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Short-term association between hot nights and mortality: a multicountry analysis in 178 locations considering hourly ambient temperature

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A R T I C L E I N F O

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A B S T R A C T

Background: The rise in hot nights over recent decades and projections of further increases due to climate change underscores the critical need to understand their impact. This knowledge is essential for shaping public health strategies and guiding adaptation efforts. Despite their significance, research on the implications of hot nights remains limited.

Objective: This study estimated the association between hot-night excess (the sum of excess heat during the nighttime above a threshold) and duration (the percent of nighttime with a positive excess) based on hourly ambient temperatures and daily mortality in the warm season over multiple locations worldwide.

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Methods: We fitted time series regression models to mortality in 178 locations across 44 countries using a distributed lag non-linear model over lags of 0–3 days, controlling for daily maximum temperature and daily mean absolute humidity. Next, we used a multivariate *meta*-regression model to pool results and estimated attributable burdens.

Results: We found a positive, increasing mortality risk with hot-night excess and duration. Assuming 0 as a reference, the pooled relative risks of death associated with extreme excess and duration, defined as the 90th percentile in each index, were both similar at 1.026 (95 % CI, 1.017; 1.036) and 1.026 (95 % CI, 1.013; 1.040). The overall estimated attributable fractions were also observed to be closely similar at 0.60 % (95 % CI, 0.09; 1.10 %) and 0.62 % (95 % CI, 0.00; 1.23 %), respectively.

Discussion: This study provides new evidence that hot nights have a specific contribution to heat-related mortality risk. Modeling thermal characteristics' sub-hourly impact on mortality during the night could improve decision-making for long-term adaptions and preventive public health strategies.

1. Background

The Intergovernmental Panel on Climate Change (IPCC) stated that the rise in hot days and nights over most land areas is virtually certain (Seneviratne, et al., 2021). There is also clear statistical evidence of a significant increase in minimum temperatures recorded in 70–75 % of continental measurements (Smith et al., 2013; Cox et al., 2020; Mishra et al., 2015). Nighttime exposure has likely been exacerbated in urban areas due to the known heat island effect and increasing rapid urbanisation worldwide, and it is projected to intensify further in the coming decades, with the consequent greater impacts on human health, energy demand, and overall urban livability (Laaidi, 2012; Heaviside et al., 2017; Deilami et al., 2018; Sun et al., 2019; Macintyre et al., 2021; Rodrigues, 2023; Rodrigues et al., 2021). Moreover, in the context of climate change, heat-related mortality extremes of the past climate will eventually become commonplace under warming levels of 1.5 °C and 2 °C (Lüthi et al., 2023), while anthropogenic climate change has already contributed to a third of heat-related deaths, as documented by Vicedo-Cabrera et al. (2021).

The heat-related mortality risk has been well documented by numerous studies, most of them focused on daytime exposure or the exposure across the entire day (Gasparrini et al., 2015; Guo et al., 2017; Son et al., 2019; Green et al., 2019; Zhao et al., 2021; Burkart et al., 2021; Alahmad et al., 2023; Rodrigues et al., 2020). Other studies explicitly focused on rapid adaptation and addressed different dimensions of the thermal environment, such as intra-day and inter-day temperature variability, demonstrating independent effects on mortality (Wen et al., 2024). The elevated temperature at night, however, can exacerbate heat-related risks not only by prolonging thermal stress but also by depriving the human body of essential nocturnal rest. Heat can lead to alteration and deprivation of sleep due to the necessary processes of thermoregulation (Buguet, 2007; Joshi et al., 2016; Lan et al., 2017; Obradovich et al., 2017; Royé, 2017; Royé et al., 2021; Murage et al., 2017; Rifkin et al., 2018; Buguet et al., 2023; Chevance et al., 2024). In particular, the initial stage of sleep, compared with subsequent phases, is described as the most sensitive and can show major alterations due to the accumulative effect of heat stress (Okamoto-Mizuno et al., 2005; Okamoto-Mizuno and Mizuno, 2012). In fact, rising night temperatures could impact human sleep globally, according to a recent study (Minor et al., 2022). They may erode 50–58 h of sleep per person-year, with climate change producing geographic and socioeconomic inequalities, as some populations have greater resources (e.g., air conditioning, infrastructure, or public health strategies), although this does not always imply effective adaptation (Martín and Paneque, 2022). Furthermore, higher temperatures have been associated with prolonged QT segments (Mehta et al., 2014), hypomethylation of TLR2 (Bind et al., 2014), lower HDL and higher LDL levels (Halonen et al., 2011), and reduced heart rate variability (Ren et al., 2011), all of which are associated with cardiovascular mortality.

On the other hand, studies focused on nighttime temperature and mortality often rely on the use of daily minimum temperature as an exposure indicator. However, this is a controversial metric for that purpose, as the minimum temperature is typically reached not during the night but in the early morning hours. Current evidence on heat-related mortality risks could greatly benefit from a detailed nighttime perspective based on more accurate indicators (Vicedo-Cabrera et al., 2016; Lubczyńska et al., 2015).

Recently, Royé et al. (2021) quantified the effects of the night thermal environment on mortality using indices based on hourly local temperature data. In particular, the indices developed by Royé (2017) focused on the night excess and duration of thermal stress with potential synergy effects (Murage et al., 2017). In an ad-hoc search of studies focusing on nighttime mortality effects, we found only regional or local analyses, mainly from Asia, using various statistical methods and metrics, including, in some cases, the Hot Night excess metric (Table S1). The rise in hot nights over recent decades and projections of further increases due to climate change underscores the critical need to understand their impact and to develop new public health actions and adaptation planning (Rodrigues et al., 2021; Lee and Hughes, 2017; Hurlimann et al., 2021; Wang et al., 2021; Choi et al., 2022; van Daalen et al., 2022; Goodwin et al., 2023). This study is novel in developing dynamic, sub-daily hot-night excess and duration metrics—based on hourly temperatures and a 90-day rolling 95th-percentile threshold—that isolate nocturnal heat effects while controlling for daytime heat and humidity within a unified distributed-lag *meta*-regression across 178 global cities.

This study aims to fill that gap by estimating the effects of hot-night excess and hot-night duration—two complementary hour-based indices— during the warm season in different locations worldwide, characterised by different climates and socio-economic features. The assessment used a state-of-the-art analytic approach that controls for daytime heat and humidity while accommodating between-city heterogeneity, considering the complex association between nighttime temperatures and mortality.

