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RESEARCH ARTICLE

Impact of climate change on hospital admissions: a case study of the Royal Berkshire Hospital in the UK

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Abstract

Global warming is projected to have major implications on global health. It is however not yet clear how this will translate to impacts on the healthcare system. By linking changes in temperature with changes in required bed days at a hospital level, through the use of a simple bed model, we quantify the projected impacts UK hospitals will need to adapt to. We show that there is already a local peak of bed days required in the main summer months due to hot temperatures. The results further show that there will be a significant increase during the main summer in both the mean and maximum number of beds needed, but a non-significant decrease during the peak winter months. These changes lead to a more constant need of care of the year and shift the seasonal cycle of lowest hospital needs.

KEYWORDS

admissions, health systems, heat morbidity, impact

1 | INTRODUCTION

The healthcare systems in many parts of the world are under significant pressure due to ageing populations with complex healthcare needs, growing population size and increasingly expensive treatments (World Economic Forum's Global Future Council on Health and Healthcare, 2019). The unequal need for emergency healthcare in the United Kingdom over the season, with much more resources required during the winter period due to the seasonal influenza and other respiratory diseases, complicates staff and bed planning (M. Claridge, personal communication, 17 February 2022). In addition to these existing issues, the health impact of global warming is quickly becoming an area of high importance around the world. This is especially highlighted by the joint office set up by World Meteorological Organization and World Health Organization (WHO, 2020), the growing number of publications linking warmer weather with health impacts (e.g., Åström et al., 2013; Ebi et al., 2021; UK Health Security Agency, 2021; Watson et al., 2020), and some very recent UK specific publications analysing both past exposures (Lo et al., 2022) and future projections (Kennedy-Asser et al., 2022). The COVID-19 pandemic has clearly demonstrated the vulnerability in many healthcare systems to sudden, large shocks, and the issues with a backlog of non-urgent health care once a threshold is crossed (Imperial College Healthcare NHS Trust, 2022). Hospitals and health systems therefore need to start planning now for the near future impact due to projected global warming, currently without knowing what those impacts are. The lack of awareness around the impact of heat, and therefore the very limited planning for it, at hospitals in England has been highlighted in the evaluation report of the Heatwave Plan for England (Williams et al., 2019).

A large number of papers have been published in recent years on the changes in the mortality rate due to high temperatures (e.g., Gasparrini et al., 2015; Green et al., 2019) because of its devastating implications for individuals. However, from a healthcare system point of view, a high mortality rate does not necessarily translate to a high impact on hospital capacity because many people who die due to non-optimal temperature will not use additional hospital resources (Kovats et al., 2004; Ye et al., 2012). A further limitation on the currently available information is that it is often presented as a change at a national or on a regional scale (Åström et al., 2013; Huang et al., 2022), but very rarely at the local level where resources are provisioned and allocated. This makes it very difficult for hospitals to design adaptation strategies because in the best case there is information about, for example, what all of South East England should prepare for.

In this article, we aim to describe the near-term (2050s, 2050-2059) projected impact on hospital operations for a representative hospital, expressed in changes of required bed days, only due to climate change. That is, we are not considering any other factors such as changes in population size, demographics or the population health but only changes in daily temperature. Another way to describe this experiment is that we are taking today's population and modelling what their hospital needs would be in the 2050s. The Royal Berkshire Hospital (RBH) in Reading, UK is chosen as our representative hospital for this study. The population of Reading has a very similar distribution to the South East as a whole, with just a slightly lower proportion of elderly people and higher proportion of young adults (Profile of Reading, 2022). Despite being one of the most affluent areas of the United Kingdom, it also has some of the most deprived areas, making it comparable to the rest of South East England in terms of household composition and average salary (Fenton, 2021).

Our aim with the study is to estimate the current seasonal cycle of temperature-related occupied beds and projected changes in these to highlight shifts in low- and high-pressure periods, which is important for staff planning, and quantify any changes in the required number of beds at the hospital. To relate changes in admissions with changes in hospital capacity needed, we co-designed the study with staff at the RBH through multiple workshops (Section 2) to gain real-world insights to our modelled numbers and ensure actionable conclusions. This lead to a co-developed bed model (Section 3), with which we conducted our analysis to understand differential bed use between different patient groups and to quantify thresholds for significant resource demands (Section 4).

2 | CO-DESIGN WORKSHOPS

The co-design workshops with staff from the RBH were held throughout the project to discuss the different stages of the work. The first two 1h-long workshops were run with managers from the urgent care departments, clinical staff, people working with the future hospital design and data management staff. The aim of these workshops was to understand the major factors impacting hospital operations and the type of projection information they would like to have access to. Further two 1h-long workshops were run with the same staff to co-develop the bed model to ensure its validity, and to define the bed metrics used and confirm their usefulness. During these workshops, information about the main age groups to consider, their typical length of stays (LoS) and how LoS varies over the year were discussed, which informed the lag structure of the model (more details in Section 3.2). Three final results workshops were held with the previously involved staff plus the Net Zero and demographic modelling group to discuss the results and how they might be used in the different departmental work.

