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REVIEW

Data Considerations for Estimating Ambient Heat Exposure for Environmental Epidemiological Studies

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Abstract

Purpose Extreme heat is a public health threat. We review common meteorological data sets and metrics for estimating heat in epidemiologic studies and recommend practical advice for those just starting in this field.

Recent Findings Heat can be estimated through a variety of approaches that differ in their spatial resolution, temporal frequency, historical extent, aggregation, and population coverage. Heat exposure is operationalized as air temperature, but heat indices including additional variables (e.g. humidity, solar radiation, wind) capturing different physiological pathways and varying in their availability and interpretability are common. Defining heat waves for research and government activation is another important consideration in terms of risk and perception. Other analysis choices include defining extreme heat thresholds, population-weighting, or special considerations in urban environments.

Summary We suggest practical guidance for selecting data and metrics for specific heat health epidemiologic questions. No single "best" heat metric exists; investigators should consider their research question, population, and data availability to identify the most appropriate approaches.

Keywords Heat · Temperature exposure · Heat metrics · Exposure assessment

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Abbreviations

Measures of Heat

Albedo (α)	A measure of the shortwave reflectivity of a material or surface. Surfaces with lower albedo absorb more sunlight compared to areas with higher albedo
Cooling Degree Days (CDD)	Represents the difference between the daily mean temperature and a reference "comfortable" temperature (65 °F in the US). Typically used for estimating the energy demand needed to cool buildings.
Dry-Bulb Temperature (T)	Air temperature measured with standard thermometers shielded from direct sunlight at a height of 1.5 to 2 m above the ground. This is the temperature typically shown in weather reports.
Heat Index (HI)	The heat index combines temperature and relative humidity metrics to estimate the human-perceived equivalent temperature; this combined exposure may better approximate heat exposure for many individuals by also accounting for reduced sweat evaporation with increasing humidity. Operationally used by the U.S. National Weather Service to estimate heat risks.
Land Surface Temperature (LST)	The radiative temperature of bulk surfaces, measured by satellite (using thermal infrared sensors). Usually higher than ambient air temperature during daytime, particularly in built environments, but often correlated (depending on scale).
Universal Thermal Climate Index (UTCI)	A comprehensive metric of thermal comfort created from human energy balance models. The UTCI is not directly measured but is calculated by combining dry-bulb temperature, humidity, wind speed, and the mean radiant temperature (derived from multiple measurements of both solar and terrestrial radiation sources). Used in both extreme-heat and extreme-cold applications.
Urban Heat Island (UHI)	A phenomenon in which urban environments experience higher localized temperatures compared to their more rural or reference surroundings due to heat-trapping features of the built environment and human activity in urban spaces.
Wet-Bulb Temperature (Tw)	Lowest air temperature possible through evaporation of water; measured with a standard thermometer shielded from direct sunlight at a height of 2 m from the ground and wrapped in a damp cloth. Wet-bulb temperature is lower than dry-bulb temperature if relative humidity is < 100%.
Wet Bulb Globe Temperature (WBGT)	A weighted average of dry-bulb temperature, natural wet-bulb temperature, and black globe temperature. Traditionally estimated by combining the three temperature measurements or estimated from dry-bulb temperature, relative humidity, wind speed, and solar radiation. ISO Standard for occupational heat stress. Primarily used for extreme-heat applications and operationally used in U.S. military bases for estimating heat risks.

Other Useful Terms

Dynamically Modeled	Data products generated using physical laws governing atmosphere or earth processes.
Spatial Extent	The total area encompassed by the data (i.e. portion of the globe).
Spatial Resolution	The unit of measure for area observations. For gridded datasets, this is the size of each grid cell (e.g. 1 km x 1 km) but could also represent the administrative boundary at which data have been aggregated for derived datasets (e.g. census tract, postal code, county, etc.).
Statistically Modeled	Data products generated using statistical models to downscale (i.e. predict at a finer spatial resolution) or smooth input data into a continuous gridded format (e.g. regression, machine learning, kriging, or other approach).
Temporal Extent	The span of time covered by the data product (i.e. from beginning to end date).
Temporal Resolution	The unit of measure for frequency of time observations or model outputs (e.g. hourly, daily, annual, etc.)

Introduction

Heat is a well-established risk factor for adverse health impacts on human physiology, physical health, cognitive performance, mental health, other manifestations of morbidity, and mortality [1–5]. Extreme heat is recognized as the deadliest weather-related hazard and continues to produce public health crises [6]. The health risks posed by heat may be even greater in the future without adaptive measures [7], particularly in cities [8]. Progress towards reducing excess morbidity and mortality attributable to heat requires rigorous research to identify risks and translation of that knowledge into strategies for prevention.

There are multiple ways to define and estimate "heat" in research studies, with the best choice depending on the specific research question. The variety of available datasets, approaches, and metrics [9] can make it challenging to know where to start when first embarking on studies on the heat effects on health. For example, heat can be estimated based on temperature alone or using an index that additionally considers humidity, wind, or solar radiation and each measure can be used in either absolute (e.g., in degrees F or C) or relative terms (e.g., measured as percentiles of local conditions). How heat is assessed can influence not only the magnitude of associations with health endpoints, but also the interpretation of the results. For example, studies focused on the impacts of multiday heat events (i.e., "heat waves" defined by the intensity and duration of the heat event), those focused on daily variation in temperatures across a broader range, and those considering seasonal averages can provide very different insights about the impacts of heat on health. To add to the challenge, there are many datasets with complementary strengths and limitations to choose from.

