven reliable in capturing typical overheating patterns and their primary drivers. Moreover, the observed reduction in overheating following the application of external shutters aligns with patterns reported in previous studies, reinforcing the reliability of the archetype framework in simulating both baseline conditions and targeted cooling interventions. Overall, the results demonstrate the approach's capability for large-scale overheating assessments and its potential to guide evidence-based strategies for mitigating summer thermal risks in the UK housing stock.

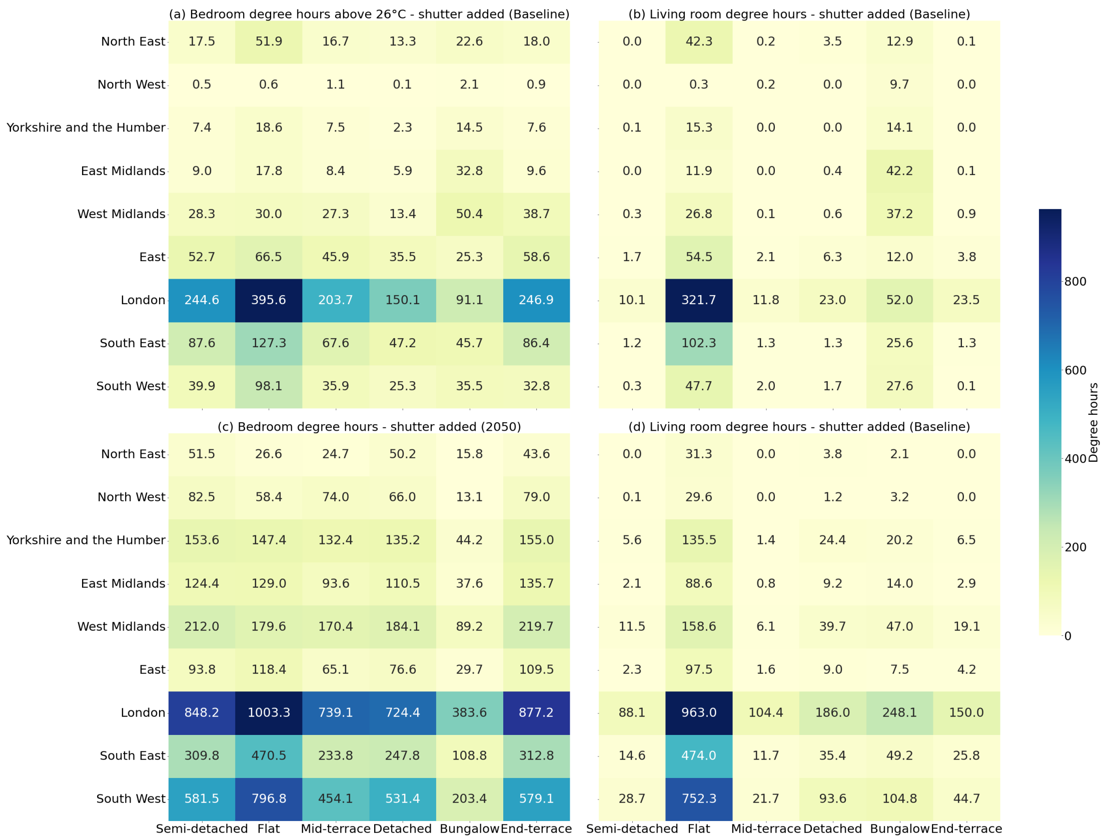


Figure 6.5: Average degree hours for bedrooms and living rooms in current and future climate after shutter placement.

Chapter 7 | Conclusion

Rising temperatures and more frequent heatwaves are intensifying overheating risks in the UK housing stock, posing challenges to occupant comfort, health, and well-being. To address these risks at a national scale, it is essential to use representative archetypes that accurately reflect the diversity of housing characteristics. This study introduced an MSF-based framework for archetype development, enabling a more comprehensive assessment of regional overheating patterns. By validating the framework through simulations and evaluating its ability to capture key overheating drivers and mitigation patterns, the research demonstrates its robustness for large-scale overheating analysis.

This chapter first discusses the research findings, outlining key insights from the analysis. It then highlights the main contributions, particularly advancements in archetype development for overheating assessments. This is followed by a discussion of research limitations, identifying areas for further refinement and proposing directions for future work.

7.1 Research findings

7.1.1 Research question 1

1. What are the primary determinants of overheating in the UK housing stock ?

This question is addressed in Section 2.7, where a review of the literature on overheating and its influencing factors was conducted. The literature review identified building design, construction and household characteristics as important factors influencing indoor overheating. There is a greater overheating risk in certain types of dwellings, such as flats and mid-terraced houses, as well as rooms that face south or west and other orientations in between. Due to the lower temperature threshold in the static overheating criterion, bedrooms are often more likely to be identified as overheated. Living rooms are typically warmer than bedrooms in flats, most likely due to greater heat gains from cooking in open-plan flats and higher solar heat gains. On the other hand, living rooms in houses are usually located on the ground floor and receive comparatively less solar heat gains than bedrooms on the first floor. The type and age of the dwelling, as well as the number of floors and floor area, may influence the difference in the internal temperature between bedrooms and living rooms.

Solid-walled constructions are less susceptible to overheating than well-insulated contemporary constructions. Therefore, the placement of wall insulation must be carefully considered because of the likely increased risk of overheating associated with internally placed insulation, given that a sizeable share of the UK housing stock still has solid-walled constructions. However, findings suggest that the increased risk of overheating caused by internal wall insulation can be avoided in the current and possibly future climate with additional passive strategies such as external solar shading, which can offer optimal cooling effectiveness in well-insulated constructions. On the other hand, cool paint has been found to be the more ideal passive strategy to reduce overheating in uninsulated dwellings.

7.1.2 Research question 2

1. For different influencing overheating factors, how does the effectiveness of passive cooling measures vary in reducing indoor temperatures ?

Section 2.9 addresses the current research question by identifying the most commonly used passive cooling measures and investigating their applications. Building on the identification of key overheating factors from the preceding section, each passive cooling strategy was introduced into a framework that assessed its relative effectiveness against different overheating factors, drawing on findings from earlier research. This framework provides a comprehensive view of how various passive cooling measures perform in relation to specific overheating influences, based on established evidence from prior studies.

Vulnerable occupants, such as the elderly or infirm, can greatly affect the effectiveness of passive cooling measures reliant on occupant interaction, like natural ventilation. Window opening or manual control of ventilation systems may not be consistently or effectively managed by these individuals, increasing overheating risks. The effectiveness of natural ventilation is significantly decreased without active occupant participation to regulate temperatures. To address this, intelligent ventilation systems that automatically adjust airflow based on real-time temperature and air quality data could ensure effective heat dissipation, maintaining thermal comfort and reducing overheating risks for those unable to manually manage these systems.

As the climate warms, the effectiveness of individual passive cooling strategies is expected to decrease, especially by the 2080s when higher ambient temperatures and more frequent heatwaves become common. Natural ventilation and thermal mass, which depend on cooler external temperatures for heat dissipation, may lose effectiveness as rising outdoor temperatures reduce the potential for natural heat loss. To address this, a combination of passive cooling measures will be necessary to reduce overheating effectively. For instance, integrating solar shading, cool roofs and automated ventilation systems can reduce solar gains and improve heat dissipation. As single strategies become less effective in extreme future climates, adopting multiple strategies together will be crucial for maintaining thermal comfort and mitigating overheating risks.

The effectiveness of passive cooling strategies varies significantly for different overheating factors, including dwelling type, occupancy and orientation. Strategies such as solar shading and cool paint perform optimally under different conditions, with solar shading being highly effective across most dwelling types, and cool paint being least affected by orientation or construction type.

Solar shading and cool paint are identified as the most effective passive cooling strategies for both current and future climates. Solar shading consistently shows high performance, in both traditional and energy-efficient dwellings, while cool paint offers significant potential in dwellings with minimal insulation and large, exposed surfaces.

7.1.3 Research question 3

1. How do methodological choices affect archetype representativeness, and what recommendations can be made for developing representative archetypes ?

There is an increasing need for representative building archetypes to better capture building diversity and improve the accuracy of building simulations and overheating risk assessments. A review of building archetype development methods identified key parameters influencing representativeness and introduced a frequency-based partitioning approach, "minimum segmentation frequency," to improve it. A sensitivity analysis investigated the impact of segmentation levels, variable counts and clustering evaluation metrics on archetype representativeness. Higher segmentation levels produced more representative archetypes, with the Davies-Bouldin index consistently identifying more archetypes with higher representativeness, followed by the Calinski-Harabasz and Silhouette indices. Lower variable counts resulted in fewer but more representative archetypes across all indices.

The sensitivity analysis informed the development of a comprehensive framework for creating representative building archetypes. The framework considers geographical and temporal scales, computational cost and research focus. Researchers aiming to develop representative archetypes may benefit from the following recommendations for selecting segmentation levels, clustering evaluation metrics and variable counts for their particular research goals:

- Lower segmentation levels can be suitable for district-scale studies with homogeneous building stock and when more resource-intensive dynamic simulations are needed. Whereas higher segmentation levels are better suited for more heterogeneous city- and national-level stocks, and when steady-state simulations are sufficient.
- If computational resources are not a limiting factor, the Davies-Bouldin index can be an effective metric for achieving high archetype representativeness. For resource-limited scenarios, the Calinski-Harabasz index offers a viable alternative, achieving a balance between representativeness and computational cost by identifying fewer archetypes. However, the Calinski-Harabasz index may not be ideal for clustering with few variables. The Silhouette index can be suitable for building stocks with one or more dominant variables, or for studies with specific objectives, as it consistently identified the least number of archetypes in this study.
- For national-scale studies with specific objectives that require dynamic simulations over a long-horizon, reducing the number of variables used for clustering can be beneficial. This approach simplifies the complexities of national landscapes, reduces computational cost, and avoids producing overly detailed archetypes that may become less relevant in the future as building trends and technologies evolve.

7.1.4 Research question 4

- Can the developed archetypes, when used in dynamic thermal simulations, reflect typical patterns of overheating risk and the cooling potential of a passive measure such as external shutters?

The analysis reveals similarity in mean internal temperature patterns across regions, dwelling ages and dwelling types. For example, London consistently shows the highest temperatures, attributed to factors such as the urban heat island effect, high-density housing and limited opportunities for night-time cooling. This trend mirrors previous studies, with the North East and North West generally recording the coolest conditions, while Midland regions fall somewhere in between. Likewise, older dwellings with less insulation tend to maintain lower internal temperatures compared to more modern constructions that retain heat more effectively. Among dwelling types, flats experience the highest internal temperatures, while detached houses and bungalows remain cooler, with bungalows, particularly their bedrooms recorded the lowest temperatures. Overall, these consistent patterns reinforce the reliability of the findings and their alignment with established research on internal temperature distributions.

Similarly, the archetypes effectively capture variations in overheating risk across regions, dwelling types and ages. Based on degree hours, newer constructions recorded the highest overheating risk due to improved insulation and airtightness, which contribute to greater heat retention. Regional differences are also well reflected, with southern regions, particularly London, experiencing the most severe overheating, while northern regions consistently record lower values. Among dwelling types, flats are the most vulnerable, accumulating the highest degree hours and recording the greatest severity, reinforcing their increased susceptibility to overheating.

The analysis also shows that external shutters provide the greatest benefit to those dwellings most susceptible to high solar heat gains, notably reducing overheating in flats and in regions with intense solar exposure, while improvements are more modest in areas with lower solar exposure. Moreover, as the climate warms, relying solely on a single passive measure such as shutters may prove insufficient, as evidenced by a decline in the number of archetypes meeting TM59 standards in 2050 compared to baseline conditions.

The results demonstrate that the developed archetypes effectively capture typical patterns of overheating risk and the key influencing factors across different regions and dwelling types. By leveraging a Random Forest model, the analysis highlights how the variation in the stock features influence degree hours, with strong predictive accuracy (R^2 values between 75–99). This demonstrates sufficient variation in key variables to identify vulnerability across dwelling types and regions, making them a reliable tool for informing mitigation strategies and policy decisions.

The comprehensive analysis confirms that simulating the developed archetypes can capture the spatial and typological variations in both internal temperature distributions and overheating risks across the UK housing stock. The typical pattern of shading potential is well reflected, and the Random Forest model reveals that key variations influencing overheating risk are effectively captured.

7.2 Research contributions

This research synthesises existing knowledge through a literature review on passive cooling measures and factors influencing indoor overheating. A comprehensive framework was established to describe the potential effectiveness of various passive cooling strategies, considering factors influencing overheating, including climate, material and building design, thereby providing valuable insights for future research and policy development.

A detailed sensitivity analysis of segmentation levels, clustering metrics and variable counts represents another key contribution of this research. This investigation provides valuable insights into how different methodological choices influence the representativeness of building archetypes.

A central contribution of this thesis is the introduction of the minimum segmentation frequency (MSF) and framework for archetype development that systematically integrates MSF selection. The MSF approach, a unique pre-clustering segmentation step, preserves the feature diversity inherent in the building stock at different levels. The framework guides the development of archetypes a desirable level of representativeness by strategically balancing granularity and scalability, capturing essential variations in the housing stock while remaining feasible for large-scale simulations.

The archetypes developed using the MSF approach within the framework were tested through dynamic thermal simulations, demonstrating their ability to replicate established overheating and cooling patterns across different UK regions and dwelling types. Their capacity to capture regional and typological variations in overheating risk makes them a reliable tool for assessing the thermal resilience of the housing stock under current and future climates. Additionally, the application of a Random Forest model to the archetype-derived dataset achieved high predictive accuracy across different typologies, highlighting the MSF-driven archetypes' ability to preserve and leverage the inherent diversity of the housing stock. These findings reinforce the applicability of the MSF approach in building stock modelling, demonstrating its potential for scenario testing, policy development and targeted mitigation strategies aimed at reducing overheating risks in dwellings.

7.3 Limitations and future works

This research reviewed both domestic overheating studies and archetype development works to inform the creation of archetypes tailored for national-scale overheating assessments. However, several limitations that could potentially offer new contributions are discussed in the following subsections.

7.3.1 Archetype development

The use of minimum segmentation frequency improved archetype representativeness noticeably. However, its effectiveness is sensitive to the distribution of the variables, being less pronounced for skewed distributions. Future research can explore alternative segmentation approaches to account for the skewness in the data. Clustering can also be investigated without setting thresholds on the number of cases per segmented subset. Further research could also look into the application of MSF in conjunction with clustering algorithms other than k-prototype. These investigations may enable the exploration of further objectives, including minimising the number of archetypes while maintaining sufficient representativeness, even with increasing variable counts.

Compared to the larger geographies such as the United States and China, UK housing stock can be considered homogeneous, despite noticeable regional variations. On the other hand, dense cities in the developing Asia are often characterised by a larger share of multifamily buildings that are more homogeneous in nature than the UK housing stock. The generalisability of the proposed approach for the development of representative archetypes can be investigated in other contexts of varying homogeneity and stock characteristics.

The physical, thermal and system characteristics of non-domestic buildings vary significantly depending on building type, use and location. Although the use of MSF for pre-clustering segmentation resulted in higher representativeness for the investigated dwelling stock, further research should be conducted on how well the combined MSF and *k*-prototype work on non-domestic building stock, particularly focusing on the effects of knowledge- and frequency-based segmentation on representativeness.

7.3.2 Overheating analysis

The modelling of internal layouts for archetypes used a simplified two-zone approach, with a ground floor living room and a first floor bedroom. While practical, this method may not capture the diverse internal layouts found in the UK housing stock. Future research could use machine learning or predictive techniques to generate more detailed layouts based on factors like floor area, number of rooms and dwelling type. Additionally, generative design methods, such as generative adversarial networks (GANs), could be explored to create prototype layouts. Incorporating more accurate layouts could enhance overheating risk assessments and lead to more effective design and policy interventions that address the thermal performance of various dwelling types.

Converted flats were excluded from the overheating modelling due to their unique characteristics and complex, varying surrounding environments. Converted flats often have irregular layouts and variable thermal properties. These factors make it challenging to apply the two-zone model used in this study, which assumes a more consistent internal layout. These complexities, including the diverse thermal behaviours and interactions with surrounding structures, were beyond the scope of this work. Future studies could explore these unique factors to better assess the overheating risks specific to converted flats.

