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# From heatwaves to 'healthwaves': A spatial study on the impact of urban heat on cardiovascular and respiratory emergency calls in the city of Milan

Doruntina Zendeli [a,b,*], Nicola Colaninno [a], Daniela Maiullari [b], Marjolein van Esch [b], Arjan van Timmeren [b], Gianluca Marconi [c], Rodolfo Bonora [c], Eugenio Morello [a]

[a] *Department of Architecture and Urban Studies, Politecnico di Milano, Milan, Italy*
[b] *Department of Urbanism, Delft University of Technology, Delft, Netherlands*
[c] *Agenzia Regionale Emergenza Urgenza (AREU), Milan, Italy*

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ABSTRACT

In recent decades, the increasing frequency, intensity, and duration of heatwaves generated by climate change has posed significant challenges to public health, particularly in urban areas. Despite extensive research on the impacts of heatwaves on human health, there is still a need for enhanced understanding of how, and to what extent, the spatial attributes of urban environments exacerbate these effects at the very local scale. This research addresses this gap and emphasises the importance of analysing the relationship among urban form, climate and health through high resolution geo-spatial data. By investigating the spatial correlations between geolocated cardiovascular and respiratory emergency calls, the modelled universal thermal climate index (UTCI) and selected socio-demographic factors during the summer of 2022 in Milan, this study aims to enhance our understanding of the complex interaction among heat, the built environment, and specific health outcomes. The findings identify geographical locations where emergency calls occur more frequently and where health concerns emerge during hot spells. Morphological and socio-demographic factors both play a critical role in determining vulnerability to heat stress. The results provide valuable insights for identifying high-risk areas, where tailored interventions in terms of planning, governance and urban design may be implemented to address heat-resilience and health-equity in cities.

## 1. Introduction

In recent decades, the adverse consequences of climate change induced by human activities have led to the exacerbation of extreme temperatures across the world, resulting in unbearable heatwaves that have become progressively severe, frequent, and prolonged (Ballester et al., 2023; IPCC, 2021; Perkins-Kirkpatrick & Lewis, 2020). The past eight years' recorded global temperatures have consistently been the highest of any previous year, and the year 2022 comes in as the fifth-highest year on record (Ballester et al., 2023; Coperncius, 2022). Among other natural disasters, heatwaves - also referred to as *'the silent killer'* can significantly impact fatality rates (Johnson et al., 2009; Klinenberg, 2002; Kotharkar & Ghosh, 2022; Luber & McGeehin, 2008). Elevated temperatures pose a significant threat to vulnerable populations, increasing the incidence of heat-related health problems (Ebi et al., 2021; WHO, 2021, 2023) and mortality (Argaud et al., 2007; Ballester et al., 2023; Martínez-Solanas et al., 2021; Robine et al., 2008). For instance, the heatwaves in Chicago in 1995 and throughout Europe in 2003 resulted in a notable increase in hospitalisations and deaths, especially among vulnerable populations, including older people, socially isolated, low-income individuals, minority groups, and those with pre-existing diseases (Bassil et al., 2009; Klinenberg, 2001; Robine et al., 2008; Semenza et al., 1996; Whitman et al., 1997). Nearly two decades after the mega heatwave of 2003, the heatwave of 2022 in Europe caused a notable number of deaths due to heat-related causes (Ballester et al., 2023). This trend is expected to intensify in the coming years, and the decisions made now and in the near future will determine how much hotter and altered the world will be for current and future generations (Romero et al., 2023).

Heat-related illness and mortality are generally linked to prolonged exposure to extreme temperatures, which hinder the body's ability to regulate its temperature, resulting in heat fatigue, heat sickness, and heat stroke (Lin et al., 2021; Meade et al., 2022; Meade, Notley, Akerman, McGarr et al., 2023). Heat stroke, a severe condition caused by the

* Corresponding author at: Department of Architecture and Urban Studies, Politecnico di Milano, Milan, Italy.
*E-mail address:* doruntina.zendeli@polimi.it (D. Zendeli).

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exposure to excessive heat, results in a body temperature of 40 °C or higher and central nervous system malfunction, which can be fatal (Quick, 2024; Sorensen & Hess, 2022). Furthermore, prolonged exposure to heat can also aggravate pre-existing medical conditions, including respiratory and cardiovascular diseases (CVD), thereby increasing mortality risk (Quick, 2024; Sorensen & Hess, 2022). While evidence suggests that heat stress avoidance strategies can mitigate health effects during heatwaves, the general effectiveness of these measures remains inadequately documented (Ballester et al., 2023; de' Donato et al., 2015).

Research on the cardiovascular system response to heat exposure is notably scarce in the literature. Cardiovascular health outcomes are primarily associated with the effect of (green) open spaces to increase physical activity, with a secondary effect on psychological effects from being active in outdoor (natural) environments (Markevych et al., 2017). Most studies have focused on individuals with heart failure (Chaseling et al., 2023) or heat-related mortality (Ballester et al., 2023; Pascal et al., 2024). However, extreme heat events worldwide have shown that adverse cardiovascular events are major contributors to illness and death, particularly among older adults and those with pre-existing cardiovascular conditions (Chaseling et al., 2023). A more recent study emphasises the disparities and vulnerabilities in urban heat exposure by exploring the relationship between heat index patterns and heat-related emergency medical service (EMS) incidents (Seong et al., 2024).

The literature indicates that CVD events can be influenced by climate-related factors, including temperature, humidity, air pressure, sunshine duration, wind intensity, and wind direction (Abrignani et al., 2022). A major constraint of these investigations is the lack of data on individual exposure to heat during heatwaves and the difficulty of obtaining comprehensive health data. Previous studies underline the significance of heat disasters in Europe and the United States (Robine et al., 2008; Semenza et al., 1996), where the leading cause of illness and mortality are not the direct effects of heat, such as heat stroke and dehydration, but rather cardiovascular complications (Chaseling et al., 2023). Myocardial infarction, in particular, is a common outcome, especially among older adults and individuals with pre-existing cardiovascular diseases (Loughnan et al., 2010; Semenza et al., 1996). Evidence for respiratory health effects is theorised by the air pollution mitigation pathway, which is well documented (Diener & Mudu, 2021; Xing & Brimblecombe, 2018). Its association with urban morphologies and green spaces is still limited (Yang et al., 2021). Current studies show a positive link between heat and respiratory conditions: higher temperatures increase respiratory diseases, hence stressing the need for more research in this area (Alari et al., 2023; Anderson et al., 2013; Fallah Ghalhari & Mayvaneh, 2016; He et al., 2022; Shao Lin et al., 2009; Zhao et al., 2019). These findings show how urgently human health impacts from heat are becoming a paramount issue (Seong et al., 2024).

In addition to the public health domain, this emergency has generated attention in the field of urban studies and other allied fields. Urban morphology aspects have the potential to reduce urban heat island effects and mitigate the exposure to heat, for example by air-exchange corridors and (green) open space (Gunawardena et al., 2017; Kuang et al., 2015; Ren et al., 2016; Wong et al., 2010). Research indicate that municipalities with less impervious surfaces, more tree coverage and green spaces, and higher incomes, had lower all-cause and cardiovascular heat-related mortality (Pascal et al., 2024). Another study employs urban morphology data and satellite-derived temperatures to identify and characterize heat-prone neighbourhoods using a data-driven approach aiming to inform urban heat management and supports evidence-based adaptation strategies in climate resilience planning (Sützl et al., 2024).

Furthermore, heatwaves in urban living environments have been investigated for their spatial and temporal consequences on cities and urban health (Chow et al., 2012; Liu et al., 2021; Ma et al., 2021; Seong et al., 2024; Tian et al., 2021). Given that heatwaves may cause significant heat-related morbidity and death (Brooke Anderson & Bell, 2011; Lee, 2014; Li & Zha, 2020), it is crucial to investigate the spatial patterns and their correlation with urban temperatures and other demographic and social factors during extreme heat events. Understanding these spatial correlations may help to create effective adaptation plans and efficient deployment of resources, decreasing heat exposure and sensitivity.

While heat sensitivity mainly depends on individual health-related factors, heat exposure is highly determined by one's immediate thermal environment. This environment is created by the interplay of humidity, wind speed, radiation coming from the sun and the reflection, absorption and re-emission of this radiation by the earth's surfaces, including buildings, ground cover and other objects, as well as the atmosphere. The perceived result of this complex interplay can be expressed as the universal thermal climate index (UTCI), which can serve as an indicator of heat exposure. A few studies have shown already that heat-related illnesses are more prevalent in areas with greater susceptibility to heat, characterised by higher levels of heat exposure, increased heat sensitivity among individuals with lower socio-economic status, and limited ability to adapt to extreme heat events (Browning et al., 2006; Cheng et al., 2021; Mallen et al., 2019). This susceptibility is often exacerbated in urban areas, where the built environment can amplify heat exposure due to factors such as heat-retaining materials, building orientation, and the dense city layout, which limits air flow and traps heat, also known as urban heat island (UHI) effect (Mills, 2008; Oke et al., 2017). However, research investigating heat patterns and related effects on urban health at a high spatial resolution remains limited, mainly due to restrictions in accessing health data and their aggregation at the census or administrative units.

This study investigates how the interrelation of urban morphology, climate, socio-demographics, and health outcomes can vary across different areas in the city of Milan, Italy, considering both scholarly debates and public awareness. The objective is not solely to understand the interaction of urban climate, urban health, and space but also to provide valuable insights into the complex nature of heat vulnerability in urban environments. Additionally, it aims to better inform climate-proof planning, public health initiatives (including preparedness and heat-health early warning systems), and emergency response strategies prioritising interventions and equity, in alignment with global sustainability goals, including the Sustainable Development Goals (SDG 3, 11, and 13).

## 2. Data and methods

### *2.1. Study context*

This study focuses on Milan, an Italian city in the northwest Lombardy region, covering 181.7 km$^2$ and home to around 1.37 million residents. Italy is currently among the European countries most susceptible to extreme heat in summer. A study by Ballester et al. (2023) identifies Italy as having the highest number of heat-related deaths in Europe in the summer of 2022, with approximately 18,010 fatalities. According to the Italian National Plan of Adaptation to Climate Change (MATTM, 2018), Milan is highly vulnerable to heatwaves and saw a notable rise in mortality rates from extreme heat during the 2003 heatwave (Conti et al., 2005; Michelozzi et al., 2006). More recently, the impact of heatwaves on public health was further evidenced by a rise in out-of-hospital cardiovascular events during the 2020–2021 period (Nawaro et al., 2023).

Milan has a continental climate marked by hot, humid summers labelled 'Cfa', a humid subtropical designation (Koppen, 1936; Peel et al., 2007). In Milan, summertime maximum air temperatures can reach up to 38.9 °C, whereas maximum humidity levels can be up to 99 %. The latter can aggravate the discomfort associated with high temperatures, exacerbating heat-related health hazards, which significantly affect urban inhabitants. In response, the municipality has introduced various initiatives to mitigate these impacts, such as '*The Plan Against Heat*' which in Italian stands for '*Piano Anticaldo*' and '*The Plan of Air and Climate*' (*Piano Aria e Clima*). Data from emergency medical services (EMS) events recorded from May to August 2020–2022 were used to identify the critical year for this study analysis, after which the data from May to July 2022 were selected for further in-depth analysis. This period aligns with the occurrence of heatwaves in Milan, enabling a thorough investigation of the patterns and correlation of EMS calls with climate and socio-demographic factors in a high spatial resolution.

