

Rising temperatures increase added sugar intake disproportionately in disadvantaged groups in the USA

Received: 10 August 2024

Accepted: 3 July 2025

Published online: 8 September 2025

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Extreme heat may affect added sugar consumption through the increased intake of drinks and frozen desserts, but such an impact is rarely quantified. Here, using individual transaction-level data for US households in 2004–2019, we find that added sugar consumption is positively related to temperature, notably within 12–30 °C at a rate of 0.70 g °C⁻¹. This is primarily driven by the higher consumption of sugar-sweetened beverages and frozen desserts. The magnitude of such impact is larger among households with lower income or educational levels. Our projections indicate a substantial nationwide increase in added sugar consumption of 2.99 g per day by 2095 (or equivalently 5 °C warming level), with vulnerable groups at an even higher risk. Our results highlight the critical need to mitigate health risks from the over-intake of added sugar and to explore dietary adaptation to climate change.

Climate affects food consumption and nutrition through multiple pathways. Changes in temperature and precipitation patterns influence crop yields^{1,2}, crop nutrient contents^{3,4}, seafood abundance and distribution^{5,6}, and livestock health and productivity^{1,2}, which impact food prices⁷, nutrient adequacy⁸ and nutrition-associated diseases⁹. Extreme weather events can disrupt transportation and distribution networks, threatening food security¹⁰. Climate-related factors, such as changes in carbon dioxide levels, can lower the nutritional quality of crops⁴. Despite the large body of literature on the supply side, few studies have evaluated how climate affects dietary demand. Hot weather may increase the need for hydration as higher metabolism increases water loss^{11,12}. High temperatures often drive individuals to consume chilled items such as frozen beverages and desserts¹³. As a result, climate change could exacerbate excessive added sugar consumption with critical health consequences, especially in countries and regions accustomed to consuming food and drinks with an intensive sugar content.

The socio-economic heterogeneity of climate impacts on the demand side calls for further exploration. Differences in sugar-sweetened beverage (SSB) intake, food choices and nutritional quality

across socio-economic groups have been well documented, particularly in the USA and other high-income countries^{14–16}. Lower income, lower educational attainment and certain ethnic groups are associated with a lower intake of nutrients and poorer dietary quality, mediated by socio-economic characteristics such as dietary knowledge, food affordability and accessibility, cultural norms and the food environment. How climate change interacts with socio-economic inequality to affect nutritional quality has been examined, although predominantly on undernutrition issues in developing countries, such as sufficient food supply and affordability¹⁷. A more nuanced examination of the moderating effect of socio-economic drivers is required for developing targeted interventions and policies aimed at promoting healthier dietary habits and reducing disparities in added sugar consumption across different population groups.

Excessive consumption of added sugar has substantially increased the risk of obesity, various metabolic disorders, cardiovascular diseases, cancer and other health complications¹⁸. Individuals aged 2 years and above consumed over 70 g (17 teaspoons) per day in 2017–2018, far surpassing the dietary guidelines of less than 10% of daily calories

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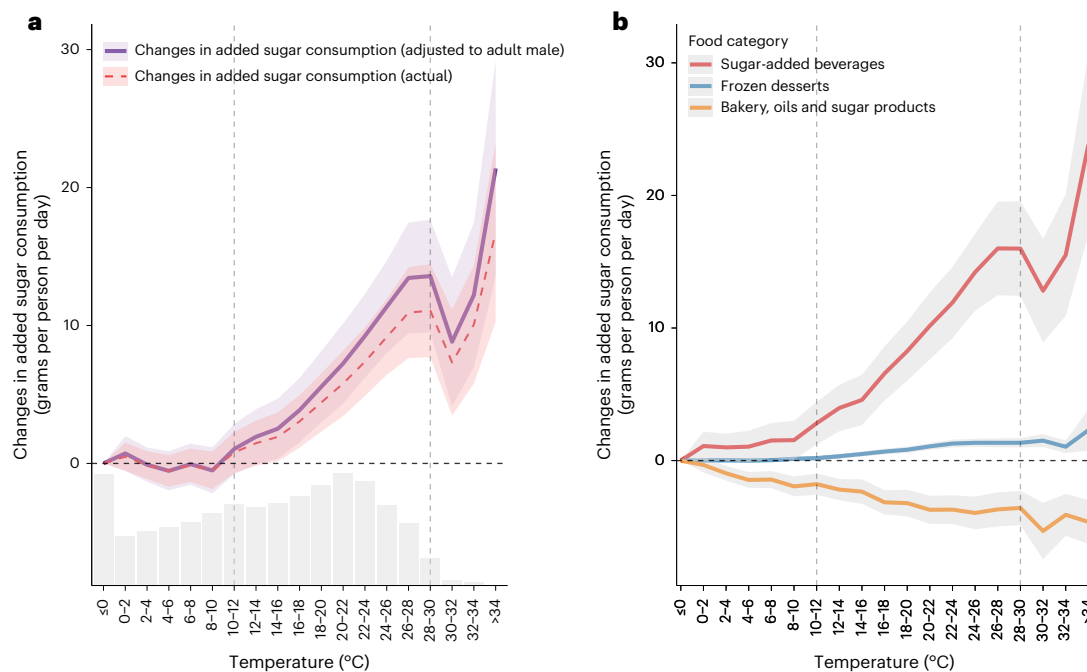


Fig. 1 | Effects of temperature on added sugar consumption. a, The total effect of temperature on added food consumption. **b,** The effect of temperature on added food consumption by food groups. Food groups were identified using the WWEIA food categories (Methods and Supplementary Table 1), which provide

an application to analyse foods and beverages as consumed in the American diet based on the FNDDS. The statistics are from two-sided *t*-tests based on regression analysis, and complete results are presented in Supplementary Tables 3 and 9. The shaded areas show the 95% confidence intervals (mean \pm 1.96 s.e.m.).

from added sugars, equivalent to about 60 g on a 2,400 calorie diet¹⁹. The American Heart Association recommends even lower limits of 24 g for women and 36 g for men²⁰. In this study, we examine the impact of weather conditions on added sugar consumption in the USA during 2004–2019. Using household-level food purchase scanner data, we quantitatively estimate how meteorological factors affect added sugar consumption and investigate the sources of added sugar from various food groups. We further explore the socio-economic and geographical heterogeneity of the effect based on a rich set of consumer characteristics nationwide. Finally, future added sugar intakes are projected in climate scenarios to provide policy implications for food and nutrition interventions.

The impact of weather on added sugar consumption

We first examined how monthly average temperature affects averaged daily added sugar consumption per person, adjusted to the calorie requirement of an adult male to exclude the effect of physical differences due to age and sex (Methods). Added sugar consumption increases with temperature (Fig. 1a), mildly below 10 °C and 12 °C (approximately 0.09 grams per degree celsius per capita-day), then steeply between 12 °C and 30 °C (approximately 0.70 grams per degree celsius per capita-day), before plateauing or even declining beyond 30 °C, which should be interpreted with caution as only 0.8% of observations go beyond 30 °C (Fig. 1a). The results are similar for unconverted, actual consumption (Fig. 1a). Wind speed shows a significant negative impact ($-1.14 \text{ g m}^{-1} \text{ s}$), precipitation has a positive impact ($+0.06 \text{ g mm}^{-1}$) and relative humidity has negligible impact (Supplementary Table 3).

The monthly average temperature may even out the possible impacts of extreme heat. We used the daily mean temperature to calculate the number of days within specific intervals per month for robustness checks (Supplementary Table 8), in 2 °C increments with separate categories for extreme cold (<0 °C) and extreme heat (>30 °C). The results confirm increasing added sugar consumption with rising temperatures, with the effect intensifying as temperatures increase.

While the impact remains relatively modest and less statistically significant in lower temperature ranges (0–20 °C), a marked escalation in consumption occurs when temperatures exceed 20 °C, peaking in the 24–30 °C range. Notably, positive effects persist even above 30 °C. We also adopted a 5 °C interval classification (Supplementary Table 8). A 5 °C interval classification yields similar trends but with slightly weaker coefficients at high temperatures. These results imply that the potential impacts of extreme heat may be obscured, reinforcing the value of granular temperature stratification.

