Building and occupant characteristics as predictors of temperature-related health hazards in American homes

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# Highlights

# Graphical Abstract

# Abstract

1. Introduction
   1. Background

Though less visibly destructive than floods, hurricanes, and other hazards, prolonged periods of extreme temperatures are the leading cause of weather-related deaths in the United States (Berko et al. 2014). Globally, extreme ambient temperature (either or hot or cold) contributes to 6.5-10% of all deaths (Sera et al. 2019; Zhao et al. 2021). While the media focus is largely on extreme heat, in both studies, nearly 90% of global deaths attributed to temperature were cold-related, which is consistent with findings in the United States (Berko et al. 2014). It is hard to pinpoint the true public health impact of extreme temperature because it aggravates underlying conditions, but may not be noted as a contributing cause on hospital records or death certificates (Ostro et al. 2009; Lane 2018). At least 17 chronic conditions such as heart disease, diabetes, kidney disease, and respiratory infection show a J-shaped relationship with temperature (Burkart et al. 2021), meaning that the disease prevalence increases in both extreme high and low ambient temperatures. In addition to these serious health impacts, extreme temperature exposure impairs labor productivity (Lai et al. 2023), sleep quality (Obradovich et al. 2017), and cognitive performance (Laurent et al. 2018).

Several trends necessitate prioritizing emergency planning and disaster mitigation with regards to extreme temperatures, the first being anthropogenic climate change. Future projections show rising ambient temperatures as well as increasing frequency and intensity of heat waves (IPCC 2021). Individuals may also be exposed to hazardous temperatures in the event of a power outage coinciding with an extreme weather event, as was seen across the Northeastern United States following Hurricane Sandy in 2012 (Henry and Ramirez-Marquez 2016) the state of Texas in February 2021 (King, Rhodes, and Zarnikau 2021). Major electrical grid failures have increased by more than 60% in recent years (Stone et al. 2021). The final trend is global aging. In 2019, less than a tenth of the global population was over the age of 65 and by 2050 this number will increase to 1 in 6 (United Nations 2020). Age is a well-documented risk factor for temperature-related morbidity and mortality (Oudin Åström, Bertil, and Joacim 2011), so an older population has greater vulnerability.

* 1. Municipal planning for extreme temperatures

Most cities face substantial variation in intra-city vulnerability to heat0F[[1]](#footnote-1). Many cities and other jurisdictions use heat vulnerability indices (HVI) to better allocate resources on emergency response to heat, such as the location of cooling centers (Reid et al. 2009; Rinner et al. 2010; Uejio et al. 2011; Nayak et al. 2018). An HVI is typically a weighted sum of variables related to heat vulnerability such as income or poverty level, age, social isolation, and land cover characteristics calculated at a localized level like census tract.

HVI seldom include variables related to the local building stock even though building characteristics can exacerbate or mitigate occupant exposure to heat. Indoor exposure, particularly at home, accounts for a sizable portion, 38-85%, of heat-related deaths (Fouillet et al. 2006; Wheeler et al. 2013; Iverson et al. 2020). An individual will on average spend around 67% of their time in a residence, out of 87% of their total time indoors (Klepeis et al. 2001). This proportion is even higher for vulnerable populations such as infants and the elderly, who on average spend 89% and 78% of their time in a residence respectively (Matz et al. 2014).

A review by Samuelson et al. (Samuelson et al. 2020), found that out of 20 HVI’s from different cities and regions, eight included the year of construction, nine included central air-conditioning (AC) ownership, three included floor of residence, and one included rooftop albedo and thermal mass. Many building characteristics that could potentially impact indoor heat exposure such as orientation, envelope properties, and typology are not included. City-level tax assessor data typically records year of construction and the presence of central AC at the parcel level, so these variables are attractive proxies for the contribution of the built environment. However, there is no obvious link between these variables and heat vulnerability.

HVI for New York State (Nayak et al. 2018) and the cities of Toronto (Rinner et al. 2010) and Philadelphia (Uejio et al. 2011) all considered older homes to have a higher risk for heat exposure due to a presumption of lack of insulation, lower likelihood of AC, and correlation with other risk factors like poverty. However, several studies monitoring temperatures in European residences found that older buildings had significantly cooler temperatures than newer ones (Beizaee, Lomas, and Firth 2013; Maivel, Kurnitski, and Kalamees 2015; Pathan et al. 2017), perhaps because of the thermal mass properties of stone construction typical of older European homes. Temperature monitoring in American residential buildings did not find a strong correlation between construction age and measured indoor temperature during times the home was actively heated or cooled (Booten et al. 2017). A simulation-based comparison of housing archetypes in Boston found older typologies had lower maximum indoor temperatures (Samuelson et al. 2020). These studies demonstrate that construction age alone cannot capture indoor heat exposure.

