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Household energy use response to extreme heat with a biophysical model of temperature regulation: An Arizona case study

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Abstract

Rising temperatures associated with climate change are impacting household energy use. Many of today's industrial-technological-urban humans thermoregulate in the face of varying temperatures using extra-metabolic energy use for heating and cooling our indoor microclimates. Previously, household energy use as a function of temperature change over seasons and time has been described using a three-part model of thermoregulation, the Extra-Metabolic Scholander-Irving model (EMSI), where energy use is lowest in the thermal neutral zone around room temperature and increases in colder and hotter temperatures. However, the EMSI model has only been evaluated for moderately warm cities to date, covering only two parts of the three-part model and lacking evaluation of data for extremely hot temperatures. We show that household energy use in Arizona, a U.S. state that includes hot semi-arid environments, varies across topography, and increases in response to the hottest summer months–exemplifying the third part of the EMSI model. Additionally, household energy use is lowest in the spring and fall and increases in response to colder temperatures in the winter. This relationship has hysteresis related to differences in household income; service regions with lower-income households delay the onset of extra-metabolic energy use for cooling. We use this model to gain predictive insights into energy use demand due to ongoing warming in the context of the desert city of Yuma, Arizona, where a relatively small increase in mean temperatures of ~1.5˚C since the Industrial Revolution produced a 20-day increase (6%) in cooling days annually. Our study expands the EMSI model of thermal regulation to the previously missing hot part of the model, thereby gaining insights into the unique challenges of sustaining extra-metabolic thermoregulation in the face of global warming.

Introduction

Addressing heat stress is one of the greatest challenges facing humans because climate change is increasing the frequency, intensity, and duration of hot extremes [1]. Several recordshould provide amble guidance for both the replication and reproduction of this study.

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Abbreviations: AJO, Ajo Improvement Co; APS, Arizona Public Service; EMSI, Extra Metabolic Scholander-Irving; EIA, Energy Information Administration; HIFLD, Homeland Infrastructure Foundation-Level Data; MOR, Morenci Water & Electric; MOV, Mohave Electric Co-Op; NUA, Navajo Tribal Utility Authority; NVP, Navopache Electric Co-Op Inc.; S-I, Scholander-Irving; SRP, Salt River Project Agricultural Improvement and Power District; TEP, Tucson Electric Power; TRC, Trico Electric Cooperative; UHI, Urban Heat Island; UNS, UNS Energy Corporation.

breaking heat events occurred around the globe in 2021 [2]. These heat events are unequivocally caused by climate change and in urban areas, their effects are compounded by the urban heat island (UHI) effect [3]. The UHI effect is caused by the planning, design, and mechanical operation of urban areas which results in increased temperatures compared with rural areas at their peripheries [4]. Cities in the U.S. are projected to be on average 5.55˚C hotter in the afternoon and 7.77˚C hotter at night by the end of the century [5]. Indicative of hotter locations around the globe, cities in the U.S. Southwest are getting hotter faster, illustrated by the fact that the top four fastest-warming cities are in the U.S. Southwest [6]. Despite clear climatic, regional, and scientific evidence of increasing heat stress in this region, there is a noticeable lag in heat planning and governance compared to other climate risks [7]. Thus, a better understanding of future energy consequences of heat in cities and inequities in heat mitigation and management efforts is needed as temperatures continue to increase [7].

To fully address the challenges affecting energy use in cities due to climate change and the UHI effect, we investigate the nexus of energy use and temperature to help inform heat planning and governance. Multiple frameworks can be used to assess energy use and temperature [8–10]. In this study, we link heat with temperature and energy use through an extended Scholander-Irving (S-I) model [11]. This approach has the advantage of being grounded in biophysical theory rather than being a statistical approach that adds socio-environmental variables as needed, while simultaneously contributing to a general understanding of energy use and temperature relationships. This biophysical model for thermoregulation in warm-blooded animals provides insights into the energetic cost of household thermoregulation in modern humans [12, 13]. Warm-blooded animals have evolved to maintain constant body temperatures (homeostasis) in the face of varying environmental temperatures by modulating biological metabolism regulated by the hypothalamus, and humans are no exception [14]. For example, humans use biological metabolism to sweat and cool themselves via evaporative cooling with increasing temperatures. Modern humans are unique, however, because they can also incorporate "extra-metabolic" energy using fossil fuels and renewable energy to thermoregulate our microhabitats in variable environments [15]. The functional role of the hypothalamus in maintaining homeostasis has been replaced mechanically by a thermostat [16]. Increasing or decreasing temperatures from a thermal neutral zone in the biological S-I models correspond with increasing biological energy demand. Despite a clear overlap between the S-I and EMSI, the EMSI extension has yet to be evaluated for hot temperatures in urban humans [12, 13].