We further examined the temperature effects by breaking down the added sugar into different food groups (Fig. 1b). Sweetened beverages emerge as the main driver, with consumption rising sharply between 12 °C and 30 °C (added sugar, $0.73 \text{ g } ^\circ\text{C}^{-1}$). The consumption of frozen desserts increases much slower ($0.06 \text{ g } ^\circ\text{C}^{-1}$). Sugar from bakery goods, oils and raw sugars slightly decreases, suggesting a potential substitution towards more chilled, hydrating items. Above 30 °C, consumption growth from beverage slows, but declines from bakery goods, oils and sugars persist, explaining the downwards trend in total added sugar intake at higher temperatures (Fig. 1a).

These effect probably stem from physiological and psychological demand for fluids and refrigerated products in warmer weather, or weather-based promotion strategies. To disentangle these factors, we controlled the average price per 100 g of the major food groups (Supplementary Table 10). Prices of sugar-added beverages and bakery goods negatively affect added sugar consumption, whereas price increases in added sugar-free drinks such as 100% juice (distinguished from the ‘fruit drinks’ as the former does not contain added sugar while the latter belongs to the subcategory of SSBs), milk and diet beverages significantly increase the consumption of added sugar, indicating a possible substitution effect. However, price volatility was low (s.d. -0.02) and temperature effects remained stable, indicating that this increase is more likely attributed to physiological and psychological factors. Still, temperature change does facilitate promotion, as the product price drops in hotter days (Supplementary Table 12 and Supplementary Fig. 3).

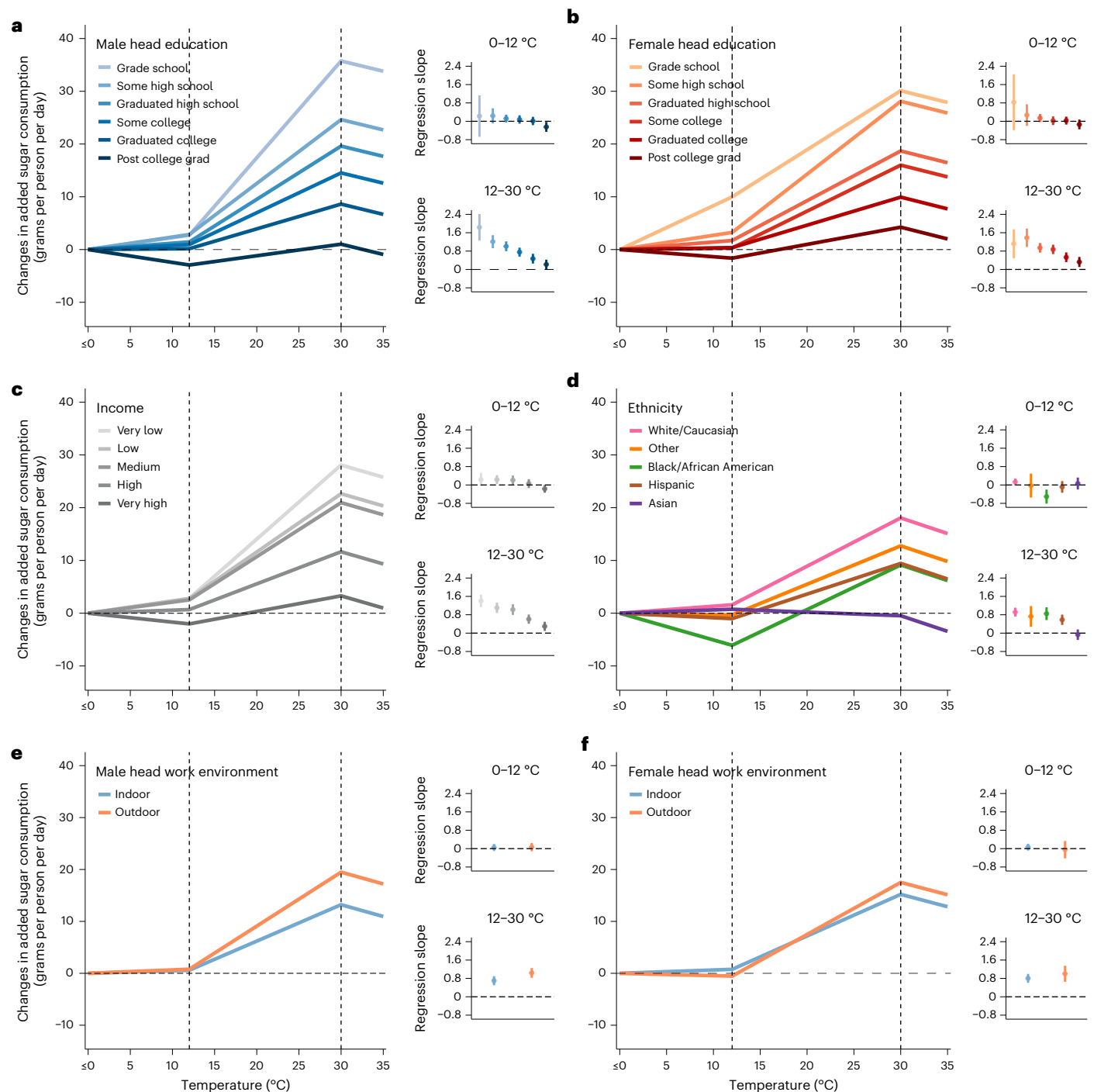


Fig. 2 | The heterogeneous effect of temperature on added sugar consumption. a,b, The effect of temperature by education level for households with a male head (a) and female head (b). **c,d,** The effect of temperature by income (c) and ethnic group (d). **e,f,** The effect of temperature by work environment for households with a male head (e) and female head (f). We divided the household income into five income groups according to the data collection methodologies of Nielsen Company (annual income <US\$24,999 (very low), US\$25,000–49,999 (low), US\$50,000–69,999 (medium), US\$70,000–\$99,999

(high) and >US\$100,000 (very high)) and categorized the work environment based on the occupation of male/female heads into indoor and outdoor settings. The statistics are from two-sided *t*-tests based on regression analysis and the complete results are presented in Supplementary Tables 14 and 15. The graphs on the right show the slopes of the linear model at 0–12 °C ($n = 2,736,315$) and 12–30 °C ($n = 4,116,587$) respectively, and the vertical lines show the 95% confidence interval (mean \pm 1.96 s.e.m.). The analysis is based on a total sample size of $n = 6,908,936$.

Heterogeneous effects of temperature

We also tested for heterogeneous responses using segmented linear regression to identify vulnerable groups (Methods). Compared with the binned approach, segmented regression reduces the number of parameters in a model, thereby allowing for more robust estimates

when breaking down data further by ethnic or socio-economic groups. Added sugar consumption is less responsive to temperature among higher educational levels and higher income groups (Fig. 2a–c and Supplementary Table 14), with those earnings >US\$100,000 or holding post-college education showing near indifference. The effects are

