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Dwelling conversion and energy retrofit modify building anthropogenic heat emission under past and future climates: A case study of London terraced houses

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ABSTRACT

Energy demand per capita is expected to increase with smaller dwelling units in Europe, as less energy is shared linked to the trend of fewer people per household. To meet the demand for more smaller units, a popular retrofitting approach is to split existing large dwellings. As this type of dwelling conversion (DC) affects both household size (HHS) and therefore the likely energy use behaviour of residents, building thermal performance and anthropogenic heat emission ($Q_{F,B}$) to outdoor environment are impacted. Here, the UK time use survey (TUS) provides activity information to allow comparison of the implications of DC to energy conservation measures (ECM) for terraced houses in both past and future London climates. Our results show that ECM can substantially reduce both heating energy demand and $Q_{F,B}$ during cold seasons, whilst due to the absence of space cooling in UK residential buildings the ECM ineffectively diminishes summer demands. Further to this, the increased occupancy density resulting from DC increases summer peak $Q_{F,B}$ by 53.8% at 17:00, which could intensify canopy-layer urban heat island effects. Although climate projected for the 2050′s should result in a decreased wintertime $Q_{F,B}$, the potential increase in summertime space cooling energy demand will see an associated increase in summertime $Q_{F,B}$. Occupancy patterns need to be considered as part of retrofitting assessments and climate change impacts due to their influence on HVAC usage schedule. The role of occupancy behaviour extends beyond retrofit strategies themselves, to larger urban extents (e.g. planning, policy making, urban weather/climate feedbacks) to ensure both energy saving and urban heat mitigation.

1. Introduction

Global warming, mainly characterised by elevated air temperature and its profound impact on both indoor and outdoor environment, demands concerted efforts to mitigate climate change. The Intergovernmental Panel on Climate Change (IPCC) emphasizes that substantial reductions in CO_2 emissions are crucial to limit global warming to 1.5°C above pre-industrial levels, a threshold that marks significantly increased risks to human well-being and ecological stability [1]. In response, countries worldwide are committing to more aggressive reductions in carbon emissions, with the UK's target of 100% reduction (cf. 1990) or net-zero emission by 2050 [2].

Of the nearly 30 million residential buildings in the UK, around 75% are predicted to still be in use in 2050 [3,4]. In 2023, residential building stocks account for 27% national energy use [5] and 16% carbon emission [6]. Of this around 60% of energy is attributed to space heating [7]. The old buildings associated with single-glazing windows, solid wall, roof and floors without insulation, contribute to poor thermal performance and remarkable heating energy waste [8]. Thus, retrofitting old buildings to increase energy efficiency is emerging as primary strategy to cut carbon emission [8–10], with around 1% of old buildings being retrofitted each year [11].

However, at the same time other retrofitting is occurring, notably dwelling conversion (DC) in response to more smaller households with a different energy use impact (cf. energy retrofitting). From 1970 to 2000, the number of UK households increased by 6.4 million, but with the

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average household size shrinking from 2.9 to 2.3 individuals [12], and expected to continue to decrease 1.2% per year [4]. People are increasingly living alone, with this accounting for 13% of the population and 30% of households in 2022 [13]. This trend toward smaller household is driving housing reconfiguration, with retrofitting splitting existing dwellings into multiple smaller units (i.e. dwelling conversion DC). This is becoming increasingly popular [14], in addition to new construction, but is recognised as influencing both spatial and temporal patterns of domestic energy consumption.

For instance, increased domestic energy use per capita in smaller household size (HHS) has been well documented (e.g. [15,16]). As energy demanding activities are shared (e.g., cooking) or have sublinear scaling [17] with occupancy (e.g., refrigeration, lighting in shared spaces), energy consumption per capita is expected to increase with DC for smaller HHS [18–20]. Thus, there may be conflicting effects from energy retrofit to reduce energy use. The smaller household size trend, facilitated by DC, could impact internal heat gains and building thermal conditions, not only modifying space heating and cooling energy to satisfy the indoor thermal comfort, but also their interaction with external environment.

One critical interaction is linked to the anthropogenic heat flux from buildings ($Q_{F,B}$), or the additional heat emissions from buildings to the atmosphere due to human activities. This important heating source in urban area, can elevate near-surface air temperatures and strengthen the canopy-layer urban heat island, as shown in numerous urban climate modelling studies (e.g. [21–23]). Previous studies explore the influence of building thermal parameters on $Q_{F,B}$ profiles, such as U-value and thermal mass (e.g. [24]), energy conservation measures (ECM) for retrofitting (e.g. [25]), cooling system efficiency along with external surface reflectivity (e.g. [26]). These strategies, designed to reduce building energy consumption, should theoretically diminish $Q_{F,B}$ release to the ambient environment.

However, the focus on building materials and system efficiencies have overlooked socio-economic factors, such as changes in household size assocated with dwelling conversion. It raises the question of how does dwelling conversion, with its associated reduction in household size, alters $Q_{F,B}$ profiles in different seasons. Additionally, as smaller household sizes could potentially increase appliance energy use, it is essential to determine whether energy savings from ECM are offset by dwelling conversions. These questions highlight the need for a more comprehensive approach to studying $Q_{F,B}$ modifications taking both technological and socio-economic perspectives.

Apart from building itself, weather and climate also influence building energy use and $Q_{F,\ B}$ [27]. For instance, warmer temperatures reduce heating demand in winter but increases the likelihood of considering use of cooling in summer [28]. Historically, cooling systems have been uncommon in UK dwellings (only 3% of UK buildings are equipped with a cooling systems [29]). Adoption of mechanical cooling may increase as part of people adapting to hotter summers in the future. Switching from natural ventilation to mechanical cooling not only consumes more energy, but also alters the timing and magnitude of heat release [24]. How climate change may impact the effectiveness of these retrofitting activities needs to be addressed.

Within the context of rising demand for smaller residences but potentially conflicting with energy retrofitting efforts, we compare and demonstrate the impacts of different building retrofitting strategies (DC, ECM and their combined effects, CE) on diurnal $Q_{F,B}$ profiles for UK dwellings under different climate projections. The key findings will answer and explain: (1) how dwelling conversion (DC) associated with decreased HHS and ECM impacts seasonal $Q_{F,B}$ profiles in the UK climate context; (2) when two measures are combined, does the energy-saving from ECM get offset by DC; and (3) how will future weather impact $Q_{F,B}$ under different retrofitting approaches. The insights derived from these analyses will provide guidance for urban planners, building refurbishment practitioners and weather/climate modellers to consider when working to mitigate urban heat stress.

2. Methods

2.1. Base case and retrofitting scenarios

To address our research questions (Section 1) we use a variety of data sources and methods (Fig. 1). First, we use the UK Time Use Survey (UK-TUS) to estimate the representative internal heat gains profiles for different HHS and patterns (Section 2.2.2), causing key differences with dwelling conversion. Second, building properties (type, geometry, thermal) are determined by construction age from literature values to assess the energy retrofit. Third, the building energy modelling is undertaken and the $Q_{F,B}$ from individual dwelling units are aggregated for the entire terraced house stock.

This study specifically focuses on mid-terraced houses built before 1919, as they are identified as prime candidates for retrofitting to enhance energy conservation but with the space for unit conversions. In the latest English Housing Survey [29], England's dwelling types are predominately terraced houses (29.1%), followed by semi-detached (24.5%) and detached houses (17.4%). In urban areas new dwellings arise from conversions (2.4% cases in 2021) at a rate nearly triple that of rural areas [31]. This implies a high potential exists for terraced houses conversion in British cities because of their high frequency [31]. This is consistent with London's Borough of Merton reporting terraced houses are most commonly converted into smaller flats [14].