2. Methods

2.1. Data collection

The study area includes 178 cities from 44 countries worldwide. Daily counts of deaths for natural (ICD-10: A00-R99) or all-cause were assembled from these locations through the MCC Collaborative Research Network (Gasparrini et al., 2024). The city selection was based on the availability of hourly temperature data, which was rarely available before the 2000s. The meteorological data was obtained from the Integrated Surface Global Hourly Dataset, which is accessible via the National Oceanic and Atmospheric Administration (NOAA) (https://www.ncdc.noaa.gov/isd), and from the French and German national meteorological services (Météo-France, DWD) for the corresponding cities in Germany and France. The weather stations chosen for this research are mainly located at the airports of each city. Despite a finer temporal resolution in some cities, hourly average air temperatures were calculated for all locations. In a linear regression model, missing values were estimated using the nearest reanalysis point (to the centre of raster cells) of ERA5-Land data (Royé et al., 2020). Additionally, the daily mean absolute humidity from ERA5-Land was extracted to control for its potential effects, as meteorological station data were unavailable for all locations. A descriptive data summary of all included locations is presented in Table S2.

2.2. Hot night indices

The indicator proposed by Royé (2017) and Royé et al. (2021) relies on hourly air temperature data during each hour i in each day j within the study period (T_{ij}). The hot night duration (HNd) index, which describes the duration of the nighttime heat, is calculated as the sum of hours during the night for which a temperature threshold (T_{thr}) is exceeded. Subsequently, the value obtained is divided by the total number of night hours to allow direct comparisons between all nights in the year. Therefore, HNd is expressed as a percentage of night hours exceeding a threshold (Eq. (1)):

$$HNd_j = \frac{\sum_{i=1}^{n_j} \mathrm{I}_{Tthr_j}(t_{ij})}{n_j} \cdot 100 \tag{1}$$

where n_j is the number of night hours of day j, t_{ij}: mean temperature during the hour i in day j, and I_{Tthr} the index function of $\{x \in \mathbb{R} | x > T_{thr}\}$, that is:

$$\mathrm{I}_{Tthr}(t_{ij}) = \begin{cases} 0 if t_{ij} \le Tthr \\ 1 if t_{ij} > Tthr \end{cases}$$

A second index (Eq. (2)), hot night excess (HNe) in °C, allowing for the evaluation of nocturnal thermal stress, is obtained through the sum of excess heat during the time period with temperatures equal to or greater than Tthr.

$$HNe_j = \sum_{i=1}^{n_j} (t_{ij} - Tthr_j) \cdot \mathrm{I}_{Tthr}(t_{ij}) \tag{2}$$

In each city, we defined Tthr as a moving 95th percentile of minimum temperature with a window of the previous 90 days. For each calendar day t, the threshold is recalculated using only the set of minimum-temperature observations recorded in the immediately preceding 90-day period (from day t–90 through day t–1) The local specific thresholds consider population acclimatization processes for each climate zone. In addition, we decided to include a moving window of 90 days to capture the seasonal past to consider the idea that people acclimate to their local climate with respect to its temperature variation throughout the year (Nairn and Fawcett, 2014; Brown et al., 2022). Night of day t is defined as the local period between the sunset of day t and the sunrise of day t + 1. All the necessary processes for calculating the indicators were carried out with the statistical environment R (version 4.3.2) (R Core Team, 2023). The Sun-methods {maptools} package, which uses the NOAA algorithm, was used to calculate the hours between sunset and sunrise.

2.3. Warm season identification

We restricted the period to the warm season in each location to develop the timing indices and evaluate their association with mortality analyses. The set for the warm season in each city was based on the respective detrended series of daily mean temperature and defined as at least five consecutive months with monthly averages over 10 % of the general mean (Wilks, 2019; Pyrina et al., 2021).

2.4. Statistical analysis

A two-stage approach was used to examine the associations between the two hot nights indicators and daily mortality. In the first stage, city-level effect estimates were obtained by applying a conditional quasi-Poisson regression (Armstrong et al., 2014) to seasonal data with a distributed lag nonlinear model (DLNM) (Gasparrini, 2014). We controlled for daily maximum temperature (Tmx) to obtain the independent effect of night-attributable mortality, and we also controlled for absolute humidity (ahum), which was considered a potential confounder.

$$Y_{it} \sim poisson(\mu_{it})$$

$$log(\mu_{it}) = \alpha_{it} + cb(HN_i, nlag = 3)_t + cb(Tmx_i, nlag = 10)_t + ahum_{it},$$

where Y_{it} is the count of deaths on day t in location i; α_{it} is the specific intercept for the stratum, st, in which the day t is included, with strata defined as the same calendar day of the week of the same month within the same year; cb is the cross-basis function for each HN index HN_i and daily maximum temperature $(Tmx)_i$ in location *l, both* at the percentile scale. The cross-basis was applied to lags of 0–3 days and 0–10 days for HN and Tmx, respectively. They were defined by: (a) a natural cubic spline for the dose–response relationship, with two internal knots placed at the 50th, and 95th percentiles of the indicator distribution excluding zeros, and (b) another natural cubic spline for the lag-response relationship, with one and two internal knots for HN and Tmx, respectively, placed at equally spaced values in the log scale. The specific model parameter choices described in the previous paragraph were selected using QAIC from a wide range of possibilities: {3, 5, 7, 10} as the maximum number of examined lags (allowing for different choices for Tmx and HN), {1, 2, 3} as the possible number of knots for lag-response relationships, and {(25, 75), (50, 90), (50, 95), (10, 90), (10, 95)} as potential knot locations for dose–response relationships.