HVI also typically consider AC prevalence, particularly that of central AC systems. In homes where AC is present, the cost of operating and maintaining AC systems may prohibit their use in a way that sufficiently protects residents from the adverse effects of heat. In recent investigations of indoor heat deaths, the Maricopa County Department of Public Health (MCDPH) found that in 91% of cases, AC was present (MCDPH 2019). In those cases, the AC was either broken (87%), disconnected from electricity (5%), or functioning but not turned on (8%). Clearly, the sheer presence of AC alone is not a protective factor against overheating.

The primary barrier to including additional building level characteristics is data availability at sufficient scale. However, new methods of data acquisition are rapidly becoming available such as smart thermostat data (Ecobee 2021) and satellite and street-level imagery (New et al. 2020). Understanding the role of the building and other household characteristics will enable public agencies to target emergency planning efforts and resources in the short-term like locations of cooling and warming centers and the long-term such as social programs and building weatherization.

* 1. Research gaps and objectives

Several research gaps relate to the role of building characteristics on temperature-related morbidity and mortality.

First, is the lack of empirical evidence to link building characteristics to temperature-related morbidity and mortality. Studies assessing the sensitivity of overheating risk to building characteristics often use building performance simulations. These studies use simulation outputs such as maximum daily room temperature (Samuelson, Baniassadi, and Gonzalez 2020; Mavrogianni et al. 2012), percent of time in different U.S. Occupational Safety and Health Administration (OSHA) heat index (HI) risk categories (Sun, Specian, and Hong 2020), or the degree-hours the wet-bulb globe temperature (WBGT) index exceeded a threshold value (Baniassadi, Heusinger, and Sailor 2018) to model the risk of overheating. Holmes et al. (Holmes, Phillips, and Wilson 2016) discuss the suitability of different thermal indices with building performance simulation outputs and recommend acceptable thresholds for residential spaces based on WBGT. While there are many thermal indices, as yet none of them are validated for personal exposure in residential environments, meaning the recommended thresholds are not based on empirical observations of temperature-related health hazards in this context (Kuras et al. 2017). Recently, the Occupational Safety and Health Review Commission criticized OSHA’s use of HI to assess risk for heat exposure in occupational settings due to the lack of scientific evidence for risk categories (“Secretary of Labor v. A.H. Sturgill Roofing, Inc.” 2019).

The second research gap is limited consideration for building characteristics in conjunction with other markers of socioeconomic vulnerability such as income and age. Very few studies using building performance simulations review the interaction of building and occupant characteristics. Baniassadi et al. (Baniassadi et al. 2019) account for some effects of occupant income by modeling AC non-functionality and occupant age by using a conservative value for their overheating threshold.

To overcome these research gaps, this study uses supervised machine learning to predict temperature-related morbidity based on a large-scale survey of building and household characteristics in American homes. We compare model performance with different groups of input features, including building characteristics and demographics. Reviewing the relative importance of model input features can help public agencies prioritize data collection to improve model accuracy. More accurate predictions will allow public agencies to better identify at-risk households and strategize limited resources for short-term planning like locations of cooling and warming centers and long-term planning like building weatherization and social programs.

1. Materials and methods
   1. Residential energy consumption survey (RECS) data

The primary source of data for this study is Residential Energy Consumption Survey (RECS), which is administered by the U.S. Energy Information Administration (EIA) (EIA 2018; 2022). RECS is a periodic survey that has collected detailed energy characteristics, usage patterns, and demographics of American households since 1978. The primary objective of RECS is to estimate future energy demand and improve energy efficiency and building design.

Of relevance for this study, the two most recent cycles of RECS, 2015 and 2020 ask respondents if in the last year, if anyone in their household needed medical attention because the home was too hot or too cold (EIA 2016; 2020). This study treats an affirmative response to either question as a temperature-related morbidity. While the questions are vague regarding duration and severity of extreme temperatures and who in the household needed medical assistance, it provides a source of empirical evidence that the household experienced a thermally hazardous interior environment.

