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Projecting temperature-related mortality impacts at urban scale under climate scenarios: A methodological review

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ABSTRACT

Global warming and resulting extreme weather patterns are expected to substantially increase temperature-related mortality, with urban populations especially at risk due to high density, rapid urbanization, and the urban heat island effect. While projections of the climate-health impacts in urban contexts have proliferated in the literature, systematic evaluation of methodological approaches underpinning the studies remains limited. Understanding of the methods is crucial for interpreting the projected outcomes, uncertainties, and policy relevance. Here, we conducted a PRISMA-guided review of 110 studies published between 2015 and 2025 and synthesized a six-domain urban scale methodological framework spanning climate scenarios, environmental epidemiology, demographic and socioeconomic projections, urban characteristics and processes, health impact assessment, and uncertainty and sensitivity analysis. Our review shows how divergent methodological choices, such as climate data inputs, static versus dynamic demographics, or adaptation considerations, drive large differences in projected health outcomes. We also highlight coverage gaps in existing literature that most studies focus on high-income areas, leaving low- and middle-income countries (LMICs) underrepresented despite their greater vulnerability and limited adaptive capacity. Building on these findings, we propose a roadmap for next-generation urban-scale projections that integrate high-resolution climate data, scenario-consistent demographic and socioeconomic projections, intra-urban vulnerability, urban heat island and land-use dynamics, and multi-faceted adaptation modeling. This approach enables more credible, equitable, and policy-relevant assessments of climate-related health risks, strengthening the evidence base for urban resilience planning and climate-health governance.

1. Introduction

Exposure to heat or cold extremes causes substantial adverse health impacts, notably increased premature deaths (Gasparrini et al., 2015; Zhao et al., 2021). Temperature extremes are strongly linked to cardiovascular and respiratory diseases, and growing evidence highlights their role in exacerbating conditions such as diabetes and kidney disorders (Burkart et al., 2021). With climate change driving more frequent and intense extreme temperature events, these health risks are projected to escalate further in the coming decades (Ebi et al., 2021; Gasparrini et al., 2017). Global assessments consistently demonstrate that future climate change will result in net increases in temperature-related mortality across populations, with high-emission pathways projecting more severe health impacts than moderate-emission scenarios (Gasparrini et al., 2017; Vicedo-Cabrera et al., 2018). While climate change is projected to reduce cold-related deaths in many regions, these reductions prove insufficient to offset substantial increases in heat-related mortality under warming scenarios (Hebbern et al., 2023; Martinez et al., 2018a; S. Wang et al., 2025; Wang et al., 2016).

Temperature-related health risks are especially pronounced in urban environments, where dense populations concentrate vulnerability and extensive built infrastructure intensifies heat exposures (Hao et al.,

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2025; Oleson et al., 2015; Papalexiou et al., 2018). Urban heat island (UHI) effects, where cities experience higher temperatures than surrounding rural areas, further elevate risk by raising nighttime temperatures and limiting physiological recovery periods (Chaston et al., 2022; Heaviside et al., 2016; Keppas et al., 2021). Rapid urbanization compounds these risks both by contributing emissions and by concentrating populations in heat-amplified settings (UN DESA, 2019). The global urban population is projected to increase from 53.9% in 2015 to 68.4% in 2050, while demographic transitions (particularly rapid aging in developed and middle-income countries) multiply risks since elderly populations are disproportionately vulnerable to temperature extremes (K. Chen et al., 2024a; Crouzier et al., 2024; Huang et al., 2023; Lee & Dessler, 2023; Rodrigues et al., 2020).

Adaptation interventions can reduce temperature-related mortality, but even comprehensive measures rarely eliminate projected excess mortality under high-emission scenarios. The benefits are unevenly distributed, favoring higher-income regions (Huber et al., 2022; M Rai et al., 2022; Shindell et al., 2020). Urban adaptation strategies could involve trade-offs: while UHI lowers winter cold-related mortality, they may inadvertently increase summer heat-related mortality (Macintyre et al., 2021a). These converging pressures underscore the urgent need for robust, location-specific assessments of climate-health risks that account for the diverse vulnerabilities and adaptive capacities within and across urban contexts (Chen et al., 2023; Marí-Dell'Olmo et al., 2019; Voosen, 2025).

Accurately assessing future health impacts of temperature-related mortality at the urban scale under climate change necessitates methodological frameworks capable of capturing localized characteristics (Dominianni et al., 2018; Marginean et al., 2024; Zhao et al., 2014), informing targeted policy responses (Vargo et al., 2016), and guiding effective adaptation strategies (Absar & Preston, 2015; Muccione et al., 2024). However, though existing studies frequently rely on urban-scale epidemiology data, critical gaps persist in other aspects, including localized socioeconomic and demographic information, adaptation modeling, and urban-specific characteristics such as intra-urban heterogeneity (K. Chen et al., 2024b; Jiang & O'Neill, 2017; Guillaume Rohat et al., 2019). These methodological gaps limit the applicability and utility of projection results for targeted urban resilience planning and climate-health interventions.

Previous reviews have explored specific dimensions of climate-health projections, such as health impacts (J. Y. Lee et al., 2018; Weber et al., 2023), urban characteristics (Deilami et al., 2018; Feng et al., 2023; Ye et al., 2021), and influencing factors like demographics (Chen et al., 2020a) and adaptation (Cordiner et al., 2024; Johar et al., 2025). Yet, a comprehensive synthesis of the diverse methodological approaches underlying urban-scale temperature-mortality studies is still lacking. This gap matters because methodological choices are not merely technical as they shape projection outcomes and policy implications (Xu et al., 2016). Recognizing this, our review systematically reviewed studies focusing specifically on urban-scale projections of temperature-related mortality under climate scenarios published between 2015 and 2025. We provide a structured synthesis of methodologies employed in 110 studies, assess key limitations and divergences, and identify equity and coverage gaps. We further outline a roadmap for advancing urban-scale projections toward more credible, equitable, and policy-relevant assessments of climate-health risks, supporting targeted urban resilience and adaptation strategies.

2. Methodology

2.1. Databases and search strategy

To identify relevant literature, we conducted a structured search following the PRISMA guidelines (Moher et al., 2015; Page et al., 2021). Our search was based on Web of Science (Core Collection) and PubMed, two multidisciplinary databases with strong coverage in environmental health, epidemiology, and climate science. The search, conducted on June 26, 2025, was restricted to studies published between 2015 and 2025, a period marked by the publishing of climate models (e.g., Coupled Model Intercomparison Projects, CMIP) and the development of scenario-based impact studies.

The search strategy was built around five thematic concepts: temperature, projections, climate change, urban context, and mortality. For each, a range of relevant synonyms and keyword variations was included to enhance comprehensiveness. Specifically, the search terms included: 1) "temperature" OR "heat" OR "cold"; 2) "projection" OR "projecting" OR "future" OR "forecast" OR "forecasting"; 3) "climate change" OR "global warming"; 4) "urban" OR "city" OR "cities" OR "metropolitan" and 5) "mortality" OR "death". This strategy was applied consistently in both databases. All identified records were initially screened in Rayyan, an online systematic review management tool, to facilitate initial decision-making selections. Final selections were organized using the Zotero reference management software.

2.2. Study selection and screening process

To ensure that the resulting studies are aligned with the objectives of this review, we apply a set of pre-defined selection criteria. Eligible studies are limited to peer-reviewed original research articles published in English that include empirical analyses, while review articles, editorials, and conceptual papers are excluded. We focus on studies that present quantitative assessments of temperature-related mortality, including analyses of heat-related, cold-related, or both. Only studies that incorporate climate scenarios extending at least to the 2050s or beyond are considered, and emphasis is placed on those that utilized or analyzed urban-scale or urban-specific data in their modeling framework. The screening process is conducted in two stages. In the first stage, titles and abstracts are reviewed to exclude studies that do not meet the inclusion criteria. In the second stage, full-text articles have been assessed for eligibility based on a detailed review of their methods and scope. In cases where multiple exclusion criteria apply, the most relevant or primary reason is recorded for consistency in documentation.

Our search in the databases has returned a total of 1167 papers, including 815 from Web of Science and 352 from PubMed. 180 duplicates are processed and deleted accordingly. 987 papers are left for title and abstract screening, and 814 are excluded in this step due to their publication type (90 papers) and irrelevance (724 papers). Then, in the full text screening, 77 out of the remaining 173 papers are not considered for the final inclusion because they are not related to mortality (45 papers), not related to projections (28 papers), or not in English (4 papers). Finally, we identify additional studies from relevant studies using 'snowballing' methodology, including references cited by the initially included papers and articles that cited the included studies. An additional 14 studies found through additional literature searching that meet the same inclusion criteria are added, resulting in a final total of 110 studies for data extraction and analysis (Fig. 1).

2.3. Information extraction and organization

To support a consistent and transparent synthesis, we extracted information from each included study using a predefined coding template focused on methodological content (Table S2). The first section of the information captures general bibliographic and contextual details, including the study, location, and projection period. The second section focuses on the methodological approach, detailing the six-domain methodological framework. The six categories of this framework include (1) Climate change scenarios and temperature projections, (2) Environmental epidemiology, (3) Demographic and socioeconomic projections, (4) Urban dynamics, (5) Health impact assessment, and (6) Uncertainty and sensitivity analysis. The detailed information of the first section for the included studies can be found in Table S3.

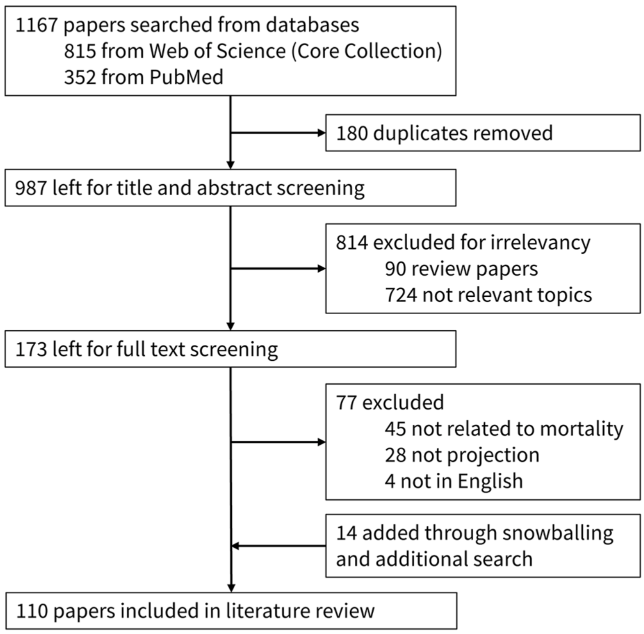

Fig. 1. Flow chart of the literature selection process in this review.