In the second stage, an extended multivariate *meta*-regression model was built to summarise the reduced cumulative associations among locations (Gasparrini et al., 2012; Sera and Gasparrini, 2022). The model was specified as a two-level hierarchical random-effects *meta*-regression with city nested in country by climate zone as a random-effect structure and the average of temperature as a fixed-effects predictor. This *meta*-analytical model was selected after exploring the heterogeneity explained by the geographical, climatic, and socio-economic characteristics of cities by including each characteristic, one by one, as fixed-effects predictors in a basic *meta*-analytical model without a hierarchical random-effects structure. Concretely, we tested the following variables: geographical region (region), Koppen-Geiger climate classification (Kottek et al., 2006) in the four main categories (kz), the average of annual temperature (avtmean), the range of annual temperatures (rgtmean), the range of HNe > 0 values (rangeHNe), the percentage of days with HNd reaching the maximum (100 %) (p100HNd), deprivation, human development index (human_develop), human modification of terrestrial system (human_modterrest), land surface summer maximum temperature (lst_summer_mx) (Florczyk et al., 2019) (MCC Database (Gasparrini et al., 2024).

We used our *meta*-analytical model (avtmean as fixed effect predictor and city nested country by climate zone as random structure) to make predictions of the overall relative risk at extreme excess and duration defined as the 90th percentile of positive values (HN > 0) with respect to no excess (0 in each index). Also, we transformed RR into attributable fractions (AF), more easily interpreted by both the public and policy-makers, by using the common procedure in the DLNM context, further described elsewhere (Gasparrini and Leone, 2014). The overall and extreme attributable fractions are defined as the mortality fraction attributable to HN > 0 and HN > 90th percentiles, respectively. We also summarized attributable fractions by region, country, and climate zone by using the exposure–response curves for each location derived from our *meta*-analytical model (BLUP curves). All models, statistical analyses, and graphic results were performed with the free software environment R, version 4.3.2 (R Core Team, 2023).

2.5. Sensitivity analyses

The adequacy of our models and the robustness of our results were evaluated using several proofs and sensitivity analyses:

1. QAICs across the wide range of model specifications (n = 180) tested were primarily sensitive to specifications related to the lag window width. Therefore, we explored the sensitivity of the overall curves to model specifications within a smaller subset covering the most relevant paradigms for this parameter. This subset included our model (the one with the lowest QAIC) as well as the worst-performing model in terms of QAIC from the full set.
2. We explored the sensitivity of the results to not controlling for absolute humidity and not controlling for daily maximum temperature.
3. We explored the sensitivity of the results (overall curves) to the use of other typical daily metrics (daily minimum and daily mean) as a control since the beginning, i.e., before selecting the lag window for our indices.

3. Results

3.1. Hot night indices and mortality set

Over all analysed locations, 73 % showed a threshold higher than 20 °C, ranging between 14 °C in Ecuador and 36.7 °C in Kuwait. The spatial distribution of hot night excess and duration of the 178 locations in 44 countries during the study period is shown in Fig. 1. The multi-city, multi-country analysis is characterised by different climates and socio-economic features. On the whole, the hot night excess is geographically coherent, as it delineates some of the physiographic and landscape units in the affected countries, mainly showing latitudinal effects and continental influence. The highest values were observed in the Central and South-eastern Mediterranean Basin with a median of daily hot night excess from 30 °C to up to >70 °C. The percentage of warm season days with hot nights ranges from 20 % to 99 %, with a variability expected due to local climate differences. The hot night duration index showed similar spatial patterns but was more variable. The median of daily HNd varies between 20 % and 100 %. It is relevant to remember that a high HNd value does not necessarily result in high night excess. In total, more than 14 million all-cause deaths within the period 1990–2018 were analysed in this study. A descriptive data summary of all included locations (listed in Table S2) is presented in Table S3.

3.2. Hot night mortality associations

The overall pooled hot night indices-mortality association, even controlled by diurnal temperature, shows a monotonic, close to a linear increase in relative risks (RR) (Fig. 2). The difference in shape between HNe and HNd is minimal; while the second displays an increased slope at higher doses, the former shows a slight decrease, but both were closely linear (linearity test p-values = 0.56 and 0.78, for HNe and HNd, respectively).

The pooled RRs of death associated with extreme excess (90th percentile HNe, 27.2 °C) and duration (HNd, 93.7 %) were 1.026 (95 %

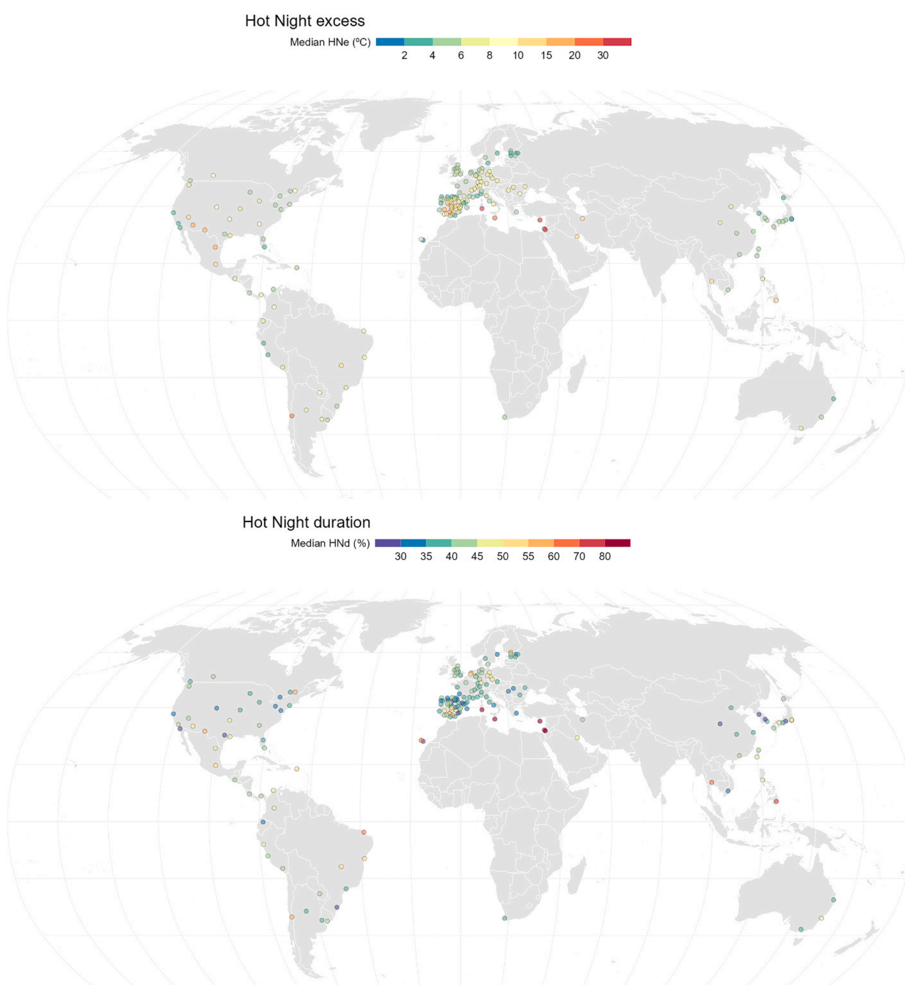

Fig. 1. Average hot night excess (HNe) and hot night duration (HNd) for the study locations.