3 | DATA AND METHODOLOGY

From the workshops run with the RBH, we learned that long periods of high occupancy, which currently mostly are experienced from December to February, put the most strain on the trust and when occupancy levels become so high that scheduled operations need to be moved and this builds up a 'health debt'. The health debt refers to the accumulation of non-urgent care due to delaying it in favour of delivering urgent care, resulting in a larger amount of healthcare needing to be delivered within the usual time frame (Imperial College Healthcare NHS Trust, 2022). The method developed here is therefore based on two parts: estimating admissions attributable to non-optimal temperatures (AANOT), and in the next step how these admissions affect the number of occupied beds. There is not a one-to-one relation between increases in admissions and occupied beds because some patients stay for more than one night, hence an accumulation effect will occur, depending also on the time history of non-optimal temperature exposure.

3.1 | Future admissions

The total daily future admissions are assumed to be a combination of the seasonally varying average admissions and the AANOT (temperature-dependent admissions), that is, for day t

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$$\text{adm}_t = \text{seasonal.adm}_t + \text{temp.adm}_t, \tag{1}$$

where seasonal.adm_t is the long-term daily average given the weekday, day of the year and if it is a public holiday, and temp.adm_t is the AANOT. To model the link between temperature and admissions, we will follow the method developed in Gasparrini (2014) and applied in a climate-health setting in Vicedo-Cabrera et al. (2019). The exposure–admissions component is modelled through a distributed lag non-linear model, which uses non-linear models to simultaneously model the exposure–admission relation and its associated lag structure, which forms a cross-basis dependent on temperature and days since the exposure (lag). The full model is estimated through a generalized linear model (GLM), with admissions modelled by a quasi-Poisson model. The GLM uses as input, temperature, time (modelled by a natural cubic spline to account for any trends during the year or over multiple years), day of the week, if the day is a public holiday or not and emergency admission data (see Supplementary material Section 1). From this model, the temperature associated with the lowest number of admissions and the increase in risk of admissions for higher and lower temperatures can be estimated (the relative risk [RR]) for the 2 weeks following exposure to a non-optimal temperature. By splitting up the admissions into age groups, we can additionally gain insights into how this risk varies among the population. The model is fitted for people over 75 years (elderly), under 75 years, children (up to 18 years) in addition to the full population.

To estimate the fixed seasonal background admissions, we take the average of the splines time component of the fitted GLM for the last 5 years, to isolate the impact of climate change from other factors such as population increase, the day of the week and holiday factors.

For fitting the temperature admissions model, daily mean temperature data from the HadUK-Grid and emergency (non-elective) admissions from the Office of National Statistic are used. The HadUK-Grid data are available as regional averages of the 1-km resolution gridded dataset from 1960 to 2020, and is used as this is the currently best available estimate of daily temperature on the scale of UK regions, incorporating extensive quality control and validation (Hollis et al., 2019). The admissions data cover the period 1991–2018 and are split into six age groups. For both data sets, observations from South East England, as defined by the Nomenclature of Territorial Units for Statistics level 1 (NUTS 1), are used. To downscale the estimated admissions to hospital-level numbers, admissions and discharge data from 2016 to 2021 and occupied beds data from December 2018 to 2021 are provided by the RBH. Only data up until January 2020 are included to exclude any COVID-19 effects.

The reason for fitting the model with the admissions data collected in South East England instead of the RBH data is the much longer time period it covers, resulting in more robust model estimates. Extensive exploratory analysis was first performed to establish that RBH and South East England data had a similar distribution in terms of fraction of admissions from the different age groups and that RBH admissions constituted a near-constant proportion of the South East England total admissions and are well correlated.

By combining the estimated RR curves with the projected daily mean temperature data, we can estimate the fraction of AANOT for each day. Multiplying this fraction by the average/seasonal admission estimated in the previous step, one obtains the number of daily AANOT (temperature admissions). To estimate this, the 12 ensemble members from the Met Office Hadley Centre climate model available at a regional level in the 2018 UK Climate Projections (UKCP18) for the emissions scenario RCP8.5 are used (Met Office Hadley Centre, 2018), again only for the South East England administrative region. The UKCP18 models use a 360-day calendar with 30 days in each month. Following Huang et al. (2022), the UKCP18 climate data are bias-corrected against the HadUK data before being used in the analysis.

Figure 1 illustrates the two admissions components, their dependencies and individual contributions, to the total daily admissions. The admissions are for the full population, based on the downscaled South East England data. As this is mainly for illustrative purposes to demonstrate the constant seasonal pattern for the seasonal admissions (blue) and the slowly increasing temperature admissions (orange), the time windows are different (8, 3, 20 years) to better display the main features of each graph.

3.2 | Bed model

To estimate the impact of admissions due to non-optimal temperature on hospital occupancy, a simple bed model has been constructed to estimate the number of extra bed days needed due to the temperature-dependent admissions (see Figure S1 in Supplementary material for visual description). The significantly different LoS for healthy adults and elderly motivated the splitting of the two population groups. Difference in the LoS for different times of the year, due to the conditions mainly admitted with or other social factors guided the choice to include an additional winter peak factor. The final parameter is the general occupancy level, which is needed to obtain when more hospital beds are needed than what is available.

