

Evaluating ERA5-Land air temperature and dew point biases in built-up environments in the UK

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ABSTRACT

ERA5-Land reanalysis provides spatiotemporally continuous meteorological data that can serve as a practical proxy in observation-scarce regions. However, its known biases must be understood before it is used to support decisions. Here, we comprehensively evaluate ERA5-Land surface air temperature and dew point against hourly observations across the UK, and examine how biases vary with built-up areas. We then quantify how these biases propagate into representative downstream urban climate studies and impact applications. Our analysis reveals that ERA5-Land does not fully capture the extreme values of air temperature and dew point, with daily maximum air temperature underestimated by 0.66 °C and daily minimum air temperature overestimated by 0.44 °C. The performance also degrades with increasing impervious surface area ratio, leading to stronger underestimations of air temperature in more built settings. Despite these limitations, ERA5-Land usefully informs the onset of heat events, but it tends to underestimate the total annual hours of extreme heat in both urban and rural areas. The mortality risk and building energy analysis are presented as downstream case studies to illustrate how ERA5-Land temperature and dew point biases may propagate into applied modeling frameworks. Overall, this study clarifies where ERA5-Land can inform analyses and decisions when better local observations are unavailable, and where caution or bias-aware adjustments are needed to avoid underestimating the heat exposure profile, particularly in urban areas.

1. Introduction

Meteorological services provide basic data for decision-making across diverse sectors, including marketing (Panetsidou and Synapis, 2025), energy (Tang et al., 2021), sociodemographic vulnerability (Lo et al., 2025), human health (Anderson and Gough, 2026), and ecosystem (Feng et al., 2021). Meteorological data can be derived from observations and reanalysis products. However, observations are often constrained by limited spatial coverage and temporal discontinuities (Thornton et al., 2022). Alternatively, reanalysis products, generated through the assimilation of multi-source observations (satellite and in situ) into models, have gained prominence (Buontempo et al., 2025). These products provide long-term, gridded datasets that are widely used in climate studies (Cai et al., 2024a,b), hydrological simulations (Liu et al., 2021; Dalla Torre et al., 2024), as well as energy (Ramirez Camargo

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and Schmidt, 2020; Wu et al., 2023) and climate-health assessments (Masselet et al., 2023; Yang et al., 2025). Several reanalysis datasets are available, including the fifth generation ECMWF reanalysis (ERA5) (Hersbach et al., 2020), Japanese 55-year Reanalysis (JRA-55) (Kobayashi et al., 2015), and Modern-Era Retrospective analysis (MERRA) (Rienecker et al., 2011). In addition to these coupled datasets, offline land surface models offer greater temporal consistency. Examples include the Global Offline Land-surface Data-set, MERRA-Land, and ERA5-Land, which possess enhanced continuity and completeness of land surface fields (Copernicus Climate Change Service, 2019). Among them, ERA5-Land, an offline, land-only simulation driven by atmospheric forcing from ERA5, is widely used for localized studies due to its enhanced spatial resolution of 0.1° (Copernicus Climate Change Service, 2019).

Surface air temperature and dew point are among the most widely used variables derived from ERA5-Land. They are critical proxies in indicating heat waves/cold spells, estimating heat exposure, and climate-health modeling. Despite widespread use, the surface air temperature of ERA5-Land has been reported to exhibit systematic biases in certain regions (Ma et al., 2025; Zhao et al., 2023; Zhang et al., 2025; Yilmaz, 2023), and its performance may degrade in areas with complex terrain and heterogeneous surfaces, e.g., forests and built-up areas (Zou et al., 2022). The current land surface model of ERA5-Land lacks a sophisticated representation of urban land surface processes, leading to underestimations of temperature in built-up areas (Zou et al., 2022; Goddard and Tett, 2019). This underestimation stems from the model's inability to fully capture the urban heat island (UHI) effect, which leads to a hotter thermal environment in urban areas (Goddard and Tett, 2019). Since utilizing biased reanalysis data for further analysis may propagate the bias in downstream applications, the evaluation of reanalysis data should not be limited to the error statistics. However, a comprehensive, multi-sectoral evaluation framework quantifying how these reanalysis biases propagate across different downstream models remains scarce.

The purpose of this study is to evaluate the performance of ERA5-Land air temperature and dew point across the UK with a particular focus on built-up areas, utilizing open-access data from Met Office Integrated Data Archive System (MIDAS). The UK presents an ideal testbed for this evaluation due to its combination of intense urbanization, complex maritime atmospheric conditions, and a wealth of open-source data (Keat et al., 2021; Bassett et al., 2020). By analyzing air temperature and dew point errors across various temporal scales, we established an error benchmark based on ERA5-Land. We then quantified the relationship between reanalysis bias and built-up areas. Finally, we demonstrated the multifaceted impacts of the biases from air temperature and dew point by tracing their propagation into downstream applications, including exposure assessment, and case studies on temperature-related mortality risk and building energy analysis. While prior studies examined ERA5 biases in single sectors, e.g., urban heat Jacobs et al. (2024) and health (Mistry et al., 2022), an integrated evaluation is scarce. Our study is among the first to trace reanalysis biases through multiple impact models concurrently, offering guidelines for the community relying on ERA5-Land air temperature and dew point.

2. Methods and data

2.1. Reanalysis data

Reanalysis data of surface air temperature and dew point are obtained from ERA5-Land, a reanalysis dataset that provides land variables over several decades, with an enhanced spatial resolution (9 km) compared with ERA5 (Copernicus Climate Change Service, 2019). ERA5-Land is an offline land surface model simulation product using the Carbon Hydrology-Tiled ECMWF Scheme for Surface Exchanges over Land (CHTESSEL) and forced with atmospheric forcing from ERA5 (Muñoz-Sabater et al., 2021). The main differences between ERA5-Land and ERA5 are related to non-linear dynamical downscaling with corrected thermodynamic input (Muñoz-Sabater et al., 2021). The grid coordinates, after being aligned with the selected station coordinates, are matched for comparison. For each station, the station latitude and longitude were used to identify the nearest ERA5-Land grid cell, and the corresponding grid cell time series were extracted for further comparison. Furthermore, the ERA5-Land time series is aligned with the observation data by removing periods where observational data are missing. Relative humidity was not evaluated separately because ERA5-Land does not provide it directly, and it must be derived from air temperature and dew point. Since both variables are evaluated in this study, an additional relative humidity evaluation would not be independent.

2.2. Observational weather data

The observational weather data were retrieved from MIDAS Open, an open data version of MIDAS that provides the quality-controlled version of the data annually (Met Office, 2019). Here, we retrieved the quality-controlled version (qc-version-1) v202407 that includes data from 1853 to 2023 (last accessed: August 2025). It should be noted that only weather stations with hourly air temperature and dew point observations were considered in this study. The subsets of stations were then extracted for different tasks. First, to get the long-term continuous data for temporal trends analysis, we selected stations with start years no later than 1990 and end years later than 2020 and excluded any years with more than 5% of missing data. In total, 64 stations and 14,904,132 records were selected for analysis. While this subset is ideal for temporal analysis, its sparse spatial distribution limits its utility for capturing localized urbanization effects. Therefore, to conduct a robust urban-rural difference analysis, we incorporated more newly established stations by focusing on the recent 2021–2023 period, classifying them based on urban boundary data to thoroughly investigate the impacts of urbanization (Section 2.7).