The goal of this paper is to provide a practical overview of approaches to estimating heat in epidemiologic studies, with the goal of facilitating further public health research on the adverse health impacts. We first provide a review of the methods for estimating heat metrics over space and time. We next compare the relative advantages of different heat metrics, consider definitions and proxies of heat events, discuss considerations for selecting specific time scales or averaging periods, and metrics for quantifying urban heat islands and the impacts of microenvironments. We conclude with a set of recommendations and key considerations.

We assert upfront that no single dataset, metric, or approach will be optimal in all settings. We recognize that the optimal meteorological dataset, metric, or approach will depend on the hypothesis under study and the unique features of each study. Primary drivers of decisions typically include whether investigators are primarily interested in studying short-term or long-term effects of exposure, whether variation in exposure over space or time are of primary interest, and the spatial and temporal extents and resolution of the health data. We also recognize that measures of outdoor heat often provide an imperfect or inadequate surrogate for personal heat exposure, with the latter often being the quantity of causal interest. We limit our review and discussion to meteorological datasets that are relevant to the study of heat, broadly accessible, and applicable to large population studies, acknowledging that other approaches may be advantageous in many settings. Finally, although all the data products considered can also be used to study cold, we limit this review to the study of heat. Notwithstanding these recognized limitations, we seek to offer some initial guidance to those new to this field while avoiding the temptation to provide an exhaustive list of possible approaches.

Estimating Heat Exposure for Health Studies

In modern epidemiologic studies, particularly those assessing population-level outcomes, heat is typically assessed using spatially and temporally resolved, gridded meteorological datasets (e.g. NetCDF, GRIB, GeoTIFF file types). These products offer broad spatial and temporal coverage, are often publicly available, and provide standardized metrics. In this section, we summarize some of the common approaches and compare and contrast the features of different publicly available meteorological datasets. Table 1 includes some of the most commonly used temperature products, particularly in the United States, while eTable 1 in the supplement provides a more exhaustive list of temperature data products available. It is important to note that the recommendations we propose are specific to public health studies; while many of these datasets can also be used for other purposes, the pros and cons identified below may not be relevant for those dissimilar contexts.

Meteorological Datasets

Assessments of meteorological exposure typically rely on direct observations, remote sensing, and dynamic or statistical models, with many modeled products assimilating observational and satellite data. Each approach has strengths: direct observations (weather stations, personal monitors) provide measured values at known locations and times and are valuable for validation and short-term studies; remote sensing offers high spatial coverage and fine spatial contrast (for example land surface temperature and vegetation indices) that are useful for mapping intra-urban variability; and dynamic or statistical models produce continuous, gap-filled spatiotemporal fields with broad historical and geographic coverage, enabling consistent exposure assignment across large populations and long time periods. Combining these

Table 1 Gridded datasets commonly used for ambient air temperature metrics in environmental health studies

Dataset	Type of model	Source	Spatial Resolution & Domain	Temporal Resolution & Domain	Heat Metrics Possible	Data Notes
Daymet V4	Statistical	NASA [10]	1 km; CONUS, Hawaii, Puerto Rico	Daily; 1980–present	Temperature, Heat Index, Precipitation	High resolution by modeling ground observations and topography. Coverage limited to CONUS, Puerto Rico, and Hawaii. Suitable for air temperature and heat index only. R software package for data access: daymetr.
ERA5-LAND	Dynamic	European Centre for Medium-Range Weather Forecasts (ECMWF) [11, 12]	~9 km (1/10th degree); Global	Hourly; 1950-Present	Temperature, Heat Index, Precipitation, WBGT, UTCI	One of the few datasets available globally with a multitude of atmospheric variables and a long historical extent. Large data volume can make download and data storage complicated. R software package for data access: ecmwfr.
gridMET	Hybrid	Abatzoglou et al. [13]	~4 km; CONUS	Daily; 1979–present	Temperature, Heat Index, Precipitation	Combines PRISM (for temperature) and NLDAS reanalysis (for humidity, wind, etc.). Coverage limited to CONUS. R software package for data access: amadeus.
HRRR-Analysis	Dynamic	NOAA [14]	3 km; CONUS	Hourly; 2014–present	Temperature, Heat Index, Precipitation, WBGT	High-resolution real-time dataset, though only recent years available. Coverage limited to CONUS. Planned to be replaced by Rapid Refresh Forecast System (RRFS). Data can be accessed via Herbie Python package [15] and Amazon Web Services S3 Open Registry in Zarr format [16]
NAM-Analysis	Dynamic	NOAA/ NCEP [17]	3–12 km; North America	3-hourly (00, 06, 12, 18); 2004–present	Temperature, Heat Index, Precipitation, WBGT	High-resolution real-time dataset, though only available back to 2004. Sub-daily estimates.
NLDAS-2	Dynamic	NASA [18]	12 km; CONUS (parts of CAN & MEX)	Hourly; 1979–2024	Temperature, Heat Index, Precipitation	High-resolution data for North America, limited to CONUS+ parts of Canada and Mexico.
PRISM	Statistical	PRISM Group at Oregon State University [19]	4–800 m; CONUS	Monthly (1895–present) or Daily 1981–present	Temperature, Heat Index, Precipitation	Daily high-resolution coverage across the US; widely used in public health and climate studies. Coverage limited to CONUS, and no sub-daily estimates. R software package for data access: amadeus.
TopoWx	Statistical	Pennsylvania State University [20]	800 m; CONUS	Daily; 1948–2016	Temperature	High resolution data, limited to CONUS. Limited temperature metrics but includes a suite of atmospheric variables more relevant for climate-specific studies.

Note: An expanded table of gridded climate datasets, some of which are less used in health studies, can be found in the supplement.