### 2.2. Period of study

Given the anticipated increase in the frequency, duration, and intensity of heatwaves, it is crucial to understand their impact on people's health. However, due to the varying acclimatization and adaptation of individuals to heatwaves in different places, there is no universally agreed criterion for defining heatwaves (Liu & Qin, 2023; Tong et al., 2015). Generally, a heatwave is characterised as an extended duration of higher temperatures than normal, usually lasting more than two consecutive days (NWS, 2024; WMO, 2021). Nevertheless, even though the overall definition of heatwaves varies depending on the context, it generally refers to extreme temperature values, established thresholds (maximum, mean or average) percentiles values (90th or above) and durations (Cheng et al., 2024; Lee et al., 2018; Liu & Qin, 2023; Xu et al., 2016). As there is no official definition of heatwaves in Italy, therefore, hot periods in the city of Milan were identified using the ERA5 dataset produced by the European Centre for Media-Range Weather Forecasts (ECMWF) (Blunden & Boyer, 2021). To define a heatwave for Milan, the 90th percentile of the daily maximum temperatures of the historical period from 1980 to 2022 was calculated and compared with the daily maximum of the period of interest (in our case the year 2022). As shown in Fig. 1(a) heatwave day occurs when the daily maximum temperature in 2022 (the red line) exceeds the 90th percentile threshold (the grey line). Additionally, a comparison was conducted between two different years, specifically the heatwave events of 2003 Fig. 1(a) and 2022 Fig. 1 (b), to showcase the difference in the heatwave characteristics over time, with the highest temperatures of 2022 occurring in July.

To identify the period during which there is a significant increase in heat health-related incidents, in our case emergency calls, which can be directly associated with an extreme heat event, uses respiratory and cardiovascular emergencies from the database of the Regional Agency of Emergency and Urgency from the Lombardy Region (Agenzia Regionale Emergenza Urgenza - AREU). Unfortunately, the 2003 emergency calls data is unavailable, preventing a direct comparison to the most severe recorded heatwave hitting Milan in the past decades.

During the heatwave of July 2022, we identified days with air temperatures ranging from 34 °C to 38 °C. Among these, July 26th stood out as one of the hottest days, also recording the highest number of emergency calls. This day was selected for modelling the UTCI at a higher spatial and temporal resolution. Data on key population structure and characteristics were obtained from the recently published 2021 Census by the National Institute of Statistics (Istituto Nazionale di Statistica - ISTAT).

### 2.3. Methodology

The methodology revolves around three main steps (Fig. 2). Each step is elaborated in detail in the subsequent sections (2.3.1, 2.3.2, and 2.3.3), providing a thorough understanding of the processes and techniques employed in this study. The initial stage involves data collection and preparation, including climate, health, and socio-demographic data. The second step focuses on the spatial aggregation of data into varying grid sizes to observe spatial patterns. In the final step, spatial patterns and correlations between health outcomes, climate, and socio-demographic variables are explored, employing different methods, including descriptive analysis, spatial autocorrelation with Local Moran's I (Getis & Ord, 1992), ordinary least squares (OLS) and geographically weighted regression (GWR).

#### 2.3.1. Data sources and preparation

*2.3.1.1. Climate data.* The UTCI is a widely used bioclimatic metric selected in this study to indicate thermal perception. It assesses human physiological comfort across diverse meteorological circumstances (Jendritzky et al., 2012; Liu & Qin, 2023) and is measured in degrees Celsius with different ranges of thermal stress (perception). This measure has been used in several contexts (Heidari et al., 2024; Thapa et al., 2024; Yang et al., 2024). It expresses the perceived temperature felt by the human body including the collective influences of air temperature, wind velocity, humidity, and mean radiant temperature (Fiala et al., 2012). Mean radiant temperature is a key parameter considered when modelling UTCI, as it accounts for all types of solar radiation, such as direct and diffuse radiation, as well as long-wave radiation released by the surrounding environment, including the sky, ground, and surfaces. Research has shown that higher mean radiant temperatures are

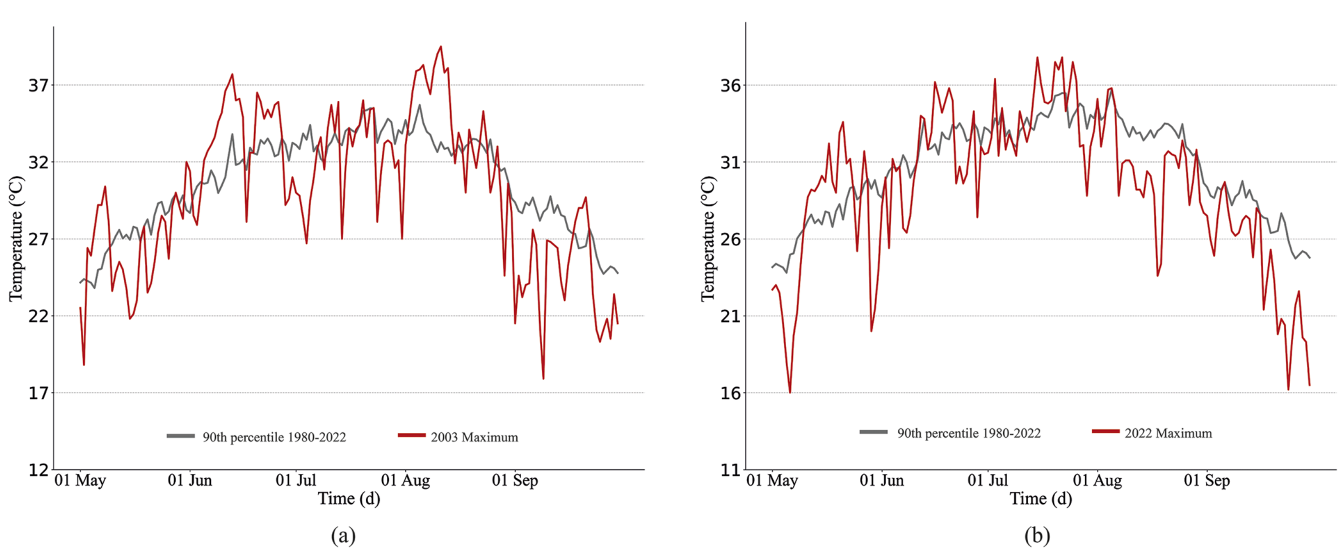



**Fig. 1.** a) Heatwaves of 2003; b) Heatwaves of 2022. Source: Authors' elaboration based on ERA5 /Copernicus data.

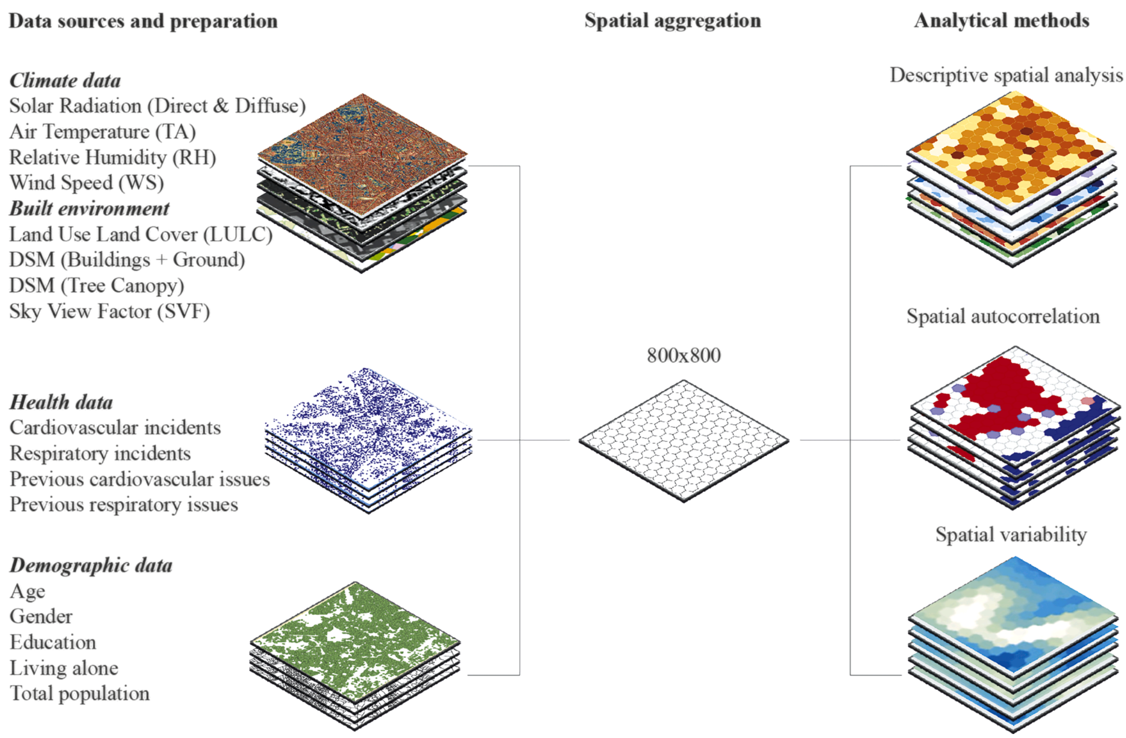



**Fig. 2.** The methodological flow.

associated with increased mortality rates (Thorsson et al., 2014). UTCI at a 1 m pixel resolution was modelled by simulating the city's climate through the LiDAR, ERA5 and Land Use Land Cover (LULC) dataset. The Urban Multi-Scale Environmental Predictor (UMEP) toolbox in QGIS was used for this step (Lindberg et al., 2018; Thorsson et al., 2007). Necessary climate input values of solar radiation (both direct and diffuse), relative humidity, and wind velocity were retrieved from ERA5. Additionally, from LiDAR data, a 1-metre digital surface model (DSM) for buildings and trees, and a digital terrain model (DTM) for the ground, were used in order to compute a high-resolution sky view factor (SVF).

In order to compute the shortwave and longwave solar energy at different times, along with UTCI, the SOLWEIG model used in UMEP was selected (Lindberg & Grimmond, 2011; Lindberg et al., 2018). This model is a globally accepted and effectively tested model in various areas with high accuracy (Buo et al., 2023; Chen et al., 2016; Lindberg & Grimmond, 2011). It incorporates LULC data to accommodate diverse albedo and emissivity values. For urban materials, the wall albedo was set at 0.20, with an emissivity value of 0.90. Ground albedo and emissivity values were sourced from the land cover map. Using the weather data from ERA5, DSM, DTM, SVF, wall height and aspect, and land cover, the SOLWEIG model computed the shortwave and longwave solar energy and UTCI.

*2.3.1.2. Health data.* Geolocated cardiovascular and respiratory emergency call records were used in this study to identify emergency medical services (EMS) potentially related to heat impacts. This dataset was provided from AREU as anonymised geolocated point data. The database contains, per each call, gender, age, time, location and any previous cardiovascular or respiratory issues. The classification of health conditions, including cardiovascular and respiratory diseases, is provided directly by AREU, which applies standardized protocols to categorize cases within emergency call data during the initial interview conducted by a qualified technical-health operator to determine the patient's principal clinical concern and severity code using conventional questions. This interview follows a standardized sequence of questions about the patient's condition, allowing for the identification of the primary clinical issue. This process ensures the dispatch of the most appropriate resources to meet the patient's specific needs. Although the data had specified the location of the calls, neither the protocol nor the database includes information on the patient's thermal conditions; for instance patients who experienced an out-of-hospital cardiovascular or respiratory event related to exposure to a sudden change in climate, i.e., such as transitioning from direct outdoor sun exposure to a cool indoor environment. Therefore, we included all data types without distinguishing between indoor or outdoor exposure. Each call has a unique patient ID, which was used to eliminate duplicates. Additionally, the data were grouped based on gender (female or male), age group (0–17, 18–59, and 60>), time of day, and if they had previous cardiovascular and respiratory issues.

*2.3.1.3. Socio-demographic data.* Socio-demographic data for this study were sourced from the 2021 census provided by ISTAT. For the spatial models several indicators were considered, such as age, gender, education level, living alone and total population. The census data were originally polygonal, representing census tracts. To integrate census data with health data in a spatial grid framework, we first distributed the census data from tracts to buildings, based on building volume, and then converted it to centroids. This study focuses on residents rather than city users, so only residential buildings were included. We re-distributed socio-demographic data across buildings using their volume, then were transformed as centroids. This process involved aggregating the latter data into a hexagonal grid for the analysis. Although this method is a proxy way to transform census data into building units and might have some limitations on redistributing some of the variables, it serves as an intermediate step to transform census data to hexagons.

