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Data Availability
The data associated with this publication are available at:
https://github.com/anaijazi/RECSThermalMorbidity

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

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Abstract

Many cities and regions are making significant investments towards planning for extreme temperature and in particular extreme heat. A heat vulnerability index (HVI) is a metric to track spatial variation in extreme temperature risk to target mitigation interventions. Most HVIs focus on demographic characteristics, which generally relate to vulnerability, and lack information about the building stock, which mediate the occupant's exposure to extreme temperatures. In this study, we use the Energy Information Administration's (EIA) Residential Energy Consumption Survey (RECS) to estimate prevalence of temperature-related illness in the United States and develop machine learning models using climate, demographic, and building characteristics to predict them. Temperature-related illness affects approximately 2 million households annually, around 1% of the total population. The models we developed predict temperature-related illness with up to 85% accuracy. The most important feature is energy insecurity, which describes the household's ability to maintain and operate heating, ventilation, and air conditioning (HVAC) systems. Our results offer guidance for municipalities to improve data collection, enabling them to better identify at-risk households and strategize resources for short-term and long-term interventions.

1. Introduction

1.1. 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 too hot or too cold) contributes to 6.5-10% of all deaths (Sera et al., 2019; Zhao et al., 2021). Nearly 90% of global deaths attributed to temperature are cold-related, which is consistent with findings in the United States (Berko et al., 2014). The public health impact of extreme temperatures is undercounted because it aggravates several underlying conditions, but may not be noted as a contributing cause on hospital records or death certificates (Lane, 2018; Ostro et al., 2009). 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 macro trends are pushing policy makers to prioritize emergency planning and disaster mitigation with regards to extreme temperatures. The first is anthropogenic climate change, which is increasing the frequency and intensity of extreme weather (IPCC, 2021). Second, individuals may be exposed to hazardous temperatures during power outages, as was seen across the Northeastern United States following Hurricane Sandy in 2012 (Henry and Ramirez-Marquez, 2016) and in Texas in February 2021 (King et al., 2021). Major electrical grid failures have increased by more than 60% in recent years (Stone et al., 2021). Finally, aging global populations mean more individuals will be susceptible to extreme temperature stress. 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 illness and death (Oudin Åström et al., 2011), so an older population has greater vulnerability.

1.2. Heat Vulnerability Indices enable planning for extreme temperatures

Most cities face substantial variation in intra-city vulnerability to extreme temperatures. The discourse in public agencies and academic literature around thermal vulnerability focuses on extreme heat, even though the mortality rate from extreme cold is significantly higher than that of extreme heat (Berko et al., 2014). This focus is likely because the overall share of heat-related deaths will increase as climate change impacts manifest. In principle, many of the socioeconomic vulnerabilities contributing to heat-related illness and death also apply to extreme cold. Many cities and other jurisdictions use a heat vulnerability index (HVI) to better allocate resources on emergency response to heat, such as the location of cooling centers (Nayak et al., 2018; Reid et al., 2009; Rinner et al., 2010; Uejio et al., 2011). 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.

HVIs seldom include variables related to the local building stock. However, building characteristics such as level of insulation, presence of HVAC system, and air tightness 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; Iverson et al., 2020; Wheeler et al., 2013). An individual will on average spend around 67% of their time in a residence (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 HVIs 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. Among HVI that considered building characteristics, many features that could potentially impact indoor heat exposure such as orientation, envelope properties, and construction type, 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 mixed evidence linking these variables to heat risk, which we discuss in more detail in the subsequent paragraphs.

HVIs 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 indoor temperatures in European residences without air-conditioning found that older buildings had, in summer, significantly cooler temperatures than newer ones (Beizaee et al., 2013; Maivel et al., 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 representative housing models in Boston on the hottest day of the year found older typologies had lower maximum indoor temperatures (Samuelson et al., 2020). These studies demonstrate that construction age alone cannot capture indoor heat exposure.

HVIs also typically consider AC prevalence, particularly that of central AC systems. In homes where AC is present, the cost of operating and maintaining systems may prohibit AC 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), but the AC was either broken (87%), disconnected from electricity (5%), or functioning but not turned on (8%). Clearly, the presence of AC alone is not a protective factor against overheating.

The primary barriers to including additional building-level characteristics in HVIs are data availability at a sufficient scale and awareness of their importance. However, new methods of data acquisition are rapidly becoming available, such as self-reported data related to energy benchmarking (Hsu, 2014), smart thermostat data (Ecobee, 2021), and satellite and street-level imagery (New et al., 2020). This study helps elucidate which additional variables may be most informative for predicting the risk of temperature-related health hazards.

1.3. Research gaps and objectives

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

First, there is a lack of empirical evidence that examines the link between building characteristics and predicting temperature-related illness and death. Studies assessing the sensitivity of overheating risk to building characteristics often use building performance simulations to model the indoor temperature exposure. These studies model the risk of overheating by using simulation outputs such as maximum daily room temperature (Mavrogianni et al., 2012; Samuelson et al., 2020)(Mavrogianni et al. 2012; Samuelson et al. 2020), percent of time in different U.S. Occupational Safety and Health Administration (OSHA) heat index (HI) risk categories (Sun et al., 2020)(Sun, Specian, and Hong 2020), or the degree-hours the wet-bulb globe temperature (WBGT) index exceeded a threshold value (Baniassadi et al., 2018)(Baniassadi, Heusinger, and Sailor 2018). While there are many thermal indices, as yet none of them are validated for personal exposure indoors, meaning the recommended thresholds are not based on empirical observations of temperature-related health hazards in this context (Kenny et al., 2019; Kuras et al., 2017)(Kuras et al. 2017; Kenny et al. 2019).model the risk of overheating by ing

The second research gap is the limited understanding of how personal attributes, such as race and age, affect vulnerability, compared to how building characteristics affect exposure in temperature-related health hazards. Risk is a product of vulnerability and exposure (IPCC, 2023)(IPCC 2023), but few HVIs include detailed building characteristics and few studies using building performance simulations review the interaction of building and occupant characteristics. Baniassadi et al. (Baniassadi et al., 2019)(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. how ,such as,compared to how , but f

To overcome these research gaps, this study trains and evaluates models that predict temperature-related illness based on a nationwide survey of building and household characteristics in American homes. This study revolves around two research questions:

1. Would an HVI with detailed information about the building be more accurate for predicting the risk of health hazards? If so, by how much?
2. Which building and occupant characteristics contribute most to predicting the risk of health hazards?

To answer these questions, we leverage state of the art machine learning models and a train-validate-test pipeline to identify the best performing models and their hyperparameters. Note that our focus is on what data are most valuable for temperature-related illness *prediction*, rather than identifying causal relationships between variables and health outcomes.

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. Understanding the contributions of building and occupant characteristics can prioritize data collection efforts.

2. Materials and methods

2.1. Residential energy consumption survey (RECS) data

The main source of data for this study is the Residential Energy Consumption Survey (RECS), which is administered by the U.S. Energy Information Administration (EIA) (EIA, 2022, 2018)(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 three most recent cycles of RECS—2009, 2015, 2020—ask respondents “in the last year, did anyone in your household need medical attention because the home was too hot?” or “too cold?” (EIA, 2020, 2016)(EIA 2016; 2020). This study treats an affirmative response to either question as a temperature-related illness. While the questions are self-reported and do not specify duration and severity of extreme temperatures and who in the household needed medical assistance, it provides a source of ground truth that the household experienced a hazardous interior thermal environment. We focus on the two most recent RECS surveys from 2015 and 2020. Responses to our questions of interest are not available in the public data file for the 2009 RECS due to infrequent responses risking disclosure of sensitive and confidential household information.

