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LETTER

Predicting future UK nighttime urban heat islands using observed short-term variability and regional climate projections

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Abstract

By 2050, 68% of the world's population and 90% of the UK's population are estimated to be living in urban areas. It is widely acknowledged that urban areas tend to be warmer than rural areas (the urban heat island (UHI) effect), and that increased summer temperatures increase morbidity and mortality. It is therefore important to know how the UHI intensity will change in the future. Recent work has used observed daily UHI-temperature relationships to suggest that the UHI intensity may decrease under warming temperatures. Here we analyse the ability of the regional UK Climate Projections, UKCP18-regional, to model the summer nighttime UHI intensity of ten UK cities. When compared to HadUK-Grid observational data, we find that the model accurately simulates both the mean magnitude of the UHI intensities and the daily relationship between urban and rural temperature. In particular, in 9 of the 10 cities, the model and observational data both show a decrease in UHI intensity with warmer temperature over the 1980–2020 period analysed. We then analyse the correlation between the projected future UHI intensities using UKCP18-regional and those inferred from the historical daily UHI-temperature relationships. We find that this relationship is not statistically significant and that the model-projected change in UHI intensity is greater than the change inferred from the historical relationship for all cities analysed. We conclude that using short-term variability to predict future UHI change, as proposed by some recent work, may not be appropriate. Our results motivate further research to understand processes impacting UHI changes on different timescales and in different regions.

1. Introduction

Howard (1833) was the first scientist to study the urban heat island (UHI) effect in the UK. Since his discovery in 1833, we have been aware that urban cities can be several degrees warmer than the surrounding countryside (Wilby *et al* 2008). The age of urbanisation meant the formation of large cities, where anthropogenic activity is concentrated (Dincer and Zamfirescu 2014). By 2050, it is estimated that 68% of the world's population will be living in an urban area (United Nations 2019). Compared to their rural surroundings, urban areas have a higher temperature due to anthropogenic alterations of land surfaces, and a large amount of energy use and the consequential generation of excess waste heat.

A number of factors influence the intensity of the UHI, i.e. the temperature difference between an urban and a rural site, in each city (Oke *et al* 1987, Shahmohamadi *et al* 2010). Some of these include:

(1) Non-evaporative and impermeable surfaces, due to their high thermal conductivity, heat capacity and low albedo (Gartland 2008, Schlünzen and Bohnenstengel 2016).
(2) Lack of vegetation, leading to a higher thermal inertia, lower albedo, and a reduction in evapotranspiration (Reed 2010).

(3) Complex urban geometry, which traps heat and causes a decrease in wind speeds in urban areas. This leads to increased warm, stagnant air and absorption of solar radiation and less evaporative cooling (Unger 2004, Chen *et al* 2012).
(4) Anthropogenic heat from cooling and heating buildings, lighting, transport and industrial factories, which heats cities through conduction, convection, and radiation (Reed 2010).

An increase in waste heat due to these anthropogenic processes is caused by an increase in energy use (Oke 1987, Akbari *et al* 2005), which can change depending on the time of day or year (Ohashi *et al* 2007). Currently, around 86% of the nighttime UHI intensity has been shown to be caused by anthropogenic heat. This value decreases to 36% in the daytime (Ryu and Baik 2012).

Studies have shown, using a variety of methods, that the frequency and intensity of heatwaves are predicted to increase due to climate change (Perkins *et al* 2012, Christidis *et al* 2015, IPCC 2021). It is also known that high temperatures have a direct effect on health and mortality (Linares *et al* 2015). For example, the 2003 European heatwave was associated with between 20 000 and 70 000 deaths, depending on the source (Met Office; Robine *et al* 2008). Heatwaves affect the young, the elderly and those with respiratory and cardiorespiratory diseases in particular, and amplify mortality in these groups (D'Ippoliti *et al* 2010; Arbuthnott and Hajat 2017).

A positive UHI intensity trend on top of a warming climate, therefore, is likely to execabate the health risk associated with heat. The nighttime effects of UHIs have been found to be particularly damaging during a heat wave, as urban residents are subject to higher temperatures than rural residents (Loughnan *et al* 2013), with higher death rates shown in urban areas (Pyrgou and Santamouris 2018). As such, nighttime UHI is the focus of this study.