*2.3.2. Spatial aggregation*

In order to analyse data of different spatial natures (points, raster, polygon), and to avoid the modifiable areal unit problem (MAUP) by using census areas of different sizes, data were spatially aggregated using a hexagonal grid to ensure uniformity in spatial analysis as well as to effectively capture the organic urban morphology of Milan. This is also supported by previous studies that have demonstrated the advantages of hexagonal grids in spatial analysis (Birch et al., 2007). On the other hand, the selection of the grid size was chosen by testing alternative grid scales, including 200, 400, 600, 800 and 1200 m (Fig. A1 and Table A.1). The analysis revealed that smaller grid sizes (i.e., 200–600 m) produced models with weaker correlations, indicating a less stable representation of spatial patterns. Furthermore, small spatial scales raised concerns about the sensitivity regarding privacy of the health data analysis at these scales. In contrast, grids larger than 800 m are beyond this study's objectives, and are inadequate to capture the community level. For this study's objectives, we found the scale of 800 m x 800 m to be suitable to identify vulnerable areas without compromising data anonymity and having consistency throughout the aggregated data capturing the community level in the city of Milan. Emergency call data points in hexagonal cells were summed for aggregation, while for UTCI we used per-pixel 90th percentile values obtained between 8 a.m. to 8 p.m. to each hexagonal spatial unit. This period covers most human activity, including regular working hours and post-work activities, capturing the hours during which people's movement and interactions are most common.

### 2.3.3. Analytical methods

*2.3.3.1. Descriptive spatial patterns.* Descriptive analysis also includes calculating summary statistics spatialised through the use of spatial aggregative units, enabling comparisons between different urban areas. Visually depicting and summarising trends in georeferenced datasets is fundamental to analyse the spatial distribution of emergency calls, socio-demographic variables, and UTCI. This analysis serves as an initial step, offering initial insights into the spatial characteristics of the data. It lays the groundwork for further spatial statistical analyses, such as spatial autocorrelation and regression models, which aim to elucidate more complex quantifiable relationships.

*2.3.3.2. Spatial autocorrelation.* We conducted a spatial autocorrelation analysis to determine whether areas with similar emergency call patterns tended to cluster geographically. Moran's I was employed to enable the predicted spatial variations and evaluate the extent of similarity in values across different locations. Moran's I is one of the most commonly known spatial autocorrelation methods used in exploratory spatial data analysis. Local Moran's I is essential for determining spatial autocorrelation at a localised level, enabling the detection of clusters with either similar or dissimilar values within a study area (Anselin, 1995; Getis & Ord, 1992). This statistic helps in understanding localised spatial processes and validating the spatial distributions observed in maps by pinpointing specific areas that exhibit significant spatial patterns. By applying spatial autocorrelation to each variable, we were able to compare and contrast the geographical distribution of cold and hot spots across the study area. This comparison facilitated the analysis of geographical patterns within the city. Hot and cold spots were found by means of spatial autocorrelation analysis of all variables considered, namely, total calls, UTCI, gender (female), age (people >60), level of education (less than high school), family status (living alone), and total population. This method assigns a label to each hexagon such as high-high (HH) and low-low (LL) to show clusters of similar values, while high-low (HL) and low-high (LH) indicate clusters of contrasting values for each variable used. This analysis facilitated a comparison of how and where hotspots and cold spots for each variable show either similar or distinct spatial patterns across the city of Milan.

*2.3.3.3. Regression models: ordinary least squares (OLS) and geographically weighted regression (GWR).* The multi-linear regression model uses the OLS to explore the linear interconnections among the dependent (the total calls) and independent variables, namely UTCI, gender (female), age (people >60), level of education (less than high school), family status (living alone), and total population, in a spatial aggregated form. To evaluate model performance more comprehensively, we also included Geographically Weighted Regression (GWR) analysis, to explore the spatial variation in correlation between total emergency calls (cardiovascular and respiratory) and explanatory factors (UTCI, gender, age and more). GWR is relevant as it captures localised relationships by allowing coefficients to vary spatially, providing valuable insights into how contextual factors influence outcomes differently across various locations. This makes GWR particularly suitable for analysing spatial heterogeneity. Table 1 describes the list of selected variables in detail. This selection was based on a statistical analysis of all the variables in the datasets and their multicollinearity. The p-value is a metric used to check the significance of each independent variables in relation to the dependent variable, usually set to $< 0.05$. A widely acknowledged principle is that if the p-value of all independent variables is less than 0.05, they are statistically significant predictors.

## 3. Results

This section presents the results and interpretations of the study. First, the total number of emergency calls (CVEC and REC) in relation to air temperature from 2020 to 2022 (Fig. 3), as well as the short and long-term effects of heatwaves on emergency calls (Fig. 4) are reported. We then examined the daily and hourly distribution of calls and air temperature across each month (May to July) of the reference year 2022 (Fig. 5), and the relationship between emergency calls and UTCI during May, June, and July 2022 (Fig. 6). Section 3.1 follows with a descriptive spatial analysis, which highlights key variables and their spatial distributions across the city. Section 3.2 showcases the examination of the spatial autocorrelation for the chosen variables, i.e., emergency calls, UTCI, gender (female), age (people >60), level of education (less than high school), family status (living alone), and total population, aiming at clustering areas with similar values. Lastly, Section 3.3 highlights the results of two different regression models on the spatially aggregated data to explore the spatial relationships between the dependent variable and explanatory variables.

Fig. 3(a) illustrates the relationship between the total emergency calls and temperature during the summer months (May to August) for the years 2020–2022, underscoring the adverse health impacts of extreme heat. Whereas the Fig. 3(b) focuses on the summer of 2022 only,

**Table 1**
Description of the datasets – dependent and independent variables.

| | *Variables* | *Descriptions* | *Source* | *Data type* | *Aggregation unit* |
|---|---|---|---|---|---|
| Independent variable | Age | Nr. of people age group 60 > | Census | Points | 800 × 800 |
| | Gender | Nr. of females | Census | Points | 800 × 800 |
| | Education | Nr. of people with lower than high school education | Census | Points | 800 × 800 |
| | Living alone | One person registered as occupying a dwelling | Census | Points | 800 × 800 |
| | Total population | Nr. of people recorded in the census | Census | Points | 800 × 800 |
| | UTCI | 90th percentile from 8 a.m. to 8 p.m. | LiDAR + ERA 5 | Raster, 1 m | 800 × 800 |
| Dependent variable | Total calls | CVEC & REC calls | AREU | Points | 800 × 800 |

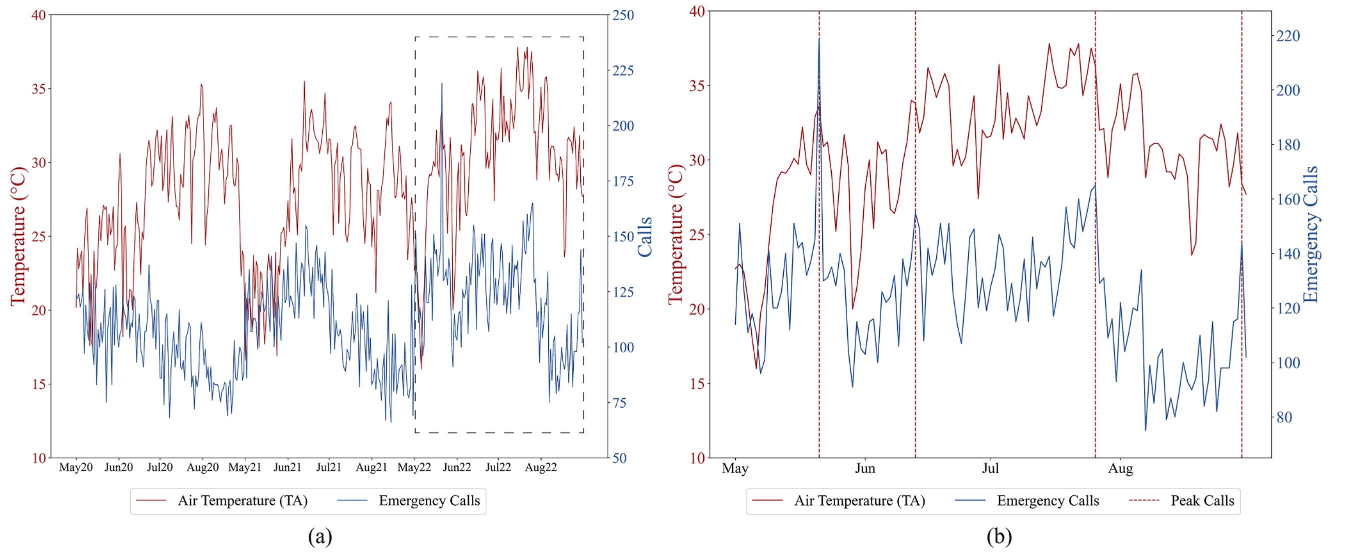



**Fig. 3.** Emergency calls and air temperature: a) Emergency calls during summer months from May, June, July, and August from 2020 to 2022 in relation to the daily maximum air temperatures; b) Emergency calls during summer 2022 from May, June, July, and August in relation to the daily maximum air temperatures. Source: authors' elaboration based on ERA5 / Copernicus and AREU data.

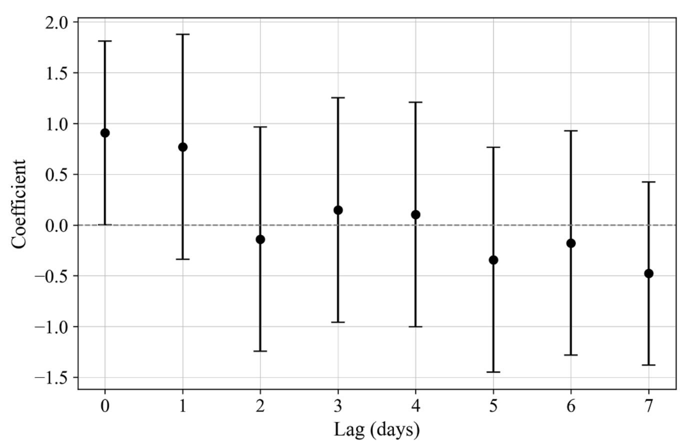



**Fig. 4.** Effects of temperature lags on emergency calls for the summer months (May to August) from 2020 to 2022 showing the coefficients of the lagged temperature variables.

highlighting the peak in emergency calls during extreme temperatures (the dotted vertical red lines) coinciding with rising temperatures, demonstrating the persistent health burden of extreme heat events in Milan. Based on our initial analysis and data, we hypothesize that the trends observed in 2020 and early 2021 were notably influenced by the COVID-19 pandemic and associated restrictions, which likely impacted emergency call patterns.

Besides, to analyse the short-term and long-term effects of heatwaves on emergency calls, a distributed lag-model was used to categorise the time-lagged impacts into two periods; short-term effects (0–1 days) and long-term effects (2–7 days) respectively (Fig. 4). Short-term effects capture the immediate health impacts of extreme heat, while long-term effects account for delayed responses, potentially due to cumulative physiological stress or lagged emergency occurrences. The analysis, based on our observations and initial findings, indicated that same-day temperature or the next day (lag 0–1) demonstrated borderline significance, whereas other lags (2–7 days) were not statistically significant (Fig. A2). This suggests that the relationship between temperature and emergency calls considering our data, reference years and context is primarily driven by short-term effects, which is in line with previous study pointing out that in Milan calls increase during heat days compared to non-heat days (Nawaro et al., 2023). It is important to note that the analysis was based on a three-year dataset, and examining a longer time period might uncover different patterns or trends.