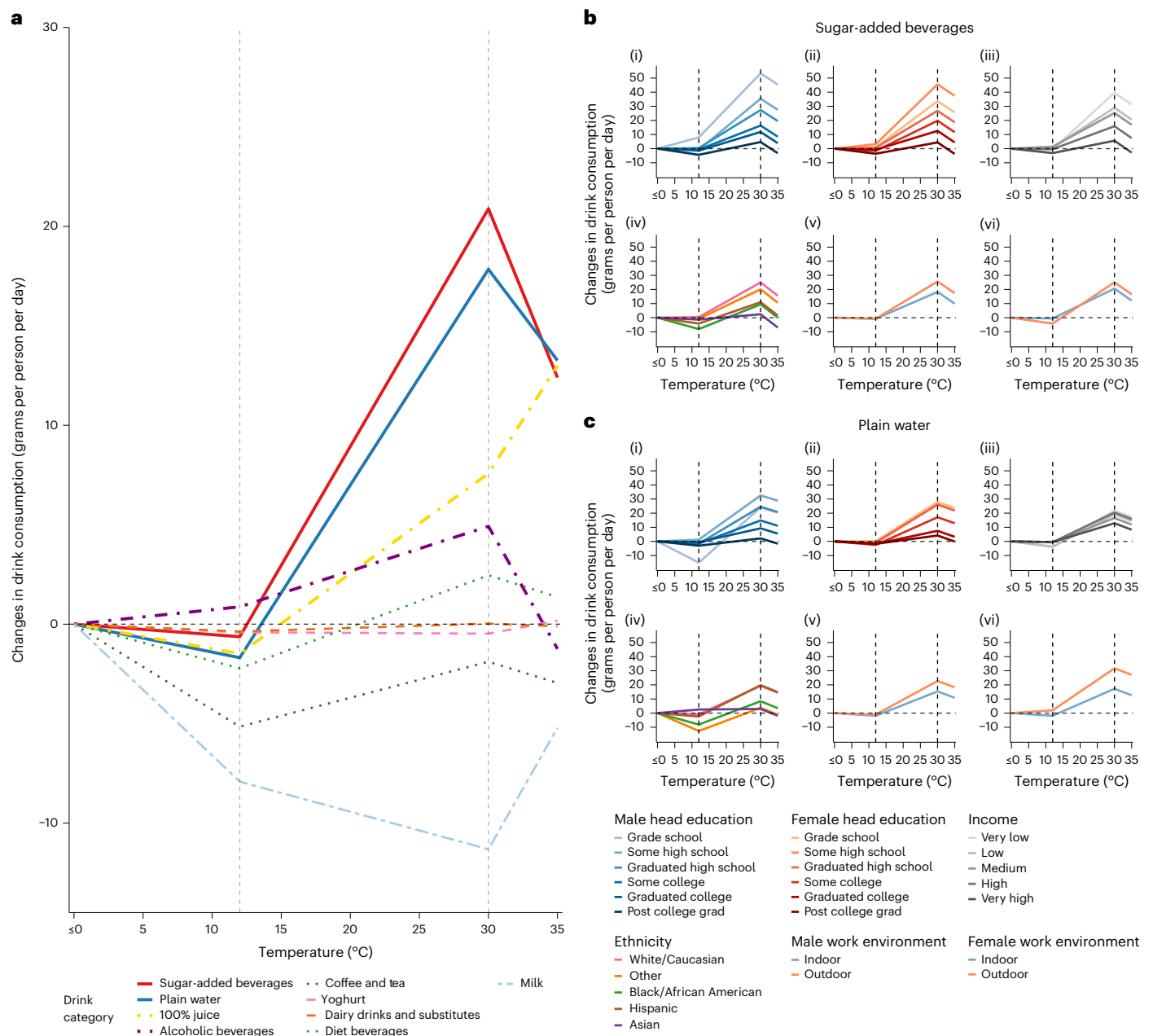


Fig. 3 | The effect of temperature on drinks consumption by type.

a, The effect of temperature on sugar-added beverage consumption for the whole sample. **b**, The heterogeneous effect of temperature on sugar-added beverage consumption by education level in households with a male head (i), education level in households with a female head (ii), income (iii), ethnic group (iv), work environment in households with a male head (v) and work environment in households with female head (vi). **c**, The heterogeneous effect of plain water

consumption by education level in households with a male head (i), education level in households with a female head (ii), income (iii), ethnic group (iv), work environment in households with a male head (v) and work environment in households with female head (vi). The statistics are from two-sided *t*-tests based on regression analysis and complete results are presented in Supplementary Tables 19–21. Household income was categorized as defined in Fig. 2.

consistent across male and female heads (Methods). Variations across ethnic groups are substantial: most ethnic groups exhibit similar positive marginal effects within the temperature range of 12–30 °C, whereas the Asian group shows a nonsignificant reaction.

The limited responsiveness of high socio-economic status groups to weather changes may stem from experience of different micro-environmental temperatures, particularly at workplaces. Stratification by working environment (Fig. 2e,f and Supplementary Table 15) shows significant differences for male heads but only minor differences for female heads. Correlation analysis also reveals a stronger income–education link among male heads (Supplementary Fig. 5). The higher

income and/or higher education groups may also opt for healthier food and drink choices out of health concerns, reflected in their lower added sugar consumption (Supplementary Table 3), although they demonstrate a larger increase in juice, which is not necessarily healthy due to the free-sugar content (Supplementary Tables 19 and 20). Moreover, they are less responsive to product promotion in hot weather as their purchase prices remain steadier across categories (Supplementary Fig. 4 and Supplementary Table 13), probably leading them to select lower-sugar beverages for hydration.

Since sugar-added beverages are the major contributors to the increased added sugar consumption, we examined how different

beverages respond to temperature (Fig. 3). While plain water and SSB consumption rose markedly, shifts in other drinks were modest (100% juice and alcoholic beverages) to negligible (others). Higher socio-economic status showed smaller responses across all drink types regardless of whether they are healthy or not (Supplementary Fig. 9), possibly due to a higher consumption of tap water, which lowers purchase needs, though only differences in sugar-added beverages and plain water are not statistically significant (Supplementary Tables 21 and 22).

Climate background may also affect behavioural responses. Residents in historically hotter areas may be acclimatized and less reactive to temperature rises, as seen in other behaviours such as air conditioner purchasing²¹. Analysis by climate zones classified by the US Department of Energy Building America Program²² indicates minimal response in the Hot–Humid Climate Zone in the southeast coastal area but largest responses come from the Marine Climate Zone in the northwest coastal area (Extended Data Fig. 1 and Supplementary Table 16). Nevertheless, the differences are not statistically significant.

Drinking habits may also play a role, with heavier drinkers of SSBs being more responsive as found in the previous studies^{23,24}. Our examination shows that the heavier drinkers (SSBs ≥ 150 g with added sugar consumption ≥ 45 g, above the recommendations of 36 g added sugar for male adults²⁰, with statistics indicating that US adults consumed 145 kcal day⁻¹ from sugary drinks in 2011–2014 from the USA²⁵) do have a significantly larger response compared with other groups (Supplementary Table 18 and Supplementary Fig. 8).

Projected added sugar consumption under future climate scenarios

We projected added sugar consumption changes using the Coupled Model Intercomparison Phase 6 (CMIP6) simulations from 25 models under the Shared Socioeconomic Pathway 5-85 (SSP5-8.5) scenario. As we found no significant difference in the effect of temperature across regions with distinct background climate, either in terms of cooling degree days (CDDs) (Supplementary Table 17 and Supplementary Fig. 7) or climate zones (Extended Data Fig. 1 and Supplementary Table 16), we used the nationwide segmented linear regression model (Supplementary Fig. 2 and Supplementary Table 4) to void small-sample bias above 30 °C. Based on an overall temperature increase of 5 °C from 2019 to 2095 and other changes in meteorological data, we project a daily added sugar consumption of 2.99 (1.40–4.62) grams per person per day on average by the end of this century. This increase has a clear seasonal cycle, with up to 3.81 grams per person per day in summer, 3.83 grams per person per day in autumn and only 1.26 grams per person per day (Fig. 4a). Although the mid-latitude continent experiences the greatest warming during winter, we find consistent warming rates (4.6–5.4 °C) over the USA throughout the year. Hence, the increased added sugar consumption from seasonality is primarily due to different sensitivity associated with distinct baseline seasonal temperatures (3.3 °C on average in winter, but between 12 °C and 30 °C in other seasons; Supplementary Table 23). Geographically, the northern USA sees the largest projected increase (Fig. 4b), probably due to temperature increase and sensitivity of added sugar intake. Despite the higher temperatures in southern counties, summer temperatures frequently exceed 30 °C (Supplementary Fig. 10) with climate change, resulting in a slower growth in the annual average added sugar consumption growth compared with northern states.