UK dwellings are assigned energy efficiency ratings (energy performance certificate EPC) from A to G with band E to G poorest [32]. In 2022, 20.3% of the terrace houses had pre-1919 construction [29] and of these 23.4% had E-G energy ratings. Newer terrace houses are less likely to have a low energy rating, as the next largest (8.6%) is 1919–1944 construction and the least (2.2%) for post-1990 construction [33]. Thus, a substantial opportunity exists in older buildings for energy retrofitting to meet carbon emission reductions.

To undertake the building energy modelling (Section 2.2) existing building models (e.g. [34,35], Fig S.1) represent the mid-terrace house archetype. The initial, or base case (BC), is a two-storey building with three rooms (living, dining and kitchen) on the ground floor, and three bedrooms and bathroom on the second floor. Assuming the house faces south has relatively small implications, as assessed in Fig. 6 of Liu et al. [19]. To assess the household internal heat gains (Section 2.2.2) using building energy modelling, the interior layout is simplified (Fig. 2a): the upper floor has bedrooms (plus bathroom), with heat contributions from human metabolism; and the ground floor is treated as a single living space (living room, kitchen and dining room) with heat release from all domestic appliances.

The impacts of different retrofit strategies are evaluated using six scenario simulations (Table 1). The base case (BC) assumes the three-bedroom dwelling unit (Fig. 2a) is inhabited by three individuals (HHS=3). The building envelope thermal properties are derived from the TABULA (Typology Approach for Building Stock Assessment) building typologies database [36,37]. TABULA offers a harmonised categorization of residential building by type and age band in Europe, including thermal properties (e.g. building envelopes U-values, solar heat gain coefficient of windows (SHGC) for three building states (as built, usual and ambitious refurbishment). We use the English housing survey [29] dominant age band of private dwellings (i.e., pre-1919) for the envelope thermal construction, which is characterised as solid brick wall without insulation, and single-glazed windows (Table 1).

To evaluate the effect of decreased household size (HHS) by dwelling conversion, the base case (BC in Fig. 2a) is split into two independent dwelling units consisting of a one-bedroom flat on each floor (Fig. 2b). Each unit still has two thermal zones (living room and bedroom in Fig. 2b) and retains the BC thermal envelope properties. To examine whether DC effect vary with occupancy density, we further split it into two scenarios: DC-1 has one occupant (HHS=1), whereas DC-2 has two (HHS=2), representing two occupancy densities and internal heat profiles (Section 2.2.2).

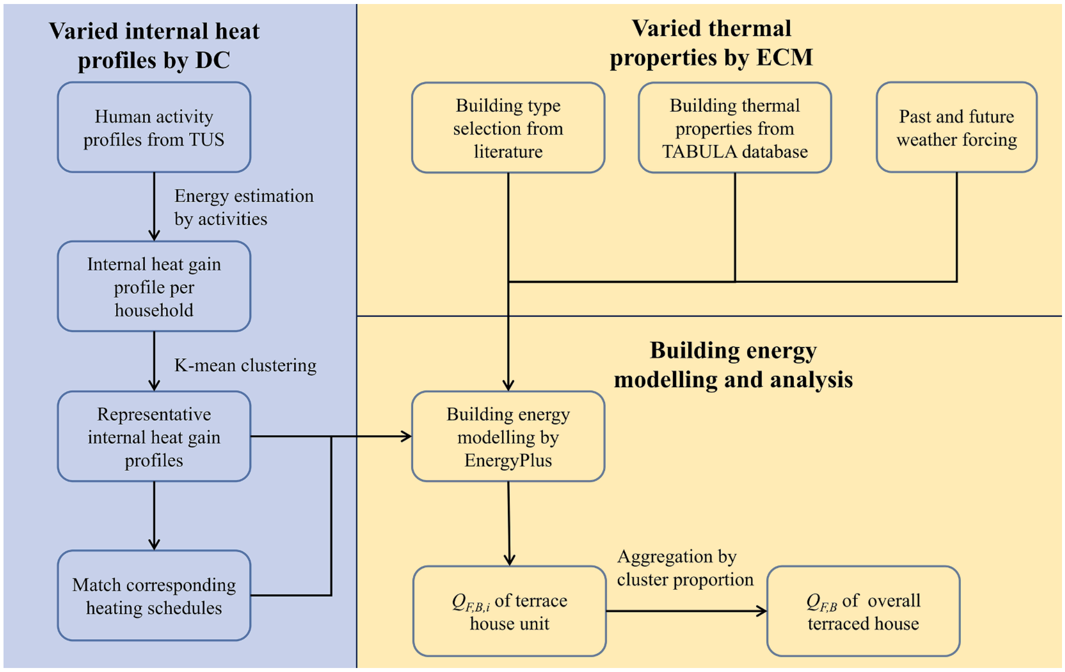

Fig. 1. Household internal heat gain profiles (including appliance energy use and occupant's metabolism heat) are estimated from UK time use survey (UK-TUS) and human activity profiles [30]). These hourly diurnal profiles are categorised using K-means clustering (Section 2.2.2). Building properties are derived from literature (Section 2.1) are used in EnergyPlus building energy simulations, for both current and future weather conditions (Section 2.2.1). The anthropogenic heat flux calculated for individual terrace house units ($Q_{F,B,i}$) are aggregated based on cluster proportions to estimate the overall $Q_{F,B}$ of terraced houses.

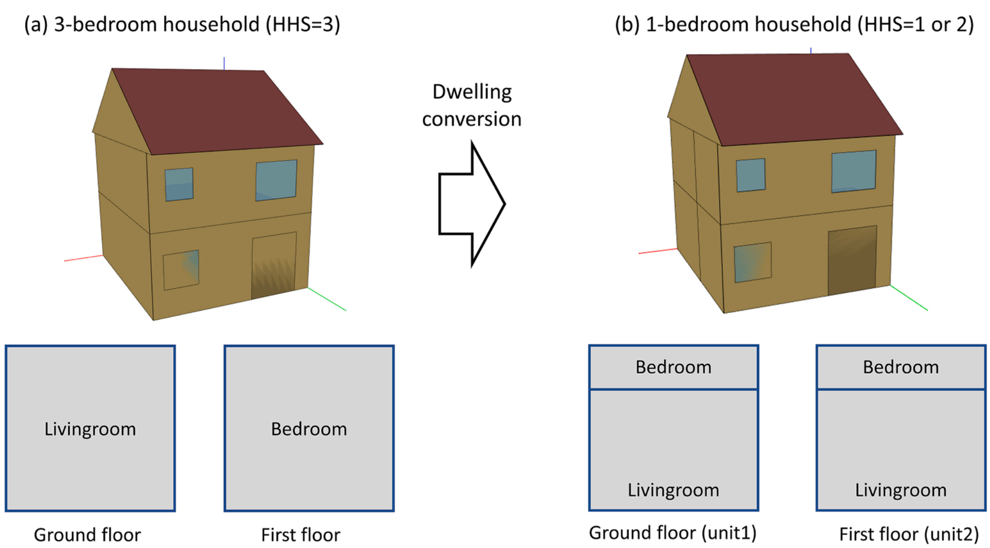

Fig. 2. Reconfiguration of a mid-terraced house unit by dwelling conversion (DC) retrofit from (a) a three bedroom dwelling unit to (b) two identical one-bedroom household units. Two thermal zones are considered in each dwelling, (a) for the three-bedroom dwelling the living room (ground floor) contains the kitchen, dining and living room plus hall in Fig. S.1, abn the bedroom (first floor) includes the bedrooms, hall and bathroom.

Energy conservation measures (ECM) are initially assessed relative to the BC, with unchanged dwelling structure and occupancy. The building fabric retrofit assumes installation of double-glazed windows, solid-wall (external) insulation and roof insulation following the refurbishment measures set out in TABULA (Table 1) [36]. To examine whether DC will offset the energy-saving and heat mitigation from ECM, we assess the net effects of these changes on building thermal performance (CM-1, CM-2, Table 1).

2.2. Building energy modelling

To evaluate the different retrofit strategies (Table 1) on anthropogenic heat emissions from buildings ($Q_{F,\,B}$) in London, EnergyPlus [38] simulations are undertaken. This widely used model can simulate building both energy use and heat emission to the ambient environment [25,39].