2.4. *Descriptive characteristics of included literature*

The annual number of studies included in this review demonstrates an increasing trend over the period of 2015 to 2025 (Fig. 2a). This temporal pattern connects to key developments in climate models and data outputs. Most studies published after 2015 adopted climate projections from CMIP5, a coordinated set of climate model experiments that became widely available in the early 2010s and provided the foundation for the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5) (IPCC, 2014; Taylor et al., 2012). From the late 2010s, the availability of CMIP6 data has supported the IPCC Sixth Assessment Report (AR6) and facilitated their uptake in studies published in recent years (Calvin et al., 2023; Eyring et al., 2016). It should be noted that these temporal trends reflect only the studies included in this review rather than the total number of publications in the field. As the core literature search was conducted on 26 June 2025, the number of studies for 2025 represents only partial-year publication output.

A geographic bias is found in the spatial coverage of included studies, as illustrated in Fig. 2b. At the continental level, 45 studies are specifically focused on Asia, followed by Europe (29 studies) and North America (17 studies). Most studies focus on East Asia (40 studies), followed by Europe (29 studies) and North America (17 studies). In contrast, regions with large numbers of low- and middle-income countries remain substantially underrepresented. Latin America and the Caribbean are represented in only four studies, while the Middle East and North Africa appear in three studies. Africa is only specifically covered as the primary study area in a single study. In addition, 11 studies adopt global or multi-regional approaches, some of which include low-income regions as part of a broader analysis.

3. Results

Our analysis of the 110 studies shows that, despite variation in specific methods and data sources, temperature-related mortality projections at the urban scale follow a common analytical structure. Through systematic coding of methodological elements (Section 2.3 and Table S2), we identified recurring components across studies: climate change scenarios, environmental epidemiology, demographic and socioeconomic projections, health impact assessment, and uncertainty and sensitivity analysis. We synthesized them into a six-domain methodological pathway capturing the analytical backbone of the field (Fig. 3). Although individual studies may emphasize certain domains or apply them with differing levels of adjustment, this common pathway offers a useful framework for comparing approaches and highlighting methodological divergences. The following sections examine each component in detail, documenting the range of approaches used and the implications of these methodological choices. The data sources of each domain required to project temperature-related mortality are summarized in Table S4.

3.1. *Climate change scenarios and temperature projections*

Based on climate change scenarios, the methodological workflow first retrieves temperature projections from climate models. These outputs are then downscaled and bias-corrected to produce high-resolution temperature metrics at the urban scale.

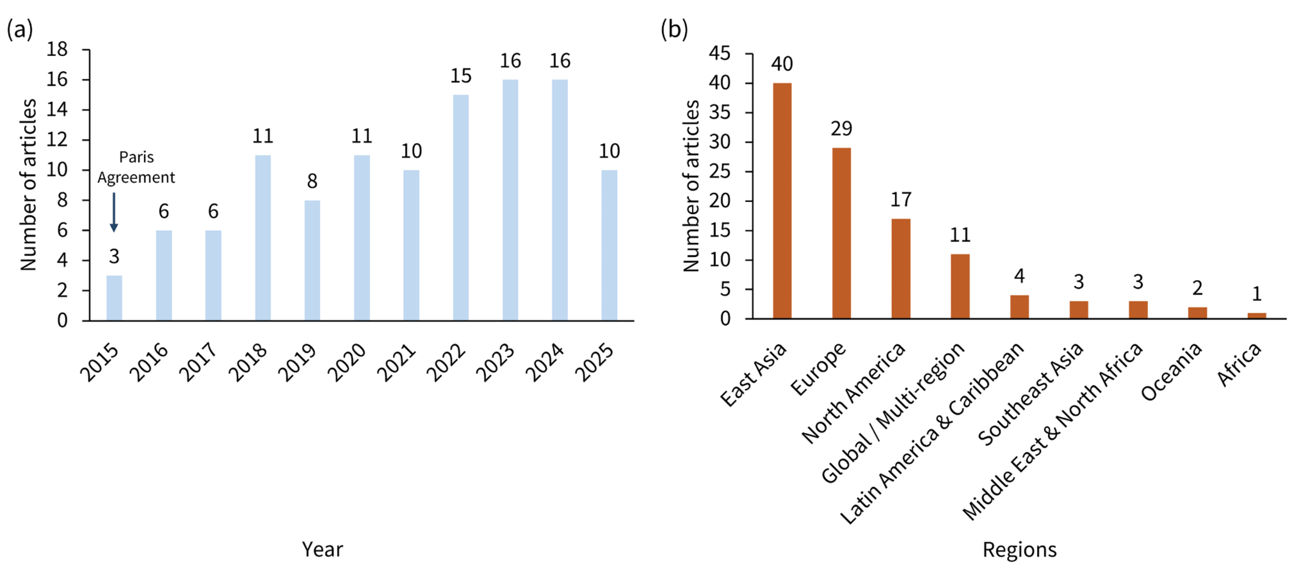

Fig. 2. Temporal and geographic distribution of the 110 studies included in the review. (a) Annual number of publications between 2015 and 2025, with the Paris Agreement (2015) indicated for reference. (b) Distribution of studies by world region based on the geographic focus of each study.

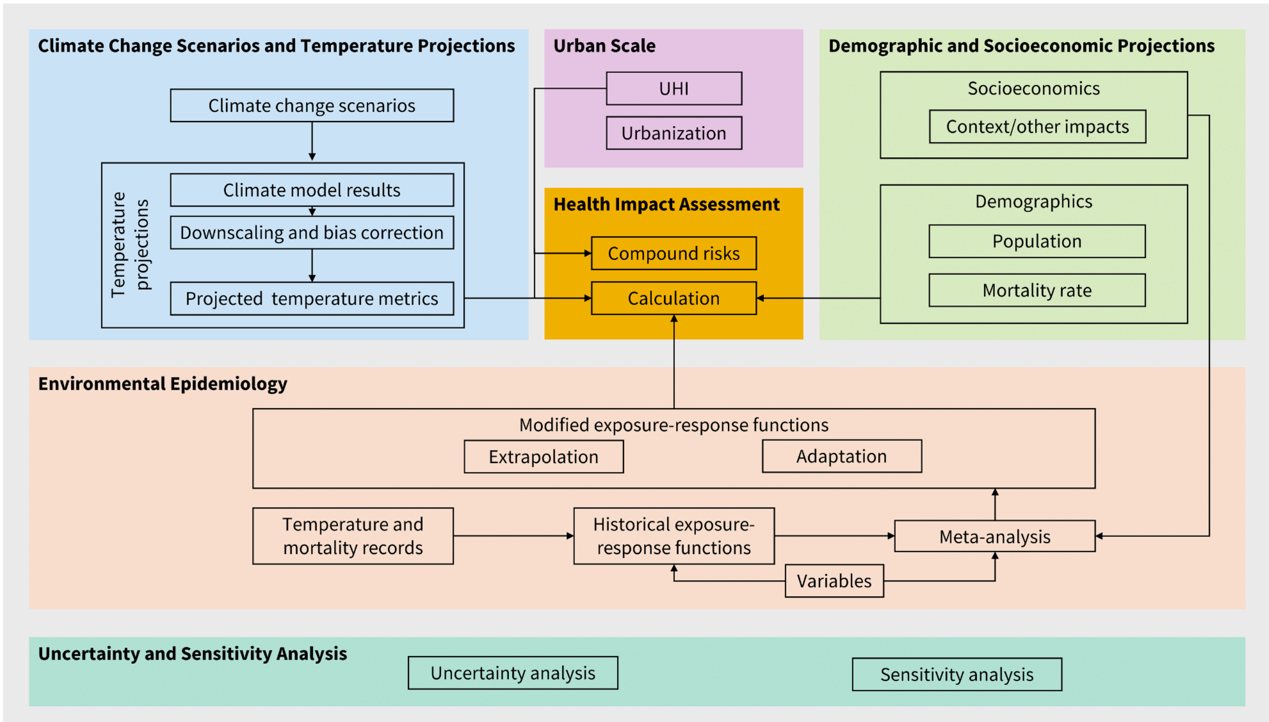

Fig. 3. Six-domain methodological framework and workflow synthesized from 110 studies for projecting temperature-related mortality under climate change scenarios at the urban scale. Arrows illustrate data flows across domains leading to the final health impact assessment.

3.1.1. *Climate change scenarios*

Across the reviewed studies, scenario coverage predominantly aligns with the CMIP frameworks used in successive IPCC assessments (Fig. 4). The most frequently applied are the Representative Concentration Pathways (RCPs), developed for IPCC AR5 and widely implemented in CMIP5 (IPCC, 2014; Taylor et al., 2012), particularly RCP8.5 (high emissions) and RCP4.5 (moderate emissions). Several studies also adapt RCPs to examine specific warming thresholds consistent with Paris Agreement targets (e.g., 1.5 °C, 2 °C, and 3 °C pathways) (Garcia-León et al., 2024; Lo et al., 2019; Vicedo-Cabrera et al., 2018).

More recent studies employ the new generation of scenarios developed under the Scenario Model Intercomparison Project (ScenarioMIP) in CMIP6, which combines RCPs with Shared Socioeconomic Pathways (SSPs) to provide integrated climate-society futures (Calvin et al., 2023; O'Neill et al., 2016; Tebaldi et al., 2021). Among these, the Tier 1 combinations (SSP1–2.6, SSP2–4.5, SSP3–7.0, SSP5–8.5) are most

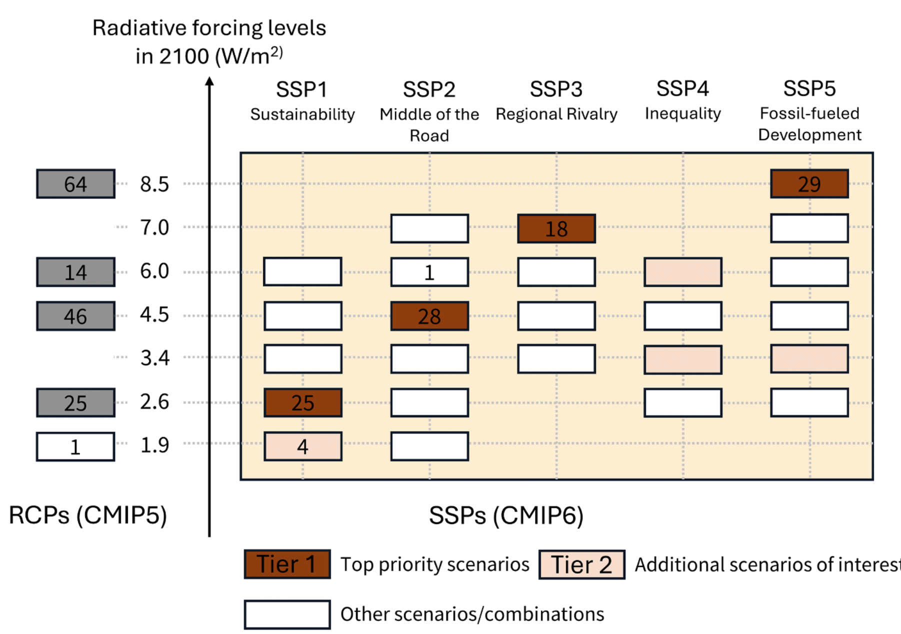

Fig. 4. Frequency of CMIP-aligned climate scenarios used in the reviewed studies. Each box represents an RCP or SSP-RCP pathway, with numbers indicating the counts of studies applying that scenario. Gray boxes denote RCPs from CMIP5. The scenario framework is adapted from O'Neill et al. (2016). Notes: counts include only studies that explicitly used CMIP5/CMIP6 scenario sets. Studies employing bespoke or earlier CMIP scenarios are not shown. A study is counted in multiple boxes if it assessed multiple scenarios.

frequently used.