The socio-economic breakdown show the highest increase is up to 6.2 (3.9–9.3) grams per person per day for households that have a male head with a graduate school education. The increase reaches 3.5 (2.3–4.8) grams per person per day and 4.9 (2.4–7.2) grams per person per day for households that have a female head without a high school degree or household income less than US\$25,000, respectively. The change in consumption is about 3.4 g for white people and exceeds 2.6 g for black people and other races, while the change in consumption of the Asian group is not significant (Fig. 4c(i–iv)).

We also project added sugar consumption changes using 16 models under the SSP2-4.5 scenario, which represents some intervention in human activities and results in a temperature rise of about 2.3 °C in 2095 relative to 2019. The results based on the degree of climate change under this scenario are about half of those under the SSP5-8.5 scenario (Supplementary Fig. 11 and Supplementary Tables 25 and 26).

Discussion

This study explores the impact of weather on added sugar consumption in the USA from 2004 to 2019 using household-level food purchase scanner data. We find that added sugar consumption increases with temperature, especially between 12 °C and 30 °C, which slows down above 30 °C, possibly due to physiological responses such as appetite suppression. The increase is mainly driven by SSBs such as soda and juice, and frozen desserts such as ice creams and gelato. Lower-income and lower-education groups exhibit stronger responses, indicating heightened vulnerability. Projections show that future climate change will aggravate health risks related to added sugar intake, particularly for socio-economically disadvantaged populations whose average daily intake already exceeds 10% of the recommendations from the 2015–2020 Dietary Guidelines for Americans²⁶ and almost 20% of the recommendations from the American Heart Association²⁰.

Our analysis provides empirical evidence on the impacts of weather conditions on added sugar consumption for cost-effectiveness analyses of sugar reduction programmes and policies under climate change. The results also highlight the urgent need to tackle nutrition and health inequalities exacerbated by climate change, identifying key populations for targeted interventions. Considering fine-tuned food policy in adapting to climate change, our analysis provides implications for achieving several Sustainable Development Goals, including No Hunger, Good Health and Well-being, Climate Action and Reduced Inequality. As the over-intake of added sugar and climate-related risks have both become pressing global concerns^{27,28}, our analysis informs food policy and climate change adaptation strategies, not only in the USA but also in other countries with increasing nutritional and health challenges.

Several limitations should be noted. The Nielsen data cover retail purchases but exclude restaurant meals and food received without purchase. Nevertheless, our main results still hold unless weather significantly affects the added sugar consumed via different channels. Moreover, our analysis reflects household-level purchases rather than individual intakes as data on post-purchase food storage, food waste and intra-household food allocation are not available. This discrepancy may be more pronounced for bulk-purchased or long shelf-life items (for example, granulated sugar and coffee/tea), raising potential issues if high-sugar items in such categories are stored for extended periods rather than consumed within a month and/or if temperature changes influence the allocation of sugar between presweetened products and sugar added manually (for example, blending the granulated sugar with coffee and tea). However, these effects are probably minimal as SSBs, as the main driver, are typically consumed immediately rather than stored for long time, and both granulated sugar and coffee/tea show relatively low sensitivity to temperature variation. Shifts in intake or waste ratios at higher temperatures are probably secondary as well. Furthermore, nutritional content is approximated by linking product labels with the USDA food content table. While the match considered the labelling information of products with low sugar or no sugar available in the Nielsen dataset, some mismatches may still exist as the variety of food products consumed in the real market can be different from that available from food content tables. In this way, the dependent variable may incur a random measurement error, which does not introduce bias but can lead to larger standard deviations of estimates. This leads to only minimal impacts on our findings as the significance of the regression analysis remains robust in various tests. The Nielsen data remains as the only dataset, to our knowledge, with high temporal resolution that allows us to capture the fluctuation of food consumption along with weather

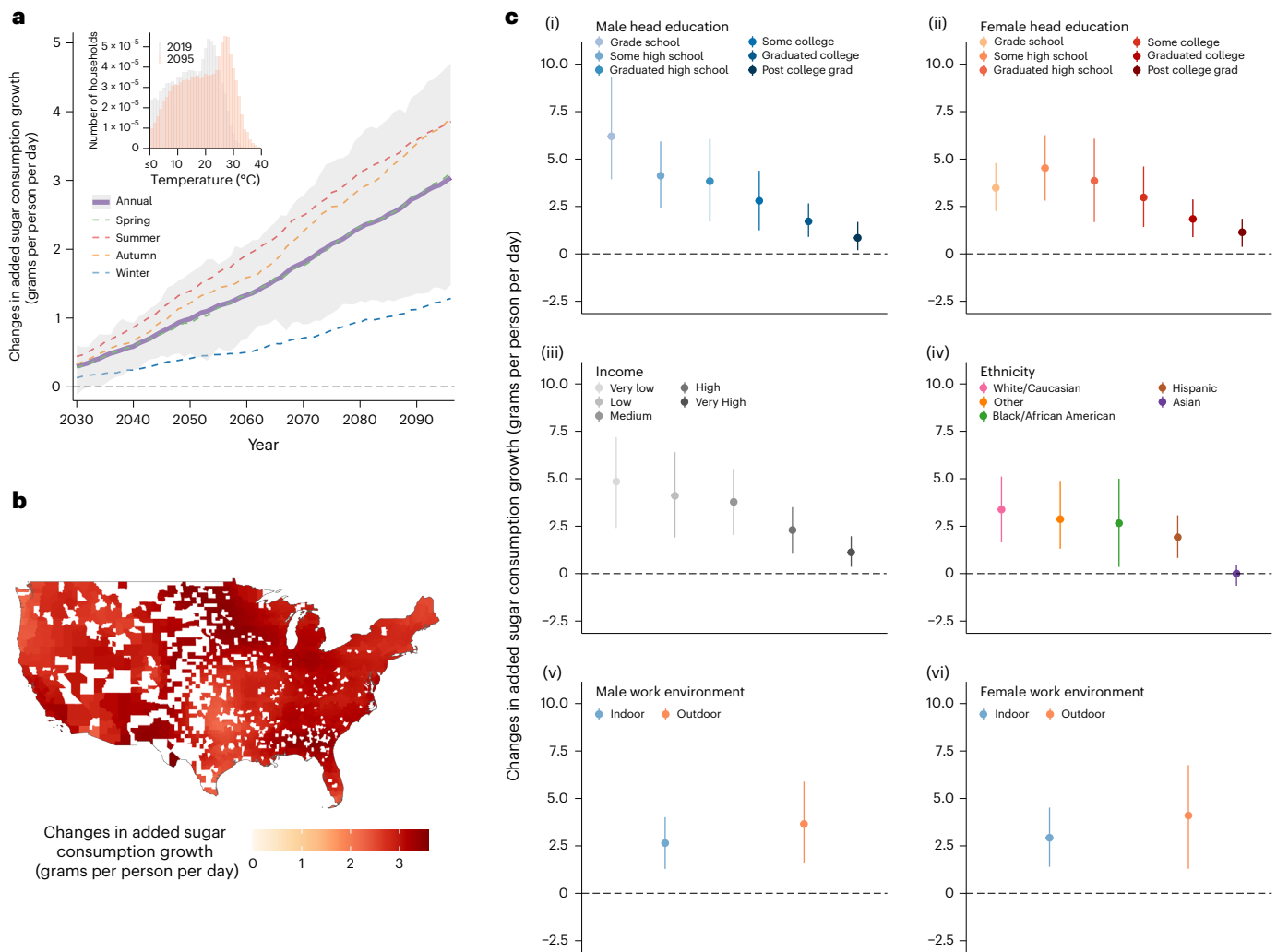


Fig. 4 | Projected added sugar consumption under the SSP5-8.5 scenario.

a, A time series of the projected consumption of added sugar. **b**, The projected added sugar consumption of counties in 2095. **c**, The projected added sugar consumption of heterogeneous groups in 2095 by education level in households with a male head (i), education level in households with a female head (ii), income (iii), ethnic group (iv), work environment in households with a male head (v) and work environment in households with female head (vi). Spring: March, April

and May; summer: June, July and August; autumn: September, October and November; winter: December, January and February. The distribution in **a** shows the temperature distribution for 2019 and 2095 for all climate models, with an average temperature increase of approximately 5 °C. The annual line and shaded area in **a** and the dots and vertical lines in **c** show the annual mean and the lowest and highest predictions of the $n = 25$ models in 2095, respectively. Household income was categorized as defined in Fig. 2.

changes. Nevertheless, trackable intake records at the individual level should be addressed in future data infrastructure construction for more accurate estimates for the USA, as well as for other countries and regions.