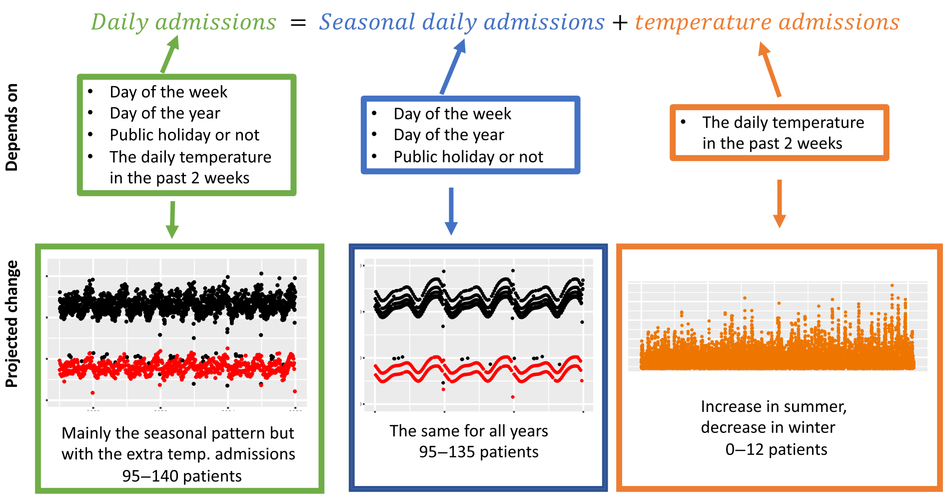

FIGURE 1 Infographic describing the dependence and magnitude of the two components producing the total daily admissions. The *x*-axis is time and the *y*-axis is daily admissions for the full population based on downscaled SE England data.

The model uses as input daily emergency admissions and day of the year to reflect the seasonal pattern of LoS, and outputs for each day the number of overnight patients and their associated length of stays. The hospital-dependent parameters are listed below, with the numbers used in this article given in brackets.

- The total number of beds (630).
- The general occupancy level (0.85, 535 beds).
- Mean LoS (4 days).
- Healthy adults typical range of LoS (1–4 days).
- Elderly patients typical range of LoS (7–10 days).
- Optional, extra long LoS during peak winter (November–February, 2% of the patients stay 11–14 days).

The algorithm for generating length of stay for each patient is based on sampling from the different specified probability distributions, in this case $P_{\text{healthy}} = \{1,2,3,4\}$, $P_{\text{elderly}} = \{7,8,9,10\}$, $P_{\text{extralong}} = \{11,12,13,14\}$. These three sets of LoS are determined based on workshop discussions and data on LoS for each patient from January 2016 provided by the RBH. The probability of sampling the different LoS is determined by assigning equal probability for each LoS in P_{elderly} and $P_{\text{extralong}}$ in the first step, and then finding the correct probabilities (P) for P_{healthy}. For this, we set $\mathrm{P}(3) = \mathrm{P}(4)$ and $\mathrm{P}(1) = \mathrm{P}(2)$, and determine each probability such that the expected value (mean) $\mathrm{E}[\mathrm{LoS}] = 4$.

Using the following notation, $i = 1,\ldots,T$ is the time step, n_i is the total number of patients admitted on day i, f_i is the fraction of elderly patients on day i, $j = 1,\ldots,r_i$ is the index of elderly patients admitted on day i, with $r_i = n_i \times f_i$, $k = 1,..,s_i$ is the index of extra long staying patients on day i with $s_i = 0.02 \times n_i$ if winter and 0 else, $l = 1,..,t_i$ is the index of healthy patients with $t_i = n_i - r_i - s_i$ and $p_{i,q}$ the length of stay for patient $q = 1,\ldots,n_i$ on day i. The winter proportion 0.02 was chosen to match the observed slightly longer LoS.

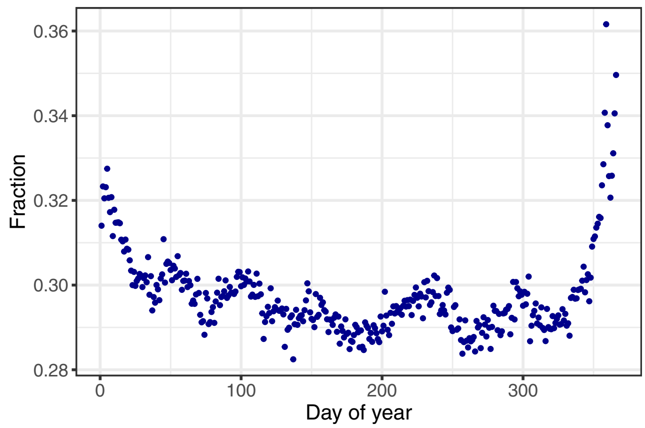

FIGURE 2 Fraction of patients over 75 years for each day of the year.