Abbreviations: *CONUS*: Contiguous United States (i.e. lower 48 states, excluding Alaska and Hawaii), *ECMWF*: European Centre for Medium-Range Weather Forecasts. *GSFC*: Goddard Space Flight Center, *NASA*: National Aeronautics and Space Administration, *NCEP*: National Centers for Environmental Prediction, *NOAA*: National Oceanic and Atmospheric Administration, *NWS*: National Weather Service

sources often yields the most robust exposure estimates because models can assimilate observations and satellite products while preserving broad coverage and resolution.

Direct Observations

Direct observations include fixed weather stations and short-term personal monitoring. Weather stations provide continuous, research-grade or operational measures (air temperature, humidity, dew point, etc.) at known locations and are useful for validating models and capturing short-term temporal variation. However, station data can be spatially biased because stations are often sited at airports, universities, or other convenient locations, and their representativeness declines with distance, changes in land surface, or elevation [21]. Stations also suffer from missing data, instrument

changes, and local setup differences such as wind exposure or proximity to buildings; these issues complicate long-term trend analysis and require careful quality control to minimize the opportunity for errors and biases present in direct observations to propagate to models built on these data.

Personal monitoring yields the most direct measure of individually experienced temperature (including indoor conditions) because devices travel with participants. For example, using personal monitors to assess exposure on a limited number of individuals can be attractive for studies where the health impacts of very short-term variability (minutes to hours) of exposure are of primary interest, such as those examining heart rate variability or other rapidly varying biological parameters. Personal monitoring can also be particularly useful when evaluating exposures in specific settings, such as occupational settings [22]. However, personal monitoring is costly, administratively intensive, and typically feasible only for small samples or short durations. Protocol nonadherence (for example, leaving a sensor in direct sun or in a hot car) can introduce error. Importantly, outdoor measures commonly used in epidemiologic studies are an imperfect proxy for individually experienced temperatures: people in the United States spend most of their time indoors, and indoor environments and time-activity patterns often decouple personal exposure from outdoor conditions [23]. Studies report only modest correlations between outdoor estimates and personal temperatures except during periods spent outdoors [24–28]. Methods that integrate indoor and outdoor measures with time-activity data to model individually experienced temperatures remain early in development [29].

Dynamically Modeled Estimates

Dynamically modeled datasets use physical equations to interpolate conditions between observations, often assimilating station and satellite inputs. This category includes three related but distinct types of products: satellite-derived land surface temperature (LST), reanalysis, and operational numerical weather prediction (NWP) models. All are physics-based, but they differ in resolution, temporal focus, historical continuity, and typical applications.

- **Satellite-derived LST**. Global polar-orbiting sensors such as MODIS (≈1 km) and Landsat (resampled to ≈30 m; raw resolution of 90 to 120 m) provide medium to high spatial-detail LST, and several geostationary instruments (for example SEVIRI over Europe) now provide high-frequency regional LST that can capture diurnal and spatial variability. LST measures the radiative temperature of surfaces and is strongly influenced by urban form (e.g., tree canopy, albedo, impervious surfaces) [30, 31]. Because surface temperatures are often higher than near-surface air temperature during the daytime, LST is useful for mapping intra-urban contrasts and surface-driven exposures but can misrepresent physiologically relevant ambient air temperature and thermal comfort if used as a direct substitute [32]. LST has been used most successfully in health settings to help quantify a first-order estimate of intra-urban variations in temperature and their relationship to environmental exposures [33–37].
- **Reanalysis Products**. Products such as ERA5/ERA5-Land combine a fixed physical model with historical observations to produce continuous, globally consistent retrospective datasets [11, 12]. Reanalysis products offer long temporal coverage and many atmospheric variables at regular temporal cadence, making them attractive for population-level and long-term health studies. Their coarser spatial resolution (typically kilometers to tens of kilometers) and reliance on model physics mean they are less able to resolve the neighborhood- or microclimate-scale variation which is frequently of interest in health research.
- **Operational NWP models**. Systems like GFS [38], NAM [17], HRRR [14] (and planned successors such as RRFS) are physics-based forecasting systems that generate high-frequency gridded fields for many variables (e.g., temperature, humidity, wind, radiation, pressure) for real-time and short-term applications. Compared with reanalysis products, operational NWPs can provide finer temporal and/or spatial resolution. These products can be valuable for event-focused analyses, sub-daily exposure assessment, and studies that require forecast-like fields. Important caveats for epidemiologic use include frequent model updates and versioning, changes over time in how observations are assimilated into the model, and the primary operational focus on short-term forecasting rather than long-term homogeneity. These factors complicate their use in studies over long time periods and for reproducible research.

In practice, these dynamically modeled sources are complementary. Reanalysis products and some operational NWP models provide temporally continuous, gap-filled atmospheric fields useful for exposure assessment across large populations and long periods. Satellite LST delivers fine spatial contrast that is especially valuable for intra-urban mapping and identifying surface-driven hotspots but cannot directly measure ambient air temperature or thermal comfort exposures. Combining sources, for example by merging satellite LST with reanalysis air temperature via statistical downscaling or data fusion, can yield applicable exposure surfaces for health research while preserving broad coverage and improved spatial detail.