These findings underscore the urgent public health implications of climate-induced dietary changes, especially for low socio-economic groups and particularly during warmer temperatures. The USA needs to further strengthen its policies aimed at reducing the intake of added sugars, especially from SSBs, in the context of climate change. While SSB taxation has been effective in reducing purchases in certain US cities and around the world^{29,30}, the nationwide implementation of such taxes could face crucial challenges and delays. Additionally, proposals to modify the Supplemental Nutrition Assistance Program to encourage the purchase of healthier items face considerable debate and are slow to implement³¹. Continuous nutritional education programmes and nutrition warning labels on SSBs³² should also be considered and prioritized moving forwards. As consumers become increasingly health conscious, there is a potential for the industry to respond by reformulating products to reduce the sugar content in beverages.

Our findings also provide important implications for public health in the context of climate change adaptation. The results demonstrate

potential adverse health impacts associated with weather-induced shifts in dietary behaviours, emphasizing the need for potential policy interventions for added sugar intake in the context of climate change. This is particularly crucial in minimizing the additional disease burden and mitigating escalating medical costs for conditions attributed to excessive sugar consumption. Moreover, our research stresses the importance of targeting disadvantaged groups in interventions under climate change who exhibit a more substantial response to temperature-induced changes, potentially due to less mindful choices or constrained options with budget limitations^{33,34} and less control of the occupational/living environmental temperature.

Our results and policy implications offer insights not only for the USA. Given that the USA encompasses a diverse range of climate types found across many countries and regions, the conclusions of our study have broad applicability and relevance on a global scale. Therefore, these findings apply both to other developed countries and to nations in the global south²⁷, such as Brazil³⁵, South Africa³⁶ and Mexico^{37,38}, owing to changes in the food environment and increased purchase power that raises the accessibility and affordability of added sugar³⁹. While progressive public health measures, such as soda taxes and front-of-pack

labelling, have been implemented in some countries in both the global north and global south, dietary challenges persist due to the learning process of policy intervention lagging behind the rapid changes faced by consumers⁴⁰. In developed countries where regulations have been put in place, sugar intakes have only begun to decline in recent years and it remains at high levels causing considerable health challenges^{41,42}. Additionally, climate-related factors pose shared challenges: rising global temperatures are expected to exacerbate health risks, particularly for populations in both developed and developing nations with a high proportion of individuals working in nonclimate-controlled settings. Together, these factors intensify the health risks associated with dietary shifts driven by climate change²⁷. Future research could add more on-the-ground evidence of how weather and climate affect the physical and psychological demand for food in various geographical and socio-economic backgrounds to address the urgency for strategies for safeguarding nutrition and health.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at <https://doi.org/10.1038/s41558-025-02398-8>.

References

- Springmann, M. et al. Global and regional health effects of future food production under climate change: a modelling study. *Lancet* **387**, 1937–1946 (2016).
- Parry, M. L., Rosenzweig, C., Iglesias, A., Livermore, M. & Fischer, G. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. *Glob. Environ. Change* **14**, 53–67 (2004).
- Rezaei, E. E. et al. Climate change impacts on crop yields. *Nat. Rev. Earth Environ.* **4**, 831–846 (2023).
- Myers, S. S. et al. Increasing CO₂ threatens human nutrition. *Nature* **510**, 139–142 (2014).
- Free, C. M. et al. Expanding ocean food production under climate change. *Nature* **605**, 490–496 (2022).
- Cheung, W. W. L. et al. Climate change exacerbates nutrient disparities from seafood. *Nat. Clim. Change* **13**, 1242–1249 (2023).
- De Winne, J. & Peersman, G. The adverse consequences of global harvest and weather disruptions on economic activity. *Nat. Clim. Change* **11**, 665–672 (2021).
- Myers, S. S. et al. Climate change and global food systems: potential impacts on food security and undernutrition. *Annu. Rev. Public Health* **38**, 259–277 (2017).
- Fanzo, J. C. & Downs, S. M. Climate change and nutrition-associated diseases. *Nat. Rev. Dis. Primers* **7**, 90 (2021).
- Malik, A. et al. Impacts of climate change and extreme weather on food supply chains cascade across sectors and regions in Australia. *Nat. Food* **3**, 631–643 (2022).
- Galagan, D. J., Vermillion, J. R., Nevitt, G. A., Stadt, Z. M. & Dart, R. E. Climate and fluid intake. *Public Health Rep.* **72**, 484–490 (1957).
- Sohn, W., Heller, K. E. & Burt, B. A. Fluid consumption related to climate among children in the United States. *J. Public Health Dent.* **61**, 99–106 (2001).
- Marriott, B. M. (ed) in *Nutritional Needs in Hot Environments: Applications for Military Personnel in Field Operations* Ch. 5 (National Academies Press, 1993).
- Desbouys, L., Méjean, C., De Henauw, S. & Castetbon, K. Socio-economic and cultural disparities in diet among adolescents and young adults: a systematic review. *Public Health Nutr.* **23**, 843–860 (2020).
- Novaković, R. et al. Socio-economic determinants of micronutrient intake and status in Europe: a systematic review. *Public Health Nutr.* **17**, 1031–1045 (2014).
- Backholer, K. et al. Differential exposure to, and potential impact of, unhealthy advertising to children by socio-economic and ethnic groups: a systematic review of the evidence. *Obes. Rev.* **22**, e13144 (2021).
- Salm, L., Nisbett, N., Cramer, L., Gillespie, S. & Thornton, P. How climate change interacts with inequity to affect nutrition. *Wiley Interdiscip. Rev. Clim. Change* **12**, e696 (2021).
- Huang, Y. et al. Dietary sugar consumption and health: umbrella review. *Br. Med. J.* **381**, e071609 (2023).
- Scientific Report of the 2020 Dietary Guidelines Advisory Committee: Advisory Report to the Secretary of Agriculture and the Secretary of Health and Human Services (Agricultural Research Service, 2020).
- Johnson, R. K. et al. Dietary sugars intake and cardiovascular health: a scientific statement from the American Heart Association. *Circulation* **120**, 1011–1020 (2009).
- He, P., Liu, P., Qiu, Y. & Liu, L. The weather affects air conditioner purchases to fill the energy efficiency gap. *Nat. Commun.* **13**, 5772 (2022).
- Baechler, M. C. et al. *Building America Best Practices Series: Volume 7.3. Guide to Determining Climate Regions by County* (Pacific Northwest National Lab, US Department of Energy, 2015).
- Etilé, F. & Sharma, A. Do high consumers of sugar-sweetened beverages respond differently to price changes? A finite mixture IV-Tobit approach. *Health Econ.* **24**, 1147–1163 (2015).
- Ng, S. W., Rivera, J. A., Popkin, B. M. & Colchero, M. A. Did high sugar-sweetened beverage purchasers respond differently to the excise tax on sugar-sweetened beverages in Mexico? *Public Health Nutr.* **22**, 750–756 (2019).
- Rosinger, A., Herrick, K., Gahche, J. & Park, S. Sugar-sweetened Beverage Consumption Among US Adults, 2011–2014. *NCHS Data Brief.* **2017**, 1–8 (2017).
- Dietary Guidelines for Americans 2015–2020* (Dietary Guidelines Advisory Committee, 2016).
- Afshin, A. et al. Health effects of dietary risks in 195 countries, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. *Lancet* **393**, 1958–1972 (2019).
- Romanello, M. et al. The 2023 report of the Lancet Countdown on health and climate change: the imperative for a health-centred response in a world facing irreversible harms. *Lancet* **402**, 2346–2394 (2023).
- Kaplan, S. et al. Evaluation of changes in prices and purchases following implementation of sugar-sweetened beverage taxes across the US. *JAMA Health Forum.* **5**, e234737 (2024).
- Global Report on the Use of Sugar-sweetened Beverage Taxes, 2023* (World Health Organization, 2023).
- Schanzenbach, D. W. Pros and cons of restricting SNAP purchases. *Brookings* <https://www.brookings.edu/articles/pros-and-cons-of-restricting-snap-purchases/> (2017).
- Leung, C. W. et al. Warning labels reduce sugar-sweetened beverage intake among college students. *J. Nutr.* **151**, 179–185 (2021).
- Blaylock, J., Smallwood, D., Kassel, K., Variyam, J. & Aldrich, L. Economics, food choices, and nutrition. *Food Policy* **24**, 269–286 (1999).
- Benus, J., Kmenta, J. & Shapiro, H. The dynamics of household budget allocation to food expenditures. *Rev. Econ. Stat.* **58**, 129–138 (1976).
- Crepaldi, B. V. C., Okada, L. M., Rauber, F., Levy, R. B. & Azeredo, C. M. Social inequality in food consumption between 2008 and 2019 in Brazil. *Public Health Nutr.* **25**, 214–224 (2022).
- Bercholz, M., Ng, S. W., Stacey, N. & Swart, E. C. Decomposing consumer and producer effects on sugar from beverage purchases after a sugar-based tax on beverages in South Africa. *Econ. Hum. Biol.* **46**, 101136 (2022).