Earlier research relies on the Special Report on Emission Scenarios (SRES) employed in CMIP3 (Guo et al., 2016 Heaviside et al., 2016; Limaye et al., 2018), while a small subset of studies applied national or model-specific frameworks to address local policy contexts (Botzen et al., 2020; Huynen & Martens, 2015; Mills et al., 2015).

3.1.2. Temperature projections

Based on the climate change scenarios, studies first obtain temperature projection results from global or large-scale climate models, which reflect both radiative forcing trajectories and climatic conditions. These outputs are then downscaled and bias-corrected to generate localized, high-resolution temperature field data. Table 1 summarizes the main approaches applied in this section and their implications.

Climate model results. General circulation models (GCMs) and Earth system models (ESMs) are the primary tools for climate projections (i.e., providing physically based simulations of the Earth's climate system). The reviewed studies predominantly utilize results from multi-model ensembles from CMIP5 or CMIP6. We have summarized the counts of the GCMs applied per scenario in the individual study in Table S5. Several studies use alternative or complementary models tailored to policy or nation-specific contexts. For example, the Integrated Assessment Model (IAM)-linked probabilistic projections that provide temperature and humidity to compute apparent temperature (Ignjacevic et al., 2024) or country-specific ensembles used for urban country-specific analyses in the UK, Sweden or Belgium (Crouzier et al., 2024; Fonseca-Rodríguez et al., 2023; Heaviside et al., 2016; Murage et al., 2024). Due to computational constraints, GCMs typically operate at coarse spatial resolutions (~100–250 km), which are insufficient for urban-scale exposure assessment and cannot directly resolve urban thermal heterogeneity.

Downscaling and bias correction. There are two widely applied downscaling and bias correction methods to bridge the gap between coarse GCM outputs and the required high-resolution data. The first category is statistical downscaling, which is applied by most studies. The statistical methods relate large-scale fields to local observations (stations or reanalysis), and the common approaches include quantile mapping, regression-based corrections, bias-corrected spatial disaggregation (BCSD), constructed analogs, and delta-change techniques. Widely used datasets such as the National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) and Multivariate Adaptive Constructed Analogs (MACA) provide bias-corrected CMIP5 and CMIP6 outputs at 0.25° to 1/16° resolution (Arnold et al., 2022, 2022; Liu et al., 2025; Ma et al., 2024; Yi et al., 2024). These methods are computationally efficient and can achieve high spatial resolution (down to 1 km). Yet, they rely on the assumption that historical statistical relationships will persist, which may be violated under nonlinear climate change or urban expansion.

The second category is dynamic downscaling with Regional Climate Models (RCMs): this method employs RCMs by feeding GCMs' results to simulate climate processes at finer scales (typically 10–50 km) (Wilcke et al., 2013). This process would enable the RCMs to capture mesoscale dynamics such as coastal breezes and urban microclimates with enhanced physical realism. Yet the biases inherited in GCMs may be inevitable, and this method increases computational cost. There are also common frameworks developed specially for certain regions or countries like Europe and North America (Jung et al., 2020; Lee & Dessler, 2023; G Rohat et al., 2019). In reviewed studies, the spatial resolution of temperature projections ranges from coarse GCM scales (~100 km) to very fine grids (250 m to 1 km), with most adopted resolutions falling between 0.1° (~10 km) and 0.5° (~50 km). Additionally, studies commonly use high-resolution historical temperature observations drawn from national meteorological station networks, gridded observational products, and reanalysis. These are often aggregated, bias-corrected, or validated against local stations to parameterize city-specific associations between temperature and mortality (Riahi & Khorsandi, 2025). In the reviewed LMIC applications, climate inputs are most commonly derived from CMIP multi-model ensembles or other global products rather than locally calibrated urban climate simulations (Palmeiro-Silva et al., 2025; Zhu et al., 2025). This reflects a broader methodological constraint, as high-resolution urban climate data and bias-corrected downscaled products are often limited or unavailable for many LMIC cities.

Table 1
Synthesis of methodology choices in temperature projections in the reviewed studies. Illustrative examples of studies applying approaches are provided in the subsection text.

Component	Most common approaches	Alternative approaches	Key implications
Climate model results	Multi-model ensembles from CMIP5/CMIP6, mainly GCMs/ ESMs and often accessed through ready-to-use downscaled products (e.g., NEX-GDDP).	Single or small sets of GCMs; regional climate model ensembles; country-specific ensembles; IAM-linked projections; urban climate models.	Multi-model CMIPs ensembles improve robustness to inter-model spread and are widely available, but GCM resolution remains coarse for urban-scale exposure assessment. RCMs and urban climate models can better represent local climatic gradients, but they require high computation and are less consistently available across cities.
Downscaling and bias correction	Statistical downscaling and bias correction, including quantile mapping, BCSD, delta-change methods	Dynamic downscaling using RCMs or WRF; station-based local calibration; interpolation-based or hybrid approaches.	Statistical downscaling is a feasible approach for multi-city studies with its scalability and relatively fine grids, but it highly depends on statistical choices and assumes that historical statistical relationships remain valid under future climate and urban change. Dynamical downscaling is more suitable for urban-scale studies as it better captures mesoscale processes such as coastal effects and urban heat amplification, but it is much more data- and computation-intensive.
Projected temperature metrics	Daily mean temperature	Daily maximum or minimum temperature; percentile-based extreme indices; heatwave/cold-spell indicators; excess heat factor; SSC weather types; degree-days; diurnal temperature range; apparent temperature or heat index.	Metric choice affects estimated burden and comparability across studies. Daily mean temperature is widely available and compatible with many epidemiological models, while extreme indices and heat stress metrics may better capture heatwave-related health risks.

Projected temperature metrics. The choice of temperature metric is a first-order determinant of estimated mortality burdens and crossstudy comparability. The reviewed studies employ a diverse set of temperature metrics to capture extremes, persistence, diurnal conditions, and humidity-mediated heat stress. Daily mean temperature emerges as the predominant metric due to its widespread availability in climate projection datasets and established compatibility with existing epidemiological exposure-response relationships. Extreme temperature indicators, including extremes using percentile-based thresholds (e.g., 90th percentile), maximum or minimum daily temperature, are also considered alongside daily mean temperature to capture seasonality impacts (Amnuaylojaroen et al., 2024; Wang et al., 2018). Some studies move beyond single-day temperature exposures to episode-based hazards, modeling heatwaves or cold spells defined by percentile or absolute thresholds sustained over several days (Huang et al., 2023; Li et al., 2018).

To represent intensity and persistence of extreme temperature events, specialized metrics such as the excess heat factor, Spatial Synoptic Classification (SSC) weather classification and heat/cold duration indices are also investigated (Fonseca-Rodríguez et al., 2023; Pin Wang et al., 2022). Degree-day and seasonal indices such as mean summer temperature (MST) or annual hot and cold degree-days have also been applied (Huber et al., 2022; Pin Wang et al., 2022; Wang et al., 2018). Others incorporate diurnal temperature range or night-time minimum to reflect nocturnal heat risk, which is often amplified in cities (Ai et al., 2023; Lee et al., 2020; Morefield et al., 2018; Qi et al., 2023; G Rohat et al., 2019). For heat-related assessments, specialized metrics like the Heat Index or Apparent Temperature, which integrates both temperature and humidity, are also employed (Ignjacevic et al., 2024; Kivimaki et al., 2023; Limaye et al., 2018). The choice of temperature metric proves critical as different definitions influence the health impact estimates (Abadie and Polanco-Martínez, 2022). This is particularly demonstrated for heatwave-mortality magnitudes, which could vary across different temperature definitions (Xu et al., 2016).

3.2. Environmental epidemiology

Environmental epidemiology forms the core link between projected temperature exposure and mortality outcomes. Most projection studies first estimate exposure–response functions (ERFs) from historical temperature and mortality records. In multi-location studies, these city-specific ERFs are often followed by multivariate meta-analysis to account for heterogeneity across locations. In many cases, the historical ERFs are then applied directly to future temperatures, with limited treatment of extrapolation beyond observed temperature ranges or of adaptation over time. Table 2 summarizes the main methodological choices in this domain and their implications.

3.2.1. Historical exposure-response functions

Across the studies, quasi-Poisson time-series models with Distributed Lag Nonlinear Models (DLNM) are the dominant approach (~60%). Meanwhile, heterogeneity in lag windows, functional forms, pooling, and covariate adjustment introduces non-trivial variation in estimated ERFs and hence in projected burdens.

The DLNM framework is often integrated with generalized linear models (GLMs) or generalized additive models (GAMs) (Gasparrini et al., 2010). It uses spline functions to simultaneously capture the nonlinear, typically U- or J-shaped relationship between temperature and mortality and the delayed (lagged) effects of temperature levels. Common lag windows range from 14 to 21 days, capturing more immediate effects of 0–3 days (heat-related) and more delayed impacts of 21–30 days (cold-related). Models routinely adjust for seasonality/long-term trend, day-of-week, humidity, and occasionally air pollution, and are frequently age-stratified. Key model outputs include the minimum mortality temperature (MMT), representing the temperature associated with the lowest mortality, and relative risks (RR) that quantify increased mortality risks at temperature ranges. Some studies estimate ERFs using linear or piecewise-threshold models,

Table 2
Synthesis of methodology choices in environmental epidemiology in the reviewed studies. Illustrative examples of studies applying approaches are provided in the subsection text.