There have been a number of studies aiming to quantify changes in urban climates under future climatic change (Oleson *et al* 2011, McCarthy *et al* 2012). Lo *et al* (2020) used the U.K. Climate Projections (UKCP18-regional) to estimate future trends in summer daytime and nighttime urban and rural temperatures for the ten largest UK cities from 1981 to 2079. Using the 12 km climate model simulations, Lo *et al* found that the UHI intensity is set to increase rapidly during the nighttime in particular. They estimate an overall increase in the nighttime UHI intensity by 0.01 °C–0.05 °C every decade in all cities measured (Lo *et al* 2020). This result may, however, be sensitive to model configuration; a more recent study using high resolution 2.2 km simulations (UKCP18-local) found smaller trends in nighttime UHI intensities for the UK (Keat *et al* 2021).

A contrasting approach to infer future UHI changes can be taken using observational data. Scott *et al* (2018) compared the daily maximum and minimum urban and nearby rural temperatures of 54 cities in the US, using meteorological station data from 2000 to 2015. They found that, on daily timescales, warmer temperatures are associated with a reduced UHI for the majority of cities. Using this relationship, they proposed that as the climate warms, the UHI intensity of these cities may decrease.

This study has two main goals: (a) to apply the method of Scott *et al* (2018), in studying the relationship between UHI intensity and temperature in observational data for UK cities; and (b) to determine whether this historical temperature dependence of the UHI can be used to predict future changes in UHI magnitude under climate change. Throughout, we focus on the summer nighttime UHI.

2. Methods

2.1. HadUK-Grid

HadUK-Grid is a collection of gridded climate variables formed as a result of UK land near-surface observations (Hollis *et al* 2019). The dataset covers a large time period, from 1862 to the present day, however, the start time depends on both the climatic variable and temporal resolution chosen. The HadUK-Grid dataset is provided at 1 km, 12 km, 25 km, and 60 km resolutions.

In this study, we aim to investigate changes in summer nighttime UHI intensities based on daily minimum air temperatures (tasmin) in June, July, and August (JJA). Therefore, we use the 1980–2020 JJA daily tasmin data from HadUK-Grid at 12 km resolution. This ensures we can directly compare against UKCP18-regional, which is also at 12 km resolution, and for bias correction.

2.2. UKCP18-regional

The regional climate model projections were produced as part of the UK Climate Projection 2018 project (Murphy *et al* 2018). These simulations cover Europe over a 100 year period, from 1980 to 2080. UKCP18-regional are constituted of 12 perturbed parameter ensemble (PPE) members from the regional atmospheric model HadREM3-GA7-05, at 12 km horizontal resolution. These PPE simulations are driven by the Met Office global coupled atmosphere-ocean model ensemble, HadGEM3-GC3.05-PPE (Murphy *et al* 2018). Specifically, each regional simulation is driven at its lateral boundaries with the surface pressure, wind, temperature and moisture output, as well as prescribed sea surface temperature (SST) and sea-ice cover fields from the corresponding GC3.05-PPE member.

The 12 PPE members were selected from a larger initial ensemble to provide a range of plausible

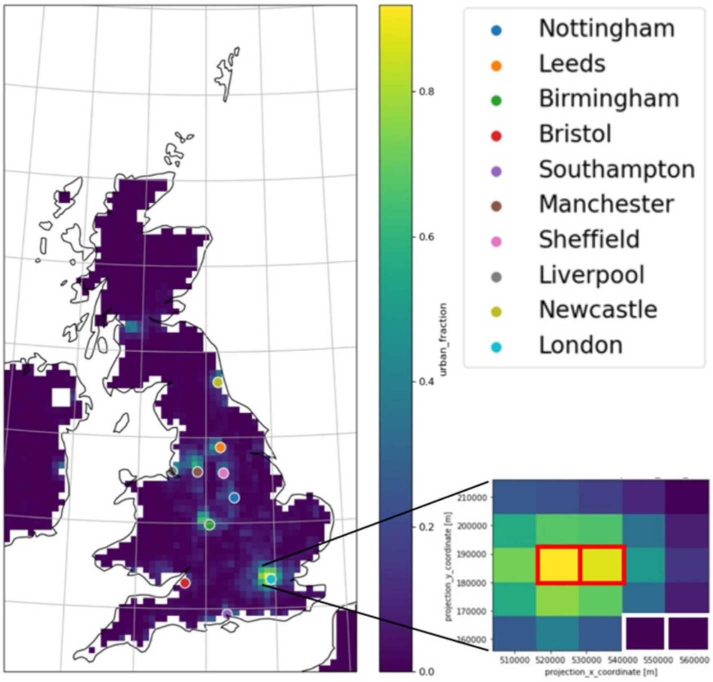

Figure 1. (Left to right) OSGB map layered with urban fraction of England and Wales. The coloured points represent the 10 UK cities that are the focus of this study; 5 × 5 grid centred on the projected *x* and *y* coordinates of London, transformed from its OSGB coordinates (−0.128 W, 51.507 N). Red and white boxes show highest and lowest urban fractions respectively.

