



A high-resolution indoor heat-health warning system for dwellings

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ABSTRACT

Climate change projections indicate that the world's most populated regions will experience more frequent, intense and longer-lasting heatwave periods over the coming decades. Such events are likely to result in widespread overheating in the built environment, with a consequential increase in heat-related morbidity and mortality. In order to warn the population of such risks, *Heat-Health Warning Systems* (HHWSs) are being progressively adopted world-wide. Current HHWSs are, however, based solely on weather observations and forecasts and are unable to identify precisely where, when, or to what extent individual buildings (and their occupants) will be affected. In contrast, *AutoRegressive models with eXogenous inputs* (ARX) have been demonstrated to reliably forecast indoor temperatures in individual rooms using minimal data. Thus, the large-scale deployment of forecasting models could theoretically enable the development of a high-resolution *indoor HHWS* (iHHWS). In this study, ARX models were tested over the long-lasting UK heatwave of 2018 using hourly monitored dry-bulb temperature data from 25 rooms (12 living rooms and 13 bedrooms) in 12 dwellings, located within the London *Urban Heat Island* (UHI). The study investigates different approaches to improving the reliability of room-based heat exposure predictions at longer forecasting horizons. The effectiveness of the iHHWS system was assessed by evaluating the accuracy of predictions (using fixed and adaptive temperature thresholds) at different lead times (1, 3, 6, 12, 24, 48 and 72 h ahead). Compared to forecasted indoor temperatures, a *Cumulative Heat Index* (CHI) metric was shown to increase the reliability of heat-health warnings up to 24 h ahead.

1. Introduction

1.1. Background

Overheating and prolonged periods of hot weather have a significant impact on society, increasing mortality and morbidity [1–4]. Extended heatwaves also place additional strain on infrastructure including power, water, transport and emergency services [5]. Climate change projections indicate that the world's most populated regions will experience more frequent and intense heatwave periods over the coming decades [6–8]. Currently, the *Housing Health and Safety Rating System* (HHSRS) [9] is the only legally enforceable standard in relation to assessing overheating risks in UK dwellings. Whilst standards such as the HHSRS are designed to assess the extent of overheating risks in existing dwellings they can only be applied retrospectively and cannot be used to predict the extent of impending risks. To prepare for this emerging

global health risk, national *Heat Health Warning Systems* (HHWSs) [5], such as the Heatwave Plan for England [10], are currently operational (or planned) in almost all European countries [11–13]. According to the *World Meteorological Organization* (WMO) and *World Health Organization* (WHO) [5,p.37], the overall aim of HHWSs is to “alert decision-makers and the general public to impending dangerous hot weather and to serve as a trigger point for the implementation of advice on how to avoid negative health outcomes associated with hot weather extremes”. Nevertheless, the WMO and the WHO acknowledge that current HHWSs do not explicitly account for indoor conditions and rely upon warning criteria that are solely based on outdoor meteorological observations. Most of the vulnerable sectors of the population, however, spend the majority of their time indoors [11] where the building envelope acts as a pronounced modifier of heat exposure. Therefore, reliance upon HHWSs based on external weather observations and forecasts alone renders it impossible to identify precisely where, when, or to what extent

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individual buildings (and the people in them) will be affected.

Understanding how individual rooms and zones within buildings are likely to respond to heatwaves is critical to mitigating their potential impacts on occupant thermal comfort, health and wellbeing. The complexity of this problem originates in the unique time-varying nature of the thermal response of any given building, which is influenced both by its physical characteristics and the unique way in which it is occupied and operated [14,15].

Many sectors of society are vulnerable to excess heat including the elderly, who are at an increased risk of heat-related illness [16] with those over the age of 65 years having a higher risk of heat-related mortality [17]. Older individuals are less tolerant to heat stress than younger people due to the decreased secretory abilities of their sweat glands and the diminished capacity of their cardiovascular systems to dissipate heat through increased cutaneous blood flow [18]. These physiological limitations result in a reduced ability to maintain a steady core temperature when exposed to heat and a longer adaptation period. Furthermore, some elderly people (such as those who are bedridden, disabled or suffer from Alzheimer's or cognitive impairment) are likely to be more susceptible to such risks than others, due to their impaired ability to regulate their living environments [19]. Because of the rising average life expectancy in the UK and other developed nations [20], premature mortality rates are anticipated to increase when similar heatwave events occur in the future.

It is well known that climatic modifiers, such as urbanisation, expose specific sub-populations to higher temperatures [21,22]. The phenomenon, whereby urban areas have higher temperatures than their rural surroundings, is known as the *Urban Heat Island* (UHI¹) [23]. According to Hajat et al. [17], the fact that heat-related mortality risks in urban areas are particularly severe can be largely attributed to the UHI phenomenon. In fact, during the summer of 2018, the majority of excess deaths in the whole of England occurred in London [24], which is the city with the largest and most intense UHI in the UK [22,25].

However, excess mortality during hot weather cannot be solely attributed to excessive heat exposure, with evidence suggesting that a multi-causal relationship exists, including exposure to elevated ground-level air pollutants [5]. Nonetheless, epidemiological studies have shown that even small rises in atmospheric temperature, compared to the usual summer conditions for the local climate, can lead to a considerable increase in heat-related mortality [26]. Notably, the localised impact of heatwaves is usually worse in cities that are characterised by a colder climate, where elevated temperatures are less frequent [27]. This suggests that thermally adverse conditions are dependent on the exceedance of the environmental conditions that are characteristic for the local area. Thus, whilst heat-related mortality risks may be greater in cities, people living in other urban or rural environments, who are accustomed to predominantly lower temperatures, are also at risk [28].

Although mechanical air conditioning might be adopted to reduce indoor temperature and mitigate heat-related risks, such systems remain relatively uncommon in UK homes. Their uptake is, however, projected to increase rapidly [29,30] as warmer summers become increasingly commonplace [30]. Whilst the use of air conditioning is seen as a potential solution to overheating, its widespread adoption would substantially increase the energy demand from the built environment [31] and thereby compromise carbon emission targets [21]. Furthermore, analysis of the rapid uptake of air conditioning in both the USA [32] and Australia [33] has shown that it has had a major impact on the diurnal load profile of summertime electricity demand and is associated with an increased risk of major power outages [34]. There is also a growing

¹ This is primarily caused by the higher heat capacity and lower albedo of the fabrics comprising urban landscapes (i.e. buildings, pavements, roads etc.) compared to rural landscapes, which leads to higher heat absorption during the day [45].

awareness of fuel poverty and the difficulties that certain socio-economic groups may face in paying for the energy needed to maintain cool indoor temperatures [35]. For these reasons, air conditioning cannot be considered to be either a sustainable or socially equitable solution to overheating [21,36]. Accordingly, the Committee on Climate Change recently advised that "Passive cooling measures should be adopted in existing and new homes to reduce overheating risks before considering active measures such as air conditioning" [37, p.47]. Similarly, energy efficiency standards and policies enacted by the European Commission have placed increasing emphasis on the importance of investigating and promoting requirements to use passive cooling solutions [38,39].

Whereas window opening might appear to be one of the simplest options to mitigate high indoor temperatures, it is not always feasible due to localised problems associated with noise, pollution and crime [21,40]. Furthermore, when elevated external temperatures exceed internal overheating thresholds, the use of natural ventilation as a heat purging strategy becomes counter-productive. External shading devices are an obvious passive strategy for reducing excessive solar gains, however, they remain uncommon in the existing housing stock of many cooler countries, including the UK [3].

Irrespective of the overheating mitigation strategy used, advanced warning of impending risks is essential if future heat-related morbidity and mortality are to be minimised [41]. In this regard, the positive correlation between human-body core temperatures and indoor temperatures [42], points to the potential of developing indoor heat-health indices based directly on indoor temperatures. Because indoor thermal conditions do not depend solely on the external weather conditions, but also on the building characteristics, UHI and occupant behaviour, it is clear that associating heat-related risks exclusively with external temperatures at a regional or national level is inadequate and that the development of local, dwelling-based indices, should be a priority [21].

In this paper, a novel high-resolution *indoor Heat-Health Warning System* (iHHWS) is proposed. The development of a dwelling- or room-based iHHWS provides a significant opportunity to tailor the system to the vulnerability of the occupant(s). In this way, heat-related risks could be directly associated with both the propensity of a room to overheat and the susceptibility of the occupant(s) to these temperatures. A real-time iHHWS, which utilises a room temperature sensor and a self-learning predictive model, will thus be unique to the thermal conditions of the space, occupant behaviour and susceptibility of the occupant (s). Such an iHHWS would allow facility managers to alert vulnerable occupants (or their carers) well in advance of impending critical conditions, and if necessary, trigger the intervention of primary care services.