Following Liu et al. [40], $Q_{F,\,B}$ is calculated by considering the difference in energy balance fluxes between the building in 'occupied' (o) and 'unoccupied' (uo) states (Fig. 3). The uo state refers to an idealised empty building baseline (or pre-operational occupation). Thus, the

Table 1
Thermal properties (from TABULA database in [36] and household size (HHS) varied in simulated scenarios, with number (N) of dwellings per terraced house unit (Fig. 2). The thermal transmittance (U-value) is a measure of the rate of heat transfer through a material or assembly of materials. The solar heat gain coefficient (SHGC) indicates the fraction of solar radiation transmitted through a window.

Case		HHS	N	Building envelope U-value			Windows SHGC
				Wall	Roof	Window	
Base	BC	3	1	2.1	2.3	4.8	0.85
Energy conservation measure	ECM	3	1	0.3	0.13	2.2	0.63
Dwelling conversion	DC-1	1	2	2.1	2.3	4.8	0.85
Combined measure	CM-1	1	2	0.3	0.13	2.2	0.63
Dwelling conversion	DC-2	2	2	2.1	2.3	4.8	0.85
Combined measure	CM-2	2	2	0.3	0.13	2.2	0.63

difference tracks all heat flux changes from human activities, concluding that the energy source of $Q_{F,B}$ is derived from energy consumption (Q_{EC}) and changes in storage heat flux ($\Delta S_{o\text{-}uo}$):

$$Q_{F,B} = Q_{EC} - \Delta S_{o-uo} \tag{1}$$

2.2.1. Weather data and related assumptions

The building scenarios (Table 1) are simulated using test reference year (TRY) data for both 'baseline' and future weather. Typically, a 30-year Normal (here 1961–1990 for baseline climate) of observed weather data are used, from which the most representative of the climatology for each month is selected, with TRY being the synthetic year of 'real' monthly weather sequences. For the future weather, data [41] are used to select each months weather from the PROMETHEUS project, which has been used for evaluating climate change impacts on building energy use (e.g. [42]) or thermal comfort (e.g. [43,44]) in the UK. The UKCP09 climate projections are used by PROMETHEUS to create the future probabilistic reference years (five percentiles, 10th, 33rd, 50th 66th and 90th, ordered by monthly mean air temperature) by generating 100 sets of 30-year long hourly data for three decades (e.g. 2030s, 2050s, 2080s) and two emission scenarios (medium or high emissions). We selected the medium emission scenario for the 2050s to simulate the future weather.

For 'baseline' conditions, we assume buildings only use natural ventilation for passive cooling as most residential buildings are currently unequipped with air conditioning. The window area is assumed to be half opened when the indoor air temperature is warmer than both the outdoor air temperature and the ventilation set-point (Table 2). Whereas in the future weather scenario, we assume buildings have mixed-mode ventilation maintaining thermal comfort as an adaptation under elevated temperatures (Table 2).

2.2.2. Internal heat gain profiles

If no HVAC system is used, major building heat sources are: internal heat gains from human metabolism, lighting, and appliance use. The heat gains are considered to vary with household occupancy, therefore impacting both timing and intensity of heat exchange between indoor and outdoor environment.

The 2014/15 UK Time Use Survey (UK-TUS) has been used extensively in energy demand studies to link activity and timing of those activities to energy consumption [45]. TUS provide a high temporal resolution (10 min) database of 'individual' activities and locations, across nationally representative population samples that (amongst other population characteristics) capture ages and household sizes of respondents (e.g. [46,47]). With this information, probable appliance type and, therefore, energy usage can be inferred, as well as time periods of home occupancy [48–51]. This dataset enables the generation of representative internal heat gain profiles which reflect the variability in energy use induced by dwelling conversion across different household sizes.

For this study, the weekday diaries when people are at home are used. For each 10-min time block, metabolic rates, appliance power use, and assumptions based on lighting usage are assigned ([52,30]). The metabolic rates vary with age and activity energy expenditure ([30]). All members of a household complete a diary, except for the youngest children (under 8 years old). They are accounted for by assigning them to an adult, so their residential occupancy is retained. The appliance power usage values (W) are assigned based on manufacturer power ratings of typical devices sold in the UK (December 2023), to give an overall power value to each activity (Table. S.1) ([52,30]). The appliance power is the total electrical energy consumption for up to four activities co-occurring at each timestep.

To identify representative diurnal internal heat gain patterns by HHS from 2903 weekday diurnal profiles for the simulations, we use K-mean clustering to segregate the dataset into a pre-chosen number (K) of clusters, each having internal homogeneity relative to other clusters. This algorithm is selected for its stable performance (e.g. [53–55]).

The cluster analysis is an iterative process with the objective of minimizing intra-cluster inertia [56]:

$$C(P,\mu) = \sum_{i=1}^{n} \sum_{x_i \in P_k} \|x_i - \mu_k\|^2 \tag{2}$$

where $P_k = (P_1, P_2, \cdots\cdots P_k)$ is the set of clusters, $\overline{\mu} = (\mu_1, \mu_2, \cdots\cdots, \mu_k)$ is

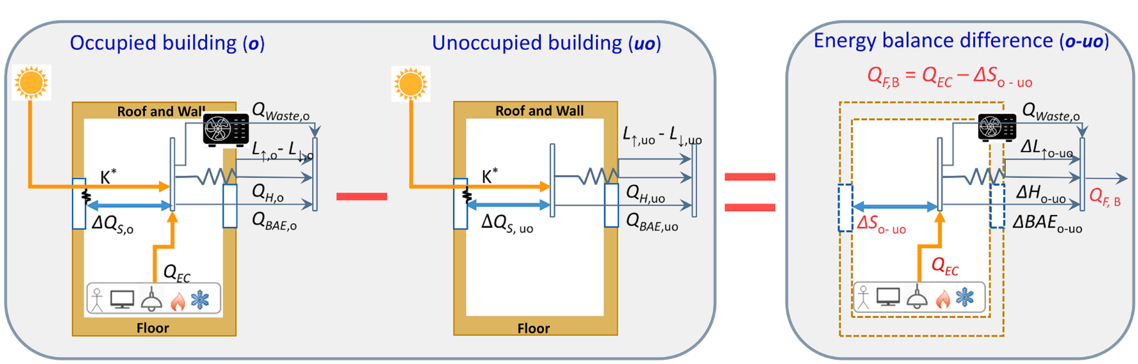

Fig. 3. Schematic of principles used to derive anthropogenic heat emission from buildings ($Q_{F,B}$) by considering the differences in heat fluxes between an 'occupied' (o) and 'unoccupied' building (uo). At the building external envelope, shortwave (K) and longwave (L) radiation, and turbulent or convective sensible heat flux (Q_H) are considered. As is the heat transfer through building air exchange (e.g. natural ventilation through openings and exfiltration through cracks, Q_{BAE}) or the waste heat (Q_{waste}) from heating, ventilation and air conditioning system (HVAC), the storage heat flux in the whole building volume (ΔQ_s) and the building energy use in the building (Q_{EC}). Figure adapted from Liu et al. (2023).

Table 2
Assumed heating, cooling (future weather only) and natural ventilation set points temperatures used in the EnergyPlus building retrofitting simulations (Table 1) undertaken for two weather conditions (baseline and 2050s).

Weather	Ventilation setpoint (℃)		Heating setpoint (℃)		Cooling setpoint (℃)	
	Bedroom	Livingroom	Bedroom	Livingroom	Bedroom	Livingroom
Baseline	25	23	21	21	na	na
2050s	25	23	21	21	26	26

the centroid of each cluster, x_i is a genetic data point belonging to P_k. The main steps are to [54]: (a) initialize K number of centroids randomly, (b) assign each dataset point to its nearest centroid by minimizing $C(P,\mu)$, (c) update the new centroids to the mean in each cluster, and (d) repeat (b) and (c) until convergence occurs.