For the winter time, the expression for the LoS for all patients is

$$P_{i,w} = E_i + H_i + L_i + P_{i-1}, \tag{2}$$

with the four factors E_i, H_i, L_i, P_{i-1} given by

1. The set of elderly patients: $E_i = \left\{e_j \in P_{\text{elderly}}\right\}_{j=1,..,r_i}$.
2. The set of long staying patients: $L_i = \left\{lo_k \in P_{\text{extralong}}\right\}_{k=1,..,s_i}$.
3. The set of healthy patients: $H_i = \left\{h_l \in P_{\text{healthy}}\right\}_{l=1,..,t_i}$..
4. Staying patients from the previous day: $P_{i-1} = \left\{p_{i-1,q} \geq 2\right\}$.

and for the summer

$$P_{i,s} = E_i + H_i + P_{i-1}, \tag{3}$$

with the three factors given by the same expressions, with $s_i = 0$.

When the total daily admissions are used (seasonal admissions + temperature dependent), the proportion of elderly admissions, for which we sample from P_{elderly}, is determined by the historical 'day-of-the-year' proportion (Figure 2). When only the AANOT are considered, the proportion of vulnerable population sampled from P_{elderly} is instead set to 0.67 (roughly twice as large compared with all admissions). This is because we assume that patients admitted due to non-optimal temperatures are on average more vulnerable than the general population, since it is mostly patients with underlying health conditions, or vulnerable for other reasons, who are admitted (Public Health England, 2015). Hence the temperature-dependent admissions group should on average have longer LoS than when considering the regular, seasonal admissions.

To evaluate the bed model, a test simulation with observed admissions was compared with observed bed occupancy, both at a daily scale and on a monthly averaged scale (see Figure S2 in Supplementary material for monthly averaged difference). Mean difference per month, week, and daily for weekdays and weekends were all calculated to find any systematic errors. The model evaluation results were discussed during one of the workshops to confirm its usefulness and realistic design.

3.3 | Changes in bed occupancy

For each of the 12 UKCP18 RCP8.5 regional daily temperature series, the daily AANOT is estimated from the fractions obtained using the 'backward' setting of the attribution function described in Gasparrini and Leone (2014) and multiplied by the seasonal admissions obtained from the stationary GLM. The 'backward' setting means that the admissions assigned each day is the accumulated number of admissions based on the temperature from the previous 2 weeks. Hence, the 'backward' attribution takes into account both the temperature admission due to day 0 temperature but also the lag-effect from the previous 14 days. Each of these AANOT time series are then combined with the bed model to generate 12 bed occupancy time series. From these daily occupancy time series, five different metrics are considered to evaluate the change in average and peak admissions:

1. The total number of additional bed days required per month in 2050–2059 compared with 2010–2019, that is, the total number of bed days required in a given month in the 2050s minus the total number of bed days required in the 2010s.

2. The daily mean number of temperature-dependent beds in 2010–2019 and 2050–2059.

3. Number of days with the same number of temperature-dependent beds as today's highest occupancy days (top 5% days). With 30 days in a month, 5% × 30 days = 1.5 days in 2010–2019.

4. Maximum number of daily temperature dependent beds in 2010–2019 and 2050–2059.

5. Average number of daily occupied beds in 2010–2019 and 2050–2059.

These five metrics were chosen because they reflect changes in the mean and peak behaviour for temperature admissions. By considering both of these aspects, one can estimate both changes in the daily and peak requirements, corresponding to bed requirements for the different months, and compare these to the peak annual requirements, which is the total number of beds required. The different bed metrics are calculated as a decadal average for all the temperature models. Hence, the monthly estimates are the average value from 120 estimates (12 models, 10 years) and the daily 3600 estimates (30 days in each month). The uncertainty bands in the graphs are given by the spread from the 12 decadal averages. There are a number of other factors of uncertainty to these estimates, especially from the bed model and the exposure–admissions curves (Figure 3). Uncertainty estimates of the exposure–admissions model can be obtained from the model (Figure 3) through Monte Carlo simulations as no analytic expressions exist. It is however not obvious how to combine these with the climate model uncertainty, because a simple addition of the two uncertainty estimates would probably lead to an unrealistically large spread. As it has been shown in the study by Huang et al. (2022) that the exposure–admission uncertainty is much smaller compared with the climate model uncertainty and we want to be able to clearly communicate where the uncertainties come from to long-term planners at hospitals, we decided to only focus on the climate model uncertainty.

Uncertainty in the bed model could be investigated by running a Monte Carlo simulation to find the variability due to the random sampling of LoS at each time step, but will most likely be of lower magnitude than the climate model uncertainty given the large number of samples drawn. There is also uncertainty in the bed model itself, because we only had 1 year of data to evaluate it against due to COVID impacting all data after January 2020. Reliable uncertainty estimates of the bed model could therefore not be obtained and are not further considered. A development of this work would be to combine these different sources of uncertainty in a sensible way.