Considering the elevation difference between ERA5-Land grid cells and stations, we applied a vertical adjustment to the reanalysis data. The corrected variables (T_{adj}) were calculated using the following elevation-adjustment equation:

$$T_{adj} \approx T_{ERA5-Land} + \Gamma \cdot (H_{station} - H_{grid}),$$

where H_{station} and H_{grid} represent the elevations of the observation site and the ERA5-Land grid cell, respectively. The atmospheric lapse rate (Γ) for air temperature was set to -0.0065 °C/m (Zhang et al., 2023). For dew point temperature, a lapse rate of -0.0018 °C/m was adopted to reflect the vertical profile of moisture content in the lower troposphere (Daidzic, 2019). This procedure ensures that the comparison effectively isolates the model performance from terrain-induced gradients.

2.3. UK local gridded products

The HadUK-Grid dataset created by the Met Office includes gridded climate variables integrated from land surface observations across the UK (Hollis et al., 2019). By accounting for geographic and topographic factors, this dataset interpolates surface observations into a continuous 1 km resolution grid. This dataset provides the daily mean air temperature, daily maximum air temperature, and daily minimum air temperature. Maximum and minimum air temperatures were determined based on 24-hour windows: from 09:00 UTC (day D) to 09:00 UTC (day $D + 1$) for the maximum, and from 09:00 UTC (day $D - 1$) to 09:00 UTC (day D) for the minimum.

We also used the UK Climate Projections (UKCP18) dataset provided by the Met Office Hadley Centre for comparison (Centre, 2019). These projections are dynamically downscaled to a high resolution of 2.2 km using a convection-permitting model. The data span from 1980 to 2080 under the RCP8.5 high-emissions scenario. To address climate uncertainty, UKCP18 provides an ensemble of members generated from different model initial conditions and perturbed physics. It is important to note that, due to internal climate variability, these ensemble members represent plausible climate realizations rather than deterministic predictions of specific historical events.

2.4. Built-up areas data

The global artificial impervious area (GAIA) data contain the annual change in global impervious surface area from 1985 to 2018 at a 30 m resolution (Gong et al., 2020). The impervious pixels are defined as the pixels with an imperviousness higher than 50%. The year of the transition (from pervious to impervious) can be identified from the pixel value, ranging from 34 (year: 1985) to 1 (year: 2018). The dataset is hosted on Google Earth Engine (https://developers.google.com/earth-engine/datasets/catalog/Tsinghua_FROM-GLC_GAIA_v10). The urban boundaries of UK were extracted from Li et al. (2020), which used the GAIA data for mapping the urban boundaries. The data show a good agreement with results derived from nighttime light data and human interpretation, and can well delineate the urban extent of cities when compared with high-resolution Google Earth images (Li et al., 2020). Here, the most recent urban boundaries (2018) were employed to identify the urban-rural station pairs.

2.5. Error metrics

The mean bias (MB), root mean squared error (RMSE), and unbiased root mean squared error (uRMSE) are employed to indicate the direction and magnitude of overall errors. MB, RMSE and uRMSE are given by Eqs. (1)–(3):

$$\text{MB} = \frac{\sum(T_r - T_o)}{n}, \quad (1)$$

$$\text{RMSE} = \sqrt{\frac{\sum(T_r - T_o)^2}{n}}, \quad (2)$$

$$\text{uRMSE} = \sqrt{\text{RMSE}^2 - \text{MB}^2}, \quad (3)$$

where T_o and T_r are the observation and reanalysis data, respectively. n is the sample size.

2.6. Impervious surface area metrics and stratification

The impervious surface area (ISA) ratio around each station was calculated for different years using buffer radii of 100, 200, 500, 800, 1000, 2000, 3000, 4000, and 5000 m to quantify the influence of built-up areas (Cao et al., 2022). The ISA ratio is the percentage of areas of impervious pixels to the buffer areas. Since the impervious surface dataset is only available up to 2018 (Gong et al., 2020), the ISA-based analysis period was limited to 1990–2018. Since a 500 m radius is commonly regarded as the representative theoretical footprint of a weather station, the subsequent analysis was conducted using this radius (Zhang et al., 2023; Oke, 2004).

Urbanization cannot be neglected for contributing to the background warming (Chakraborty and Qian, 2024). To separate local and background urban effects, we further computed ISA ratio in two ways: within 500 m buffers (ISA_{500}) and within the corresponding ERA5-Land grid cells (ISA_{grid}). The first approach reflects localized influences induced by the built-up areas, while the second reflects the background influences induced by the built-up areas. We stratified the data into four zones: (1) low-local/low-background with $\text{ISA}_{500} \leq 40\%$ and $\text{ISA}_{\text{grid}} \leq 10\%$; (2) low-local/high-background with $\text{ISA}_{500} \leq 40\%$ and $\text{ISA}_{\text{grid}} > 10\%$; (3) high-local/low-background with $\text{ISA}_{500} > 40\%$ and $\text{ISA}_{\text{grid}} \leq 10\%$; and (4) high-local/high-background exceeding both thresholds.

2.7. Urban heat island and heat exposure hour

We selected weather stations whose observation periods fall within 2021–2023 and are located within the 2018 urban boundaries; these are referred to as urban stations. We also selected stations with the same observation period that fall within a 25 km buffer zone surrounding the urban boundaries of the corresponding urban stations, and these were referred to as rural stations. While the 2018 global urban boundary is widely used (Li et al., 2020; Wang et al., 2025; Li et al., 2026), the selected rural stations may be potentially affected by post-2018 urban expansion. To assess whether the 2018 global urban boundary classification remained appropriate for the 2021–2023 UHI analysis, we cross-checked the selected rural stations against the World Urban Areas dataset from Esri, updated in 2025 (Esri, 2025). The results show that all selected rural stations were located outside the World Urban Areas boundaries. A total of 8 urban boundaries, 11 urban stations, and 15 rural stations were selected. The UHI intensity was quantified using paired urban-rural stations. For ERA5-Land, UHI intensity was calculated using two approaches: (1) assigning each paired station the corresponding ERA5-Land grid cell and computing the urban-rural difference, and (2) computing area-weighted urban and rural temperatures based on the urban boundary and buffer-zone polygons. We then quantified the occurrence of extreme hot hours at these stations, defined as hours when the temperature exceeded the thresholds defined by Met Office (Met Office Press Office, 2022; McCarthy et al., 2019). These thresholds are derived from recent 1991–2020 climate averaging (Met Office Press Office, 2022) (Figure S1). Each urban boundary was assigned a heatwave threshold according to the county containing its centroid. The same threshold was applied to both the urban stations and their paired rural stations to avoid different thresholds. The urban-rural classification was based on the GAIA-derived urban boundaries and did not explicitly include detailed urban morphology, building openness, local human-intervention indicators, water bodies, and vegetation, which is acknowledged as a limitation of the station-pair analysis.