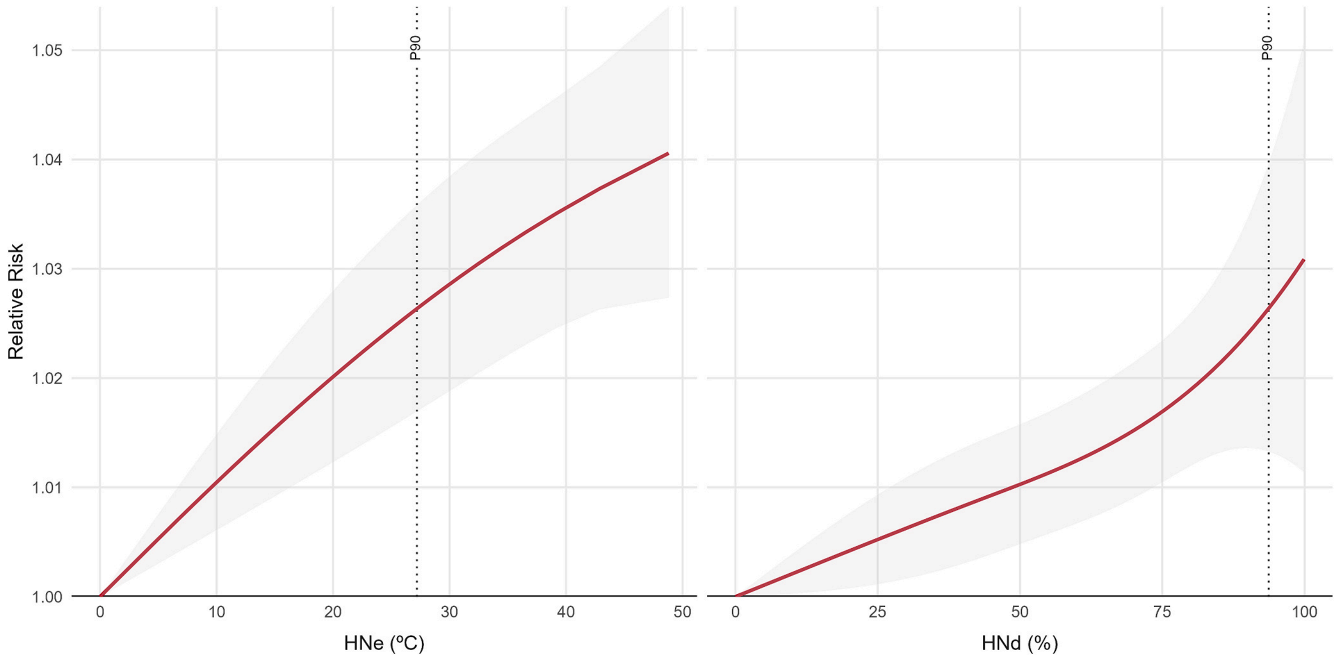

Fig. 2. Pooled exposure–response relationships between hot night indices, hot night excess (HNe) and hot night duration (HNd), and relative risk (RR) of mortality from 178 cities in 44 countries.

CI, 1.017; 1.036) and 1.026 (95 % CI, 1.013; 1.040). The overall estimated attributable fractions (AF) were also closely similar at 0.60 % (95 % CI, 0.09; 1.10 %) and 0.62 % (95 % CI, 0.00; 1.23 %), respectively. The lag structure for extreme excess and duration showed the highest risks on the same and the first day after exposure, decreasing steadily up to 3 days after the exposure (Fig. S1).

Avtmean, Region, country, and the interaction between country and climate zone explained heterogeneity as separate fixed-effects predictors in both indices in the basic model, with the latter being the most relevant in terms of reducing I^2 but considerably increasing AIC. Thus, we opted to choose a *meta*-analytical model for both indices that includes country by climate zone as a random effect and avtmean as fixed effects. Our *meta*-analytical model (summarised in Table S4) showed moderate heterogeneity for the overall dose–response association ($I^2 = 32.2$ % and 24.1 %, for HNe and HNd, respectively) and improved all of these basic models in terms of AIC. Interestingly, a socio-economic indicator, human development, was a fixed-effect predictor marginally explaining heterogeneity in our *meta*-analytical model, but only for HNe, so we decided not to include it.

Regarding sensitive and additional analyses, QAICs among the different sets of tested configurations, results were primarily sensitive to the lag window width. In particular, those models with higher QAIC were those with a long lag window for HN and a short lag window for Tmx, and only they showed a sensibly different pattern. All the rest parameter settings led to were pretty similar, and overall dose–response curves showed little sensitivity to the model specifications (Fig. S12). Control by ahum slightly reduced the association with our indices (Fig. S13). Control by Tmx substantially reduced but did not eliminate the association with our indices, with a slightly higher impact on the excess indices. Regarding the control by other daily metrics (Tmn and Tmean), as expected, given that our exposure is to some extent included in this indicator, the use of daily mean temperature as control almost eliminated the association. and surprisingly, the use of daily minimum temperature left the association close to the raw (no controlled) association.

3.3. Regional and climate zone associations

The regional exposure–response comparison of the differences between HNe and HNd share the general pattern (Figs. S2-3), being remarkable for HNe having the greater magnitude and uncertainty in western Asia and the non-existence for HNd of association with mortality in Northern Europe. The estimated overall AF for HNe ranged from 0.12 % (95 % CI, −0.2; 0.42 %) in North Europe to 2.5 % (95 % CI, −0.07; 4.99 %) in Western Asia (Table 1). For HNd, the highest effects were found in Western and South-eastern Asia, with 2.24 % (95 % CI, 0.39; 4.05 %) and 2.02 % (95 % CI, 0.24; 3.74 %). In some areas, the duration dimension seems less relevant than the night excess for mortality. However, the high slope found in Western Asia for excess with an RR at extreme HNe of 1.14 (95 % CI, 1.08; 1.20) and the absence of a strong association in Northern Europe for the duration with RR at extreme HNd of 1.004 (95 % CI, 0.988, 1.021) is remarkable (Fig. 3, Table S5). The greatest difference between HNe and HNd effects was in Western Asia, with an RR of 1.039 (95 % CI, 1.027; 1.052) for extreme HNd. Although the difference between the two indices was small, there was a higher risk in Eastern and South-eastern Asia for HNd (see Table 2).