The primary aim of the present work is to investigate how advanced temperature predictions might be deployed to provide maximum utility as part of an iHHWS whilst reducing the possibility of false and missed warnings of overheating. One precondition for the effectiveness of any HHWSs is that the temperature threshold(s) used for triggering the warnings must be aligned to future indoor temperatures and that the advanced warning (or lead time) is constrained according to the reliability of the system [5]. The study aims, therefore, to evaluate both the accuracy of the predictions and the potential confidence of iHHWSs across different forecasting time horizons (1, 3, 6, 12, 48 and 72 h).

1.2. Considerations for early detection of heat-related risks in individual rooms

Previous studies [43,44] have demonstrated that in free-running dwellings it is possible to predict indoor temperatures up to three days in advance with adequate forecasting accuracy. This means that such an approach could form the basis for a more sophisticated iHHWS [43] as described above. Previous work by Anderson et al. [21] established that whilst the development of dwelling-based indoor thresholds, tailored to the occupants and buildings, should be a priority, the paucity of

epidemiological research in this area means that the definition of such thresholds requires further research to support their implementation.

If iHHWSs were deployed to track the indoor thermal conditions and thereby infer the well-being of the occupants during a period of extreme heat, the lead time of the warnings would need to be sufficiently long to allow timely mitigation of the risks. In cases where external intervention is required, the reliability of the forecasts should be as high as possible to reduce the risk of false and missed warnings. To meet these objectives in the context of developing an iHHWS, there are several important issues to consider.

Firstly, what is understood by the reliability of the forecasts? Every temperature forecast is affected by prediction errors (i.e. the difference between the forecasted and measured internal temperatures), which will gradually increase as the forecasting horizon lengthens [43]. Therefore, if deterministic thresholds are adopted to classify the indoor thermal conditions associated with either thermal comfort, morbidity or mortality, there will inevitably be some misclassifications (i.e. the model will either overestimate or underestimate the actual indoor thermal conditions at times). This is a problem common to all model predictions and is especially pronounced at longer forecasting horizons and when the predicted temperatures lie close to the defined thresholds.

Secondly, if we are mainly concerned with morbidity and mortality risks, which metric should be used? Several overheating criteria [45,46], based on thermal comfort, involve evaluating overheating using the operative temperature (which is a metric combining the *Dry-Bulb Temperature* (DBT) and *Mean Radiant Temperature* (MRT)). In practice, most large-scale overheating monitoring studies have observed only the DBT instead of operative temperatures [3]. In occupied spaces, it is difficult (and often impractical) to measure pure DBT or MRT. Commonly deployed temperature sensors (unless carefully shielded from direct and indirect radiation) will usually record some unspecified mix of the DBT and MRT [3]. On the other hand, more complex heat stress indices (originally developed for external environments) such as the *Wet-Bulb Globe Temperature* (WBGT) might provide a more representative metric for the identification of the indoor heat exposure [47]. However, the complexity of continuously logging the numerous input parameters required for the derivation of such indices (i.e. MRT, humidity, air velocity and also the occupants' metabolic rate and clothing level) represents a major limitation for their implementation in an iHHWS.

Thirdly, should the developed risk thresholds be fixed (i.e. static) or adaptive? In the built environment overheating criteria are currently used to assess whether a space is thermally comfortable or not, and are typically evaluated (using dynamic models) in relation to a specific reference summer or weather-year [45,46,48,49]. In more recent years, the steady-state model of thermal comfort (as presented in the ISO 7730 [50]) was challenged by an adaptive theory of thermal comfort, which has been adopted by national guidelines (e.g. CIBSE TM52 [46], CIBSE TM59 [49] and ANSI/ASHRAE standard 55 [51]) as well as international standards (BS EN 15251 [52]). Prevailing adaptive standards vary the thermal discomfort threshold according to the exponentially weighted running mean of the outdoor temperature [53,54]. Wherein it is assumed that occupants can and will modify their behaviour and adapt their thermal environment in response to their experience of external stimuli. Conversely, it is argued, that current adaptive comfort models have been predominantly derived from field studies of healthy adult workers in free-running office buildings [53,55,56]. Whilst such metrics may have some applicability to the overheating assessment of healthy individuals in residential buildings, in the case of elderly and bedridden occupants that might be unable to adjust their indoor environment, a static overheating approach might be more appropriate [57]. From a mortality perspective, evidence shows that heat-related mortality is greater during early summer [28] and also increases with the extent (or duration) of a heatwave [58]. In combination, these characteristics suggest that an approach which is both adaptive and exposure-weighted might best account for mortality risks.

Lastly, are forecasts based on temperatures at a particular moment in

time sufficient to identify heat-related risks to the occupants, or would a metric such as the running mean indoor temperature be more appropriate for the identification of the heat-exposure risks? It is known that heat-related mortality is not an instantaneous response, attributable to momentary exposure (e.g. a single hour) above a given threshold, but rather it is related to the persistence of elevated temperatures over a prolonged period [26,58]. Heat exerts a cumulative effect on the body's ability to regulate temperature, which puts a strain on the entire thermoregulatory system [28]. According to Lee et al. [59], whilst excess deaths do occur on the hottest day of a heatwave, the majority of them are observed on the days following the peak, with the indoor conditions over the previous three days having the largest influence. This delayed response is attributed to the physiological processes occurring. According to Hori [18], sweating is the primary mechanism of heat dissipation for people in a hot environment, with most of the short-term adaptation (e.g. increase in the rate of sweating) occurring 3–5 days after the exposure. This suggests that the danger peaks during the first 3–5 days of heat exposure.

1.3. Objectives

It is acknowledged that the precise medical basis for establishing dwelling-based indoor heat stress thresholds requires further research [21], which is outside the scope of this article. This definition aside, the application of zonal indoor temperature forecasts as a basis for the early detection of adverse conditions with the use of temperature thresholds is herein advanced by addressing three objectives:

1. To determine whether indoor temperatures can be reliably predicted in different dwellings and rooms, across a large urban conurbation, with the use of a single weather data stream.
2. To establish the accuracy of the prediction and classification of the indoor thermal conditions (using fixed and adaptive thresholds) in an iHHWS which is deployed in different rooms and dwellings across different forecasting horizons (e.g. 1, 3, 6, 12, 48 and 72 h).
3. To evaluate whether the adoption of a weighted cumulative heat stress metric, based on the running mean of the indoor temperature forecasts, could provide a more reliable identification of adverse indoor thermal conditions, in comparison to a static approach, in the context of developing an iHHWS.

2. The monitored data set

To evaluate the reliability of the previously developed time series forecasting models [43,44] when deployed in a larger urban context, the models were tested using monitored data from dwellings located in London. This dataset was recorded during the summer of 2018 and contained an elevated UHI intensity [22,25]. In the UK the summer of 2018 was characterised by multiple hot spells in late June, July and early August, with the most pronounced peaks in the outdoor temperature reaching 35.3 °C on the 26th of July (at Faversham, Kent) and 32.7 °C on the 3rd of August (at Kew Gardens, London) [60]. July 2018 was the second warmest July recorded in the UK, since 1910, in terms of both the daily mean and mean daily maximum temperatures [61].