2.8. Temperature-mortality association modeling

Since ERA5-Land data is frequently used as a proxy for ambient temperature in climate-health associations, we further evaluated the temperature-mortality association using different sources of temperature, following the methods and parameters in Gasparrini and Leone (2014). Constrained by the accessibility of mortality data, Greater London was selected as a case study. The models were constructed using different sources of air temperature and all-cause mortality across different age groups. Specifically, we applied distributed lag non-linear models (DLNM). Daily deaths were modeled with a quasi-Poisson regression and a cross-basis for temperature, with a maximum lag of 25 days. The model can be expressed as:

$$Y_t \sim \text{quasi-Poisson}(\mu_t), \quad \log(\mu_t) = \alpha + \sum_{l=0}^L f(T_{t-l}, l) + s(t) + \text{DOW}_t, \quad (4)$$

where Y_t denotes daily deaths, T_{t-l} is the temperature at lag l , $L = 25$ days, $f(\cdot)$ is the cross-basis function, $s(t)$ is a natural spline for long-term and seasonal trends, and DOW_t represents day-of-week. The temperature-response function used a quadratic B-spline with 4 degrees of freedom and equally spaced knots, while the lag-response used a natural cubic spline with three knots on the log scale. Long-term and seasonal trends were controlled using a natural spline of time (10 degrees of freedom per year), and day-of-week was included as a categorical covariate. The minimum mortality temperature (MMT) was identified as the temperature minimizing the cumulative relative risk (RR) and cross-predictions were centered at this MMT. Attributable numbers (AN) and attributable fractions (AF) were computed using 1000 Monte Carlo simulations, separately for total, heat (above MMT), and cold (below MMT) contributions.

2.9. Building energy modeling

To probe how the bias of air temperature and dew point affect building energy modeling, we designed a sensitivity analysis of data on theoretical thermal load using the standard EnergyPlus Case 600 test model. The Case 600 model is a simple building model, with no complex air conditioning system and no personnel activities. The parameters of Case 600 model are derived from ANSI/ASHRAE (2007). Such model represents a single-zone lightweight building (8 m × 6 m × 2.7 m; 48 m² floor area) with two south-facing windows (3 m × 2 m each), an infiltration rate of 0.5 air changes per hour, and constant internal gains of 200 W (60% radiative, 40% convective) (ANSI/ASHRAE, 2007; Narowski et al., 2013; Fan et al., 2020). An ideal loads air system was used with heating and cooling setpoints of 20 °C and 27 °C, respectively, to isolate the effect of weather inputs on thermal loads (ANSI/ASHRAE, 2007; Narowski et al., 2013; Fan et al., 2020). Here, we focused on the inputs of air temperature and dew point. A full-year simulation was run using a London weather file, and we replaced the ambient temperature and humidity (dew point) with ERA5-Land and MIDAS time series, while keeping other meteorological variables unchanged. This setup isolates the effect of air temperature and dew point differences between the observation and ERA5-Land datasets. Therefore, differences in simulated cooling and heating loads are interpreted as a controlled case-study response to these meteorological input differences, rather than a full validation of building energy performance.

Table 1

Descriptive statistics of hourly MIDAS observations and elevation corrected ERA5-Land values across all selected stations and matched time steps.

	T_{MIDAS} (°C)	$T_{\text{ERA5-Land}}$ (°C)	D_{MIDAS} (°C)	$D_{\text{ERA5-Land}}$ (°C)
Mean	9.85	9.79	6.61	6.48
Min	-24.20	-19.23	-31.10	-23.06
25%	6.00	5.99	3.00	2.99
50%	9.80	9.77	6.90	6.71
75%	13.70	13.62	10.30	10.15
Max	39.60	38.02	28.20	22.70
Std	5.57	5.38	4.97	4.92

Note: “T” indicates air temperature and “D” indicates dew point temperature. Percentages indicate empirical quantiles. Min and Max are the minimum and maximum hourly values in the full matched sample.

3. Results and discussion

3.1. Overall performance of ERA5-Land

The elevation-corrected ERA5-Land air temperature shows better agreement with MIDAS than the raw data, with RMSE decreasing from 1.35 °C to 1.23 °C, and R^2 increasing from 0.9421 to 0.9512. Thus, the following analyses were based on the elevation-corrected ERA5-Land data. The mean air temperature of MIDAS is 9.85 °C, while that of ERA5-Land is 9.79 °C in the UK (Table 1). This indicates that ERA5-Land tends to underestimate the air temperature. The paired t-test confirms this systematic cold bias is statistically significant ($p < 0.001$). The variability analysis shows that ERA5-Land exhibits a lower variance than MIDAS ($p < 0.001$ for the Chi-squared test). This indicates ERA5-Land underestimates the observed climatic variability, failing to capture the extreme maximum and minimum values (Table 1), which was also proposed in a previous study (Choudhury et al., 2023). The statistics of dew point show a similar pattern of air temperature, showing that the ERA5-Land underestimates the dew point too.

We evaluated the error metrics of ERA5-Land air temperature against MIDAS observations at hourly, daily, and monthly scales, respectively (Fig. 1a). The MB is relatively stable across temporal scales (−0.07 to −0.06 °C), and RMSE decreases with temporal aggregation, with a lowest RMSE of 0.32 °C for monthly mean air temperature. Larger errors were observed for temperature extremes. The daily and monthly maximum temperatures show MB of −0.66 °C and −0.65 °C, respectively, while the minimum temperatures exhibited positive MB of 0.44 °C and 0.43 °C, respectively. This suggests that ERA5-Land tends to underestimate maximum temperatures and overestimate minimum temperatures. While HadUK-Grid shares this similar bias, it demonstrates smaller error. Furthermore, an evaluation of the UKCP18 at 2.2 km resolution shows larger RMSE and MB than ERA5-Land (Figure S2). The error metrics of dew point also have similar patterns with those of air temperature (Figure S3). Among all evaluated metrics, the daily minimum air temperature of ERA5-Land have the highest RMSE of 1.50 °C. These results are similar to the previous results on evaluating the daily extreme of ERA5, indicating the limitation of the model of ERA5 in capturing the full amplitude of air temperature and dew point (Lopes et al., 2024). Therefore, ERA5-Land is more suitable for analyses based on daily or longer-term aggregation, while hourly applications related to acute exposure or peak demand require greater caution.

Using the RMSE of all seasons as a baseline, the results show that RMSE of air temperature is higher in summer and winter compared to other seasons (Fig. 1b). This pattern is consistent across both the ERA5-Land and HadUK-Grid datasets. The elevated summer RMSE mainly occurs in the estimation of daily and monthly maximum temperatures, and the monthly minimum temperature. However, for dew point estimation, a higher RMSE is observed in spring (Figure S4).