simulations. The selection process included assessments against observed and simulated (Coupled Model Intercomparison Project Phase 5; CMIP5 (Taylor *et al* 2012)) historical atlantic meridional overturning circulation strength, SSTs, trends in average Northern Hemisphere surface air temperature, and biases in winter and summer European climatological averages of surface air temperature and precipitation (Murphy *et al* 2018).

Compared with observed UK-averaged surface air temperature in 1981–2000, the regional PPE range encompasses the observations in all months except April and May (Murphy *et al* 2018). In summer hot extremes (99th percentile of diurnal mean temperatures) in 1981–2000, the regional PPE biases warm in London and Birmingham and biases cool in other places in the UK, although this warm bias represents a reduced bias compared to GCM3.05-PPE.

Projections from 2005 onwards were based on the high-emissions RCP8.5 scenario (Moss *et al* 2010). This scenario was chosen so as to more easily identify the risks posed due to climate change. UKCP18-regional projections are made up of 12 PPE members at 12 km horizontal resolution. These PPE members are from the regional atmospheric model HadREM3-GA7-05 and are driven by their corresponding global simulation, HadGEM3-GC3.05 (Murphy *et al* 2018). The 12 PPE members make up an ensemble, which are then used to estimate a range of projections.

UKCP18-regional represents land surface types using the Joint UK Land Environment Simulator (JULES) tiling system, whereby one of nine surface types can be applied on a sub grid-scale. An aggregated surface energy balance is then calculated from these fluxes (Best *et al* 2011). This one-tile urban scheme uses bulk representation for urban areas, modifying parameters required to model an urban surface. These include a reduced albedo and increased heat storage capacity, however, does not include waste heat generation.

2.3. UHI intensity calculation

The urban fraction of England and Wales was overlaid with the boundaries of the ten most populous built-up areas in England, as visualised in figure 1. The grid boxes with the highest urban fractions were mainly located in the ten most populous built-up areas in England and Wales (Lo *et al* 2020; their figure 1). The urban fractions do not change over time in the simulations; therefore, any UHI trends simulated are due to climate forcing, not changes in urbanisation. The built-up areas were defined by the Office for National Statistics (2013). In this paper we study the UHI effect in these ten cities: Nottingham, Leeds, Birmingham, Bristol, Southampton, Manchester, Sheffield, Liverpool, Newcastle and London.

A 5 × 5 grid box, centred on each of the ten chosen cities, was plotted on an OSGB map layered with their urban fractions, as demonstrated in figure 1 for London. From this, the two grid boxes with the highest urban fractions (seen highlighted in red) and two grid boxes with the lowest urban fractions (seen highlighted in white) were selected. These represent the urban and rural parts of the city and surrounding area. The method outlined follows that from Lo *et al* (2020), which demonstrated that this definition was adequate to distinguish between urban (urban fractions $\geqslant\sim 0.2$) and rural (fractions < 0.07) areas around all major cities in England. Although Lo *et al* (2020) noted that this definition may be underestimating UHIs in the cities, changing the number of grids to 1 or 6 did not change their main results, so we do not repeat this sensitivity analysis here.

The urban temperature, T_{u}, and rural temperature, T_{r}, are calculated as the average temperature across the two urban and rural grid boxes respectively. We have taken UHI intensity to be 'the near-surface' air temperature (at 1.5 m) difference between urban and rural grid boxes in the same area, as defined by Lo *et al* (2020). Therefore, the UHI intensity of a given city (°C) is assumed to be given by $T_{\mathrm{u}} - T_{\mathrm{r}}$.