Each RECS is an independent cross-sectional study of residential energy use, so each iteration of the survey is slightly different as far as specific questions. Theoretically, it's possible the same home is included in multiple iterations, but it is highly unlikely and occurs rarely. 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, 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 use a clustered sampling method like in 2015. The impact of this change is a three-fold increase in sample size – from 5,686 in 2015 to 18,496 in 2020. Sample size is inversely proportional to the standard error, so larger samples generally result in narrower confidence intervals for both population and subpopulation estimates.

Table 1 shows the counts of households with heat-, cold-, or any temperature-related illness, meaning either which is the sum of heat- or cold-related or in some cases, both illness in the 2015 and 2020 RECS. For the predictive model, we treat each sample as an independent observation. However, for population estimate, we reviewed the results of each year separately due to differences in sampling methods. For each year, RECS calculates the sample weight, which represents the number of households in the population that a given observation corresponds to. The inclusion of replicate weights allows for the calculation of sampling error. We followed the EIA's procedure for calculating population estimates, standard errors, and confidence intervals in R programming language (EIA, 2023, 2019)(EIA 2019; 2023).

Table 1. Observations of temperature-related illness in RECS

Temperature-related illness	**2015**	**2020**	**Total**
Heat-related	39	76	115
Cold-related	54	120	174
Any temperature	81	171	252
None	5,605	18,496	24,101

To explore patterns in households reporting temperature-related illness we narrowed the over 750 household characteristics described in the RECS dataset to approximately 25, focusing on those related to either vulnerability or exposure to extreme temperature. These variables fall under 3 categories: climate, demographics, and buildings. We describe these building and household characteristics in the subsequent sections. Table 1

Buildings: construction

Building construction includes variables related to the building age and form. As mentioned in Section 0, several city and state-level HVIs use construction age as a catch-all or a proxy for other building characteristics that affect the indoor thermal environment (Nayak et al., 2018; Rinner et al., 2010; Uejio et al., 2011). 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. Mobile or manufactured homes may also increase heat or cold exposure due to poor energy efficiency (Harrison and Popke, 2011), an issue common in even newer mobile homes (Hart et al., 2002). , several city and state-level HVIs use construction age as a catch-all or a proxy for other building characteristics that affect the indoor thermal environment (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. Mobile or manufactured homes may also increase heat or cold exposure due to poor energy efficiency (Harrison and Popke 2011), an issue common in even newer mobile homes (Hart et al. 2002).

Table 2. Summary of household characteristics derived from the RECS dataset relevant to the household's vulnerability or exposure to extreme temperature.

Category	**Variable**	**Variable description**	**Type** [a]
Climate	Cooling design temperature	Dry bulb design temperature (°F) expected to be exceeded 1% of the time	N
	Heating design temperature	Dry bulb design temperature (°F) expected to be exceeded 99% of the time	N
Demographic	White race	Householder (respondent) race is white	B
	Black race	Householder (respondent) race is black	B
	Asian race	Householder (respondent) race is Asian	B
	Mixed race	Householder (respondent) race is mixed	B
	Other race	Householder (respondent) race is other	B
	Hispanic ethnicity	Householder (respondent) ethnicity is Hispanic	B
	Older than 65	Respondent or household member age is $\geq$ 65	B
	Lives alone	Number of household members = 1	B
	Large household (7+ members)	Number of household members $\geq$ 7	B
	Poverty	Calculated from gross income and number of household members based on U.S. Census Bureau definition for poverty threshold for that year	B
	Unemployed	Respondent is unemployed or retired	B
	Low education	Respondent highest education attained is high school or equivalent	
	Renting	Household pays rent	B
	Pays for electricity	Household pays for electricity	B
	Pays for natural gas	Household pays for natural gas	B
	Pays for propane	Household pays for propane	B
	Pays for fuel oil	Household pays for fuel oil	B
Buildings: construction	Construction age	Estimated year when housing unit was built	N
	Apartment	Type of housing unit is low-rise or high-rise apartment	B
	Mobile home	Type of housing unit is a mobile home	B
Buildings: envelope	Exterior wall thermal mass	Estimated thermal mass based on exterior wall material and presence of insulation	N
	Roof thermal mass	Estimated thermal mass based on exterior roof material and presence of insulation	N
	Insulation	Level of insulation	N
	Infiltration	Frequency of draft	N
	Windows per room	Number of windows per room as an approximation for window-to-wall ratio	N
	Glazing type	Type of glass in most windows	N
Buildings: HVAC	AC type	Air conditioning equipment used	N
	Heating type	Space heating equipment used	N
	HVAC operation	Household reported difficulty paying energy bills or that they had kept their home at unsafe temperatures because of cost concerns	B
	HVAC maintenance	Household reported difficulty repairing or replacing broken heating or cooling equipment	B
	Fans	Number of ceiling, floor, window, and/or table fans used	N
	Off-grid	Home has back-up generator or on-site solar electricity generation	B

[a] Type includes numerical (N) and binary (B)

Buildings: envelope
The building envelope refers to the materials that separate the interior from the exterior of the building. Building performance simulations show that wall insulation reduces the overheating risk when it is applied to the exterior, but may increase overheating risk when applied to the interior (Mavrogianni et al., 2012; Porritt et al., 2012)(Mavrogianni et al. 2012; Porritt et al. 2012). Porritt et al. (Porritt et al., 2012)(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)(Samuelson et al. 2020) suggests that other building envelope characteristics, such as infiltration and window-to-wall ratio, may also be significant. One HVI considered houses with thermally massive materials to have greater adaptive capacity (Inostroza et al., 2016)(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. refers to from the show that it is ()suggests ,such as ,,

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Building HVAC characteristics describe the presence (Curriero et al., 2002)(Curriero et al. 2002), type (O'Neill et al., 2005)(O'Neill, Zanobetti, and Schwartz 2005), and functionality (MCDPH, 2019; Naughton et al., 2002)(Naughton et al. 2002; MCDPH 2019) of HVAC systems. Fans are a cost-effective and energy efficient solution to keep people comfortable indoors in warm weather by increasing evaporation and convective heat losses (Jay et al., 2021, 2015; Kent et al., 2023; Miller et al., 2021)(Jay et al. 2015; 2021; Miller et al. 2021; Kent et al. 2023). Finally, we also consider the availability of alternate power sources, such as back-up generators or on-site solar panels, as they may help reduce interruptions to HVAC systems.sa sin warm weather the ,s,help

provides an overall summary of all input variables.

By default, the RECS dataset encodes all variables as numerical quantities. We retained the numerical values for household characteristics that are truly numerical, such as construction age. We also retained the numerical values for ordinal categorial data, meaning there is an ordering of the categories, such as insulation level or draft frequency. We transformed non-ordinal categorical variables, such as race and ethnicity, into dummy variables. Other variables are binary such as the presence of back-up generator or on-site solar. We also derived new variables of interest such as poverty, which combines household size with income level, and thermal mass, which combines insulation level with exterior wall or roof material.