Component	Most common approaches	Alternative approaches	Key implications
Exposure–response function (ERF)	City-specific time-series models using quasi-Poisson or Poisson regression with DLNMs (usually nonlinear U-/ J- shaped) with lag structure (shorter for heat and longer for cold).	GLM/GAM without DLNM, case-crossover designs, threshold or linear-threshold models, degree-day approaches, negative binomial models, Bayesian hierarchical models, machine-learning models, or transferred ERFs from previous studies.	DLNMs flexibly capture nonlinear and lagged temperature–mortality relationships and are well suited for time-series data. Modeling choices (lag length, spline specification, thresholds) can affect projected outcomes and affect comparability. Transferred ERFs expand geographic coverage but may weaken local validity when applied to different climatic or socioeconomic contexts.
Meta-analysis	Two-stage framework in multi-location studies: city-specific ERFs estimated first, then pooled through multivariate meta-analysis, often with BLUPs.	No pooling in single-city studies; simpler fixed-effects pooling; pooling by climate zone, region, or country only.	Two-stage pooling improves statistical stability, improving inference in cities with limited data. However, pooled ERFs depend strongly on the representativeness of included cities and the choice of meta-predictors, which may influence projected risk patterns across regions.
Variables	Seasonality, long-term trend, day of week, and humidity, age (most common).	Additional: Air pollution, urbanization, population density, GDP per capita, healthcare capacity, air-conditioning prevalence, education, deprivation, and UHI-related indicators.	Variable choice shapes both the estimated ERF and its interpretability. Inconsistent variables selection could limit comparability and interpretability. Broad social and environmental variables improve policy relevance but increases data requirements and collinearity risks.
Extrapolation	Historical ERFs are most often applied to future temperatures with little or no change in shape, threshold, or slope.	Log-linear extrapolation beyond observed ranges; capped RR at historical maximum; threshold updating; future ERFs estimated through meta-regression; machine-learning-based projection of future curves;	Extrapolation assumptions could be a major source of structural uncertainty, especially under high warming or in cities with limited historical temperature range.

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Table 2 (*continued*)

Component	Most common approaches	Alternative approaches	Key implications
Adaptation	No explicit adaptation modelingwith fixed ERFs, thresholds/ MMT, and constant vulnerability.	warming-increment approaches. Threshold/ MMT shifts, slope attenuation, combined threshold and slope adjustment, analogue-city approaches, GDP-based adaptive-capacity adjustments, and exposure-side intervention scenarios such as greening, tree canopy, or cool roofs.	Adaptation modeling remains limited and is often stylized when considered. Different adaptation assumptions about acclimatization, infrastructure, or socioeconomic development can lead to large divergence in projected outcomes.

event-based designs with binary heat-wave indicators, or degree-day metrics. Alternative epidemiologic frameworks include case-crossover, negative-binomial or panel Poisson, and difference-in-differences. Examples include linear increases above a city-specific threshold or heat-wave indicators for extremes (Chaston et al., 2022) and linear effects above 21.3 °C (Li et al., 2015). In the environmental epidemiology domain, several LMIC-focused studies rely on simplified exposure-response specifications, such as linear-threshold relationships or coefficients transferred from other regions where long-term mortality datasets are available (Chapman et al., 2022; Hajat et al., 2023). Some apply published ERFs from other studies with a similar study scope (Macintyre et al., 2021b; Mills et al., 2015). A smaller subset explores machine-learning (e.g., neural networks, random forests) either to derive ERFs from historical data or to project RRs conditional on changing socioeconomic factors (S. Wang et al., 2025). These design choices, especially lag structure, threshold definition, and pooling strategy, could materially shape effect sizes and comparability of ERFs across settings.

3.2.2. Meta-analysis

In multi-location studies, the two-stage meta-analysis is applied to generate robust pooled estimates and assess the impact of modifiers. This step provides more stable and representative ERFs, particularly when cities possess different climate and socioeconomic conditions (Gao & Wang, 2023). In stage one, city- or region-specific DLNMs (or analogous time-series models) generate ERF coefficients and their variance-covariance. In stage two, these coefficients are pooled with multivariate meta-analysis, typically using best linear unbiased prediction (BLUP). The framework also supports BLUP for each location (improving estimates for small samples), multi-level pooling, and targeted pooling by age group or season (Guo et al., 2018; C. He et al., 2023). Some applications use the meta-regression to project ERFs under changing modifiers (e.g., GDP, urbanization) or to probe adaptation trends (e.g., decade terms) (Lee et al., 2020; Petkova et al., 2017; Sun et al., 2021). A minority of studies either omit pooling or employ simpler fixed-effects averaging (Huber et al., 2020). Compared with studies from high-income settings, LMIC applications also less often employ meta-analytic exposure-response functions or include multiple socioeconomic modifiers.

3.2.3. Variables

Beyond temperature and mortality, additional variables play three distinct roles in urban-scale studies. (1) Covariates for adjustment in time-series ERFs models: most studies include temporal controls such as seasonality and long-term trend (splines), day-of-week, and often holidays alongside meteorological co-exposures such as relative humidity (RH) and wind speed. Air pollutants ($PM_{2.5}$, PM_{10}, O_3, NO_2, SO_2) are variably included either as adjustment covariates or as interaction terms to test compound heat-air-pollution risks (Ai et al., 2023; Gao & Wang, 2023; Li et al., 2016; Martinez et al., 2018a). A subset deliberately omits pollutants to avoid over-adjustment or mediation bias, reporting them instead as sensitivity checks (Heaviside et al., 2016). (2) Effect modifiers used via stratification or interactions to describe heterogeneity in ERFs: heterogeneity is most commonly explored by age (especially ≥65, often finer 4–5 bands), and sometimes sex, cause of death, urban/rural, or deprivation/education (Hebbern et al., 2023; Ignjacevic et al., 2024; Kivimaki et al., 2023). Built-environment and thermal-context indicators, including urbanization/density, UHI, mean summer/winter temperature, heat/cold-spell characteristics, are used via stratification or interactions to reflect baseline climate and urban form (Chua et al., 2022; Yi et al., 2024). (3) Meta-predictors in meta-analysis, each materially influencing ERF estimates and their comparability: In multivariate meta-regressions pooling city-specific ERFs, studies commonly include region, Köppen-Geiger climate class, latitude/altitude, and temperature summaries (mean or range) (Qi et al., 2023; Vicedo-Cabrera et al., 2018; Wang et al., 2018). Socioeconomic/infrastructural predictors such as GDP per capita and healthcare capacity are used to explain between-city variability and to derive location-specific curves (J. Y. Lee et al., 2019; Liu et al., 2024; Orlov et al., 2024; Zhang et al., 2023b). A minority exclude meta-predictors to minimize the risk of spurious correlations and documents this via sensitivity analyses (Huber et al., 2022).

3.2.4. Modified exposure-response functions

Although most studies assume stationarity of historical ERFs over time, modification becomes essential when projected temperatures exceed the historical span, especially under high-emission pathways. Two modification approaches emerge: (1) extrapolation beyond observed temperatures and (2) explicit adaptation parameterizations.

Extrapolation. Only a small set (~23%) of included studies considers extrapolation. Yet, how ERFs behave outside the observed temperature range can strongly influence tail risk and thus projected outcomes. The most common practice is to apply the historical ERF to future temperatures without altering its shape, threshold, or slope. The curve is extended smoothly beyond the maximum/minimum observed temperature using log-linear or spline tails so that RR increases monotonically at high temperatures (Gasparrini et al., 2017; Petkova et al., 2017; Wang et al., 2024). This approach is simple and tractable but implicitly assumes no evolution in physiological, infrastructural, or behavioral responses, introducing non-trivial structural uncertainty.

A smaller set of papers imposes conservative constraints to avoid implausible risk escalation. Examples include capping RR at the maximum historically observed temperature, holding RR constant beyond a cutoff, or limiting extrapolation to predefined upper bounds (Sharma et al., 2023; Weinberger et al., 2017). Others avoid explicit curve extension altogether by applying fixed ERFs within historical percentiles and updating the threshold for forecast rather than full-curve extrapolation (Jung et al., 2020; Martinez et al., 2018b; Sharma et al., 2023). A few papers forecast ERFs themselves (e.g., via meta-regression on modifiers) to yield implied changes in MMT or slopes. While often framed as adaptation, this processing also functions as an extrapolation mechanism (Huber et al., 2022; Wang et al., 2018). Across approaches, studies consistently note that extrapolation design could shift projected outcomes. The results should be interpreted as scenario-based projections conditional on explicit functional assumptions rather than forecasts. The sensitivity analyses should also report alternative tail risks alongside the temperature range as support.

Adaptation. Roughly two-thirds of studies do not model adaptation, holding the ERFs, MMT, and RRs fixed to isolate the climate change effect. Where adaptation is modeled, it is typically implemented through stylized scenario assumptions designed to test its potential effect rather than through full adaptation mechanisms (Cordiner et al., 2024).

Around one-third of the studies account for future adaptation to reflect how population sensitivity to heat or cold may evolve due to behavioral, infrastructural, or socioeconomic changes. Four adaptation methods emerge: (1) A common approach is the threshold-shift model, where the MMT or high-temperature threshold moves over time to reflect acclimatization. Shifts are applied as fixed increments (e.g., 0.25 °C per 20 years or 1–4 °C scenarios), by keeping thresholds at constant percentiles (e.g., p89–p99), or by linking MMT to background climate (e.g., mean/seasonal temperatures such as MST). These designs capture physiological/behavioral adjustment without changing the underlying ERF shape (Huber et al., 2022; Wang et al., 2018). (2) A second family uses slope attenuation, scaling down risks above the MMT through fixed factors or smooth decay. They occasionally adjust the attenuation on adaptive-capacity proxies such as air-conditioning penetration or GDP per capita to reflect socioeconomic adaptation (Sun et al., 2021; Wang et al., 2024). (3) Several studies implement combined schemes, shifting thresholds and attenuating slopes to represent both acclimatization and improved preparedness (e.g., heat-health plans, clinical capacity). These hybrids aim to capture plausible adaptation ways under alternative socioeconomic pathways (Huynen & Martens, 2015; M Rai et al., 2022; Pin Wang et al., 2022). (4) Another strand uses an analog-city transfer approach, proxying future ERFs with curves from presently warmer locations that share climatic and urban characteristics, sometimes with comparability constraints (Lee & Dessler, 2023; Li et al., 2018; Mills et al., 2015).