Furthermore, based on our contextual knowledge, observations, and preliminary data analysis, we identified a significant decline in Milan's population during August 2022, likely attributed to national holidays. Since this study focuses on residents rather than city users, we excluded August from further analysis. Additionally, August 2022 did not exhibit heatwaves comparable to the preceding summer months (May to July), justifying its omission from the subsequent phases of our data analysis.

Fig. 5 shows the temporal distribution of hourly air temperature data and the corresponding number of emergency calls during the selected summer months of 2022. In May, the number of calls is notably concentrated during the afternoon hours, aligning with a moderate rise in air temperature, particularly in the second half of the month. In contrast, June exhibits a pronounced midday peak in both air temperature and the number of calls, with the hottest day around mid-month correlating with increased calls. Finally, July shows an intensified pattern, where an extended period of high temperatures corresponds with consistently elevated emergency calls throughout the day, peaking in the afternoon and early evening hours.

Additionally in 2022 overall 11,901 out-of-hospital cardiovascular and respiratory emergency events were reported from May to July, with females and elderly over 60 years being predominant compared to younger ages. When assigning UTCI values to the geolocated emergency calls from May to July 2022, as shown in Fig. 6, the distribution depicts that most calls fall within a particular range, mainly above 36 to 38°C UTCI, which corresponds to the literature stating that strong heat stress is experienced from 32 to 38°C of UTCI (Bröde et al., 2012; Skutecki et al., 2019; Yang et al., 2024). This finding provides reasonable evidence that heat stress significantly influences the incidence of respiratory and cardiovascular conditions.

### 3.1. Descriptive spatial patterns

Henceforth, the analysis will pertain to spatialised data, specifically where different variables have been aggregated within hexagonal grid cells. Fig. 7(a) showcases the 90th percentile of UTCI from 8 a.m. to 8 p.m., whereas Fig. 7(b) instead shows the aggregated pixel-based UTCI (8 a.m. to 8 p.m.) values across the hexagonal grid. It is important to note that only open spaces were considered, excluding building rooftops in

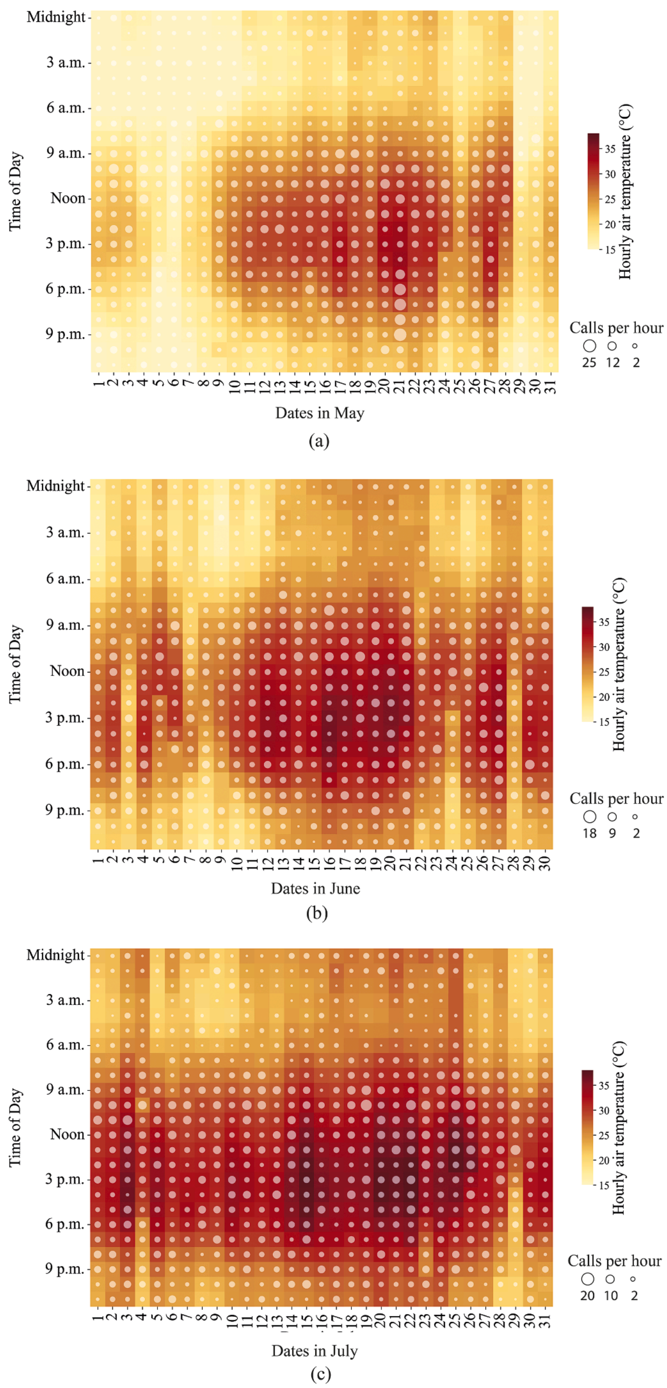



**Fig. 5.** Daily and hourly air temperature and emergency calls in May (a), June (b), and July (c) 2022.

the aggregated UTCI map. The pattern of UTCI values across the city is clear: on the outskirts where there is more presence of natural areas, the UTCI is generally lower compared to the urbanised dense areas in the city with values above 35°C of UTCI, excluding big urban parks as Parco Sempione, Giardini Indro Montanelli, Parco Vittorio Formentano, along with other smaller parks in the city.

Fig. 8(a) illustrates the spatial patterns of the total emergency call data across Milan from May to July 2022, while Fig. 8(b) presents a zoomed-in view of hexagons, illustrating varying cell densities and corresponding morphological patterns. Notably, high call volumes were reported not only in central areas such as Duomo Square, Central Station, or Garibaldi featured the most calls, but also in the eastern and southwestern regions of Milan.

The analysis of spatial distribution of total calls across hexagonal grid cells, illustrating how these calls correlate with urban density calculated as Floor Space Index (FSI) and total population, is depicted in Fig. 9. One scatterplot indicates a correlation ($R2$=0.655) between total calls and FSI, while the other shows a correlation (R2=0.749) between total calls and population density. This analysis underscores two key phenomena: (1) a contrast between primarily residential urban areas with high population and other zones featuring intense activities but relatively low population (e.g. Business districts, industrial zones, or specialized-use areas), and (2) the presence of outlier cells whose emergency call patterns deviate from the main trend, offering critical insights into site-specific challenges.

For instance, cell 226 exhibits high urban density and an elevated number of calls, reflecting a typical central area frequented by many city users and a distinct morphological configuration. Such characteristics suggest the need for tailored policies, including the strategic allocation of emergency services and enhanced public safety measures to support the large influx of non-residents. In contrast, cell 194 represents a high-density dormitory district marked by social and public housing, and a high volume of calls. This highlights the necessity of strengthening healthcare access, implementing cooling initiatives to mitigate heat stress, and addressing broader social vulnerabilities in these neighbourhoods. Meanwhile, cell 302 falls below the curve, combining low building density with a relatively large population but exhibiting fewer calls. Such a pattern may suggest that strong social networks and cohesion can bolster resilience against heat-related events (Browning et al., 2006; Klinenberg, 2001, 2002). Policymakers can leverage these findings to reinforce community ties and encourage social cohesion in urban neighbourhoods, thereby improving heat resilience during heatwaves.

Fig. 10 shows the spatial patterns of the total calls across all age groups, including both females and males extracted from AREU dataset. Specifically, Fig. 10(a) illustrates the spatial distribution of cardiovascular emergency calls (CVEC), while Fig. 10(b) depicts respiratory emergency calls (REC). Additionally, Fig. 10(c) shows the correlation between cases without previously registered cardiovascular or respiratory conditions and the total number of emergency calls. To be noted that each call has recorded information if they had either previously cardiovascular or respiratory problems. The analysis shows that emergency calls related to patients without a history of cardiovascular or respiratory conditions have a strong correlation with the total number of emergency calls, with an $R^2$ value of approximately 0.9 (Fig. 10c). This observation is particularly significant as it indicates that heat-related health impacts are not always confined to individuals with pre-existing vulnerabilities. This may be related to the severity and duration of heatwaves or other problems, suggesting a potential increase in the broader population's susceptibility to heat stress, although this has not been directly demonstrated by our analysis.

While previous figures illustrate the overall number of emergency calls and the differences between CVEC and REC, Fig. 11 focuses on the spatial distribution of calls by gender extracted from AREU dataset. Specifically, Fig. 11(a) represents total calls (CVEC and REC) among

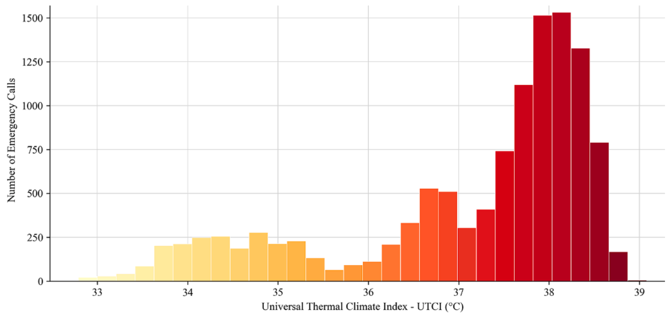



**Fig. 6.** Number of emergency calls (May, June, July 2022) in relation to UTCI.

females and Fig. 11(b) represents all calls (CVEC and REC) among men. Additionally, a scatterplot in Fig. 11(c) highlights the differences between total emergency calls and those categorised by gender, indicating that the correlation for females is slightly higher ($R^2 = 0.96$) compared to men ($R^2 = 0.94$). The latter suggests potential gender-based differences in heat-related health impacts, with females showing slightly greater vulnerability to heat compared to males. The difference of the physiological responses to heat between men and women is well documented in other studies (Folkerts et al., 2022; Ishigami et al., 2008).

The spatial maps of the calls for different age groups, specifically those aged over 60 (Fig. 12b), who generally are located farther from the city centre, and those aged 18–59 (Fig. 12a), who are predominantly concentrated around the city centre. Additionally, Fig. 12(c) features a scatterplot illustrating the correlation between age groups and the total number of calls. The analysis indicates that older people (age 60 and above) exhibit a higher correlation with the total number of calls ($R^2 = 0.86$) compared to the 18–59 age group ($R^2 = 0.83$). This reflects the greater physiological susceptibility of older individuals to heat stress, compounded by age-related factors such as reduced thermoregulation, higher prevalence of chronic conditions, and potential limitations in accessing timely care or adaptive measures. The impact of heat on the elderly has been extensively examined in prior studies (Giang et al., 2014; Vandentorren et al., 2006).

Lastly, Fig. 13 illustrates the distribution of emergency calls based on time, dividing them into two periods: 8 a.m. to 8 p.m. (Fig. 13a) and 8 p.m. to 8 a.m. (Fig. 13b). These maps reveal that daytime calls mostly occur in workplaces or busy areas, while nighttime calls are more dispersed and away from the city centre. The observed patterns align with typical urban usage, where central areas are more populated during the day by workers and visitors, while residential areas see higher activity at night when local residents are present. Additionally, Fig. 13(c) includes a scatterplot that explores the correlation between nighttime total calls and the day-time total calls, and the number of individuals living alone (the living alone data derived from Census). These variables show a correlation of the daytime with an approximately $R^2 = 0.68$, explaining the direct solar exposure, and the significance of the night-time hours and those living alone in relation to the heat-related potential emergency calls with an $R^2 = 0.73$. Additional examination of these patterns can yield valuable information for targeted urban planning and resource allocation, enhancing the efficiency of emergency responses and deepening our understanding of the city's spatial dynamics.