Here, we build on this literature to evaluate the unique human relationship between "extra-metabolic" energy use and temperature by expanding the EMSI model with data for regions that experience high average temperatures and extreme heat events. We draw on the Scholander-Irving biophysical model for warm-blooded animals, which includes three parts: a zone of cold regulation, a thermal neutral zone, and a zone of heat regulation (Fig 1A), as seen in both the desert cottontail (Fig 1B) and humans (Fig 1C). Previous studies of cities have shown that the EMSI biophysical model for warm-blooded animals can be applied to the thermoregulation of households [Fig 1D, 12, 13, 16] for the cold and moderate parts of the three-part model. However, there is currently no study exploring the use of the EMSI model in cities that experience high annual temperatures–the third part of the model (Fig 1D). We studied Arizona, a state in the U.S. Southwest that includes seasonally hot cities in diverse hot semi-arid environments, to evaluate the third part–the hot temperatures on the right side–of the EMSI curve. Arizona is an ideal state to study for the third part of the curve as it has cities with monthly high temperature averages of 42.7˚C.

We combine data for "extra-metabolic" energy use and temperatures from 2019 to i) develop empirical models of the household energy use response to temperatures to evaluate the hottest part of the EMSI model and ii) produce future projections of household energy use.

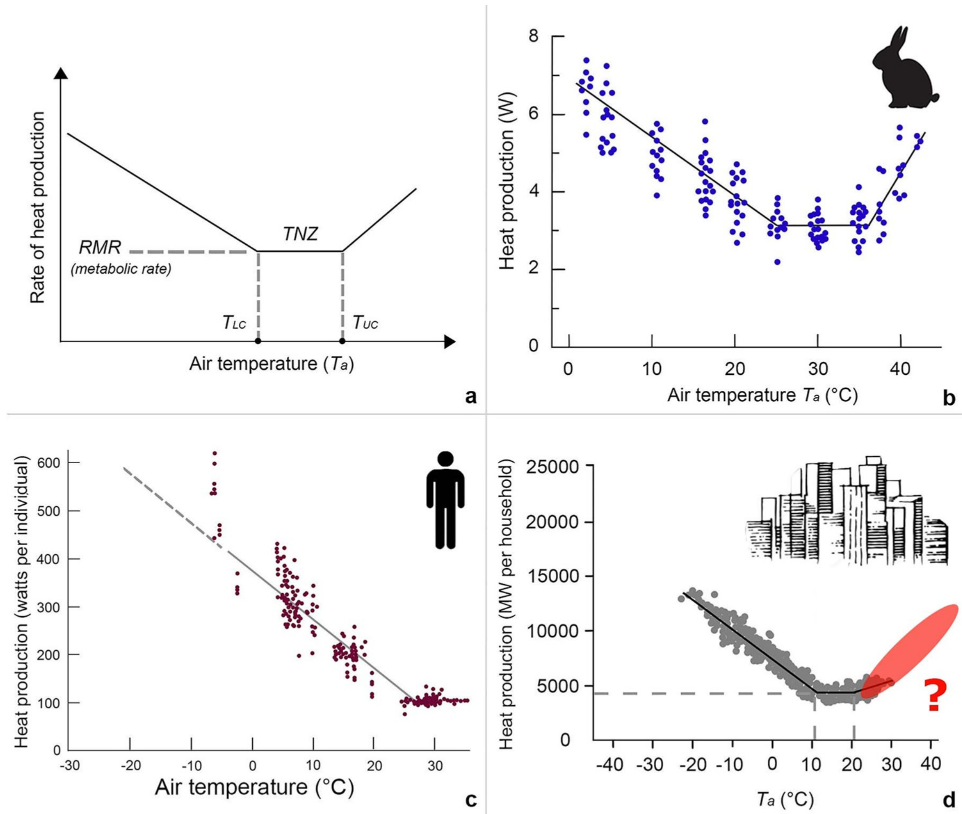

Fig 1. The evolution of the Extra-Metabolic Scholander-Irving model. The Scholander-Irving model of metabolic energy use in thermoregulation in mammals is displayed through A) A conceptual/theory model, B) empirical data for desert cottontail rabbit (*Sylvilagus audubonii)* from Tucson, AZ which is modified from [17], C) Human biological metabolic data of naked humans adjusted from Hill et al. (2013). The human S-I curve lacks hot temperature data because of ethical research standards. The TNZ line is approximately the same width as cities and animals (10˚C). Adding insulation measures, like clothing, to base human data would decrease the slope of the line left of the TNZ. (See Hill et. al 2013 for an in-depth explanation of the human S-I curve), and D) Extra-Metabolic Scholander-Irving model for a previous City study from Hill et al. (2013) modified to show a lack of hot data. Note the scale differences due to the data resolution (monthly vs. daily) and collection methods.