Each RECS is an independent cross-sectional study of residential energy use, so each iteration of the survey is slightly different. The EIA selects samples to statistically represent all U.S. households occupied as a primary residence at the time of the survey. The most significant difference between the 2015 and 2020 survey cycles is the mode of execution. The 2015 survey cycle collected data through a combination of computer-assisted personal interviews (CAPI), internet, and mailings. The 2020 survey cycle relied entirely on self-administered web and paper questionaries. Because there were no in-person interviews, the 2020 survey did not rely on a clustered sampling method like in 2015. The impact of this change is a three-fold increase in sample size – 5,686 in 2015 to 18,496 in 2020. Sample size is inversely proportional to the standard error and, so larger samples generally result in narrower confidence intervals for population and subpopulation estimates.

In this study, to combine the 2015 and 2020 surveys, we treat each sample as an independent observation. When making population estimates, we will display results for each year separately, using the sample weights for that survey iteration.

Table . Description of dataset used for the analysis of this paper

|  |  |
| --- | --- |
| **Group** | **2015** |
| Heat-related morbidity | 54 |
| Cold-related morbidity | 39 |
| Any temperature-related morbidity | 81 |
| None | 5605 |

To explore patterns in households that experienced temperature-related morbidity we narrowed the over 750 household characteristics described in the RECS dataset to approximately 30 related to either vulnerability or exposure to extreme temperature. These variables fall under 5 categories: climate, demographic, building construction, building envelope, and building HVAC. We describe these building and household characteristics in the subsequent sections. Table 2 provides an overall summary of all input variables.

Climate

Ground surface temperature is a climatic variable often reported in HVI (Uejio et al. 2011), because it represents local exposure to high temperatures. Due to the EIA’s objective to forecast energy demand, climatic variables in RECS are oriented towards HVAC system operation, such as cooling and heating degree-days, cooling and heating design-temperature, and climate zone.

Demographic

Many epidemiological studies have investigated the relationship between different demographic and socioeconomic variables on heat-related mortality. Several studies identify elderly age as a vulnerability factor, but there is some ambiguity around the cut-off for higher risk: 60, 65, 70, or 75 (Applegate et al. 1981; O’Neill, Zanobetti, and Schwartz 2003; Ballester et al. 1997; Centers for Disease Control and Prevention (CDC) 1995; Conti et al. 2005). The elderly may be more likely to have co-morbidities and take medication that affect thermoregulation. They also may have limited mobility to access cooling centers or limit AC usage due to fixed income. Several studies also suggest a link between income and heat-related mortality as measured by poverty (Naughton et al. 2002; Curriero et al. 2002), unemployment (Nayak et al. 2018), renter status (Uejio et al. 2011; Wright et al. 2020), and utility payment (Wright et al. 2020). Klinenberg’s sociological analysis of the 1995 Chicago heat wave found a higher risk of death in individuals with limited social connections such as those living alone (Klinenberg 2015). These individuals may be at higher risk of not being checked on regularly during a heat emergency. On the other hand large households (7+ members) may have elevated heat mortality risk (Uejio et al. 2011). The impact of race and ethnicity on heat-related mortality is mixed, with some studies finding a higher risk for African Americans or non-white racial and ethnic groups (O’Neill, Zanobetti, and Schwartz 2005; Schwartz 2005).

Building construction

Building construction represents variables related to the building age and form. As mentioned in Section 1.2, several city and state-level HVI use construction age as a catch-all for other building characteristics (Rinner et al. 2010; Uejio et al. 2011; Nayak et al. 2018). A building performance simulation study of London dwellings found a significant impact of archetype, a combination of construction age and construction type on overheating risk (Mavrogianni et al. 2012). Samuelson et al. (Samuelson et al. 2020) suggests that detached buildings may be less vulnerable due to a greater potential for exposed walls to exchange heat and more opportunities for cross-ventilation. Similarly, Lomas (Lomas 2021) singles out flats or apartments because of more limited opportunities for natural ventilation.