To check the sensitivity to the admissions model, the total number of daily admissions is also estimated using

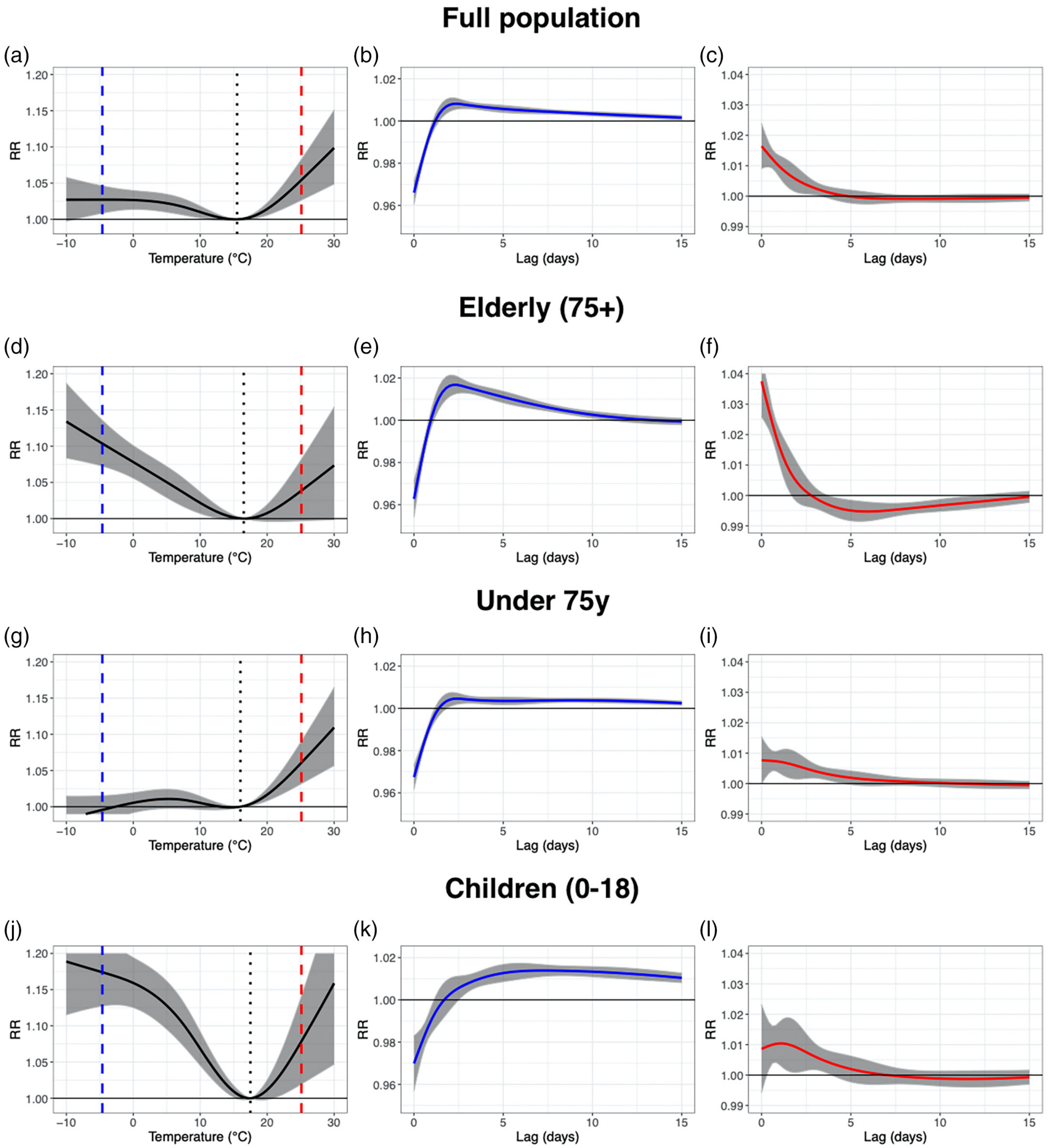

FIGURE 3 Exposure–admission relative risk curves for (top) full population, (upper middle) over 75 years, (lower middle) under 75 years and (bottom) children. The different curves show (left) 15-day accumulated RR as a function of daily mean temperature, (middle) 15-day lag structure for cold events (5°C) and (right) 15-day lag structure for hot days (22°C). The colour dashed lines mark the maximum and minimum mean temperature observed and the black dotted the temperature associated with the lowest risk of admissions.

the much shorter RBH data to fit the seasonal GLM and estimate the AANOT. As only 4 years of daily admissions data are available from the RBH, a very small number of sample points are used to estimate each covariate in the GLM model, leading to a less reliable model. As the RBH admissions behave like scaled South East England data, the RBH GLM model will be estimated by similar, but different, admissions numbers. By combining our bed model with both admissions models, we can evaluate how sensitive it is to the exact admissions numbers. The mean estimate from this method is also included, but not the confidence interval to ease readability of the graphs.

4 | RESULTS

4.1 | Exposure–admissions model for different age groups

Similar to results obtained in earlier mortality and admissions studies following exposure to non-optimal temperatures, there is a decrease in the RR for the first 2 days for cold temperatures (Figure 3, middle column) followed by a large increase for those aged above 75 (Figure 3e). This is because medical conditions related to cold temperature are not triggered until a couple of days after the extreme cold day (RBH workshops). Also, similar to previous studies, the increase in risk for hot temperatures occurs on the hot day and the next following day (lag = 1). The following decrease in risk (RR < 1) is due to the so-called 'harvesting principle' (Toulemon & Barbieri, 2008), which means that the population is temporarily less susceptible to heat because vulnerable people have already been admitted to hospital in the first 1–3 days, resulting in a lower proportion of vulnerable people out in the general population.