### 3.2. *Spatial autocorrelation of emergency calls and UTCI patterns*

In this section, we explore the spatial interdependence across several variables, including total emergency calls, UTCI, gender (female), age (people >60), level of education (less than high school), family status (living alone), and total population, using the Local Moran's I spatial autocorrelation method (Fig. A 3). The results in Fig. 14(a) shed light on clear high-high (H—H) clusters in the central and eastern urbanised

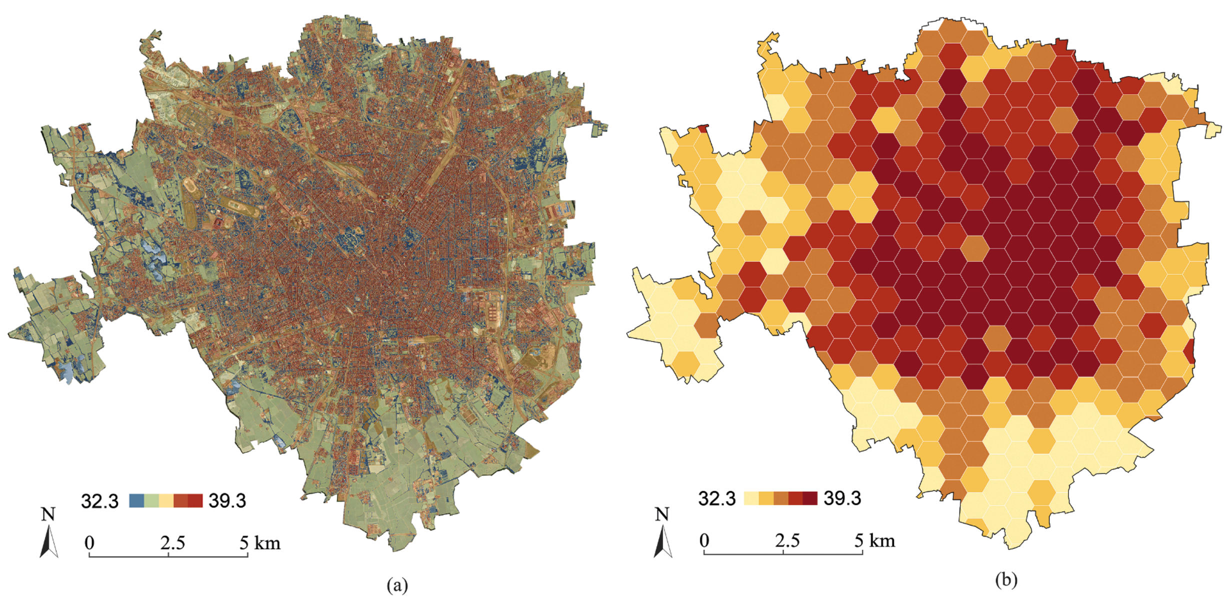
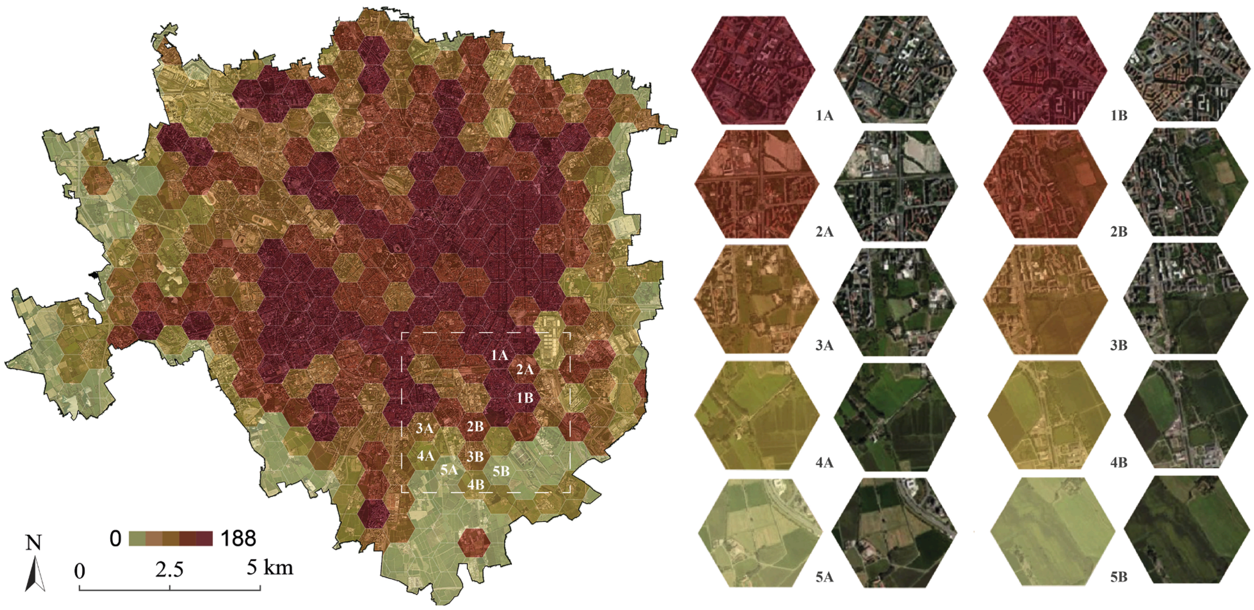



**Fig. 7.** a) The 90th percentile UTCI map from 8a.m. to 8p.m. at 1 m per pixel spatial resolution; b) The 90th percentile UTCI aggregated at the 800 × 800 hexagon grid.




(a) (b)

**Fig. 8.** a) Spatial patterns of total calls (all ages and both females and males) from May to July 2022; b) Zoom-in hexagons of different degrees of calls and morphological patterns.

areas, revealing a positive spatial autocorrelation in the distribution of emergency calls. On the other hand, low-low (L-L) clusters were mostly discovered in the peripheral agricultural regions, which have smaller population densities. The autocorrelation map further reinforces these patterns, where the red hexagons signify regions with similar emergency call frequencies, pointing to strong spatial clustering. Grey hexagons denote areas where no significant spatial correlation exists, while blue hexagons identify locations with low similarity in call numbers, suggesting a lack of clustering in these areas.

Similarly, the UTCI analysis (Fig. 14b) revealed comparable trends with high-high (H—H) clustering and positive spatial autocorrelation in central urban areas, where higher temperatures are more prevalent in the densely urbanised regions of Milan. In contrast, rural and agricultural zones exhibited lower temperatures, corresponding to a low-low (L-L) clustering pattern, which aligns with the UTCI maps presented in the previous section. These results highlight the clear spatial patterns and geographic factors influencing the observed distributions.

### 3.3. *Regression models: ordinary least square (OLS) and geographically weighted regression (GWR)*

To investigate the relationships between the dependent and explanatory variables, an ordinary least squares (OLS) and geographically weighted regression (GWR) models were used. Table 2 presents the results of the OLS model (Model I) and the GWR model (Model II). It is important to note that for both models spatial aggregated data were used. The OLS model demonstrates that the explanatory variables collectively account for a significant portion of the variance, highlighting their predictive importance. Meanwhile, the GWR emphasizes geographic heterogeneity, with the spatial variability of each variable is summarized by its mean, standard deviation (STD), minimum, median, and maximum values. These findings demonstrate the need for spatially sensitive approaches in analysing different aspects of potentially heat-related emergency call patterns. Results show that the GWR model outperforms the OLS model by capturing spatial variability, with a higher R-squared (0.883 vs. 0.816), while key predictors such as total population, low education, elderly, females, living alone, and UTCI illustrates spatial variation in their effects across the city (Fig. A4).

## 4. Discussion

The findings of this study contribute to shed light on the intricate spatial and contextual dynamics of health outcomes during heatwaves in urban environments. To the best of our knowledge, this is the first study for the city of Milan that uses very-high spatial resolution UTCI and EMS to investigate cardiovascular and respiratory emergency calls along with other socio-demographic indicators. While other studies in different contexts have spatially explored heat-related mortality or EMS and other heat-related indices (Pascal et al., 2024; Seong et al., 2024), our study differs by using high-resolution geolocated emergency calls data and modelling a widely used bioclimatic metric such as UTCI at 1 m pixel resolution in the city of Milan. In our context, the spatial distribution of calls reflects on the spatial vulnerabilities, making it a relevant dataset for understanding spatial disparities in heatwave susceptibility in line with previous studies (Jeong et al., 2024; Klopfer & Pfeiffer, 2023; Xiang et al., 2022). Although Copernicus data provide useful climate inputs and enable replication across different settings, they pose some limitations to capture fine-grained spatial variations in UTCI. To address this, we integrated high-resolution morphological data derived from 1-meter resolution LiDAR and land use/land cover (LULC) datasets. This approach enhanced the spatial precision of our model, allowing a more nuanced analysis of urban form, building orientation, and sky view factor (SVF). Such precision is critical, as accurate UTCI modelling not only improves the reliability of thermal condition estimates but also directly informs localized adaptation strategies, helping stakeholders identify high-risk areas that require urgent interventions and guiding urban planning solutions to mitigate heat stress. Consequently, our methodology ensures robust, replicable and reliable outcomes despite the inherent constraints of averaged climate datasets from Copernicus.

Moreover, we acknowledge that Milan's unique conditions may lead to some context-specific findings. Nonetheless, our methodological framework is designed to be replicable and adaptable to other urban settings experiencing similar challenges. This adaptability enables future studies to apply the approach in other locations while accommodating local distinctions. The geographical hotspots of emergency calls suggest that certain areas are disproportionately susceptible to heat-related health risks, underscoring the critical role of spatial and

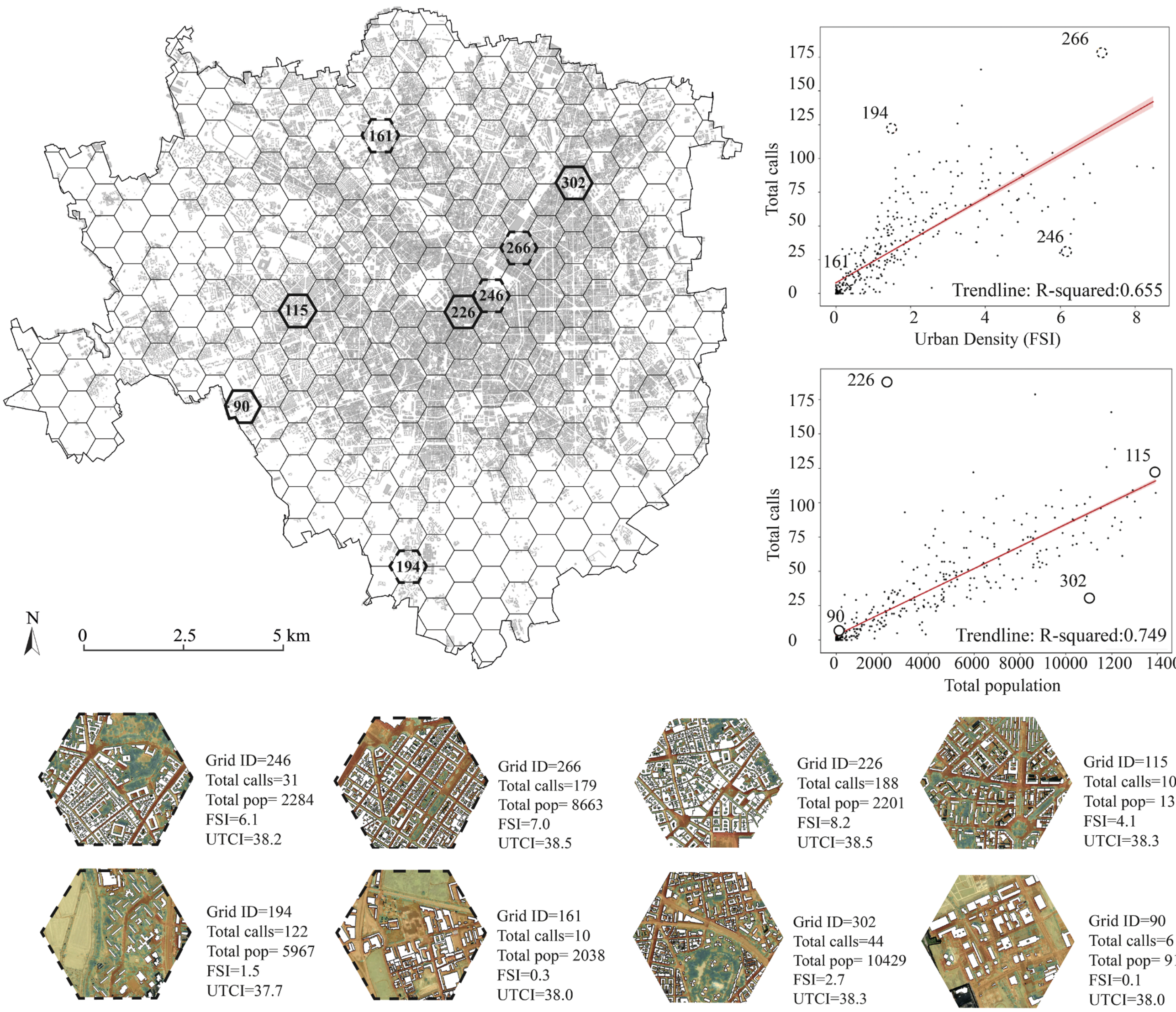



**Fig. 9.** The correlation between built-up density and population density with the total number of emergency calls, highlighting how urban and demographic factors might influence emergency response demand.