3. Results

3.1. Difference between model and observations

We first aimed to investigate how well UKCP-18 regional can simulate the climate, particularly the urban and rural temperatures. To do this, we compared the relationship between the minimum daily T_{u} and minimum daily T_{r} using both model and observational data. As seen in figure 2, the left column shows this relationship using UKCP18-regional simulations whereas the right column uses HadUK-Grid observations. This is shown for London, Liverpool and Manchester from top to bottom respectively, from 1980 to 2020. Liverpool and Manchester are chosen as their regression slopes using UKCP18-regional are the smallest and largest respectively, among the ten cities, however, this relationship is shown for all analysed UK cities in figure S1 (supplementary information). The relationship between T_{u} and T_{r} can tell us the magnitude of the UHI intensity. Specifically, the gradient of the least squares regression line gives the relationship between UHI and temperature, while comparing the regression line to the 1:1 line, gives the UHI magnitude.

In all of the subpanels shown, the regression line and the majority of the individual points are above the 1:1 line, meaning that the UHI intensity is positive for almost all summer nights. The greater the difference between the lines, the greater the UHI intensity in that particular city. Notably, the slope of the regression line for each city, for both the observational data and model, is less than the 1:1 line. This indicates a reduction in UHI intensity with warmer temperatures, in line with the results of Scott *et al* (2018) for US cities.

We validated the simulations against observational data by comparing the gradient of the regression line using both HadUK-Grid observational data and UKCP18-regional model simulations. We found that the gradients from the model and observations were very similar for Manchester and Liverpool, and slightly less so for London (see comparison of all cities in figure S2).

3.2. Difference in UHI between cities

To further validate the model simulations of UHI, we now show mean UHI intensity, and corresponding standard error, obtained from UKCP18-regional and HadUK-Grid from 1980 to 2020 for each city (figure 3). Most cities (7/10) have median UHI intensities above 0 °C for both model and observations. Three of the cities (Nottingham, Leeds and Birmingham) have median UHI intensities less than 0 °C when using model simulations. For all of these cases, the median UHI intensities using observational data are greater than 0 °C.

London and Birmingham are cities with a particularly large 95% confidence interval and interquartile range, whereas Bristol has a smaller spread of results. Out of the ten cities, six have an average UHI intensity larger in the observational data than in the model simulations.

We found a strong, significant correlation between the 1980 and 2020 UHI intensities obtained from HadUK-Grid observational data, and those estimated by UKCP18-regional simulations ($r = 0.85$, $p = 0.002$, assuming mean UHI magnitudes are independent). Overall, the UHI intensities estimated from model simulations are very closely related to those from HadUK-Grid observational data. This gives us confidence that the UKCP18-regional simulations are accurately capturing the magnitude of the UHI effect for UK cities.

3.3. Future change in UHI intensity

We next determine whether the historical temperature dependence of the UHI can be used to predict future changes in UHI under climate change. We show the change in UHI intensity as the difference between the average of 1980–2000 and 2060–2080 using UKCP18-regional simulations against the predicted change in UHI intensity from the model's historical relationship (figure 4).

This predicted change in UHI was calculated as follows:

$$\mathrm{UHI} = T_{\mathrm{u}} - T_{\mathrm{r}} = (m-1)\,T_{\mathrm{r}} + c, \tag{1}$$

where $T_{\mathrm{u}} = mT_{\mathrm{r}} + c$. Hence

$$\Delta\mathrm{UHI} = \Delta T\,(m-1)\,. \tag{2}$$

Here the slope m represents the change in T_{u} per increase in T_{r}, as determined through a total least-squares linear regression shown in figure 2, ΔT is the difference in rural temperatures between 1980 and 2080, and c is a constant determined by the linear regression. In figure 4, the different coloured points indicate each of the ten chosen UK cities, defined in the legend to the right of the graph. The trendline is