In parallel, a smaller set of studies models adaptation on the exposure side with urban characteristics, built-environment interventions, or socioeconomic proxies. These approaches include urban intervention scenarios such as cool roofs, greening, tree canopy expansion, shading, albedo modification, or UHI-mitigation measures. They are translated into reduced projected temperatures or modified heat exposure (Chaston et al., 2022; Liu et al., 2025; Macintyre et al., 2021b; Taylor et al., 2024). Other studies represent adaptation indirectly through air conditioning, GDP-based adjustment, or adaptation capacity indices (Kouis et al., 2021; Rai et al., 2022; Sun et al., 2021). A related statistical approach is to update future relative thresholds or percentile-based heat definitions as a proxy for acclimatization. Although still limited, these approaches indicate that adaptation can differ within cities because intervention uptake, vegetation, housing conditions, and cooling access are uneven across urban neighborhoods.

Across methods, introduction of adaptation reduces projected heat-attributable mortality on the order of tens of percent but does not eliminate risk under high-warming pathways (e.g., SSP5–8.5) even under aggressive assumptions. The benefits of adaptation are geographically uneven and tend to plateau in already hot, high-air conditioning regions (Sun et al., 2021; Wang et al., 2018). Socioeconomic pathways matter as adaptation potential is constrained under SSP3 and enhanced under other sustainability-focused or wealthier pathways (G Rohat et al., 2019). Many papers that omit explicit adaptation acknowledge their estimates likely upper-bound heat impacts due to potential overestimation of mortality (Heaviside et al., 2016; Lee et al., 2017).

3.3. Demographic and socioeconomic projections

Demographic assumptions have a major influence on projected temperature-related mortality, mainly through population size, age structure, and baseline mortality. Table 3 summarizes the main methodological choices identified in this domain and highlights the contrast between common static assumptions and more dynamic, scenario-consistent alternatives. Overall, static population and mortality assumptions remain widespread, while more advanced approaches increasingly incorporate SSP-based demographic projections and time-varying mortality. Socioeconomic variables are still used mainly as contextual modifiers rather than being directly integrated into health-impact calculations.

Table 3
Synthesis of methodology choices in demographic and socioeconomic projection in the reviewed studies. Illustrative examples of studies applying approaches are provided in the subsection text.

Component	Most common approaches	Alternative approaches	Key implications
Population	Static population or UN/WPP-based national projections.	SSP-based gridded population projections, often age-specific and spatially explicit; cohort-component models; subnational or city-level demographic projections; country-specific statistical systems.	Static populations separate the climate effect but ignore demographic dynamics like aging, potentially underestimating future vulnerability. Scenario-consistent projections better capture demographic change and spatial distribution but are less consistently available at fine urban scales.
Mortality rate	Baseline mortality usually held constant.	Dynamic mortality projections, including age-specific survival or mortality trends from Wittgenstein Centre, EUROPOP, model life tables, or national demographic system.	Constant mortality simplifies modeling but may bias future burdens by ignoring health transitions.
Socioeconomics	Usually omitted, discussed qualitatively, or used as context.	GDP, urbanization, income, air-conditioning access, education, healthcare, or broader adaptation-capacity indicators are used in meta-regression or adaptation scenarios.	Limited integration of socioeconomic change constrains representation of adaptive capacity, inequality, and differential vulnerability within cities.

3.3.1. Demographics

Population. Population projections show a clear methodological divide. Although demographic change fundamentally shapes temperature-related vulnerability, over one-third of studies (36%) hold population size and age structure constant. This static assumption may underestimate future burdens driven by population aging and urban growth.

Among studies that incorporate population dynamics, the most common source is the United Nations World Population Prospects (WPP). However, WPP projections are based mainly on fertility variants and do not directly align with climate-socioeconomic scenario frameworks (Gasparrini et al., 2015; J. Lee et al., 2019; Martinez et al., 2018a, 2018b). More recent studies increasingly adopt SSP-based demographic projections, which incorporate fertility, mortality, and migration assumptions consistent with scenario narratives (KC & Lutz, 2017). The availability of gridded SSP datasets further offers spatial resolutions down to 1 km^2 (Jones & O'Neill, 2016; Li et al., 2017; Zhang et al., 2023a). The availability of these gridded datasetsallows closer alignment with urban mapping and climate-scenario analysis (Ai et al., 2023; Ignjacevic et al., 2024; Marsha et al., 2018; Zhang et al., 2023a). In LMIC settings, projections often rely on global or national-level datasets. While these sources enable projections in such data-sparse contexts, they are relatively coarse and therefore may not capture demographic dynamics within rapidly growing LMIC cities. Single-country and subnational studies often rely on locally calibrated cohort-component models, which are more directly relevant for planning and can better capture demographic heterogeneity than global grids. Examples include the UK Office for National Statistics regional projections (Heaviside et al., 2016), Statistics Canada's SSP-aligned scenarios (Hebbern et al., 2023), Statistics Portugal (Rodrigues et al., 2020), Taiwan's National Development Council data (Sharma et al., 2023), and city-level projections in Finland (Kivimaki et al., 2023).

Migration remains an underexamined component of demographic change but is an important influencing factor of future climate risk (Hoffmann et al., 2020). It is embedded within broader projection frameworks, including SSP-based scenarios and cohort-component models, yet only a few studies explicitly assess its effects. For example, Qi et al. (2023) showed that migration could redistribute diurnal temperature range-related mortality across China, while Petkova et al. (2017) demonstrating that alternative in- and out-migration scenarios substantially changed projected heat-related mortality in New York City.

Stratification of population and related mortality estimates varies across studies, reflecting different approaches to capturing vulnerability heterogeneity. Approximately a quarter of studies apply no demographic stratification, implicitly assuming homogeneous vulnerability across populations. Roughly half of the reviewed studies explicitly stratify by age, most often separating older adults (e.g., ≥65, ≥75, or 85+) from younger populations (Crouzier et al., 2024; Lee & Dessler, 2023; Limaye et al., 2018). Some use finer age bands (e.g., 20–44, 45–64, … ≥85) compatible with SSP-based age pyramids (Masselot et al., 2025). Additional layers include cause of death (notably cardiovascular and respiratory diseases) (Huynen & Martens, 2015), urban-rural residence (Ignjacevic et al., 2024), sex (Kivimaki et al., 2023) or combined status (Qi et al., 2023; Yi et al., 2024).

Mortality rate. Mortality rate assumptions reveal another major modeling constraint. Approximately three-quarters of studies hold mortality rates constant across projection periods, typically by applying historical averages or fixing rates to a baseline year. This simplifies the projection and isolates climatic effects, but may underestimate the combined influence of health transitions, aging, and healthcare change on future mortality.

A smaller subset of studies incorporates dynamic mortality trajectories. First, adjusted future mortality rate from local-level demographic projections utilizing national statistical sources such as ONS (Heaviside et al., 2016), Eurostat(Garcia-León et al., 2024) and Statistics Netherlands (Huynen & Martens, 2015). Another route draws directly on SSP-consistent age-specific mortality from the Wittgenstein Centre Human Capital Data Explorer (Wang et al., 2024; P Wang et al., 2022), converting survival ratios to scenario-specific death rates (Masselot et al., 2025) or smoothing SSP3/SSP5 age-specific series(K. Chen et al., 2024). A few studies combine evolving mortality rates with detailed age- and cause-of-death stratification, yielding internally coherent burdens under alternative pathways. Rai et al. (2022) represents a more detailed case where they combine evolving mortality rates with detailed age- and cause-of-death stratification.

3.3.2. Socioeconomics

Context/other impacts. Around two-thirds do not incorporate socioeconomic indicators directly into projection beyond the demographic assumptions described above or only mention them qualitatively. A smaller group refers to SSP-based GDP or urbanization trajectories to frame broader scenarios but does not integrate these variables into the health-impact assessment itself. For example, Botzen et al. (2020) monetize future mortality changes using the value of a statistical life (VSL) and value of a life year (VOLY), adjusting for age-specific life expectancy in the Netherlands. Belova et al. (2022) use VSL estimates, which are adjusted for inflation, income growth, and elasticity, to quantify the economic burden of climate-related suicide risk in the US. A few studies include socioeconomic proxies in meta-regressions or embed urbanization in the exposure module via urban climate parameters, as mentioned in previous sections. In these cases, however, socioeconomic change remains weakly integrated into the health-impact assessment.

3.4. Urban characteristics and processes

3.4.1. UHI

Urban characteristics, particularly the UHI effect, are important modifiers of temperature-related mortality by amplifying heat exposure and shifting risk toward nighttime (Deilami et al., 2018). Urban heat exposure is also shaped by adaptation-related factors such as vegetation cover, reflective surfaces and form of building, and access to cooling, which are heterogeneous within cities (Kouis et al., 2021; Macintyre et al., 2021b). However, most studies (∼80%) do not model them explicitly and treat cities as spatially uniform exposure units. This simplification may underestimate heat-related mortality in dense urban cores and limit the spatial targeting of adaptation strategies.

Across the reviewed studies, four approaches of UHI representation are identified. First, most studies conduct city-level analyses using observed or downscaled temperature matched to administrative boundaries, nearest grid cells, or population-weighted averages, without distinguishing intra-urban variation. Some incorporate simple urban-rural splits or county-based classifications, but without modeling UHI specifically. (Limaye et al., 2018; Wang et al., 2022). Second, UHI intensity is estimated using empirical relationships with urbanization indicators such as population density, urban land cover, or land-surface versus air-temperature differences. It is modeled as a function of urban population size or density and applied as an adjustment to projected temperature surfaces in several studies (Botzen et al., 2020; Ignjacevic et al., 2024; Kivimaki et al., 2023). Others fit separate ERFs for urban and non-urban populations to capture the differentiated risks (Chen et al., 2017). These approaches partially account for urban amplification but rely on statistical proxies rather than explicit physical simulation. Third, some studies also define urban areas using satellite-derived built-up extents and compute population-weighted temperatures using high-resolution gridded population data (Bakhtsiyarava et al., 2025; Zhu et al., 2021). While not explicitly modeling UHI, these approaches better align exposure with actual residential distribution and reduce aggregation bias. Fourth, a smaller subset employs high-resolution regional climate models that could be coupled with multi-layer urban canopy schemes (Macintyre et al., 2021b; G Rohat et al., 2019; Wang et al., 2024). These models incorporate morphological parameters, such as street canyon geometry, vegetation cover, and parcel-level land-use projections to simulate urban heat processes dynamically. These physically based approaches allow representation of multiple processes but are computationally intensive and remain limited in application.

An important methodological distinction emerges between static and dynamic representations of UHI. Static approaches assume that present-day urban-rural temperature differentials remain constant over time. UHI adjustments are considered based on current density or urban-level damage functions and are applied uniformly to projections (Ignjacevic et al., 2024). This assumption may omit potential changes in urban extent, morphology, and land-use conversion, especially under different pathways. Dynamic approaches could further simulate how future urban transformations alter UHI intensity. Examples include multi-phase urbanization models linking city size to UHI intensity and integrating parcel-level land-use projections into high-resolution RCM frameworks (Liu et al., 2025; Rohat et al., 2019). Although methodologically more consistent with scenario-based projections, dynamic UHI modeling remains rare.