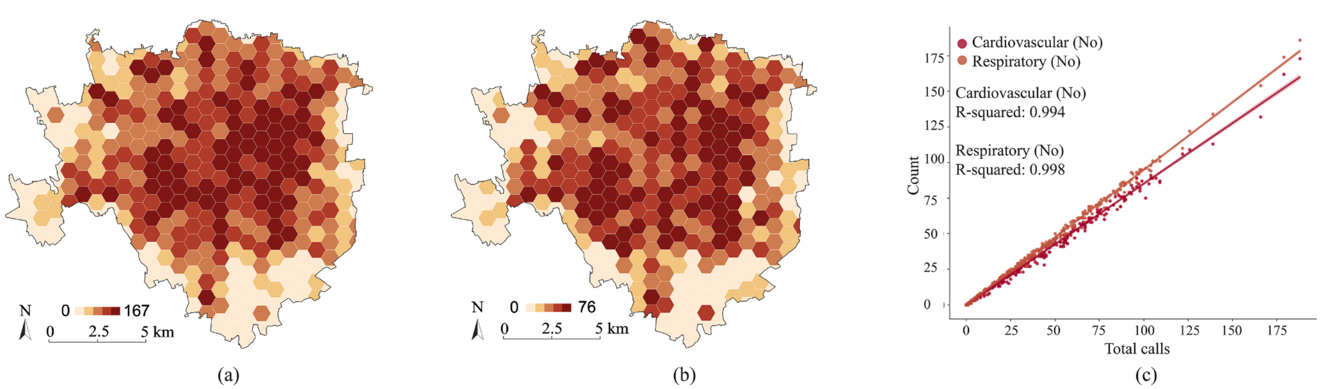



**Fig. 10.** Spatial patterns of total calls. a) Cardiovascular emergency calls (all ages and both females and males); b) Respiratory emergencies calls (all ages and both females and males; c) The scatterplot of the relationship between cases without previously registered cardiovascular or respiratory conditions from the total number of calls (data used from AREU).

social contexts in shaping public health outcomes. Given the global relevance of such challenges, an interdisciplinary approach, one that integrates socioeconomic and demographic data with thermal comfort analysis becomes essential. This broader perspective illuminates how factors such as urban form, climate conditions, and health disparities intersect to create or exacerbate vulnerabilities. For instance, demographic variables, economic status, preexisting health conditions, and social isolation all can contribute to thermal inequities (Browning

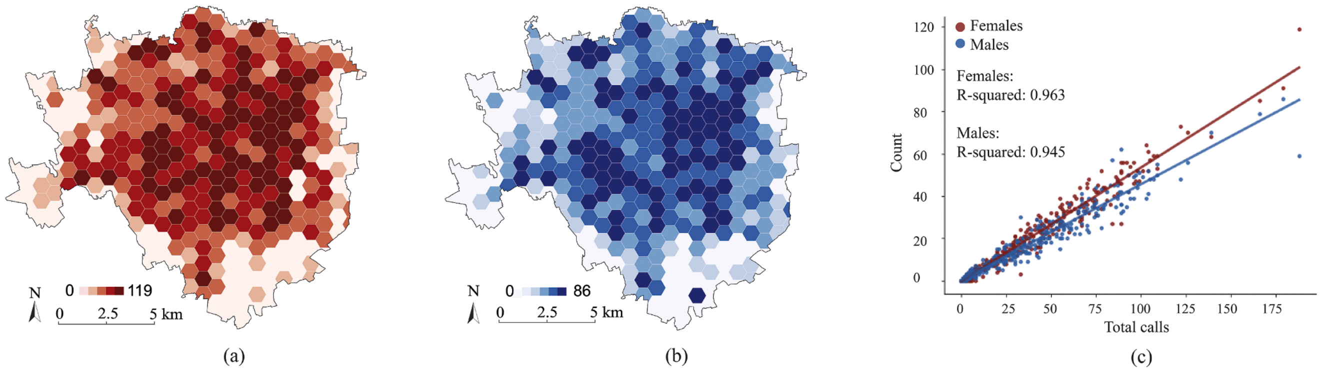



**Fig. 11.** Spatial patterns of the total calls (CVEC and REC): a) Females (all ages); b) Males (all ages); c) The scatterplot showing the relationship between total calls by both females and males (data used from AREU).

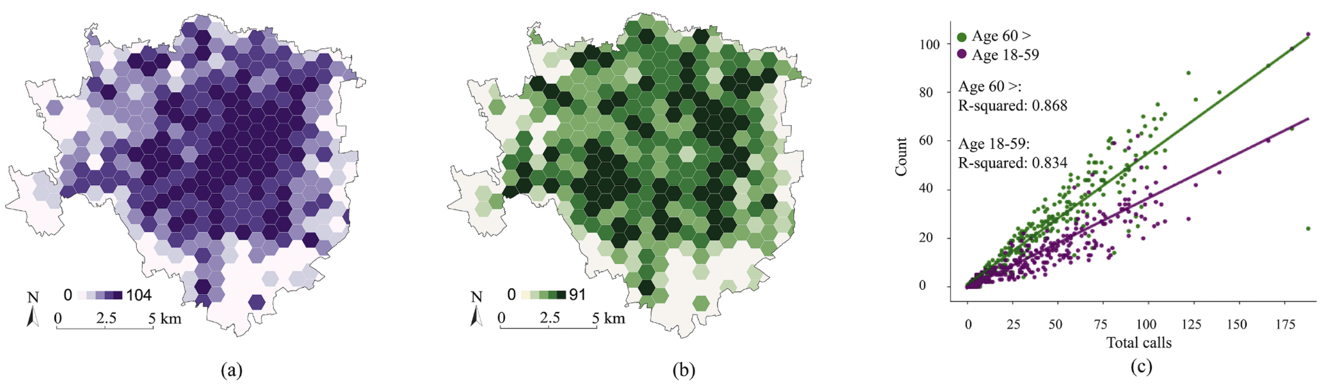



**Fig. 12.** Spatial patterns of total calls. a) Age 18–59 (both females and males); b) Age 60 > (both females and males); c) The scatterplot of the relationship between both variables (data used from AREU).

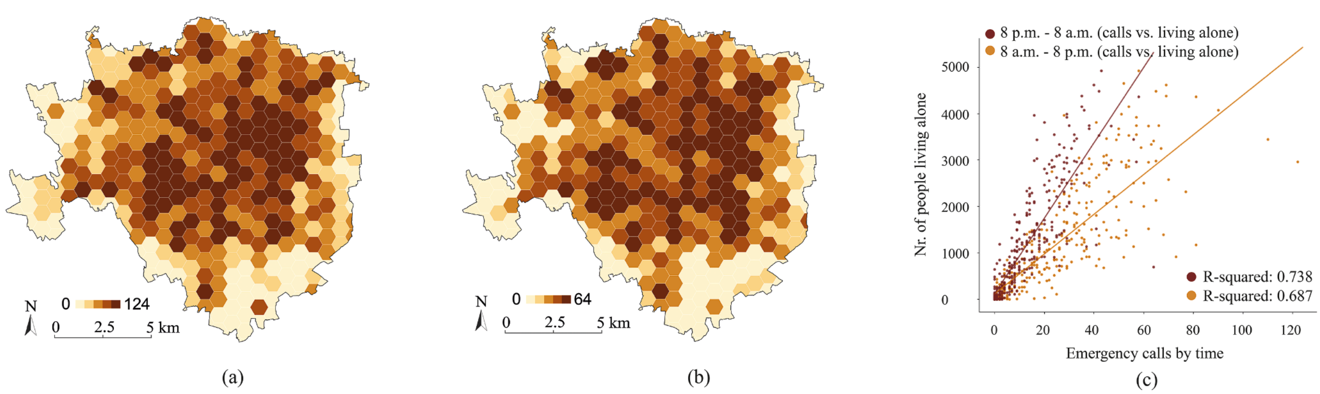



**Fig. 13.** Spatial patterns of total calls during the day. a) From 8a.m. – 8p.m. (All ages, both females and males); b) From 8p.m.–8a.m.(all ages, both females and males) (time occurred calls data used from AREU); c) The scatterplot of the relationship between calls from 8 p.m. until 8 a.m. and people living alone (living alone data from Census).

et al., 2006; Klinenberg, 2001; Li et al., 2024).

The UTCI map reveals a significant correlation with the number of emergency calls, highlighting the profound impact of the urban microclimate on health during the summer months in Milan. This demonstrates that higher UTCI levels are strongly associated with an increase in heat-related health emergencies (CVD and RD), confirming that the urban microclimate is one of the key determinant of urban health. UTCI was explored also in previous studies, where conditions of strong heat stress indicated a rise in mortality rates (Di Napoli et al., 2018; Pantavou et al., 2024). The detailed spatial analysis further reveals that these health impacts are not uniformly distributed across the city, but are concentrated in specific areas where UTCI is exceptionally high. These findings suggest that urban planning and design, which can retrofit outdoor climate, play a crucial role in shaping the health effects of CVD and RD during heatwaves. Although current computational costs remain still too high for high resolution UTCI calculations over extended periods, developing new approaches is essential to enable time-series studies and investigate the long-term effects of heatwaves on health patterns. In this study, we use the Universal Thermal Climate Index (UTCI) because it provides a comprehensive measure of outdoor thermal perception by integrating multiple meteorological and physiological factors. Other thermal indices, such as for instance, Physiological Equivalent Temperature (PET), Predicted Mean Vote (PMV), Standard Effective Temperature (SET) or similar, have distinct advantages and

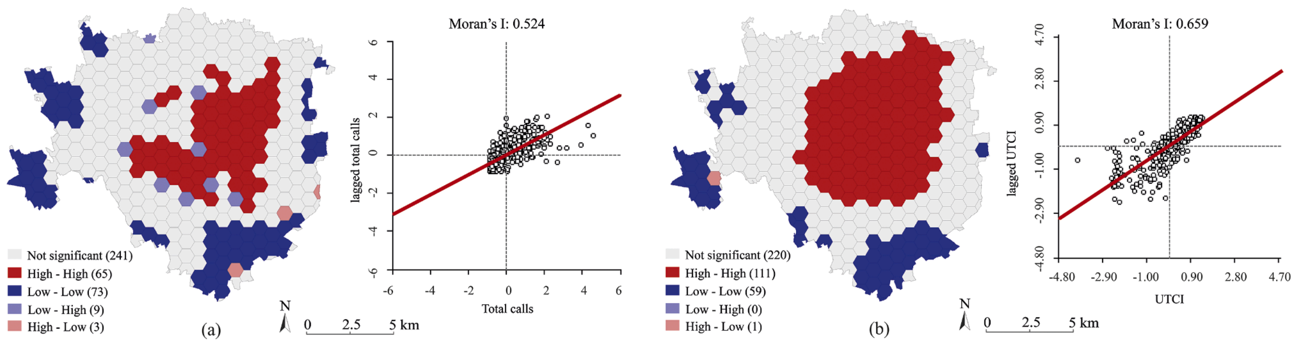



**Fig. 14.** Spatial autocorrelation analysis of the total calls and UTCI: a) Local Moran's I for the spatial autocorrelation of the total emergency calls; b) Local Moran's I for the spatial autocorrelation for UTCI.