Statistically Modeled Estimates

Statistically modeled datasets use empirical models to interpolate or downscale observations by leveraging measured patterns and geophysical covariates. Examples of products that are freely available and widely used in health research include PRISM [19], GridMET [13], Daymet [10], and TopoWx [20]. These products often achieve finer spatial resolution than many physics-based reanalysis products, but vary in temporal cadence, geographic extent, and modeling approach. Many include only one or a few countries, which limits their use in studies seeking international comparability. For example, in the North American context, GridMET, TopoWx, and PRISM are limited to the contiguous US, and Daymet covers all of North America. Medium-resolution global products have recently emerged at ~1 km (e.g. [39, 40]), but validation challenges mean accuracy can be uneven across climates and environments. Even statistical surfaces estimated at relatively high spatial resolutions such as the PRISM 800 m product may omit local drivers of microclimate variability (for example building geometry or small-scale irrigation), reducing their ability to fully capture intra-urban contrasts.

Hybrid or satellite-enhanced approaches combine ground observations, remote sensing, and machine learning to produce high-resolution spatiotemporal predictions [41]. These methods are computationally intensive but can incorporate fine-scale covariates such as imperviousness, urban morphology, and vegetation cover, improving spatial detail and predictive performance for urban exposure assessment. In practice, traditional statistically modeled products remain useful for long-term, computationally efficient exposure assessment across large geographic areas, while satellite-enhanced fusion methods may be ideal for studies focused on intra-urban variability.

Summary and Recommendations for Meteorological Datasets

No dataset or approach is optimal for every study or circumstance. Nonetheless, we offer some recommendations that may be useful for many environmental epidemiologic studies assessing the health effects of heat. For multi-country analyses, we suggest prioritizing a single, consistent dataset that covers the full study domain; ERA5-Land is a practical default because it offers global land coverage, hourly fields, and broad use in the literature, which facilitates comparability with other studies. However, ERA5-Land's relatively coarse spatial resolution limits its ability to resolve neighborhood- or intra-urban variability, so where finer spatial detail is needed consider higher-resolution statistical or fused products that integrate observations and remote sensing. For example, for US-focused studies, the PRISM 800 m product is a reasonable choice for accessibility, spatial detail, and comparability with many published studies. Neither ERA5-Land nor PRISM is optimal for studies of within-city differences; investigations of intra-urban health impacts should combine a high-resolution gridded product with targeted urban-heat assessments (for example surface or canopy UHI layers, sensor networks, or satellite-enhanced fusion models) to capture microclimatic contrasts.

Note that most large-scale gridded datasets are made available using a single reference time zone, usually Coordinated Universal Time (UTC), and need to be transformed to match the time zone(s) of the health data before analysis. Additionally, modeled datasets use interpolation or prediction to produce continuous risk estimates over space and time. These estimates are measured with uncertainty; this source of measurement error will be propagated throughout the analysis.

Metrics of "Heat"

Common Metrics

Heat is more than air temperature, but dry-bulb temperature is by far the most commonly used exposure metric in health research because it is simple, widely available, and easy to interpret. A large number of metrics exist that attempt to capture the perceived or physiologically relevant burden of heat by combining temperature with humidity, wind, and/or solar radiation. Common examples include the Heat Index (HI, temperature plus humidity), the Wet-Bulb Globe Temperature (WBGT, which incorporates temperature, humidity, wind, and solar radiation or globe temperature), and the Universal Thermal Climate Index (UTCI, a comprehensive thermal comfort index derived from human energy-balance models) [42]. These composite indices can better reflect how hot it feels and how the body responds under different atmospheric conditions and may be particularly useful for populations with substantial outdoor exposure, occupational settings, or studies focused on thermal comfort and heat stress.

In many epidemiologic settings these indices are highly correlated with dry-bulb temperature, such that in practice results are often similar across metrics [43–45]. Nonetheless, alternative indices may be preferable in contexts where humidity, solar radiation, or wind are expected to materially alter physiological strain. For example, outdoor workers and school-age children may spend substantial amounts of time outside where direct sunlight increases and wind decreases thermal stress. The US Occupational Safety and Health Administration (OSHA) recommends the use of specific absolute WBGT thresholds for onsite monitoring

of outdoor workers [46], and some school jurisdictions use WBGT thresholds for their outdoor athletics programs [47].

Not all indices can be calculated from every data product. Estimation of HI requires data on humidity and estimation of WBGT and UTCI requires data on additional variables which are not available in all meteorological datasets [48]. For example, WBGT and UTCI can be derived from ERA5-Land but not PRISM, GridMET, or Daymet. Therefore, choosing a metric for a given study requires balancing interpretability (absolute temperatures are easiest to communicate), data availability (some datasets lack the variables needed for complex indices), and situational relevance (indices may be warranted for outdoor or occupational settings even if they are less widely available or at a coarser spatial resolution).

Heat metrics are often available at hourly resolution or aggregated to daily minimum, maximum, or mean values. Many epidemiologic studies of heat health impacts focus on daily maximum temperature because it captures daytime peak exposure, but daily mean temperature can better represent overall thermal burden across the 24-hour cycle, and daily minimum temperature (which typically occurs at night) may be most relevant for outcomes tied to nighttime comfort, sleep disruption, or heat effects that accumulate overnight. In practice, at any given location daily minimum, maximum, and mean values are frequently highly correlated over time, and disentangling their independent health impacts is analytically challenging [44].

Defining "Extreme Heat" and "Heat Waves"

Many epidemiologic studies of heat-related health effects focus on extreme heat events rather than average conditions. Classifying extreme heat typically involves measure of both the intensity and duration of the heat. A single day is often labeled extreme if it exceeds a specified threshold. A heat wave commonly refers to a period of consecutive extreme days characterized in terms of the duration (number of consecutive extreme days), severity (how far values exceed the threshold), and timing in the season. Heat waves are typically designated by local weather services or governments using locally relevant thresholds, sometimes accompanied by service activation or other resource allocation [49]. Researchers typically present sensitivity analyses to evaluate how varying the definition of extreme heat events or heat waves impacts the results since definitions can vary across contexts and localities [50]. Recent heat literature has found it useful to organize these concepts to separately investigate the concepts of intensity, frequency, and duration of heat exposure [51].