Where UHI is represented, studies consistently find elevated heat-related mortality in urban cores, driven by increased nocturnal temperatures and heat accumulation. UHI intensifies heat exposure, often shifting the burden toward nighttime minima, and exacerbates vulnerability in high-density or aging residents. Some studies suggest that seasonal complexity emerges as UHI also mitigates cold-related mortality, creating geographic and temporal trade-offs dependent on local adaptation capacity and climate context (Macintyre et al., 2021b). Urban-specific interventions such as vegetation enhancement or albedo modification show potential for reducing summer mortality notably, though some strategies may adversely affect colder months (Wang et al., 2025). Several studies modeling explicit UHI report higher heat-related mortality and lower cold-related mortality estimates in dense urban cores, suggesting that spatially uniform exposure assumptions may systematically misestimate urban heat or cold risk (Chaston et al., 2022; He et al., 2022; Macintyre et al., 2021a; Wang et al., 2025). Overall, neglecting UHI representation may bias burden estimates downward for highly urbanized areas and obscure intra-urban inequities.

3.4.2. Urbanization

Beyond the UHI, urbanization and land use change also influence health outcomes, but remain rarely considered. Most studies assume a static urbanization level, while some employ multi-phase urbanization models that quantify relationships between urban expansion and warming effects (Liu et al., 2025). One study calibrates urban climate models to incorporate detailed land-use patterns such as reduced vegetation in the city center (Martinez et al., 2018b). These factors are mainly included as influencing variables to capture between-city heterogeneity or assess their impacts on mortality (Sun et al., 2022).

3.5. Health impact assessment

Health impact assessment is the final stage that translates projected exposure into outcomes. The dominant practice is to estimate attributable fractions (AF) and/or attributable numbers (AN) using projected temperatures, exposure-response functions, and demographic assumptions. However, studies vary in both the reporting metrics and the consideration of compound risks. Table 4 summarizes the main methodological choices and their implications.

3.5.1. Calculation of health impacts

The reviewed studies quantify temperature-related mortality using a range of epidemiological measures. Most calculate daily temperature-attributable deaths and then aggregate results by season or year in various geographic settings (city, region, or country). The dominant outputs are AN, representing the absolute count of excess deaths associated with non-optimal temperature, and AF, which facilitates comparison across scenarios and places (K. Chen et al., 2024b; Huang et al., 2023; Rodrigues et al., 2020; Rezaee et al., 2025). Results are often stratified by age, especially older populations (≥65), and by cause of death.

Some studies additionally report mortality ratios relative to baseline conditions, excess mortality fractions, or event-specific burdens such as heatwave-attributable deaths and tail risks at extreme percentiles relative to MMT (Arnold et al., 2022; Riahi & Khorsandi, 2025). A smaller subset expresses results as standardized mortality rates (e.g., deaths per 100,000) to improve comparability across space and time (Amnuaylojaroen et al., 2024; Chen et al., 2017; J. Lee et al., 2018; Limaye et al., 2018; Pin Wang et al., 2022). Studies with a stronger policy focus sometimes calculate avoidable fractions or avoidable deaths by comparing adaptation or mitigation scenarios, and occasionally extend the assessment to years of life lost or economic valuation (e.g., present discounted value) (Liu et al., 2023; Lo et al., 2019).

3.5.2. Compound risks

Heat-related mortality can be exacerbated by compound environmental stressors, especially during extreme events when multiple hazards co-occur. Yet explicit compound-risk modeling remains uncommon in urban-scale projections: around 85% of the reviewed studies do not model such interactions directly. This would likely understate the complexity of urban heat-health risk, particularly in humid, polluted, and densely built cities. Where compound risks are considered, they influence estimated impacts either by redefining heat exposure using composite indices or by incorporating co-exposures that modify the exposure-response relationship. A first group of studies uses composite heat-stress metrics that combine temperature with humidity, such as apparent temperature, heat index, humidex, heat stress index (HIS), or Wet Bulb Globe Temperature (WBGT). Some also distinguish daytime and nighttime heat to better capture physiological stress pathways (Lee et al., 2018; Lee & Dessler, 2023). A second group evaluates joint temperature and air-pollution effects. Most include pollutants such as PM_{10}, $PM_{2.5}$, or ozone as covariates, sensitivity terms, or interaction terms in ERF models. Others report higher risks during hot and polluted days, suggesting potentially compound effects (Gu et al., 2020; Jung et al., 2020; Martinez et al., 2018a; Zhang et al., 2023a). A few consider broader multi-hazard contexts, such as co-occurring hurricanes and heat, or interactions involving urban heat island effects (Gao & Wang, 2023).

Table 4
Synthesis of methodology choices in health impact assessment in the reviewed studies. Illustrative examples of studies applying approaches are provided in the subsection text.

Component	Most common approaches	Alternative approaches	Key implications
Calculation of health impacts	Attributable number/deaths (AN/AD) and attributable fraction (AF), usually calculated at daily scale and then aggregated by season, year, or geography; heat and cold often separated using MMT or fixed thresholds.	Mortality rates per 100,000, age-standardized mortality rates (ASMR), excess mortality fractions, avoidable fractions, YLL, or economic valuation (e.g., VSL, VOLY).	Different metrics limit comparability. Choice of metrics also affects interpretation: AN/AD emphasize burden size, while AF/rates improve comparability.
Compound risks	Most studies assess temperature as a single exposure. t.	Humidity or air pollution is occasionally included only as adjustment covariates or in sensitivity analysis Metrics include composite heat-stress indices (e.g., apparent temperature, humidex, heat index, HSI, WBGT), interaction terms with air pollution (e.g., PM_{10}/O_3), explicit heatwave duration/intensity metrics, and occasional multi-hazard settings.	Limited treatment of compound risks may underestimate urban temperature-health burdens, especially in humid, polluted, or hazard-prone cities.

3.6. Uncertainty and sensitivity analysis

Uncertainty and sensitivity analysis are essential for interpreting the robustness of projected results. Table 5 summarizes the methodological choices in this step and their implications.

Table 5
Synthesis of methodology choices in uncertainty and sensitivity analysis in the reviewed studies. Illustrative examples of studies applying approaches are provided in the subsection text.

Component	Most common approaches	Alternative approaches	Key implications
Uncertainty analysis	Sources of uncertainty are commonly discussed across climate scenarios, GCM/RCM choice, ERF specification, population assumptions. Quantification of uncertainty are mostly through empirical confidence intervals derived from Monte Carlo simulation and multi-model climate ensembles.	Additional sources of uncertainty include downscaling and bias-correction choices, exposure metrics, UHI representation, extrapolation beyond observed temperature range, co-exposures, and socioeconomic assumptions. Other quantification methods include bootstrap methods, Bayesian posterior or predictive distributions, variance decomposition/ ANOVA, Bayesian model averaging, prediction intervals, and back-testing/ validation metrics such as RMSE and R square.	In many studies, climate-model spread is the dominant source. Most studies quantify parameter and climate forecast uncertainty, but only a subset explicitly maps uncertainty across drivers. Reported uncertainty ranges are therefore often not directly comparable across studies.
Sensitivity analysis	Tests of ERF specification, lag length, spline degrees of freedom, exposure metric choice, climate scenario/model choice, and demographic assumptions.	Additional tests include adaptation scenarios, alternative thresholds, pollution adjustment, bias-correction methods, spatial exposure definitions, leave-one-city-out checks, and cross-validation.	Projected mortality is often responsive to methodological choices, especially changes in ERF form, exposure definition, adaptation assumptions, and demographic inputs.

3.6.1. Uncertainty analysis

Uncertainty could arise throughout the workflow. On the climate inputs, spread arises from scenario choice, inter-model differences among GCMs and RCMs, and downscaling or bias-correction methods. Additional variance comes from the choice of exposure metric (e.g., daily mean vs. extreme indices), spatial resolution, and representation of urban characteristics. In environmental epidemiology, estimates depend on model specification of the ERFs regarding lag windows, spline degrees of freedom, and the baseline MMT, and extrapolations beyond observed temperature ranges. For the demographics, assumptions about population size, age structure, spatial distribution, and future mortality rates can directly shift attributable burdens. Further uncertainty stems from adaptation parameterization, co-exposures such as humidity and air pollution, and data quality or aggregation choices.

Across the reviewed studies, the choice of climate models and downscaling strategy is a major source of uncertainty as they directly determine the magnitude and spatial pattern of future exposure. Demographic assumptions are another key source because they directly scale the exposed population. The choices of ERF application, extrapolation methods, and adaptation parameterization are less consistently assessed. Yet they also introduce substantial uncertainty in projected burdens, especially under high warming and extreme heat conditions.

The quantification of uncertainty reported in most studies includes: (1) Monte Carlo sampling of ERF parameters to derive empirical confidence intervals is commonly reported (S. Chen et al., 2024; Hebbern et al., 2023; Huber et al., 2022); (2) multi-model climate ensembles (CMIP5/6) summarized as ranges or with simple/model-weighted means (Kivimaki et al., 2023; Lee & Dessler, 2023); (3) bootstrap procedures for AF variability. A subset attributes variance using Analysis of variance (ANOVA)/variance decomposition or applies Bayesian model averaging to combine model structures (Chen et al., 2017; Li et al., 2016; Wang et al., 2024). (4) model checking, with reporting Root Mean Square Error (RMSE) and R square to ensure intervals are consistent with out-of-sample performance (Amnuaylojaroen et al., 2024; He et al., 2023; Taylor et al., 2024).

Data quality and availability also represent an important source of uncertainty in projection studies. Table S4 summarizes the main input datasets used across the reviewed studies, including variables, indicators, data sources, and their native temporal and spatial resolutions. The major data inputs include: (1) historical and projected temperature data from meteorological stations and climate models; (2) historical mortality records and projected population or mortality rate datasets; and (3) contextual datasets such as socioeconomic indicators, land use, air pollution, humidity, and UHI-related proxies. These datasets differ substantially in spatial resolution, temporal coverage, completeness, and reporting standards. While coarse-resolution datasets may be sufficient for regional-scale assessments, they may mask intra-urban temperature variability and population exposure patterns that are critical for city-scale risk assessment. In particular, mortality and health data availability vary widely across countries, with many LMICs lacking long-term, high-quality mortality records. Future projection studies would benefit from more transparent documentation and clearer assessment of uncertainties associated with data limitations.