Concerning the climate zones, once more, a positive trend of increasing mortality risk with increased heat can be observed for all zones (Fig. S4-5). The pattern was essentially linear, with minor deviations at higher dose levels (Fig. S4-5). The magnitude of effects ranged from 1.018 to 1.035 (Fig. 3, Table S5), slightly higher in tropical and arid climates. The highest AF with HNe is found for the arid climate, at 1.21 % (95 % CI, 0.10; 2.30 %), while the largest burden has been estimated for the tropical climate zone for HNd, at 1.17 % (95 % CI, −0.17; 2.49 %) (Table 1).

In coherence with Fig. 1, at the city level, some heterogeneity within regions and countries may be appreciated (Figs. 4, S6-11). The highest overall AFs for HNe are found in Western Asia (Cyprus and Israel) and Southern Europe (Spain and Italy), with values greater than 3 %. The lowest fractions below 0.1 % are located in the northernmost locations, for instance, Great Britain or Canada. The hot night duration index, albeit with marked differences across cities, reinforces the observed pattern. The estimated fractions were exceptionally high in Western Asia

Table 1
Overall and extreme attributable mortality fractions (%) by region for hot night excess (HNe, °C) and duration (HNd, %).

REGION	NUMBER OF CITIES	HNe AF (95 % CI)	HNe P90	HNd AF (95 % CI)	HNd P90
Overall					
Northern America	23	0.28 (−0.11–0.67)	25.8	0.35 (−0.14–0.84)	93.1
Latin America and the Caribbean	24	0.73 (−0.17–1.60)	21.8	0.61 (−0.49–1.70)	87.6
Northern Europe	17	0.12 (−0.20–0.42)	20.9	0.11 (−0.36–0.55)	100.0
Western Europe	26	0.91 (0.51–1.32)	25.9	0.80 (0.23–1.34)	97.6
Southern Europe	52	1.32 (0.67–1.92)	29.8	1.11 (0.41–1.80)	93.0
Eastern Europe	6	1.11 (0.22–1.98)	27.6	1.04 (0.13–1.93)	94.4
Sub-Saharan Africa	1	0.28 (−0.28–0.81)	19.2	0.36 (−0.46–1.18)	91.7
Eastern Asia	17	0.25 (0.07–0.43)	17.4	0.44 (0.15–0.73)	92.3
South-eastern Asia	4	1.21 (0.20–2.24)	19.0	2.02 (0.24–3.74)	90.9
Western Asia	5	2.50 (−0.07–4.99)	102.7	2.24 (0.39–4.05)	96.2
Australia	3	0.51 (0.09–0.93)	27.5	0.89 (0.33–1.44)	93.6
Global	178	0.60 (0.09–1.10)	27.2	0.62 (0.00–1.23)	93.7
>P90					
Northern America	23	0.12 (0.03–0.20)	25.8	0.06 (0.00–0.13)	93.1
Latin America and the Caribbean	24	0.21 (0.05–0.36)	21.8	0.13 (−0.02–0.28)	87.6
Northern Europe	17	0.05 (−0.03–0.12)	20.9	0.00 (0.00–0.00)	100.0
Western Europe	26	0.22 (0.13–0.32)	25.9	0.01 (0.00–0.02)	97.6
Southern Europe	52	0.32 (0.18–0.45)	29.8	0.18 (0.09–0.27)	93.0
Eastern Europe	6	0.28 (0.09–0.45)	27.6	0.19 (0.10–0.28)	94.4
Sub-Saharan Africa	1	0.13 (0.04–0.21)	19.2	0.10 (−0.07–0.25)	91.7
Eastern Asia	17	0.08 (0.04–0.11)	17.4	0.07 (0.03–0.10)	92.3
South-eastern Asia	4	0.37 (0.18–0.54)	19.0	0.10 (0.03–0.18)	90.9
Western Asia	5	0.68 (0.21–1.10)	102.7	0.24 (0.12–0.37)	96.2
Australia	3	0.18 (0.07–0.29)	27.5	0.14 (0.07–0.21)	93.6
Global	178	0.17 (0.07–0.27)	27.2	0.08 (0.02–0.15)	93.7

Note: The analysis includes data from 178 cities within the study period 1990–2020 from the Multi-Country Multi-City (MCC) Collaborative Research Network. Detailed years included by city can be found in Table S2.

and Southern Europe, reaching values above 3 %. Finally, extreme AFs were of very low magnitude but statistically significant in more locations compared to the overall (66 % vs. 50 %, respectively). A ranking of those locations with the highest AFs per continent can be found in Table S6-7 for both hot night indices.

4. Discussion

We estimated the effects of night air temperature on mortality in 178 locations in 44 countries using two thermal indices (hot night excess and hot night duration). The study found strong evidence of an increased mortality risk associated with hot-night indices across all climates and regions, except in Northern Europe, where the association was only suggestive. Despite some methodological differences, this study's findings align with those reported for Southern Europe by Royé et al. (2021). However, we used a moving 95th percentile of minimum temperature as the threshold for calculating the indices, while in Royé et al. (2021), the threshold was fixed at 20 °C (standard tropical night definition). Also, the daytime effect has now been controlled using the daily maximum temperature instead of the daily mean temperature. The substantial reduction of effect when controlling for daily mean temperature is not surprising and can be explained by the fact that it includes part of the nighttime temperature. This does not undermine the value of the results, as public health policies must be tailored according to the extent to which day and night heat is important. The average temperature fails to distinguish between night and day.