Thresholds for classifying days as "extreme" can be defined on either the absolute or relative scale. Absolute thresholds use fixed values of a chosen metric (for example daily maximum temperature, heat index, or WBGT exceeding a set number of degrees) and are straightforward to interpret and communicate. Beyond convenience, absolute thresholds may be attractive when they map directly to physiological limits or mechanistic hypotheses; for example, studies of temperature effects on male fertility, heatstroke risk in vulnerable patients, or "livability" may be more closely tied to absolute temperature cutoffs linked to biological responses rather than local acclimatization [52–54]. Some studies adopt locally relevant operational thresholds, such as the criteria used to trigger municipal heat advisories or heat warnings, as their definition of extreme heat [55–58].

On the other hand, many studies define extremes with respect to local climate, for example days above the 95th or 97.5th percentile of the warm-season distribution, in order to account for local acclimatization and facilitate comparison of study results across climates (e.g. [59]), . Defining extreme heat relative to local climate may yield very different thresholds in different locations. For example, hot days may be defined as those with a maximum daily temperature of 88˚F in Seattle versus 110˚F in Phoenix, but both represent the experience of a relatively infrequent high temperature for a population acclimatized to their local climate. Relative thresholds also help account for differences in the expected structural capacity to extreme heat (e.g. differences in availability of residential air conditioning).

One of the challenges for interpretation of relative percentile-based heat measures is the lack of a standard method for percentile definition. Defining percentile thresholds requires first defining the historical reference period across which percentiles should be estimated, deciding whether to use warm-season temperatures exclusively for derivation (and if so, how to characterize the warm-season), selecting a percentile value for extreme heat (95th or 97.5th), and determining whether percentiles are defined at the most granular level (e.g. grid cell) or at some larger geographic scale that encompasses a larger locality where people may live, work, or play (i.e. city or county). These decisions are expected to yield highly correlated measures of extreme heat but will yield differing absolute numbers of extreme heat days over a study period and may impact the interpretation of results. The selection of the time frame across which percentiles are defined is especially relevant given the increase in mean global temperature over time [60]. A 30-year time frame is typically standard for discussing long term meteorological climate trends, but people's lived climate memory is shorter; for health studies it is typical to use ten years of data to calculate percentiles as this may be a more relevant timeframe for human acclimatization.

There are several additional approaches to characterizing extreme heat that are less commonly used in epidemiologic

studies but may be useful to consider. Cooling degree days (CDD) sum degrees above a set base temperature over a period and are a practical proxy for cooling demand, making them relevant for studies of energy use, air-conditioning access, and the economic costs or health benefits of or barriers to cooling [54, 61]. If the base temperature is allowed to vary according to local climate, the resulting metric is referred to as an anomaly, which is a promising metric for use in multi-climate studies [62]. Synoptic or weather-type classifications group days by large-scale atmospheric patterns (for example into a small set of circulation types), which can capture complex combinations of temperature, humidity, and stagnant-air conditions that favor heat stress and air pollution accumulation [63–65]. The excess heat factor (EHF) is a short-term metric that combines the recent 3-day temperature anomaly with longer-term climatology to identify unusually intense heat events relative to local conditions [66]; it has been used operationally to classify heatwave severity [67]. Studies also sometimes distinguish night-time heat events (multi-night periods of elevated minimum temperatures) from daytime or day–night heat waves, because sustained high nighttime temperatures can prevent physiological recovery, disrupt sleep, and drive distinct health risks [68–71]. Choosing among these alternatives depends on the study question: CDD may best suit energy and adaptation analyses, synoptic types can illuminate meteorological drivers, EHF targets heatwave intensity relative to local baselines, and night-focused definitions are important when nocturnal warming or sleep-mediated outcomes are of interest.

Temporal Scales and Averaging Windows

When choosing averaging windows and aggregation methods, it is important to match the temporal scale of the exposure to the biological mechanism and study design: assessments of the impacts of short-term (hours to days), medium-term (weeks to months), and long-term (months to years) exposures call for different data and statistical models and imply different causal contrasts. Temperature throughout the year follows distinct seasonal patterns and researchers interested in short- or medium-term heat health effects must take this seasonality into account to model a plausible counterfactual scenario (e.g. consider a time-stratified reference group selection [72], adding in a spline term for the seasonal pattern [73], or conditioning or stratifying by time of year [74]).

Epidemiologic studies of short-term heat effects typically compare health outcomes on hot days (or over hours to a few consecutive days) with outcomes on comparable, cooler periods [75, 76]. The causal contrast in these studies is usually straightforward: what would the health outcome have been had that day not been unusually hot. Time-series and case-crossover designs are commonly used to estimate effects of transient exposures on acute, discrete events (e.g., emergency visits, hospital admissions, or deaths); for example, the effect of extreme heat on hospitalization among older adults with Alzheimer's disease and related dementias [77]. For continuous outcomes, linear or mixed-effects models (to account for repeated measures within individuals) are often applied; for example, short term impacts on cognitive function by temperature on the day of the test [78]. In these short-term analyses, daily summary values (maximum, mean, or hourly-derived summaries) are usually sufficient, though sub-daily (hourly) data can be important when the exposure–response window of interest is very short.