37. Batis, C. et al. Comparison of dietary intake before vs after taxes on sugar-sweetened beverages and nonessential energy-dense foods in Mexico, 2012 to 2018. *JAMA Netw. Open* **6**, e2325191 (2023).
38. Pineda, E., Barbosa Cunha, D., Taghavi Azar Sharabiani, M. & Millett, C. Association of the retail food environment, BMI, dietary patterns, and socioeconomic position in urban areas of Mexico. *PLoS Glob. Public Health* **3**, e0001069 (2023).
39. Ronto, R., Wu, J. H. & Singh, G. M. The global nutrition transition: trends, disease burdens and policy interventions. *Public Health Nutr.* **21**, 2267–2270 (2018).
40. Popkin, B. M. & Hawkes, C. Sweetening of the global diet, particularly beverages: patterns, trends, and policy responses. *Lancet Diabetes Endocrinol.* **4**, 174–186 (2016).
41. Lara-Castor, L. et al. Sugar-sweetened beverage intakes among adults between 1990 and 2018 in 185 countries. *Nat. Commun.* **14**, 5957 (2023).
42. Lara-Castor, L. et al. Burdens of type 2 diabetes and cardiovascular disease attributable to sugar-sweetened beverages in 184 countries. *Nat. Med.* **31**, 552–564 (2025).

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Methods

Data source

We used the food purchase data from the Nielsen Homescan Consumer Panel dataset as a proxy of food consumption of the households in the sample. The dataset tracks the product purchase records from 40,000–60,000 US households, with sample sizes varying by year. The same households are tracked for multiple years before replacement and thus constitute a longitudinal panel. The purchase records contain detailed transaction information including the Universal Product Code, product name, quantity, price and promotions of each product purchased, as well as the date of the trip and the county of the store. The food items cover all retail outlets across the USA except Alaska and Hawaii, though consumption data at restaurants are not included. The dataset also collects the demographic and socio-economic characteristics of the households such as the income, education and occupation of male and female heads; as well as the age, sex and ethnic group of each member; the county of the residence and so on. The panel is nationally representative with a sampling weight applied. The dataset is available from 2004 to 2023, and we excluded the data after 2019 to avoid the confounding effects from COVID-19. Although the purchased foods can be stored rather than consumed in a short period, this issue is partially relieved in our analysis since (1) we focus on monthly food consumption, (2) most products with high added sugar content such as sweetened beverage are typically consumed within a short period following purchase, unlike items that are often stored for extended durations before use such as flour and (3) even for the items that are likely to be stored such as sugar, our analysis provides conservative estimates (in which the purchase of sugar is less immediately responsive to changes in the temperature).

We focus on all the food items to retrieve the consumption of added sugar for each household. Unfortunately, the nutrition facts are not directly available from the Nielsen dataset, and a direct search to obtain these nutrition facts using the product name is not feasible as only the abbreviation of the name is available other than the 716 product modules, which describe the nature of the products (sweetened beverage, cake, ice cream and so on) and special characteristics (low sugar, zero sugar and so on) in the Nielsen dataset. Therefore, we match the products with the items in the Food and Nutrient Database for Dietary Studies (FNDDS)⁴³, which is updated every 2 years and describes the amounts of nutrients/food components in the most common foods and beverages consumed by Americans. Since the majority of food items stay the same, we adopted the 2017–2018 version for matching. We conducted multiple rounds of manual matching with the description of more than 6,000 food items in the FNDDS, after which a manual check was conducted to randomly sample the Nielsen products and inspect their matchings to ensure that the matches best reflect the nutrition facts of the products. For some food ingredients that are not included in FNDDS, such as cake flour and beverage powders, we used the Food Patterns Equivalents Ingredients Database (FPIED) to complete the matching, which is an equivalent ingredient database developed based on multi-ingredient foods in FNDDS. To demonstrate the response by product categories, we used the What We Eat in America (WWEIA) categories, which provide a concise division of food items with nutritional implications and are directly available for every food item in FNDDS. For the FPIED-matched items, we manually assigned the WWEIA category. A full relation between Nielsen products and WWEIA categories is available in Supplementary Table 1. Note that such method can only quantify the added sugar consumption rather than the actual intake, the limitation of which is examined in ‘Discussion’ section.

The ground-station level meteorological records are from Global Surface Summary of the Day (GSOD)⁴⁴, which provides daily meteorological records, including atmospheric temperature, precipitation, wind speed, humidity and so on. We matched each household with all the climate stations within a 100 km buffer of the county where it

is located, similar to previous research²¹. The spatial distributions of the stations and the counties in which data are available are shown in Supplementary Fig. 1. The records of the matched climate stations were then averaged to indicate the meteorological condition that the household was experiencing during a specific day.

Empirical strategy

The specification was constructed as

$$y_{irt} = f(\text{temp}_{irt}) + \delta \mathbf{W}_{irt} + \mu \mathbf{H}_{irt} + \alpha_i + \gamma_{rc} + \lambda_{tc} + \varepsilon_{irt}, \quad (1)$$

where y_{irt} is the indicator related to added sugar consumption per capita per day in household i in month r of year t . Despite the consumption data being available from every trip that the households make, the location of the destination stores and the date for making the trip can be affected by the weather¹⁶. Particularly, unpleasant weather would lower the shopping frequencies since people tend to avoid outdoor travelling⁴⁵. As a result, regression at the trip level may show a smaller correlation between high temperatures and added sugar consumption, potentially leading to an underestimation issue. Therefore, we aggregated the data at the monthly level to avoid the capture of such confounding effects with the change of product type and quantity sustained. $f(\text{temp}_{irt})$ is a response function of temperature, describing how each household reacts to a particular temperature level in consuming added sugar and other food and nutrient components. The vector \mathbf{W}_{irt} contains other meteorological variables including precipitation, wind speed, relative humidity and its squared terms. \mathbf{H}_{irt} is the vector of household characteristics including the household income, household size, educational level and age of male and female head, presence and age of children, marital status and ethnic group. Among them, the original income is a categorical variable representing nominal annual income ranges. It is converted to a continuous variable by assigning mid-point values, simplifying high-income categories to 150,000, adjusting for inflation (2010 as base year) and standardizing by dividing by 10,000 to reflect real purchasing power in 10,000 units for regression analysis (Supplementary Table 2). Notably, the Nielsen survey employed a stratified sampling design to ensure sample representativeness, balancing nine key household characteristics including household income, which was categorized into six distinct levels for stratification purposes. Based on this framework, we combine two adjacent middle-income tiers (US\$25,000–34,999 and US\$35,000–49,999) to create a five-category structure for subsequent heterogeneity analysis, as illustrated in Fig. 2c. We also include fixed effects for household (α_i), the interaction between month of year and climate zone (γ_{rc}) and the interaction between year and climate zone (λ_{tc}). The classification of climate zones are classified by the US Department of Energy Building America Program in determining the standards of building construction²². This classification provides a concise way in separating the background climate. The error term ε_{irt} is clustered at the county level.

