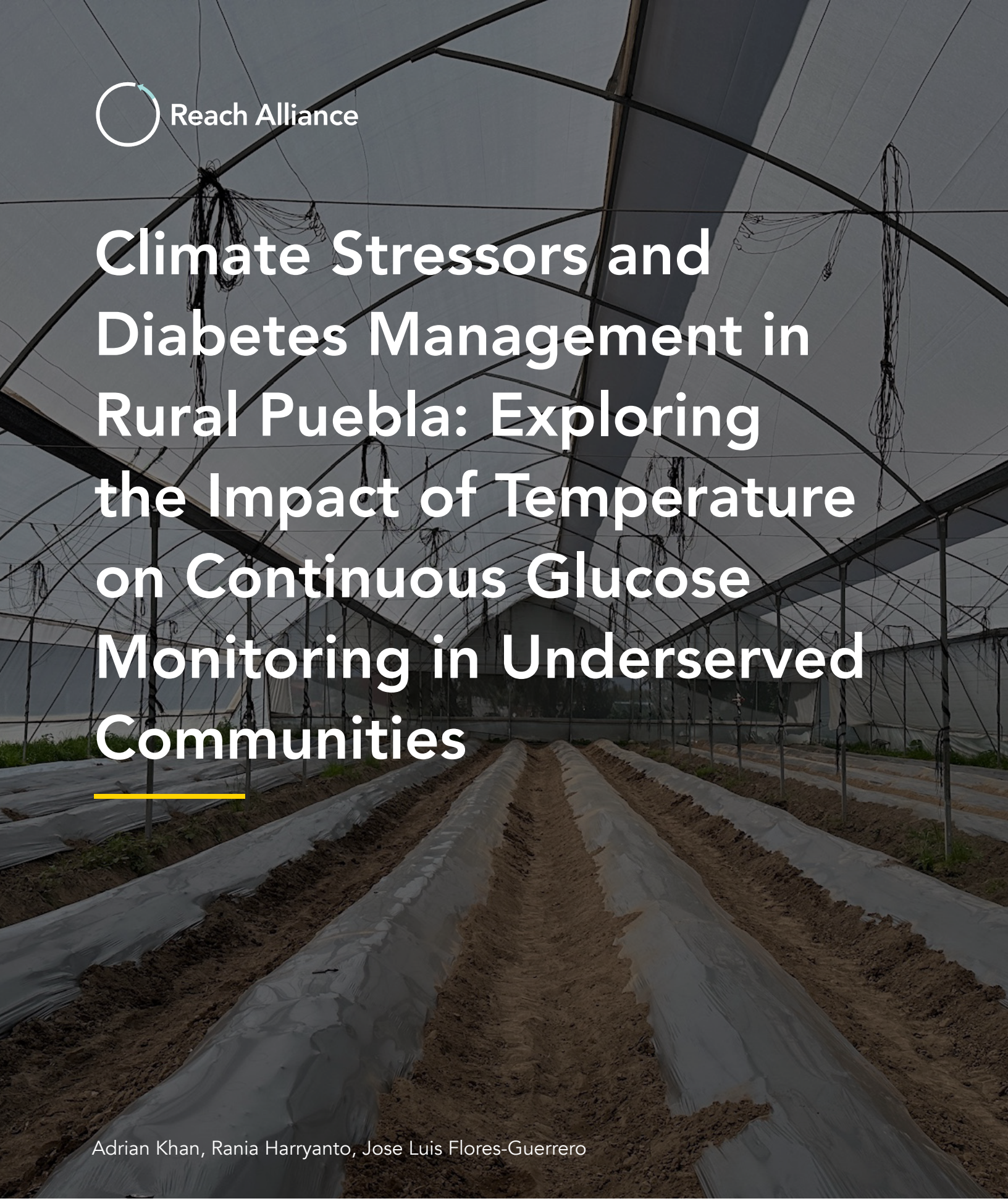


Reach Alliance

Climate Stressors and Diabetes Management in Rural Puebla: Exploring the Impact of Temperature on Continuous Glucose Monitoring in Underserved Communities

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The Reach Alliance

The Reach Alliance is a consortium of global universities — with partners in Australia, Canada, Ghana, Kenya, Mexico, Singapore, South Africa, United Kingdom, and the United States — developing the leaders we need to solve urgent local challenges of the hard to reach — those underserved for geographic, administrative, or social reasons. Working in interdisciplinary teams, Reach's globally minded students use rigorous research methods to identify innovative solutions to climate, public health, and economic challenges. Research is conducted in collaboration with local communities and with guidance from university faculty members, building capacity and skills among Reach's student researchers. The power of the Reach Alliance stems from engaging leading universities to unleash actionable research insights for impact. These insights have been published in leading journals and taken up by policymakers and sector leaders around the world.