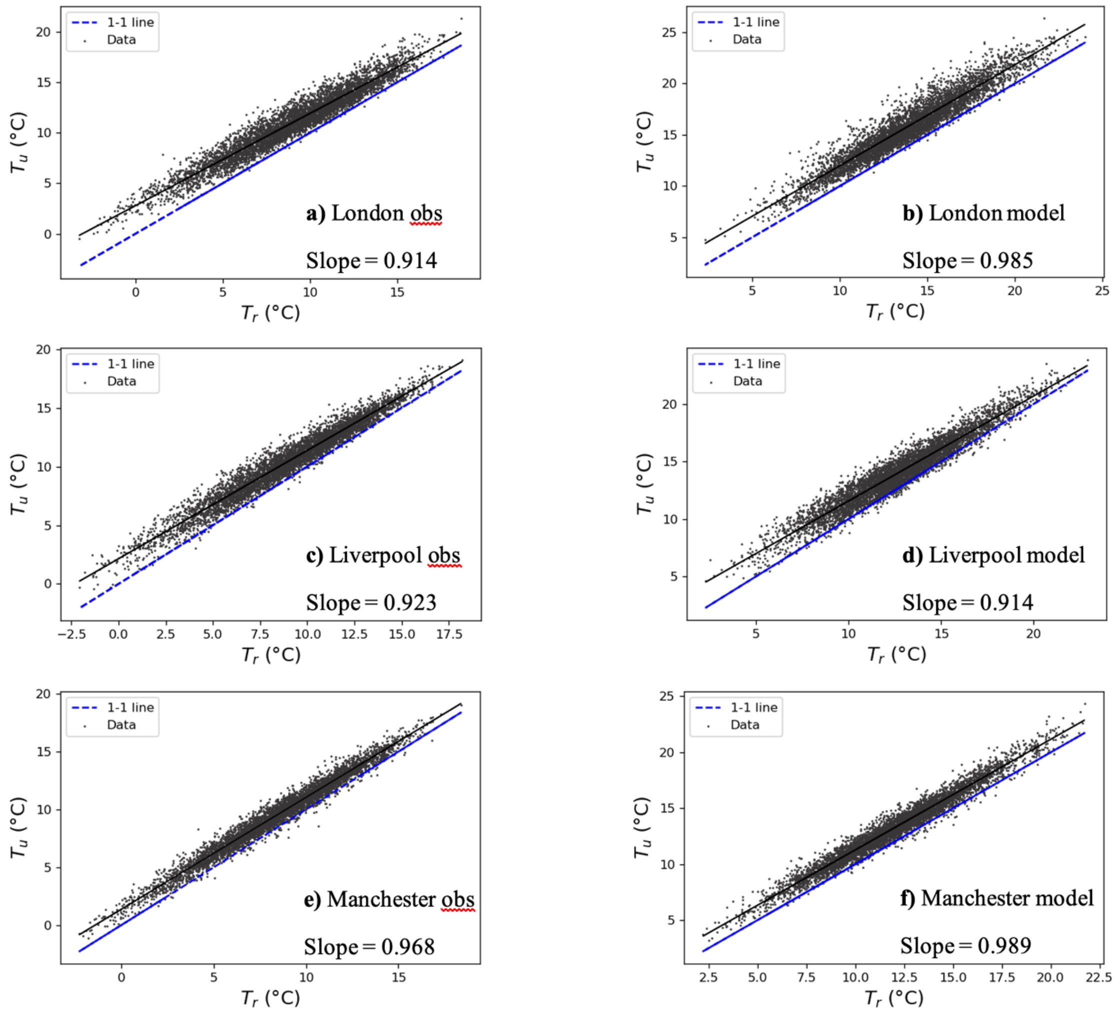

Figure 2. Left column: daily minimum T_r versus T_u for data from JJA 1980–2020 for (a) London, (c) Liverpool and (e) Manchester using HadUK-Grid observational data. Right column: daily minimum T_r versus T_u for data from JJA 1980–2020 for the same three cities using UKCP18-regional simulations. The black line shows the total least squares regression, and the blue line shows the 1:1 line.

shown as a black dotted line, which can be compared to the 1:1 line, shown as a solid blue line.

We then assessed the statistical significance of the proposed correlation using the Pearson correlation coefficient. We obtain an r-value of 0.47, indicating a slightly positive correlation. The r^2 value is 0.22, indicating that around 20% of the spread in the model UHI intensity change is explained by the spread of the predicted UHI intensity using historical simulations. We assess the statistical significance of this correlation by calculating the p-value, which we found to be 0.18. The result is therefore not statistically significant. When using Spearman's rank correlation coefficient, we find $r = 0.66$, $p = 0.04$, which does indicate a statistically significant (at the 5% level), positive correlation between the ordering of the cities in the two methods of predicting future UHI intensity.