The major difference between the admissions curves obtained here and the previously modelled mortality curves is the absolute RR values. For hot temperatures (daily mean above 23°C for northern Europe), the RR values for mortality have been estimated to be around 15%–25% (Gasparrini et al., 2015), whereas we here estimate it to be only around 4% for admissions in all age groups. This is partly due to the fact that many more people are admitted to hospitals on a daily basis than those who die, hence the AANOT is a much smaller proportion of the total number of admitted patients, even on hot days, compared with the proportion of mortality attributed to non-optimal temperature (MANOT) on hot days.

Only considering the modelled admissions curves, we can see that the optimal temperature (black dotted line) is nearly the same for all age groups. The increase in RR for hot events has the same shape and magnitude for all age groups, but is vastly different for cold events. For the over 75 years age group (Figure 3d), there is an increase in admissions for all temperatures below the optimal temperature, whereas there is no accumulated increased risk for the below 75 years age group (Figure 3g).

The uncertainty around the lag response for the hot temperature for the below 75 years age group (Figure 3i) is larger compared with the above 75 years age group (Figure 3f), despite being the larger group. This could be due to the many different behaviour patterns in the larger group compared with the more uniform behaviour for the smaller 75+ group. This is highlighted by the significantly different behaviour for children (Figure 3j–l), compared with the full under 75 years age group. This is not further explored because we here only model the behaviour for the full population, but would be a natural extension to this work.

4.2 | Changes in bed days

Figures 4 and 5 displays the five bed day indicators for the 2010s and 2050s. The blue line and uncertainty band are estimated using scaled South East England data and the orange line RBH data. These uncertainty bands are most likely smaller than the true uncertainty of the estimates because only the mean value of the exposure–admissions curve is used. Therefore, based on only considering the future temperature uncertainty, if the current population of Berkshire served by the RBH were exposed to the 2050s climate, the main impacts found are as follows:

- There would be a significant increase in both the mean and peak for the summer months of July and August.
- The mean number of temperature-dependent bed days would be of equal magnitude in July and August as currently seen in January and February.
- Winter bed occupancy would remain mostly unchanged, with the change for all the metrics being insignificant.
- The winter months would remain the most resource-intensive period. This is because most of the seasonal admissions are from infectious diseases (such as the seasonal flu), and we assume that the number of admissions from these factors will be unchanged.

A general pattern is the small decrease in all indicators, except the daily maximum (Figure 5d), in the winter but a significant increase in the summer. A second important thing to notice is the peak in July/August for the daily mean and max bed use (Figure 5c,d), which is currently not being noticed (personal communications RBH workshop, 10 November 2021) because it is smaller and shorter than the winter peak, but would become much more prominent in a climate like that projected for the 2050s.

When considering the total daily admissions in Figure 4, and specifically the mean number of occupied beds, we can see that there is a significant increase in the main summer months June, July and August, and a very small decrease in the winter months. This suggests that the winter period will not be much less resource-intensive compared with today, but summer will have more patients admitted both on average and on the highest occupancy days under the 2050s climate. Similar patterns can be seen for the 2030s and 2040s climate, and the summer peak is significantly different for the 2040s climate (not shown here).

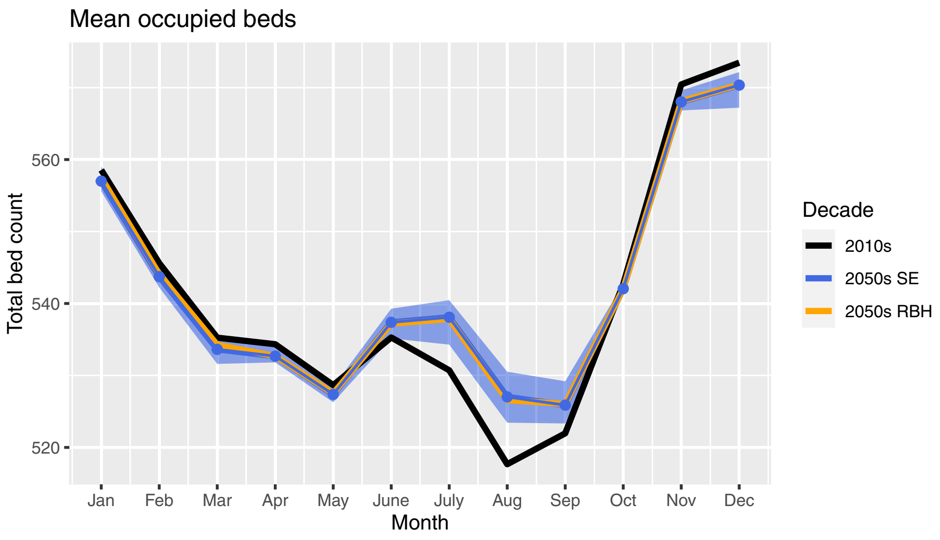

FIGURE 4 Mean daily number of occupied beds for the RBH in 2050s (orange and blue line) and 2010s (black line). Uncertainty envelope is the spread from the 12 climate model ensembles estimates.