This study aimed to determine whether passive cooling patterns could be captured using the developed archetype framework, with external shutters selected as the focus due to their suitability in the literature. Shutters were identified as an appropriate measure within the study's scope, given their dynamic control and ability to reduce summer overheating without compromising winter solar heat gains. Unlike fixed shading solutions, shutters allow for seasonal adaptability, preserving heat retention during colder months. Future research could build on this framework by developing archetypes that account for both summer and winter conditions, incorporating additional variables such as fuel type and heating system efficiency to explore a broader range of adaptation strategies.

Assuming passive cooling strategies are operated once internal temperatures exceed 22°C oversimplifies real-world behaviour. Occupants may limit window or shutter use due to security concerns or comfort preferences, influencing the effectiveness of these measures. This assumption overlooks the variability in how households manage ventilation and shading. Future research could incorporate monitoring data from observations, surveys or smart technology to model actual usage patterns.

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Appendix A | Appendix

A.1 Research landscape

The distribution of journals and conferences for the overheating literature is shown in Figure A.1. Most of the articles selected were in building energy-oriented journals such as Energy and Buildings and Building and Environment, which accounted for 16% and 13.4% of the total studies respectively. The search method is provided in Table A.1

Figure A.2 shows the methodologies, overheating criteria and contexts of the studies reviewed, as well as the percentage of dwelling types. Only 8% of the studies adopted a mixed methodology of modelling and monitoring, with modelling methodology accounting for 58% of the total studies. More than half of the studies were conducted in the UK (60%). 27% and 13% of the papers were from Europe and other countries such as the USA, Australia and Canada respectively. The Passive House Planning Package (PHPP) overheating criteria (Passivhaus Trust, 2018) which was the least used overheating criteria, was used in 10% of the studies, followed by the Chartered Institution of Building Services Engineers (CIBSE) Technical Memorandum 59 (TM59) (Chartered Institution of Building Services Engineers, 2017). Chartered Institution of Building Services Engineers Guide A (Chartered Institution of Building Services Engineers, 2006) was used in 33% of the total studies, which was the most employed overheating criteria. Detached dwellings were the most considered dwelling type, considered in 28% of the studies, followed by purpose-built flats (21%), while converted flats were the least studied dwelling type. Both mid and end-terrace dwellings were considered for calculating the dwelling type percentage for studies on 'terraced' dwellings.

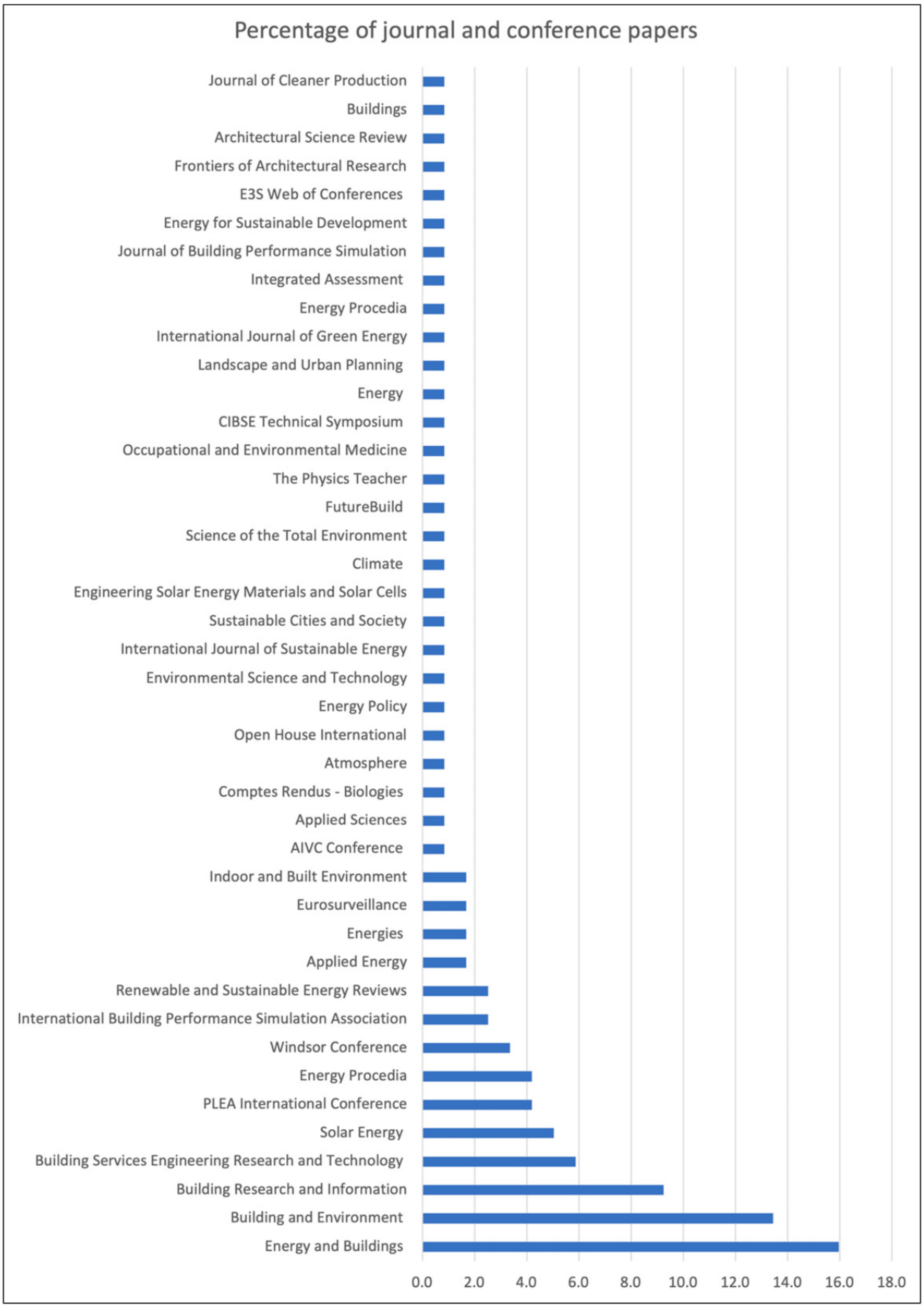

Figure A.1: Distribution of sources covered in this review paper.

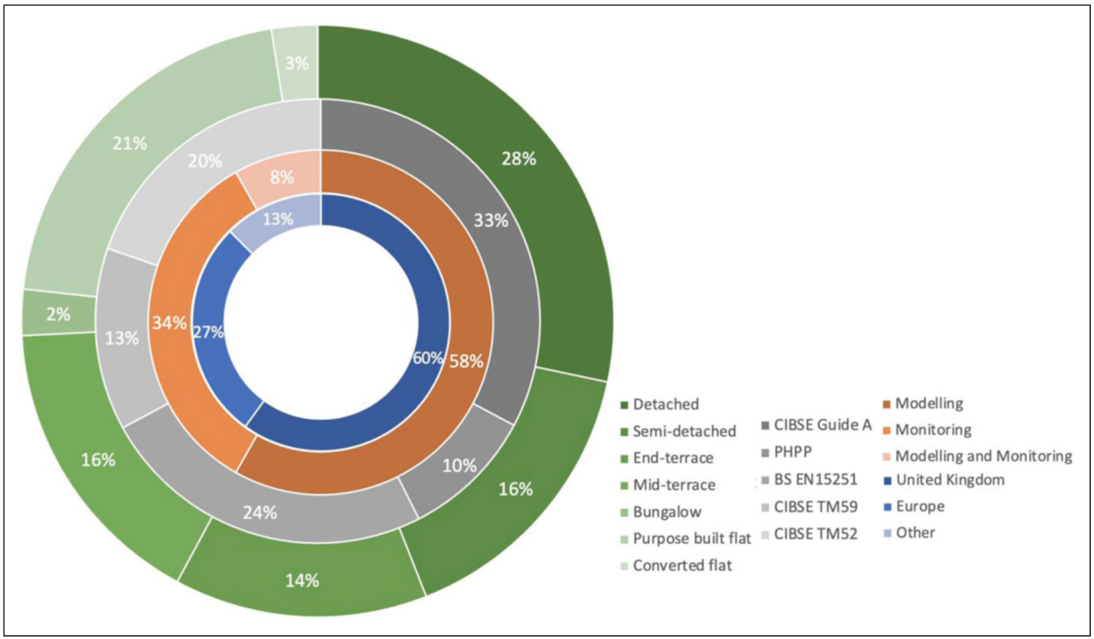

Figure A.2: Distribution of dwelling types, thermal comfort criteria, methodology and the context covered in the reviewed publications.

Table A.1: Search strings used for finding the literature.

Search strings and Boolean operators		
AND	**OR**	**Theme**
"overheating", "natural ventilation"	"window opening"	Natural ventilation
"overheating", "vegetation"	"green roof", "green wall"	Vegetation
"overheating", "solar shading"	"fixed shading", "solar protection", "shutter"	Solar shading
"overheating", "thermal mass"	"PCM", "heavyweight construction", "lightweight construction"	Thermal mass
"overheating", "cool paint"	"cool roof", "cool wall", "albedo"	Cool paint
"overheating", "passive cooling", "wall insulation"	-	Wall insulation
"overheating", "Passivhaus", "natural ventilation", "thermal mass", "cool paint", "vegetation", "wall insulation"	All the above strings for "OR"	Passive cooling strategies - Passivhaus

A.2 Indoor temperature variation

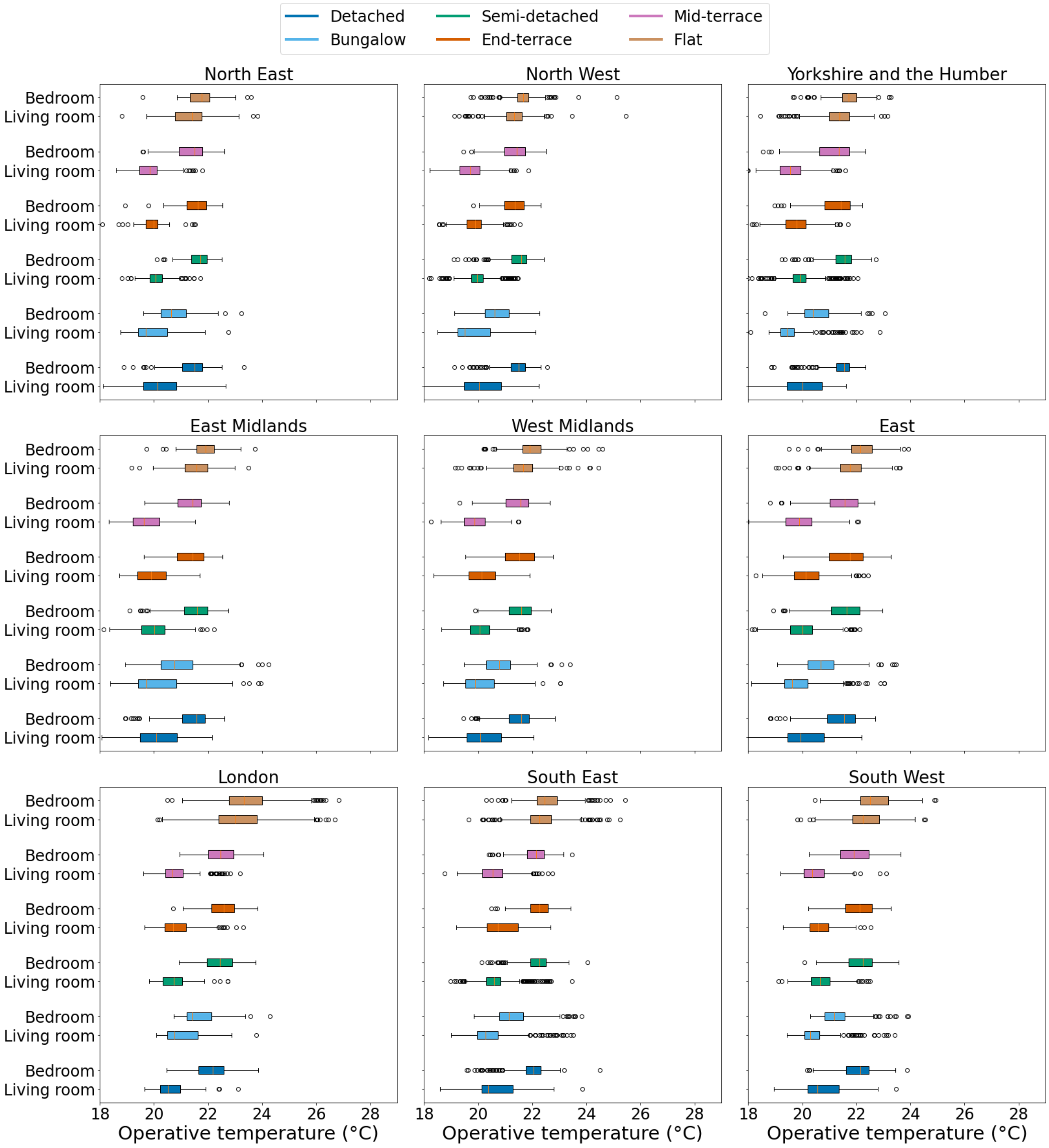

Figure A.3: Daily average maximum temperature distribution in living rooms and bedrooms across regions and dwelling types (base climate no shutter).

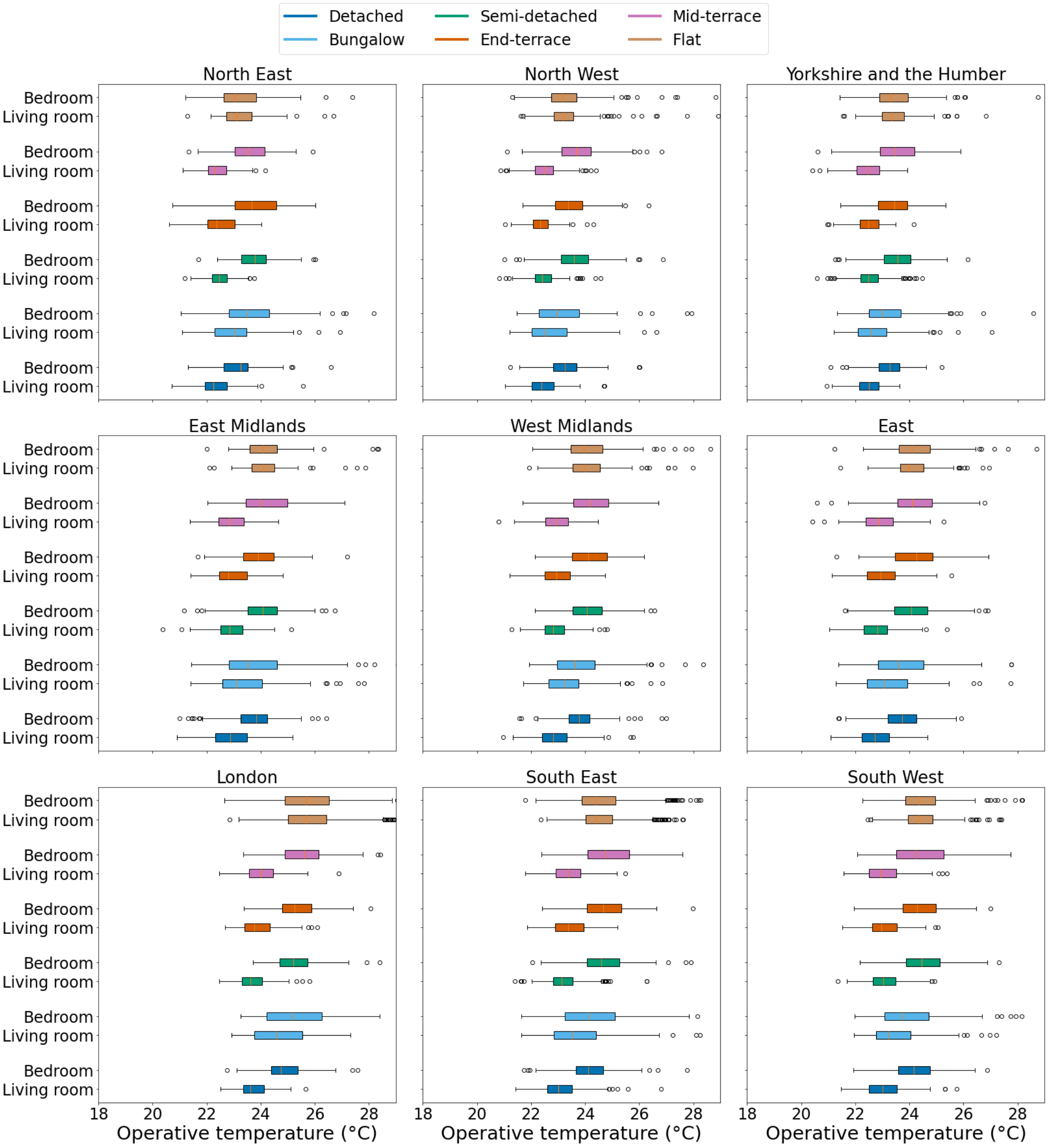

Figure A.4: Daily average minimum temperature distribution in living rooms and bedrooms across regions and dwelling types (base climate no shutter).