Studies of medium-term exposure examine health effects accumulated over weeks to months, for example effects of seasonal heat on pregnancy outcomes, infectious disease dynamics, or subacute physiologic changes. These analyses often require aggregating exposure over longer windows (weekly, monthly, or trimester-level averages or counts of extreme days) and careful attention to exposure timing relative to periods of etiologic interest (for example, specific gestational windows). Common study designs include cohort analyses with exposure windows defined relative to assessment activities, panel studies with repeated measures over weeks to months, and time-series comparisons that capture seasonal patterns. The causal contrast in these studies is somewhat less straightforward but presumably corresponds to the health effects of a particularly warm (vs. less warm) period, combining contrasts over both space and time. The choice of metric and averaging period should align with the biologic or behavioral mechanisms hypothesized, considering that cumulative measures (such as number of extreme heat days or cumulative heat degree-days) may be more relevant than single-day peaks for some outcomes.

There is growing interest in understanding the potential health consequences of prolonged exposures to higher average temperatures or repeated exposures to extreme temperatures [79, 80]. These investigations typically use annual, multi-year, or decadal exposure summaries (for example annual mean temperature, long-term trends in extreme heat event frequency) and cohort designs or ecological comparisons across regions. Because long-term exposures conflate climatic differences with many other geographic or temporal changes, causal inference requires explicit counterfactual framing to ensure rigorous control for confounding and results that are interpretable. In studies of long-term exposures, spatial resolution and temporally consistent exposure products are critical: choices of dataset, aggregation method, and handling of model versioning or station changes can materially affect trend estimates.

Spatial Scales and Spatial Aggregation

In many studies a key consideration is the spatial extent and resolution of the available health data. Personal health data is often highly restricted to safeguard individuals' identity, privacy, and potentially sensitive health information. Thus, environmental data often must be aggregated into administrative units such as ZIP code or county for analysis. In fact, the unavailability of data at the desired spatial and temporal resolution is one of the most frequently cited barriers to research in climate and health [81]. When aggregating to larger geographic units, the best practice is to population-weight the meteorologic measures so that the resulting estimates are a better representation of outdoor conditions where people live, work, and play (e.g. [48]), .

The purpose of population-weighting is to make exposure estimates in aggregated geographies more reflective of the average exposure for an average individual in the geography. There are two common approaches: (1) to use a gridded population dataset as the weight matrix for the gridded exposure dataset during aggregation (i.e. each exposure grid cell is weighted by the count of people within that cell), or (2) to utilize a smaller nested administrative geography where population estimates are available in a two-stage approach (i.e. aggregate the gridded data at the smaller geography and then aggregate up to the parent geography weighted by the areal-level population estimates). In the US, this nested approach could involve using Census geographies such as block groups to perform initial aggregation before calculated weighted sums of exposure within tracts [21]. Commonly used and highly resolved gridded population datasets include LandScan (global at 1kmx1km, annual), WorldPop (global at up to 100 m resolution, released every 5-years), and Global Human Settlement Population grids (GHS-POP) (global at 100 m resolution, at 5-year intervals), though other global and country-specific datasets exist. While all these datasets provide estimates of the count of people within each grid cell, WorldPop and GHS-POP represent the residential population whereas LandScan measures the ambient population, or people who are around during the day, accounting for travel patterns like commuting for work or school. The choice of which version to use depends upon the health outcome data; a residential population dataset is more appropriate for health data based on patient residence like most claims and electronic health records, whereas an ambient population dataset may be preferred if using data based on incident location, for example Emergency Medical Services data.

The exception to this de facto spatial aggregation is if researchers have access to address information or point location data, and are able to merge the geocoded points to gridded datasets while preserving participant privacy (a common and large challenge). Unfortunately, there is also direct tradeoff between spatial resolution and data storage and computational intensity, so the highest-resolution data – particularly if covering a large geographic extent – may require extra time or computing cluster infrastructure to prepare for analysis. While the existing datasets described here can be used in most of the world, open-source methods for producing temperature or heat stress data are often useful in creating more locally applicable metrics that researchers can prepare for themselves (Engel et al. 2026 forthcoming) [82].

Urbanization changes local weather and climate, most clearly by raising temperatures through the urban heat island (UHI) effect. Many commonly used statistical interpolation products do not assimilate the land-surface features that drive urban microclimates (e.g., land cover, building materials and heat capacity, vegetation, albedo, and irrigation) and can understate intra-urban variability. Because it is impractical to site observational stations everywhere in a city, microclimates remain under-resolved in most gridded datasets, which affects both identification of UHIs and assessment of long-term urban trends [83–86]. Even relatively high-resolution gridded products such as HRRR (3 km, hourly) or PRISM (800 m, daily) often miss differences in temperatures between adjacent neighborhoods. However, mapping UHI intensity and intra-urban temperature variation is essential for identifying inequities in heat exposure, especially since most people live in cities [30, 87]. As a result, researchers interested in fine-scale urban exposures typically rely on high-density sensor networks [88–90], statistical downscaling that explicitly includes land-surface covariates [86], or a combination of high temporally resolved temperature data with time-invariant neighborhood characteristics [91], crude temperature proxies (e.g. NDVI [92], tree canopy [93], albedo [94], or land cover zone (LCZ) [95]), or UHI intensity effect modifiers. Perhaps the most accessible UHI intensity dataset is the Global Surface UHI Explorer, a 1 km resolution surface urban heat island (SUHI) developed using MODIS satellite data for virtually all urban areas globally [96], though more recent data includes a canopy urban heat island (CUHI) intensity dataset (i.e. air rather than surface temperature) [97]. Finally, it is worth noting that UHI is a relative measure: it describes how urban conditions compare to a chosen non-urban reference. UHI magnitude therefore depends on local climate, urban form, and land-use practices, and it is not necessarily directly comparable across cities without careful definition of the reference and context [98].