Building envelope

The building envelope represents the materials that separate the interior and exterior of the building. Building performance simulations find wall insulation reduces the overheating risk when applied to the exterior, but may increase overheating risk when applied to the interior (Mavrogianni et al. 2012; Porritt et al. 2012). Porritt et al. (Porritt et al. 2012) also found a correlation between roof and wall surface reflectivity i.e., inverse of solar absorptivity and overheating risk. Samuelson et al. (Samuelson et al. 2020) infers that other building envelope characteristics like infiltration, and window-to-wall ratio may also be significant. One HVI considered houses with thermally massive materials to have greater adaptive capacity (Inostroza, Palme, and de la Barrera 2016). Thermal mass describes building materials with high heat capacity, such as brick, stone, and concrete, which can buffer temperature fluctuations.

Building HVAC

Building HVAC characteristics describe the presence (Curriero et al. 2002), type (O’Neill, Zanobetti, and Schwartz 2005), and functionality (Naughton et al. 2002; MCDPH 2019) of HVAC systems. Samuelson et al. (Samuelson et al. 2020) also suggests consideration for electric fans. While fans cannot reduce air temperature, they can aid evaporative cooling in air temperatures as high as 50 °C and 10% relative humidity (Jay et al. 2015). Finally, we also consider availability of alternate power sources such as a back-up generator or on-site solar panels as they may reduce interruptions to HVAC systems, which to our knowledge has not been considered in any previous work.

Table . Summary of household characteristics from or derived from the RECS dataset relevant to the household’s vulnerability or exposure to extreme temperature

| **Category** | **Household characteristic** | **RECS dataset variable description** | **Type a** | **Reference** |
| --- | --- | --- | --- | --- |
| Climate | Cooling design temperature | Dry bulb design temperature (F) expected to be exceeded 1% of the time | N | (Uejio et al. 2011) |
| Heating design temperature | Dry bulb design temperature (F) expected to be exceeded 99% of the time | N | (Uejio et al. 2011) |
| Demographic | Non-white | Householder (respondent) race is non-white, or ethnicity is of Spanish descent. | B | (Schwartz 2005) |
| Age >65 | Respondent or household member age is >65 | B | (O’Neill, Zanobetti, and Schwartz 2003; Medina et al. 2006) |
| Lives alone | Number of household members = 1 | B | (Klinenberg 2015; Naughton et al. 2002) |
| Large households (7+ members) | Number of household members > 7 | B | (Uejio et al. 2011) |
| Poverty | Calculated from gross income and number of household members based on U.S. Census Bureau definition for poverty threshold | B | (Naughton et al. 2002; Curriero et al. 2002) |
| Unemployed | Respondent is unemployed or retired | B | (Nayak et al. 2018) |
| Education < High School | Highest education attained is high school or equivalent |  | (Curriero et al. 2002; O’Neill, Zanobetti, and Schwartz 2003; Medina et al. 2006) |
| Renting | Household pays rent | B | (Uejio et al. 2011; Wright et al. 2020) |
| Pays utility or for other fuel | Household pays for electricity, natural gas, propane, and/or fuel oil | B | (Wright et al. 2020) |
| Building construction | Construction type | Type of housing unit | C | (Mavrogianni et al. 2012) |
| Construction age | Estimated year when housing unit was built (taken as the maximum of the range in RECS response coding) | N | (Mavrogianni et al. 2012) |
| Building envelope | Wall type | Major outside wall material | C | (Porritt et al. 2012) |
| Roof type | Major roofing material | C | (Porritt et al. 2012) |
| Thermal mass | Wall or roof type is a thermally massive material (brick, stone, or concrete) |  |  |
| Insulation | Level of insulation | N | (Mavrogianni et al. 2012) |
| Infiltration | Frequency of draft | N | (Samuelson et al. 2020) |
| Window-to-wall-ratio | Number of windows | N | (Samuelson et al. 2020) |
| Window frame | Window frame material | C | (Mavrogianni et al. 2012) |
| Glazing type | Type of glass in most windows | N | (Mavrogianni et al. 2012) |
| Building HVAC | AC type | Type of air conditioning equipment used | C | (O’Neill, Zanobetti, and Schwartz 2005; Samuelson et al. 2020) |
| Heating type | Main space heating equipment type | C | (O’Neill, Zanobetti, and Schwartz 2005; Samuelson et al. 2020) |
| Energy insecurity | Household reported difficulty paying energy bills; repairing or replacing broken heating or cooling equipment; or that they had kept their home at unsafe temperatures because of cost concerns | B | Naughton et al. 2002; MCDPH 2019) |
| Ceiling fans | Number of ceiling fans used | N | (Samuelson et al. 2020) |
| Floor fans | Number of floor, window, or table fans used | N | (Samuelson et al. 2020) |
| Resilience | Home has back-up generator or on-site solar electricity generation | B |  |

a Type includes categorical (C), numerical (N), and binary (B)