Climate
Ground surface temperature is a climatic variable often reported in HVIs (Uejio et al., 2011)(Uejio et al. 2011), because it represents local exposure to extreme 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 design-temperatures, cooling degree days (CDD), and heating degree days (HDD). These are derived as the weighted average of nearby weather stations with similar altitude (EIA, 2020)(EIA 2020). We chose to use cooling and heating design temperatures because they align with HVAC system capacity.

Demographics
Epidemiological studies have investigated the correlation between different demographic and socioeconomic variables on heat-related mortality. Elderly age is a vulnerability factor, but there is

some ambiguity around the cut-off for higher risk: 60, 65, 70, or 75 (Applegate et al., 1981; Ballester et al., 1997; Centers for Disease Control and Prevention (CDC), 1995; Conti et al., 2005; O'Neill et al., 2003)(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 or take medication that affect thermal perception and regulation. They might also have limited mobility to access cooling centers or restrict their AC usage due to fixed income. Economic conditions and heat-related mortality are related. Economic factors have been measured by poverty (Curriero et al., 2002; Naughton et al., 2002)(Naughton et al. 2002; Curriero et al. 2002), unemployment (Nayak et al., 2018)(Nayak et al. 2018), renter status (Uejio et al., 2011; Wright et al., 2020)(Uejio et al. 2011; Wright et al. 2020), and utility payment (Wright et al., 2020)(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)(Klinenberg 2015). These individuals may be at higher risk of not being checked on regularly during a heat emergency and they may have less help in coping with heat. On the other hand, large households (7+ members) may also have elevated heat mortality risk (Uejio et al., 2011)(Uejio et al. 2011) perhaps due to overcrowding resulting in greater internal gains and lower ventilation rates (Vellei et al., 2017). Evidence for 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 et al., 2005; Schwartz, 2005)(O'Neill, Zanobetti, and Schwartz 2005; Schwartz 2005) whereas other found no association (Green et al., 2010; Madrigano et al., 2013; Pillai et al., 2014)(Green et al. 2010; Madrigano et al. 2013; Pillai et al. 2014)or might restrict their Efactors have been ,,Evidence for t whereas other found no association

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2.2. Machine learning
We used machine learning to predict the reporting of a temperature-related illness event, treating it as a binary classification problem since the RECS survey responses are coded as a "yes" or "no" response. The input features for the machine learning model are described in

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Table 2. Summary of household characteristics derived from the RECS dataset relevant to the household's vulnerability or exposure to extreme temperature.

Category	**Variable**	**Variable description**	**Type** [a]
Climate	Cooling design temperature	Dry bulb design temperature (°F) expected to be exceeded 1% of the time	N
	Heating design temperature	Dry bulb design temperature (°F) expected to be exceeded 99% of the time	N
Demographic	White race	Householder (respondent) race is white	B
	Black race	Householder (respondent) race is black	B
	Asian race	Householder (respondent) race is Asian	B
	Mixed race	Householder (respondent) race is mixed	B
	Other race	Householder (respondent) race is other	B
	Hispanic ethnicity	Householder (respondent) ethnicity is Hispanic	B
	Older than 65	Respondent or household member age is $\geq$ 65	B
	Lives alone	Number of household members = 1	B
	Large household (7+ members)	Number of household members $\geq$ 7	B
	Poverty	Calculated from gross income and number of household members based on U.S. Census Bureau definition for poverty threshold for that year	B
	Unemployed	Respondent is unemployed or retired	B
	Low education	Respondent highest education attained is high school or equivalent	
	Renting	Household pays rent	B
	Pays for electricity	Household pays for electricity	B
	Pays for natural gas	Household pays for natural gas	B
	Pays for propane	Household pays for propane	B
	Pays for fuel oil	Household pays for fuel oil	B
Buildings: construction	Construction age	Estimated year when housing unit was built	N
	Apartment	Type of housing unit is low-rise or high-rise apartment	B
	Mobile home	Type of housing unit is a mobile home	B
Buildings: envelope	Exterior wall thermal mass	Estimated thermal mass based on exterior wall material and presence of insulation	N
	Roof thermal mass	Estimated thermal mass based on exterior roof material and presence of insulation	N
	Insulation	Level of insulation	N
	Infiltration	Frequency of draft	N
	Windows per room	Number of windows per room as an approximation for window-to-wall ratio	N
	Glazing type	Type of glass in most windows	N
Buildings: HVAC	AC type	Air conditioning equipment used	N
	Heating type	Space heating equipment used	N
	HVAC operation	Household reported difficulty paying energy bills or that they had kept their home at unsafe temperatures because of cost concerns	B
	HVAC maintenance	Household reported difficulty repairing or replacing broken heating or cooling equipment	B
	Fans	Number of ceiling, floor, window, and/or table fans used	N
	Off-grid	Home has back-up generator or on-site solar electricity generation	B

[a] Type includes numerical (N) and binary (B)

Buildings: envelope

The building envelope refers to the materials that separate the interior from the exterior of the building. Building performance simulations show that wall insulation reduces the overheating risk when it is applied to the exterior, but may increase overheating risk when applied to the interior (Mavrogianni et al., 2012; Porritt et al., 2012)(Mavrogianni et al. 2012; Porritt et al. 2012). Porritt et al. (Porritt et al., 2012)(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)(Samuelson et al. 2020) suggests that other building envelope characteristics, such as infiltration and window-to-wall ratio, may also be significant. One HVI considered houses with thermally massive materials to have greater adaptive capacity (Inostroza et al., 2016)(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. refers to from the show that it is ()suggests ,such as ,,

Buildings: HVAC

Building HVAC characteristics describe the presence (Curriero et al., 2002)(Curriero et al. 2002), type (O'Neill et al., 2005)(O'Neill, Zanobetti, and Schwartz 2005), and functionality (MCDPH, 2019; Naughton et al., 2002)(Naughton et al. 2002; MCDPH 2019) of HVAC systems. Fans are a cost-effective and energy efficient solution to keep people comfortable indoors in warm weather by increasing evaporation and convective heat losses (Jay et al., 2021, 2015; Kent et al., 2023; Miller et al., 2021)(Jay et al. 2015; 2021; Miller et al. 2021; Kent et al. 2023). Finally, we also consider the availability of alternate power sources, such as back-up generators or on-site solar panels, as they may help reduce interruptions to HVAC systems.sa sin warm weather the ,s,help

. We focused on comparing the performance of models trained with and without building characteristics.

As shown in Table 1, that there is a significant imbalance in the RECS data—less than 1% of all households reported temperature-related illness. This imbalance presents a challenge, because a naïve model that always predicts the majority class, (i.e., no temperature-related illness) will have a high accuracy—99% in this case—but will fail to predict any observations in the minority class (i.e., occurrence of temperature-related illness). Imbalanced data is a common issue in other domains of machine learning prediction, such as disease diagnosis, customer churn prediction, and fraud detection. As in our case, imbalanced data problems generally have a high cost associated with failure to predict the minority class, which is often the more critical one to predict accurately. We employ several techniques in the machine learning model building process to address the imbalanced data (He and Garcia, 2009; Kaur et al., 2019; Krawczyk, 2016)(He and Garcia 2009; Kaur, Pannu, and Malhi 2019; Krawczyk 2016), described in more detail below. ,a significant—presents a challenge,(,)——(,) of machine learning prediction, , which is often the more critical one to predict accurately, d in more detail

We checked the data set for variables with zero or near-zero variance. These variables can negatively impact model performance as they may become zero variance after the data is subdivided. We opted not to remove variables with near-zero variance because our target variable itself is highly imbalanced. We checked for highly correlated variables based on a magnitude of Spearman's correlation coefficient > 0.75, but no variables met the threshold for removal. Supplementary Fig. 1 reports the Spearman's correlation coefficient between machine learning model input variables. We also checked for linear combinations using QR decomposition, but found no linear dependencies. We then normalized input variables to range from 0 to 1. This step prevents variables with larger numerical quantities from having undue influence, particularly in regression-based modeling methods.