Heat Alerts, Preparedness, and Behavioral Responses

Preparing for heat-related risk requires acting on the intermediate steps between exposure and harm: clear risk

communication so people recognize their vulnerability, early warning systems that prompt protective behaviors, public messaging about available resources, and in-home or neighborhood cooling options. Many national and regional meteorological services issue heat watches, warnings, advisories, or similar alerts tailored to local climates. Local agencies, emergency managers, and media commonly use these alerts to trigger response actions, such as opening cooling centers, extending pool hours, adjusting work schedules for outdoor workers, or activating targeted welfare checks for vulnerable residents or patients.

Researchers sometimes use historical records of heat alerts to study the effects of heat early warning and response plans on health outcomes (for example emergency department visits or excess mortality) or behavior change [99, 100]. Aggregated data on internet searches has been used to gain novel insights into changes in attitudes, risk perception, and behaviors across space and time associated either with extreme heat events or heat alerts [101–103]. Similarly, social media posts, resource use data (e.g., visits to cooling centers, parks, or other shaded and air-conditioned public spaces), and mobility data derived from smart devices or wearable sensors can be leveraged to understand real-time adaptive behaviors in various at-risk populations [104–106]. The existing evidence compellingly shows that implementation of heat action plans, including heat early warning systems, has been effective at reducing heat-related health impacts [107–109]. However, the evidence also suggests that messaging alone may have limited impacts on risks and that effective risk reduction is heavily dependent on the local context and resources.

Summary and Recommendations for Estimating Outdoor "Heat" Exposure

There is no single metric of "heat" that is optimal in all health studies or contexts. Investigators are encouraged to choose the heat metric and extreme-heat definition that best matches their study question, population, and data availability. Dry-bulb temperature (absolute values) is a practical default for general population studies within a single climate zone, where clear communication to a lay audience is important, when exploring physiologic thresholds that are not substantially impacted by adaptation, or when connecting research to emergency response or other operational systems. On the other hand, percentile-based relative thresholds that account for local climate and acclimatization are preferable when comparability across locations with different climates is important. When calculating percentiles, it is common to use a 10-year period prior to the study data. Although dry-bulb temperature is most available and easiest to communicate, composite indices (e.g., Heat Index, WBGT, UTCI, or many others) may be preferable when humidity, solar radiation, or wind are expected to materially alter physiological strain (e.g., for example in occupational or outdoor-exposed populations). But these indices are not available in all meteorological datasets, and investigators will have to balance choice of metric and choice of dataset.

In terms of temporal aggregation, select the aggregation that reflects the biological window of interest (hourly or daily maxima for acute, short-term effects; weekly or monthly aggregates or counts of extreme days for medium-term outcomes; annual or multi-year summaries for long-term impacts). For studies of intra-urban variation or mitigation interventions, supplement gridded air-temperature surfaces with LST, urban-heat-island layers, temperature-proxy variables, or satellite-enhanced high-resolution products to allow for that small-scale spatial comparison. Finally, all studies should report the choices of metric, threshold, averaging window, and rationale transparently, and perform sensitivity analyses using alternative metrics and thresholds so readers can assess robustness and facilitate comparison with other studies.

Conclusions

There is a wealth of climatic datasets available for use in health analysis. There is no single meteorologic dataset that is "best," rather, the choice of which dataset to use should be based on the specific research question, study design, and spatiotemporal scale of interest. However, there are a few guiding principles for how to select the correct data source for your analysis, which we have outlined in this introductory guide with common scenarios summarized in Table 2. For example, absolute temperatures may be preferable for studying a population in a single location since it is more readily interpretable for the local context. However, if an analysis includes populations across different climate zones, then it is important to consider a temperature metric that incorporates humidity and/or convert temperature metrics into percentiles to compare dissimilar contexts and account for local acclimatization. Similarly, when studying populations that spend substantial time outdoors, using a composite index that incorporates other weather variables, such as solar radiation and wind, is likely warranted. Ultimately, it is a good idea to select the most appropriate heat metric for your primary analysis and then conduct sensitivity analyses using a different metric for comparison. In the overall population, studies have found similar associations between mortality or morbidity and various heat metrics [44], but this may not hold true for all populations or for other outcomes.

It is important to note that most of the datasets described here are publicly accessible and available to download but

Table 2 Specific recommendations and decision points for studying heat and health