The spatial distribution shows that temperatures are underestimated at 37 stations and overestimated at another 27 stations (Fig. 2a). The temperature trends of MIDAS and ERA5-Land are highly consistent across the annual, daytime, and nighttime (Fig. 2b–d and Table S1). ERA5-Land shows a lower warming trend than MIDAS in the annual mean and annual daytime mean. For the annual mean temperature, the trend is 0.20 °C per decade for MIDAS, compared with 0.18 °C per decade for ERA5-Land, yielding a difference of 0.02 °C per decade. These trends show higher values in daytime, and the difference between MIDAS and ERA5-Land is 0.05 °C per decade, which is higher than the annual and nighttime trends. These results suggest that ERA5-Land underestimates both the actual temperature levels and the warming trends in the UK, particularly during daytime.

3.2. Evaluation in built-up areas

Across all buffer radii, the greater underestimation by ERA5-Land was observed in high ISA ratio regions (Fig. 3). This underestimation is present in both daytime and nighttime, but is more pronounced in daytime. Fig. 3 shows an empirical transition range in air temperature bias at approximately 30%–50% ISA, above which the ERA5-Land cold bias becomes more pronounced. This range is broadly consistent with thresholds commonly used to distinguish urban from non-urban areas (Zhang et al., 2023; Stewart and Oke, 2012; Gong et al., 2020; Oke, 2007; Oleson and Feddema, 2020). However, this transition range is derived from the UK station sample and may depend on the GAIA-based ISA product and station distribution. Moreover, ISA represents built-up intensity but does not fully capture vegetation, water bodies, and urban morphology. Therefore, it should be interpreted as an indicative transition range rather than a universal applicability boundary. For dew point, the bias did not markedly increase/decrease when the station had a different ISA ratio (Figure S5).

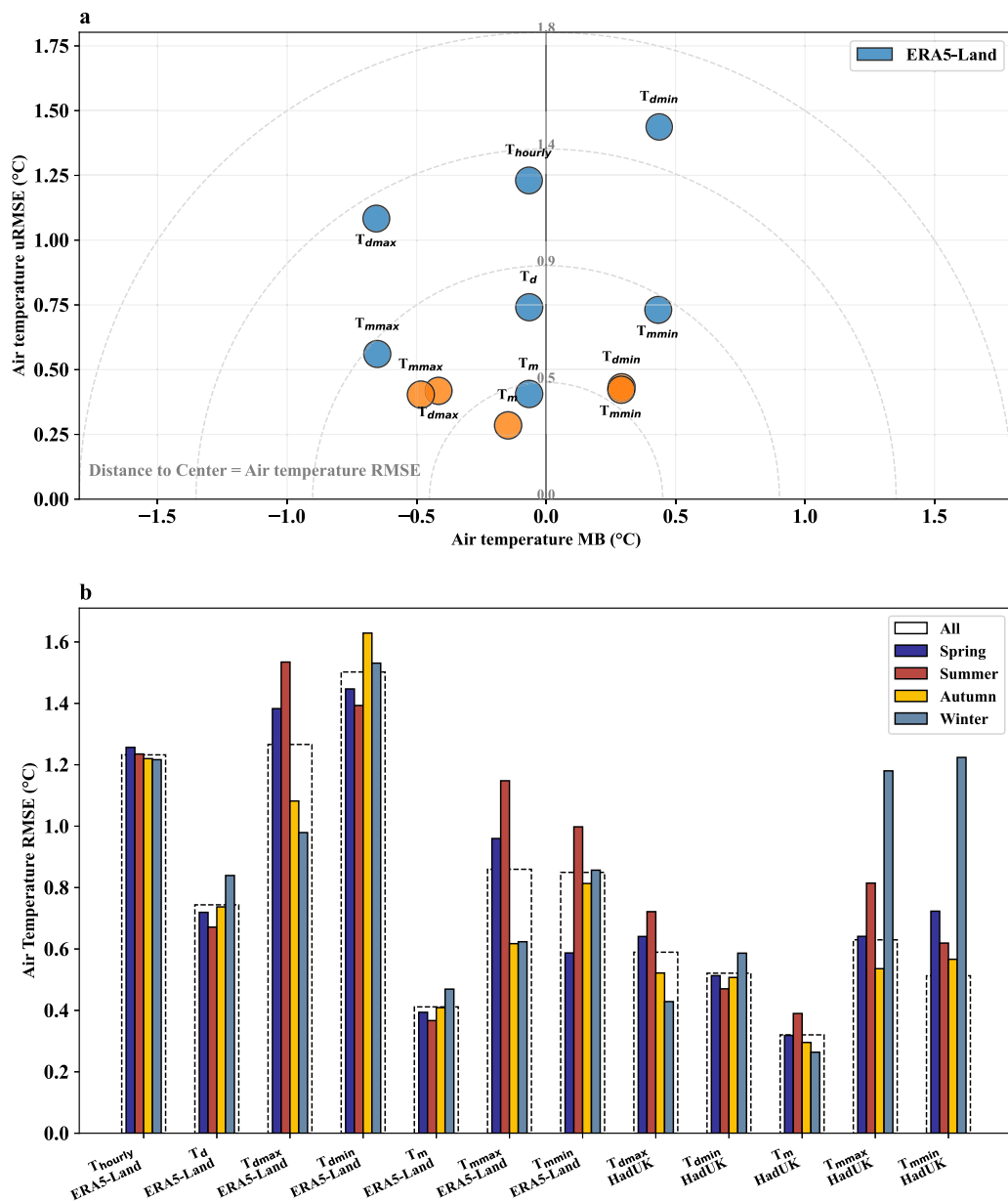


Fig. 1. Air temperature error metrics of ERA5-Land and HadUK-Grid compared to MIDAS. **a** Target plot of temperature across different indices and data sources. Blue color is ERA5-Land and orange color is HadUK-Grid. **b** RMSE of ERA5-Land and HadUK-Grid compared to observational data in different seasons. “hr”: hourly; “d”: daily; “m”: monthly; “dmax” and “mmax”: maximum of daily and monthly, respectively; “dmin” and “mmin”: minimum of daily and monthly, respectively.

We also investigated the correlations among mean bias of air temperature, ISA ratio of 500 m radius, distance to the coast, and station elevation (Figure S6). During the day, the relatively stronger correlation between mean bias of air temperature and ISA ratio ($r = -0.22$, $p < 0.05$), compared with station elevation ($r = 0.12$, $p < 0.05$) and distance to the coast ($r = 0.05$, $p > 0.05$), suggests that ISA ratio is a primary relevant factor for the observed daytime ERA5-Land air temperature bias. In contrast, during the night, the mean bias shows stronger correlations with distance to the coast ($r = -0.41$, $p < 0.05$) and station elevation ($r = -0.37$, $p < 0.05$), while the correlation with ISA ratio ($r = -0.24$, $p < 0.05$) is less pronounced. These results suggest that the factors associated with ERA5-Land air temperature bias vary between daytime and nighttime conditions. While daytime air temperature bias is more related to ISA ratio, nighttime air temperature bias appears to be more associated with coastal influence and elevation.