Although the used dataset comprised of 23 dwellings and 46 rooms, roughly half of the recorded measurements commenced too late in the summer to allow sufficient time to train the forecasting models during the hottest period in August. For this reason, only 12 dwellings, providing a total of 25 rooms (12 living rooms and 13 bedrooms), were modelled and validated (i.e. comparison of the model predictions with the actual observations) from 1st to 15th of August (Fig. 1). This period comprised of one week of hot weather (1–8 August) and one week of milder weather (8–15 August). Because the forecasting models adopt a 72-h forecasting window, the forecasts start three days before the beginning of the validation period (i.e. 29th of July) and end three days after the end of the validation period (i.e. 18th of August). Previous

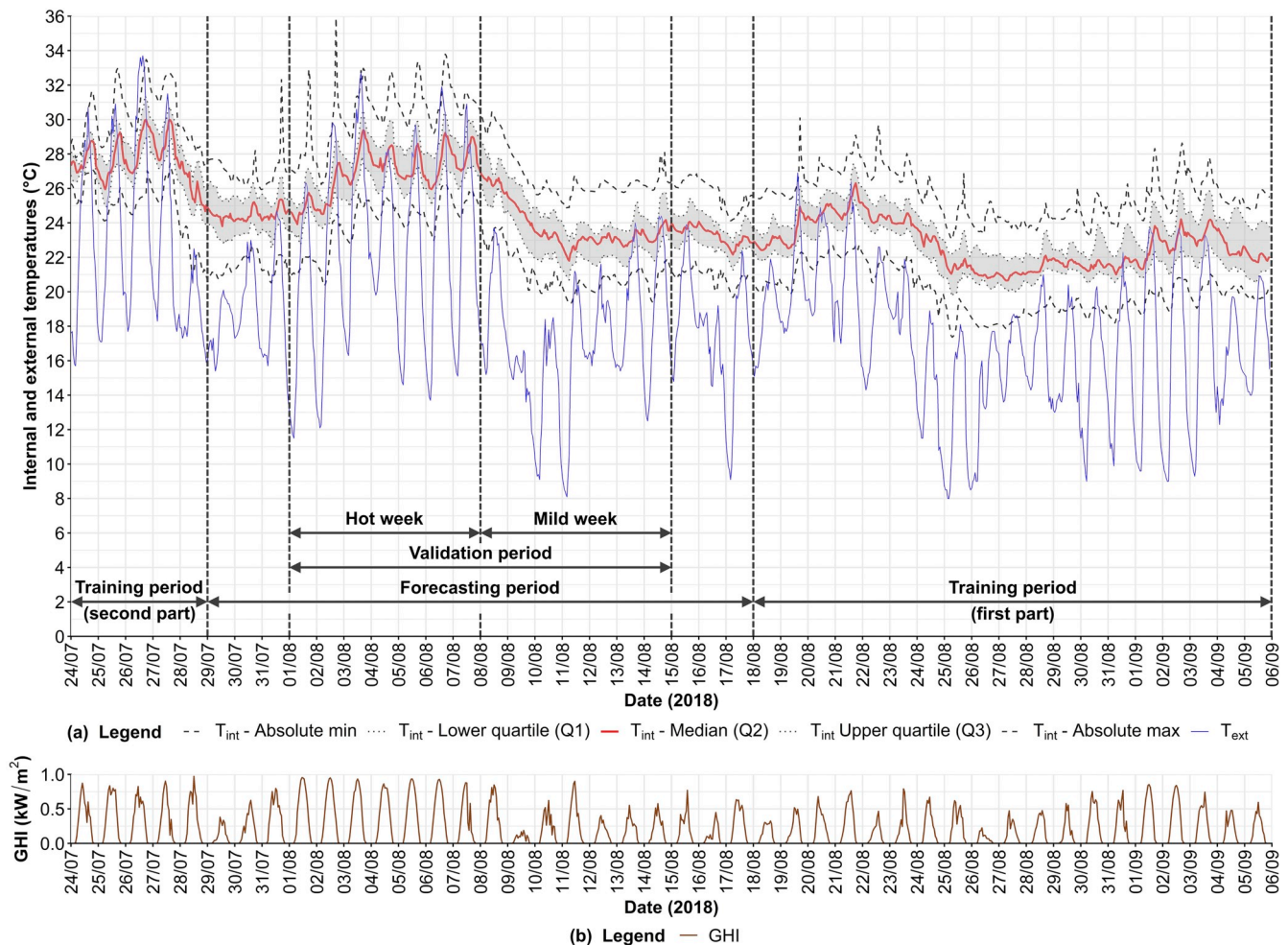


Fig. 1. (a) Hourly internal temperatures (T_{int} ; absolute min/lower quartile (Q₁)/median (Q₂ – red line)/upper quartile (Q₃)/absolute max; the grey band indicates the interquartile range) and external air temperatures (T_{ext}) for the 25 rooms used in this study from 24th of July 2018 to 6th of September 2018; (b) Global Horizontal solar Irradiance (GHI). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

research showed that a 21-day training period was required to produce optimal results [43]. Since the monitoring here started relatively late in the summer, the training data comprises a combination of observations from late July (2–5 days from 24–27 to 29 July depending on the starting date of the observations) and from late August (16–19 days from 18 August to 3–6 September depending on the required number of observations). Notably, both of these periods experienced considerably lower temperatures than the validation period.

The *internal temperatures* (T_{int}) were logged at 10-min intervals. The weather data, consisting of the *external air temperatures* (T_{ext}) and *Global Horizontal solar Irradiance* (GHI) was obtained through the *Centre for Environmental Data Analysis* (CEDA) Archive [62], and was recorded at the nearby Kew Gardens meteorological station at hourly intervals. For this reason, the T_{int} data, recorded in the dwellings, was down-sampled for use in the models by averaging the sub-hourly values to obtain hourly mean values (centred on each hour).

For the majority of the rooms, the hourly internal temperature (T_{int}) in the 25 rooms was usually within ± 1 °C of the median value (Q₂), but at each hour there was a considerable temperature range (of about 6 °C on average) between the hottest and coldest rooms in the dataset (Fig. 1). During the hot spells of late July and early August, indoor temperatures exceeded 30 °C in several rooms for a prolonged period. On the 8th of August, after the hottest period, the outdoor and indoor temperatures profiles dropped substantially and remained relatively low throughout the rest of August (Fig. 1).

By looking in more detail at the indoor temperature distributions

over the hot week (1–8 August), it can be observed (Fig. 2) that there was a considerable temperature difference between individual rooms, both in terms of median and variance. During the August hot spell, 30 °C was reached in 11 out of the 25 spaces.

In most cases (Fig. 2), the bedrooms (BR) were warmer than the living rooms (LR). There were, however, a few exceptions where the indoor temperatures displayed similar profiles (No. 6, No. 7 and No. 9 in Fig. 2) or where the bedrooms were colder than the living rooms (No. 8 - BR-2 and No. 10 – BR in Fig. 2). In these cases, the higher temperatures in the living rooms were probably caused by the rooms being located on different floors (No. 8, Table 1) or the living room having a south-facing orientation (No. 10, Table 1). The lowest indoor temperatures were experienced in the living rooms of dwellings No. 2, No. 3 and No. 11. The most plausible explanations for this, include: the occasional use of a portable *Air Conditioning* (AC) unit (No. 2, Table 1); the location of the flat on the ground level with external shading from trees and neighbouring buildings (No. 3, Table 1); and having only one exposed façade which thereby limited the external gains (No. 11, Table 1).

The highest temperatures were observed in the bedrooms of dwellings No. 4 and No. 11, which can be explained by the internal gains arising from the restaurant located immediately beneath (No. 4, Table 1) and by the room being on the highest floor of the building (No. 11, Table 1). Interestingly, some of the highest temperature variances can be observed in dwellings that extend across two floors (No. 5, No. 8 and No. 11 in Fig. 2 and Table 1). It has to be noted that the outliers observed for the living room in dwelling No. 5 (Fig. 2) were most probably caused by