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We present results showing that the EMSI model applies to cities in hot climates and that there is spatial variability in household energy use between hot cities differing in income. We also demonstrate that heat waves and changing climate will affect household energy use. Finally, we discuss the benefits of this modeling system, and the broader implications that increased heat has on health and urban planning. We end with opportunities for extension and future studies. The 3-part EMSI model shown here bridges disciplinary divides by linking a foundational biophysical model of thermoregulation to the unique human ecology in the face of global change. The result is a holistic perspective on urban metabolism and heat vulnerability discourse in the face of rising temperatures.

Methods

Energy and temperature data

We obtained energy use data from the Energy Information Administration (EIA) [18]. Nine energy service regions provided the monthly data required for our analysis, with 36 total regions in Arizona. The data are reported as megawatt-hours used per month and the number of residential customers for each service region, or service provider and electric utility. We used the formula, 1,000,000*[megawatt hours per month] / [number of customers] to calculate monthly watt-hours per capita. The 9 service regions evaluated were: Ajo Improvement Co., Arizona Public Service, Morenci Water & Electric, Mohave Electric Co-Op, Navajo Tribal Utility Authority, Salt River Project Agricultural Improvement and Power District, Tucson Electric Power, Trico Electric Cooperative, and UNS Energy Corporation. The research team contacted the energy company, Navopache Electric Cooperative, and obtained the monthly average energy use for 2019 from their head office. We incorporated these data into the EIA data for 10 total service regions.

We extracted temperature data for the models from the dataset PRISM [19]. We used average monthly temperatures for each service region weighted by population. For example, in the service region that largely consists of Maricopa County and the Phoenix metropolitan area, we used monthly average urban temperatures for each municipality. We then weighted these values such that, if a service region had two cities, A and B, with A consisting of 75% of the population of the service region and B with 25%, the temperature value for the region would have city A accounting for 75% of the average temperature and B accounting for 25%. We obtained population data from the 2019 American Community Survey 5-year estimates provided by the U.S. Census Bureau and organized through the program Social Explorer [20]. The polygons for each city were overlaid with the polygons from the Homeland Infrastructure Foundation-Level Data (HIFLD) data set to determine which cities, townships, and census-designated areas were within the bounds of a particular service region [21].

The total population of all service regions included in our analysis was 5.52×10^6 people, representing approximately 78% of Arizona's estimated population in 2019.

Per capita income calculations

We used two sets of geo-referenced data to calculate each service region's median per capita income. The first is the HIFLD polygons for the boundaries of the service region. The second is the polygons for census tracts from the 2010 Census provided by Esri and the Census Bureau. We then obtained median per capita income data from the Census Bureau through the 5-year estimate 2019 American Community Survey for each census tract [22]. We used ArcGIS Pro (ver 2.9.0) to display both sets of polygons and identify where each census tract fits within the boundaries of the electric regions. The census tract polygon had to be inside part of the service region bound to be included; in the case that two service regions evenly shared a census tract, we determined which region had more surface area allocated and assigned the tract to that region. The data along these contested borders were reviewed to ensure that the service region's boundaries were comparable and, therefore, would not affect the results of the assignment of the census tract to one utility.

In the cases where census tracts encompassed multiple utilities (e.g., Mohave and UNS), the population distribution within each census tract was checked using the Google Earth application and data from Social Explorer [20]. The municipality in question was also cross-referenced with the utility's "users" list to ensure that the population within the census tract was receiving the assigned service region's energy. The incomes per census tract were arranged in Microsoft Excel and analyzed to produce a median per capita income calculation for each service region.