We grouped the data according to the ISA_{500} and ISA_{grid} classifications (Fig. 4). For the low-local and low-background zone, an air temperature MB of nearly 0 °C indicates that ERA5-Land performs well in rural areas. In the low-local and high-background

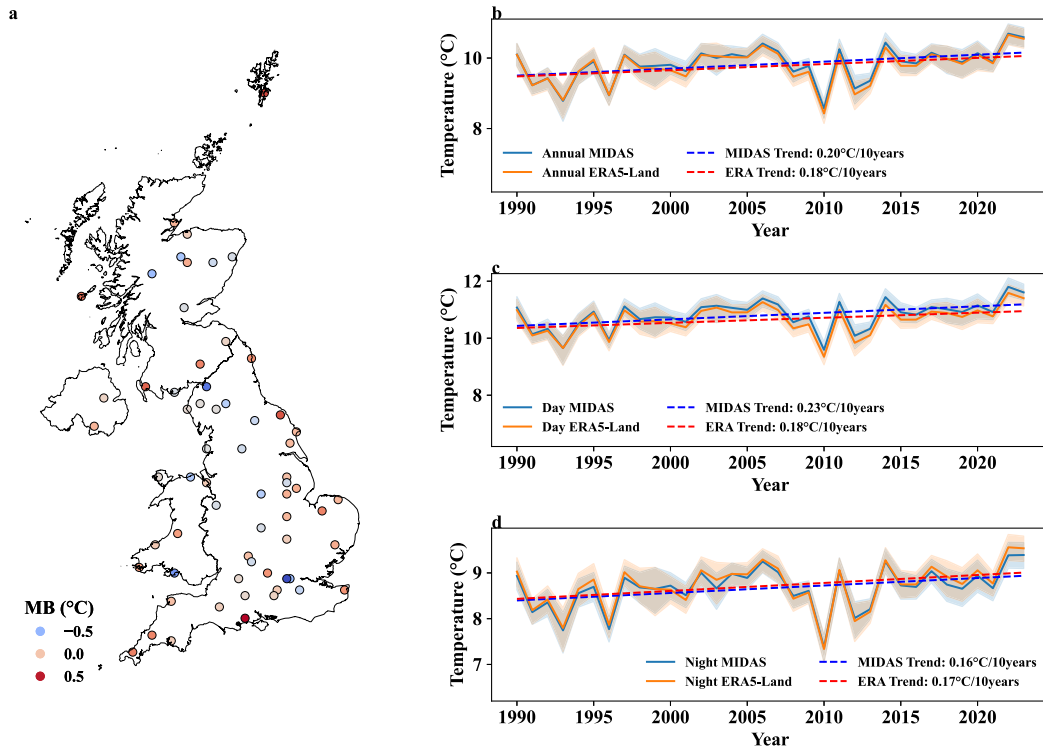


Fig. 2. Spatial distribution of air temperature error and the warming trends. **a** Spatial distribution of the mean bias (MB) of air temperature. **b** Annual mean of air temperature and its trends. **c** Annual mean of air temperature at daytime and its trends. **d** Annual mean of air temperature at nighttime and its trends. Daytime is from 06:00 to 18:00, while nighttime includes the periods from 00:00 to 06:00 and from 18:00 to 24:00. The detailed statistical information of trend estimation is presented in Table S1.

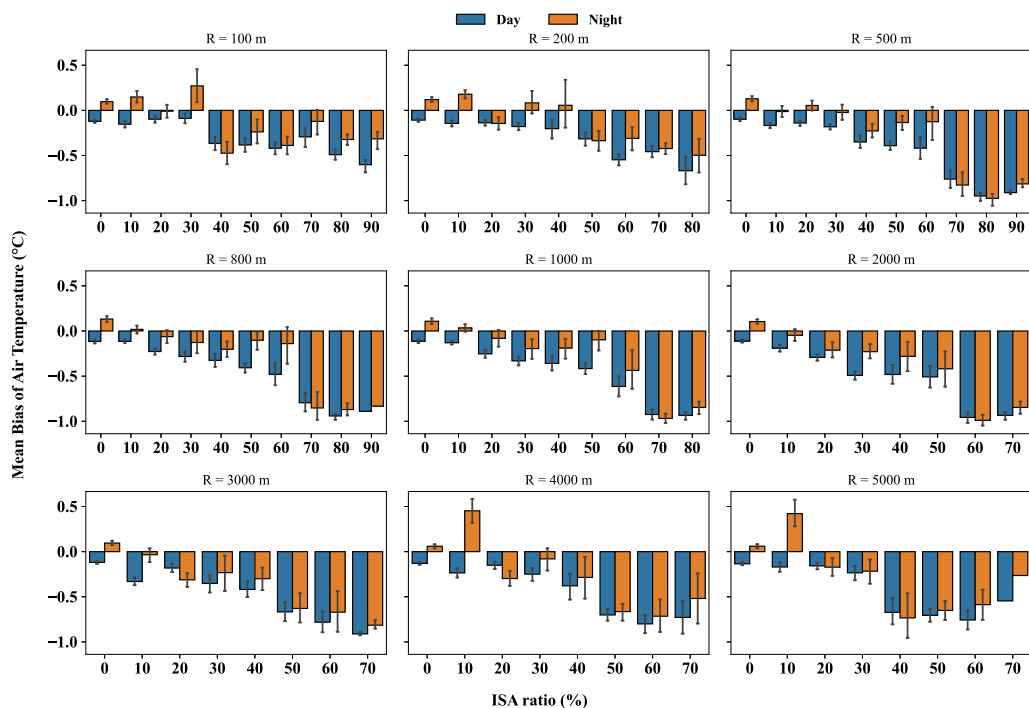


Fig. 3. Effects of the ISA ratio around the observational stations on air temperature bias. “R” indicates the radius of buffer to calculate the ISA ratio of the observational stations. Error bars are the 95% CI. Mean bias is calculated separately for each ISA group using Eq. (1).