We normalize the diurnal profiles with the hourly peak value (x_{max}) to emphasize their shapes while mitigating the distorting effects of their absolute magnitude to ease pattern recognition [55,57]:

$$x_i^{'} = x_i / x_{max} \tag{3}$$

where x_i is the hourly internal heat with $i \in [0,23]$.

To determine an appropriate K value we use the 'Clustergram' algorithm [58]. This assesses the weighted mean of the first component of a principal component analysis (PCA) in each cluster. It shows the how variances between cluster change with increasing K values. The optimal K value determined in our analysis is 4 (Supplementary material Fig. S.2), which offers clear separation between clusters.

The four clusters obtained from the diurnal patterns are sub-divided by household size (HHS=1, HHS=2, HHS=3). We defined representative internal heat profiles for each HHS subgroup by averaging their hourly profiles (Section 2.3, Fig. 4a), for use in the building energy modelling.

Given the TUS provides activities rather than heating operations (Supplementary material Section SM 3), we additionally only permit typical heating schedules [59] within a period of assumed active occupancy (i.e. home and awake): (1) *cluster0-cluster2* on from 07:00 to 23:00 (non-workday schedule), and (2) *cluster3* from 07:00 to 09:00 and 16:00 to 23:00 (workday schedule). We similarly limit the cooling schedule arising from future weather, to the same active occupancy period constraints.

2.3. Data aggregation

Building simulations (Section 2.2) are undertaken for individual units with their distinct internal heat gain patterns due to variable occupancy between different households across the entire mid-terraced structure. Each building scenario and climate creates a different $Q_{F,B,i}$ profiles per dwelling unit linked to the four internal heat clusters identified (Fig. 4a). These are aggregated for the mid-terraced structure in fraction (f_i) of cluster types for each HHS group:

$$Q_{F,Bave} = \sum_{i=0}^{3} Q_{F,B,i} f_i \tag{4}$$

In the aggregation, we assume: (1) all dwelling units in the mid-terraced building have the same thermal properties and household size; and (2) the fraction of cluster types (f_i) in each HHS group (Fig. 4b) is used as the actual frequency of varied household behaviours to aggregate $Q_{F,B}$ from dwelling unit to entire terraced unit. This fraction is calculated by number of households for each cluster divided by the total household number for each HHS group. The weighted-mean $Q_{F,B}$ are compared to evaluate both retrofitting options and climate change impacts across the building stock, rather than individual dwelling units. Hour to hour

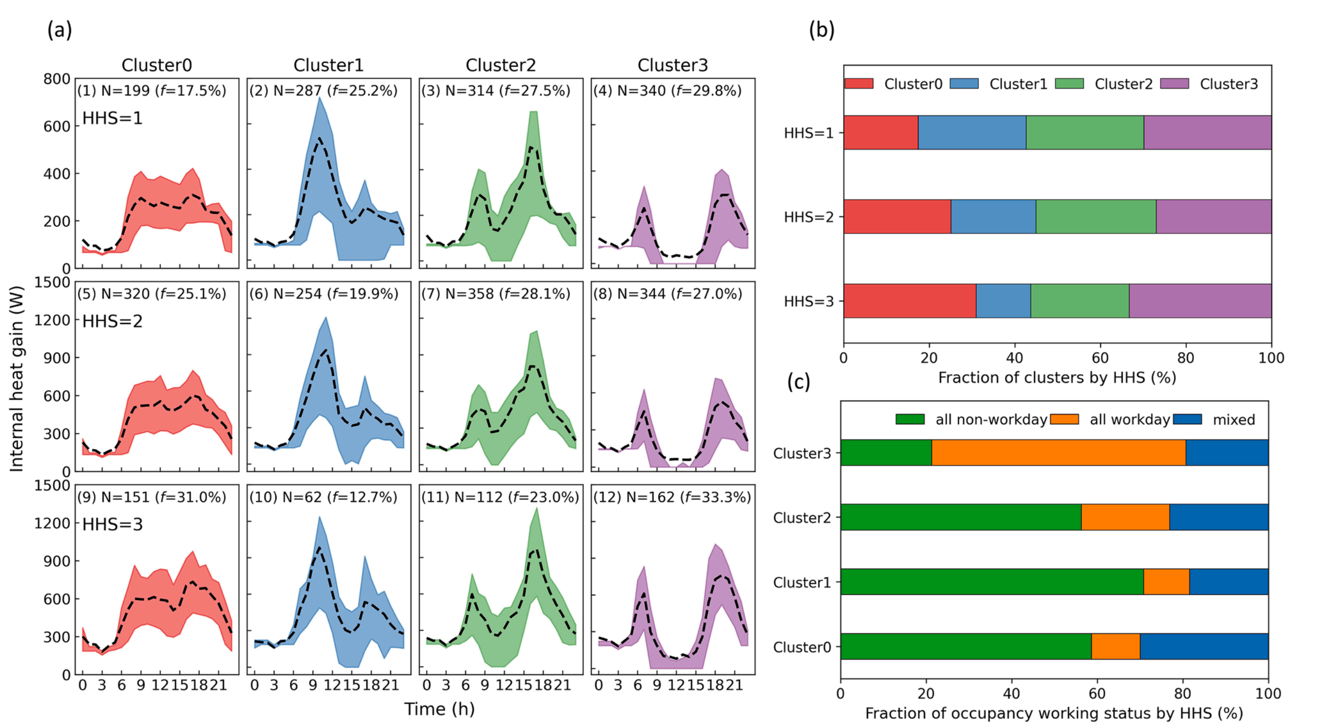

Fig. 4. (a) Four (K=4, Section 2.2.2) internal heat profiles clusters (columns) and three household sizes (HHS; rows) with mean or centroid (dashed line) and interquartile range (IQR, shading), with N indicating the number of profiles and their fraction in each HHS group (row); (b) relative number of each cluster type by HHS (f_i used in Eq. (4), and (c) relative number of people working in each cluster. Mixed households has both working and non-working occupants.

differences in $Q_{F,B}$ for the entire terraced house are calculated to evaluate the impacts of climate change.

3. Results and discussion

3.1. Clustering of internal heat gains

Following clustergram analysis (Supplementary material Fig. S.2) of the UK households internal heat gains, four is selected as the optimal number of clusters for energy consumption modelling (Fig. 4a). Household size (HHS) does not affect the clustering patterns, although more occupants increase the energy consumption magnitude.

Across clusters, *cluster0* has the lowest diurnal variability (Fig. 4a, column 1). *Cluster1* and *cluster2* show distinct peaks, indicating different lifestyles driving energy consumption at varying times (Fig. 4a, columns 2–3). *Cluster3* is the most consistent with occupants being away at work for a full-day (Fig. 4c) as energy is primarily used before and after 9–5 working schedule. This cluster has is the largest across all household size groups (Fig. 4b, purple).

3.2. Effect of different building retrofitting on building anthropogenic heat

The internal heat gain profiles are used in EnergyPlus simulations to calculate the annual mean hourly anthropogenic heat emission ($Q_{F,B}$) for individual dwelling units and then aggregated to an entire terraced house (Eq. (4) for the 12 scenarios: six buildings (Table 1) and two climates (Table 2).

3.2.1. Energy conservation measures (ECM)

The energy-conversation measures (ECM) impact the diurnal $Q_{F,B}$ in all seasons relative to the base case (BC). Under the baseline weather, the BC (poor insulation and windows properties, Table 1) requires winter heating, resulting in a median peak $Q_{F,B}$ of 39.2 W m^{-2} (Fig. 5d). This peak occurs early in the morning (07:00) when heating demand is largest because the outdoor air temperature is coolest before sunrise. This coincides with the building cooling down overnight as heating is switched off when occupants are sleeping. Enhancing the building's thermal properties results in a substantial reduction in $Q_{F,B}$ magnitude, including a 36.7% decrease in the winter median peak (Fig. 5d).