3.6.2. Sensitivity analysis

Sensitivity analysis serves as a test of the robustness of the projected results. The largest shifts in projected outcomes most often arise from the following five categories: (1) epidemiological specification about changing lag windows, exposure-response forms, spline degrees of freedom, sometimes with Akaike's information criterion (AIC) selection or leave-one-city-out checks (Hebbern et al., 2023; Huber et al., 2020; Rodrigues et al., 2020); (2) exposure specification on swapping temperature metrics, spatial representations, and event definitions (Arnold et al., 2022; Lee & Dessler, 2023); (3) climate models downscaling choices engage with using multi-GCMs/RCMs ensembles, alternative bias-corrections, and scenario sets to measure sensitivity in climate modeling(Vicedo-Cabrera et al., 2018); (4) demographic specifications on switching population projections/age strata or holding mortality rates fixed versus dynamic to separate climate effects from demographic change(Chen et al., 2017; K. Chen et al., 2024b; Chua et al., 2022). (5) adaptation parameterization on shifting MMTs, attenuating heat slopes, combining shift attenuation, or using analog-city assumptions. Sensitivity to co-exposures is also explored by adding or removing $PM_{2.5}$, PM_{10}, O_3, NO_2, SO_2, and humidity, or by estimating interaction terms (Martinez et al., 2016; Orru et al., 2019; Yang et al., 2021).

Computationally, robustness summaries typically combine Monte Carlo draws of ERF coefficients combined with multiple GCMs exposure series to derive empirical confidence intervals. Variants include Latin-hypercube sampling, bootstrap of AF, Bayesian posterior sampling in meta-regressions, and ANOVA. Results are typically reported as effect sizes of projected outcomes with ranges or weighted summaries.

4. Challenges and outlook

The 110 studies included in this review reveal limitations in regional coverage and methodological gaps in current projection studies. The studies are heavily skewed toward high-income countries and major urban centers, while LMIC regions and smaller cities are limited. Africa remains underrepresented despite its higher vulnerability and less adaptive resources. This geographical bias is compounded by a predominant focus on higher-end emission pathways such as RCP8.5 or SSP5–8.5, which are argued to represent increasingly unlikely scenarios (Hausfather & Peters, 2020; Ritchie & Dowlatabadi, 2017). Temperature-related risks exhibit pronounced spatial heterogeneity across regions and within cities, reflecting differences in climatic context, urban forms, demographics, and adaptation provision (Ai et al., 2023). This spatial complexity underscores the critical importance of urban scale or finer-resolution projections to inform effective urban planning and public health interventions (Sun et al., 2021; Wang et al., 2018). However, developing such high-resolution and locally relevant projections faces multiple technical challenges. The complexity of drivers affecting urban areas requires comprehensive consideration of multiple interacting effects from global warming, population growth, urban development, and evolving adaptive capacity (Broadbent et al., 2020).

Here, we identified five critical challenges spanning the workflow synthesized in the previous section. We also propose practical recommendations and potential methodological advancements identified in the broader literature, with particular attention to the constraints faced by LMICs.

4.1. High-resolution urban climate projections and uncertainty quantification

The primary limitation concerns the climate inputs from climate models, which remain coarse to capture nuanced urban-scale temperature exposure. Recent advancements have emerged toward higher-resolution projections. A work from Schwingshackl et al. (2024) leverages regional climate model ensembles to deliver urban-scale heat projections across multiple metrics. Such productions are also beginning to filter into health applications (Crouzier et al., 2024). Downscaling and bias correction remain essential to reconcile coarse climate forecasts with local observations. It is demonstrated that quantile-mapping strategies can systematically correct CMIP6 temperature fields for hundreds of megacities worldwide, improving urban heat projections (Rajulapati et al., 2022). For LMIC and data-scarce cities, projections may need to rely on multiple complementary data sources. Where dense local observations are unavailable, high-resolution global or regional climate products can be combined with available station or satellite observations (Codyre et al., 2025). High-resolution regional climate models with dynamic downscaling could be ideal as they possess a balance of granularity and complexity in the urban context.

Uncertainty associated with the climate projections should also be explicitly quantified. At the urban scale, projections vary markedly across GCMs/RCMs because of structural differences (e.g., convection schemes, land-atmosphere coupling, representation of urban processes). Relying on a single model or a small, homogeneous ensemble may collapse these structural differences and pull estimates toward the ensemble mean, which can understate the upper tail where the extremes occur. Sampling broadly across multi-model ensembles or using urban climate emulators calibrated to those ensembles could mitigate structural uncertainty and characterize tail risks (Zheng et al., 2021).

4.2. Scenario-consistent demographic and socioeconomic projections

The second limitation is the treatment of demographic and socioeconomic change. The reviewed literature demonstrates that demographic dynamics, including population increase and population aging, are fundamental in shaping vulnerability (Chen et al., 2020b; K. Chen et al., 2024b; Huang et al., 2023; Sun et al., 2022). Population aging is critically amplifying climate risk, particularly in rapidly aging megacities with elderly populations bearing disproportionately higher health burdens (Li et al., 2016). This demographic shift necessitates enhanced healthcare infrastructure and targeted public health initiatives designed to protect the elderly (Hebbern et al., 2023; Lee & Kim, 2016).

However, many studies hold demographics constant, overlooking aging, migration, and urbanization, and consequently weaken the policy relevance. Evidence shows that the choice of population dataset can materially affect exposure estimates. While global patterns remain broadly consistent across SSP-based projections, sub-continental projections diverge substantially, underscoring the need to incorporate localized forecasts (Zhang et al., 2025). Urban-scale study further demonstrates that projecting daily mortality with age-specific weights notably changes results compared with static assumptions (Bakhtsiyarava et al., 2025). Migration also requires more explicit consideration in population projections, as climate-related mobility may increasingly shape urban population dynamics under global warming. Evidence from related literature shows that heat stress can increase long-term migration patterns and shift population flows toward urban areas (Baez et al., 2017; Mueller et al., 2014). Such dynamics may also alter socioeconomic composition and demand for urban health services.

Methodological advances are emerging to address these limitations. SSP-consistent subnational population scenarios can now be embedded directly in health-impact assessments. Examples include state-level projections for the United States (Jiang et al., 2020) and sub-national projections for Mexico (Regules García et al., 2024). These scenarios enable alignment of demographic futures with climate scenarios. High-resolution population datasets are also advancing the spatial granularity of risk assessments. Globally, new 1-km, SSP-consistent population projections improve accuracy in dense urban areas and better capture built-up dynamics (Li et al., 2022). Projections by age, sex, and education support fine-scale heat-vulnerability modeling (Marginean et al., 2024). For China, spatially explicit downscaling that treats urban and rural populations separately and accounts for urbanization provides more credible grid-level population projections for climate-health analyses (Xu et al., 2024).

Local socioeconomic conditions also influence projected outcomes by affecting exposure, physiological sensitivity, and adaptive capacity (Chen et al., 2026; T. He et al., 2023). Heterogeneity in these conditions, including income, education, housing quality, and access to cooling, heating, and healthcare, are associated with differential vulnerability within cities (J. Lee et al., 2018; Liu et al., 2025). Targeted protections for low-income and socially marginalized groups are essential (Masna Rai et al., 2022; G Rohat et al., 2019). There are advances in quantifying these socioeconomic aspects needed for scenario-consistent projection. Examples include SSP-aligned high-resolution income projections for Europe (Mikou et al., 2025) and globally gridded GDP (Wang & Sun, 2022). In many LMIC cities, detailed city-level socioeconomic statistics are limited. In such cases, global gridded datasets or national scenario-consistent projections can provide a practical intermediate basis (Bakhtsiyarava et al., 2025; Hajat et al., 2023).

4.3. Intra-urban variability and social vulnerability

Underrepresentation of LMICs in projections risks skewing global adaptation agendas toward rich regions. To generate estimates that are both actionable and equitable, future projections should consider intra-urban vulnerability and social vulnerability. Cities exhibit intra-urban variability in urban characteristics (building density, green space coverage, surface materials), demographic composition (age structure), and socioeconomic conditions (income distribution, housing, healthcare access, adaptive capacity) (Li et al., 2023). Yet this heterogeneity is rarely represented explicitly in projection studies. Treating cities as uniform exposure units risks masking neighborhood-level hotspots and underestimating the burden borne by disadvantaged groups. This matters especially for LMIC cities where intra-urban variability could be significant, though the neighborhood-level data may not be available. In such cases, studies can still improve projection realism by linking gridded global population data with available local socioeconomic proxies to identify hotspots of vulnerability (Ahmadalipour & Moradkhani, 2018; Zhu et al., 2023).

Several approaches have emerged to better represent intra-urban heterogeneity. Recent advances in urban climatology and modeling frameworks provide tools for integrating more detailed urban characteristics into climate projections (Masson et al., 2020). High-resolution urban climate modeling combined with spatial population datasets can generate neighborhood-level exposure that captures variations in urban morphology and vegetation cover. Spatially explicit satellite-derived temperature metrics allow opportunities to identify localized heat-risk hotspots. For example, H. Zhao et al. (2024) demonstrate how the morphology and expansion patterns of UHI influence population exposure at both city and raster scales, improving neighborhood-level exposure measurement.

Growing evidence suggests the shaping effect of intra-urban variability in temperature-related health risks, reflecting the complexity of vulnerability (He et al., 2019). Comparative analyses of Seoul and Tokyo reveal that climate change and demographic shifts heat-exposure hotspots of the elderly population (Park et al., 2021). High-resolution projections further indicate that neighborhoods already vulnerable today are likely to exacerbate under most socioeconomic pathways (Marginean et al., 2024).

Social conditions systematically modify temperature-related health risks through multiple facets (Nishimura et al., 2021; Roberts et al., 2025). A scoping review identifies a core set of vulnerability indicators (e.g., age, sex, education, income, access to green space, and healthcare) while highlighting the need to capture structural and institutional drivers beyond individual conditions (Li et al., 2023). Empirical studies document thermal inequity that wealthier districts experience cooler conditions than poorer ones (Boyle, 2023). Sera et al. (2019) show that higher population density, $PM_{2.5}$, GDP, and income inequality amplify heat-related mortality, whereas urban greenery attenuates it. Localized analyses confirm stronger respiratory mortality effects with higher density and $PM_{2.5}$, particularly among females (Zafeiratou et al., 2023). Chen et al. (2018) reveals that social vulnerability intensifies risks in less-urbanized cities and suburban fringes, while highly urbanized cores remain high-risk due to UHI and density.