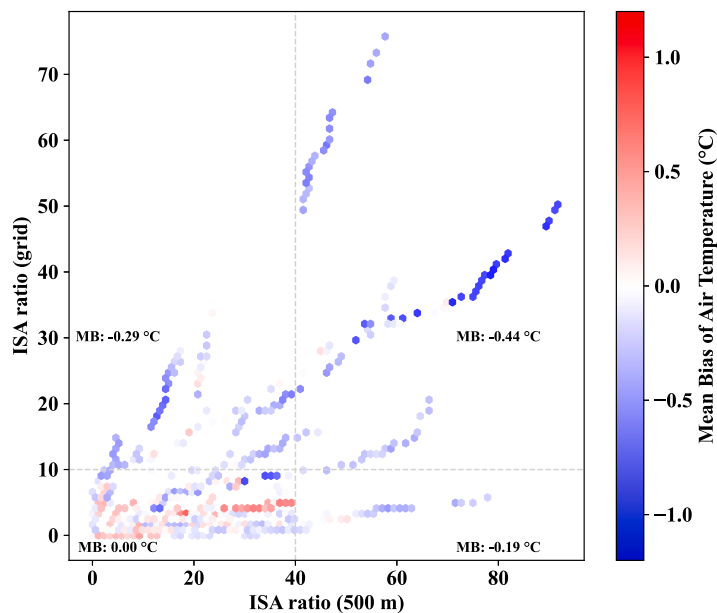


Fig. 4. Effects of the ISA ratio around the observational stations and the ISA ratio of ERA5-Land grid cells on air temperature bias. Mean bias is calculated separately for each ISA group using Eq. (1). The color of bin represents the cumulative value.

zone, the air temperature MB drops to -0.29°C . This underestimation occurs because the model lacks the physical representation of urban processes, failing to reproduce the warming felt by stations induced by urbanization. The bias is more evident in the high-local and high-background zone, where the bias reaches -0.44°C . This is attributed to the localized and background urbanization jointly affecting the station air temperature. In the high-local and low-background zone, the air temperature MB (-0.19°C) is still larger than that of the low-local and low-background zone. This is likely caused by the spatial averaging of the ERA5-Land grid, which smooths out localized urban heat signals. Therefore, ERA5-Land air temperature biases are jointly influenced by localized urban effects surrounding stations and the insufficient representation of urban surfaces within the model grid.

While temporal aggregation (from hourly to monthly scales) reduces the overall magnitude of air temperature RMSE by mitigating random noise, the disparity in RMSE between different built surface covers becomes more pronounced (Fig. 5). Specifically, at the hourly scale, the air temperature RMSE shows minor fluctuations with increasing ISA_{500} . However, when aggregated to daily and monthly scales, the air temperature RMSE gap between built-up and non-built-up areas widens markedly. This temporal aggregation can reduce random errors, and then highlights the systematic errors of ERA5-Land in estimating air temperatures in built-up areas (Fig. 5). Similarly, dew point RMSE does not exhibit a marked trend with ISA_{grid} (Figure S7). With ISA_{500} increasing, the dew point RMSE decreases slightly (Figure S7). It should be noted that the smaller sample size in high ISA groups mainly reflects the uneven distribution of UK weather stations, which are less frequently located in highly built-up areas (Zhang et al., 2026). This sampling imbalance may affect the representativeness of high-ISA results.

3.3. Urban-rural heat difference of ERA5-Land

The above results indicate that the built environment affects the performance of ERA5-Land data. However, ERA5-Land can reproduce the UHI effect, especially the yearly average UHI (Fig. 6). ERA5-Land tends to underestimate the UHI in summer (and nighttime) while overestimating the UHI in winter (and daytime) (Fig. 6).

Results from MIDAS indicate that the annual exposure curves of extreme air temperature for urban and rural stations are similar, although urban stations experience slightly more hot hours. ERA5-Land can also reproduce a similar pattern, with urban areas experiencing similar hot exposure hours compared to rural areas. However, ERA5-Land largely underestimates the extreme air temperature exposure time in both urban and rural areas (Fig. 6).

Heat stress is affected not only by air temperature but also by atmospheric moisture. We conducted a supplementary analysis using Humidex. Humidex combines air temperature and humidity information and was used here to examine whether the temperature-based exposure patterns were qualitatively altered when dew point differences were also considered. Following Buzan et al. (2015), a Humidex threshold of 30°C was used to indicate discomfort conditions. The Humidex analysis suggests a similar pattern with air temperature, indicating that the ERA5-Land can capture the difference in urban and rural areas, but underestimates the yearly exposure hours compared to MIDAS (Figure S8). The annual curves of MIDAS and ERA5-Land are generally similar in shape, although differences in peak values are evident. These results indicate ERA5-Land air temperature and dew point may not fully capture the extreme heat exposure. Due to the limited number of eligible urban-rural station pairs, this assessment reflects selected station-pair characteristics rather than a comprehensive nationwide evaluation.

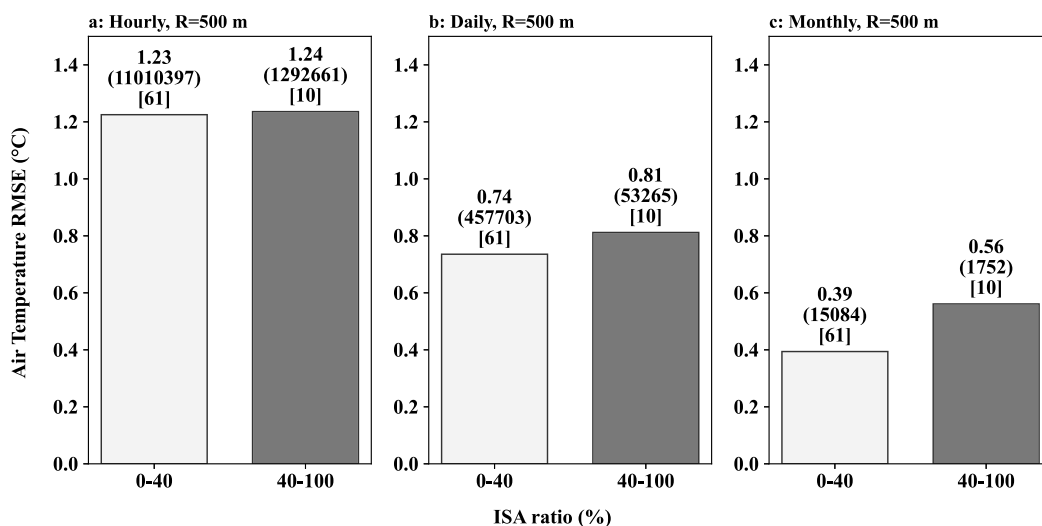


Fig. 5. Comparison of air temperature RMSE across hourly, daily, and monthly scales under different ISA ratio groups at a buffer radius of $R = 500$ m. The labels above the bars represent the RMSE, the number of samples in (-), and the number of stations in [-], respectively. RMSE is calculated separately for each ISA group using Eq. (2).