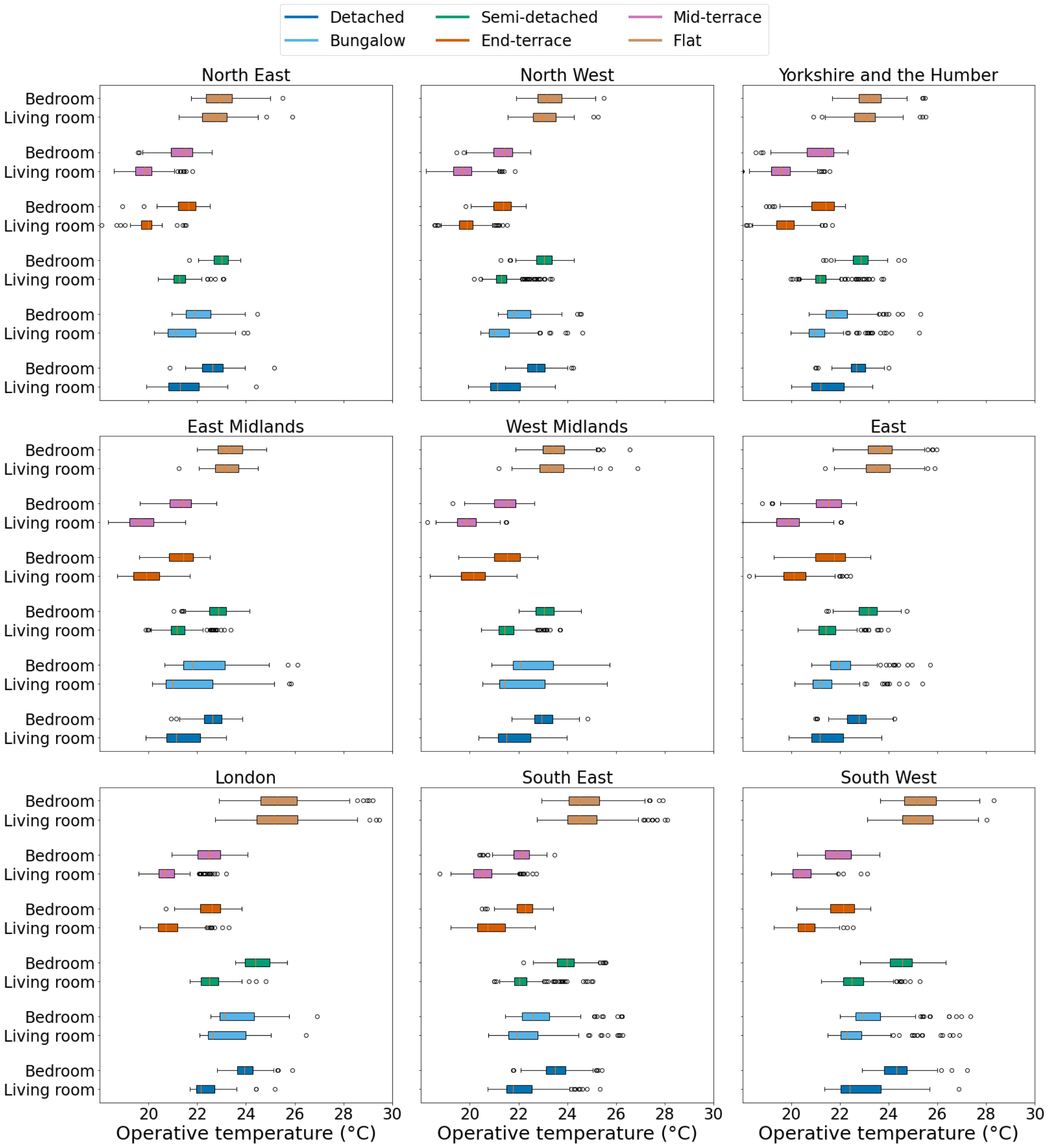

Figure A.5: Daily average minimum temperature distribution in living rooms and bedrooms across regions and dwelling types (2050 climate no shutter).

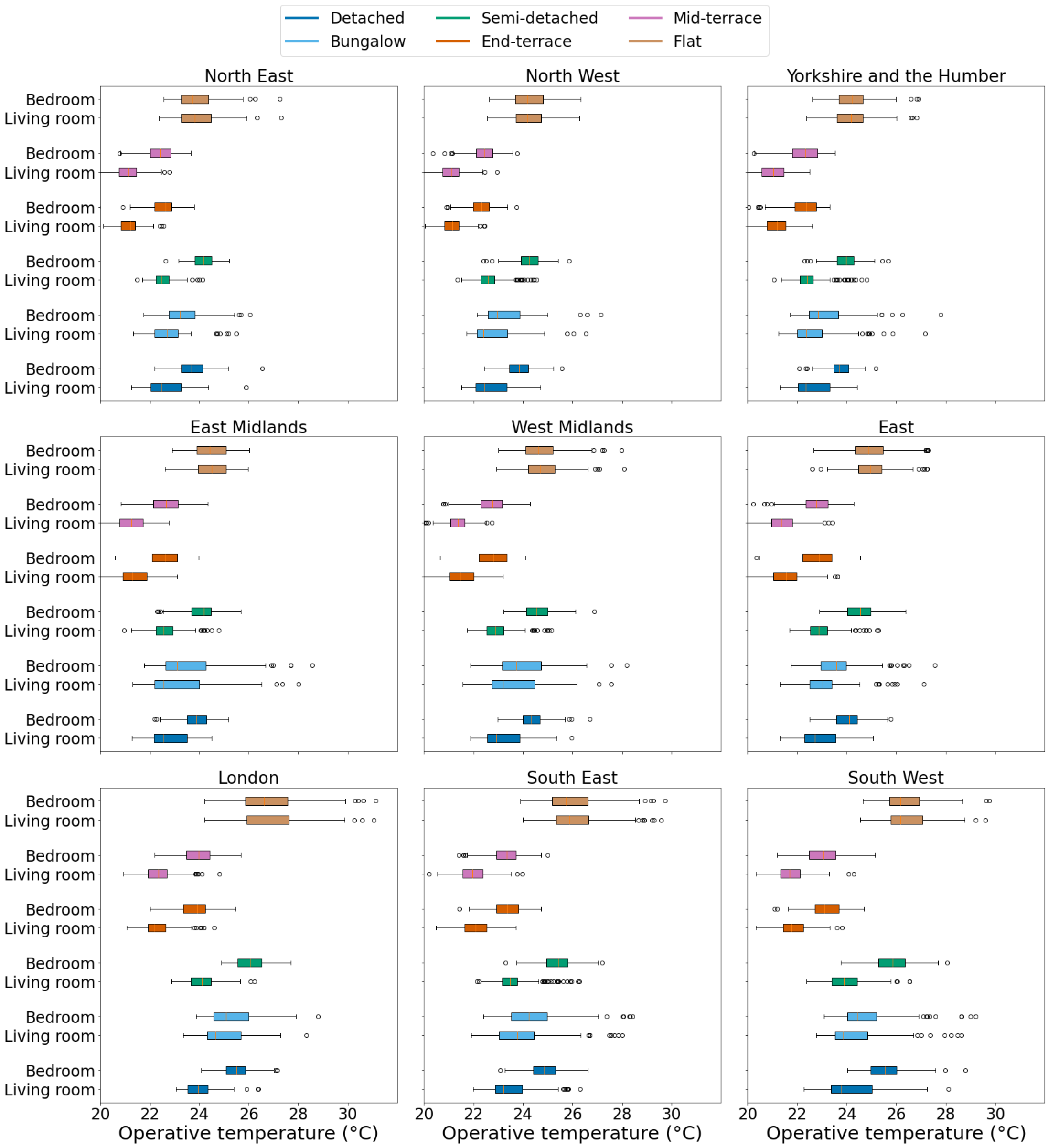

Figure A.6: Daily average mean temperature distribution in living rooms and bedrooms across regions and dwelling types (2050 climate no shutter).

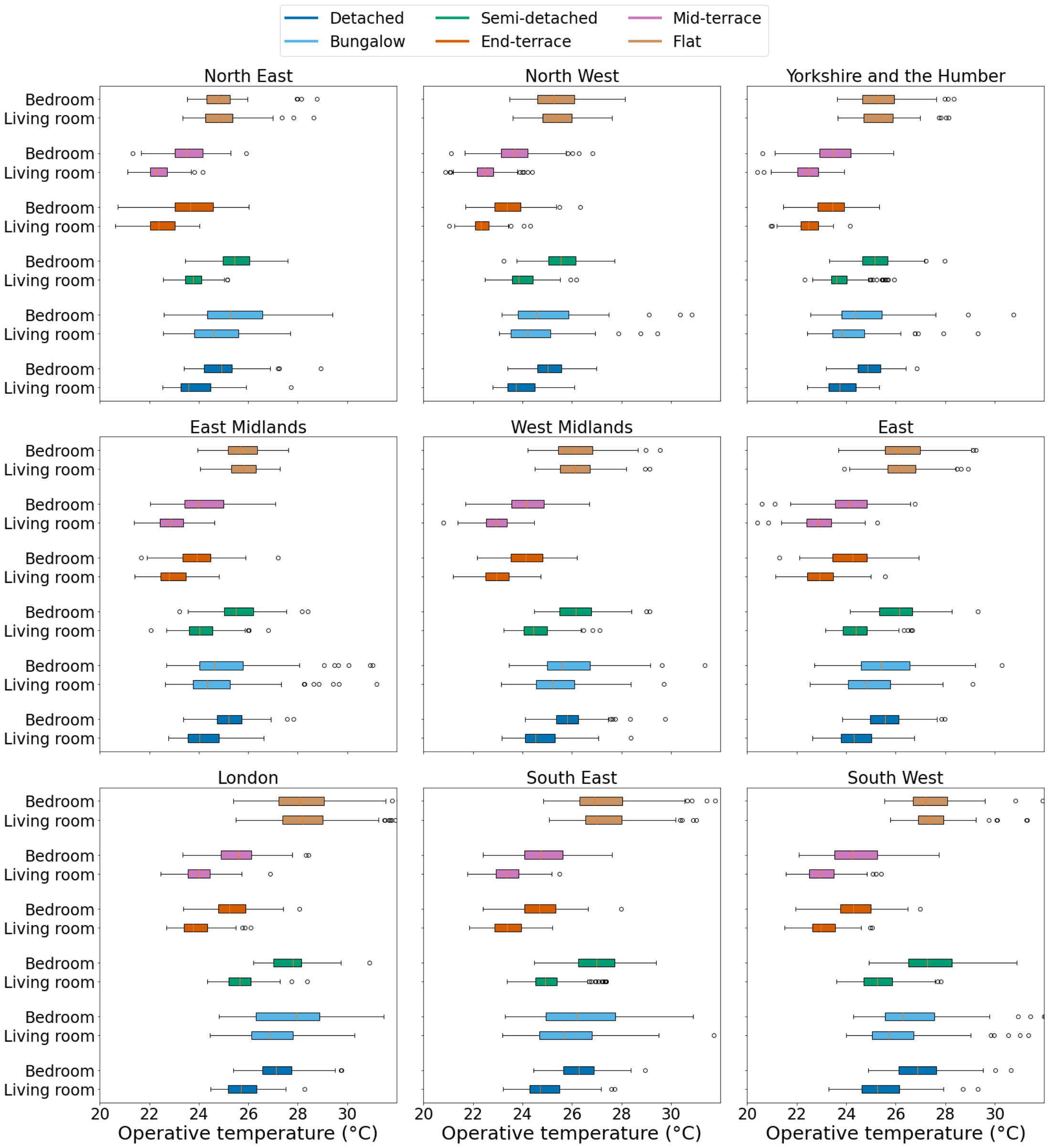

Figure A.7: Daily average maximum temperature distribution in living rooms and bedrooms across regions and dwelling types (2050 climate no shutter).

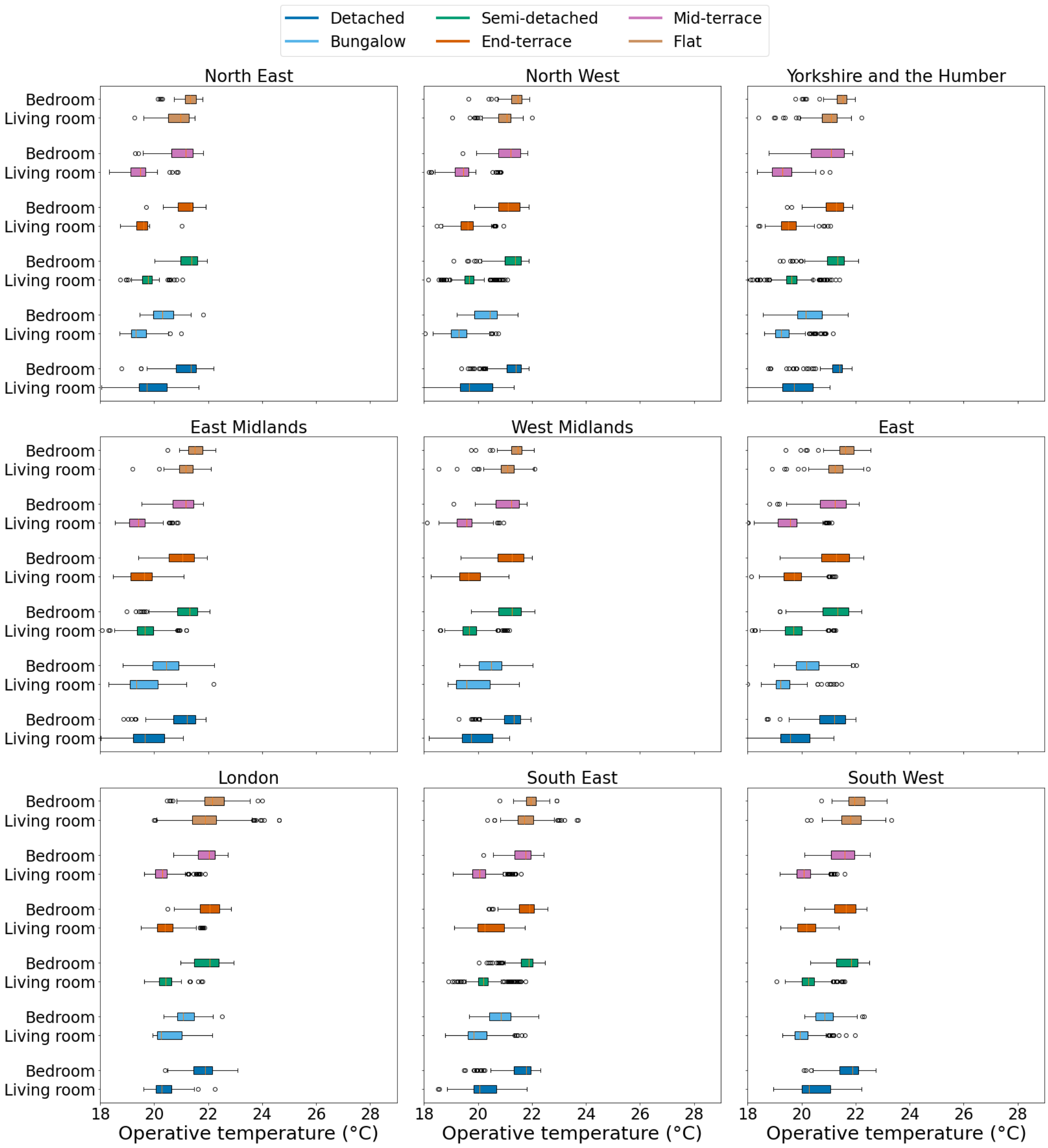

Figure A.8: Daily average minimum temperature distribution in living rooms and bedrooms across regions and dwelling types (base climate shutter added).