4. Discussion

When examining the sensitivity of how T_u changes with T_r on daily timescales, we found that, for the majority of the cities (9/10), the slope is less than 1, indicating that T_u and T_r become more similar (and therefore the UHI magnitude decreases) as T_r increases. As the average slope of the ten cities indicates that T_u increases by about 0.95 °C for every 1 °C increase in T_r. This result broadly agrees with that of Scott et al (2018), who found that in 38 of the 54 US cities sampled, the UHI intensity decreased with increasing rural temperatures, with an average T_u increase of about 0.88 °C for every 1 °C increase in T_r. Scott et al (2018) suggested that this decrease in UHI intensity could be due to changing moisture levels in the soil: as the temperatures get warmer, the rural areas get drier due to evapotranspiration, this causes the moisture levels of the urban and rural areas to become more similar, as in turn do their respective temperatures.

A key motivation of our study is to test whether the same mechanism can be expected to operate on longer time scales, such that UHI intensities would decrease under global warming. To do so, we used UKCP18-regional simulations which we showed to

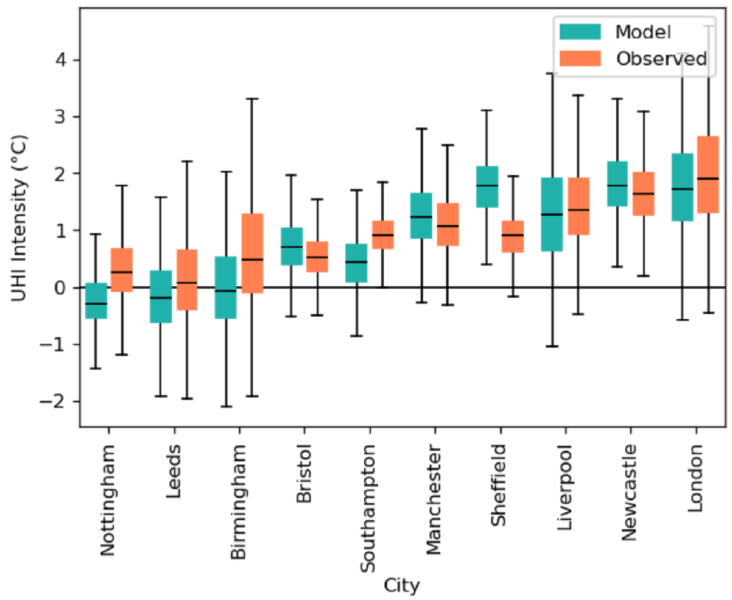

Figure 3. Comparison of 1980–2020 JJA nighttime mean UHI intensity between HadUK-Grid data and UKCP18-regional simulations for ten UK cities. For the lines in the box and whisker plot: error bars are the 95% confidence interval, the bottom and top of the box are the 25th and 75th percentiles, the line inside the box is the median.

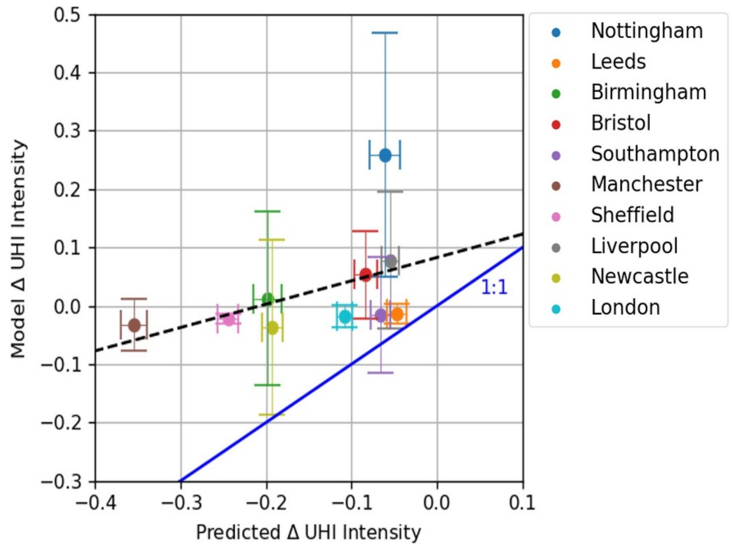

Figure 4. Change in UHI intensity using UKCP18-regional simulations from 2020 to 2080 versus predicted change in UHI intensity using historical climate model simulations. The x-axis error bars represent the uncertainty due to our linear regression slope, seen in figure 2. The y-axis error bars represent the uncertainty from the modelled change in future UHI intensity. Black dashed line is a total least-squares linear regression, blue line is the 1:1 line.