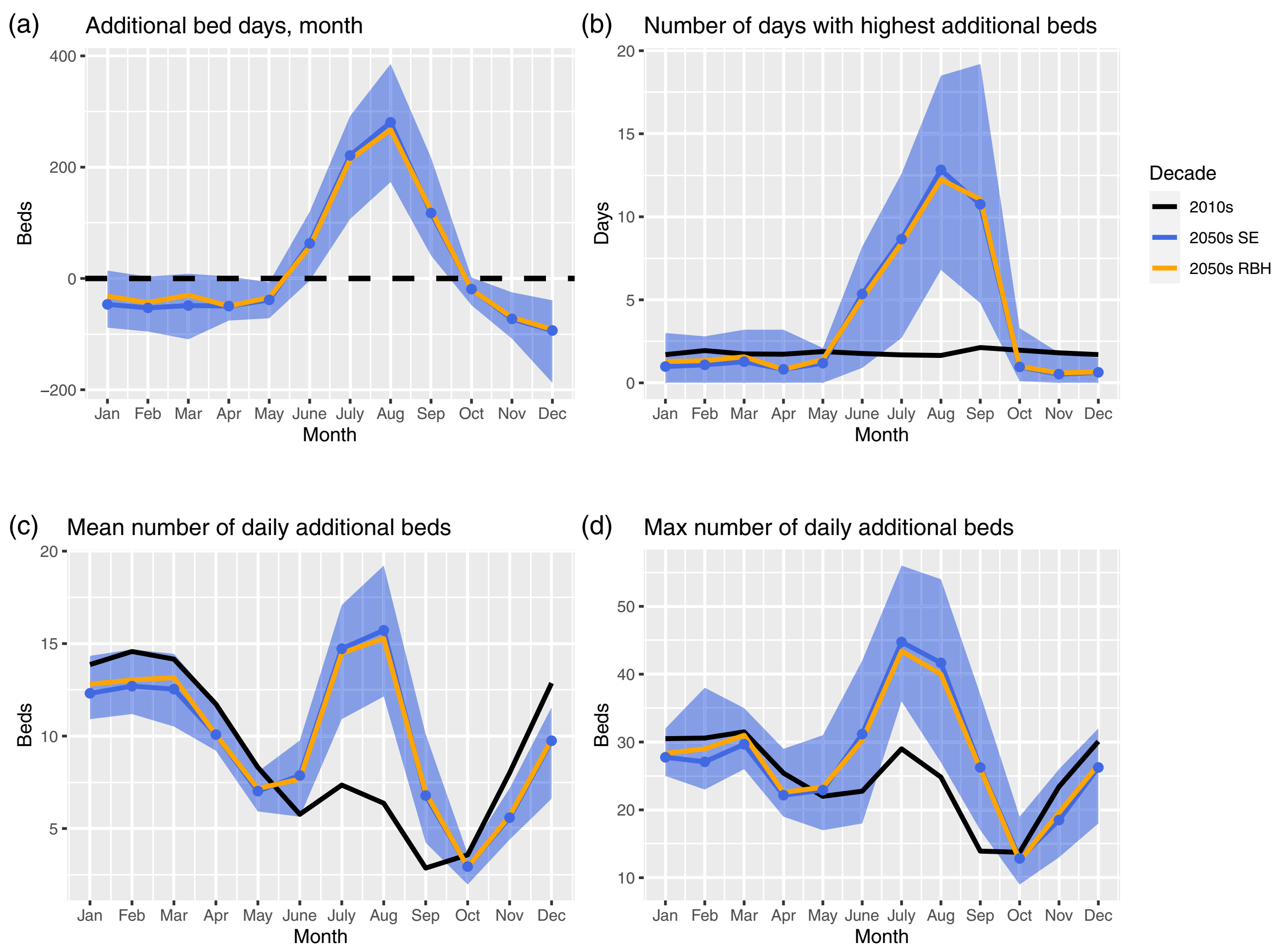

FIGURE 5 Projected number of temperature-dependent beds for four different metrics for the decade 2050s (blue and orange line) compared with 2010s (black line). Uncertainty envelope is the spread from the 12 climate model ensemble estimates. The four metrics are (a) mean number of additional bed days, (b) number of days with 2010s highest occupancy level, (c) daily mean number of temperature beds and (d) maximum daily number of temperature beds.

5 | DISCUSSION AND CONCLUSIONS

In order for hospitals to start adapting their operations to a warming climate, they need to be able to assess how their resource use might change in the future. In this article, we have presented a methodology for translating regional temperature projections to the number of extra bed days needed at a specific hospital, the Royal Berkshire Hospital, under two different climate scenarios. The method has been developed in collaboration with staff from various departments at the RBH to ensure that the model is realistic and the results are useful from an operational and planning perspective.