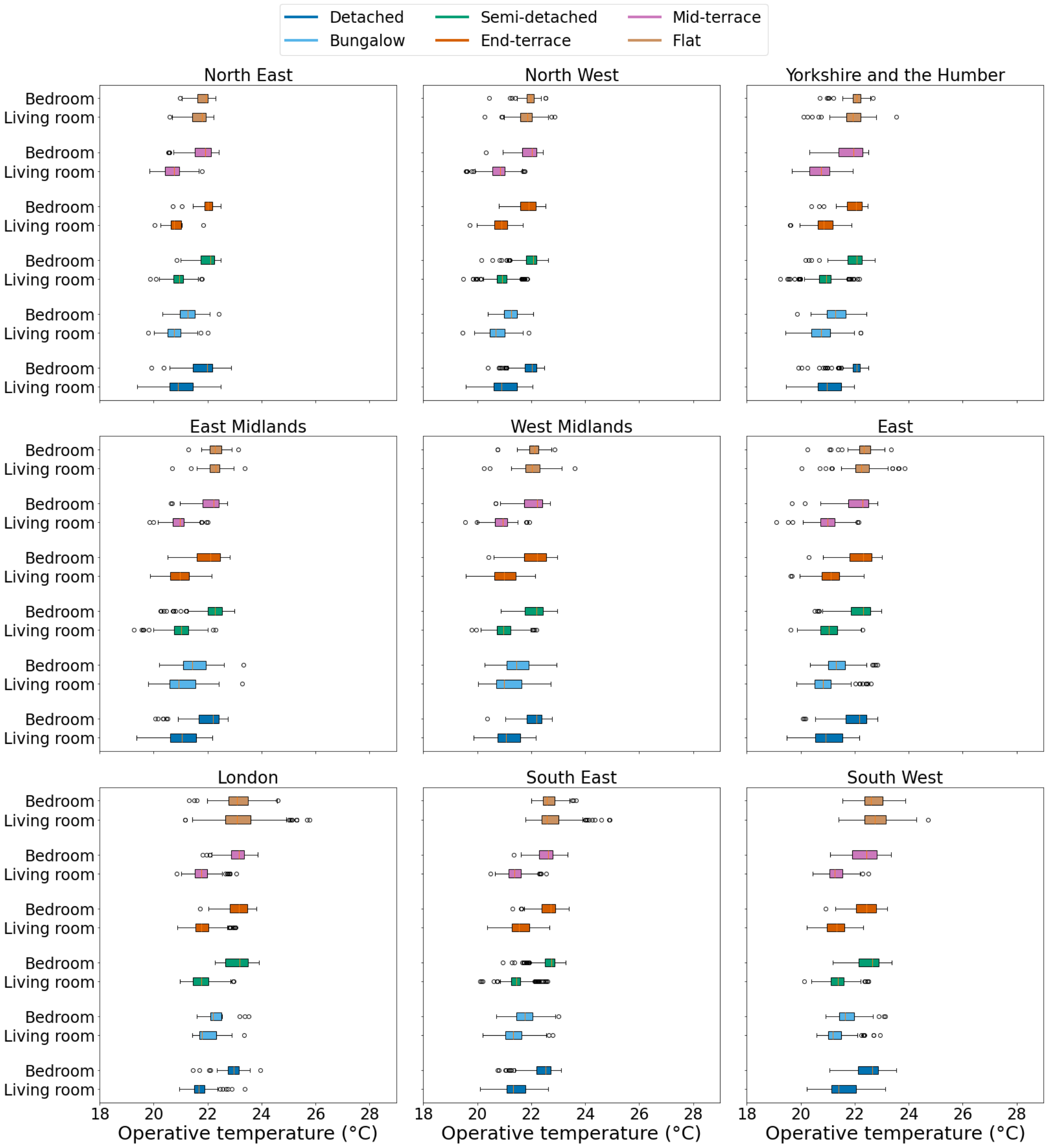

Figure A.9: Daily average mean temperature distribution in living rooms and bedrooms across regions and dwelling types (base climate shutter added).

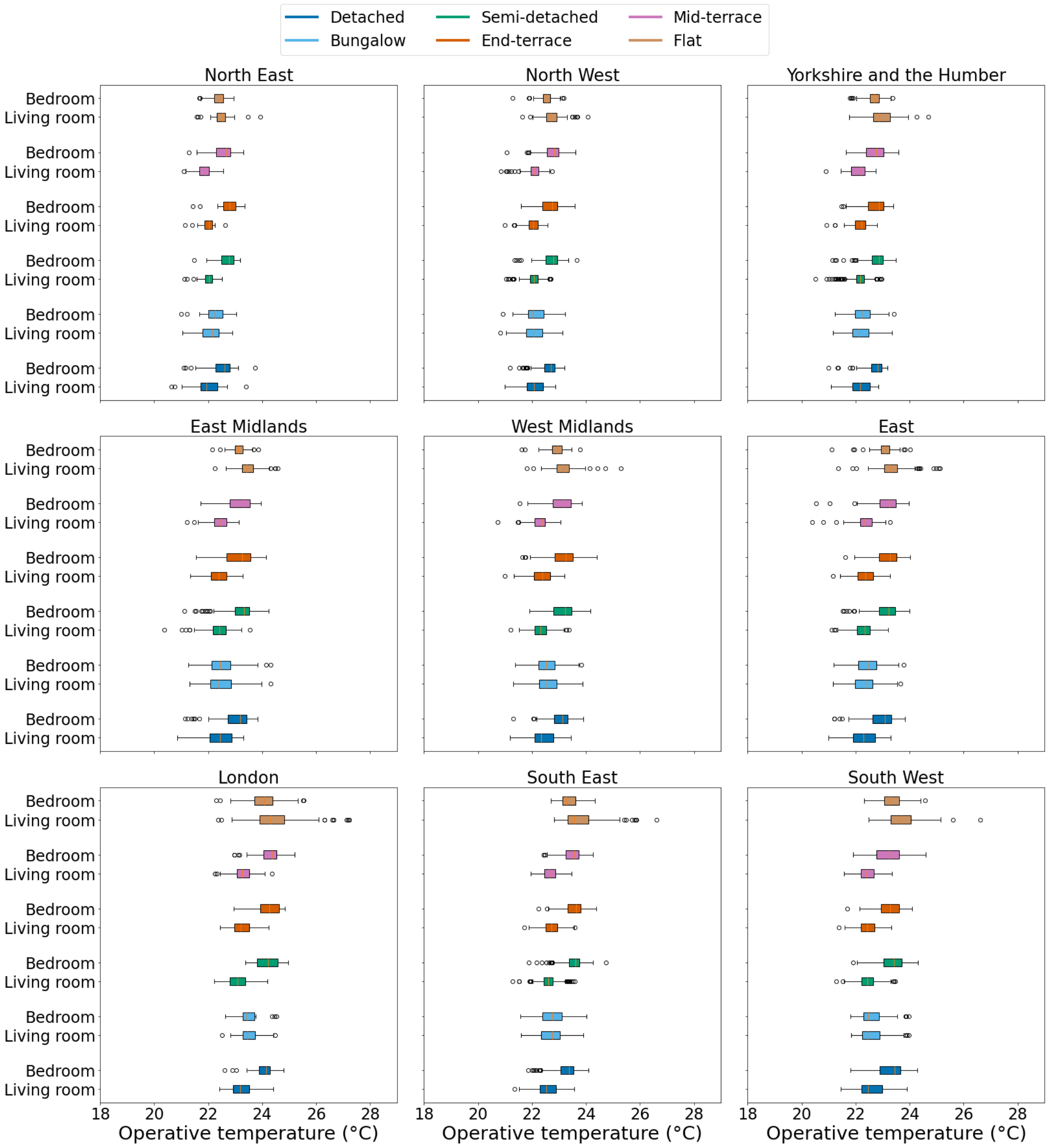

Figure A.10: Daily average maximum temperature distribution in living rooms and bedrooms across regions and dwelling types (base climate shutter added).

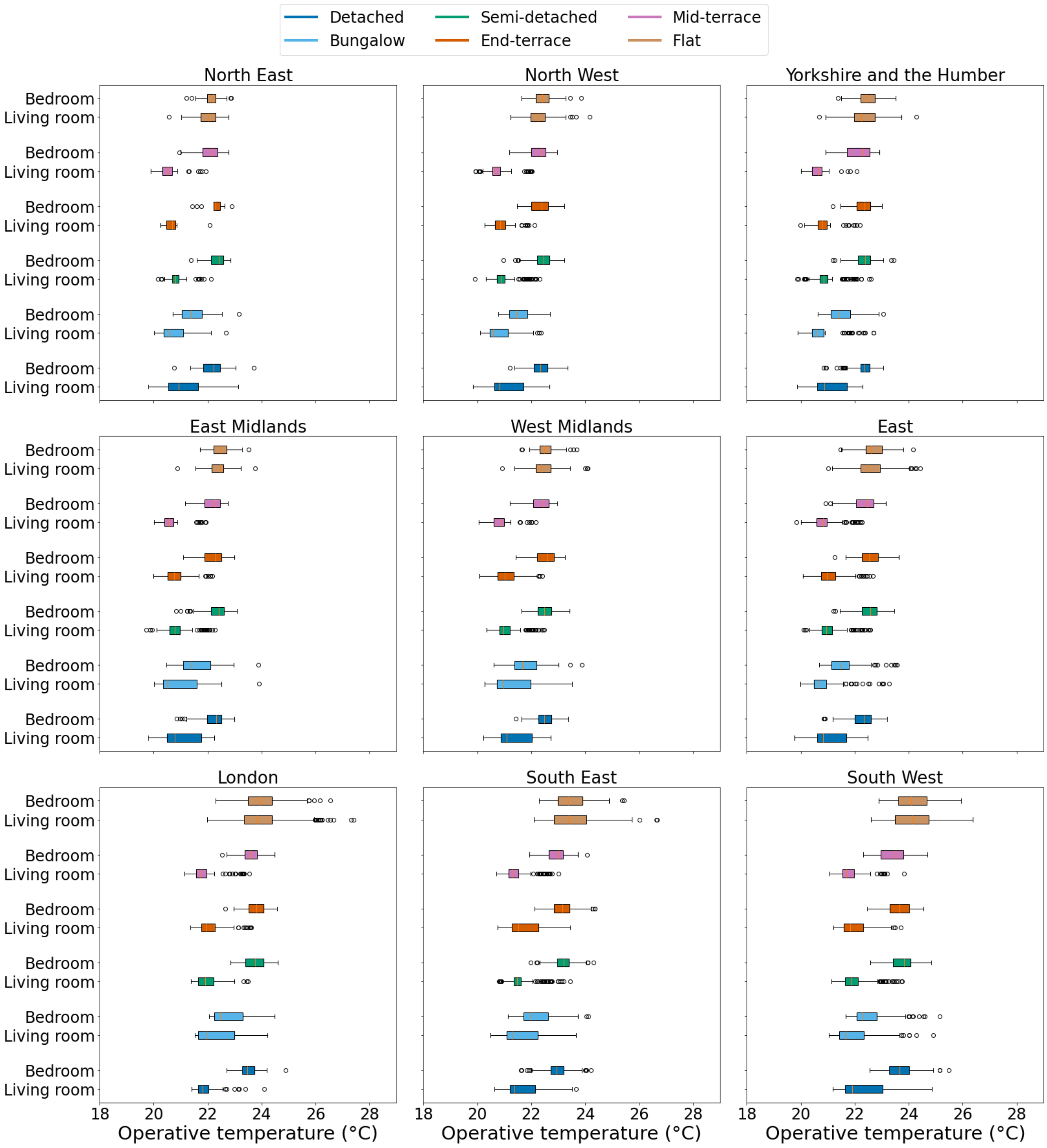

Figure A.11: Daily average minimum temperature distribution in living rooms and bedrooms across regions and dwelling types (2050 climate shutter added).

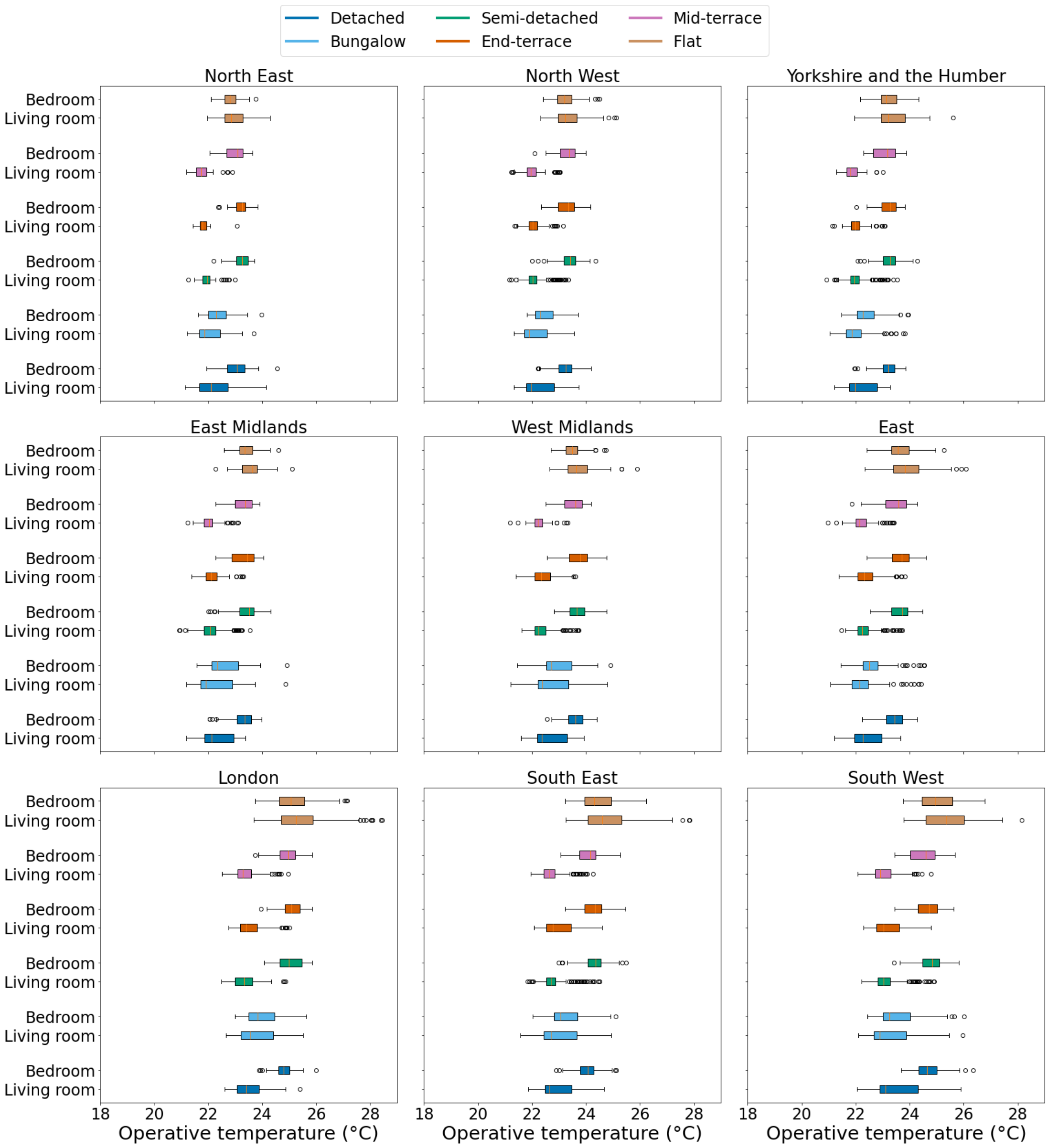

Figure A.12: Daily average mean temperature distribution in living rooms and bedrooms across regions and dwelling types (2050 climate shutter added).