We then split the RECS dataset into training and test data, using 80% for training and reserving 20% for testing, which prevents overfitting. We bootstrapped this pTess with 30 iterations to quantify the uncertainty in model performance due to the training data split. This is the minimum sample size from Central Limit Theorem, for assumptions of a standard normal distribution to hold. For each training and test split, we then used 5-fold cross validation repeated 5 times to further split the training data into training and validation sets for selecting machine learning model hyperparameters.

We compared performance from several machine learning algorithms, listed in Table 3. These algorithms vary in their underlying structure and assumptions about input features. We selected these algorithms because of their ability to accept class weights and availability in the R *caret* package. We applied an exhaustive grid search of 100 values to find the best performing hyperparameter settings for each machine learning algorithm.

Table 3. Summary of machine learning algorithms

Algorithm	**Hyperparameters (min, max)**	**R implementation**
Generalized linear model	None	glm (Kuhn et al., 2023)(Kuhn et al. 2023)
Penalized discriminant analysis	Shrinkage penalty coefficient: (0, 0.1)	pda (Hastie and Tibshirani, 2023)(Hastie and Tibshirani 2023)
Penalized multinomial regression	Weight decay = (0, 0.1)	Multinom (Ripley and Venables, 2023)(Ripley and Venables 2023)
Bagged classification and regression tree	None	treebag (Meyer et al., 2023; Peters et al., 2023; Wickham, 2023)(Peters et al. 2023; Wickham 2023; Meyer et al. 2023)
Stochastic gradient boosting	# Boosting iterations: (50, 500) Max. tree depth: 1 Shrinkage: (5×10^{-3}, 5×10^{-2}) Min. terminal node size: 10	gbm (Greenwell et al., 2022; Wickham, 2023)(Greenwell et al. 2022; Wickham 2023)
Random forest	# Randomly selected predictors: (1, # of variables) Splitting rule: Gini impurity, extremely randomized Min. node size: (1, 5)	ranger (Greenwell et al., 2022; Meyer et al., 2023; Wickham et al., 2023)(Meyer et al. 2023; Greenwell et al. 2022; Wickham et al. 2023)
Single layer neural network	# Hidden units: (1, # of variables) Weight decay: (10^{-7}, 10^{-1})	nnet (Ripley and Venables, 2023)(Ripley and Venables 2023)

We employed the following strategies to address the inherent class imbalance in the RECS data set: 1) stratified sampling; 2) fewer cross-validation folds; 3) class weights; 4) sub-sampling; and 5) appropriate performance metrics.

First, stratified sampling means that any time we created divisions in the data set such as splitting the training and test data or subdividing the training data into cross-validation folds, we partitioned the data based on occurrence of temperature-related illness. This way each subset maintained the same proportion of the dependent variable as the original dataset.

Secondly, we also set 5 folds versus the common practice of 10 folds for cross-validation. This allowed us to hold more observations of temperature-related illness for the validation set when tuning hyperparameters.

Thirdly, we test the effect of class weights on model performance. Class weights impose a heavier cost on errors in the minority class. We employed inverse class frequency to determine class weights. In our binary classification scenario, this simplifies to assigning the weight for the minority class as the ratio of the number of majority class samples to the number of minority class samples. This directly adjusts the decision threshold based on the class imbalance.

Fourth, we considered the effect of several sub-sampling techniques during cross-validation. Oversampling randomly replicates instances of the minority class, while undersampling removes samples from the majority class. Due to the extreme class imbalance, we did not consider undersampling as it may remove important classification information from the majority class. Oversampling can lead to overfitting on the training data, meaning the model is not generalizable (McCarthy et al., 2005)(McCarthy, Zabar, and Weiss 2005). We addressed this risk by also testing two hybrid methods, the synthetic minority oversampling technique (SMOTE) and random oversampling examples (ROSE), which both down-sample the majority class and synthesize new data points in the minority class. SMOTE draws artificial samples by choosing points on the line connecting minority class observations to its nearest neighbors in the feature space (Chawla et al., 2002)(Chawla et al. 2002) while ROSE uses smoothed bootstrapping to draw artificial samples from the feature space neighborhood around the minority class (Menardi and Torelli, 2014)(Menardi and Torelli 2014). SMOTE is widely used and extremely popular—nearly 33,800 citations since Jan 27, 2025—because of its simplicity yet effectiveness, particularly in binary classification problems. ROSE may have an advantage in data structure with extreme class imbalance, such as that exhibited in the RECS data set (Menardi and Torelli, 2014)(Menardi and Torelli 2014). All three methods—oversampling, SMOTE, and ROSE—are also well documented and easy to implement within cross validation in the R caret package. Other methods such as Generative Adversarial Networks can be powerful tools, but they are also more complex and computationally expensive. A recent study of thermal comfort data found GAN performed similarly to SMOTE (Quintana et al., 2020)(Quintana et al. 2020) Over, while undersampling removes samples from the majority class Due to the extreme class imbalance, we did not consider undersampling as it may remove important classification information from the majority class. Oversampling can lead to overfitting on the training data, meaning the model is not generalizable . We addressed this risk by also testingboth whileSMOTE is widely used and extremely popular—nearly 33,800 citations since Jan 27, 2025—because of its simplicity yet effectiveness, particularly in binary classification problems. ROSE may have an advantage in data structure with extreme class imbalance, such as that exhibited in the RECS data set . All three methods—oversampling, SMOTE, and ROSE—are also well documented and easy to implement within cross validation in the R caret package. Other methods such as Generative Adversarial Networks can be powerful tools, but they are also more complex and computationally expensive. A recent study of thermal comfort data found GAN performed similarly to SMOTE

Finally, we considered the class imbalance in our choice of performance metric. As illustrated earlier, the model's overall accuracy (ratio of correct classifications to total observations) can be biased for heavily imbalanced classes. The routine choice for binary classification problems is the Receiver Operating Characteristic (ROC) curve. To understand this metric, we define a positive and negative class—the two outcomes of the predictive model. In our imbalanced data set, the positive class is the minority class (temperature-related illness) and the negative class is the majority class (no temperature-related illness). The ROC curve plots the true positive rate (senstivity)—True Positives / (True Positives + False Negatives)— versus the false positive rate (1 – specificity, the true negative rate)—False Positives / (False Positives + True Negatives). This was done with different discrimination thresholds. The area under the receiver operator curve (AUROC) summarizes the ROC curve into a single metric that represents the prediction accuracy of the model. This metric can be misleading for imbalanced data because the false positive rate becomes very small when the number of negatives is very large. (Davis and Goadrich, 2006; Fawcett, 2006)(J. Davis and Goadrich 2006; Fawcett 2006). The Precision-Recall (PR) curve, on the other hand, plots the precision—defined as the ratio of correct positive predictions to the total number of positive predictions (True Positives / (True Positives + False Positives), against recall—which quantifies the number of correct positive predictions relative to the total number of actual positives (True Positives / (True Positives + False Negatives)), essentially the same as the true positive rate in the ROC curve.