Additional determinants reinforce the importance and complexity for incorporating intra-urban details. Upgrading low-efficiency housing stock can reduce indoor heat stress and associated mortality (Alam et al., 2016). Daily mobility patterns raise residents' heat-wave exposure relative to static home-based estimates, implying that commuting and activity spaces should be considered (Yang et al., 2019). Emerging indoor heat-health warning systems show promise for anticipating dwelling-level overheating and guiding targeted alerts and interventions (Gustin et al., 2020). Together, these insights argue for coupling neighborhood-scale exposure modeling with more nuanced indicators to quantify inequities within cities. Such integrated approaches are essential for developing targeted adaptation strategies that protect the most vulnerable populations across diverse urban contexts.

4.4. Urban dynamics modelling

Most projection studies still treat cities as homogeneous exposure units, rarely modeling explicit UHI effects or other urban processes. Urban-specific adaptation strategies require careful consideration of local contexts and potential trade-offs to optimize health outcomes (Lee et al., 2019; Lee & Dessler, 2023; Liu et al., 2025; Masselot et al., 2025; Wang et al., 2018). While climate mitigation and adaptation strategies yield the greatest overall benefits, urban interventions present unique challenges (Kivimaki et al., 2023; Rohat et al., 2019; Wang et al., 2022). UHI mitigation and cooling strategies, including urban greening and cooling infrastructure, substantially reduce summer heat-related mortality but can inadvertently elevate winter cold-related mortality, particularly in temperate regions (Wang et al., 2025). This complexity requires careful considerations of seasonal dynamics and local climatic contexts to avoid unintended consequences (Guo et al., 2016; Madaniyazi et al., 2024). Strategy thus should be guided by city-specific conditions rather than one-size-fits-all prescriptions.

UHI intensity and its mitigation potential depend on various factors such as background climate, population, evapotranspiration, and urban form (Mirzaei, 2015; Mohammad Harmay & Choi, 2023). Greener and higher-albedo strategies are most effective in dry climates, whereas tropical cities may require different solutions (Manoli et al., 2019). Exceptionally large UHI is not confined to megacities but also occurs in medium-sized cities and varies with season, topography, and vegetation (Amorim et al., 2024). Recent work cautions that using short-term variability to infer future UHI change can be misleading. Process-based projections and rigorous evaluation against observations are needed (Speville et al., 2023). Together, these findings argue for embedding empirically calibrated UHI modules and for testing city-specific mitigation plans (greening, reflective surfaces). Although process-based urban climate models are valuable in quantifying UHI, they are data- and computation-intensive and may not be feasible for many smaller cities. A practical alternative is to incorporate urban effects using empirically calibrated UHI adjustments, land-cover proxies, or satellite-based exposure information (Jack et al., 2024).

A related gap is the limited treatment of urbanization and land-use change (Lindberg et al., 2016; Wang, 2021). Evidence shows that urban expansion systematically intensifies UHI and elevates heat risk. Globally, newly built-up areas have experienced stronger summer UHI and higher heat-related risk (Hao et al., 2025). In China, compound hot extremes have risen with detectable fingerprints of both greenhouse forcing and urbanization (J. Wang et al., 2021), and urbanization exerts nighttime extreme heat (Q. Zhao et al., 2024). The relationship between urbanization and heat vulnerability is also context-dependent, as some places see lower vulnerability with urban development due to improved services (Q. Wang et al., 2021). Methodologically, projections could represent feedback between urban form and exposure and allow vulnerability and ERFs to evolve with the urbanization stage. An additional methodological direction is the Local Climate Zone (LCZ) framework. Recent studies show that LCZ classifications can help distinguish thermal environments across different urban forms, ranging from compact high-density districts to more open or natural areas (Z. Wang et al., 2025; Xiong et al., 2025; Yin et al., 2025). LCZ-based approaches provide a promising way to link urban morphology, spatial heat exposure, and adaptation measures in a more spatially explicit framework for projections.

Current empirical evidence is also skewed toward large metropolitan areas, while small- and medium-sized cities remain less frequently studied. These cities often differ from megacities in adaptive capacity, infrastructure, and exposure patterns, limiting direct transfer of methods. Future studies should therefore broaden coverage across cities of different scales and consider locally specific conditions. Combining gridded climate data with high-resolution population datasets could enable population-weighted exposure estimates for smaller cities where observational data are limited.

Emerging machine learning (ML) approaches show potential to improve predictive performance in projection studies, especially in data-scarce regions. Recent studies demonstrate that ML models can capture complex nonlinear interactions among meteorological, demographic, and socioeconomic predictors. Examples include estimating heat-related health outcomes across multiple regions simultaneously (Boudreault et al., 2024) and integrating remote sensing, sensor networks, and urban morphology data to improve UHI analysis (Snaiki & Merabtine, 2025).

4.5. Holistic adaptation beyond simple quantitative adjustments

Adaptation modeling of people and non-optimal temperature exposure often needs to be based on strong assumptions. In reviewed studies, a common approach is applying modifications based on bespoke adaptation scenarios. Yet this approach, usually through quantitative adjustments, may not fully reflect how adaptation develops over time or differs across places and populations. Conceptual and review work shows adaptation operates across physiological, cultural, and political domains at both individual and societal levels (Navas-Martín et al., 2024). These adaptation mechanisms can typically be quantified through three categories of ERF-based approaches (e.g., shifting MMT/thresholds), exposure-based approaches (e.g., greening, cool roofs), and adaptive-capacity approaches linking to socioeconomic and infrastructural indicators (e.g., air-conditioning prevalence) via stratification or meta-regression (Cordiner et al., 2024). Meanwhile, empirical evidence of rising MMT supports the case for dynamic thresholds in projections (Luo et al., 2024). Gosling et al. (2017) suggest that the treatment of adaptation can dominate overall uncertainty and favor transparent threshold shifts and slope reductions of ERF when empirical evidence is limited. In urban settings, evaluations of physical adaptations show both potential and limits. Heatwave can be mitigated by cool or green roofs under moderate scenarios, yet this effect could fall short under high-emissions futures (Aminipouri et al., 2019; Liu et al., 2022). Adaptation modeling should therefore represent specific urban-climate interventions and test their performance across emissions pathways (Coccolo et al., 2018; Kim et al., 2025).

Longitudinal evidence shows air-conditioning reduces heat-related mortality, and broader societal changes have bolstered resilience (Lenzer et al., 2020; Sera et al., 2020). Yet air-conditioning also releases anthropogenic heat, warming urban microclimates and partially offsetting benefits, especially in warmer cities (Chua et al., 2023). Since access and use of air conditioning are related to income, housing, and grid constraints, projections should jointly consider their penetration, affordability, and corresponding energy consumption aspects (Hu et al., 2023a, 2023b; Salvo, 2018).

Adaptation benefits are heterogeneous across regions and subpopulations (Vargo et al., 2016). Extended two-stage designs now allow explicit modeling of nonlinear risks, multilevel structure, age-specific effects, and modifiers such as air-conditioning (Sera & Gasparrini, 2022). Empirical trends of acclimatization are context-dependent. Broader reviews find decreasing heat sensitivity in many developed contexts linked to warnings, awareness, and improved living conditions (Sheridan & Allen, 2018), while some report increasing heat sensitivity alongside declining cold-spell impacts (Wang et al., 2023).

In data-constrained settings, adaptation does not need to be represented only through complex mechanistic models. A feasible first step is to test adaptation scenarios based on simple mathematical adjustments while clearly stating uncertainty and implications. These assumptions can also be complemented with locally informed pathways linked to available variables (e.g., air-conditioning access and health-system capacity) (Feng et al., 2023). These insights advocate adaptation modeling to be evidence-based, drawing on observed trends or empirically evaluated interventions. Adaptation mechanisms should also be consistent with socioeconomic scenario narratives and account for heterogeneous impacts. To assess adaptation effectiveness more transparently, studies can report metrics such as “avoidable” mortality by comparing baseline and adaptation scenarios.

Taken together, these challenges suggest practical priorities for next-generation urban temperature-mortality projections. First, projections should use climate inputs that better reflect urban-scale exposure, either through high-resolution urban climate modeling or transparent proxy-based approaches where data are limited. Second, demographic assumptions should move beyond static population baselines to include age structure, migration, and, where possible, scenario-consistent mortality change. Third, cities should no longer be treated as internally homogeneous units, and future studies should better capture intra-urban differences in exposure, vulnerability, and adaptive capacity. Fourth, urban characteristics such as UHI intensity, land-use change, and greening should be treated as dynamic drivers rather than fixed background conditions. Finally, adaptation should be modeled using transparent and empirically informed scenarios, with uncertainty and feasibility clearly reported.

5. Conclusion

This review systematically examines methodological approaches in 110 studies projecting temperature-related mortality at the urban scale over the past decade (2015–2025), synthesizing a comprehensive six-domain methodological framework that covers both data sources and analytical approaches. We identify rapid uptake of CMIPs, dominant reliance on DLNM-based ERFs, and substantial variation in how studies treat demographics, adaptation, urban characteristics, and uncertainty and sensitivity analysis. As our analysis demonstrates, methodological choices could influence the projection outcomes and their policy relevance. Several cross-cutting methodological limitations emerge from this synthesis: frequent stationarity assumptions for demographic and epidemiological relationships, coarse spatial resolution that underrepresents UHI and intra-urban heterogeneity, and oversimplified or absent modeling of adaptation. We discuss practical improvements from scenario-consistent demographic trajectories to uncertainty quantification that can enhance the policy relevance and comparability across settings.

While our systematic review provides a comprehensive overview of current methodological approaches, it also highlights important limitations in the existing evidence base. The geographical bias toward high-income countries and major megacities limits generalizability to LMIC regions where climate vulnerability may be highest. Additionally, the complexity of urban climate-health systems requires continued methodological innovation to better capture dynamic interactions between demographic, environmental, and socioeconomic factors. The synthesized methodological framework indicates the typical workflow through the components. We note that feedback loops or iterative processes between them are not fully captured as a limitation.

For the research community, the methodological roadmap developed in this review provides detailed guidance for next-generation modeling on climate-health projections at the localized scale. From a practice perspective, more credible and equitable projections are needed to continue to narrow the gap between research and real-world planning. For urban planning, they can help identify neighborhood-scale hotspots and evaluate the health implications of built environments such as greening and cool roofs. For public health sectors, they can support planning during temperature extremes and targeted protection of vulnerable groups. For policymakers, they can guide priorities and the integration of health into urban climate adaptation and mitigation strategies.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used AI-assisted tools (including ChatGPT, Claude and Perplexity) in order to improve readability and language. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Kedi Liu: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Software, Visualization. **Ranran Wang:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization, Investigation, Methodology. **Arnold Tukker:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Resources. **Samir KC:** Supervision, Investigation. **Rutger Hoekstra:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Resources.

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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Data availability

No data was used for the research described in the article. All reviewed literature included in the Supplementary Info.

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