In general terms, the results indicated an association between increased mortality and nighttime heat (HNd and HNe), independent of any association with daytime temperature. This pattern is consistent with findings from previous studies on heat effects on mortality (Gasparrini, 2015; Alahmad et al., 2023; Zhao et al., 2019; Masselot et al., 2023). Likewise, our results showed that a proportion of deaths was related to extremely hot night excess and duration exposure. A similar impact was found for both HNe and HNd, in contrast to Royé et al. (2021), where duration had a lesser impact.

Our results align well with related work on hot night effects. A recent study in Japan based on different threshold definitions of minimum temperature showed strong associations in cause-specific mortality (Kim et al., 2023). The same study found a higher mortality risk from hot nights in early summer compared to late summer in all regions. In China, a comparison between daytime and nighttime high temperatures based on the hot night and day indices revealed a greater impact of nighttime heat exposure on hospital cardiovascular outpatients (Tao et al., 2023). In Switzerland, Rippstein et al. (2023) found tropical nights to be a relevant health hazard for a large part of the Swiss population. Murage et al. (2017) found an additional contribution of nighttime exposure to heat-related mortality in London, particularly for stroke. For dementia and sudden cardiac arrest-related deaths, immediate and significant risks were associated with nighttime heat in China (Wang et al., 2024; Gao et al., 2024). In India, Wei et al. (2021) found significant effects of minimum temperature, controlling for maximum temperature in Ahmedabad. Under future climate change scenarios, the hot night excess provided evidence for a significant increase in mortality risks and burdens across Japan, South Korea, and China (He et al., 2022). The observed attributable fractions in Asia are similar to those found in our study.

From a physiologic standpoint, the results are coherent with the biological mechanisms put forward to explain that changes in the thermal environment at night with different climate and socio-economic features lead to increased disorders and even death. High night temperatures can reduce the nocturnal recovery of the human body from diurnal heat stress, leading to cumulative physiological strain and increased risk of mortality and burden (Buguet et al., 2023). The potential impacts range from the cardiovascular, respiratory, nervous, and renal systems to an increase in the likelihood of suffering heart attacks, strokes, kidney failure, or dehydration (Majeed and Floras, 2022). High air temperatures during the night can lead to an increase in wakefulness and a decrease in rapid eye movement (REM) phases and slow-wave sleep, i.e., disrupt sleep quality and quantity, which can mutually impair thermoregulation, immune function, and cardiovascular health (Buguet et al., 2023; Okamoto-Mizuno et al., 2005; Okamoto-Mizuno and Mizuno, 2012; Haskell et al., 1981; Cao et al., 2022; Wan et al.,

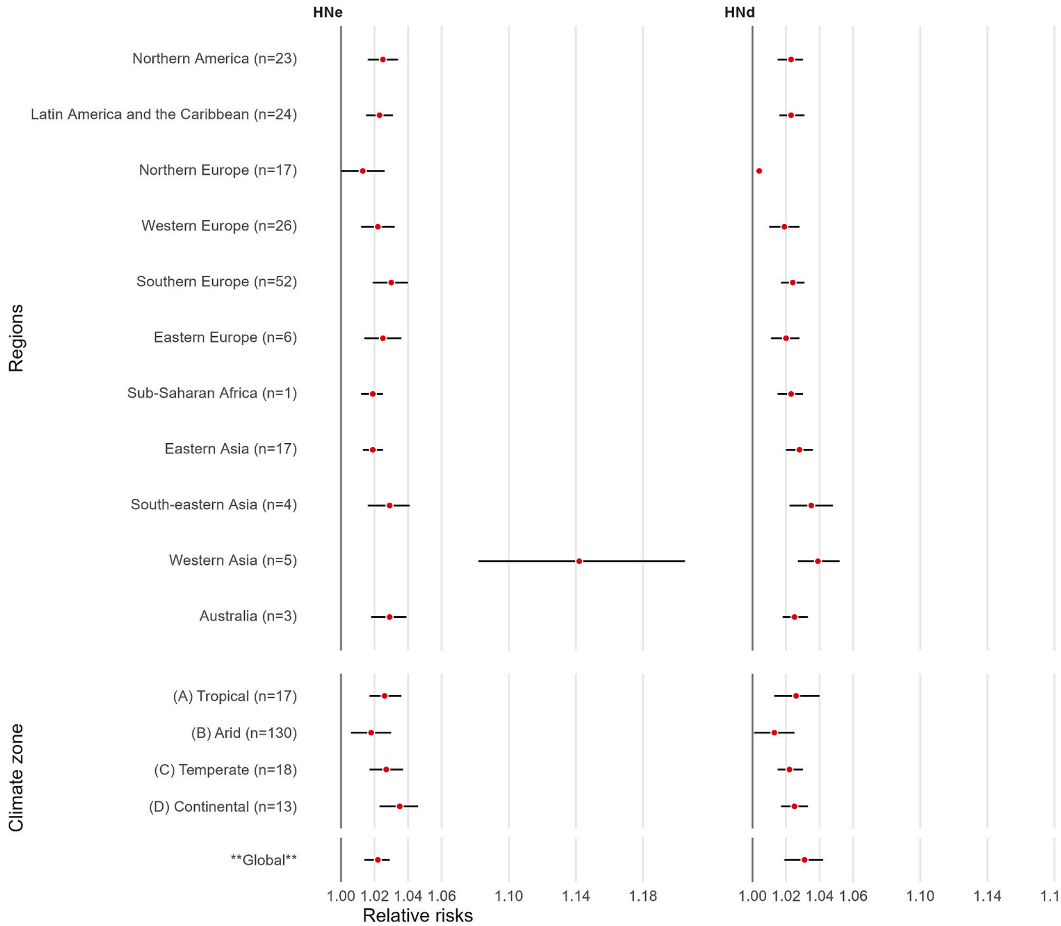

Fig. 3. Region and climate zone-specific relative risks for hot night excess (HNe) and hot night duration (HNd) at the 90th percentile with respect to 0 in each index from 178 cities in 44 countries.

Table 2
Overall and extreme attributable mortality fractions (%)by climate zone for hot night excess (HNe, °C) and duration (HNd, %).