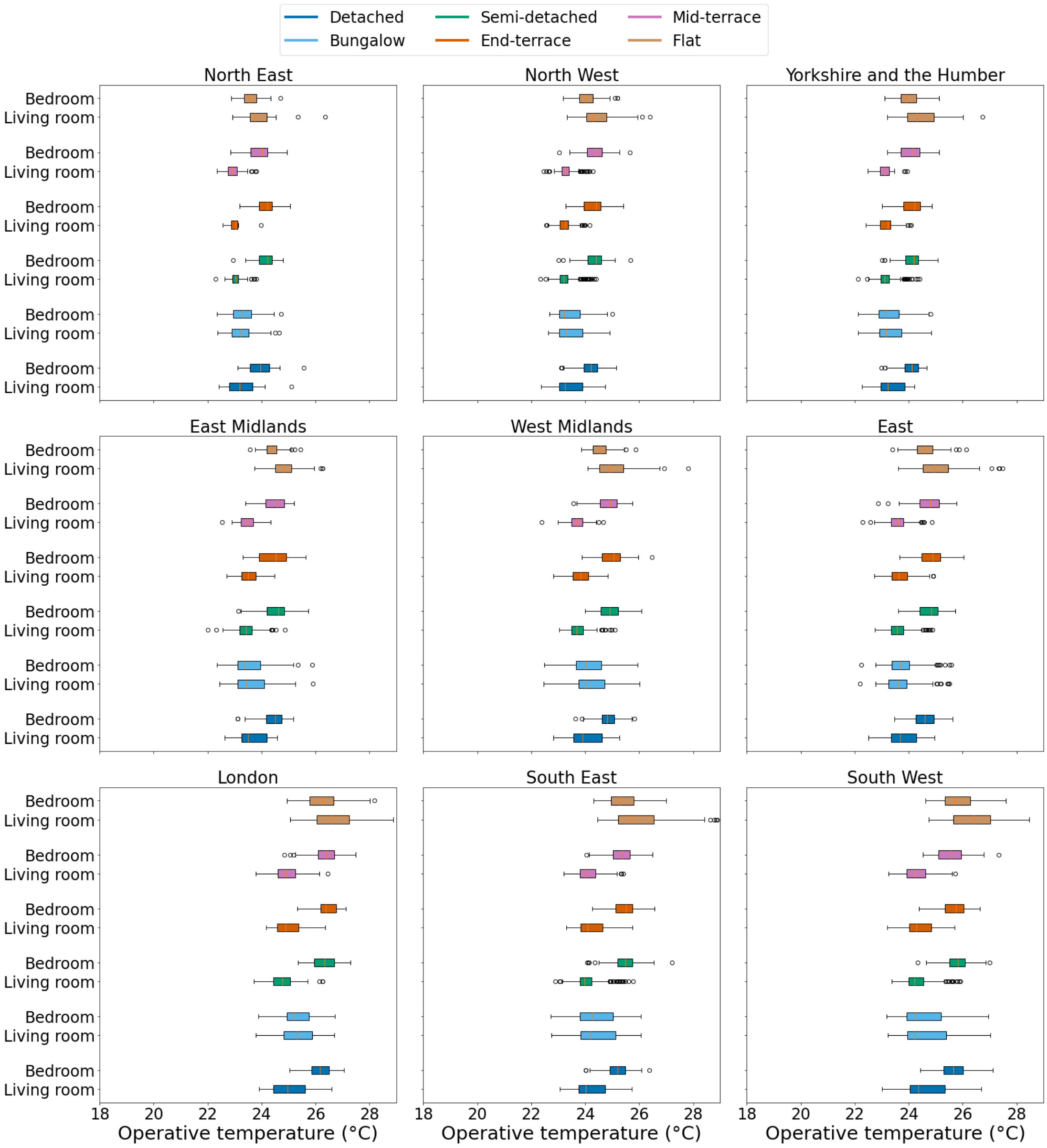

Figure A.13: Daily average maximum temperature distribution in living rooms and bedrooms across regions and dwelling types (2050 climate shutter added).

A.3 External temperature variation

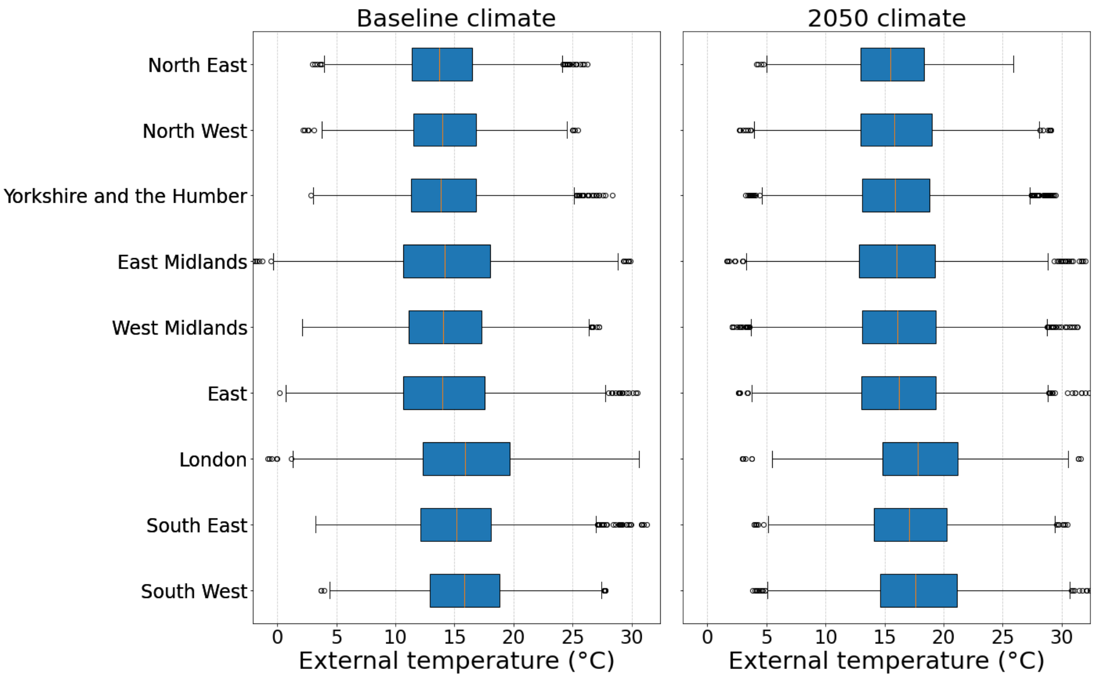

Figure A.14: The distribution of external temperatures per region used for each cliamte scenario.

A.4 Random Forest analysis of overheating drivers across regions and dwelling types

Table A.2: Top features influencing overheating in bedrooms and living rooms in each dwelling type across the regions.

Region	Dwelling type	Top feature (Bedroom)		Top feature (Living room)	
		Baseline	**2050**	**Baseline**	**2050**
East	Bungalow	dwage5x_wallinsz	dwage5x_wallinsz	dwage5x_wallinsz	dwage5x_wallinsz
	Detached	felorien	winsiz	dwage5x_wallinsz	winsiz
	End-terrace	felorien	felorien	dwage5x_wallinsz	floory
	Flat	winsiz	hhsizex	winsiz	winsiz
	Mid-terrace	winsiz	winsiz	winsiz	winsiz
	Semi-detached	felorien	felorien	dwage5x_wallinsz	dwage5x_wallinsz
East Midlands	Bungalow	winsiz	dwage5x_wallinsz	winsiz	winsiz
	Detached	felorien	dwage5x_wallinsz	felorien	dwage5x_wallinsz
	End-terrace	hhsizex	hhsizex	floory	dwage5x_wallinsz
	Flat	winsiz	hhsizex	winsiz	winsiz
	Mid-terrace	felorien	winsiz	felorien	floory
	Semi-detached	winsiz	felorien	area3x	dwage5x_wallinsz
London	Bungalow	floory	dwage5x_wallinsz	floory	floory
	Detached	felorien	dwage5x_wallinsz	felorien	dwage5x_wallinsz
	End-terrace	felorien	winsiz	felorien	dwage5x_wallinsz
	Flat	winsiz	winsiz	winsiz	winsiz
	Mid-terrace	felorien	felorien	felorien	dwage5x_wallinsz
	Semi-detached	winsiz	area3x	winsiz	winsiz
North East	Bungalow	winsiz	dwage5x_wallinsz	dwage5x_wallinsz	dwage5x_wallinsz
	Detached	winsiz	floory	floory	floory
	End-terrace	loftins4	felorien	winsiz	felorien
	Flat	winsiz	winsiz	winsiz	winsiz
	Mid-terrace	felorien	winsiz	floory	floory
	Semi-detached	winsiz	felorien	floory	dwage5x_wallinsz
North West	Bungalow	winsiz	dwage5x_wallinsz	winsiz	winsiz
	Detached	floory	dwage5x_wallinsz	floory	dwage5x_wallinsz
	End-terrace	winsiz	winsiz	winsiz	dwage5x_wallinsz
	Flat	winsiz	hhsizex	winsiz	winsiz
	Mid-terrace	winsiz	winsiz	floory	floory
	Semi-detached	winsiz	felorien	floory	dwage5x_wallinsz
South East	Bungalow	dwage5x_wallinsz	dwage5x_wallinsz	winsiz	dwage5x_wallinsz
	Detached	felorien	dwage5x_wallinsz	dwage5x_wallinsz	dwage5x_wallinsz
	End-terrace	felorien	felorien	dwage5x_wallinsz	dwage5x_wallinsz
	Flat	winsiz	hhsizex	winsiz	winsiz
	Mid-terrace	winsiz	winsiz	felorien	dwage5x_wallinsz
	Semi-detached	felorien	felorien	dwage5x_wallinsz	dwage5x_wallinsz
South West	Bungalow	winsiz	dwage5x_wallinsz	winsiz	dwage5x_wallinsz
	Detached	winsiz	dwage5x_wallinsz	winsiz	dwage5x_wallinsz
	End-terrace	felorien	winsiz	felorien	dwage5x_wallinsz
	Flat	winsiz	winsiz	winsiz	winsiz
	Mid-terrace	winsiz	winsiz	winsiz	winsiz
	Semi-detached	winsiz	winsiz	floory	dwage5x_wallinsz
West Midlands	Bungalow	winsiz	dwage5x_wallinsz	winsiz	dwage5x_wallinsz
	Detached	felorien	winsiz	winsiz	dwage5x_wallinsz
	End-terrace	felorien	felorien	felorien	dwage5x_wallinsz
	Flat	winsiz	winsiz	winsiz	winsiz
	Mid-terrace	winsiz	winsiz	felorien	winsiz
	Semi-detached	winsiz	hhsizex	winsiz	dwage5x_wallinsz
Yorkshire	Bungalow	winsiz	dwage5x_wallinsz	floory	floory
	Detached	winsiz	dwage5x_wallinsz	winsiz	dwage5x_wallinsz
	End-terrace	winsiz	felorien	winsiz	area3x
	Flat	winsiz	winsiz	winsiz	winsiz
	Mid-terrace	winsiz	winsiz	winsiz	winsiz
	Semi-detached	felorien	dwage5x_wallinsz	floory	dwage5x_wallinsz

Note: *dwage5x_wallinsz* represents a composite variable consisting of combinations of variables dwelling age (*dwage5x*), type of wall and insulation (*wallinsz*). The variables are dwelling age, and type of wall and insulation (*dwage5x_wallinsz)*, orientation (*felorien*), household size (*hhsizex*), terrain (*area3x*), total window area (*winsiz*) and floor area (*floory*)

Table A.3: Feature importance output for overheating risk using Random Forest for the baseline climate.

Region	**Dwelling type**	**Feature**	**Bedroom**	**Living room**
South East	Detached	*dwage5x_wallinsz*	0.2308	0.2850
South East	Detached	*felorien*	0.2492	0.2471
South East	Detached	*winsiz*	0.1937	0.1999
South East	Detached	*floory*	0.1220	0.1179
South East	Detached	*area3x*	0.0702	0.1132
South East	Detached	*hhsizex*	0.1035	0.0215
South East	Detached	*loftins4*	0.0306	0.0155
South West	Detached	*dwage5x_wallinsz*	0.1214	0.1083
South West	Detached	*felorien*	0.2260	0.1821
South West	Detached	*winsiz*	0.2776	0.3278
South West	Detached	*floory*	0.2294	0.2814
South West	Detached	*area3x*	0.0995	0.0753
South West	Detached	*hhsizex*	0.0269	0.0141
South West	Detached	*loftins4*	0.0192	0.0109
North West	Detached	*dwage5x_wallinsz*	0.0264	0.0000
North West	Detached	*felorien*	0.1784	0.0000
North West	Detached	*winsiz*	0.2328	0.0000
North West	Detached	*floory*	0.4043	0.0000
North West	Detached	*area3x*	0.1200	0.0000
North West	Detached	*hhsizex*	0.0274	0.0000
North West	Detached	*loftins4*	0.0107	0.0000
East Midlands	Detached	*dwage5x_wallinsz*	0.1346	0.1459
East Midlands	Detached	*felorien*	0.2935	0.2820
East Midlands	Detached	*winsiz*	0.2820	0.1343
East Midlands	Detached	*floory*	0.1247	0.0984
East Midlands	Detached	*area3x*	0.0490	0.1092
East Midlands	Detached	*hhsizex*	0.0696	0.0201
East Midlands	Detached	*loftins4*	0.0466	0.2102
East	Detached	*dwage5x_wallinsz*	0.2415	0.3936
East	Detached	*felorien*	0.2449	0.2258
East	Detached	*winsiz*	0.2421	0.1980
East	Detached	*floory*	0.0834	0.0932
East	Detached	*area3x*	0.0792	0.0439

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Region	**Dwelling type**	**Feature**	**Bedroom**	**Living room**
East	Detached	*hhsizex*	0.0837	0.0162
East	Detached	*loftins4*	0.0252	0.0293
Yorkshire and the Humber	Detached	*dwage5x_wallinsz*	0.2112	0.1671
Yorkshire and the Humber	Detached	*felorien*	0.1920	0.2427
Yorkshire and the Humber	Detached	*winsiz*	0.3760	0.2872
Yorkshire and the Humber	Detached	*floory*	0.1513	0.2246
Yorkshire and the Humber	Detached	*area3x*	0.0115	0.0273
Yorkshire and the Humber	Detached	*hhsizex*	0.0350	0.0209
Yorkshire and the Humber	Detached	*loftins4*	0.0230	0.0302
West Midlands	Detached	*dwage5x_wallinsz*	0.1186	0.0967
West Midlands	Detached	*felorien*	0.3169	0.2651
West Midlands	Detached	*winsiz*	0.2859	0.3702
West Midlands	Detached	*floory*	0.1957	0.2231
West Midlands	Detached	*area3x*	0.0387	0.0179
West Midlands	Detached	*hhsizex*	0.0294	0.0250
West Midlands	Detached	*loftins4*	0.0149	0.0020
North East	Detached	*dwage5x_wallinsz*	0.0269	0.0062
North East	Detached	*felorien*	0.0982	0.0862
North East	Detached	*winsiz*	0.4513	0.3242
North East	Detached	*floory*	0.3371	0.5029
North East	Detached	*area3x*	0.0429	0.0673
North East	Detached	*hhsizex*	0.0411	0.0126
North East	Detached	*loftins4*	0.0025	0.0005
London	Detached	*dwage5x_wallinsz*	0.0631	0.2580
London	Detached	*felorien*	0.4792	0.4301
London	Detached	*winsiz*	0.2157	0.1161
London	Detached	*floory*	0.1371	0.0789
London	Detached	*area3x*	0.0387	0.0387
London	Detached	*hhsizex*	0.0274	0.0242
London	Detached	*loftins4*	0.0389	0.0540