* 1. Machine learning

We used machine learning to predict the occurrence of a temperature-related morbidity event, which we treated as a binary classification problem. The input features for the machine learning model are the building and household characteristics described in Table 2. The RECS responses represent the ground truth to validate model performance. We compare it to a model with the potential to use all the household characteristics in Table 2, which has significantly more detailed information about building characteristics. We also compare performance with different machine learning algorithms. These algorithms vary in their underlying structure and assumptions about input features, allowing us to account for potential modeling issues like correlation between input features. For several algorithms, we can also review the contribution of each variable post facto to interpret the importance of individual input features. This outcome can help prioritize data collection for more accurate assessment of temperature-related morbidity risk.

To avoid overfitting the predictive models to the training data, we first split the RECS dataset into training and test data, using 80% for training and holding 20% for testing while preserving the class distribution of the dependent variables in the overall data. We applied the same data split across all machine learning algorithms to allow for direct comparison of model performance. We then used 5-fold cross validation repeated 10 times to further split the training data into training and validation sets to reduce bias that may be introduced by certain training data splits.

By default, the RECS dataset encodes all variables as numerical quantities. We retained the numerical values for truly numerical household characteristics like the number of household members, categorical household characteristics describing ordinal data such as educational attainment and the level of insulation, or binary variables such as HVAC system presence. We converted nonordinal categorial household characteristics such as race and wall type into dummy variables encoded in a series of zeros and ones. After this step, we removed variables with a frequency ratio, defined as the ratio of the count of the majority class to that of the second majority class, greater than 49, which we considered near-zero variance. We also standardized input variables to have zero mean and unit variance.

We applied an exhaustive grid search to find the best performing hyperparameter settings for each machine learning algorithm. For selecting the final tuned model and assessing model performance in the test set, we used the Area Under the Receiver Operating Characteristic (AUROC) Curve (Majnik and Bosnić 2013). For a binary classifier, the Receiver Operating Characteristic (ROC) curve plots the true positive rate versus the false positive rate with different discrimination thresholds. The AUROC summarizes the ROC curve into a single metric that represents the prediction accuracy of the model. By definition, AUROC can vary between 0 and 1, with 1 representing perfect accuracy. An AUROC of 0.5 is analogous to random chance for binary classification. Another benchmark for model performance is the no information rate (NIR). This would be the model’s accuracy if it assumed all predictions were the majority class, which in this case is no temperature-related morbidity.

Since, we are especially interested in the model’s ability to predict temperature-related morbidity, we will also report the model’s true positive rate, or sensitivity. Like AUROC, this value can vary between 0 and 1, with 1 representing perfect accuracy. A sensitivity of 0.5 is also analogous to random chance, but the NIR is 0.

We consider two approaches to address class imbalance in the dependent variable, 1) subsampling and 2) tuning the discrimination threshold. Subsampling artificially balances the class imbalance by randomly sampling the majority class (down-sampling) or the minority class (up-sampling) in the training data. An alternative approach is to change the discrimination threshold (Provost 2000). For classification problems, the machine learning algorithms predict a probability for class membership, which we interpret using a discrimination threshold to assign a class label. For a two-class problem, the default is to consider a threshold of 0.5, where class probabilities greater than or equal to the threshold map to one class and class probabilities less than the threshold map to the other class. For problems with severe class imbalance, this default threshold may result in poor performance. We test if tuning the discrimination threshold based on the inflection point of the ROC curve improves model performance over a default threshold of 0.5.

We use the statistical software R (R Core Team 2021) and its associated integrated development environment RStudio (RStudio Team 2021) to build and analyze all machine learning models. In particular, I will use the tidyverse package (Wickham and RStudio 2021) for reading, manipulating, and visualizing data and the caret package (Kuhn et al. 2021) as a wrapper to conduct data pre-processing, resampling, and cross-validation as well as interface with the different machine learning algorithms. Table 3 describes the machine learning algorithms, hyperparameter search settings, and R implementation we use in this study.