The PR curve is better suited for imbalanced data sets training because it is not concerned with negative class predictions i.e. the majority class. As with the ROC curve, the area under the PR curve summarizes the curve into a single metric, which we use to select the best hyperparameter values during cross-validation. In the test set, we evaluated the model along three performance metrics, all derived from the confusion matrix: 1) balanced accuracy, 2) recall, and 3) precision. The confusion matrix is a table used to characterize the performance of a classification model. Each row represents the instances in an actual class, i.e., positive or negative, while each column represents the instances in a predicted class. The diagonal of this matrix represents all instances that are correctly predicted. Balanced accuracy is defined as the average accuracy on either class or, in other words, the arithmetic mean of the sensitivity and specificity. For a naïve model that always predicts the majority class the sensitivity is 0, the specificity is 1, and so the balanced accuracy is 0.5. This serves as a benchmark for a minimum performance value. Recall and precision are of interest because of the high-cost of not only temperature-related health hazards but also preventive measures.

For statistical analysis, we used a paired t-test by bootstrap iteration, i.e., the same training and test data split to compare models trained with different groups of input features i.e. with and without detailed building characteristics. For results with statistical significance, $p < 0.05$, we used Cohen's d to quantify the effect size. We interpreted Cohen's d as follows: $0.4 \leq |d| < 1.15$ for recommended minimum practical effect, $1.15 < |d| < 2.70$ for moderate effect, and $|d| > 2.70$ for strong effect (Ferguson, 2009)(Ferguson 2009).

We used the statistical software R (R Core Team, 2022)(R Core Team 2022) and its associated integrated development environment RStudio (Posit Software, 2023)(Posit Software 2023) to build and analyze all machine learning models. In particular, we used the *tidyverse* package (Wickham and RStudio, 2023)(Wickham and RStudio 2023) for reading, manipulating, and visualizing data and the *caret* package (Kuhn et al., 2023)(Kuhn et al. 2023) as a wrapper to conduct data pre-processing, resampling, and cross-validation as well as interface with the different machine learning algorithms.

3. Results

3.1. Prevalence of temperature-related illness in population

We estimated the prevalence of temperature-related illness in U.S. households using sample weights provided by the EIA. Figure 1 compares the inferred number of households affected by heat-related, cold-related, or any temperature-related illness in 2015 and 2020. Like the global and national trends discussed in Section 1.1, we find that cold-related hazards were more widespread than heat-related ones. While overall the number of households with any temperature-related illness represents less than 1% of the total population, this still means that nearly 2 million households report needing medical attention for temperature related illness annually in the United States.

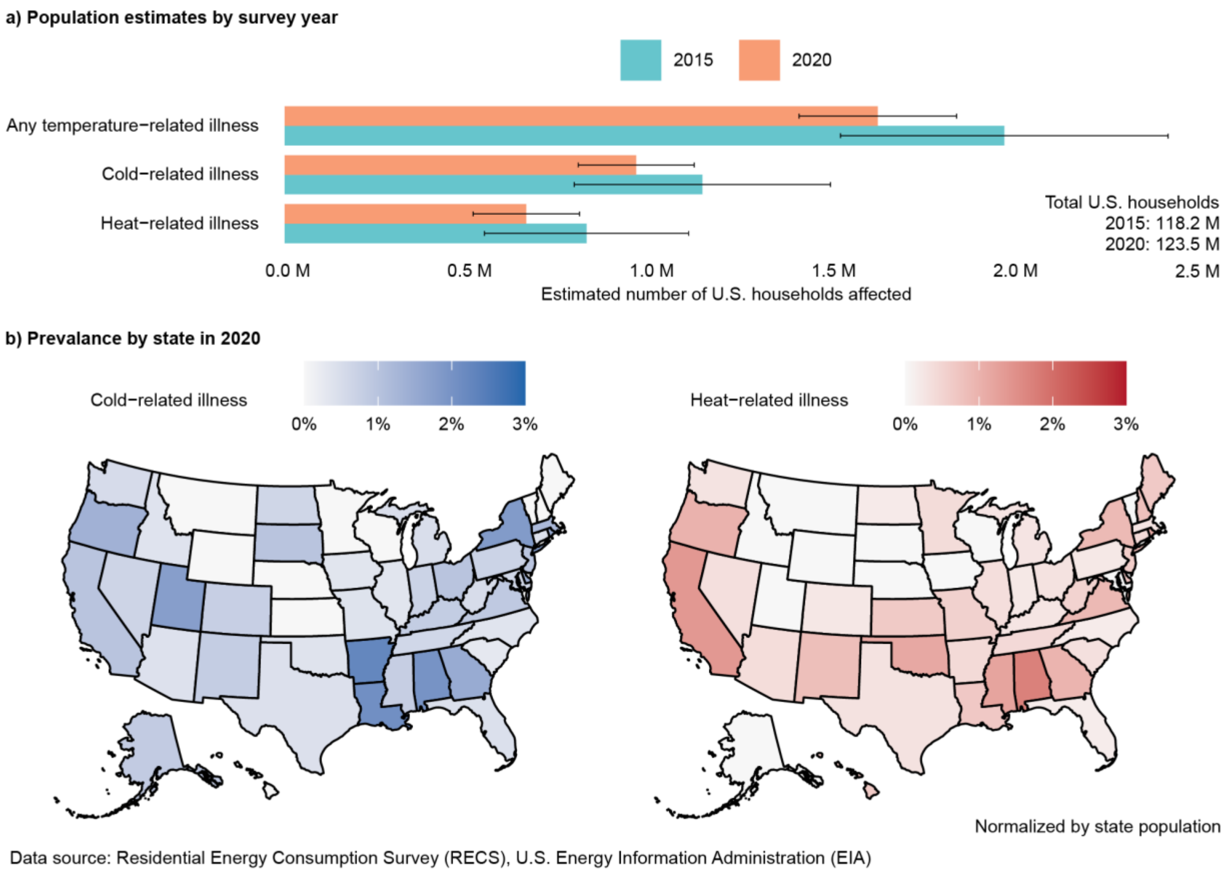

Figure 1: Prevalence of temperature-related illness in U.S. households by a) survey year and b) state. We calculated population estimates and standard errors from sample weights and replicate weights as recommended by the EIA (EIA, 2023, 2019)(EIA 2019; 2023). Error bars represent the 95% confidence interval.

3.2. Predicting temperature-related illness

We constructed machine learning models to predict any temperature-related illness. Regression models allow for clearer interpretability of variable contributions, so even though this is not the best performing model for either input features group, its performance is within the 95% confidence interval. The best regression model is a penalized multinomial regression (Nibbering and Hastie, 2022)(Nibbering and Hastie 2022) with ROSE sub-sampling. This model type performs regularization, which reduces the number of input features by forcing coefficients of insignificant variables towards 0. We greyed out points where the 95% confidence interval included 0, representing the null hypothesis. Our focus here is on identifying variables that make the strongest contribution towards predicting temperature-related illness, rather than identifying causal relationships. We found that in the “Climate + Demographics” model, the variables with the largest magnitude are (in decreasing order): poverty, Hispanic ethnicity, and renting. For the “+ Buildings” model, the variables with the largest magnitude are (in decreasing order): HVAC operation cost, HVAC maintenance cost, and infiltration. When comparing the input groups, we see that the model selects almost the same demographics variables; however, the magnitude of the coefficient is higher for the same variables in the “Climate + Demographics” model.