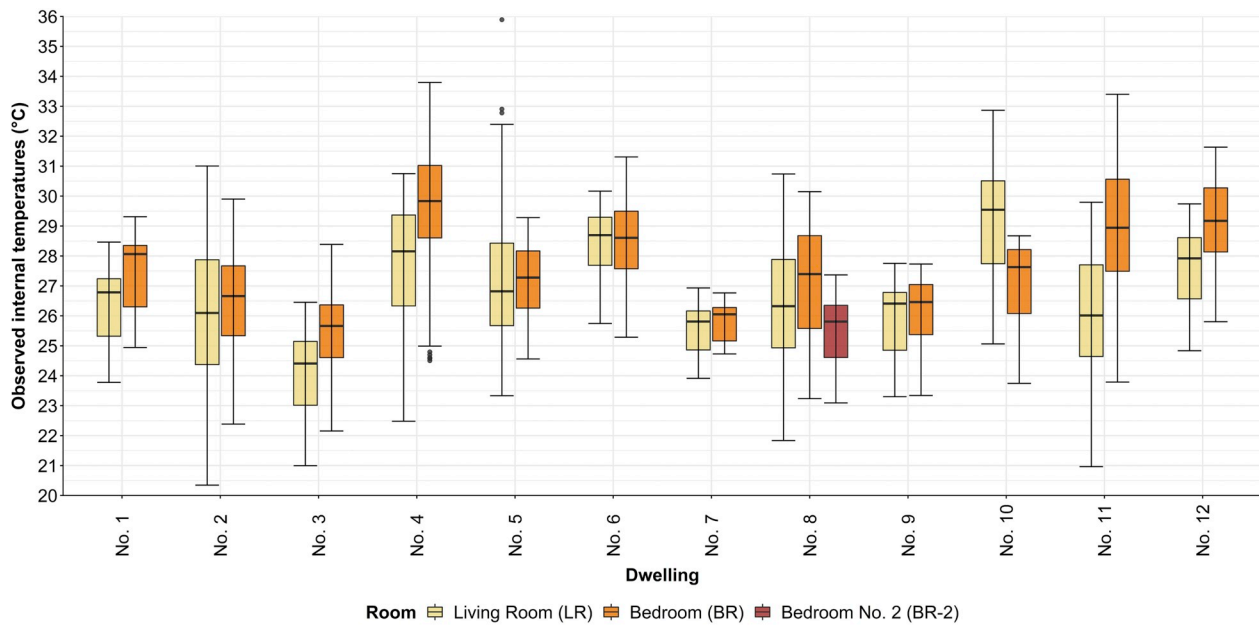


Fig. 2. Boxplots of the observed indoor temperature distributions in the monitored dwellings and rooms during the hot week (1–8 August 2018).

Table 1
Characteristics of the monitored dwellings and rooms. [2-column fitting table].

No.	Building typology	Construction age (refurbishment)	No. occupants	No. of storeys (floor level)	Orientation of monitored rooms	Shadings	Electric fans and Air Conditioning (AC)	Observations
1	n/s	n/s	n/s	n/s	n/s	n/s	n/s	n/av
2	Terraced (flat)	1970 (2010)	1	3 (3)	South	Louvre and curtains	Electric Fan, Portable AC (evaporative cooler)	a
3	Semi-detached (flat)	1900 (n/av)	2	3 (0)	South-West	Neighbouring house, trees	No	n/av
4	Purpose build (flat)	1970 (2000)	1	4 (1)	West	Blinds	Electric Fans	b
5	Terraced (flat)	1900 (n/av)	3	3 (1–2)	East-West	Curtains	Electric Fans	c
6	Purpose build (flat)	2006 (n/av)	1	5 (3)	South	From balcony above (LR), Curtains (BR)	Electric Fan (BR)	n/av
7	Other (flat)	1890 (1980)	2	5 (0)	North-East	Curtains	Forced ventilation, Electric Fan in the Evening	d
8	Semi-detached (house)	1930 (n/av)	5	2 (1–2)	East (BR) West (LR)	Curtains	No	n/av
9	Terraced (flat)	1900 (n/av)	2	2 (0)	South-West (BR), North-East (LR)	Curtains (LR), Curtains and Blinds (BR)	Electric Fan (BR)	e
10	Bungalow (house)	2005 (n/av)	2	1 (0)	South (LR), East (BR)	Curtains and front building (LR), Curtains (BR)	Ceiling electric fan (LR)	f
11	Block (flat)	1980 (2008)	2	4 (3–4)	South-West	Curtains	Electric fan	g
12	Detached (flat)	1900 (n/av)	3	4 (1)	East (BR), West (LR)	Curtains and Blinds (BR)	No	h

Legend: n/s = not specified; n/av = not available; a = airtight, well-insulated; b = mouldy BR, restaurant’s kitchen directly under the flat’s kitchen; c = curtains often closed during the day; d = old factory conversion with double height storeys, large glazing area, thick brick walls without cavity, BR upstairs; e = single glazing; f = roof insulation; g = two-storey flat, loft insulation, only one exposed façade (North-West) with party walls on the other three sides; h = big windows, dark (blue) blinds, internal gains from pipework.

a sensor being exposed to direct solar irradiance in the late afternoon (west-facing room), which caused the rapid increase in the temperature readings that can be observed between the 31st of July and 3rd of August (absolute max T_{int} in Fig. 1).

3. Methods

3.1. Adopted forecasting models and validation

Previous work [44] has investigated the optimal model structure for

forecasting indoor temperatures in free-running dwellings. That work showed that more complex non-linear forecasting models and the use of additional predictor variables do not necessarily improve the forecasting accuracy achieved by linear models, especially when forecasting indoor temperatures at longer time horizons [44]. For this reason, in this work, simpler linear *AutoRegressive models with exogenous inputs* (ARX), rolling training and forecasting windows, and a limited number of predictor variables (as demonstrated in a previous study [43]) were adopted. For the prediction of the indoor temperature, the models utilise the lagged effects of the internal temperature (T_{int}), external air temperature (T_{ext})

and Global Horizontal solar Irradiance (GHI). To constrain the complexity and computational time of the models, a maximum lag (n), of the autoregressive (T_{int}) and exogenous inputs (T_{ext} and GHI) was set to 5 h as established in previous work [43,44,63].

The optimal structure of each model (was as in the previous studies [43,44], based on the minimisation of the *Akaike Information Criterion* (AIC). To provide rapid automatic identification of a near-optimal model, a *backward stepwise regression* [64,65] selection procedure was implemented [44]. The model selection is performed only once for each room based on the initial training period.

The selected forecasting models adopt a *rolling window* approach (i.e. sliding fixed-length 21-day training window) whilst performing multi-step-ahead predictions (1–72 h ahead) across the forecasting period (Fig. 1). This results in hourly forecasts which span different forecasting horizons across the entire validation period (1–15 August). In order to visualise the gradual decrease of the forecasting accuracy (at longer time horizons), boxplots of *Absolute hourly forecasting Errors* (AE) were created for each of the different forecasting horizon ($h = 1, 3, 6, 12, 24, 48, 72$ h). The forecasting accuracy was assessed in this way for the hot week (1–8 August), the mild week (8–15 August) and the total (combined) validation period (1–15 August) (Fig. 4).

3.2. Definition of a weighted heat stress metric: Cumulative Heat Index

In order to reliably determine when adverse heat stress conditions may occur (as previously discussed in section 1.2) the metric used needs to account for the evolution of the indoor thermal conditions during the most recent period (e.g. past three days). Such an approach has been previously proposed by Lee et al. [59], where the researchers developed an Accumulated Heat stress Index (AHI) based on a time-weighted function across the previous 72 h, in which time-dependent weights were applied chronologically. To obtain the AHI, the researchers standardised the Accumulated Heat (AH) level for each meteorological station to account for regional acclimatisation and then estimated its probability distribution. In its original form, the index was not intended for use in the context of an indoor warning system based on forecasted data. In order to adapt it for this purpose, a more direct approach was achieved by back-calculating the time-weighted accumulated heat stress function across the previous 72 hourly time steps at each forecasting horizon. Effectively, this creates a weighted running mean indoor temperature which could be compared to a location-specific heat-stress threshold, defined for the local climate. This approach could be further refined by the inclusion of additional time-varying thresholds (to account for seasonal adaptation according to the specific month) and consideration of the health-related characteristics of the occupants (e.g. elderly, chronically ill etc.).

Use of such a weighted metric can directly account for the different dimensions of heat-health related risks (i.e. duration and intensity of heat) by considering the profile of the indoor conditions across the previous 72 h and applying gradually higher weightings to the more recent values, relative to the desired forecasting horizon. In this way, a threshold can be breached only if hot indoor conditions persist for a prolonged period or if there is a spike in the indoor conditions considerably above the threshold. The proposed *Cumulative Heat Index* (CHI) (equation (1)), is based on a combination of the forecasted and observed (when $h < 72$ h) indoor temperatures. Modified weightings were then applied to the temperature time series, as proposed by Lee et al. [59], in order to place a higher influence on the most recent indoor thermal conditions. Forecasting indoor temperatures with recursive autoregressive models at longer lead times (e.g. 72 h) means that all of the predictions 1–71h ahead need to have been made, to be available for subsequent computation. The calculation of the hourly indoor weighted CHI becomes increasingly reliable as the forecasting horizon shortens since more observed temperatures are used.

$$\begin{aligned} CHI(t+h) &= \frac{\sum_{i=0}^{71} W_i T_{int}(t+h-i)}{\sum_{i=0}^{71} W_i} = \frac{\sum_{i=0}^{71} \frac{1}{i+1} T_{int}(t+h-i)}{\sum_{i=0}^{71} \frac{1}{i+1}} \\ &= \frac{1}{4.86} \sum_{i=0}^{71} \frac{1}{i+1} T_{int}(t+h-i) \end{aligned} \quad (1)$$

where:

$CHI(t+h)$ forecasted Cumulative Heat Index at the forecasting horizon h after the time step t ($^{\circ}\text{C}$)

$T_{int}(t+h-i)$ forecasted/observed hourly internal temperature i time steps before the forecasting horizon h ($^{\circ}\text{C}$)

t hourly time step (h)

h forecasting horizon, hourly time steps ($h = 1, \dots, 72$) (h)

i time step(s) before the forecasting horizon h

W_i weight of T_{int} , i steps before the forecasting horizon h

3.3. Reliability of forecasted indoor temperatures and the Cumulative Heat Index

In order to evaluate whether a weighted indoor running mean CHI metric can provide a reliable identification of the likely heat exposure risk, the forecasted indoor temperatures and CHI were compared with known values, for both fixed and adaptive thresholds across different forecasting horizons ($h = 1, 3, 6, 12, 24, 48, 72$ h). In the first test, the ability to correctly forecasting indoor temperatures and the CHI across a wide spectrum of temperature ranges ($<22^{\circ}\text{C}$, $22\text{--}24^{\circ}\text{C}$, $24\text{--}26^{\circ}\text{C}$, $26\text{--}28^{\circ}\text{C}$, $28\text{--}30^{\circ}\text{C}$, $30\text{--}32^{\circ}\text{C}$ and $>32^{\circ}\text{C}$) was evaluated. The ability of the model to correctly predict indoor temperatures and the CHI into observed ranges (that could represent different thermal comfort or heat stress thresholds) was evaluated by calculating the percentage of correctly predicted, overpredicted and underpredicted temperature ranges at the various lead times across the sample of 25 rooms. In the second test, the forecasted indoor temperatures and CHI were compared with the observed values according to the adaptive thermal comfort standard BS EN 15251 by evaluating the degree hours above the adaptive threshold for three different categories (CAT I: high level - vulnerable occupants; CAT II: normal level - new building and renovations; CAT III: acceptable/normal level - existing buildings). In this test, the performance of the forecasting models is assessed in relation to the exceedance of the upper adaptive threshold limit by calculating the percentage of the observed degree hours that are forecasted, at the various lead times, for the 25 rooms. These two tests will indicate whether the adoption of a weighted metric, such as the CHI, can reduce the risk of false (i.e. overestimated risk) and missed (i.e. underestimated risk) warnings in the operation of an iHHWS.

4. Results

4.1. Forecasting accuracy

The forecasts of the T_{int} indicate that for lead times of 12 h (Fig. 3) the models are capable of closely following the observed temperatures, both in the warmer rooms (e.g. No. 4 – BR and No. 11 – BR) and the mildly overheated rooms (e.g. No. 8 – LR). Nevertheless, in some cases (No. 4 – BR and No. 11 – BR) the models are slightly underpredicting the observed indoor temperatures during the final part of the heatwave (5–7 August in Fig. 3). On the days following the end of the heatwave (11–13 August in Fig. 3), with the sudden drop of the outdoor and indoor temperatures, the models tend to overpredict the indoor thermal conditions in all rooms. Nevertheless, the predictions, stabilise during subsequent days (14–15 August in Fig. 3) with a considerable improvement of the forecasting accuracy. Analogous remarks can be made for the CHI, however, due to its weighted nature, compared to the T_{int} , the CHI is capable of following the observed values with a much

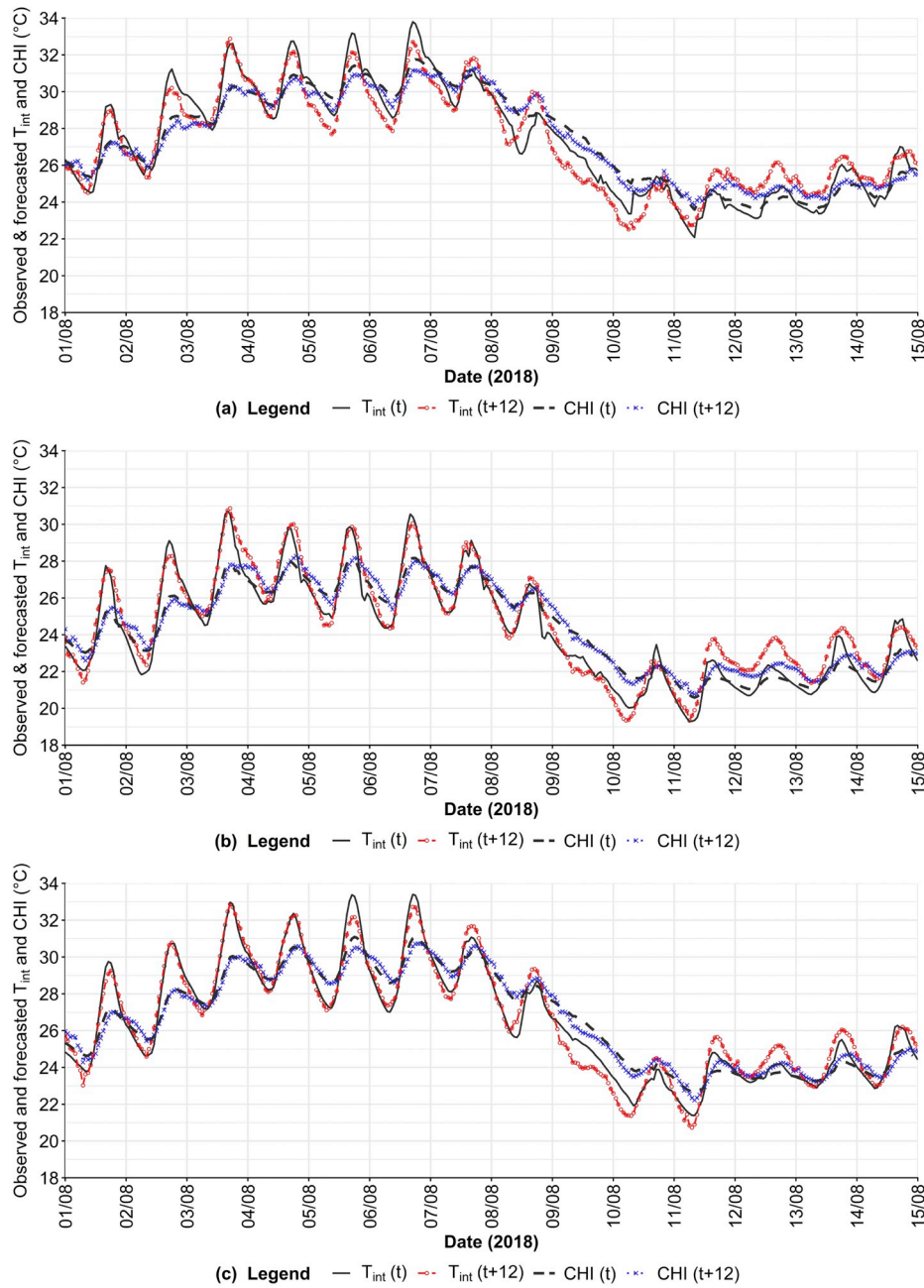


Fig. 3. Observed, $T_{int}(t)$ and $CHI(t)$, and 12 h ahead predictions, $T_{int}(t+12)$ and $CHI(t+12)$, of the hourly internal temperatures and Cumulative Heat Index, for rooms No. 4 - BR (a), No. 8 - LR (b) and No. 11 - BR (c).

higher degree of accuracy at all times.

As could be expected, the results indicate a gradual decrease in the forecasting accuracy in relation to the length of the forecasting horizon, both in terms of the median *Absolute Error* (AE) and the variance (Fig. 4). Across the 25 rooms, the median AE increased from 0.10 °C for one-step-ahead forecasts (i.e. 1 h) to 0.76 °C for 72 h ahead forecasts. Whereas there is no difference in the AE between the hot and mild weeks for shorter forecasts ($h \leq 3$ h), at longer forecasting horizons ($h > 3$ h) the models proved to be more accurate during the hot week (e.g. a median of 0.52 °C during the hot week compared to a median of 0.84 °C during the mild week for $h = 24$ h). Whilst when $h \geq 24$ h there are occasional errors that exceed 2 °C.