Number of cities	Climate zone	HNe AF (95 % CI)	HNe P90	HNd AF (95 % CI)	HNd P90
Overall					
13	(A) Tropical	0.78 (0.02–1.54)	16.1	1.17 (−0.17–2.49)	89.2
18	(B) Arid	1.21 (0.10–2.30)	32.0	1.00 (−0.13–2.13)	89.6
130	(C) Temperate	0.62 (0.12–1.10)	28.1	0.63 (0.04–1.20)	94.1
17	(D) Continental	0.23 (−0.08–0.53)	24.1	0.24 (−0.17–0.64)	97.6
178	Global	0.60 (0.09–1.10)	27.2	0.62 (0.00–1.23)	93.7
>P90					
13	(A) Tropical	0.22 (0.11–0.34)	16.1	0.19 (0.02–0.36)	89.2
18	(B) Arid	0.37 (0.17–0.57)	32.0	0.21 (0.02–0.39)	89.6
130	(C) Temperate	0.17 (0.07–0.27)	28.1	0.08 (0.02–0.14)	94.1
17	(D) Continental	0.09 (0.01–0.16)	24.1	0.03 (0.00–0.05)	97.6
178	Global	0.17 (0.07–0.27)	27.2	0.08 (0.02–0.15)	93.7

Note: Main climate zones based on Koppen-Geiger climate classification (Kottek et al., 2006).

2022). Okamoto-Mizuno et al. (1999) indicate that humid heat exposure during night sleep increases the thermal load, suppressing the sleep-evoked core body temperature and increasing wakefulness. Sleep rhythm disorders can trigger and aggravate the burden on the cardiovascular system (Alahmad et al., 2023; Majeed and Floras, 2022). Joshi et al. (2016) suggested that, besides the influence of light and noise, the thermal environment is the most critical parameter that can be modulated to improve sleep quality. The same authors indicated that, in several studies, 19 °C was the preferred room temperature and deviation from this temperature was accompanied by subjective discomfort. The famous dilemma in this kind of study regarding the difference between indoor and outdoor thermal environments should not be forgotten (Höppe, 2022; Ma, 2020; Waugh, 2021). Nevertheless, people are less sensitive to changes in the thermal environments outdoors than indoors, and even thermal comfort is easier to achieve outdoors than indoors (Liu et al., 2022). Finally, in the context of the 90-day windows for the moving 95th percentile of minimum temperature as seasonal acclimatization in this study, an apparent lack of heat acclimatization due to probable frequent air-conditioning use and avoidance of outdoor activity during the hottest times of day was observed for the humid continental climate in the US (Bain and Jay, 2011). Even if seasonal heat acclimatisation is induced across different climates (Brown et al., 2022), potential reduction due to increased adaptation measures (AC, avoidance of outdoor activity) must be considered in future public health actions.

4.1. Limitations of this study

Some limitations should also be acknowledged. The first one relates

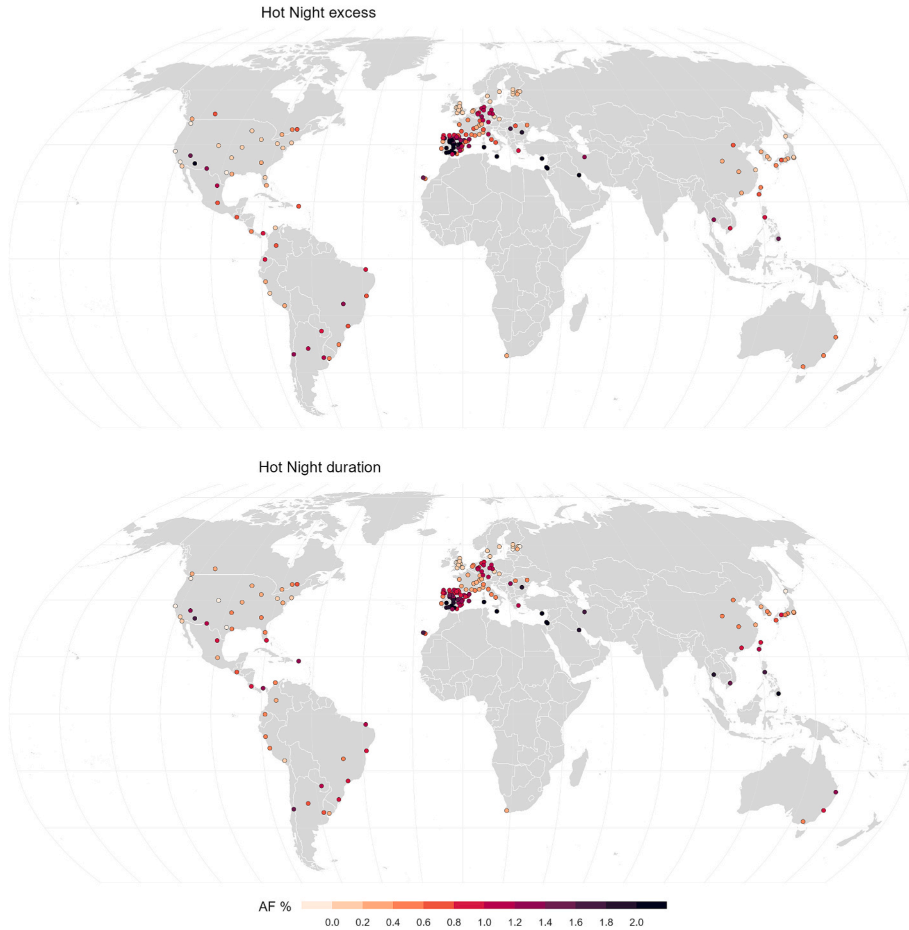

Fig. 4. City-specific hot night-mortality overall fraction (%) in the 178 cities in 44 countries.+–

to the difference between indoor and outdoor environments (nighttime heat exposure is mostly indoor), which are essential for nighttime thermal environments and will differ across locations and lead to underestimations or overestimations of the true impact of nighttime heat (Hampo et al., 2024). Individual exposure studies, for example, in New York, showed mean nighttime indoor temperatures higher than the outdoor temperature with air conditioners (AC) in summer (Quinn et al., 2017), which could affect and reduce the associated mortality relationship between ambient temperature and exposure. Specifically, they found that homes with central AC had lower indoor temperatures compared to homes with room ACs. In general, the use of AC and the thermal balance of buildings are key factors, along with infrastructure factors (i.e., green areas) and other socio-economic and cultural factors, which could influence the relevance of the metric applied in this study. In general, environmental studies based on an ecological design (time series) are unable to distinguish between indoor and outdoor exposure.