Our results of variable contribution are mostly consistent with demographic patterns previously found to be highly correlated with temperature-related health hazards, such as being of a non-white race or ethnicity, unemployment or retired status, low education level, renting, and poverty. Some variables, like being over 65 or living alone, showed a negative correlation with temperature-related illness, which contrasts with what we would have expected from the public health literature. Some variables, such as windows per room, heating design temperature, and cooling design temperature, had relatively large confidence intervals. This indicates that within our 30 bootstrapped iterations, there is a wide range of uncertainty in the contribution of these variables. While our analysis of variable contribution does not establish causal relationships, it is relevant for prioritizing data collection that can lead to more accurate predictions of the occurrence of temperature-related health hazards.

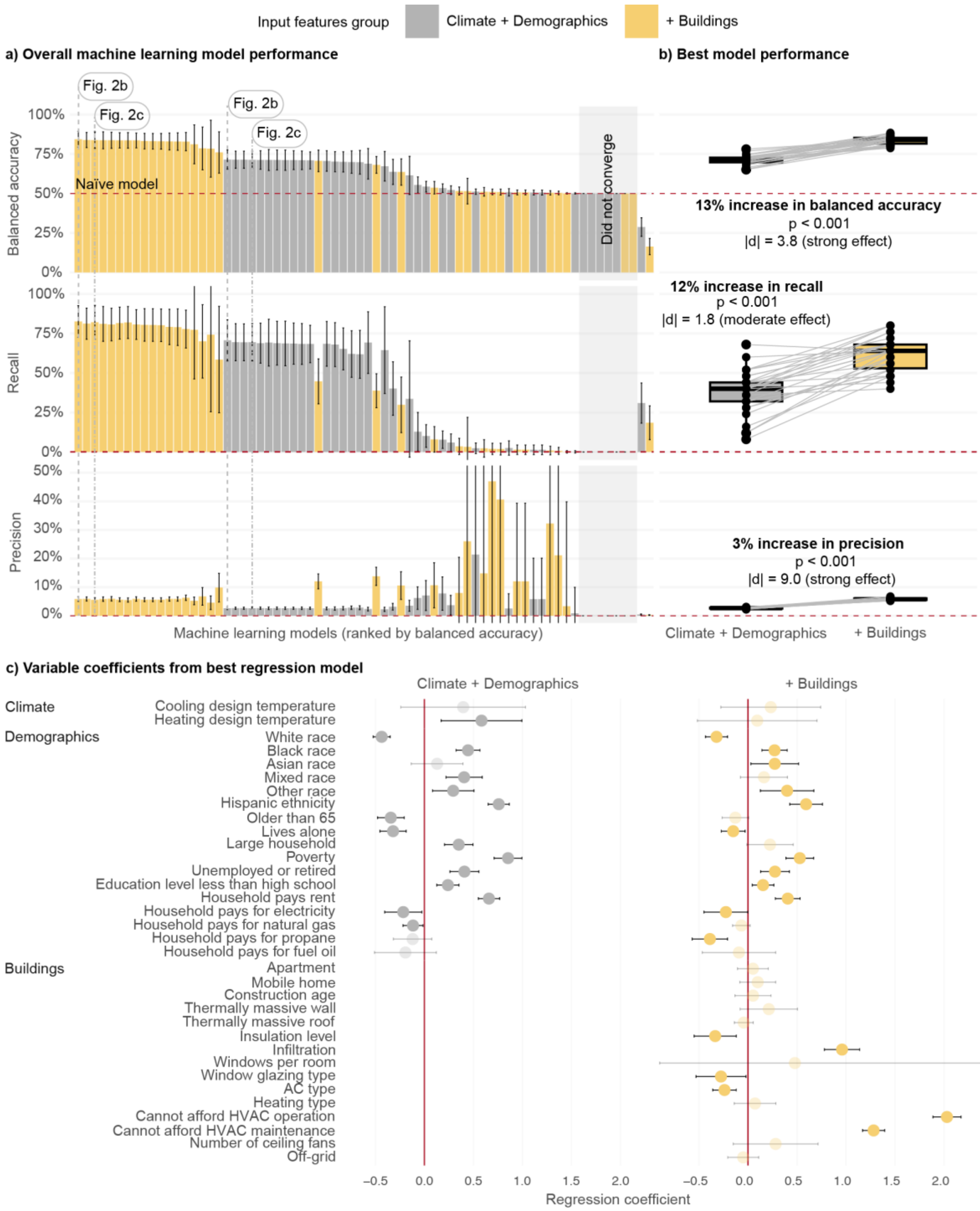

Figure 2a) shows the performance of all model iterations along three performance metrics: balanced accuracy, recall, and precision. Each bar represents machine learning models trained from the same set of input features, class imbalance scheme, and machine learning algorithm, a total of 70 models. The error bars represent the 95% confidence interval, which we calculated from 30 bootstrapped sample iterations, each with a different training and test data split. Generally, about half of the machine learning models performed significantly better than a naïve model. Several poor-performing models did not converge during model training. For well-performing models, the

balanced accuracy and recall range from 70 to 84%. In comparison, the model precision is relatively low, around 5%. This means that the models produce many false positives—households that we incorrectly predicted would have temperature-related illness.

Figure 2b) compares the best model performance from each input group. For the “Climate + Demographics” model the best machine learning algorithm was a neural network with class weights. For the “+ Buildings” model, the best machine learning algorithm was stochastic gradient boosting with up-sampling. We found that including detailed building characteristics as model inputs resulted in a 13% increase in balanced accuracy, a 12% increase in recall, and a 3% increase in precision. These results are statistically significant ($p < 0.001$) and show a moderate to strong effect size.

Figure 2c) compares the value of variable coefficients for the best regression model using the same class imbalance strategy from each input group. Regression models allow for clearer interpretability of variable contributions, so even though this is not the best performing model for either input features group, its performance is within the 95% confidence interval. The best regression model is a penalized multinomial regression (Nibbering and Hastie, 2022)(Nibbering and Hastie 2022) with ROSE sub-sampling. This model type performs regularization, which reduces the number of input features by forcing coefficients of insignificant variables towards 0. We greyed out points where the 95% confidence interval included 0, representing the null hypothesis. Our focus here is on identifying variables that make the strongest contribution towards predicting temperature-related illness, rather than identifying causal relationships. We found that in the “Climate + Demographics” model, the variables with the largest magnitude are (in decreasing order): poverty, Hispanic ethnicity, and renting. For the “+ Buildings” model, the variables with the largest magnitude are (in decreasing order): HVAC operation cost, HVAC maintenance cost, and infiltration. When comparing the input groups, we see that the model selects almost the same demographics variables; however, the magnitude of the coefficient is higher for the same variables in the “Climate + Demographics” model.

Our results of variable contribution are mostly consistent with demographic patterns previously found to be highly correlated with temperature-related health hazards, such as being of a non-white race or ethnicity, unemployment or retired status, low education level, renting, and poverty. Some variables, like being over 65 or living alone, showed a negative correlation with temperature-related illness, which contrasts with what we would have expected from the public health literature. Some variables, such as windows per room, heating design temperature, and cooling design temperature, had relatively large confidence intervals. This indicates that within our 30 bootstrapped iterations, there is a wide range of uncertainty in the contribution of these variables. While our analysis of variable contribution does not establish causal relationships, it is relevant for prioritizing data collection that can lead to more accurate predictions of the occurrence of temperature-related health hazards.