4.2. Classification of the forecasted indoor temperatures and Cumulative Heat Index

The ability to accurately identify when high-risk thresholds are expected to be exceeded in the future depends fundamentally on the forecasting accuracy of the models. Because forecasting errors gradually increase with the forecasting horizon, misclassification of the predicted levels of the indoor temperatures will be similarly affected. By classifying the measured hourly external and internal temperatures, and the forecasted internal temperatures and CHIs, into seven distinct temperature bands, it is possible to distinguish the existence of considerably different temperature and heat profiles between the various rooms/dwellings and the external environment. The heatmap (Fig. 5) illustrates the observed and predicted hourly evolution in the rooms of three different dwellings, that were selected based on their frequent

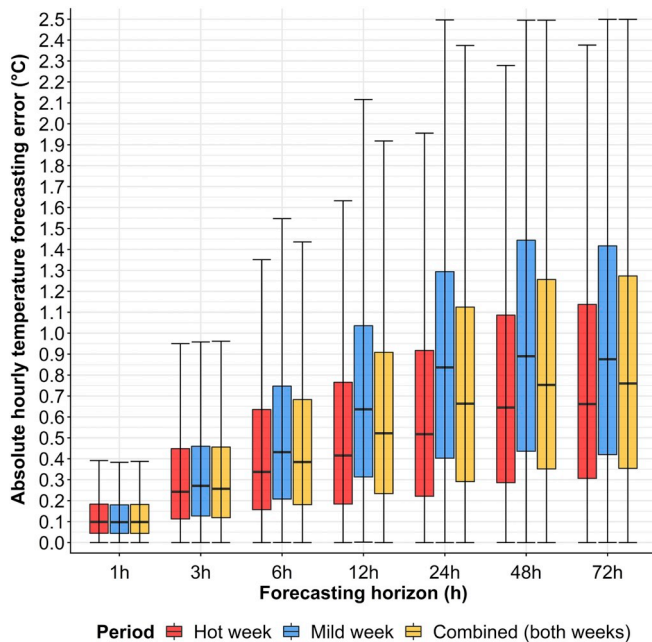


Fig. 4. Boxplots of the absolute hourly forecasting error of the forecasted indoor temperatures for the whole dataset across different forecasting horizons ($h = 1, 3, 6, 12, 24, 48, 72$ h), comparing the hot week (1–8 August 2018), mild week (8–15 August 2018) and total (combined) validation period (1–15 August 2018).

exceedance of $30\text{ }^{\circ}\text{C}$ (Fig. 2).

Because all forecasts are characterised by predictive errors which increase with the forecasting horizon, predicting values which are close to a given threshold will always engender uncertainty. As a result, misclassification can occur (e.g. the model for No. 4 – BR did not predict T_{int} to exceed $32\text{ }^{\circ}\text{C}$ across all forecasting horizons and in No. 8 – LR the indoor temperature was overestimated on the 4th of August at longer forecasting horizons).

Of the forecasted indoor temperatures, only 69.2% and 62.6% (Fig. 6) were within the correct temperature range for the 12 h and 24 h ahead forecasts respectively. In contrast, because CHI is a weighted metric which is computed across different forecasting horizons (and observations for $h < 72$ h), its classification ability is considerably improved. This increase in accuracy is especially notable in the mid-range, with the percentage of correct classifications increasing to 82.5% and 75.7% for 12 h ahead and 24 h ahead forecasts. The improvement in the classification of the indoor CHI is less pronounced at longer forecasting horizons, however, with the correct classifications increasing from 57.5% (T_{int}) to 63.2% (CHI) for 72 h ahead predictions.

4.3. Detection of the exceedance of degree hours using BS EN 15251 adaptive thresholds

Accurate determination of the number of degree hours by which the upper limit of the adaptive thresholds of the BS EN 15251 (CAT I, II and III in section 3.3) is exceeded proved to be a challenging task for the forecasting models. It is evident (Fig. 7) that the accuracy of the detection of the forecasted degree hours (above the adaptive thresholds) rapidly decreases as the forecasting horizon lengthens, with only 48.8–66.4% of the degree hours of exceedance being detected 72 h in advance. In addition, the higher the limiting threshold temperature is (e.g. CAT III cf. CAT I), the harder it is for the forecasting models to accurately identify the actual number of degree hours above the threshold. Whereas adopting the forecasted CHI instead of the forecasted indoor temperatures demonstrated a worsening of the performance at longer lead times (48–72 h) with a comparable result 24 h

ahead, for shorter lead times (3–12 h) the identification of the recorded degree hours is considerably more accurate, with more than 79.9% of the actual degree hours being identified for all three categories.

5. Discussion

5.1. Forecasting accuracy

Contrary to what might be expected, the results (section 4.1) show that longer-range forecasts were more accurate during the hottest week of the heatwave than during the following milder week. Multiple reasons underpin this decrease in forecasting accuracy. Firstly, the mild week immediately follows the hot period with many of the longer forecasts for the mild period having commenced when indoor temperatures were still high. Secondly, the outdoor and indoor temperatures fall abruptly between the 8th and 11th of August with a daily temperature profile that is continually changing during the first days of the mild week. This sudden increase in the magnitude of forecasting errors has been previously observed to correspond to the point when a heatwave is breaking, characterised by an abrupt fall in the ambient temperatures [43].

Overall the forecasting accuracy was found to be considerably better than that measured in the previous study [44], with a Mean Absolute Error (MAE) for 72 h forecasts during the hot week of $0.79\text{ }^{\circ}\text{C}$, compared to the previous study's MAE of $0.95\text{--}1.01\text{ }^{\circ}\text{C}$ [44]. This suggests that the use of additional predictor variables and a longer training period (approximately three months) as considered in the previous study [44] might have negatively affected the overall forecasting accuracy of the linear ARX models. This observation is reinforced by the similarity in the forecasting accuracy attained between this study and another previous study [43], where both studies adopted the same 21-day training period and predictor variables. Herein an MAE of $0.54\text{ }^{\circ}\text{C}$ was observed for one-step-ahead predictions compared to an MAE of $0.48\text{ }^{\circ}\text{C}$ in the previous study [43]. It has to be considered, however, that the sample considered in this study consists of 25 rooms compared to only three rooms in the previous study [43].

5.2. Indoor and outdoor temperatures

The data (Fig. 1) confirms that the outdoor air temperature is consistently a poor indicator of the indoor thermal conditions. Because of the modifying effect of the building envelope, there is always a time lag between external and internal peak temperatures. In addition, there is a considerable temperature difference between the indoor and outdoor environments, which often exceeded $8\text{--}10\text{ }^{\circ}\text{C}$ overnight (e.g. during the hot week in Fig. 1). It is notable that the peak indoor temperatures are often found to be above the maximum outdoor temperatures (e.g. dwellings No. 4 and No. 11 on the 2nd of August in Fig. 4).

5.3. Cumulative Heat Index

Cumulative heat indices attempt to account for the effects of prolonged exposure to heat over time. Research suggests that "heat acclimation is transient and gradually disappears if not maintained by continued repeated heat exposure" [66,p.30]. Accordingly, a weighted cumulative heat exposure metric such as the CHI might provide a more realistic assessment of how excess heat impacts occupants physiologically, compared to the use of absolute hourly indoor temperatures. As such, the CHI represents a simple weighted metric that can be easily and clearly understood by the public, local stakeholders and decision-makers. In a previous study [59] a weighted metric was observed to perform well for the detection of deaths from heatwaves during a prolonged period of heat in mid-summer (July–August), but less well for sudden hot spells in early and late summer (June and September). The reasons for the lower performance of the weighted metric in relation to the detection of short-term heat-related mortality was that the deaths in these periods were observed at maximum outdoor