The Reach Alliance was created in 2015 by the University of Toronto's Munk School of Global Affairs & Public Policy, in partnership with the Mastercard Center for Inclusive Growth. It is guided by an advisory council of leaders in academia, and in the private, public, and nonprofit sectors who help to drive impact, influence and scale, and support fundraising efforts.

Note: Authors are listed by contributions to the project with the faculty mentor listed last.

Cover photo: Inside of a greenhouse, the workplace of greenhouse workers who participated in the study (photo by Adrian Khan)



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We hope this research provides new insights into climate–glucose associations and contributes to a broader understanding of climate–health vulnerability in underserved communities.

Ethical approval was granted by University College London Life and Medical Sciences Research Ethics Committee (3699) and the Benemérita Universidad Autónoma de Puebla (R-2025-2101-157).

During the preparation of this work, the authors used generative AI tools in a limited capacity to improve the clarity, readability, and concision of author-written text. This includes minor language refinement, grammar, and spelling. Generative AI was not used to generate new research content, conduct data analysis, interpret results, or develop the study's arguments or conclusions. We reviewed and edited all AI-assisted output, verified its accuracy against the underlying data and sources, and take full responsibility for the content of this work.



Contribution	Contributor (Initials)
Conception or design of the work	AK, JL, RH
Data collection	AK, JL, RH, with contribution from students from *El Programa Delfin*
Data analysis and interpretation	AK
Drafting of the case study report	AK, RH
Critical revision of the case study report	AK, JL, RH
Final approval of the version to be submitted	AK, JL, RH

A participant measuring his heart rate for pulse wave velocity (photo by Adrian Khan)

Contents

Executive Summary..... 1
Background: Increasing Diabetes Rates in Mexico..... 2
About Our Research..... 4
Results..... 9
Impact: From Climate and Health to Community Action.....20
Lessons Learned.....23





Figure 1. The view outside a greenhouse, the workplace of a few of the participants in the study (photo by Adrian Khan)

Executive Summary

Type 2 diabetes (T2D) is one of Mexico's most pressing health epidemics, with one in six adults living affected and diabetes-related mortality rising faster than almost anywhere in the world.[1] This epidemic largely impacts hard-to-reach communities like Acatzingo, Puebla, where limited healthcare access means that T2D often goes undiagnosed and untreated. To complicate the issue, climate change presents a growing threat to diabetes management: extreme heat and humidity degrade insulin function, discourage physical activity, and contribute to food-system instability that makes healthy diets difficult to maintain.

In this study, we examined short-term climate–glucose relationships using wearable devices. We recruited 15 participants in Acatzingo and asked them to wear a continuous glucose monitor (CGM) and wearable temperature sensors for 14 days. This data was combined with hourly climate data to examine how glucose levels varied alongside environmental conditions. To our knowledge, this is among the first studies to use CGMs to investigate climate–glucose associations hour by hour.

Our analysis found positive associations between glucose and body temperature, air temperature, and dew point, with dew point showing the strongest association with glucose among the environmental variables we examined. This indicates that humidity, not just temperature and heat, is an important dimension of climate exposure in glycemic research. Participant-level analyses also indicated that those with poorer glycemic control and poorer overall time in range (TIR) tended to show the greatest sensitivity to temperature changes, suggesting that existing metabolic vulnerability may compound climate-related risk. Because this study is observational and associative, these findings do not establish causality, but instead they provide early evidence that climate deserves greater attention in diabetes and health research, particularly in populations already experiencing health and socioeconomic inequalities.

Beyond our research findings, this project generated direct community benefits. Participants gained access to their own glucose data and opportunities to discuss their health with medical professionals, while children and families participated in scientific communication workshops covering nutrition, diabetes, and health literacy. Together, this demonstrates that climate–health research in hard-to-reach communities can generate value both through research and through direct community engagement, without waiting for broader policy change.