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Region	Dwelling type	Feature	Bedroom	Living room
South East	Semi-detached	*dwage5x_wallinsz*	0.1459	0.3652
South East	Semi-detached	*felorien*	0.3121	0.2429
South East	Semi-detached	*winsiz*	0.2249	0.1878
South East	Semi-detached	*floory*	0.1376	0.1156
South East	Semi-detached	*area3x*	0.0520	0.0587
South East	Semi-detached	*hhsizex*	0.0722	0.0167
South East	Semi-detached	*loftins4*	0.0554	0.0132
North East	Semi-detached	*dwage5x_wallinsz*	0.0915	0.1871
North East	Semi-detached	*felorien*	0.2187	0.1614
North East	Semi-detached	*winsiz*	0.4446	0.2558
North East	Semi-detached	*floory*	0.1401	0.2633
North East	Semi-detached	*area3x*	0.0339	0.0288
North East	Semi-detached	*hhsizex*	0.0399	0.0183
North East	Semi-detached	*loftins4*	0.0313	0.0852
West Midlands	Semi-detached	*dwage5x_wallinsz*	0.0727	0.2360
West Midlands	Semi-detached	*felorien*	0.1841	0.1172
West Midlands	Semi-detached	*winsiz*	0.3783	0.3641
West Midlands	Semi-detached	*floory*	0.1463	0.0744
West Midlands	Semi-detached	*area3x*	0.0532	0.0902
West Midlands	Semi-detached	*hhsizex*	0.0707	0.0308
West Midlands	Semi-detached	*loftins4*	0.0947	0.0873
North West	Semi-detached	*dwage5x_wallinsz*	0.1536	0.0741
North West	Semi-detached	*felorien*	0.1462	0.0986
North West	Semi-detached	*winsiz*	0.3265	0.0402
North West	Semi-detached	*floory*	0.1687	0.4413
North West	Semi-detached	*area3x*	0.1197	0.3107
North West	Semi-detached	*hhsizex*	0.0323	0.0270
North West	Semi-detached	*loftins4*	0.0530	0.0081
Yorkshire and the Humber	Semi-detached	*dwage5x_wallinsz*	0.0951	0.1157
Yorkshire and the Humber	Semi-detached	*felorien*	0.3641	0.2134
Yorkshire and the Humber	Semi-detached	*winsiz*	0.2264	0.1884
Yorkshire and the Humber	Semi-detached	*floory*	0.2062	0.3705

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Region	Dwelling type	Feature	Bedroom	Living room
Yorkshire and the Humber	Semi-detached	*area3x*	0.0439	0.0248
Yorkshire and the Humber	Semi-detached	*hhsizex*	0.0291	0.0671
Yorkshire and the Humber	Semi-detached	*loftins4*	0.0351	0.0199
East Midlands	Semi-detached	*dwage5x_wallinsz*	0.1223	0.1379
East Midlands	Semi-detached	*felorien*	0.2485	0.2674
East Midlands	Semi-detached	*winsiz*	0.2572	0.0870
East Midlands	Semi-detached	*floory*	0.1092	0.1053
East Midlands	Semi-detached	*area3x*	0.1251	0.3110
East Midlands	Semi-detached	*hhsizex*	0.0475	0.0274
East Midlands	Semi-detached	*loftins4*	0.0901	0.0640
London	Semi-detached	*dwage5x_wallinsz*	0.0914	0.1861
London	Semi-detached	*felorien*	0.2331	0.1678
London	Semi-detached	*winsiz*	0.2440	0.3283
London	Semi-detached	*floory*	0.0933	0.1729
London	Semi-detached	*area3x*	0.2316	0.0302
London	Semi-detached	*hhsizex*	0.0818	0.0442
London	Semi-detached	*loftins4*	0.0249	0.0705
East	Semi-detached	*felorien*	0.3315	0.1709
East	Semi-detached	*winsiz*	0.1782	0.2101
East	Semi-detached	*hhsizex*	0.1472	0.0237
East	Semi-detached	*dwage5x_wallinsz*	0.1090	0.4291
East	Semi-detached	*floory*	0.0926	0.0916
East	Semi-detached	*loftins4*	0.0895	0.0244
East	Semi-detached	*area3x*	0.0519	0.0504
South West	Semi-detached	*winsiz*	0.3064	0.2820
South West	Semi-detached	*floory*	0.2614	0.3010
South West	Semi-detached	*felorien*	0.1774	0.1851
South West	Semi-detached	*area3x*	0.1236	0.0753
South West	Semi-detached	*dwage5x_wallinsz*	0.0674	0.1097
South West	Semi-detached	*hhsizex*	0.0349	0.0259
South West	Semi-detached	*loftins4*	0.0289	0.0209
London	End-terrace	*dwage5x_wallinsz*	0.1690	0.2108
London	End-terrace	*felorien*	0.3456	0.2963

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Region	**Dwelling type**	**Feature**	**Bedroom**	**Living room**
London	End-terrace	*winsiz*	0.1687	0.1779
London	End-terrace	*floory*	0.1487	0.2289
London	End-terrace	*area3x*	0.0768	0.0246
London	End-terrace	*hhsizex*	0.0628	0.0371
London	End-terrace	*loftins4*	0.0284	0.0245
North West	End-terrace	*dwage5x_wallinsz*	0.1180	0.0236
North West	End-terrace	*felorien*	0.1673	0.1667
North West	End-terrace	*winsiz*	0.4266	0.3815
North West	End-terrace	*floory*	0.1119	0.1613
North West	End-terrace	*area3x*	0.1364	0.2669
North West	End-terrace	*hhsizex*	0.0353	0.0000
North West	End-terrace	*loftins4*	0.0044	0.0000
East Midlands	End-terrace	*dwage5x_wallinsz*	0.0936	0.1296
East Midlands	End-terrace	*felorien*	0.1254	0.1193
East Midlands	End-terrace	*winsiz*	0.1671	0.0905
East Midlands	End-terrace	*floory*	0.1989	0.3582
East Midlands	End-terrace	*area3x*	0.0832	0.2173
East Midlands	End-terrace	*hhsizex*	0.2999	0.0488
East Midlands	End-terrace	*loftins4*	0.0319	0.0364
South East	End-terrace	*dwage5x_wallinsz*	0.0957	0.2626
South East	End-terrace	*felorien*	0.3080	0.2534
South East	End-terrace	*winsiz*	0.2728	0.2462
South East	End-terrace	*floory*	0.0877	0.0984
South East	End-terrace	*area3x*	0.0655	0.0623
South East	End-terrace	*hhsizex*	0.1443	0.0361
South East	End-terrace	*loftins4*	0.0260	0.0411
Yorkshire and the Humber	End-terrace	*dwage5x_wallinsz*	0.0639	0.1567
Yorkshire and the Humber	End-terrace	*felorien*	0.2579	0.2483
Yorkshire and the Humber	End-terrace	*winsiz*	0.4238	0.3370
Yorkshire and the Humber	End-terrace	*floory*	0.1382	0.0836
Yorkshire and the Humber	End-terrace	*area3x*	0.0565	0.1441

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Region	Dwelling type	Feature	Bedroom	Living room
Yorkshire and the Humber	End-terrace	*hhsizex*	0.0437	0.0235
Yorkshire and the Humber	End-terrace	*loftins4*	0.0160	0.0068
East	End-terrace	*dwage5x_wallinsz*	0.1237	0.3127
East	End-terrace	*felorien*	0.3771	0.0802
East	End-terrace	*winsiz*	0.2174	0.2621
East	End-terrace	*floory*	0.1018	0.2549
East	End-terrace	*area3x*	0.0487	0.0078
East	End-terrace	*hhsizex*	0.0993	0.0472
East	End-terrace	*loftins4*	0.0320	0.0351
West Midlands	End-terrace	*dwage5x_wallinsz*	0.0517	0.2619
West Midlands	End-terrace	*felorien*	0.5669	0.2758
West Midlands	End-terrace	*winsiz*	0.1631	0.2147
West Midlands	End-terrace	*floory*	0.0529	0.1132
West Midlands	End-terrace	*area3x*	0.0287	0.0851
West Midlands	End-terrace	*hhsizex*	0.0931	0.0316
West Midlands	End-terrace	*loftins4*	0.0436	0.0178
North East	End-terrace	*dwage5x_wallinsz*	0.0679	0.0533
North East	End-terrace	*felorien*	0.3093	0.2302
North East	End-terrace	*winsiz*	0.1823	0.3901
North East	End-terrace	*floory*	0.0697	0.1628
North East	End-terrace	*area3x*	0.0047	0.0336
North East	End-terrace	*hhsizex*	0.0067	0.0560
North East	End-terrace	*loftins4*	0.3594	0.0741
South West	End-terrace	*dwage5x_wallinsz*	0.0782	0.1181
South West	End-terrace	*felorien*	0.3089	0.4388
South West	End-terrace	*winsiz*	0.1543	0.1162
South West	End-terrace	*floory*	0.1102	0.1321
South West	End-terrace	*area3x*	0.1733	0.0145
South West	End-terrace	*hhsizex*	0.1494	0.1006
South West	End-terrace	*loftins4*	0.0258	0.0798
London	Mid-terrace	*dwage5x_wallinsz*	0.0629	0.2039
London	Mid-terrace	*felorien*	0.4491	0.2462
London	Mid-terrace	*winsiz*	0.2600	0.2142

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Region	Dwelling type	Feature	Bedroom	Living room
London	Mid-terrace	*floory*	0.0932	0.2364
London	Mid-terrace	*area3x*	0.0340	0.0220
London	Mid-terrace	*hhsizex*	0.0740	0.0452
London	Mid-terrace	*loftins4*	0.0268	0.0321
East	Mid-terrace	*dwage5x_wallinsz*	0.0380	0.1757
East	Mid-terrace	*felorien*	0.3032	0.2252
East	Mid-terrace	*winsiz*	0.4065	0.3525
East	Mid-terrace	*floory*	0.0924	0.1472
East	Mid-terrace	*area3x*	0.0456	0.0381
East	Mid-terrace	*hhsizex*	0.0888	0.0305
East	Mid-terrace	*loftins4*	0.0256	0.0308
Yorkshire and the Humber	Mid-terrace	*dwage5x_wallinsz*	0.0599	0.0971
Yorkshire and the Humber	Mid-terrace	*felorien*	0.2500	0.2176
Yorkshire and the Humber	Mid-terrace	*winsiz*	0.5409	0.3608
Yorkshire and the Humber	Mid-terrace	*floory*	0.0813	0.1356
Yorkshire and the Humber	Mid-terrace	*area3x*	0.0243	0.0013
Yorkshire and the Humber	Mid-terrace	*hhsizex*	0.0305	0.0344
Yorkshire and the Humber	Mid-terrace	*loftins4*	0.0132	0.1531
South West	Mid-terrace	*dwage5x_wallinsz*	0.0585	0.0648
South West	Mid-terrace	*felorien*	0.1703	0.2510
South West	Mid-terrace	*winsiz*	0.4832	0.5354
South West	Mid-terrace	*floory*	0.0816	0.0513
South West	Mid-terrace	*area3x*	0.0794	0.0171
South West	Mid-terrace	*hhsizex*	0.0810	0.0326
South West	Mid-terrace	*loftins4*	0.0461	0.0478
North West	Mid-terrace	*dwage5x_wallinsz*	0.0362	0.0788
North West	Mid-terrace	*felorien*	0.1325	0.0961
North West	Mid-terrace	*winsiz*	0.4261	0.2447
North West	Mid-terrace	*floory*	0.2122	0.5103
North West	Mid-terrace	*area3x*	0.0133	0.0219

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Region	Dwelling type	Feature	Bedroom	Living room
North West	Mid-terrace	*hhsizex*	0.0483	0.0180
North West	Mid-terrace	*loftins4*	0.1313	0.0303
East Midlands	Mid-terrace	*dwage5x_wallinsz*	0.0605	0.0479
East Midlands	Mid-terrace	*felorien*	0.4321	0.4611
East Midlands	Mid-terrace	*winsiz*	0.2190	0.1066
East Midlands	Mid-terrace	*floory*	0.0832	0.2765
East Midlands	Mid-terrace	*area3x*	0.0789	0.0469
East Midlands	Mid-terrace	*hhsizex*	0.0826	0.0186
East Midlands	Mid-terrace	*loftins4*	0.0438	0.0424
West Midlands	Mid-terrace	*dwage5x_wallinsz*	0.0530	0.1128
West Midlands	Mid-terrace	*felorien*	0.2693	0.3268
West Midlands	Mid-terrace	*winsiz*	0.4018	0.0896
West Midlands	Mid-terrace	*floory*	0.1818	0.1366
West Midlands	Mid-terrace	*area3x*	0.0381	0.1679
West Midlands	Mid-terrace	*hhsizex*	0.0445	0.1013
West Midlands	Mid-terrace	*loftins4*	0.0115	0.0650
South East	Mid-terrace	*winsiz*	0.3214	0.2463
South East	Mid-terrace	*felorien*	0.3179	0.2718
South East	Mid-terrace	*area3x*	0.1080	0.0416
South East	Mid-terrace	*floory*	0.0905	0.1518
South East	Mid-terrace	*dwage5x_wallinsz*	0.0877	0.2326
South East	Mid-terrace	*hhsizex*	0.0565	0.0167
South East	Mid-terrace	*loftins4*	0.0181	0.0391
North East	Mid-terrace	*felorien*	0.2984	0.2039
North East	Mid-terrace	*winsiz*	0.2568	0.1030
North East	Mid-terrace	*loftins4*	0.1812	0.1277
North East	Mid-terrace	*floory*	0.1328	0.3829
North East	Mid-terrace	*dwage5x_wallinsz*	0.0729	0.0673
North East	Mid-terrace	*area3x*	0.0397	0.0589
North East	Mid-terrace	*hhsizex*	0.0182	0.0563
Yorkshire and the Humber	Flat	*dwage5x_wallinsz*	0.0426	0.0256
Yorkshire and the Humber	Flat	*felorien*	0.0552	0.0360
Yorkshire and the Humber	Flat	*winsiz*	0.7926	0.8478

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Region	Dwelling type	Feature	Bedroom	Living room
Yorkshire and the Humber	Flat	*floory*	0.0713	0.0501
Yorkshire and the Humber	Flat	*area3x*	0.0163	0.0177
Yorkshire and the Humber	Flat	*hhsizex*	0.0072	0.0122
Yorkshire and the Humber	Flat	*loftins4*	0.0149	0.0107
North West	Flat	*dwage5x_wallinsz*	0.0571	0.1017
North West	Flat	*felorien*	0.0267	0.0487
North West	Flat	*winsiz*	0.7758	0.4951
North West	Flat	*floory*	0.0828	0.3118
North West	Flat	*area3x*	0.0118	0.0089
North West	Flat	*hhsizex*	0.0331	0.0292
North West	Flat	*loftins4*	0.0126	0.0046
London	Flat	*dwage5x_wallinsz*	0.0753	0.0676
London	Flat	*felorien*	0.3003	0.2981
London	Flat	*winsiz*	0.3595	0.3810
London	Flat	*floory*	0.0879	0.1627
London	Flat	*area3x*	0.0183	0.0270
London	Flat	*hhsizex*	0.1451	0.0477
London	Flat	*loftins4*	0.0135	0.0158
North East	Flat	*dwage5x_wallinsz*	0.0293	0.0571
North East	Flat	*felorien*	0.0178	0.0181
North East	Flat	*winsiz*	0.8890	0.8015
North East	Flat	*floory*	0.0218	0.0286
North East	Flat	*area3x*	0.0064	0.0002
North East	Flat	*hhsizex*	0.0238	0.0499
North East	Flat	*loftins4*	0.0119	0.0447
South West	Flat	*dwage5x_wallinsz*	0.0507	0.0447
South West	Flat	*felorien*	0.1082	0.0934
South West	Flat	*winsiz*	0.5988	0.6577
South West	Flat	*floory*	0.0576	0.0732
South West	Flat	*area3x*	0.0066	0.0103
South West	Flat	*hhsizex*	0.1600	0.0833
South West	Flat	*loftins4*	0.0182	0.0373