The smaller early morning peaks in spring and autumn can be attributed to reduced heating requirements (e.g. median peak 19.4 W m^{-2}, Fig. 5a). However, additional evening peaks emerge correlating with increased internal heat release from activities such as cooking (*cluster1* and *3*, Fig. 4a). ECM reduce $Q_{F,B}$ between 07:00 and 15:00, with the diurnal cycle flattening as heating demands diminish. Natural ventilation becomes the primary mechanism driving internal heat dissipation to outdoors when indoor temperature elevates and $Q_{F,B}$ reaches peak around 17:00. The reduced daily $Q_{F,B}$ interquartile range (IQR, shading in Fig. 5a, c) with ECM indicates the variability associated with outdoor weather variations is decreased.

With mechanical cooling rare (assumed non-existent) in current UK residential buildings, the primary anthropogenic energy sources in summer are the internal heat from appliances. This is not influenced by the change in envelope thermal properties, resulting in small $Q_{F,B}$ difference between BC and ECM (Fig. 5b). $Q_{F,B}$ remains high between 15:00 and 21:00 when natural ventilation is required to cool down the building. However, the 2050s climate combined with the potential introduction of mixed-mode ventilation, increases the BC $Q_{F,B}$, especially between 15:00 and 20:00 (grey, Fig. 5f). This is linked to cooling demands in warmer weather. Using cooling extracts more stored heat to outdoors, resulting in less heat being released after midnight (i.e. negative change in $Q_{F,B}$, grey Fig. 5f). The 2050s weather (cf. baseline) has consistent impacts across the seasons: warmer winters reduce heating needs, with large changes in $Q_{F,B}$ at 07:00 (Fig. 5e, g, h).

These results support the current policies to promote energy conservation via enhanced thermal envelope properties to promote energy

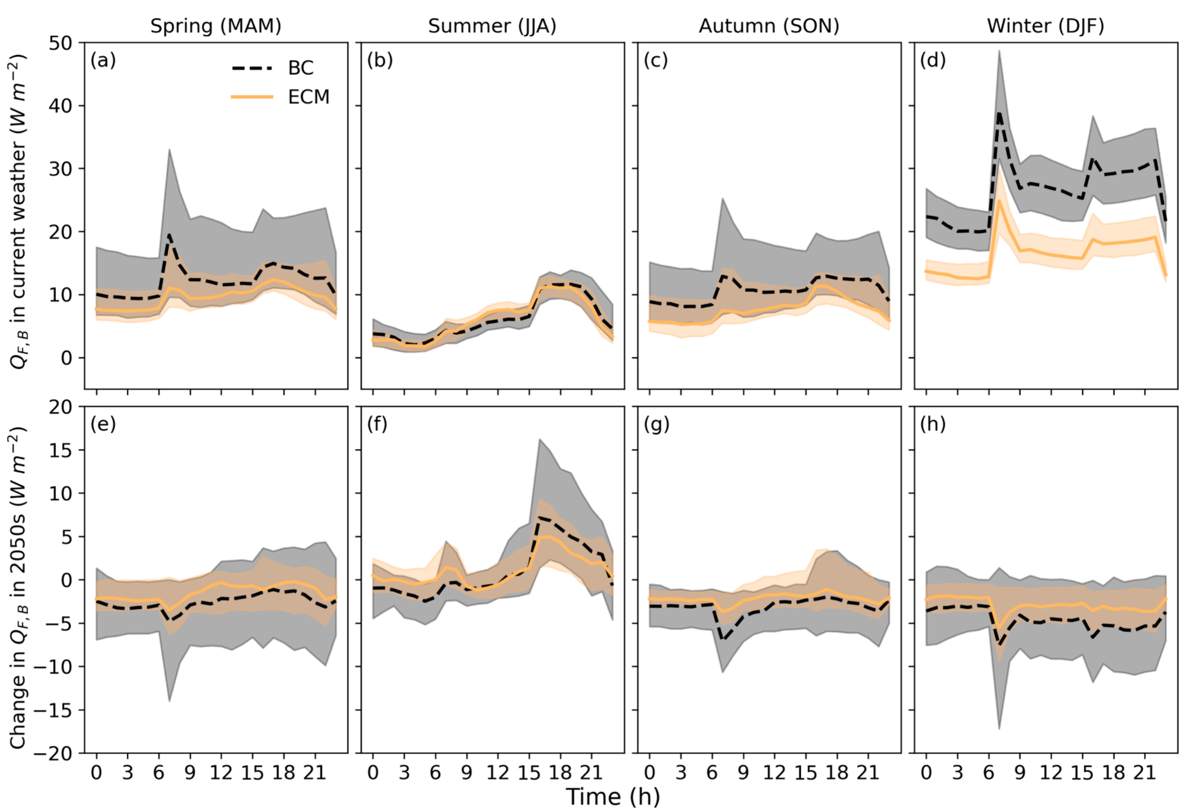

Fig. 5. Seasonal (columns) diurnal profile (median: line, interquartile range: shading) of $Q_{F,B}$ for BC (base case, black) and ECM (energy conservation measure) under (**a-d**) baseline weather, and (**e-h**) the difference caused by weather (future – baseline; for each hour).

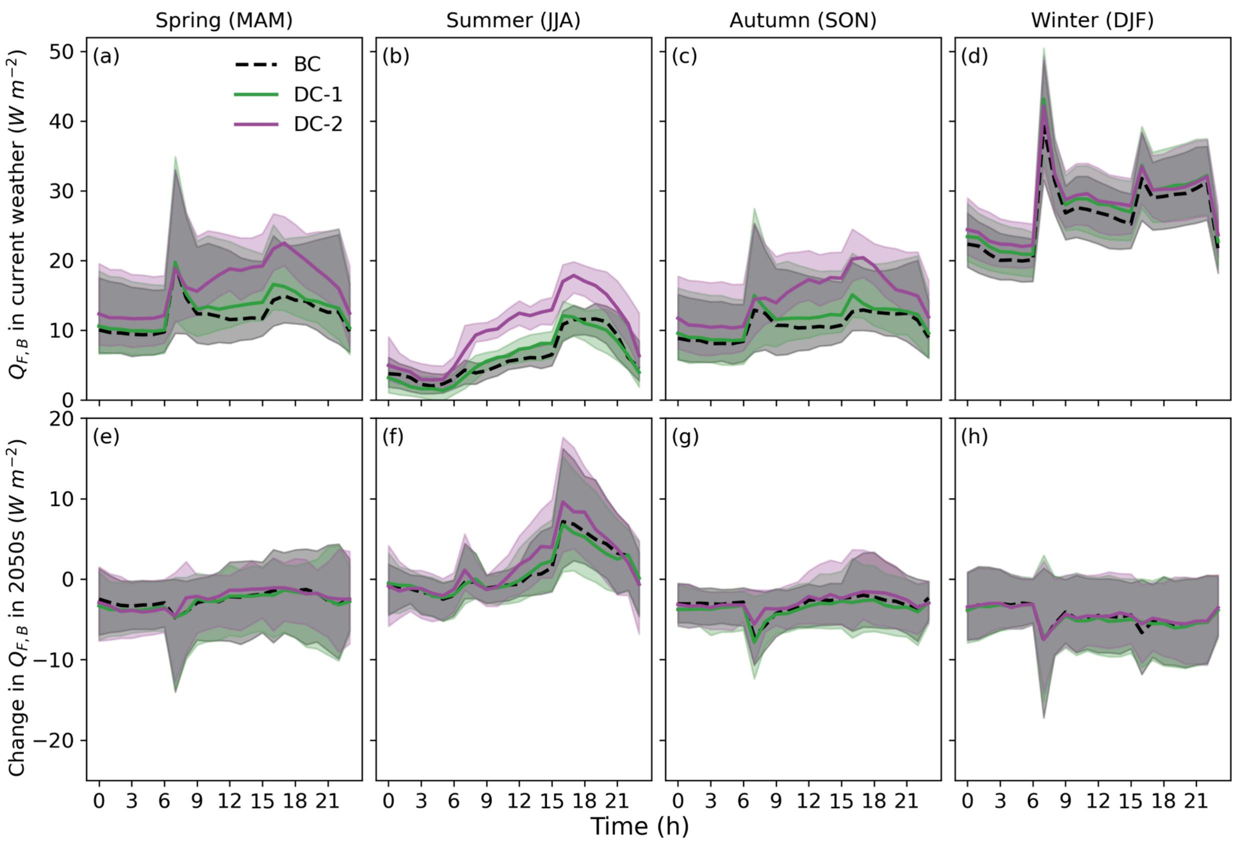

Fig. 6. As Fig. 5, but with BC compared to two dwelling conversion (DC) cases (DC-1: HHS=1; DC-2: HHS=2).