1 Claudio Alberto Dávila Cervantes and Emerson Augusto Baptista, "Mortality from Type 2 Diabetes Mellitus across Municipalities in Mexico," *Archives of Public Health* 82, no. 1 (2024): 196; R. Rojas-Martínez, C. Escamilla-Nuñez, C.A. Aguilar-Salinas, et al., "Trends in the Mortality of Diabetes in Mexico from 1998 to 2022: A Joinpoint Regression and Age-Period-Cohort Effect Analysis," *Public Health* 226 (January 2024): 128–37.

Background: Increasing Diabetes Rates in Mexico

Diabetes remains one of the most pressing global health concerns, affecting one in nine people worldwide and contributing to one death every nine seconds in 2024.[2] The global economic impact of diabetes is estimated to be USD 10.2 trillion, equivalent to 0.22 per cent of the global annual gross domestic product (GDP).[3] This burden is disproportionately found in low- to middle-income countries (LMICs), which host three-quarters of diabetes cases.[4] In Mexico, a middle-income country, type 2 diabetes (T2D) has become a major health epidemic.

Mexico ranks among the top ten countries globally for diabetes prevalence, with diabetes being the third leading cause of death in the country. Over the past 30 years, the rate of diabetes mortality in Mexico has increased by 1.2 per cent annually, one of the largest increases documented worldwide. Currently, one in six Mexican adults live with T2D.[5]

This increased prevalence of T2D is largely associated with the high prevalence of risk factors in Mexico, including obesity, tobacco use, and increased consumption of sugar-sweetened beverages, such as soft drinks, energy drinks, and the traditional Mexican drink *aguas frescas*.[6] With 74.5 per cent of people in Mexico affected by overweight or obesity and sugar-sweetened beverages associated with 17.4 per cent of diabetes cases in Mexico,[7] T2D puts extreme pressure on health systems already struggling with inequality.

Between 2010 and 2023, the Mexican government adopted 13 approved prevention plans, regulations, and policies to target the environmental and social factors affecting diabetes.[8] This includes taxes on sugar-sweetened beverages; mandatory front-of-pack warning labels for ultra-processed foods including excessive amounts of fat, sugar, and salt; and the adoption of the Mexican Health and Sustainable Food-Based Dietary Guidelines. However, there have been no policies that integrate clinical, social, and environmental approaches in tackling diabetes, since policy tools are largely developing independently and incrementally.[9]

> “Mexico ranks among the top ten countries globally for diabetes prevalence, with diabetes being **the third leading cause of death** in the country.

2 “IDF Diabetes Atlas,” International Diabetes Foundation (IDF).

3 Simiao Chen, Zhong Cao, Wenjin Chen, et al., “The Global Macroeconomic Burden of Diabetes Mellitus,” *Nature Medicine* 32, no. 1 (2026): 126–38.

4 Ibid.

5 Cervantes and Baptista, “Mortality from Type 2 Diabetes Mellitus across Municipalities in Mexico.”

6 Simón Barquera, Lucía Hernández-Barrera, Cecilia Oviedo-Solís, et al., “Obesidad En Adultos,” *Salud Pública de México* 66, no. 4 (2024): 414–24; Julio Cesar Campuzano, Jorge Martin Rodríguez, Luz Myriam Reynales, Anaid Hernández, and Diana Carolina Urrego, “Population Attributable Fraction of Tobacco Use and Type 2 Diabetes Mellitus: An Analysis of the ENSANUT 2021,” *Epidemiologia* 6, no. 4 (2025): 84; Francisco Canto-Osorio, Ana Basto-Abreu, Dalia Stern, et al., “Incident Cases and Healthcare Costs of Non-Communicable Diseases Attributable to Industrialized and Total Sugar Sweetened Beverage Intake in Mexico,” *BMC Public Health* 25, no. 1 (2025): 3685.