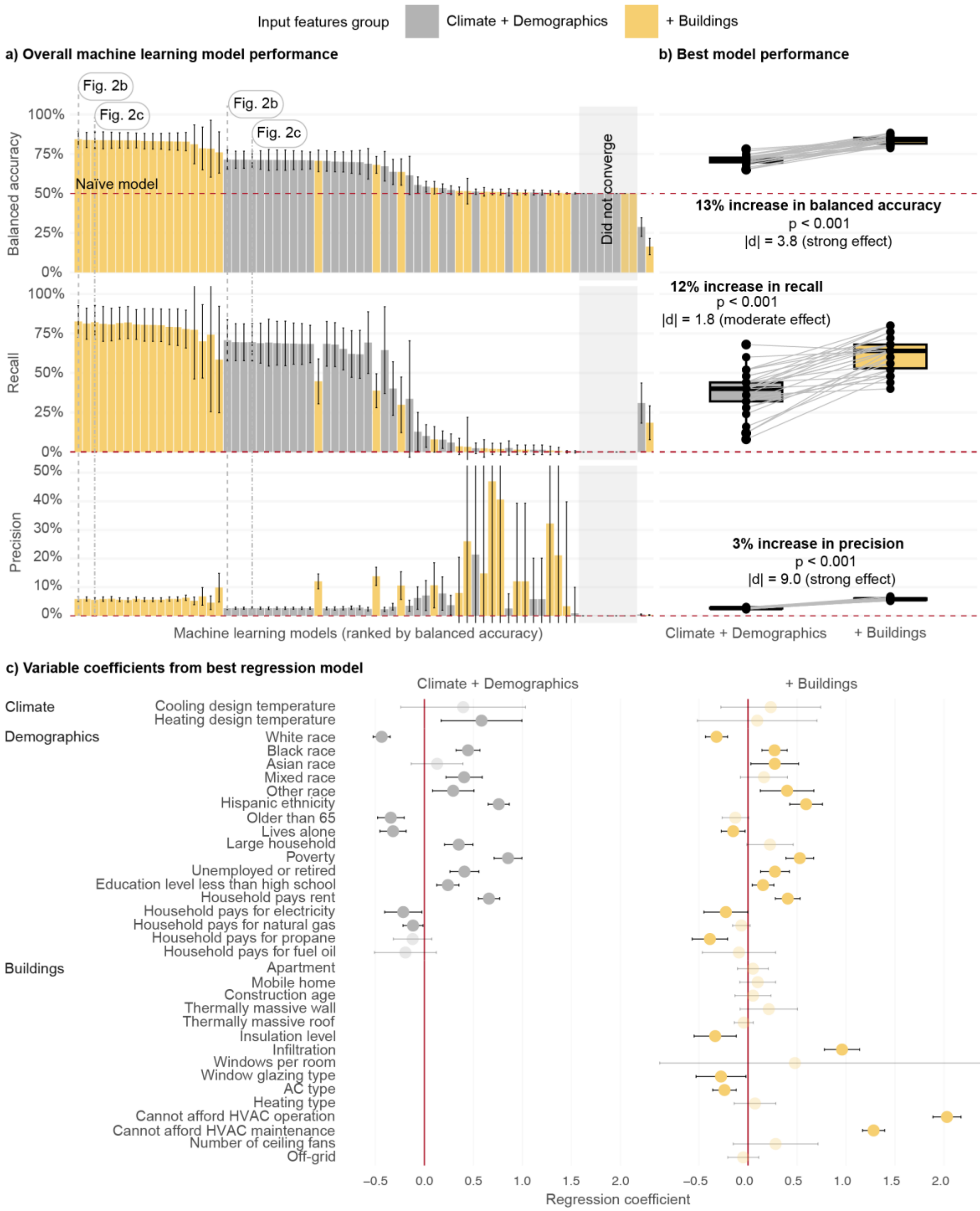

Figure 2: a) Overall machine learning model performance across all 70 iterations along three performance metrics: balanced accuracy, recall, and precision. Each bar represents a machine learning model trained with the same input features group, class imbalance handling scheme, and algorithm. The error bars represent the 95% confidence interval calculated from 30 bootstrapped samples, each with a different training and test data split. b) Shows the performance for the best machine learning model from each input features group. We calculated statistical significance using a paired t-test by bootstrap iteration i.e. the same training and test data split, and the effect size from Cohen's d. We interpreted Cohen's d as follows: $0.4 \leq |d| < 1.15$ for recommended minimum practical effect, $1.15 < |d| < 2.70$ for moderate effect, and $|d| > 2.70$ for strong effect (Ferguson, 2009)(Ferguson 2009). c) Shows the variable coefficient from the best regression model. Also, here

the error bars represent the 95% confidence interval, which we calculated from 30 bootstrapped sample iterations, each with a different training and test data split. We greyed out points where the 95% confidence interval included 0.

4. Discussion

The population estimates from RECS provide new information about the self-reported prevalence of heat, cold, and any-temperature related illness in the United States. Although there is some U.S. national data on heat-related health hazards, namely the Center for Disease Control's Heat & Health Tracker, these sources often rely on data from hospital records or emergency room visits, which have been criticized for their limited ability to properly count temperature-related issues (Lane, 2018; Ostro et al., 2009). To our knowledge there are no national statistics tracking cold-related illness or death, even though our results and others' show they constitute a higher proportion of temperature-related health hazards.

Our findings show that temperature-related illness is geographically widespread across the United States, which helps explain why we see a limited contribution from climate variables in the predictive model. Heat-related illness is not an issue confined to hotter regions of the country and, conversely, cold-related illness is not an issue limited to colder regions. States with low prevalence rates, such as Montana, likely suffer from fewer overall samples making it more difficult to accurately track an oft underreported variable like temperature-related illness. Conversely, states like California and Oregon, which both have relatively high prevalence of both heat and cold-related illness, have moderate climates. The higher rates could be attributed to a lack of acclimatization to extreme temperatures, either in terms of building design or personal adaptation. For example, both states have lower AC penetration than the U.S. national average (Davis, 2022).

Another trend from these results is the higher prevalence of both heat and cold-related illness in the Southeastern region of the United States, which includes states like Louisiana and Alabama. Historically, these states suffer from a higher energy burden, i.e., the percentage of household income spent on home energy bills (Drehobl et al., 2020). The higher energy burden could be due to energy-inefficient building construction leading to higher energy costs, poverty, or most likely both.

Our machine learning results demonstrate the feasibility of machine learning modeling to predict temperature-related illness based on climate, demographic, and building input data. Top-performing models can correctly categorize up to 85% of households (based on balanced accuracy) and identify up to 85% of households that reported temperature-related illness (based on recall). However, these models generally have poor precision, around 5%, meaning that we assign more false positive classifications (classifying reportedly unaffected households as households with temperature related-illness).

Given that temperature-related illness is generally underreported (Lane, 2018; Ostro et al., 2009), providing public health interventions to these households may still be worthwhile. Moreover, from a policy perspective it is more important to have a high recall so people that are in need are identified. Having low precision leads to a more expensive, and therefore less cost-effective, policy intervention.