conservation. While these strategies may not reduce $Q_{F,B}$ under contemporary summer conditions, they present advantages for the impending warmer climate. The external wall insulation not only restricts the conductive heat gains, but also allow the thermal mass to dampen indoor air temperature variations. Moreover, reductions in heating energy demand during colder weather can help reduce peak energy demand and with it curtail greenhouse gas emission, contributing to global warming mitigation.

3.2.2. Dwelling conversions (DC)

The two-dwelling conversion (DC) cases considered involve partitioning a large household unit (3-bedrooms, HHS=3) into two separate 1-bedroom units for one (HHS=1, DC-1) or two people (HHS=2, DC-2). As they retain the BC thermal properties (Table 1), they are primarily impacted by changes in occupancy and activities (Section 3.1).

In winter (Fig. 6d), the $Q_{F,B}$ profiles among the three cases (BC, DC-1, and DC-2) are similar, suggesting that internal heat gains from DC allow compensating heating energy. However, in summer (Fig. 6b) the two DC cases differ (cf. BC). With more occupants (DC-2) there is larger $Q_{F,B}$ throughout the day, from greater appliance usage and human metabolism (peak increases by 53.8% in Fig. 6b). Whilst DC-1 has a reduction in $Q_{F,B}$ (cf. BC) with less internal heat generated from fewer occupants. The three diurnal patterns are consistent in timing of minima, maxima and trend across the day.

In the future summer scenario (Fig. 6f) with mixed-mode ventilation, the DC-2 $Q_{F,B}$ results in a larger median peak (cf. BC) of 34.5% (+2.5 W m^{-2}). This is attributed to the higher internal heat generation, which requires prolonged cooling operations.

The spring and autumn patterns are more complex, as winter and summer trends are combined (Fig. 6a, c). When temperatures are cooler in the morning, $Q_{F,B}$ differences are negligible, as heating energy is offset by changed internal heat. But during warmer afternoons, the influence of dwelling conversion becomes more evident, consistent with summertime trends. Under the 2050s weather, the cooling systems are seldom deployed (Fig. 6 e, g).

Unlike the ECM, which has a predominant wintertime $Q_{F,B}$ influence, DC impacts are most evident in the other three seasons. Changes in both building structure (i.e., split into two units) and occupancy patterns (i.e., from HHS) shift energy usage patterns and alter the internal heat generation magnitude.

3.2.3. Combined measures (CM)

Energy conservation measures (ECM) and dwelling conversion (DC), when combined (CM-1, CM-2), result in an intricate interplay of individual retrofitting effects with multiple seasonal variations. Under baseline winter conditions and assuming heating profiles and set-point temperatures remain unaltered, the change in thermal properties (from ECM) are more important in modulating heating energy use than DC. Both CM-1 and CM-2 show decreased $Q_{F,B}$ compared to the BC, with the BC peak of 39.2 Wm^{-2} reduced to 26.8 and 25.0 W m^{-2}, respectively (Fig. 7d). This is consistent with the ECM being less impacted by future weather (Fig. 7h).

In the baseline summer conditions, when internal heat is the only additional energy source, CM-1 and CM-2 (Fig. 7b) align closely with DC-1 and DC-2 (Fig. 6b). However, in the 2050s summers several changes occur: the $Q_{F,B}$ increments for CM-1 (4.6 W m^{-2}) and CM-2 (7.0 W m^{-2}, Fig. 7b) are smaller than for the DC cases (DC-1: 6.8, DC-2: 9.6 W m^{-2}, Fig. 6f). This suggests the dual retrofitting strategy could enhance resilience in countering urban heating, compared to only undertaking dwelling conversion.

The spring and autumn CM-1 and CM-2 show no early morning peak $Q_{F,B}$ (Fig. 7a, c), because of the reduced heating demand. Instead, an evening peak emerges, predominantly driven by natural ventilation with the magnitude closely tied to internal heat variations from occupancy levels. The 2050s autumn has a distinctive shift in CM-2 (Fig. 7g) compared to both DC-2 (Fig. 6g) and ECM (Fig. 5g). The evening

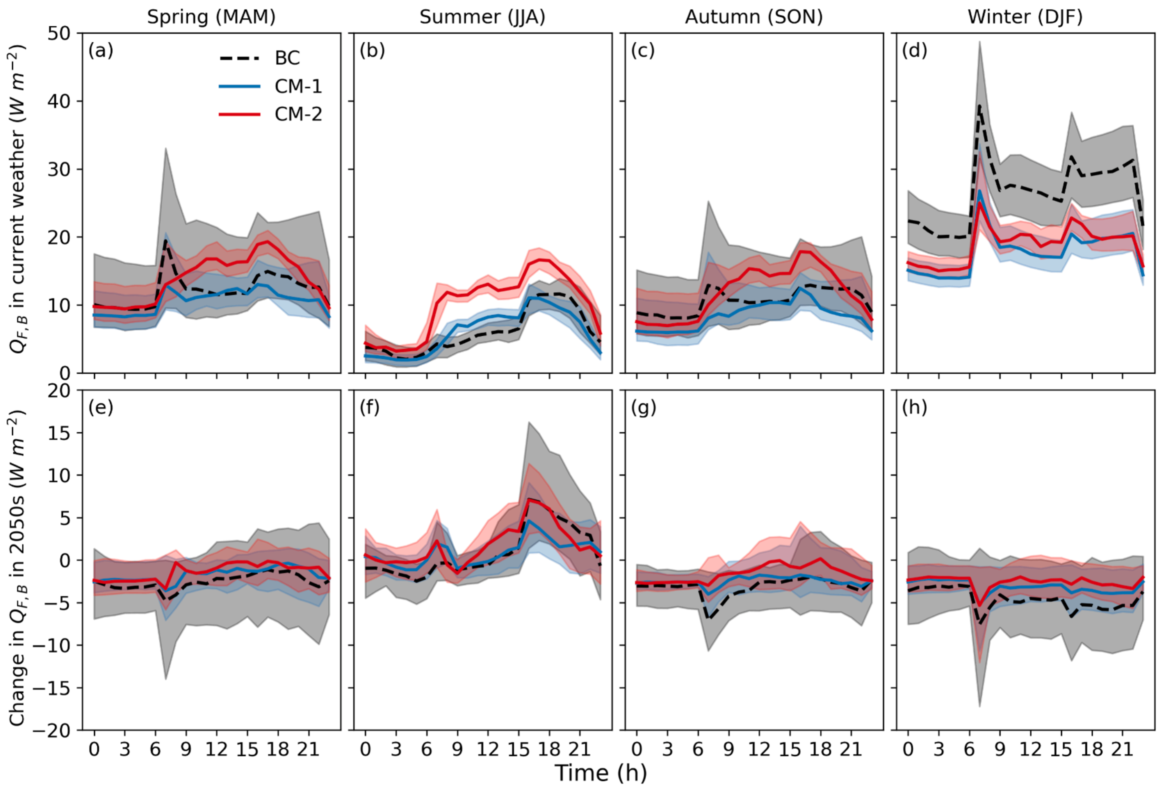

Fig. 7. As Fig. 6, but BC compared to two combined measures (CM-1, CM-2).

increase indicates potential need for mechanical cooling interventions, especially when internal heat generation coincides with enhanced building insulation.