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Region	Dwelling type	Feature	Bedroom	Living room
South East	Flat	*dwage5x_wallinsz*	0.0793	0.0977
South East	Flat	*felorien*	0.1222	0.1105
South East	Flat	*winsiz*	0.5747	0.6096
South East	Flat	*floory*	0.0916	0.1020
South East	Flat	*area3x*	0.0191	0.0287
South East	Flat	*hhsizex*	0.1024	0.0383
South East	Flat	*loftins4*	0.0106	0.0132
East Midlands	Flat	*winsiz*	0.5756	0.3756
East Midlands	Flat	*floory*	0.1211	0.1286
East Midlands	Flat	*felorien*	0.0991	0.2250
East Midlands	Flat	*dwage5x_wallinsz*	0.0857	0.0955
East Midlands	Flat	*hhsizex*	0.0733	0.0288
East Midlands	Flat	*loftins4*	0.0253	0.0947
East Midlands	Flat	*area3x*	0.0200	0.0519
East	Flat	*winsiz*	0.3683	0.4454
East	Flat	*felorien*	0.2317	0.3316
East	Flat	*hhsizex*	0.1932	0.0424
East	Flat	*floory*	0.1212	0.1204
East	Flat	*dwage5x_wallinsz*	0.0562	0.0431
East	Flat	*loftins4*	0.0157	0.0097
East	Flat	*area3x*	0.0135	0.0074
West Midlands	Flat	*winsiz*	0.5139	0.5017
West Midlands	Flat	*felorien*	0.1721	0.1549
West Midlands	Flat	*floory*	0.1310	0.1259
West Midlands	Flat	*area3x*	0.0673	0.0736
West Midlands	Flat	*hhsizex*	0.0608	0.0730
West Midlands	Flat	*dwage5x_wallinsz*	0.0456	0.0618
West Midlands	Flat	*loftins4*	0.0093	0.0091
North East	Bungalow	*dwage5x_wallinsz*	0.2002	0.2941
North East	Bungalow	*felorien*	0.1962	0.1843
North East	Bungalow	*winsiz*	0.3378	0.1670
North East	Bungalow	*floory*	0.1608	0.2149
North East	Bungalow	*area3x*	0.0290	0.0168
North East	Bungalow	*hhsizex*	0.0715	0.0721
North East	Bungalow	*loftins4*	0.0045	0.0508

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Region	Dwelling type	Feature	Bedroom	Living room
East	Bungalow	*dwage5x_wallinsz*	0.4138	0.3607
East	Bungalow	*felorien*	0.1672	0.1470
East	Bungalow	*winsiz*	0.2106	0.2679
East	Bungalow	*floory*	0.0847	0.1111
East	Bungalow	*area3x*	0.0350	0.0438
East	Bungalow	*hhsizex*	0.0448	0.0568
East	Bungalow	*loftins4*	0.0438	0.0126
South West	Bungalow	*dwage5x_wallinsz*	0.2598	0.1812
South West	Bungalow	*felorien*	0.1281	0.1131
South West	Bungalow	*winsiz*	0.4540	0.5033
South West	Bungalow	*floory*	0.0872	0.1221
South West	Bungalow	*area3x*	0.0086	0.0169
South West	Bungalow	*hhsizex*	0.0189	0.0104
South West	Bungalow	*loftins4*	0.0435	0.0529
South East	Bungalow	*dwage5x_wallinsz*	0.4099	0.2640
South East	Bungalow	*felorien*	0.0888	0.1814
South East	Bungalow	*winsiz*	0.3332	0.3489
South East	Bungalow	*floory*	0.1008	0.1362
South East	Bungalow	*area3x*	0.0583	0.0364
South East	Bungalow	*hhsizex*	0.0043	0.0238
South East	Bungalow	*loftins4*	0.0048	0.0093
Yorkshire and the Humber	Bungalow	*dwage5x_wallinsz*	0.1901	0.1001
Yorkshire and the Humber	Bungalow	*felorien*	0.0828	0.1153
Yorkshire and the Humber	Bungalow	*winsiz*	0.3332	0.3360
Yorkshire and the Humber	Bungalow	*floory*	0.2957	0.3435
Yorkshire and the Humber	Bungalow	*area3x*	0.0540	0.0577
Yorkshire and the Humber	Bungalow	*hhsizex*	0.0213	0.0135
Yorkshire and the Humber	Bungalow	*loftins4*	0.0230	0.0339
East Midlands	Bungalow	*dwage5x_wallinsz*	0.1170	0.0548
East Midlands	Bungalow	*felorien*	0.0446	0.0821

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Region	**Dwelling type**	**Feature**	**Bedroom**	**Living room**
East Midlands	Bungalow	*winsiz*	0.7345	0.7278
East Midlands	Bungalow	*floory*	0.0854	0.0819
East Midlands	Bungalow	*area3x*	0.0084	0.0228
East Midlands	Bungalow	*hhsizex*	0.0020	0.0167
East Midlands	Bungalow	*loftins4*	0.0081	0.0140
West Midlands	Bungalow	*dwage5x_wallinsz*	0.0494	0.0937
West Midlands	Bungalow	*felorien*	0.0932	0.0687
West Midlands	Bungalow	*winsiz*	0.7817	0.7136
West Midlands	Bungalow	*floory*	0.0552	0.0625
West Midlands	Bungalow	*area3x*	0.0132	0.0076
West Midlands	Bungalow	*hhsizex*	0.0021	0.0329
West Midlands	Bungalow	*loftins4*	0.0052	0.0210
North West	Bungalow	*dwage5x_wallinsz*	0.0856	0.0189
North West	Bungalow	*felorien*	0.1324	0.0872
North West	Bungalow	*winsiz*	0.6569	0.6856
North West	Bungalow	*floory*	0.0612	0.1327
North West	Bungalow	*area3x*	0.0263	0.0114
North West	Bungalow	*hhsizex*	0.0284	0.0235
North West	Bungalow	*loftins4*	0.0092	0.0407
London	Bungalow	*dwage5x_wallinsz*	0.3621	0.1998
London	Bungalow	*felorien*	0.0244	0.0690
London	Bungalow	*winsiz*	0.0407	0.0601
London	Bungalow	*floory*	0.4743	0.5506
London	Bungalow	*area3x*	0.0381	0.0391
London	Bungalow	*hhsizex*	0.0411	0.0623
London	Bungalow	*loftins4*	0.0193	0.0192

The following variables are considered: dwelling age, and type of wall and insulation (*dwage5x_wallinsz)*, *felorien* (*felorien*), household size (*hhsizex*), *area3x* (*area3x*), total *winsiz* (*winsiz*), loft insulation thickness (*loftins4)* and *floory* (*floory*)

Table A.4: Feature importance output for overheating risk using Random Forest for the 2050 climate.

Region	**Dwelling type**	**Feature**	**Bedroom**	**Living room**
North West	Detached	*dwage5x_wallinsz*	0.3170	0.3319
North West	Detached	*floory*	0.2338	0.2490
North West	Detached	*hhsizex*	0.1390	0.0561

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Region	Dwelling type	Feature	Bedroom	Living room
North West	Detached	*felorien*	0.1115	0.1280
North West	Detached	*area3x*	0.0979	0.1129
North West	Detached	*winsiz*	0.0832	0.1030
North West	Detached	*loftins4*	0.0176	0.0191
Yorkshire and the Humber	Detached	*dwage5x_wallinsz*	0.4100	0.6948
Yorkshire and the Humber	Detached	*winsiz*	0.1795	0.0920
Yorkshire and the Humber	Detached	*floory*	0.1728	0.0871
Yorkshire and the Humber	Detached	*hhsizex*	0.1138	0.0221
Yorkshire and the Humber	Detached	*felorien*	0.0885	0.0913
Yorkshire and the Humber	Detached	*area3x*	0.0245	0.0068
Yorkshire and the Humber	Detached	*loftins4*	0.0108	0.0060
South West	Detached	*dwage5x_wallinsz*	0.3079	0.4774
South West	Detached	*floory*	0.2523	0.1881
South West	Detached	*winsiz*	0.1791	0.1960
South West	Detached	*felorien*	0.1591	0.1085
South West	Detached	*area3x*	0.0469	0.0192
South West	Detached	*hhsizex*	0.0385	0.0054
South West	Detached	*loftins4*	0.0162	0.0054
East	Detached	*winsiz*	0.2263	0.3358
East	Detached	*dwage5x_wallinsz*	0.2237	0.2027
East	Detached	*floory*	0.1927	0.1748
East	Detached	*felorien*	0.1363	0.1451
East	Detached	*hhsizex*	0.1063	0.0330
East	Detached	*area3x*	0.0912	0.0812
East	Detached	*loftins4*	0.0235	0.0273
West Midlands	Detached	*winsiz*	0.2834	0.3139
West Midlands	Detached	*dwage5x_wallinsz*	0.2251	0.4398
West Midlands	Detached	*floory*	0.1571	0.0957
West Midlands	Detached	*hhsizex*	0.1304	0.0161
West Midlands	Detached	*felorien*	0.1209	0.1021

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Region	Dwelling type	Feature	Bedroom	Living room
West Midlands	Detached	*area3x*	0.0673	0.0234
West Midlands	Detached	*loftins4*	0.0159	0.0089
South East	Detached	*dwage5x_wallinsz*	0.3811	0.6226
South East	Detached	*floory*	0.2065	0.1500
South East	Detached	*felorien*	0.1519	0.1347
South East	Detached	*hhsizex*	0.1047	0.0151
South East	Detached	*winsiz*	0.0970	0.0605
South East	Detached	*area3x*	0.0347	0.0116
South East	Detached	*loftins4*	0.0241	0.0056
East Midlands	Detached	*dwage5x_wallinsz*	0.2661	0.4945
East Midlands	Detached	*felorien*	0.2323	0.1963
East Midlands	Detached	*winsiz*	0.2083	0.1543
East Midlands	Detached	*floory*	0.1313	0.0813
East Midlands	Detached	*hhsizex*	0.1065	0.0169
East Midlands	Detached	*area3x*	0.0306	0.0257
East Midlands	Detached	*loftins4*	0.0249	0.0310
London	Detached	*dwage5x_wallinsz*	0.2283	0.4348
London	Detached	*winsiz*	0.2141	0.1257
London	Detached	*floory*	0.1975	0.2043
London	Detached	*felorien*	0.1471	0.1284
London	Detached	*hhsizex*	0.1279	0.0426
London	Detached	*area3x*	0.0533	0.0409
London	Detached	*loftins4*	0.0317	0.0232
North East	Detached	*floory*	0.4295	0.5612
North East	Detached	*winsiz*	0.2110	0.2052
North East	Detached	*hhsizex*	0.1395	0.0526
North East	Detached	*felorien*	0.1089	0.1016
North East	Detached	*dwage5x_wallinsz*	0.0590	0.0219
North East	Detached	*area3x*	0.0483	0.0519
North East	Detached	*loftins4*	0.0039	0.0056
North West	Semi-Detached	*felorien*	0.2322	0.1508
North West	Semi-Detached	*winsiz*	0.2146	0.2094
North West	Semi-Detached	*floory*	0.1566	0.1189
North West	Semi-Detached	*dwage5x_wallinsz*	0.1498	0.4085
North West	Semi-Detached	*hhsizex*	0.1296	0.0563

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Region	Dwelling type	Feature	Bedroom	Living room
North West	Semi-Detached	*area3x*	0.0770	0.0213
North West	Semi-Detached	*loftins4*	0.0402	0.0348
East	Semi-Detached	*felorien*	0.2728	0.0841
East	Semi-Detached	*hhsizex*	0.1995	0.0830
East	Semi-Detached	*winsiz*	0.1828	0.1741
East	Semi-Detached	*dwage5x_wallinsz*	0.1515	0.4011
East	Semi-Detached	*floory*	0.1053	0.1782
East	Semi-Detached	*area3x*	0.0476	0.0396
East	Semi-Detached	*loftins4*	0.0406	0.0399
South East	Semi-Detached	*felorien*	0.3060	0.2088
South East	Semi-Detached	*dwage5x_wallinsz*	0.2785	0.6012
South East	Semi-Detached	*winsiz*	0.1472	0.0875
South East	Semi-Detached	*floory*	0.0995	0.0696
South East	Semi-Detached	*hhsizex*	0.0796	0.0098
South East	Semi-Detached	*area3x*	0.0575	0.0133
South East	Semi-Detached	*loftins4*	0.0318	0.0098
Yorkshire and the Humber	Semi-Detached	*dwage5x_wallinsz*	0.2363	0.5278
Yorkshire and the Humber	Semi-Detached	*felorien*	0.2168	0.0972
Yorkshire and the Humber	Semi-Detached	*floory*	0.1991	0.0937
Yorkshire and the Humber	Semi-Detached	*winsiz*	0.1641	0.1332
Yorkshire and the Humber	Semi-Detached	*hhsizex*	0.0908	0.0299
Yorkshire and the Humber	Semi-Detached	*area3x*	0.0750	0.1077
Yorkshire and the Humber	Semi-Detached	*loftins4*	0.0178	0.0106
London	Semi-detached	*area3x*	0.2655	0.0371
London	Semi-detached	*felorien*	0.2132	0.0734
London	Semi-detached	window$_{a}rea$	0.1728	0.3454
London	Semi-detached	floor$_{a}rea$	0.1356	0.2230
London	Semi-detached	*hhsizex*	0.0997	0.0556
London	Semi-detached	*dwage5x_wallinsz*	0.0944	0.2318
London	Semi-detached	*loftins4*	0.0188	0.0336

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Region	**Dwelling type**	**Feature**	**Bedroom**	**Living room**
South West	Semi-detached	window$_{a}rea$	0.2925	0.1649
South West	Semi-detached	*felorien*	0.2405	0.0969
South West	Semi-detached	floor$_{a}rea$	0.1814	0.2636
South West	Semi-detached	*dwage5x_wallinsz*	0.1049	0.3937
South West	Semi-detached	*area3x*	0.0918	0.0314
South West	Semi-detached	*hhsizex*	0.0600	0.0262
South West	Semi-detached	*loftins4*	0.0288	0.0233
North East	Semi-detached	*felorien*	0.2900	0.0782
North East	Semi-detached	floor$_{a}rea$	0.2081	0.2115
North East	Semi-detached	window$_{a}rea$	0.1841	0.1555
North East	Semi-detached	*area3x*	0.1071	0.0418
North East	Semi-detached	*dwage5x_wallinsz*	0.1052	0.4705
North East	Semi-detached	*hhsizex*	0.0801	0.0224
North East	Semi-detached	*loftins4*	0.0253	0.0201
West Midlands	Semi-detached	*hhsizex*	0.2432	0.1822
West Midlands	Semi-detached	*dwage5x_wallinsz*	0.1641	0.4831
West Midlands	Semi-detached	window$_{a}rea$	0.1579	0.0965
West Midlands	Semi-detached	*felorien*	0.1411	0.1098
West Midlands	Semi-detached	floor$_{a}rea$	0.1236	0.0612
West Midlands	Semi-detached	*area3x*	0.1059	0.0473
West Midlands	Semi-detached	*loftins4*	0.0642	0.0199
London	Flat	*winsiz*	0.2896	0.3285
London	Flat	*felorien*	0.2844	0.3018
London	Flat	*floory*	0.1531	0.1679
London	Flat	*hhsizex*	0.1318	0.0613
London	Flat	*dwage5x_wallinsz*	0.1052	0.0986
London	Flat	*loftins4*	0.0226	0.0264
London	Flat	*area3x*	0.0134	0.0155
South East	Flat	*hhsizex*	0.3272	0.1122
South East	Flat	*winsiz*	0.2713	0.4253
South East	Flat	*felorien*	0.1628	0.1705
South East	Flat	*floory*	0.1165	0.1498
South East	Flat	*dwage5x_wallinsz*	0.0856	0.0910
South East	Flat	*area3x*	0.0213	0.0316
South East	Flat	*loftins4*	0.0153	0.0196