Temporal projections data

We obtained data from 3 land-based weather stations in Yuma, AZ, through the National Oceanic and Atmospheric Administration and the National Center for Environmental Information to investigate the temporal increase in air temperatures [23]. The stations are point measurements and record daily temperatures in Fahrenheit, both minimums and maximums, from 1893 to 2020. The data were sorted in Excel to remove missing data or days that had only the minimum or maximum temperature recorded and not both. Of the 45,168 days analyzed in the time period, 281 had incomplete data, bringing the missing days to 1.24% of the total. The remaining days were divided in half to represent two equal periods: historic (1893–1955) and recent (1955–2020). The minimum and maximum temperatures for each day were averaged and converted to˚C using Excel. We determined the average temperature shift between the two time periods using a regression line as well as the median and mode through descriptive statistics. Additionally, the Yuma data was also organized and run through R Studio to create a plot of daily temperatures for 1893–2020. We calculated the mean temperature increase over this time period as well as the increase in the frequency of days with average temperatures over 37.7˚C, a temperature which at any relative humidity level is classified on the Heat Index by the Arizona Department of Health Services [24] as "extreme caution" or "danger". We also chose 37.7˚C as a baseline because it is a temperature that is often associated with heat alerts and is a commonly used metric.

Results

1) The extension of the EMSI for service regions in Arizona

The collapsed data of all Arizona service regions follows the expected pattern of the EMSI curve (Fig 2). Across Arizona, monthly average household energy varied from 1.96 x 10^6 watt hours per month to 2.88 x 10^5 watt hours per month. Linear regression results for the warmer responsive side of the curve yielded the regression equation $y = 6.95 \times 10^4 x—9.14 \times 10^5$. Using this regression, we can predict and project the energy demanded by any energy utility at any given monthly average temperature. For example, if July in the region of Tucson Electric Power was on average 2˚C hotter (33.6˚C), the corresponding energy use would increase by 1.62 x 10^6 watt hours per household. A 2˚C increase in monthly average temperature more than doubled the energy demand per household.

2) Arizona Extra-Metabolic Scholander-Irving curves show seasonality and variability

Household energy varied use response across Arizona service regions (Fig 3). All three parts of the EMSI model were captured. There was a surprising variation in the ten service regions analyzed. The service regions spanned areas with variable geography and climates. Two patterns of EMSI curves were observed (Figs 3 and 4). The "bowtie" pattern is observed in Navajo Tribal Utility Authority, Mohave Electric Co-Op, Ajo Improvement Co., Trico Electric Cooperative, Morenci Water & Electric, and Navopache Electric Co-Op Inc. In the bowtie pattern, a hysteresis appears, showing energy use lagging behind experienced temperature. In the spring and early summer, households use less energy than in the late summer and fall, even when the experienced average temperature is nearly the same. In contrast, the "buddy" pattern, in which energy use for months roughly pairs up relative to time since the solstice, does not exhibit hysteresis. It is observed in Arizona Public Service, UNS Energy Corporation, Tucson Electric Power, and Salt River Project Agricultural Improvement and Power District. Throughout the year, the energy use pattern in these regions is more intuitive, with the hottest two summer months corresponding with the most energy use. The difference in energy use between months that share similar average monthly temperatures is minimal.

A possible answer to the hysteresis pattern observed in the "bowtie" service regions is that the service regions with the lowest per capita income showed a delayed onset of cooling (Fig