Situation	Recommendation
I want to study the short-term effects of heat.	The comparison that is most important in the study of short-term impacts of heat is over time as opposed to across space. Prioritize using data with a finer temporal resolution, even if it means a coarser spatial resolution. Most studies investigating the short-term effects of heat use a daily dataset (though hourly, or weekly are also common). **Specific data**: All the datasets in Table 1 are available at a daily or sub-daily resolution. Suggested reading: Bhaskaran et al. 2013
I want to study the long-term effects of heat.	Studying the long-term effects of heat requires thoughtful and explicit statement of the hypothesis of interest, ideally using a causal counterfactual framing. Example questions include, what are the health effects of: (a) being exposed to more (vs. fewer) heat waves, (b) living in a city with a warmer (vs. cooler) typical summer climate, or (c) living inside (vs. outside) of an urban heat island. Note that each of these questions calls for a potentially distinct exposure contrast, optimal dataset, and study design. Merely asking "what is the effect of heat on x" is not specific enough for most studies. Suggested reading: Zanobetti and O'Neill 2018
My data cover several different locations with substantially different climates.	If your study spans locations with very different warm-season temperatures, it is analytically advantageous to define "heat" based on location-specific percentiles of temperature rather than using absolute values. Percentile-based definitions help account for differences in local climate as well as acclimatization (e.g. an extreme heat day in Seattle, WA may be 88˚F while in Phoenix, AZ it may be 110˚F). Computing locally relevant relative percentiles allows you to compare "hot days" across locations with different typical temperatures. It is common to use a 10-year period prior to your study data for the calculation of percentiles in health research. If using data across dissimilar climate zones, it may also be a good idea to use a heat metric that includes humidity as this can greatly affect the human experience of heat. Suggested reading: Stafoggia et al. 2023; Gasparrini et al. 2015 [110]
All my data are from a single location.	If your study focuses on a single location, or spans multiple locations with similar climates, using absolute metrics of temperature rather than percentile-based measures will typically yield results that are easier to interpret and communicate to a lay audience. Suggested reading: Ballester et al. 1997 [111]
My study is focused on the impacts of gradients in temperatures within cities (or within small areas).	The available gridded meteorological datasets typically are not optimal for capturing within-city variation in temperature, even if the grid sizes are small. The approach we recommend is to use an air temperature product that can be used citywide to examine temporal trends, while combining or examining effect modification with environmental or social-economic variables to resolve heat risk at an intra-urban scale. There are a few datasets that assess small-scale differences in land surface temperature that might also be used to identify areas of a city that may be more prone to urban heat island effects such as surface urban heat island (SUHI) or canopy urban heat island (CUHI) datasets that can be included as effect modifiers. **Specific data**: For the temperature data, ERA5-Land data has the appropriate spatial and temporal characteristics for a city or county-level resolution and has the benefit of being globally comparable with rich temperature metrics. Using a higher-resolution dataset at the neighborhood level, along with a heat vulnerability variable and/or UHI intensity effect modifier would also be appropriate (e.g. Daymet, GridMET, or PRISM, etc.). Combine this with an explicit UHI intensity or other intra-urban effect modifier variable. Suggested reading: Chakraborty et al. 2023; Smith et al. 2025
My health outcome data are at a larger spatial resolution (i.e. city or county), or at a smaller spatial resolution (i.e. Zip Code or Census Tract) in less urban areas where administrative units are larger.	The spatial resolution of your exposure data necessarily cannot be smaller than your outcome data. However, large areas have more potential to vary in their population distribution and climatic context (e.g. King County, WA where the city of Seattle is located starts at sea-level in the highly urbanized western portion of the county and extends up to the foothills of the Cascade Mountains in the more-rural eastern portion). Even in smaller spatially resolved administrative units (e.g. ZIP Codes or Census Tracts), areas can be quite large in rural areas. In these cases, it is a good idea to population-weight your temperature metrics so they are most applicable to the locations where people live, work, and play. **Specific data**: There are a few examples of population-weighted analysis-ready datasets that have been meticulously prepared for reuse and posted to generalist repositories (e.g. the county-level Heatmetrics data [48], or Zip Code aggregated 800 m PRISM data [112]). Suggested reading: Spangler et al. 2022
I am studying a population who spends considerable time outdoors.	We recommend that you use an index of thermal comfort that includes other contextual variables such as humidity, wind, and solar radiation. WBGT or UTCI are both good choices, but just heat index may be considered if WBGT or UTCI data are unavailable for your study location or period. **Specific data**: The ERA5-Land data is by far the most commonly used source for WBGT. Suggested reading: Liljegren et al. 2008, Chakraborty et al. 2025 [113]
My priority is to make sure my results are understandable to a local non-research audience.	Absolute temperatures (˚C or ˚F) are a readily understood metric to a broader audience. Index measures like Heat Index, UTCI, or WBGT may include additional temperature-adjacent contextual information, but they are composite measures (i.e. combine different concepts so they are not singularly interpretable) and unfamiliar to most people. Suggested reading: Fouillet et al. 2008
I am studying an outcome that has been studied before by other researchers, but with a new angle.	When in doubt, harmonizing exposure metrics with previous studies in your research domain is always beneficial for producing comparable results. Similarly, choosing a dataset with a global extent may allow for better harmonization with future research as long as this does not require sacrificing scientific rigor. Suggested reading: Stingone et al. 2026 [114]

may have very large file sizes or file formats that are unfamiliar to some health researchers. However, in recent years there has been substantial investment to make such datasets easier to use in the context of population health studies, with the goal of reducing barriers to entry for health researchers without the expertise or computational resources needed to link meteorologic and health data. These efforts thus aim to accelerate research at the intersection of these two fields. Several of these datasets have been aggregated into administrative boundaries commonly used in health studies, such as county or postal code, and made publicly available; for example, twenty years of daily ERA5-Land data population-weighted using gridded estimates to the county level that includes several temperature metrics including WBGT and UTCI [48], or daily census block population-weighted 800 m PRISM data aggregated to the ZIP code level for 2000–2022 [112]. Such ready-to-use datasets are increasingly being shared via generalist repositories such as the CAFE collection on the Harvard Dataverse [115], European InfrastRucturE for humaN Exposome (EIRENE) [116], the Canadian Urban Environmental Health Research Consortium (CANUE) [117], Network for EXposomics in the United States (NEXUS) [118], and the Gateway Exposome Coordinating Center (GECC) [119], among others. The National Institute of Environmental Health Sciences (NIEHS) Connecting Health Outcomes Research Data Systems (CHORDS) program has also developed a software package *amadeus* (https://niehs.github.io/amadeus/) which provides curated data download and processing functions for several of the heat datasets discussed (PRISM, GridMet) and information about additional packages (daymetr for DayMet, ecmwfr for ERA5-Land). The CAFE GitHub repository provides applied examples for use of PRISM and ERA5-Land data, including data query, processing, and aggregation (https://github.com/Climate-CAFE).

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Declarations

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