These results suggest it is advantageous to combine retrofitting measures when buildings are converted. In winter and shoulder seasons, heating energy use is reduced, and it help to mitigate heat emissions in future summers. In addition, the inter-seasonal variability on diurnal $Q_{F,B}$ is reduced for CM-2 as weighting of heating energy is smaller and internal heat becoming more important. Overall, the energy retrofitting measures effectively reduce $Q_{F,B}$ in the heating hours. Morning and night have the more pronounced reductions, and as associated with shallower atmospheric boundary layer depths (i.e. smaller volume of near-surface air) cause larger temperature changes. Hence, neighbourhoods with energy-retrofitting could experience colder winter nights and mornings than pre-retrofitting. A similar study, which assessed replacing boilers by heat pump, estimate a 2.5-3℃ air temperature reduction in New York winter [60]. Whereas, dwelling conversions with increased occupancy density will emit more $Q_{F,B}$ in non-heating seasons, with peak emissions in the evening. This can exacerbate the urban heat island, particularly in the densely built area, like the city centre [61].

3.3. Inter-cluster variation impacts climate change and retrofitting

We extend our analysis beyond climate change and retrofitting strategies for an average mid-terraced structure (Section 3.2), to the impact arising from occupancy behaviour as characterised by the clusters (Section 3.1). This allows explore variability between neighbourhoods with different social-cultural factors (e.g. age, income, employment status and household size) to be explored. Given the similarity between DC-1 and BC (Section 3.2.2) and CM-2 and ECM (Section 3.2.3) these cases have not been analysed further.

Most occupancy clusters have similar $Q_{F,B}$ trends for the average mid-terraced house (Fig. 8), with the 2050s weather decreasing winter-time energy use for heating and hence $Q_{F,B}$, but increasing summertime cooling energy. However, the magnitude of these shifts varies by cluster. For BC and DC-2, *cluster3* responds differently to other clusters in the 2050s climate, as the longer unoccupied periods (from 09:00 to 16:00) without HVAC use lead to smaller wintertime $Q_{F,B}$ reductions (25th percentile in Fig. 8d, h, l, p) and smaller summer $Q_{F,B}$ increases (25th percentile in Fig. 8 b, f, g, n) in the daytime. However, the summer daytime heat absorbed by the building materials needs to be expelled by the cooling system when residents return the household, resulting in a massive increase in $Q_{F,B}$ (above 75th percentile in Fig. 8 b, f, g, n), potentially exacerbating the canopy-layer urban heat island effect during summer evenings.

The similarity of *cluster0-2* between present and 2050s weather indicates these occupancy differences have limited impact on future $Q_{F,B}$, but the different schedule of HVAC usage is important and differs from *cluster3*. Similar results occur for ECM and CM-2, but enhanced thermal properties make the building less sensitive to outdoor weather changes, reducing the impacts on $Q_{F,B}$.

The impact of occupancy clusters on internal heat gains and $Q_{F,B}$ with retrofitting changes under current weather conditions are also explored. The ECM − BC difference for *cluster3,* with less home occupancy and heating period (07:00–09:00 and 16:00–21:00), has smaller $Q_{F,B}$ reduction across the distribution (25%, 50% and 75%) than other clusters with longer (07:00–23:00) winter heating (Fig. 9d). This suggests heating schedules play an important role with the enhanced thermal properties of the ECMs. Unlike the inter-cluster differences in winter, summer is consistent across clusters, attributable to both an absence of cooling and homogeneity in spring/autumn heating demands.

The DC-2 − BC difference is impacted by greater occupancy, most notably in summer (Fig. 9f), with *cluster1* and *cluster2* having the largest differences. The impact is reduced in other seasons as increased heating energy compensates (Fig. 9e, g, h). Again *cluster3* $Q_{F,B}$ change is smaller than others in summer, because of lower occupancy. Hence, occupancy schedule and magnitude of internal energy usage influences need to be considered as part of assessing dwelling modifications.

The CM-2 − BC difference has both the ECM and DC-2 summer and

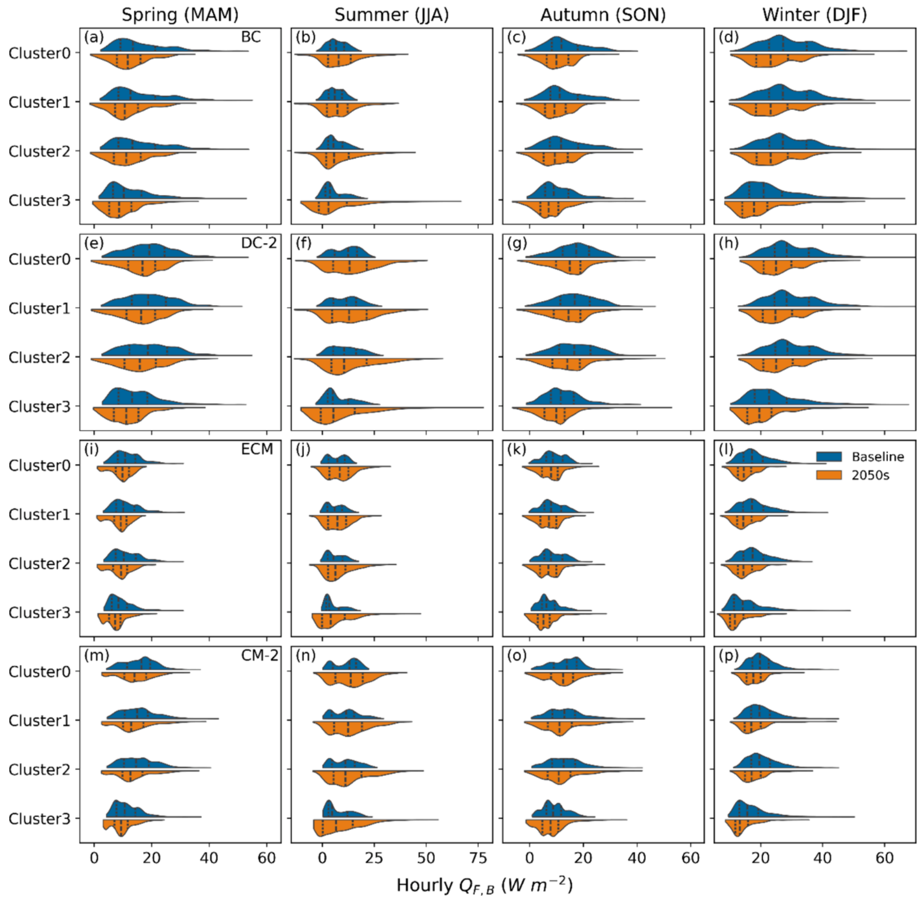

Fig. 8. Violin plots of the distribution of hourly mean $Q_{F,B}$ of individual mid-terraced unit for baseline and 2050s weather (colour) for different occupancy clusters (Section 3.1) by season (columns) and retrofit status (rows, Table 1), with median and IQR indicated (vertical lines). Note, Y scales identical on all plots, but X-scale changes with column (season).

winter characteristics, but diverges in the spring/autumn responses. Improved thermal properties reduces early morning heating demand and elevated internal heat increases natural ventilation potential, contributing to higher $Q_{F,B}$ in the afternoons. Therefore, occupancy dynamics critically modulate the viability of natural ventilation, impacting $Q_{F,B}$ during transitional seasons (Fig. 9i, k).