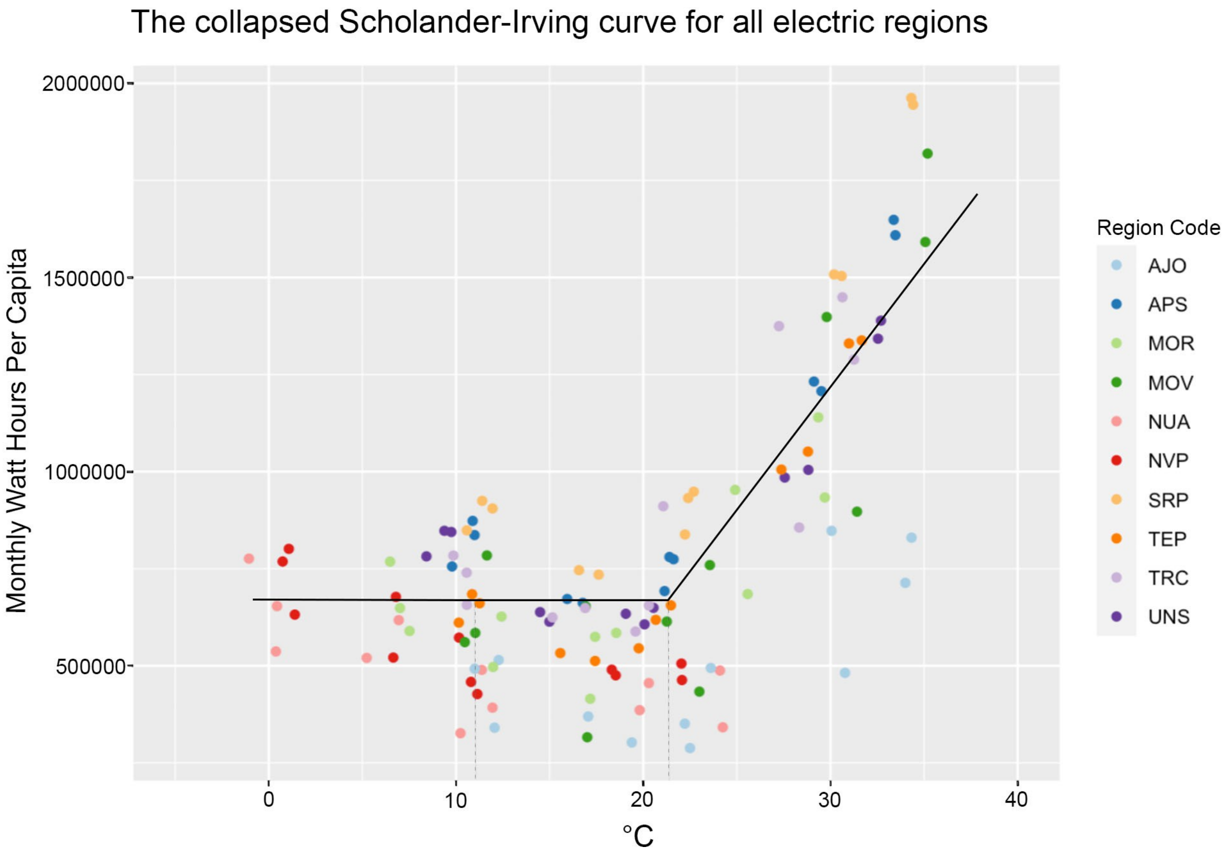

Fig 2. The collapsed EMSI curve for all service regions. Each energy utility is represented by a color and a unique three-letter code. They are, respectively, Ajo Improvement Co. (AJO), Arizona Public Service (APS), Morenci Water & Electric (MOR), Mohave Electric Co-Op (MOV), Navajo Tribal Utility Authority (NUA), Navopache Electric Co-Op Inc. (NVP), Salt River Project Agricultural Improvement and Power District (SRP), Tucson Electric Power (TEP), Trico Electric Cooperative (TRC), and UNS Energy Corporation (UNS). The lines are models for the best fit above and below the thermoneutral zone, (11˚C to 21˚C) as outlined in Hill et al. 2013 [12].

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4). Other possible causes of the variation in the shape of the response curve could include housing insulation, microclimate, and energy pricing. The delayed onset of cooling in some regions and not others is a surprising and novel finding in the study of EMSI curves.

3) Incorporating heat waves into energy predictions

Climate data for Yuma, Arizona illustrates that a small increase in mean temperature has a large impact on experienced heat and therefore energy use (Fig 5). A comparison of the historic (1893–1955) to the recent period (1955–2020) shows that the mean air temperature has risen by 1.5˚C. This is 0.4˚C greater than the global average for mean air temperature rise which is best estimated at 1.07˚C [1]. This mean shift resulted in a 6% increase in the days over 22˚C in Yuma. A day with an average of over 22˚C indicates a "cooling day", where a person would have to cool their house to stay in a thermoneutral state [12, 13]. A 6% increase in cooling days a year translates to over 20 additional days of cooling per year. Additionally, the recent period has increased in days with an average of over 37.7˚C. The historic period saw 37 total days over 37.7˚C, whereas the recent period had 381 days, resulting in an order of magnitude increase. In the recent period, the days over 37.7˚C happened in greater frequency and succession, indicating more severe heat events.