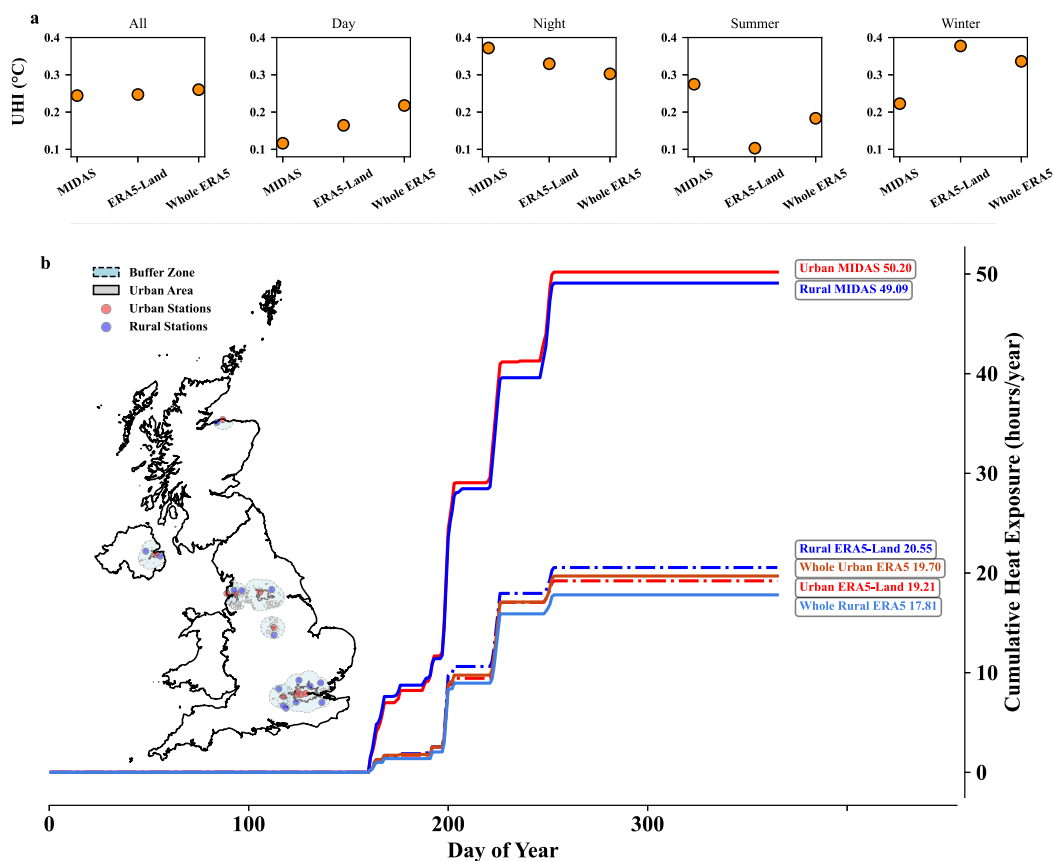


Fig. 6. Urban heat island, paired urban-rural stations map and extreme heat exposure time. **a** Urban heat island across different data. **b** Paired urban-rural stations map and extreme heat exposure profile. The map shows the selected urban boundaries, rural buffer zones, and paired urban-rural stations. Whole ERA5: the air temperatures are area-weighted from the ERA5-Land grid for urban/rural areas.

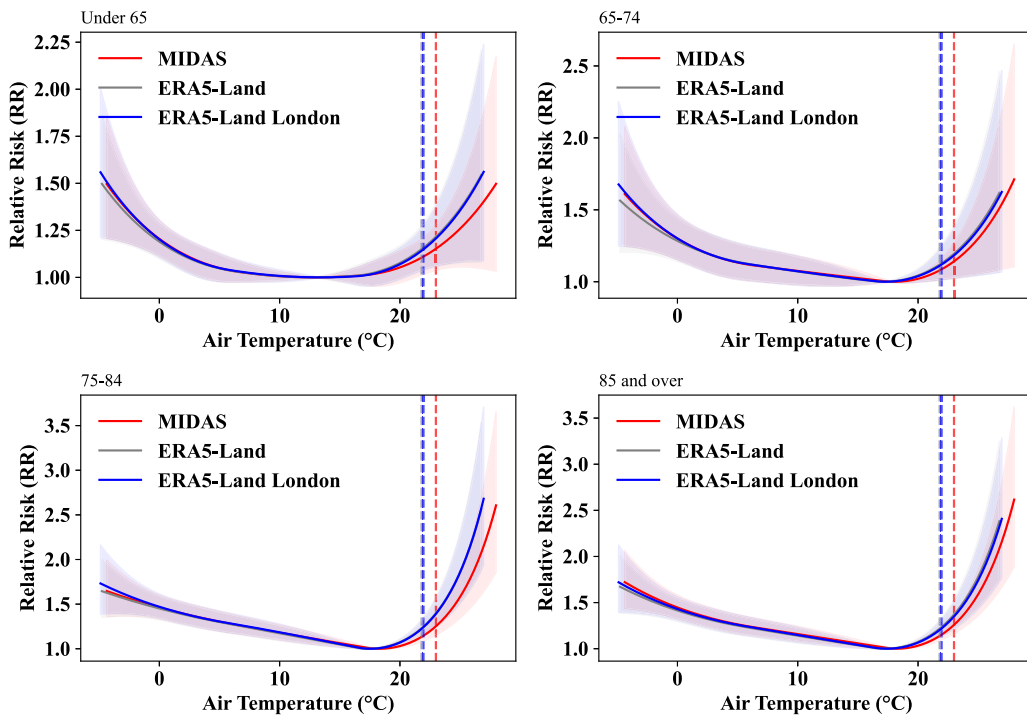


Fig. 7. Association between temperature and all-cause mortality. ERA5-Land London: the air temperatures are area-weighted from the ERA5-Land grid. The dashed line is the 99th quintile.

3.4. Case studies: Impacts on the implication to mortality risk and energy modeling

To better understand the implications of ERA5-Land air temperature and dew point biases for downstream applications, we conducted mortality risk and building energy modeling case studies. These case studies serve as sensitivity analyses to examine how biases in ERA5-Land air temperature and dew point propagate into downstream model outputs. The results show that the relative risk (RR)-temperature curves constructed using ERA5-Land data are similar to those obtained from MIDAS, indicating that air temperature of ERA5-Land is a good proxy (Fig. 7). At temperatures above the minimum mortality temperature (MMT), the cumulative RR derived from ERA5-Land is higher than that derived from MIDAS. The elevated RR can be attributable to the dampening of temperature extremes of ERA5-Land (Section 3.1). This compression of the temperature range forces the model to estimate a steeper exposure-response relationship, resulting in higher RR. The analysis of attributable numbers (AN) reveals distinct error patterns between heat- and cold-related mortality. Specifically, the ERA5-Land-derived estimates for heat-attributable AN (calculated as the median of 1000 Monte Carlo simulations) occasionally exhibit an underestimation exceeding 10% relative to MIDAS (Fig. 8). In contrast, cold-attributable AN overestimation consistently remains below 10%. These findings suggest that ERA5-Land data are prone to larger biases when attributing mortality to heat exposure compared to cold exposure.

ERA5-Land tends to underestimate cooling loads by 2.90% to 3.14%, while overestimating heating energy consumption by 3.11% to 3.38% (Fig. 9). Consequently, the difference in total energy estimation is marginal, ranging from an overestimation of only 0.58% to 0.64%. These trends are consistent with the findings of Tang et al. (2021). However, the magnitude of the bias in our study is smaller, as the analysis of Tang et al. (2021) also accounted for wind corrections. These relatively minor discrepancies suggest that ERA5-Land temperature and dew point can serve as a viable alternative for building energy estimation in data-scarce regions.