accurately capture historical mean UK UHI intensities. UKCP-18 regional also showed a decrease UHI intensity with warmer temperatures on daily time scales over the historical period for all cities, in agreement with the observational results. We then investigated whether we could use this daily variability in the historical simulations to predict the future climate change signal. While the daily historical relationship suggests a decreasing UHI intensity under a warmer climate, the climate model simulations showed that the UHI intensity will increase for 4/10 of the cities and decrease for the other 6/10. There is a slight correlation between the historically-inferred UHI change and the simulated UHI change ($r = 0.47$), however it was found to not be statistically significant ($p = 0.18$). When using UKCP18-regional to model the UHI intensity trends from 1981 to 2079, Lo *et al* (2020) found all ten chosen UK cities to have a positive UHI intensity trend. Increasing the sample size of the study to include more UK cities would be beneficial in order to get a more accurate representation of the correlation. It is clear that the simulated change in UHI intensity using UKCP18-regional is consistently larger than that inferred from historical simulations. We conclude that using the observed short-term UHI-T relationship does not necessarily imply a reduction in UHI intensity under a warming climate, as proposed by Scott *et al* (2018).

The reason for the systematic difference between climate projections inferred from short-term variability and those derived from future model simulations warrants further investigation. UKCP18 simulations show reductions in summer soil moisture over much of the UK under climate change (Kay *et al* 2022); a trend which, as proposed by Scott *et al* (2018), might be expected to drive reductions in UHI. Hence we suggest that another mechanism must be partially cancelling this by driving increased UHI within these simulations. A detailed heat budget analysis is beyond the scope of this paper, but possible candidates include nighttime cloud cover changes, or increasing humidity.

In this study, we have used the newest generation of UKCP to estimate future changes in UHI intensities in the UK. Despite having many benefits (Murphy *et al* 2018), UKCP18-regional does have some drawbacks (Keat *et al* 2021). The regional climate model uses the JULES one-tile urban scheme to represent urban areas (Best *et al* 2011). Compared to a two-tiled scheme, such as the Met Office Reading Urban Surface Exchange Scheme (MORUSES), the UKCP18-regional does not represent urban areas as well (Keat *et al* 2021). MORUSES uses two urban tiles to represent the street canyon and roof facets (Porson *et al* 2010a, 2010b). This means that it is able to account for factors such as anthropogenic heat emissions, something that is omitted from UKCP18-regional (Keat *et al* 2021). As the climate warms in the future, we expect there to be an increase in waste heat generation (Bian 2020). Many commercial, residential and transportation factors could contribute to this, one example being an increase in air conditioning usage.

There is also some potential for our results to be model-sensitive. Lo *et al* (2020) compared the trends in UHI intensity between UKCP18-regional and three regional models from the European branch of the Coordinated Regional Downscaling Experiment (EURO-CORDEX; Jacob *et al* 2014) and found varying results depending on the city, time of day, and model. The diversity of their results suggests that considering other models in similar future work is important.

5. Conclusions

We have investigated UK summer nighttime UHI intensities using both HadUK-Grid observational data and UKCP18-regional climate model simulations. We found that the climate model accurately simulates both the mean UHI intensities of UK cities (correlation of UHI intensities: 0.85) as well as the observed reduction of UHI with increasing temperature on short timescales, which was seen for nine of the ten cities studied.

Turning to UHI projections under climate change, we showed that simulated UHI intensity changes are consistently more positive (towards increasing UHI) than those inferred from the short-term historical variability of the model. We therefore conclude that caution is necessary if using the historical record to infer future UHI changes, as has been suggested by some recent studies. Our result are important for further understanding how the magnitude of the UHI intensity of UK cities may change in future and help motivate future work to understand the mechanisms impacting the UHI-temperature relationship on different timescales. Future work might also consider the effects of changing urbanisation, which was not included in the simulations analysed here.

An increase in UHI intensity will increase the disparity in heat-related health-risks between urban and rural areas. However, both urban and rural temperatures are projected to rise in the future. Therefore, even if the UHI intensity decreases in the future, there is likewise an expected increased risk of mortality. Reducing the variability and improving the accuracy of the climate model simulations will greatly improve our understanding of the measures needed to mitigate heat-related mortality.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://catalogue.ceda.ac.uk/uuid/4dc8450d889a491ebb20e724debe2dfb.

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