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Region	Dwelling type	Feature	Bedroom	Living room
North West	Flat	*hhsizex*	0.3994	0.1976
North West	Flat	*winsiz*	0.1972	0.3506
North West	Flat	*felorien*	0.1439	0.1527
North West	Flat	*floory*	0.1237	0.1837
North West	Flat	*dwage5x_wallinsz*	0.0898	0.0592
North West	Flat	*area3x*	0.0324	0.0348
North West	Flat	*loftins4*	0.0135	0.0213
South West	Flat	*winsiz*	0.5291	0.5738
South West	Flat	*hhsizex*	0.1774	0.0959
South West	Flat	*felorien*	0.1050	0.1094
South West	Flat	*floory*	0.0757	0.1049
South West	Flat	*dwage5x_wallinsz*	0.0624	0.0547
South West	Flat	*loftins4*	0.0370	0.0442
South West	Flat	*area3x*	0.0134	0.0171
Yorkshire and the Humber	Flat	*winsiz*	0.3575	0.5578
Yorkshire and the Humber	Flat	*hhsizex*	0.3342	0.1678
Yorkshire and the Humber	Flat	*dwage5x_wallinsz*	0.1010	0.0694
Yorkshire and the Humber	Flat	*floory*	0.0936	0.0856
Yorkshire and the Humber	Flat	*felorien*	0.0716	0.0559
Yorkshire and the Humber	Flat	*loftins4*	0.0285	0.0487
Yorkshire and the Humber	Flat	*area3x*	0.0136	0.0147
West Midlands	Flat	*winsiz*	0.4760	0.5186
West Midlands	Flat	*felorien*	0.1614	0.1794
West Midlands	Flat	*floory*	0.1442	0.1396
West Midlands	Flat	*hhsizex*	0.1355	0.0689
West Midlands	Flat	*dwage5x_wallinsz*	0.0526	0.0687
West Midlands	Flat	*area3x*	0.0165	0.0147
West Midlands	Flat	*loftins4*	0.0137	0.0102
East Midlands	Flat	*hhsizex*	0.3342	0.0819
East Midlands	Flat	*winsiz*	0.3296	0.4332

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Region	Dwelling type	Feature	Bedroom	Living room
East Midlands	Flat	*floory*	0.1102	0.1657
East Midlands	Flat	*dwage5x_wallinsz*	0.0836	0.0838
East Midlands	Flat	*felorien*	0.0788	0.1011
East Midlands	Flat	*loftins4*	0.0343	0.1024
East Midlands	Flat	*area3x*	0.0295	0.0318
North East	Flat	window$_a rea$	0.8014	0.8569
North East	Flat	*hhsizex*	0.0592	0.0444
North East	Flat	*dwage5x_wallinsz*	0.0496	0.0241
North East	Flat	*felorien*	0.0287	0.0284
North East	Flat	floor$_a rea$	0.0281	0.0260
North East	Flat	*area3x*	0.0245	0.0085
North East	Flat	*loftins4*	0.0085	0.0116
East	Flat	*hhsizex*	0.3487	0.1177
East	Flat	window$_a rea$	0.2634	0.4152
East	Flat	*felorien*	0.2317	0.3044
East	Flat	floor$_a rea$	0.0769	0.0818
East	Flat	*dwage5x_wallinsz*	0.0500	0.0536
East	Flat	*loftins4*	0.0160	0.0162
East	Flat	*area3x*	0.0133	0.0110
South West	Bungalow	*dwage5x_wallinsz*	0.6509	0.5131
South West	Bungalow	*winsiz*	0.1691	0.2603
South West	Bungalow	*floory*	0.0929	0.1050
South West	Bungalow	*felorien*	0.0390	0.0669
South West	Bungalow	*hhsizex*	0.0226	0.0149
South West	Bungalow	*loftins4*	0.0173	0.0312
South West	Bungalow	*area3x*	0.0082	0.0087
London	Bungalow	*dwage5x_wallinsz*	0.5616	0.3147
London	Bungalow	*floory*	0.2592	0.4114
London	Bungalow	*area3x*	0.0652	0.1036
London	Bungalow	*hhsizex*	0.0347	0.0451
London	Bungalow	*winsiz*	0.0320	0.0355
London	Bungalow	*felorien*	0.0288	0.0829
London	Bungalow	*loftins4*	0.0184	0.0068
Yorkshire and the Humber	Bungalow	*dwage5x_wallinsz*	0.5267	0.3516

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Region	Dwelling type	Feature	Bedroom	Living room
Yorkshire and the Humber	Bungalow	*floory*	0.2493	0.4202
Yorkshire and the Humber	Bungalow	*winsiz*	0.1283	0.1359
Yorkshire and the Humber	Bungalow	*felorien*	0.0420	0.0443
Yorkshire and the Humber	Bungalow	*hhsizex*	0.0241	0.0201
Yorkshire and the Humber	Bungalow	*area3x*	0.0213	0.0207
Yorkshire and the Humber	Bungalow	*loftins4*	0.0083	0.0072
North East	Bungalow	*dwage5x_wallinsz*	0.4229	0.4233
North East	Bungalow	*floory*	0.2396	0.2207
North East	Bungalow	*winsiz*	0.1341	0.1918
North East	Bungalow	*hhsizex*	0.1042	0.0445
North East	Bungalow	*felorien*	0.0756	0.0746
North East	Bungalow	*area3x*	0.0166	0.0140
North East	Bungalow	*loftins4*	0.0070	0.0310
South East	Bungalow	*dwage5x_wallinsz*	0.5994	0.5000
South East	Bungalow	*floory*	0.1742	0.1809
South East	Bungalow	*winsiz*	0.1395	0.1724
South East	Bungalow	*felorien*	0.0511	0.0701
South East	Bungalow	*area3x*	0.0241	0.0346
South East	Bungalow	*hhsizex*	0.0076	0.0278
South East	Bungalow	*loftins4*	0.0041	0.0142
West Midlands	Bungalow	*dwage5x_wallinsz*	0.4938	0.3908
West Midlands	Bungalow	*floory*	0.3826	0.3206
West Midlands	Bungalow	*winsiz*	0.0648	0.1930
West Midlands	Bungalow	*loftins4*	0.0252	0.0364
West Midlands	Bungalow	*felorien*	0.0225	0.0346
West Midlands	Bungalow	*area3x*	0.0064	0.0162
West Midlands	Bungalow	*hhsizex*	0.0048	0.0085
East	Bungalow	*dwage5x_wallinsz*	0.5496	0.4211
East	Bungalow	*winsiz*	0.2502	0.1844
East	Bungalow	*floory*	0.0746	0.1881
East	Bungalow	*felorien*	0.0508	0.1258

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Region	Dwelling type	Feature	Bedroom	Living room
East	Bungalow	*area3x*	0.0338	0.0441
East	Bungalow	*hhsizex*	0.0247	0.0257
East	Bungalow	*loftins4*	0.0163	0.0108
East Midlands	Bungalow	*dwage5x_wallinsz*	0.4543	0.3032
East Midlands	Bungalow	*winsiz*	0.3619	0.3991
East Midlands	Bungalow	*floory*	0.1445	0.2150
East Midlands	Bungalow	*felorien*	0.0215	0.0467
East Midlands	Bungalow	*loftins4*	0.0105	0.0103
East Midlands	Bungalow	*area3x*	0.0046	0.0173
East Midlands	Bungalow	*hhsizex*	0.0028	0.0084
North West	Bungalow	*dwage5x_wallinsz*	0.5130	0.2773
North West	Bungalow	*winsiz*	0.2724	0.4116
North West	Bungalow	*floory*	0.1215	0.1493
North West	Bungalow	*felorien*	0.0496	0.0643
North West	Bungalow	*loftins4*	0.0181	0.0415
North West	Bungalow	*area3x*	0.0171	0.0309
North West	Bungalow	*hhsizex*	0.0084	0.0251
South West	End-terrace	*winsiz*	0.2549	0.0710
South West	End-terrace	dwage5x$_{w}allinsz$	0.1609	0.5974
South West	End-terrace	*area3x*	0.1552	0.0934
South West	End-terrace	*floory*	0.1451	0.1034
South West	End-terrace	*felorien*	0.1256	0.0726
South West	End-terrace	*hhsizex*	0.1152	0.0396
South West	End-terrace	*loftins4*	0.0430	0.0226
North East	End-terrace	*felorien*	0.4460	0.2433
North East	End-terrace	*winsiz*	0.2445	0.1951
North East	End-terrace	*loftins4*	0.1044	0.0456
North East	End-terrace	*area3x*	0.0783	0.1912
North East	End-terrace	*floory*	0.0781	0.0666
North East	End-terrace	dwage5x$_{w}allinsz$	0.0362	0.1917
North East	End-terrace	*hhsizex*	0.0125	0.0664
South East	End-terrace	*felorien*	0.2671	0.1914
South East	End-terrace	*winsiz*	0.2472	0.2036
South East	End-terrace	dwage5x$_{w}allinsz$	0.2064	0.4761
South East	End-terrace	*floory*	0.1080	0.0674

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Region	**Dwelling type**	**Feature**	**Bedroom**	**Living room**
South East	End-terrace	*hhsizex*	0.1056	0.0254
South East	End-terrace	*area3x*	0.0384	0.0231
South East	End-terrace	*loftins4*	0.0272	0.0130
East Midlands	End-terrace	*hhsizex*	0.4126	0.0881
East Midlands	End-terrace	*winsiz*	0.1961	0.1034
East Midlands	End-terrace	*floory*	0.1212	0.2439
East Midlands	End-terrace	*felorien*	0.0875	0.1105
East Midlands	End-terrace	*area3x*	0.0848	0.0749
East Midlands	End-terrace	dwage5x$_{w}allinsz$	0.0703	0.3421
East Midlands	End-terrace	*loftins4*	0.0274	0.0371
London	End-terrace	*winsiz*	0.3168	0.2358
London	End-terrace	*floory*	0.1884	0.1658
London	End-terrace	*felorien*	0.1825	0.1349
London	End-terrace	dwage5x$_{w}allinsz$	0.1602	0.3723
London	End-terrace	*area3x*	0.0849	0.0450
London	End-terrace	*hhsizex*	0.0434	0.0272
London	End-terrace	*loftins4*	0.0238	0.0190
East	End-terrace	*felorien*	0.2376	0.0463
East	End-terrace	dwage5x$_{w}allinsz$	0.1894	0.3316
East	End-terrace	*hhsizex*	0.1819	0.0264
East	End-terrace	*winsiz*	0.1718	0.1973
East	End-terrace	*floory*	0.1526	0.3636
East	End-terrace	*area3x*	0.0351	0.0202
East	End-terrace	*loftins4*	0.0317	0.0146
North West	End-terrace	*winsiz*	0.2338	0.2000
North West	End-terrace	*felorien*	0.1895	0.2143
North West	End-terrace	*area3x*	0.1745	0.0795
North West	End-terrace	*floory*	0.1583	0.2061
North West	End-terrace	*hhsizex*	0.1563	0.0293
North West	End-terrace	dwage5x$_{w}allinsz$	0.0719	0.2525
North West	End-terrace	*loftins4*	0.0155	0.0183
Yorkshire and the Humber	End-terrace	*felorien*	0.3398	0.2215
Yorkshire and the Humber	End-terrace	*floory*	0.1653	0.1541

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Region	**Dwelling type**	**Feature**	**Bedroom**	**Living room**
Yorkshire and the Humber	End-terrace	*area3x*	0.1617	0.2812
Yorkshire and the Humber	End-terrace	*winsiz*	0.1540	0.0971
Yorkshire and the Humber	End-terrace	dwage5x$_{w}allinsz$	0.0803	0.1952
Yorkshire and the Humber	End-terrace	*hhsizex*	0.0692	0.0318
Yorkshire and the Humber	End-terrace	*loftins4*	0.0298	0.0191
West Midlands	End-terrace	*felorien*	0.3928	0.2394
West Midlands	End-terrace	*hhsizex*	0.1733	0.0279
West Midlands	End-terrace	*winsiz*	0.1477	0.0939
West Midlands	End-terrace	dwage5x$_{w}allinsz$	0.1256	0.5105
West Midlands	End-terrace	*floory*	0.0858	0.0818
West Midlands	End-terrace	*area3x*	0.0491	0.0397
West Midlands	End-terrace	*loftins4*	0.0258	0.0068
East	Mid-terrace	*winsiz*	0.2599	0.3169
East	Mid-terrace	*felorien*	0.2200	0.1541
East	Mid-terrace	*hhsizex*	0.1618	0.0729
East	Mid-terrace	*floory*	0.1419	0.1583
East	Mid-terrace	dwage5x$_{w}allinsz$	0.1187	0.2316
East	Mid-terrace	*area3x*	0.0634	0.0472
East	Mid-terrace	*loftins4*	0.0341	0.0190
Yorkshire and the Humber	Mid-terrace	*winsiz*	0.5297	0.3347
Yorkshire and the Humber	Mid-terrace	*felorien*	0.1275	0.1610
Yorkshire and the Humber	Mid-terrace	*hhsizex*	0.1266	0.0493
Yorkshire and the Humber	Mid-terrace	*floory*	0.1078	0.1996
Yorkshire and the Humber	Mid-terrace	dwage5x$_{w}allinsz$	0.0405	0.0906
Yorkshire and the Humber	Mid-terrace	*area3x*	0.0345	0.0306
Yorkshire and the Humber	Mid-terrace	*loftins4*	0.0333	0.1341
North East	Mid-terrace	*winsiz*	0.2819	0.1327

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Region	**Dwelling type**	**Feature**	**Bedroom**	**Living room**
North East	Mid-terrace	*loftins4*	0.2416	0.1077
North East	Mid-terrace	*floory*	0.1869	0.4875
North East	Mid-terrace	*felorien*	0.1279	0.0730
North East	Mid-terrace	dwage5x$_{w}allinsz$	0.0677	0.0662
North East	Mid-terrace	*hhsizex*	0.0551	0.0311
North East	Mid-terrace	*area3x*	0.0390	0.1018
North West	Mid-terrace	*winsiz*	0.3972	0.1434
North West	Mid-terrace	*felorien*	0.2263	0.1227
North West	Mid-terrace	*floory*	0.1688	0.5900
North West	Mid-terrace	*hhsizex*	0.0893	0.0251
North West	Mid-terrace	dwage5x$_{w}allinsz$	0.0620	0.0504
North West	Mid-terrace	*loftins4*	0.0306	0.0312
North West	Mid-terrace	*area3x*	0.0258	0.0371
West Midlands	Mid-terrace	*winsiz*	0.5037	0.2777
West Midlands	Mid-terrace	*felorien*	0.1750	0.2343
West Midlands	Mid-terrace	*floory*	0.1218	0.2029
West Midlands	Mid-terrace	dwage5x$_{w}allinsz$	0.0935	0.1648
West Midlands	Mid-terrace	*hhsizex*	0.0749	0.0395
West Midlands	Mid-terrace	*area3x*	0.0165	0.0276
West Midlands	Mid-terrace	*loftins4*	0.0147	0.0532
London	Mid-terrace	*felorien*	0.2875	0.1783
London	Mid-terrace	*winsiz*	0.2257	0.1508
London	Mid-terrace	*floory*	0.1505	0.1644
London	Mid-terrace	dwage5x$_{w}allinsz$	0.1369	0.4382
London	Mid-terrace	*area3x*	0.0866	0.0300
London	Mid-terrace	*hhsizex*	0.0828	0.0262
London	Mid-terrace	*loftins4*	0.0300	0.0121
South East	Mid-terrace	*winsiz*	0.2814	0.2174
South East	Mid-terrace	*felorien*	0.2712	0.1912
South East	Mid-terrace	*floory*	0.1482	0.2003
South East	Mid-terrace	dwage5x$_{w}allinsz$	0.1391	0.3005
South East	Mid-terrace	*hhsizex*	0.0913	0.0208
South East	Mid-terrace	*area3x*	0.0352	0.0339
South East	Mid-terrace	*loftins4*	0.0336	0.0359
South West	Mid-terrace	*winsiz*	0.4018	0.3026

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Region	Dwelling type	Feature	Bedroom	Living room
South West	Mid-terrace	*felorien*	0.1949	0.1659
South West	Mid-terrace	*floory*	0.1400	0.2498
South West	Mid-terrace	dwage5x$_{w}allinsz$	0.0847	0.1660
South West	Mid-terrace	*hhsizex*	0.0682	0.0355
South West	Mid-terrace	*loftins4*	0.0592	0.0491
South West	Mid-terrace	*area3x*	0.0511	0.0310

The following variables are considered: dwelling age, and type of wall and insulation (*dwage5x_wallinsz)*, *felorien* (*felorien*), household size (*hhsizex*), *area3x* (*area3x*), total *winsiz* (*winsiz*), loft insulation thickness (*loftins4)* and *floory* (*floory*)