4. Conclusions

Increasing population and decreasing household size (HHS) is enhancing demand for smaller dwellings in UK cities. Dwelling conversions (DC) occupied by fewer people share less appliance energy use, potentially counteracting the energy-savings and heat mitigation from a traditional energy retrofit. By incorporating occupancy information from the UK time use survey (TUS), we have varying internal heat gains profiles with different HHS. We evaluate impacts for three terraced house retrofitting cases (energy conservation measures ECM, dwelling conversions DC, and combined measures CM) on building anthropogenic heat emissions, with two London climates (baseline and 2050s). The results vary between seasons because of building envelope thermal properties and internal heat gains from human activities.

In the baseline climate, an ECM retrofit can effectively reduce the heating energy required and therefore $Q_{F,B}$. The reduction is largest in the early morning during winter (36.7% cf. the base case, BC), but similar reductions at the same time are evident in the shoulder seasons. However, summer $Q_{F,B}$ changes are small because mechanical cooling is currently not widely used in UK residential buildings and so was not incorporated into BC simulations.

Converting a large house into multiple smaller units, modifies the internal heat gains. These DC impacts are more pronounced than ECM in summer, with household size being a critical determinant. Specifically, DC-2 (HHS=2) causes a net increase in occupancy density and with it more internal energy emissions and a summer evening $Q_{F,B}$ maximum increase (53.8% cf. BC). The increased appliance energy use is offset by reduced heating energy use in winter. While DC-1 (HHS=1) leads to a net occupancy decrease, there are only slight difference across the whole day. Occupancy associated with full time work (*cluster3;* units are empty during the work period), leads to two heating operation periods. As other clusters have smaller impacts, we can conclude different occupancy behaviours are critically affecting the effectiveness of retrofitting strategies at neighbourhood and city scale.

The combined measures (CM) merge the effect of DC and ECM across different seasons. Winter is dominated by ECM effects because space heating is the main energy consumer and changes in internal heat are counterbalanced. Whereas, in seasons without space heating the CM-2 increased occupancy density consumes more energy and releases more $Q_{F,B}$. As regards the impact of future climates in 2050s, $Q_{F,B}$ decreases marginally in the heating season, if mechanical cooling is installed in future summers, $Q_{F,B}$ would be greater in the mid-afternoon to evening period with waste heat being emitted by air conditioning. The largest $Q_{F,B}$ rise is for DC-2 (53.7% for seasonal median peak) from cooling demand and heat emission. Improving envelope thermal properties (ECM, CM-1, CM-2) results in smaller changes. These findings support the current policy of advocating enhancing envelope thermal properties as a key strategy to reduce both building heating energy consumption and $Q_{F,B}$ in future summers, and subsequently mitigate urban heating. Decision-makers and science must not ignore the impacts of dwelling conversion on $Q_{F,B}$, especially with increased occupancy density.

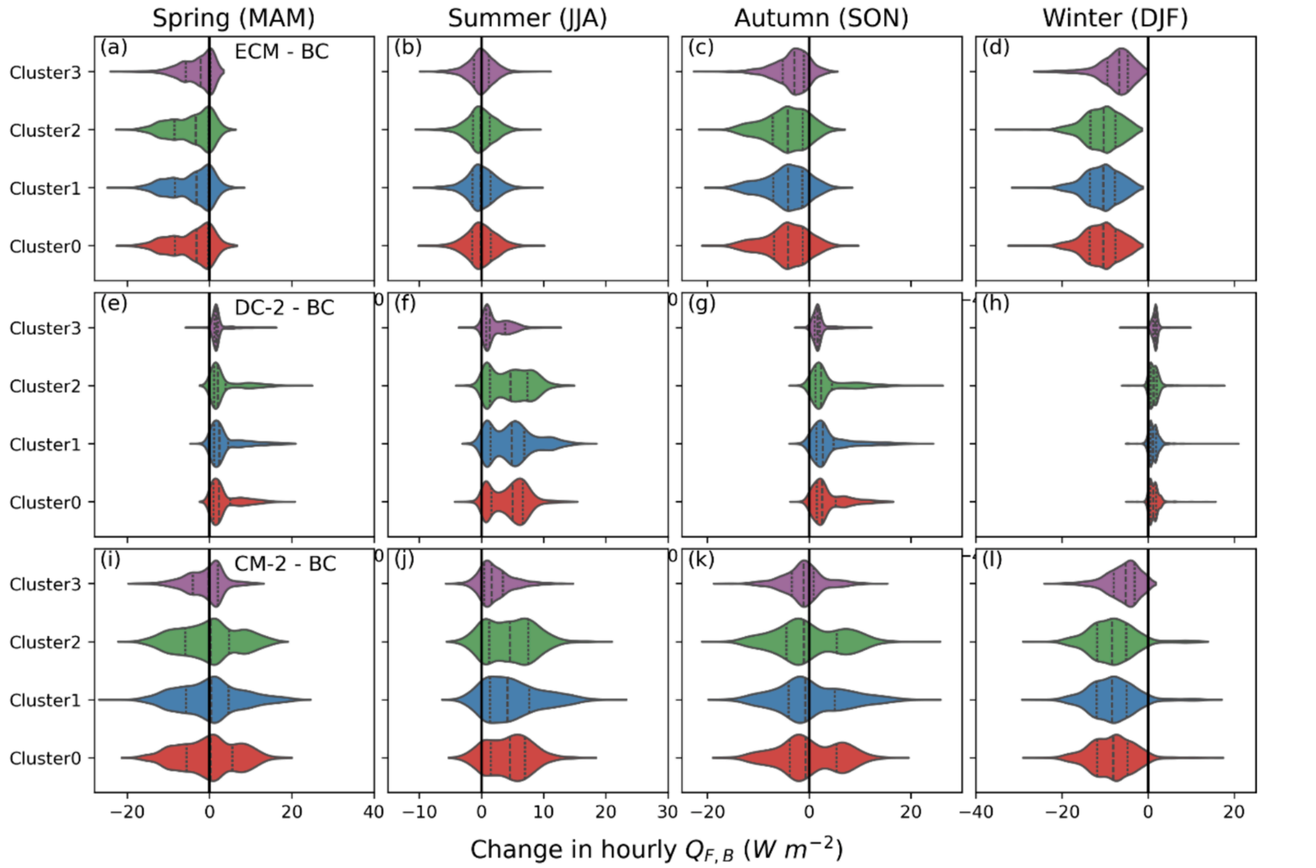

Fig. 9. As Fig. 8, but for present weather only, with change in hourly $Q_{F,B}$ from BC for these retrofits: (a-d) ECM, (e-h) DC-2, and (i-l) CM-2. Note x-axis limits vary between season with 0 W m^{-2} (verical line) indicated.

In this study, energy use profiles are produced based on TUS activities with a fixed energy usage for an activity, that does not take into account variability in sources (e.g. seasonal, or due to differences in the energy efficiency of appliances). Thus, further dynamics, including changes in behaviour will also impact the resulting $Q_{F,B}$ profiles. These results demonstrate this would be worthwhile exploring in the future.

Additionally, using pre-1919 building thermal properties as the baseline (BC) likely maximizes the ECM effect. Future analyses of retrofitting buildings for other age bands (e.g. 1919–1944, 1945–1964) and dwelling conversion will become more important, once the proportion of older dwellings are completed, but ECM may less affect $Q_{F,B.}$ unless technology changes are possible. To take a consistent approach between the baseline and 2050s weather forcing data, we do not account for urban or neighbourhood effects (e.g. varying urban heat island intensity with neighbourhood) despite their importance (e.g. [62,63]). Future studies should consider impacts of neighbourhood context with a city on the cases addressed here.

CRediT authorship contribution statement

Yiqing Liu: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sue Grimmond:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Zhiwen Luo:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Denise Hertwig:** Writing – review & editing, Data curation. **Megan McGrory:** Writing – review & editing, Data curation. **Samuele Lo Piano:** Writing – review & editing, Data curation. **Stefan T. Smith:** Writing – review & editing, Data curation.

Declaration of competing interest

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

Data availability

Data are available at https://doi.org/10.5281/zenodo.13363396.

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Appendix A. Supplementary material

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