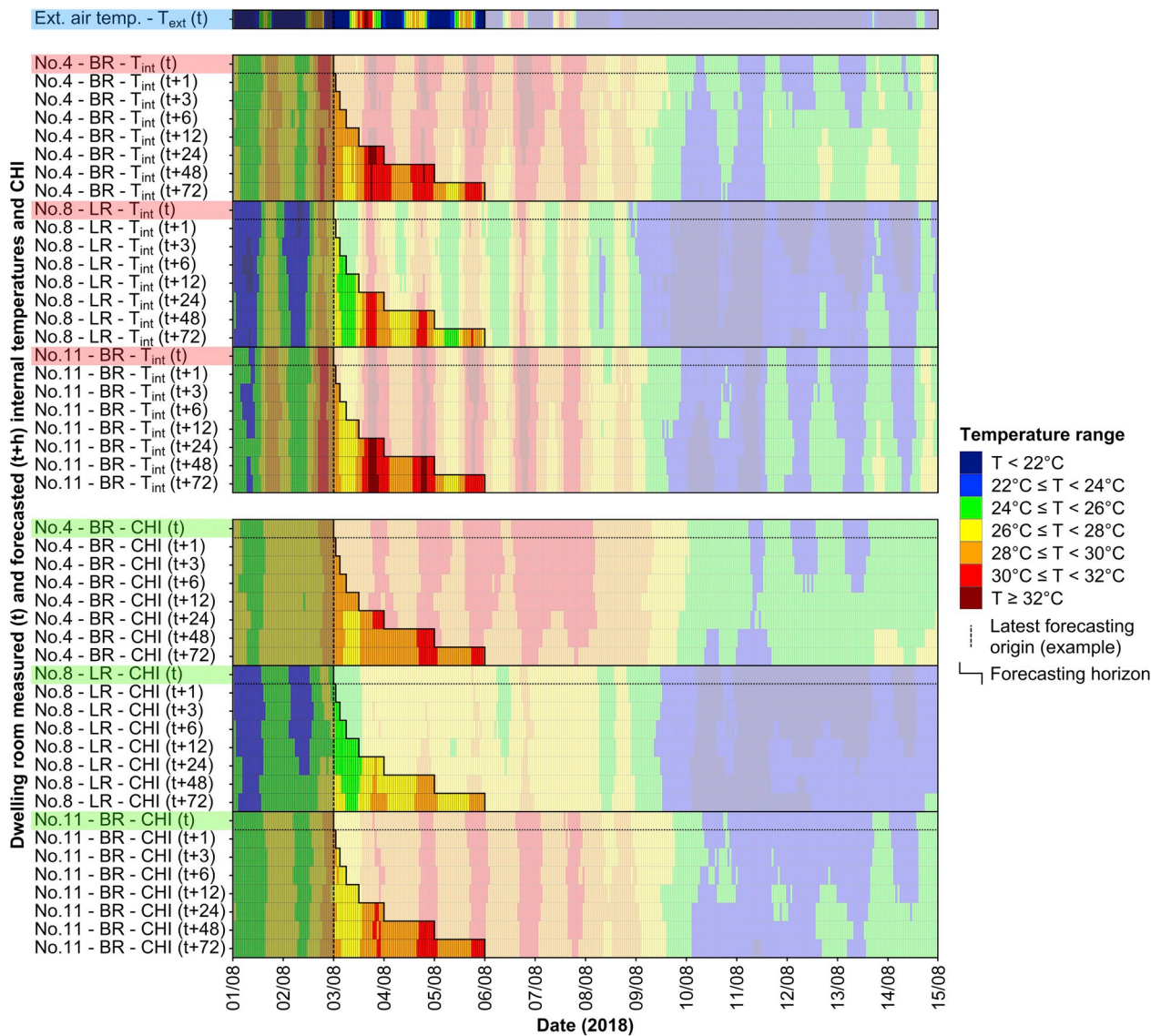


Fig. 5. Heatmap of the external air temperature (top row), showing observed (t) and forecasted (t + h) internal temperatures (middle 3 plots) and forecasted Cumulative Heat Index (bottom 3 plots) across different forecasting horizons (h = 1, 3, 6, 12, 24, 48, 72 h) in three different rooms/dwellings; example showing the latest forecasting origin set on the 3rd of August 2018 at 00:00, with darkened past data and lightened future (measured and forecasted) data.

temperatures that were as mild as 28 °C and resulted from sudden heat spikes affecting non-acclimatised individuals outside the main summer season. This finding suggests that when used to detect adverse conditions, CHI temperature thresholds should be seasonally adjusted, being lower at the beginning and end of the summer (when occupants are most vulnerable). Whilst a heatwave that follows a cold period might still cause heat-related deaths at lower thresholds, it is posited that one reason why the weighted metric used in these studies might not have performed well in the case of sudden heatwaves is that the metric defined by Lee et al. [59] puts excessive weight on historical temperature values. In their study, temperatures for the previous 14 h accounted for only 50% of the overall value, which means that during a sudden spike of the temperature (e.g. first day of a hot spell) their metric would be too low if the temperatures on the previous days were low. For this reason, the weighted metric proposed herein puts a higher emphasis on the most recent period, with the previous 6 hourly values accounting for 50% of the overall value. This means that the metric is able to identify a sudden, and dangerous, spike in the temperature during the first day of a heatwave whilst at the same time maintaining all the advantages inherent to the adoption of a weighted metric.

Reliability of the forecasted indoor thermal conditions in the context of iHHWSs.

Warnings that are currently issued by global HHWSs are based on outdoor temperature thresholds and target a whole region. Using this blanket approach, existing HHWSs require long lead times to trigger a warning and alert decision-makers and the general public to impending dangerously-hot weather (e.g. through the media). On the other hand, because iHHWSs can provide reliable information for specific spaces, with warnings that can be communicated directly to the affected occupants and their carers, extended lead times might not be required. Whereas pre-alert warnings could be sent to the occupants and/or carers at longer lead times (e.g. 24–72 h ahead via SMS, email etc.), the contact with, and/or dispatch of emergency services, could be restricted to much shorter lead times when the prediction of impending health-impacting indoor temperatures is more reliable.

Regardless of the way in which indoor temperature thresholds are defined, the implementation and deployment of an iHHWS system is only feasible if the predictions are reliable and the lead time sufficient to allow timely intervention. At shorter lead times (e.g. 12 h), the indoor temperature forecasts were reliable and able to predict the correct

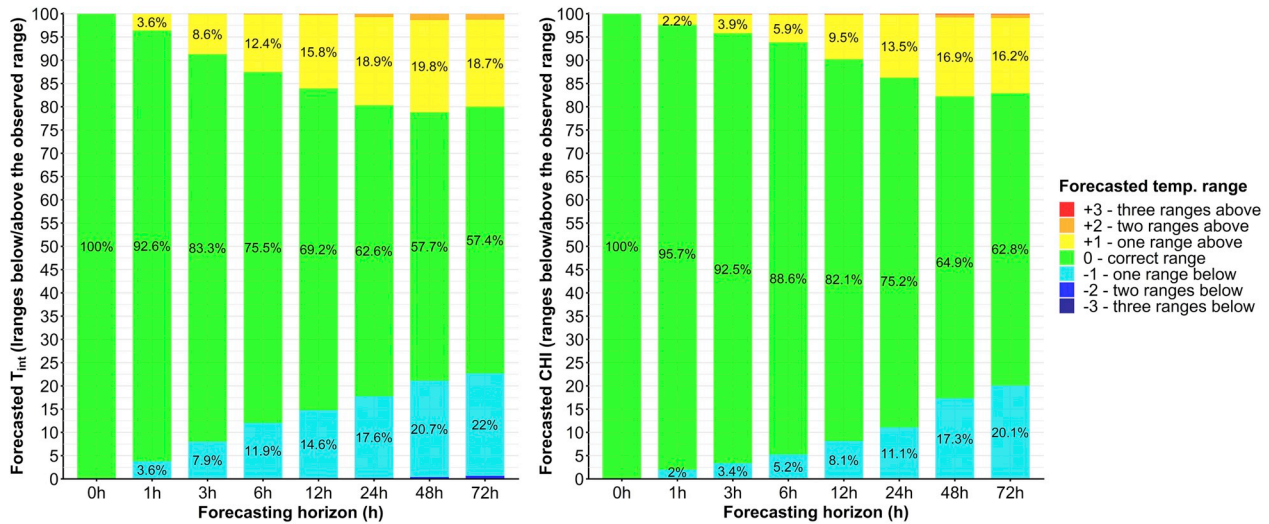


Fig. 6. Stacked bar charts indicating the percentage of correct and incorrect classifications into seven temperature ranges (of 2 °C) across different forecasting horizons (h = 0, 1, 3, 6, 12, 24, 48, 72 h), for the forecasted indoor temperatures (left) and forecasted Cumulative Heat Index (right).