Multiple indicators related to added sugar consumption are examined as y_{irt} . We first adopted the actual per-capita added sugar consumption, which distorts the discrepancy between the age–gender distribution of average energy requirements and that of sugar consumption thresholds. We thus converted the per-capita consumption to adult male equivalents to allow for better standardization and comparison of consumption across different age and gender groups⁴⁶. Since the Nielsen data provide consumption data for the entire household rather than each member, we standardized sugar consumption using the total energy requirement ratio between all the true household members and the adult equivalent members. Here, we first defined adult males as men aged 18–29 years, and for infants under 1 year old, we calculated them as 11 months. We then calculated the conversion ratio using the average energy requirement (AER) for energy of a specific age and gender with physical activity level values

of 1.6 (replaced with 1.4 when children aged 1–3 years) provided by European Food Safety Authority using the following equation:

$$\text{Conversion ratio} = \frac{\sum_{i=1}^{\text{household size}} \text{AER of member}_i}{\text{AER of adult male}} \quad (2)$$

The adult male equivalent per-capita consumption of added sugar can then be adjusted by dividing the actual per-capita added sugar consumption by this conversion ratio.

Multiple forms of $f(\text{temp}_{ijt})$ are included in our analysis. We ran the binned model for the main results with $f(\text{temp}_{ijt}) = \sum_j \beta_{jt} \text{temp}_{ijt}$, in which $\beta_{jt} \text{temp}_{ijt}$ are a set of bins indicating whether the monthly average temperature falls into a specific interval. We set 2 °C for each interval to allow a high resolution in detecting the possible nonlinear effect of temperature. The results show that all the outcome variables are monotonically increasing with temperature (Fig. 1). The default group in the final regression was set as the lowest temperature level (≤ 0 °C). We also conducted robustness checks, replacing $\sum_j \beta_{jt} \text{temp}_{ijt}$ by the CDDs and heating degree days (HDDs) aggregated to the monthly level (Supplementary Table 5). These two measures are used to estimate energy demand for heating or cooling buildings as a proxy of how much the atmosphere temperature is beyond the thermal comfort of human being. The CDD is calculated when the outdoor temperature exceeds a base temperature (for example, 18 °C or 65 °F), indicating a need for cooling, while the HDD is calculated when the temperature falls below the base, indicating a need for heating. In addition, we completed a robustness check using interactions of education (male head and female head) with month and year as fixed effects in the model and find that there is no critical change in the results (Supplementary Tables 6 and 7). We also reran the regression analysis including food price as a control to explore whether the weather fluctuation covariates with price changes. To include food category prices in the regression analysis and eliminate the impact of price changes, we calculated the monthly average price of each food category based on the purchase data of each household trip. To exclude outlier influence, we remove the top 5% of all purchase prices, and then averaged the monthly average price of each food category in each county according to the county where the household was located. We also checked the results by removing the top and bottom 5% price outliers (the low price is probably due to the discount and redeem of vouchers, but can also be due to misrecording, and the regression results do not change, as shown in Supplementary Table 10). However, some counties may have missing prices because no households purchased them. We first tried to replace them with the annual average price of the same county. In the case of missing values, we used the national average price of the same month. Furthermore, we used 2010 as the benchmark and used the food inflation index to eliminate the impact of inflation. We evaluated multicollinearity in the price model using variance inflation factor tests. The results show that, except for relative humidity and its squared term, all other variables had adjusted generalized variance inflation factor values within acceptable thresholds (<2), indicating no severe multicollinearity issues in the model (Supplementary Table 11).

We then conducted a spline regression, which exhibits higher sensitivity to changes in the independent variables compared with the binned model but provides more flexibility in capturing the potential nonlinearities of temperature compared with the CDD and HDD method. Based on the results of the binned model, the spline model divides the temperature range into three segments: 0–12 °C, 12–30 °C and above 30 °C, which allows us to better capture the growth rate of added sugars in different temperature ranges. The spline model also provides a smaller number of temperature variables to facilitate the tests on heterogeneous effects that require interaction terms between temperature indicators and the socio-economic characteristics of the households, which could otherwise involve too many regressors in the binned model. Note that we do not use the interaction above

30 °C in the heterogeneity analysis due to the insufficient number of observations so that the slope is same for all groups in this temperature interval.

Projections of added sugar consumption in future climate scenarios

Meteorological variables for projected climates are from the CMIP6. Here, we used monthly surface temperature (tas), rainfall (pr), wind (sfcWind) and relative humidity (hurs) from the r1i1p1f1 run of SSP5-8.5 (2015–2100) experiments from 25 models (ACCESS-CM2, ACCESS-ESM1-5, AWI-CM-1-1-MR, CanESM5, CanESM5-1, CAS-ESM2-0, CESM2-WACCM, CMCC-CM2-SR5, CMCC-ESM2, EC-Earth3, EC-Earth3-CC, EC-Earth3-Veg, EC-Earth3-Veg-LR, FGOALS-f3-L, FGOALS-g3, FIO-ESM-2-0, INM-CM4-8, INM-CM5-0, IPSL-CM6A-LR, MIROC6, MPI-ESM1-2-HR, MPI-ESM1-2-LR, MRI-ESM2-0, NorESM2-LM and NorESM2-MM). We subsampled model outputs at the grid box in each county with the 100 km buffers for spatial join. Although other SSP scenarios are available, we used the highest emission scenario (SSP5-8.5) to test the widest possible warming range, and results are also reported as a function of the global warming level⁴⁷.

When a county covers more than one grid box, we used the averaged value. To account for possible model biases in climatology, we calculated anomalies relative to simulated 2015–2023 monthly climatology and added observed climatology over the same time interval⁴⁸. Bias-corrected simulations were further averaged using a 9-yr running smoother to dampen interannual variability. The projection of added sugar consumption was then calculated using equation (1). Multimodel mean results are shown in Fig. 4, and descriptive statistics for individual models are listed in Supplementary Table 24.

Disclaimer

The researcher(s)' own analyses are calculated (or derived) based, in part, on (1) retail measurement/consumer data from Nielsen Consumer LLC ('NielsenIQ'), (2) media data from The Nielsen Company (US), LLC ('Nielsen') and (3) marketing databases provided through the respective NielsenIQ and the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

The conclusions drawn from the NielsenIQ and Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in and was not involved in analysing and preparing the results reported herein.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The Retail Scanner data are provided by Nielsen Company and restricted by non-disclosure terms of use but can be purchased from Nielsen. According to the official website at <https://www.chicagobooth.edu/research/kilts/datasets/nielseniq-nielsen/subscribe>, accessing the data would first require a subscription contract between a researcher's institution and Chicago Booth. The FNDDS data are available from <https://www.ars.usda.gov/northeast-area/beltsville-md-bhnrc/beltsville-human-nutrition-research-center/food-surveys-research-group/docs/fnDDS/>. The FPID data are available from <https://www.ars.usda.gov/northeast-area/beltsville-md-bhnrc/beltsville-human-nutrition-research-center/food-surveys-research-group/docs/fpid-databases/>. The GSOD data are accessed using the GSODR package in R and can also be retrieved from <https://www1.ncdc.noaa.gov/pub/data/gSOD/>. The CMIP6 climate projections are available from <https://esgf-node.ipsl.upmc.fr/search/cmip6-ipsi/>. The map of USA used in Fig. 4 and Supplementary Figs. 1, 10 and 11 comes from a previous publication⁴⁹, which is accessible in R. Source data are provided with this paper.

Code availability

The major data processing, all the regression analysis and figure production are conducted in R studio (based on R 4.2.3). All custom code is available via GitHub at <https://github.com/Z-Jscape/Rising-temperatures-raise-added-sugar-intake-especially-in-disadvantaged-groups-in-the-US> and via Zenodo at <https://doi.org/10.5281/zenodo.15576360> (ref. 50).