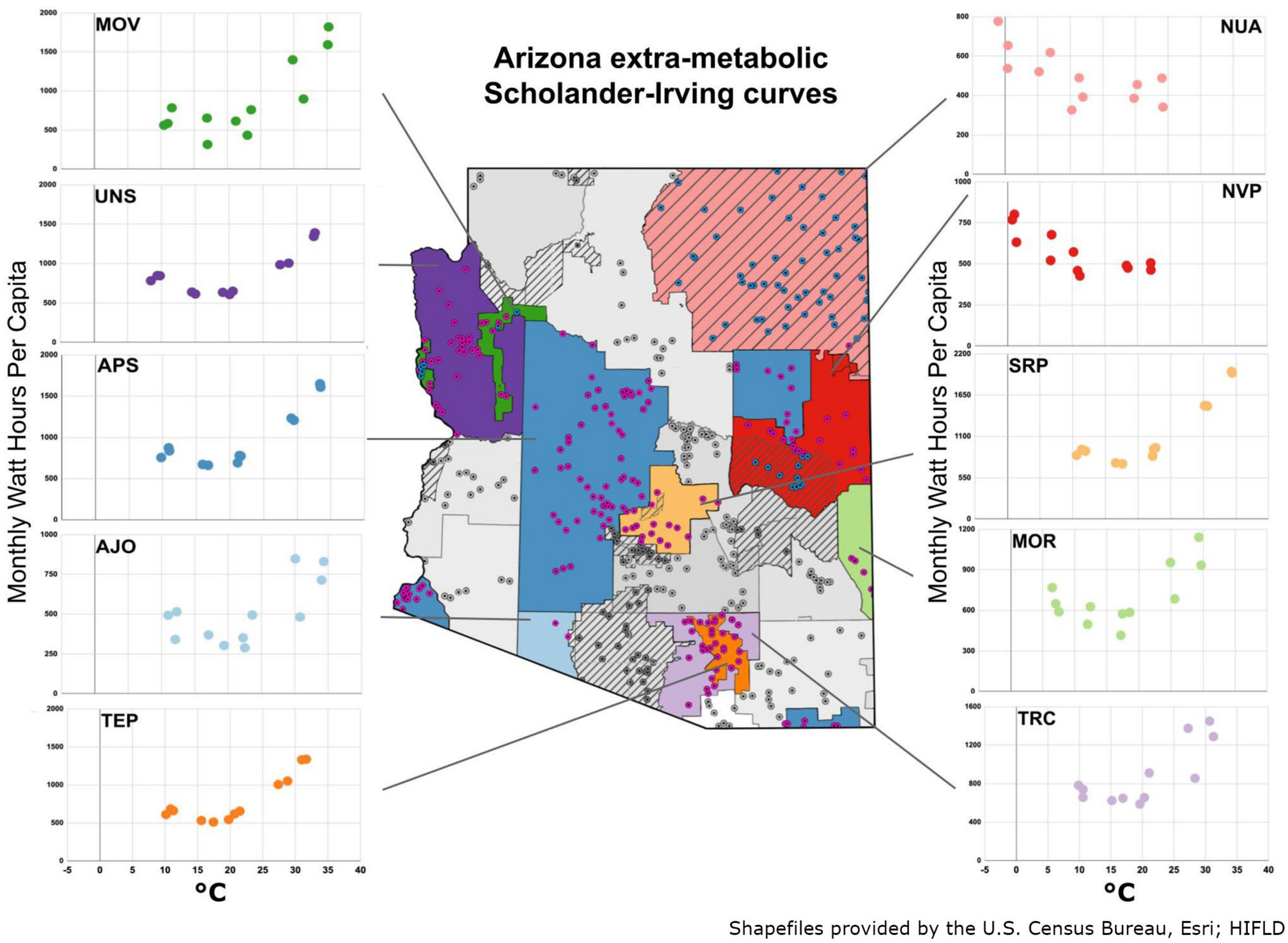

Fig 3. Arizona Extra-Metabolic Scholander-Irving curves. 12-month energy use data by service region from the EIA combined with georeferenced temperature and humidity data for Arizona cities/communities, weighted by population. Centered is a map of the state of Arizona, with outlines of all 22 service regions. The striped lines indicate lands governed by tribal nations. The pink circles represent cities or town localities, and the blue dots represent tribal localities. The service regions are color-coordinated to their respective EMSI curve graph and three-letter label. The y-axis (monthly watt hours per capita) is scaled by 1,000. Access the base shapefile here: https://services.arcgis.com/P3ePLMYs2RVChkJx/arcgis/rest/services/USA_Census_States/FeatureServer [25].

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Discussion

We discuss four major takeaways from our results. First, our results extend temperature-household energy use relationships to the novel third part of the EMSI curve, mirroring the established relationship in mammalian species. Second, our work expands on previous studies by showing that cities and energy regions can be modeled using an extended mammalian thermoregulation theory, not just in cold or thermal neutral settings, but also in hotter ones. The curves in Figs 2 and 3 confirm and extend the work shown in Hill et al. (2013; 2022) [12, 13] despite the different scaling of daily energy use versus monthly energy use. Third, our results highlighted hysteresis in energy use response to temperatures corresponding to household income. The EMSI for each individual region fell into one of two patterns, the “buddy” and “bowtie.” Our study found a loose pattern of “bowtie” shapes falling on the lower end of the service region median per capita income scale. We propose that the variability in the bowtie shape is caused by a delayed behavioral reaction (i.e., cooling measures) to warming weather.