Another limitation can be seen in the exclusive use of dry-bulb temperature as an exposure metric for the hot night indices. Although we control for the effect of humidity, it may be of interest for future research to base indices on wet-bulb temperature to catch the thermal environment of both variables. Nguyen and Dockery (2016) have found that while indoor-specific humidity often tracks with outdoor humidity, indoor relative humidity can vary significantly, affecting the perceived temperature and health outcomes. In any case, there is still an ongoing debate on the role of humidity (Armstrong et al., 2019; Sivaraj et al., 2024; Baldwin et al., 2023), and the optimal metric can vary among countries and locations, as shown by Lo et al. (2023). Finally, dry-bulb temperature can perform similarly to humidity-based heat stress metrics in estimating heat-related mortality (Lo et al., 2023).

The use of hourly temperature observations has reduced the number of locations in the entire database available in the Multi-Country Multi-City collaborative research network. Weather stations with sub-daily registers are less complete than diurnal, and using other non-standardized or automated stations could also hinder data quality and completeness. The resulting number of locations is non-representative of the entire world population. In fact, there are areas with limited coverage (the Middle East, Latin America, Australia) or no coverage at all (Northern and Central Africa, Northern Asia). Even within the most represented areas, some countries or regions contributed data from a limited number of locations, making the study representative of the 178 included locations rather than the urban populations of the 44 represented countries. Further, rural populations are not represented. Another aspect in our multi-city analysis is that the study periods vary substantially between locations (for example, Shanghai data end in 2004 or many US cities in 2007, whereas other sites extend into the 2010s). Such heterogeneity may introduce temporal heterogeneity in the temperature–mortality relationship due to evolving healthcare, housing, and adaptive behaviors. Consequently, pooling results across cities without accounting for period-specific effects could bias summary estimates. Future work should consider harmonizing periods or employing time-varying meta-analytic approaches to address these trends.

Another potential limitation is the location of weather stations. The fact that most monitor stations were located at airports could lead to under- or overestimation for specific city areas due to the urban heat island effect and other urban factors. To overcome this, an alternative for future studies could be the use of reanalysis data, which has been shown to be a valid source of exposure variables, although with its limitations given the resolution of the reanalysis model and capturing local conditions (urban heat island, etc.) and extreme values (Royé et al., 2020; Mistry et al., 2022). Further comparisons at sub-daily resolution are still needed. In any case, we decided to use observational data in this study as it is the first worldwide study. Finally, the definition of the night period used in this study (time between sunset and sunrise) could be adapted to exclude, for example, the twilight phase. However, we selected sunset and sunrise as the night thresholds as objective parameters.

4.2. Policy implications

The findings of this study have important implications for public health in the context of a changing climate in which hot nights are becoming more frequent and are projected to increase in frequency and intensity (Smith et al., 2013; He et al., 2022). The increase in hot nights in the last decades led to the need for knowledge about their health effects and, in consequence, to support public health actions or adaptation planning (Lee and Hughes, 2017; Hurlimann et al., 2021; Wang et al., 2021; Choi et al., 2022; van Daalen et al., 2022; Goodwin et al., 2023). These findings suggest that future risk assessments, solely accounting for diurnal heat, may not accurately represent the true impact on disease burden. Preventive measures may need to be different for nocturnal compared to just diurnal exposure. In conditions of high nighttime temperatures, options to reduce indoor temperatures are limited (opening the windows at night may not work anymore), and that may lead to an overall increase in indoor heat exposure. The results should lead to an intensification of adaptation measures and personal protection against the hot night effects, particularly in the known context of urban environments with huge socioeconomic and exposure differentials. Hampo et al. (2024) highlight that indoor overheating is a critical facet of public health that must be addressed urgently, acknowledging direct socioeconomic repercussionsand leading to concrete protection measures. To reduce potential risks, urban climate shelters could address intersecting vulnerabilities as shown by Amorim-Maia et al. (2023). In the context of urban heat islands, increasing greenspaces in the urban environment can help mitigate the impacts of climate change (Choi et al., 2022; Iungman et al., 2023) and, therefore, reduce hot night effects on human health. Finally, we should pay attention to social and demographic factors (Rodrigues et al., 2021; Rodrigues et al., 2020). A recent study showed that the aging of the population is a significant factor influencing the rise in deaths related to heat in the context of global warming, leading to a higher mortality rate due to these temperature extremes as the population grows older (Chen et al., 2024). Consequently, we should also adapt and improve our heat-wave prevention plans with the increasing importance of anticipating the timing and intensity of events such as nighttime heat waves (Torralba, 2024). Current warning systems for extreme heat usually focus on daytime temperatures, therefore, excess heat during the night should be taken into account as a more complete health-risk assessment of future climate change. Incorporating a detailed nighttime picture, particularly at a suburban scale, could improve public health responses, resource allocation, set priorities, and adaptation strategies. Concrete measures should include targeted interventions for groups such as the elderly, children, and those with pre-existing health conditions, but also advocate for healthcare facilities (hospitals, residences, etc.) to be better prepared for increased nighttime heat-related cases, including better bioclimatic indoor environments. These factors emphasize the need for future public health policies that guarantee indoor comfort for lower-income groups and older adults, thus promoting equity in future development (He et al., 2022).

5. Conclusions

Our multicity time-series analysis provides further evidence that the hot night indices adjusted by daily maximum temperature are associated with an increased risk of death. The need for differentiated preventive measures for day and night is underscored by the results, which suggest that susceptibility to hot night excess and duration is an independent effect of an essential part of the thermal environment. Another advantage of these exposure metrics is that they more realistically reflect thermal exposure over the entire night period rather than a single-moment temperature, such as minimum temperature. The use of hourly data allows for a more detailed assessment of the thermal characteristics of warm season nights, making it possible to accurately assess the risk of hot nights for population health and wellbeing. Public health programs could integrate real-time hot-night excess and duration indices into heat-health warning systems to trigger targeted nighttime cooling interventions, resource deployment, and outreach to at-risk populations. Further research will be necessary to study the relationship between night and day heat effects in cities in other climates and examine vulnerable subgroups. In addition, it is also unknown how heat excess and duration relate to one another, and whether short periods of very high night temperature are more harmful to human health than long high temperatures.

CRediT authorship contribution statement

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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 material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2025.109719.

Data availability

The authors do not have permission to share data.

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