7 Canto-Osorio et al., “Incident Cases and Healthcare Costs of Non-Communicable Diseases.”

8 Benjamin Aceves, Maia Ingram, Claudia Nieto, Jill Guernsey de Zapien, and Cecilia Rosales, “Non-Communicable Disease Prevention in Mexico: Policies, Programs and Regulations,” *Health Promotion International* 35, no. 2 (2020): 409–21; Juan A. Rivera, Mónica Arantxa Colchero, Carolina Pérez-Ferrer, and Simón Barquera, “Perspective: Mexico’s Experience in Building a Toolkit for Obesity and Noncommunicable Diseases Prevention,” *Advances in Nutrition* 15, no. 3 (2024): 100180.

9 Rivera, Arantxa Colchero, Pérez-Ferrer, and Barquera, “Perspective: Mexico’s Experience in Building a Toolkit.”

Climate Change and Diabetes

According to the World Health Organization (WHO), climate change is the biggest threat to human health in the 21st century.[10] Mexico is particularly vulnerable to climate change, with increased temperatures, stronger droughts, and more intense rainfall expected in the upcoming years.[11] People with T2D are especially susceptible to climate-related stressors because of their poorer thermoregulation. Climate change also destabilizes food systems, while extreme heat both discourages physical activity and degrades insulin directly.[12] In rural, agricultural communities, climate change's irregular weather patterns threaten crop growth, impacting rural livelihoods. Thus agricultural workers may have to forego diet diversity, relying on cheap ultra-processed food that increases obesity and diabetes risk. As such, climate change not only negatively affects people with T2D, but also increases the risk factors associated with new incident cases of T2D.

Our study aimed to investigate the relationship between temperature and glucose control in adults with suspected or diagnosed T2D in Puebla, Mexico. By investigating this relationship over a period of 14 days, we hoped to gain insight into how short-term temperature variation might affect glucose control among people living with or at risk of T2D.

This study supports the Sustainable Development Goals (SDGs) adopted by the United Nations (UN) in 2015 — a list of 17 global objectives aimed at ending global poverty, encouraging prosperity, and improving health outcomes. It aims to contribute to interaction of the SDG 3 (Good Health and Wellbeing), 13 (Combat Climate Change and its Impacts), and 17 (Strengthens the Means of Implementation and Revitalize the Global Partnership for Sustainable Development). In addition, this study specifically supports the sub-SDG 3.4, which aims to "reduce by one third premature mortality from non-communicable diseases [such as T2D] through prevention and treatment and promote mental health and well-being."

Heat

Whether or not people have T2D, extremely hot ambient temperatures, such as those during heatwaves and due to climate change, increase hospital admissions and mortality risk globally.[13] Epidemiologic studies have found that heat is associated with increased cases of diabetes and higher glucose levels. One USA study found that a one-degree Celsius increase in outdoor temperature may be associated with over 100,000 cases per year nationally.[14] Similarly, even after adjusting for factors such as body mass index (BMI) and lifestyle, those living in warmer environments had higher glucose levels and greater insulin resistance in Spain.[15]

For those with T2D, extreme heat can compromise well-being and degrade quality of life. People living with T2D have an impaired capacity to dissipate heat compared to healthy counterparts because heat affects key metabolic pathways involved in insulin resistance and the development of T2D.[16] This is because lower skin blood flow and impaired sweating responses in those with T2D influence cardiovascular regulation and glycemic control. Apart from physiological responses, heat dissuades people from regular exercise, and medication may need careful handling in extreme temperatures.

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10 Diarmid Campbell-Lendrum, Tara Neville, Christian Schweizer, and Maria Neira, "Climate Change and Health: Three Grand Challenges," *Nature Medicine* 29, no. 7 (2023): 1631–38.

11 Guillermo N. Murray-Tortarolo, "Seven Decades of Climate Change across Mexico," *Atmósfera* 34, no. 2 (2021).

12 "Mapped: How Extreme Weather Is Destroying Crops Around the World," Carbon Brief; Christian García-Witulski, Mariano Rabassa, Oscar Melo, and Juliana Helo Sarmiento, "Effects of Climate Change on Physical Inactivity: A Panel Data Study across 156 Countries from 2000 to 2022," *The Lancet Global Health* 14, no. 4 (2026): e500–511; Bernd Richter, Brenda Bongaerts, and Maria-Inti Metzendorf, "Thermal Stability and Storage of Human Insulin," *Cochrane Database of Systematic Reviews* 11, no. 11 (2023).