**Table 2**
Results of the statistical models based on the following models: Ordinary least square (OLS) and geographically weighted regression (GWR).

| Variables | Model I | | | Model II | | | | |
|---|---|---|---|---|---|---|---|---|
| | Ordinary Least Square (OLS) | | | Geographically Weighted Regression (GWR) | | | | |
| | Coef. | Sig. | St. Err. | Mean | STD | Min | Median | Max |
| Total population | −0.0253 | *** | 0.006 | −2.415 | 0.805 | −4.259 | −2.268 | −0.749 |
| Low education | 0.0199 | *** | 0.003 | 0.794 | 0.287 | 0.101 | 0.837 | 1.301 |
| Age (elderly) | 0.0173 | *** | 0.005 | 0.521 | 0.393 | −0.279 | 0.474 | 1.516 |
| Gender (females) | 0.0290 | *** | 0.011 | 1.200 | 0.695 | −1.122 | 1.200 | 2.950 |
| Living alone | 0.0193 | *** | 0.004 | 0.640 | 0.261 | −0.174 | 0.654 | 1.275 |
| UTCI | 12.590 | *** | 3.255 | 0.349 | 0.516 | 0.004 | 0.141 | 2.287 |
| R-Squared | | 0.816 | | | | 0.883 | | |
| Adj. R-Squared | | 0.812 | | | | 0.868 | | |

Statistical significance.
*** $p < .01$.

limitations. For a detailed comparison of these indices, refer to Park et al. (2014), Coccolo et al. (2016), Zafarmandi and Matzarakis (2025), Zare et al. (2018).

It is important to highlight that since not all health complaints lead to emergency calls, AREU data may not fully capture the spectrum of heat-related health problems, likely causing an underestimation of heatwaves' influence on public health. Although emergency call data might not capture all individuals affected by heatwaves, they provide a valuable proxy for identifying areas with the highest susceptibility during such events. Additionally, using aggregated UTCI, and socio-demographic data might hide more fine-scale fluctuations in vulnerability and exposure inside the investigated spatial units. Despite these limitations, the study reveals the disproportionate vulnerability of certain population groups to heatwaves. This finding aligns with previous research (Barrow & Clark, 1998; Klinenberg, 2002; Malmquist et al., 2022) but also adds a new layer of understanding by connecting these vulnerabilities to specific urban areas. Besides, the results show spatial health complaints, suggest that underprivileged areas, often characterised by social and public housing, social isolation and lower socio-economic levels, are more susceptible to the adverse effects of extreme heat, which is also in line with previous research (Pascal et al., 2024). These insights emphasise the importance of targeted interventions in these vulnerable areas inhabited by fragile populations. Public health strategies and sanitary management should prioritise the needs of at-risk groups.

Additionally, beyond emergency management, it is crucial to consider implications for urban planning and policy design in the development of long-term strategies and solutions to mitigate health issues during heatwaves. For instance, to reduce UTCI, urban planners should implement measures to mitigate the urban heat island effect, such as increasing green spaces (i.e., increasing tree canopy coverage and desealing paved areas) and improving the design of buildings and open spaces, including geometry, materials and colours. By addressing the spatial and socio-demographic disparities in heat vulnerability, policy makers in cities like Milan can better protect their residents from the escalating risks of climate change. To this date, much of the available evidence on a variety of health outcomes points toward a positive (public) open space-health relationship, with robust strong evidence for the beneficial mitigation effects of green space in the reduction of heat island effects (Cardinali et al., 2023). While initiatives aimed at the built environment are effectively mitigating heat-related problems, it is essential to strengthen policies and programs to sustain social equity and combat isolation and relational poverty (Browning et al., 2006; Klinenberg, 2002). An experimental investigation in Italy indicated that interventions designed to mitigate social isolation among older adults might reduce excess mortality during heatwaves (Orlando et al., 2021; Pascal et al., 2024). While another study in China examines the spatial inequalities of healthcare allocation in response to climate risks from extreme heat and air pollution, proposing strategies for equitable healthcare planning to enhance climate resilience (Cheng & Sha, 2024).

Additionally, further research should provide a more accurate representation of population distribution during heatwave events. In fact, while census data provides details on the resident population, it does not account for non-resident city users who may also be affected. In this study, we argue that the absolute number of emergency calls remains the most critical metric for understanding urban health. However, if available, good quality mobile phone data can help to capture the high-resolution location of people in real-time, enabling the weighting of emergency call data based on the actual number of people in a specific location. Although this study explores short-term and long-term effects using a distributed lag model over a three-year period, future research should consider employing more robust models over a longer time frame to better capture potential non-linear and cumulative effects. Lastly, this study explores spatial models exploring spatial autocorrelation and heterogeneity in the relationships between the independent variables and the dependent variable across the study area. Although these models offered valuable insights as an initial exploration, further studies should explore longer time periods and incorporate additional datasets. These could include indoor versus outdoor exposure, housing materials, availability of air conditioning and accessibility to cool spaces, to analyse the nexus between spatial and social-economic complexities occurring during heatwaves.

## 5. Conclusions

This study contributes to the growing body of evidence that health impacts during heatwaves are not solely determined by temperature but are deeply intertwined with the spatial and social complexities of urban environments. Urban health, as a consequence of urban intricacies, demands a holistic approach that integrates urban planning, public health, and social policy. Recognising that these emerging relationships are dynamic and context-specific is essential to effectively mitigate heat-related health risks across diverse urban settings. The findings of this initial exploration can support emergency plans, urban planners and designers, and policymakers in identifying spatial hotspots during heatwaves. In Milan, these insights can guide targeted interventions, such as urban greening, shading structure, equitable access to cooling resources, and robust health emergency plans, to address heat-related vulnerabilities. For instance, studies have demonstrated the effectiveness of strategies like combining vegetation with reflective materials to lower local temperatures, optimizing tree coverage to create favourable microclimates (Aboelata, 2021; Garcia-Nevado et al., 2020; Rahman et al., 2024; Shaamala et al., 2024), and providing public cooling centres at walking distance (Brooks et al., 2024; Meade, Notley, Akerman, McCormick et al., 2023) to enhance urban thermal perception and heat-stress resilience. These examples underscore the potential to mitigate heat-related health risks in diverse urban contexts, offering valuable insights for cities worldwide.

Besides, this study aligns with global sustainability frameworks such as the United Nations' Sustainable Development Goals (SDGs), particularly SDG 3 (Good Health and Well-being), SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action). Furthermore, it draws attention to the crucial function of spatial analysis in connecting the dots between extreme heat in cities, human health, urbanity factors and socio-demographic conditions. It extends beyond the spatial perspective to explore the correlation between the temporal and spatial dynamics of population health conditions during heatwaves and healthcare emergency management to extreme heat events. The outcomes reveal that spatial and socio-demographic contexts contribute to the susceptibility to heat stress. The findings, in particular the relevance of context-related variables, such as spatial and socio-demographic factors, can help mitigate and inform both immediate action (through health emergency preparedness and response) and long-term action (through climate-resilient urban planning and public health policies). In parallel, it better informs adaptation strategies for retrofitting urban environments, in particular enhancing open spaces with temperature mitigation solutions (i.e., vegetation, cool materials) and facilities (i.e., cool islands, such as shaded and climatised spaces, water fountains), and promoting social policies to assist fragile people (e.g. targeted assistance, incentives to build capacities). Finally, this research contributes to the growing literature on urban heat resilience, health, and equity. The methods and the results specified here can inform future research into the complex interactions in urban environments that connect to climate, built environment, health, and inequality. As cities worldwide struggle with ever-increasing temperatures and more frequent heatwaves, there is a need for comprehensive, data-driven approaches to urban and public health management and planning, advocating for an integrated, spatially informed, and just approach to construct *heat-resilient and health-equitable urban areas* in the future.

## CRediT authorship contribution statement

**Doruntina Zendeli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Resources. **Nicola Colaninno:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Resources. **Daniela Maiullari:** Writing – review & editing, Methodology, Conceptualization. **Marjolein van Esch:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Arjan van Timmeren:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Gianluca Marconi:** Resources, Methodology, Data curation. **Rodolfo Bonora:** Resources, Methodology, Data curation. **Eugenio Morello:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, 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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## Appendices

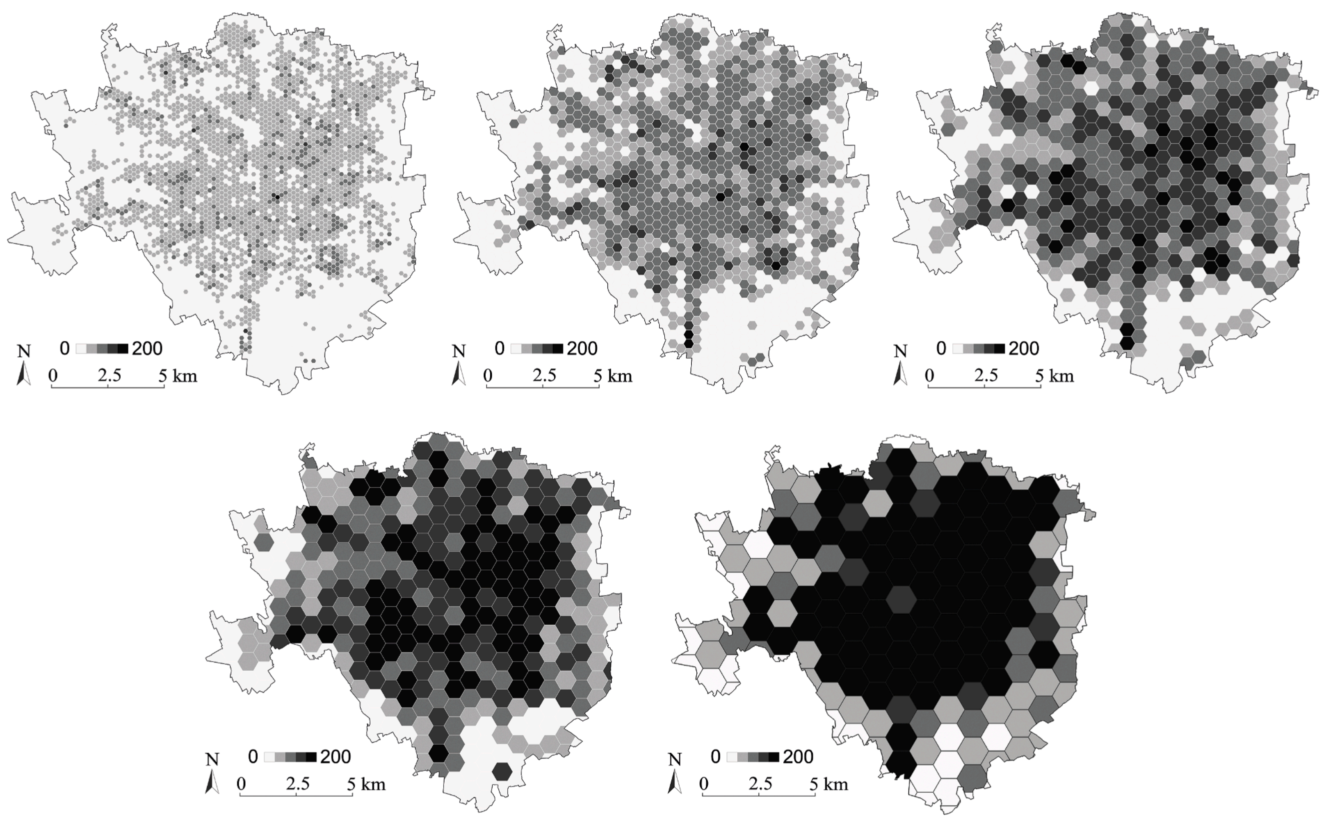


**Fig. A1.** Different grid scale: (a) 200 × 200; (b) 400 × 400; (c) 600 × 600; (d) 800 × 800; (e) 1200 × 1200.

**Table A.1**
Description of the results using different grid size for the OLS model.

| Grid Size | $R^2$ | Adj. $R^2$ | MSE | RMSE | n-RMSE |
|---|---|---|---|---|---|
| 200 × 200 | 0.162 | 0.159 | 5.792 | 2.406 | 0.2188 |
| 400 × 400 | 0.513 | 0.509 | 32.204 | 5.6749 | 0.1669 |
| 600 × 600 | 0.680 | 0.674 | 66.499 | 8.1547 | 0.1254 |
| ***800 × 800*** | ***0.816*** | ***0.812*** | ***134.035*** | ***11.577*** | ***0.1113*** |
| 1200 × 1200 | 0.884 | 0.879 | 341.64 | 18.483 | 0.0962 |