4. Conclusions

This study evaluated the efficacy of ERA5-Land surface air temperature and dew point for urban climate characterization and heat exposure estimation, and presented case studies on mortality risk and building energy analysis. Our findings reveal that ERA5-Land cannot capture the daily amplitudes, with daily maximum air temperature underestimated by 0.66 °C on average and daily minimum air temperature overestimated by 0.44 °C. In urban areas, ERA5-Land tends to underestimate air temperature, which becomes stronger with increasing impervious surface area ratio. These biases propagate unevenly into impact assessments. In extreme heat exposure hour estimation, ERA5-Land underestimates annual extreme heat exposure hours in both urban and rural areas. In case study of mortality risk modeling in Greater London, ERA5-Land and MIDAS produce similar overall RR-temperature curve shapes, but ERA5-Land can underestimate heat-attributable deaths by more than 10%, while cold-attributable differences are generally

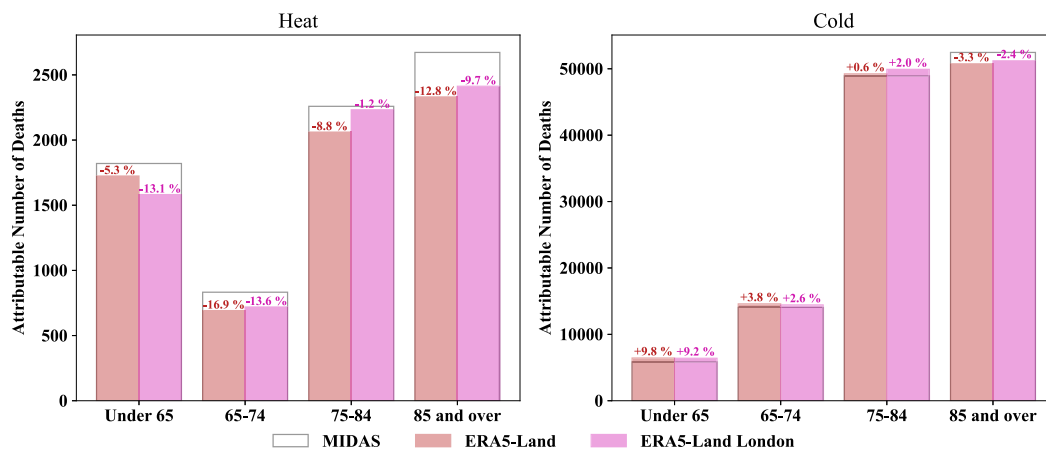


Fig. 8. Attributable number of deaths associated with air temperatures from different sources. “Heat” and “Cold” indicate that the air temperatures are higher/lower than the minimum mortality temperature derived from DLNM. The label of each bar is the difference between ERA5-Land data and MIDAS.

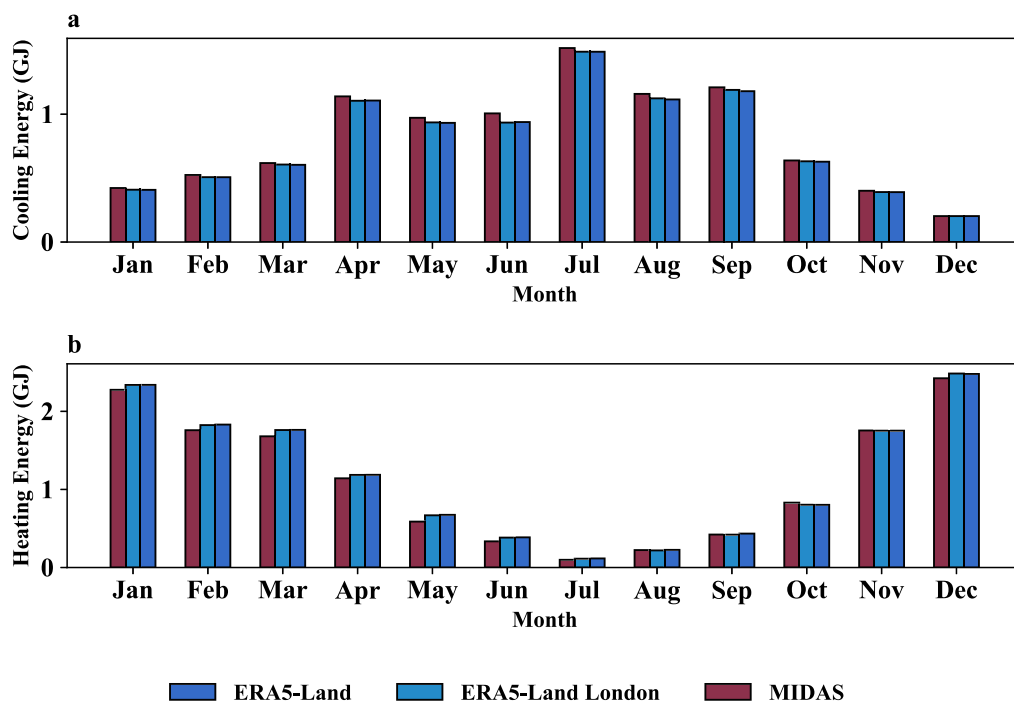


Fig. 9. Energy consumption using different sources of air temperature and humidity. ERA5-Land London: the air temperatures are area-weighted from the ERA5-Land grid.

within 10% (overestimation). For building energy analysis case, ERA5-Land underestimates cooling demand by 2.90%–3.14% and overestimates heating demand by 3.11%–3.38%, leading to a small total-energy bias (0.58%–0.64% overestimation).

Notably, the evaluation presented in this study is limited to the UK. Therefore, the quantitative errors may not be directly transferable to regions with different climate regimes, urban forms, and station densities. Although we analyzed long-term station records and multiple applications, the mortality risk assessment was constrained to Greater London due to data accessibility, which limits the generalizability of attributable-risk estimation. Similarly, the building energy analysis was based on a simplified case and therefore cannot fully represent the real urban environments. Moreover, we focused on surface air temperature and dew point, without evaluating other meteorological drivers relevant to heat stress and energy use (e.g., wind speed and radiation). Radiation was excluded due to the limited availability of long-term, quality-controlled observations, while wind speed was not evaluated because surface roughness, measurement height, and station exposure complicate direct comparison with ERA5-Land grid-mean fields. As a result, the downstream mortality risk and building energy analyses should be interpreted as case studies of air temperature and dew

point bias propagation, rather than full multi-variable assessments of heat stress or building energy modeling performance. Future work should address these limitations through a broader multi-region framework and more application-specific model chains.

CRediT authorship contribution statement

Junjie Yu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Wenyuan Li:** Writing – review & editing, Validation. **Lingcheng Li:** Writing – review & editing, Validation. **Divya Kumar:** Writing – review & editing, Validation. **Hongyu Sun:** Writing – review & editing, Validation. **David O. Topping:** Writing – review & editing, Validation, Supervision. **Guoqiang Tang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation. **Zhonghua Zheng:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

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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Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.uclim.2026.103088>.

Data availability

The scripts and data to reproduce the results and figures are available at https://github.com/envdes/code_ERA5-Land_UK_urban_eval.

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