Median per capita income calculations for ten electric regions in Arizona

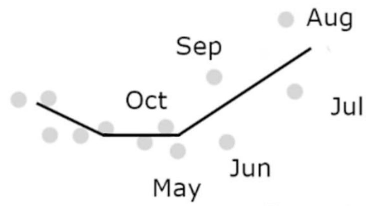
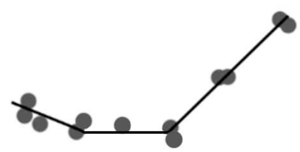
Scholander Curve Shape	Service Territory	Median Per Capita Income
 Bowtie	NUA	$12,964
	AJO	$20,483
	NVP	$22,293
	TRC	$22,692
	MOV	$23,269
 Buddy	MOR	$26,277
	UNS	$27,624
	APS	$27,859
	TEP	$28,904
	SRP	$29,478

Fig 4. Arizona service region's 2020 median per capita income. A table displaying the ordered median per capita income for each service region in Arizona. Accompanying the table are two conceptual figures of the distinct shapes of the regions' EMSI curve shapes (buddy and bowtie).

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This delayed response could be related to cost-saving measures, but more analyses would have to be done to account for possible covariates such as alternative energy sources and cooling technologies, including the use of wood in winter and evaporative coolers ("swamp coolers") in milder months. Finally, we use long-term temporal data from Yuma, AZ, to project future energy demands coinciding with temperature rise.

Broader implications

Our analysis of Arizona's energy service regions is a strong case for the successful modeling of regions that experience high average temperatures. Arizona's EMSI curves also present a large amount of temperature range variation, as shown in Fig 3. Arizona has service regions that get as hot as 35˚C on average monthly and as low as -1˚C on average monthly. This broad range of temperatures and Arizona's population density variability makes it an ideal model to assess the scalability of this methodology. The broader implication of this study is that it uses publicly available datasets which span the entire contiguous U.S. All data sets used in the study (i.e., temperature, energy use, and population) can be replicated to incorporate more states and create regional or national analyses. This study has demonstrated the relative ease with which a well-established biophysical Scholander-Irving model can be extended to understand household extra-metabolic energy demand using publicly available data. It can be a framework for other states or nations to use to inform and predict possible scenarios of heat management and heat-mitigation strategies. Furthermore, the EMSI curves illustrated here may further benefit from insights from the biophysical Scholander-Irving model, which has explored how insulation may change the slopes of the energy use response, thus having a practical use in mitigating inequities in climate change impacts.