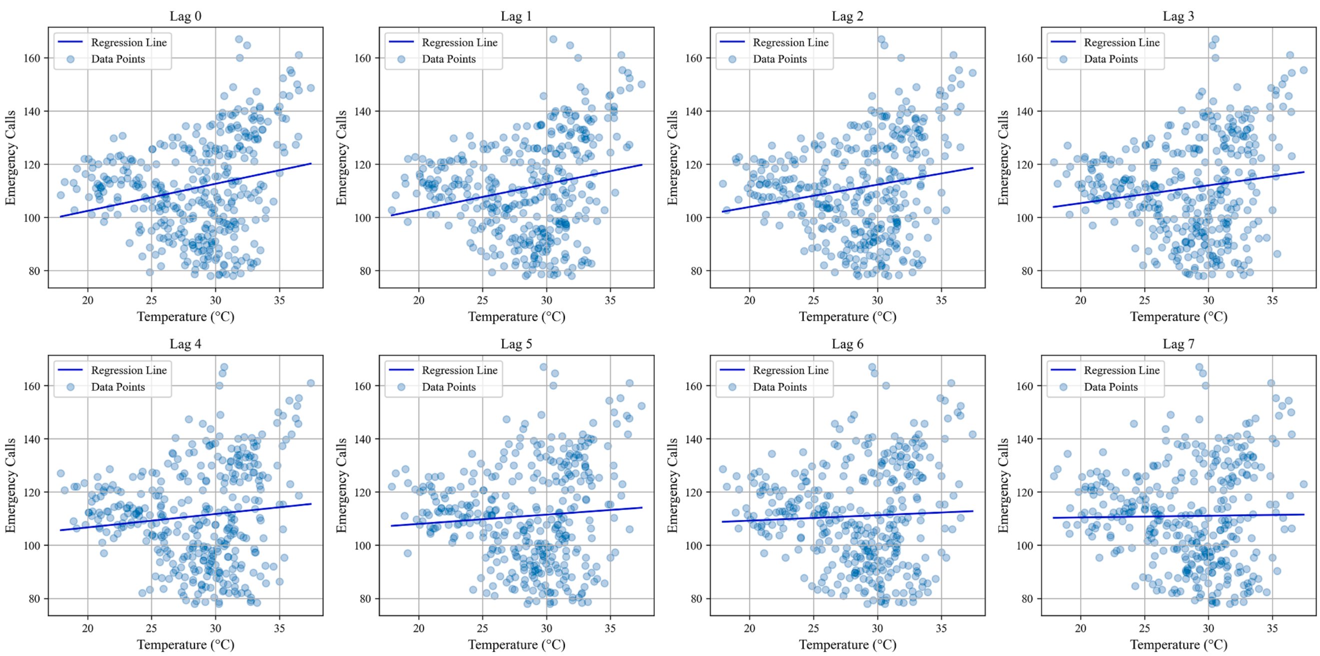


**Fig. A2.** The distributed time-lag analysis provides insights into delayed health impacts of high temperatures, each subplot visualizes the relationship for a specific lag.

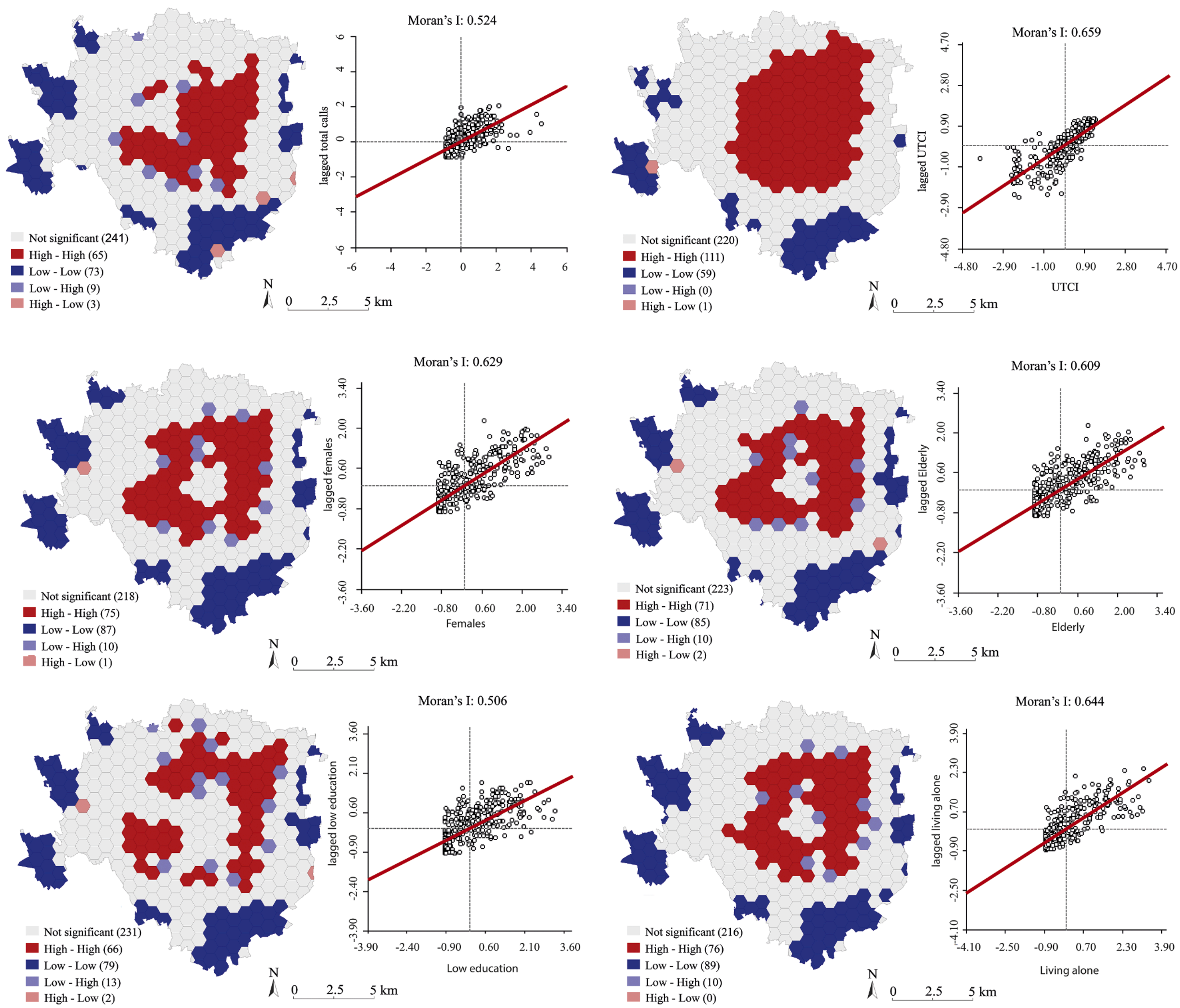


**Fig. A3.** Local Moran's I for all used variables.

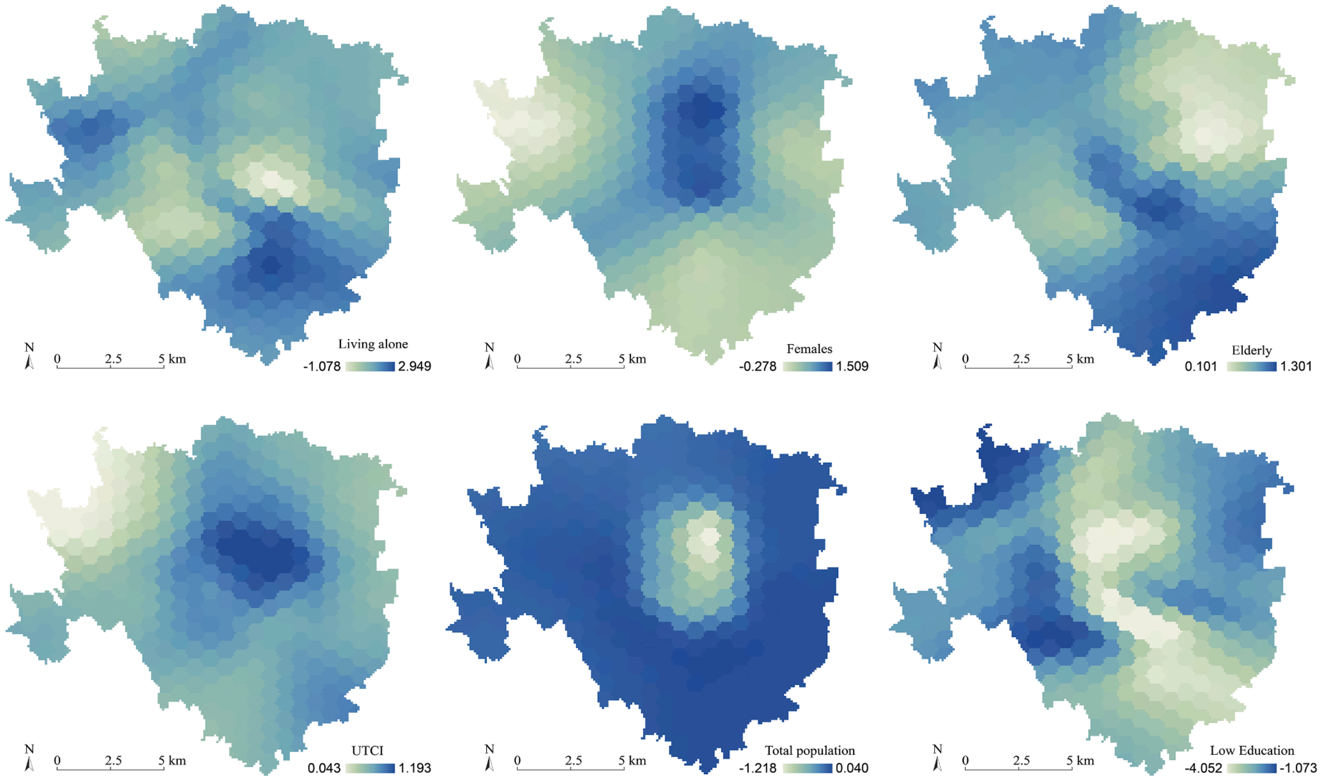


**Fig. A4.** Spatial distribution of the coefficients based on the GWR model.

## Data availability

Data will be available upon request, except for the emergency calls data, which cannot be shared due to privacy restrictions.

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