Table . Description of machine learning algorithms, hyperparameter search settings, and R implementation.

|  |  |  |  |
| --- | --- | --- | --- |
| **Machine learning algorithm** | **Description** | **Hyperparameters (min, max, step)** | **R implementation** |
| Ridge regression | This is a penalized logistic regression technique that shrinks the coefficients of less contributive input features towards zero, but still retains them in the final model. The hyperparameterrepresents the amount of coefficient shrinkage. | : (0.001, 0.101, 0.001) | glmnet (Friedman et al. 2021) |
| Lasso regression | This is a penalized logistic regression technique that forces the coefficients of less contributive input features to zero, thereby excluding them from the final model. The hyperparameterrepresents the amount of coefficient shrinkage. | : (0.001, 0.101, 0.001) | glmnet (Friedman et al. 2021) |
| Elastic net regression | This is a penalized logistic regression technique that combines the approach of ridge and lasso regression. Some coefficients of less contributive input features shrink towards zero (like ridge regression), and others become zero (like lasso regression). The hyperparameterrepresents the amount of coefficient shrinkage. | : (0.001, 0.101, 0.001) | glmnet (Friedman et al. 2021) |
| Linear support vector machine (SVM), | This method constructs a N-dimensional hyperplane with the maximum margin to separate data classes. The hyperparameter, *C*, is the penalty for a misclassified data point. | *C*: (0.1, 5.1, 0.5) | kernlab (Karatzoglou et al. 2019) |
| SVM with radial basis function kernel | This method is like linear SVM, except the input features are first transformed with a radial basis function kernel, which takes the form where and are feature vectors, is the Euclidean distance between them, and is a hyperparameter. The hyperparameter, *C*, is the penalty for a misclassified data point. | : 2^(-3, 5, 1)  *C*: (0.1, 5.1, 0.5) | kernlab (Karatzoglou et al. 2019) |
| Random forest (RF) | This method is an ensemble learning technique that uses bootstrapping, sampling with replacement, and feature randomization to build a “forest” of many decision trees. The hyperparameter is the number of randomly selected predictors. | # of randomly selected predictors (2, 52, 5) | randomForest (Cutler and Wiener 2018) |
| Neural network (NN) | This method mimics the way connections between neurons in the human brain by constructing a series of interconnected nodes. The hyperparameters are the number of hidden units and the weight decay. | # of hidden units: (1, 11, 2)  Weight decay:  (0, 0.1, 0.005) | nnet (Ripley and Venables 2021) |

* 1. Statistical analysis

We compared performance of machine learning models with access to two groups of input variables 1) A baseline, which represents a typical HVI and 2) All input variables, which contains detailed building characteristics. Depending on the machine learning algorithm, the final fitted model may not use all input variables the model had access to during training. We used the students t-test to determine whether the mean AUROC and sensitivity of the two groups of input variables is equal. We considered a critical p-value of .05 for statistical significance. For statistically significant results, we also we reviewed effect size. We computed Cohen’s *d*, defined as the difference between the two group means divided by the pooled standard deviation. Ferguson recommends |*d*| > 0.41 for recommended minimum practical effect (RMPE), |*d*| > 1.15 for moderate effect, and |*d*| > 2.70 for strong effect. There is some debate with regards to thresholds, which we discuss in Section X.X. Generally, these effect size thresholds can be conserved more conservative. We used the R package effectsize to compute Cohen’s *d* (Ben-Shachar, Makowski, and Lüdecke 2021).

1. Results
2. Discussion

RECS excludes vacant, seasonal or vacation homes, and group quarters such as prisons, military barracks, dormitories, and nursing homes.

# Conclusions

# CRediT authorship contribution statement

**Arfa Aijazi:** Conceptualization, Methodology, Software, Formal Analysis, Investigation, Data Curation Writing–Original Draft, Visualization. **Stefano Schiavon**: Supervision, Validation, Writing–Review and Editing. Duncan Callaway: Methodology, Writing–Review and Editing

# Declaration of competing interest

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# Appendix

# Reference

1. The discourse in public agencies and academic literature around thermal vulnerability focuses on extreme heat, even though the mortality rate from extreme cold is nearly double that of extreme heat (Berko et al. 2014). In principle, many of the socioeconomic vulnerabilities contributing to heat-related morbidity and mortality also apply to extreme cold.  [↑](#footnote-ref-1)