When reviewing variable contributions, we find that the ability to operate and maintain the HVAC system is highly important, aligning with investigations of indoor heat deaths in Maricopa County, Arizona (MCDPH, 2019). This confirms that the mere presence of HVAC systems is not sufficient to protect against temperature-related health hazards. The HVAC system must work, and the building occupant must be able to afford to run and maintain it. These two factors are both indicators of energy insecurity, a term describing the inability to meet basic household energy needs (Hernández, 2016). Energy-insecure households often make difficult and sometimes hazardous choices out of necessity such as payday lending, burning trash as an alternate heat source, or forgoing other basic needs like nutritious food and healthcare. These decision can lead to adverse mental and physical health outcomes, including temperature-related illness (Graff and Carley, 2020). Accurately identifying energy insecure households is challenging, due to the lack of a single, uniform index (Harker Steele and Bergstrom, 2021). For example, a recent citywide survey used to measure energy insecurity in New York City relied on ten different indicators related to energy insecurity (Siegel et al., 2024).

The inclusion of variables related to energy insecurity, and a handful of other building characteristics such as infiltration rate, resulted in significant performance improvement compared to a model using only demographic variables. This indicates the interaction between vulnerability (primarily captured in demographic variables) and exposure (largely captured in detailed building variables) in the risk of temperature-related health hazards. While demographic information about households is generally available, our findings suggest value in collecting detailed data on energy insecurity.

While our results cannot establish causal relationships, our finding of variable correlations can also help inform interventions to combat extreme-temperature related health hazards. For example, interventions that only provide HVAC units, such as a $10 million program launched by the Canadian province of British Columbia to install 8,000 portable AC units in vulnerable households over the next 3 years (Ministry of Health, 2023), could be limited in their effectiveness if they do not also provide a plan for system maintenance (e.g., fix or replace when broken) and support for its operation (e.g. financial assistance to pay utility bills).

The main limitation of this study originates from using RECS as the primary data source. While RECS uniquely provides detailed information about the households' demographic and building characteristics, the survey responses are self-reported by a single resident of the household. The survey is representative of the household only to the extent that the respondent's answers are reflect the broader household experience. The survey therefore is unable to capture or resolve heterogeneity among individuals living in the same household, which may be more important when trying to compare individuals living together as roommates versus families (Harker Steele and Bergstrom, 2021).

While survey respondents may be knowledgeable of their own and other household members' demographic information, they may be less knowledgeable about the building, particularly building attributes that are not easy to see, such as insulation level and infiltration rates, or highly technical information like HVAC system type. While further research is needed to validate RECS survey responses with on-site investigations or documentation, it is commonly known that building owners often lack awareness and knowledge to properly maintain their home (Kangwa and Olubodun, 2003).

Another limitation is that the data produced from each RECS iteration represents a single cross-section, which prohibits longitudinal analysis. RECS excludes vacant, seasonal or vacation homes, and group quarters such as prisons, military barracks, dormitories, and nursing homes. The exclusion of nursing homes is particularly relevant because they generally house a population with higher vulnerability, i.e. the elderly.

5. Conclusions

Temperature-related illness affects at least 2 million households in the United States annually. We identified households who reported temperature-related illness with 85% accuracy, but this required detailed information about building characteristics, particularly energy insecurity as it relates to the household's ability to maintain and operate HVAC systems, which can safeguard against extreme temperature exposure. This finding is significant because it provides municipalities with a pathway towards improving data collection to identify at-risk households and develop more effective public health programming aimed at preventing in-home extreme temperature health hazards.

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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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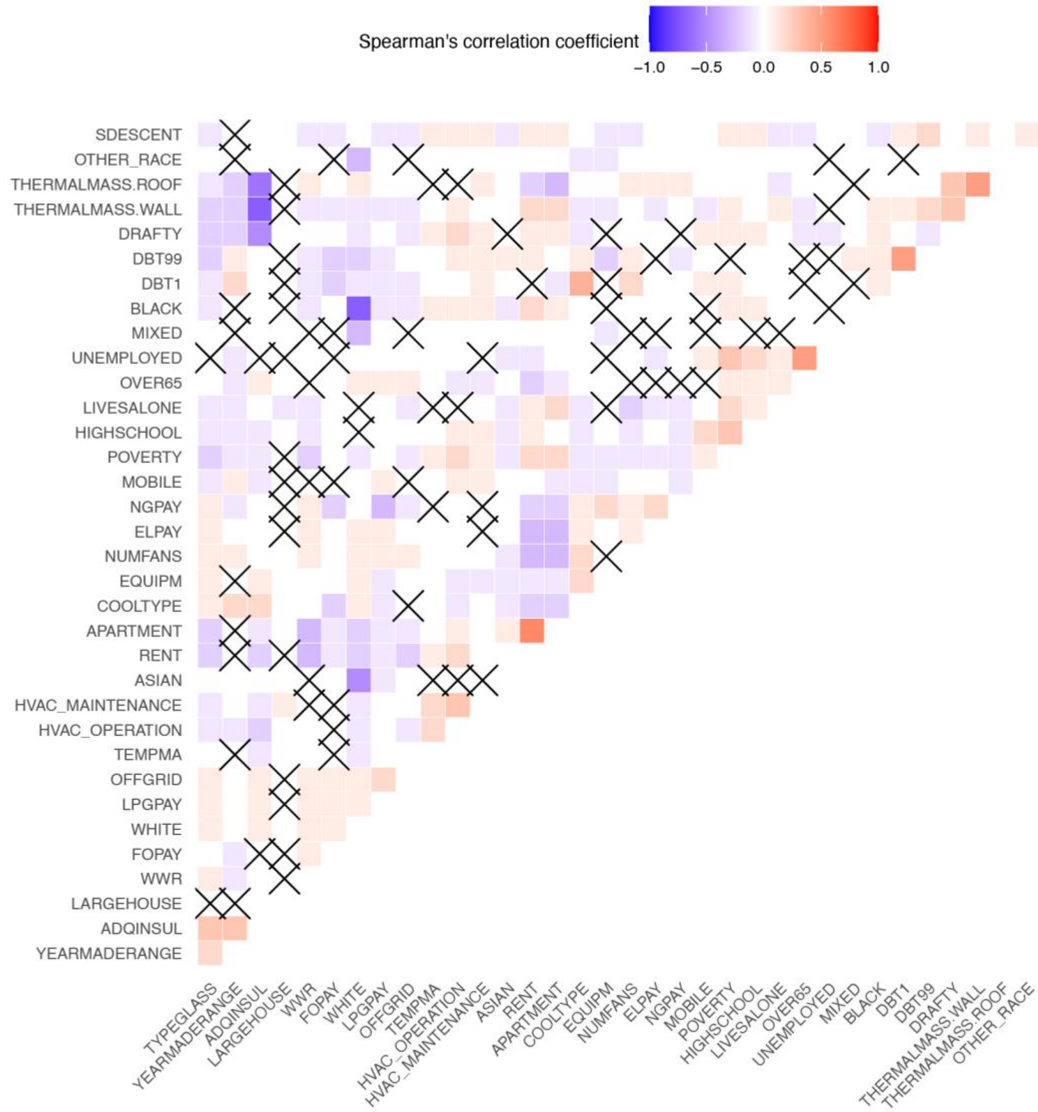
Data availability

All data and analysis code are provided on GitHub at:
https://github.com/anaijazi/RECSThermalMorbidity



Supplementary Fig. 1: Spearman's correlation matrix for machine learning model input variables. An "X" indicates p > 0.05.