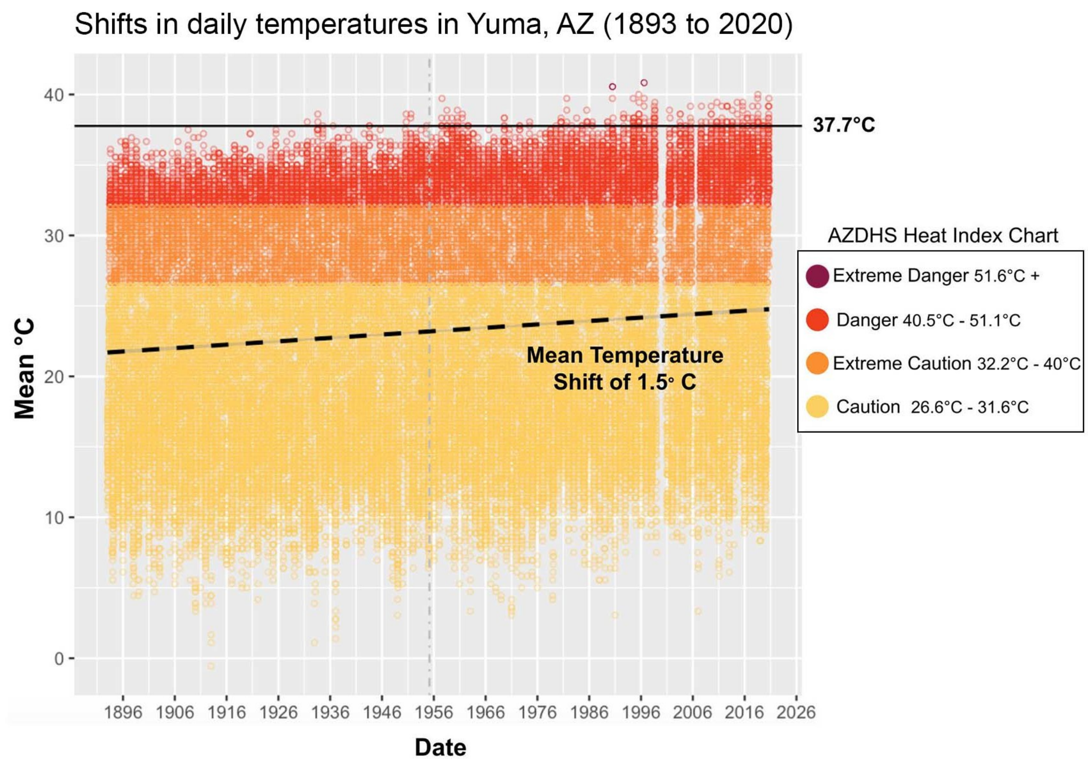

Fig 5. Shifts in daily temperatures in Yuma, Arizona (1893 to 2020). Daily average distributions for Yuma, AZ over the past century. Mean daily temperatures increased by ~1.5˚C as noted by the black dashed line. Yuma date range: "Historic" is from March 1893 –July 1955 and "Recent" is from August 1955 –Sept 2020. With some missing days (1.24%) for the total period. The color gradient is formed by the Heat Index Chart from the Arizona Department for Health and Safety [23]. The solid black line is set at 37.7˚C to show the increasing number of days in the recent period with average temperatures over 37.7˚C.

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Urban exposure to heat events has increased by 200% globally, and the U.S. lacks heat governance infrastructure to combat heat-related fatalities [7, 26]. Our study illuminates a modeling system that would be helpful in identifying vulnerable populations now and projecting their future heat exposure. Heat is the leading weather-related killer in the U.S., even though a significant number of heat-related deaths are preventable [27]. The populations that are particularly vulnerable to heat are adults aged 65 and older and children, as their bodies are less able to adapt to heat than adults, and they must rely on others to help keep them safe [27]. If the potential link to income we investigated is further validated, those with lower income would be disproportionately impacted by rising temperatures in cities and vulnerable to the health-related impacts of heat.

The data from Yuma, Arizona highlights a global shift in hotter average temperatures and the increasing frequency of extreme temperature events. There has been an increase in days defined by the Arizona Department of Health Services as being either "extreme caution" or "dangerous" has increased by 64% since 1955 (Fig 5). These health indexes get more severe as humidity increases, which is not a significant contributor to Yuma's climate but would be a concern in more humid cities. Our team acknowledges that our methods and data collection are influenced by both climate change and the UHI effect. These two contributors are entangled and our resolution of temperature data does not differentiate them as both have contributed to the increase in temperatures in urban areas [26].

Future studies and coda

The Intergovernmental Panel on Climate Change's Sixth Assessment report from Working Group 3 stresses how critical it is to act now to make communities more resilient to the effects of climate change [28]. The extension of the Scholander-Irving model to EMSI in cities helps to understand the impacts of heat and how to measure heat-related impacts essential for human well-being. This small-scale analysis is important in understanding and unpacking multi-layered problems like climate change. This study could be expanded to discover what socio-ecological variables and materials for insulation may cause the variability in the EMSI curves' shapes and sizes. The datasets used present exemplary tools to evaluate more EMSI curves for more regions and expand this methodology. Our study does have limitations regarding the resolution of the study, as monthly averages hide important variability and anomalies compared to daily resolution energy data. This study does explore extreme or maximum temperatures, which play important roles in heat management and public health monitoring.

In conclusion, with global temperatures rising and heat waves becoming more frequent, more intense, and lasting longer [29], it is essential to uncover new ways of modeling and assessing the impacts of heat. This study expands on previous work to show novel insights into how humans thermoregulate through the heating and cooling of dwelling spaces using extra-metabolic energy. The 3-part prediction for the S-I in non-human mammals was presented in the original 1950 paper to explain the relationship between environmental temperature and metabolic energy used to maintain constant internal temperatures (homeostasis). Our study is the first to show the extended EMSI model for maintaining constant household temperature even for the hottest temperatures of the 3-part S-I model. With the majority of humans living in cities, studies of urban metabolism are a critical tool for interdisciplinary studies of sustainability and urban policy [30, 31]. Addressing urban heat with as many quality tools as possible is critical; it saves lives.

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Supervision: David D. Breshears, Joseph R. Burger.

Validation: Kimberly J. Cook.

Visualization: Halley B. Hughes.

Writing – original draft: Halley B. Hughes.

Writing – review & editing: Halley B. Hughes, David D. Breshears, Kimberly J. Cook, Ladd Keith, Joseph R. Burger.

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