References

43. WWEIA Food Categories 2017–2018. USDA https://www.ars.usda.gov/ARSUserFiles/80400530/apps/WWEIA1718_foodcat_FNDDS.xlsx (2020).
44. *Global Surface Summary of Day* (National Centers for Environmental Information, 2024).
45. Moon, S., Kang, M. Y., Bae, Y. H. & Bodkin, C. D. Weather sensitivity analysis on grocery shopping. *Int. J. Mark. Res.* **60**, 380–393 (2018).
46. Weisell, R. & Dop, M. C. The adult male equivalent concept and its application to Household Consumption and Expenditures Surveys (HCES). *Food Nutr. Bull.* **33**, S157–S162 (2012).
47. Riahi, K. et al. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Glob. Environ. Change* **42**, 153–168 (2017).
48. Chan, D., Wu, Q., Jiang, G. & Dai, X. Projected shifts in Köppen climate zones over China and their temporal evolution in CMIP5 multi-model simulations. *Adv. Atmos. Sci.* **33**, 283–293 (2016).
49. Mullen, L. A. & Bratt, J. USA boundaries: historical and contemporary boundaries of the United States of America. *J. Open Source Softw.* **3**, 314 (2018).
50. Xu, Z. Rising temperatures raise added sugar intake especially in disadvantaged groups in the US. *Zenodo* <https://doi.org/10.5281/zenodo.15576360> (2024).

Acknowledgements

Our study was supported by the National Natural Science Foundation of China (NSFC) International (Regional) Cooperation and Exchange Programs (Inter-Organizational Cooperative Research (NSFC-UNEP) (International Organization)), ‘Synergizing Climate Resilience and Environmental Sustainability: Assessment and Governance for Agricultural Adaptation’ (grant no. W2412026).

Author contributions

P.H., Y.B., D.C. and P.L. designed the study. Z.X. and P.H. processed the data. Z.X. performed the analysis and drew the figures. P.H., Y.B., D.C. and P.L. participated in discussing the results. All the authors contributed to writing the paper.

Competing interests

The authors declare no competing interests.

Additional information

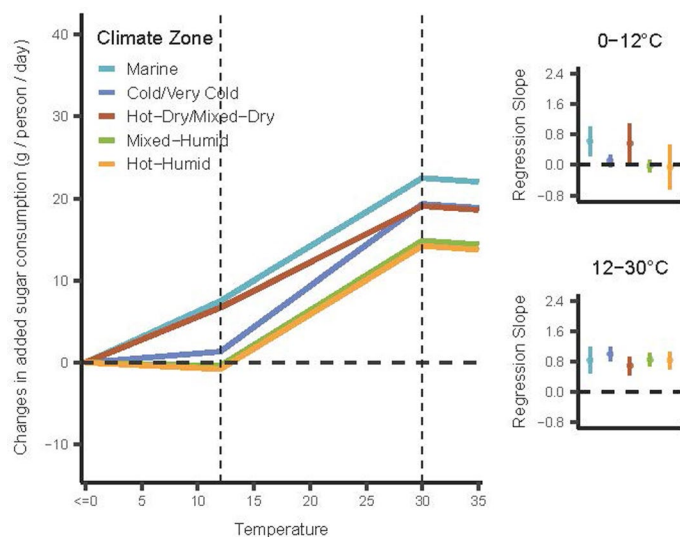
Extended data is available for this paper at <https://doi.org/10.1038/s41558-025-02398-8>.

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1038/s41558-025-02398-8>.

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Peer review information *Nature Climate Change* thanks Fabrice Etilé and Shu Wen Ng for their contribution to the peer review of this work.

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Extended Data Fig. 1 | Heterogeneous effect of temperature (climate zone).

The statistics are from two-sided t-tests based on regression analysis, and complete results are shown in the Supplementary Table 16. The two small figures on the right side show the slopes of the linear model at 0 °C–12 °C (n = 2736315)

and 12 °C–30 °C (n = 4116587) respectively, and the vertical lines show the 95% confidence interval (that is mean \pm 1.96SEM). The analysis is based on a total sample size of n = 6908936.

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Software and code

Policy information about [availability of computer code](#)

Data collection The GSOD data are accessed using GSODR package in R studio (based on R 4.2.3). Other data are downloaded from multiple sources (see the details in data availability statement) in the forms as they are and processed in R.

Data analysis The major data processing, all the regression analysis, and figure production are conducted in R studio (based on R 4.2.3). All custom code is available upon request.

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between a researcher's institution and Chicago Booth. The FNDDS data is available from <https://www.ars.usda.gov/northeast-area/beltsville-md-bhnrc/beltsville-human-nutrition-research-center/food-surveys-research-group/docs/fndds/>. The GSOD data are accessed using GSODR package in R and can also be retrieved from <https://www1.ncdc.noaa.gov/pub/data/g sod/>. The code for data download can be found at <https://github.com/hepannju/Does-the-weather-change-the-energy-efficiency-gap>. The CMIP6 climate projections are available from <https://esgf-node.ipsl.upmc.fr/search/cmip6-ipsi/>.

Human research participants

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Reporting on sex and gender	The sex and gender information of the household are collected by Nielsen company. The sample has been anonymized before our use to avoid the risk of individual identification.
Population characteristics	The study is based on second-hand purchase data provided by Nielsen company, which does not include individual-level population characteristics information.
Recruitment	No recruitment is conducted for this study.
Ethics oversight	The study is based on second-hand purchase data provided by Nielsen company. We did not conduct primary data collection involves human subjects. Ethics oversight is not applicable.

Note that full information on the approval of the study protocol must also be provided in the manuscript.

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Behavioural & social sciences study design

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Study description	Investigate the relationship of weather and the consumption of added sugar at the household level. The study is quantitative.
Research sample	General purchase outcomes provided by Nielsen Company. It is adopted as it provides a high-resolution purchase records that enable us to quantify the added-sugar content of food items and thus the consumption of households. The details of the purchase date and the geographical identifier also allow us to link this data to the meteorological records to explore the relationship between temperature and the consumption. It is also adopted as the sampling framework is of national representativeness. The home scanner dataset contains information from approximately 40,000-60,000 U.S. households with sample sizes varying by year. The same households are tracked for multiple years before replacement and thus constitute a longitudinal panel. The purchase records contain detailed transaction information including the UPC (Universal Product Code) code, product name, quantity, price, and promotions of each product purchased, as well as the date of the trip and the county of store location. The food items cover all retail outlets across the U.S. except Alaska and Hawaii, though the consumption data at restaurants are not included. The dataset also collects the demographic and socio-economic characteristics of the households such as the income, education, and occupation of male and female heads, as well as age, sex, and ethnic group of each member, county of the residence, etc. The panel is nationally representative with the sampling weight applied.
Sampling strategy	General purchase outcomes provided by Nielsen Company. Sampling strategy is controlled by Nielsen. The sampling is based on a randomization strategy to obtain a nationally representative sample for the households in the United States which provides decent reflection on consumer behaviour.
Data collection	Individual food consumption data are collected by Nielsen by requesting the participating household to report their purchases. Nielsen requests that all purchases made by all household members be recorded, with the receipt of purchase uploaded to the data collection system. Information captured include the quantity, price, and unit of the commodities purchased; the type and geographical information of the store; and the date of the trip. The demographical information of the households are also collected including the household income, household size, the educational level of the female & male head, the ethnic groups of the female & male head, etc. The researchers are blinded to experimental condition and/or the study hypothesis.
Timing	The data collection started in 2004 and is updated every year. There is no gap between collection periods, sate, and dates. At the time of analysis, the data are available for 2004-2023 and thus we included the data of 2004-2019 in the analysis to exclude the consumption records during the COVID period.
Data exclusions	No data are excluded.
Non-participation	There is no non-participation at the consumer level as once a store agrees to participate in the data collection, the purchase data is

Non-participation

recorded automatically.

Randomization

Randomization is not used in this study as it is a secondary-hand data analysis. For the original sample, randomization is conducted in the quota sampling process by the Nielsen Company.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

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