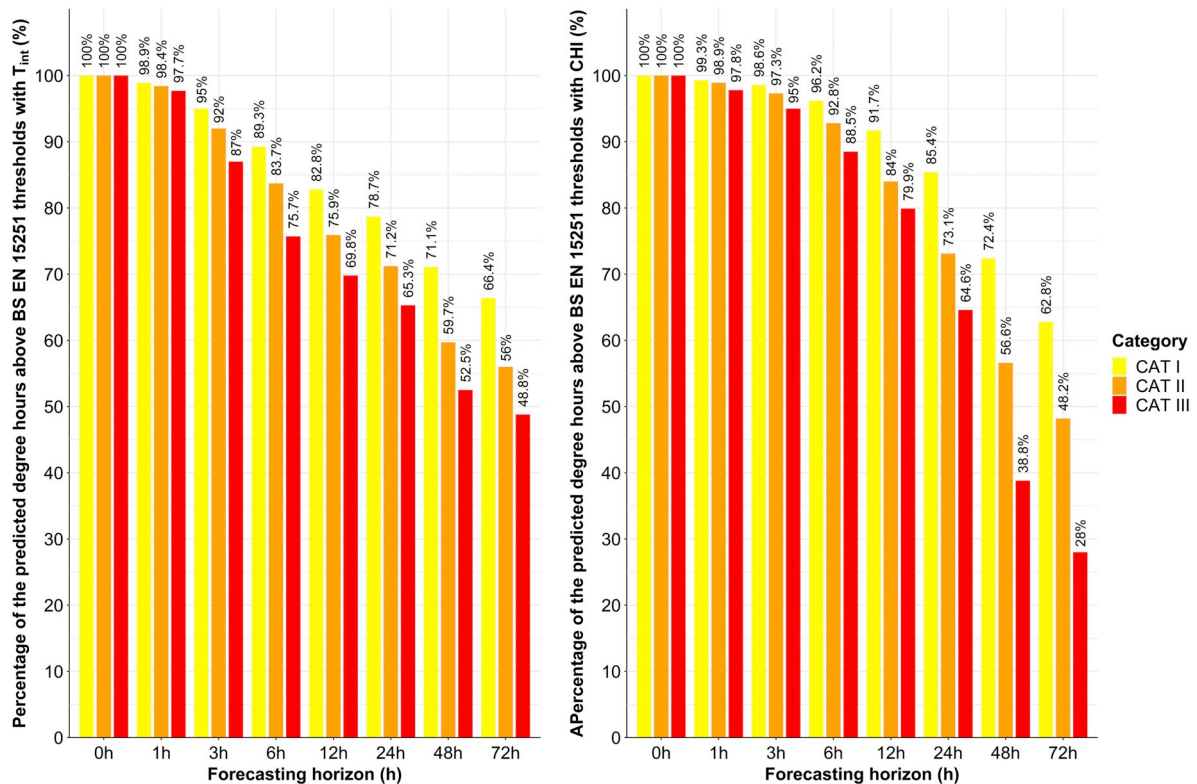


Fig. 7. Bar charts indicating the percentage (compared to observed values) of the forecasted degree hours above the adaptive thresholds CAT I, II and III of the BS EN 15251 across different forecasting horizons (h = 0, 1, 3, 6, 12, 24, 48, 72 h), when comparing the forecasted indoor temperatures (left) and forecasted Cumulative Heat Index (right).

temperature range approximately 70% of the time and with accurate detection (circa 70%) of the exceeded BS EN15251 category thresholds (i.e. CATs I–III). Inevitably however, the forecasting errors increased for longer lead times (section 4.1) hampering the reliable identification of impending heat health risks (sections 4.2 and 4.3). Nevertheless, predictions 24–72 h ahead might still be useful to inform the occupants of possible future indoor conditions, although confidence in the forecast risk level might be insufficient to issue formal warnings.

The adoption of a weighted metric, such as the CHI, further improved confidence in the detection of the indoor thermal conditions for horizons

of 3–24 h. For the 12 h horizon, more than 80% of the temperature ranges were correctly predicted and a similar improvement was observed in the detection of the exceeded degree hours, which were correct 80% of the time for each of the BS EN 15251 categories (i.e. CATs I–III). Furthermore, at lower adaptive thresholds (e.g. CAT I), the detection of the exceeded degree hours is considerably more reliable. This finding favours the detection of conditions affecting those most vulnerable to heat-related risks (i.e. elderly and ill people). It is noted, however, that whilst the adoption of a weighted metric, such as the CHI, can provide more reliable predictions of the short-term indoor

conditions, the definition of adaptive indoor temperature thresholds must reflect the slow-varying nature of a cumulative weighted metric.

More generally, there is, considerable potential for weighted cumulative heat exposure metrics to be used when predicting heat-related health risks in new or existing free-running dwellings. Such predictions may be made using building energy models as part of the dwelling design process or to assess compliance with guidelines and standards, such as the building regulations. Further work on the exact form of such a metric is however needed.

6. Conclusions

Observations from 25 rooms in London confirm that external air temperature is a poor indicator of the risk of excessive exposure to heat in occupied homes. This, and similar findings from previous studies [41, 43,44], highlight a major flaw in existing *Heat-Health Warning Systems* (HHWSs). Currently, HHWSs that are being implemented worldwide, are based solely on regional weather observations and forecasts. As a result, they are unable to identify precisely where, when, or to what extent the occupants of individual buildings will overheat. In contrast, the *indoor HHWS* (iHHWS) concept proposed here has the potential to map heat exposure at the level of individual zones in buildings.

The ability of linear ARX models to forecast indoor temperatures over the intense and long-lasting UK heatwave of 2018 has been demonstrated. The value of integrating such models into a high-resolution iHHWS for domestic buildings has been illustrated. Alongside this, a new metric was developed to better track the potential cumulative heat exposure risk of vulnerable occupants.

The efficacy of the newly developed iHHWS was investigated using hourly data from 25 rooms (12 living rooms and 13 bedrooms) in 12 dwellings, located within the UHI of London. A *backward stepwise regression* based on minimisation of the *Akaike Information Criterion* (AIC) was adopted for the automatic model selection. Recursive multi-step-ahead zonal indoor temperature forecasts were then produced using a *rolling window* approach for the entire duration of the heatwave. Forecasts were made for time horizons of 1, 3, 6, 12, 24, 48 and 72 h ahead. The out-of-sample accuracy was assessed by evaluating the absolute hourly error of the forecasted indoor temperatures for the whole dataset at each different forecasting horizon.

False and missed alerts are a major concern for decision-makers in the adoption of an iHHWS. Reassuringly, this study shows that indoor temperatures can be reliably predicted in different dwellings and rooms, across a large urban conurbation, using a single weather data stream. The indoor temperatures in the different dwellings and rooms were forecasted with a MAE of approximately 0.2–0.5 °C and 0.5–0.8 °C for time horizons of 3–12 h and 24–72 h respectively. Furthermore, approximately 70% of the forecasted temperatures were correctly classified into 2 °C temperature ranges and nearly 70% of the exceeded degree-hours determined by the BS EN 15251 adaptive comfort thresholds were correctly predicted. Adoption of a weighted *Cumulative Heat Index* (CHI) metric further increased the reliability of temperature classification between 3 and 24 h ahead, with more than 80% of the temperature band classifications being correct and with over 80% of the BS EN 15251 degree-hour exceedances correctly identified.

Unsurprisingly, the accuracy of the indoor temperature prediction decreases gradually as the forecasting horizon lengthens, with 37.4–42.5% misclassification of the (2 °C) temperature bands for lead times of 24–72 h. Forecasting the exceedance of adaptive thresholds represented an even more difficult task at longer horizons, with the accurate detection of only 48.8 (CAT III, 72 h ahead) – 78.7% (CAT I, 24 h ahead) of the observed degree hours.

In relation to the health, well-being and mortality risks for the occupants of free-running buildings, a cumulative temperature exposure metric (such as the CHI), showed considerable advantages over single hourly temperature threshold predictions, although further research is needed to define the optimal metric. It is suggested that such a metric

might also improve overheating risk assessment methodologies more generally. For example, when thermal models are used to predict heat-related health risks in free-running dwellings, or when assessing compliance with overheating design criteria (such as those defined in the HHSRS, CIBSE and ASHRAE design guides or the building regulations).

Overall, the research reported here demonstrates that time series forecasting can enable the creation of a computationally-efficient iHHWS. Such systems would provide a powerful facility to inform occupants (and/or their carers) of impending heat-related health risks and enable timely and individually-targeted interventions. This would reduce the incidence of heat-related morbidity and mortality amongst vulnerable populations as well as facilitating the coordinated response of emergency services during extreme heatwave events.

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.

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