The number of bed days is projected to increase the most in July and August, correlating with the projected increase in peak summer temperatures. The winter decrease is in contrast non-significant, leading to a more equal distribution of patients over the year. This can be beneficial from a staff planning perspective, because it will lead to a similar number of staff being required year around. It can however lead to issues for maintenance work, which often is done during the quietest periods because it usually requires hospitals to close down the affected wards. With July projected to be significantly more resource-intensive, current work patterns might need to be adjusted to meet this new peak in demand.

Even though peak summer demand is projected to increase the most, it is from a significantly lower level compared with the main winter levels, resulting in the projected number of beds required in the summer still being lower than what is currently needed during the winter, hence not leading to an increase in the physical number of beds needed. This indicates that the main adaptation is on a staff planning level, rather than material level, as enough beds exist to meet the future demand for the current population under a changing climate, but a higher number of staff would be required in the summer time to meet the increased number of patients. However, due to the above-mentioned practice of closing down wards over the summer, the total number of beds that can be used over a year changes. In our analysis, the number of beds occupied in the summer never exceeded 630 on any given day, but in reality, this is not the actual maximum number of available beds during the summer. As the number of wards being closed down varies, this was not a threshold we could include in this analysis.

A development of this work could be to set realistic season-dependent capacity thresholds and thereby be able to determine during which decade these are likely to be crossed, only considering the climate change impact. The usefulness of this estimate would however require a lot of discussion. Considering the potentially very long timescales, the changes in technology, policy and society heat awareness that could happen during that time period could substantially change this estimate. Nevertheless, it could be interesting to derive such as estimate as a 'worst-case scenario' to aid in policy work.

Our study only focuses on one hospital in one region of England, but given the similar climate projections for the rest of the United Kingdom, it provides an indication of the kind of impacts to prepare for. However, given the difference in mortality RR for the different regions of the United Kingdom related to differing health and socio-economic backgrounds (Huang et al., 2020; Kennedy-Asser et al., 2022), one can expect there to be differences for admissions as well. Hence, the next natural step would be to repeat this work for the rest of the regions to find differences and similarities.

There are a number of limitations to the methodology used here. The largest limitation is that we have only focused on the impact from climate change and not any other society or population changes. As different age groups are impacted differently (Figure 3), changes in demographics will naturally have an impact. An ageing population will further require more regular, non-temperature-dependent healthcare, hence having an amplifying effect on the care need. We are also not taking into account any adaptation measures. Given that many heat-related admissions are due to overheating homes and dehydration (RBH workshops, Josseran et al., 2009), correct implemented adaptations such as the ones outlined in the Heatwave Plan for England (Public Health England, 2015) could significantly change our projections.

For future work, one could use the recently developed shared socio-economic pathways, UK-SSP (Pedde et al., 2021), to investigate different future scenarios. These could either be coupled with UKCP18 data to look at changes in healthcare demand with climate change, or use the various trends identified in socio-economic factors to further develop the admissions and bed models presented here.

Another thing that could be interesting to look at is the types of conditions being admitted and how this changes with the magnitude of the temperature, to better understand the expertise and types of wards needed. It is known that heat mainly triggers cardiovascular and respiratory conditions (Ebi et al., 2021), but we could not model this due to the much too small sample sizes. There have been a few studies in the United States looking at the admissions patterns for certain conditions, but no consensus has been reached so far (Sun et al., 2021). A connection between high temperature and pollen has also been identified, but the exposure–admissions relation is still to be determined (Vardoulakis & Heaviside, 2012).

A final interesting extension would be to consider other environmental variables in combination with temperature, such as humidity, using one of numerous 'heat indices' available. Urban et al. (2021) concluded at a Northern European level that using the 'Universal Thermal Climate Index', which incorporates humidity, wind speed and other parameters, did not make a significant difference compared with just using temperature for warm temperatures. This could however be interesting to investigate at a local level.

Nevertheless, the results presented here demonstrate the potential impact from climate change on hospital operations, which currently is very poorly understood. It also demonstrates the possible benefits of better heat adaptation and education of the population, which could significantly lower the number of beds required in future summers.

AUTHOR CONTRIBUTIONS

Jennifer Israelsson: Conceptualization (supporting); data curation (lead); formal analysis (lead); methodology (equal); visualization (lead); writing – original draft (lead); writing – review and editing (lead). **Andrew Charlton-Perez:** Conceptualization (lead); formal analysis (supporting); funding acquisition (lead); methodology (equal); visualization (supporting); writing – original draft (supporting); writing – review and editing (supporting). **Ting Sun:** Conceptualization (supporting); formal analysis (supporting); methodology (supporting); visualization (supporting); writing – original draft (supporting); writing – review and editing (supporting).

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Temperature data were obtained from the Met Office and are available on the CEDA Archive. HadUK-Grid: https://catalogue.ceda.ac.uk/uuid/97bc0b64bc354898a242a42238e1b45c. UKCP18: https://catalogue.ceda.ac.uk/uuid/eabb6bced80049e790c7fe1c9e917d1e. Hospital admissions data for South East England was provided by NHS Digital and analysed by the Met Office. Hospital admissions and bed occupancy data for the Royal Berkshire Hospital were provided by the hospital.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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