13 Jacqueline M. Ratter-Rieck, Michael Roden, and Christian Herder, "Diabetes and Climate Change: Current Evidence and Implications for People with Diabetes, Clinicians and Policy Stakeholders," *Diabetologia* 66, no. 6 (2023): 1003–15.

14 Lisanne L. Blauw, N. Ahmad Aziz, Martijn R. Tannemaat, et al., "Diabetes Incidence and Glucose Intolerance Prevalence Increase with Higher Outdoor Temperature," *BMJ Open Diabetes Research and Care* 5, no. 1 (2017): e000317.

15 Sergio Valdés, Viyey Doulatram-Gamgaram, Ana Lago, et al., "Ambient Temperature and Prevalence of Diabetes and Insulin Resistance in the Spanish Population: Di@bet.Es Study," *European Journal of Endocrinology* 180, no. 5 (2019): 273–80.

16 Ibid.; Glen P. Kenny, Ronald J. Sigal, and Ryan McGinn, "Body *Temperature* Regulation in Diabetes," Temperature 3, no. 1 (2016): 119–45.

Besides increasing the average temperature, climate change also results in greater temperature variability. While the research on its impact is limited, a longitudinal study of German adults over a seven-year period found that a higher annual temperature variability is associated with impaired glucose metabolism.[17] As such, exposure to increasing temperature variability may result in an increasing number of T2D cases.

Hardest to Reach

Against the backdrop of increasing climate pressure, these challenges may be particularly significant for communities in Puebla whose livelihoods are closely tied to environmental conditions. In the first quarter of 2026, agriculture was the largest source of employment in the state, with approximately 225,000 people working as support workers in agriculture, alongside large workforces in retail and trade.[18] This reliance on agricultural and outdoor work may increase exposure to changing environmental conditions, potentially leading to effects on both livelihood and health.

Communities in the State of Puebla face compounded challenges, with diabetes identified as the dominant health concern in recent community needs assessments.[19] Puebla has among the highest T2D mortality rates in Mexican municipalities for those 50 years or older.[20] Consistently ranking in the top five most underdeveloped and poorest states in Mexico, Puebla's hard-to-reach communities lack basic health infrastructure, with limited access to quality healthcare, medication, and education.[21] Because low socioeconomic status is positively associated with increased T2D mortality risk, Puebla is a high-risk area for T2D mortality. With these considerations in mind, we aim to investigate whether short-term variation in temperature and other environmental conditions is associated with glucose control among adults in Puebla.



Figure 2. The temperature sensors, ready to be put on a participant (photo by Rania Harryanto)

About Our Research

Data Collection

Our observational, longitudinal study specifically focuses on how short-term changes in ambient temperatures affect glucose control by analyzing quantitative data collected over 14 days by wearable technologies and questionnaires. Our team conducted three weeks of field research in Acatzingo, a municipality of Puebla located

17 Wenli Ni, Siqi Zhang, Christian Herder, et al., "Associations of Long-Term Exposure to Temperature Variability with Glucose Metabolism: Results from KORA F4 and FF4," *Environmental Science and Technology* 59, no. 45 (2025): 24246–56.

18 "Puebla: Economy, Employment, Equity, Quality of Life, Education, Health and Public Safety," Data México, Gobierno de México.

19 "Puebla Health Needs Assessment," University of Texas Austin.

20 "IDF Diabetes Atlas."

21 "Puebla Health Needs Assessment."

approximately 50 kilometres from the historical city centre. This research was part of a larger project, in collaboration with the Benemérita Universidad Autónoma de Puebla (BUAP, The Autonomous University of Puebla) and medical students participating in the summer research program Interinstitutional Program for Strengthening Research and Postgraduate Studies in the Pacific or El Programa Delfín (The Dolphin Program). Participants were recruited by BUAP, with the following criteria:

- adults aged 18 or older who lived in urban or peri-urban areas of Puebla, Mexico
- residents of Puebla for at least 12 months, to ensure regular exposure to local environmental conditions
- adults who were not currently or planning to be pregnant during the 14-day period
- adults who were able to provide written informed consent in Spanish or English
- adults without major pre-existing cardiometabolic or respiratory conditions.

Although we initially discussed investigating people with T2D, we found that limited access to healthcare — including testing, ongoing care, and trust in medical systems — meant that many people whose glucose levels indicate T2D may not be diagnosed. This is corroborated in the literature, which estimates that in middle-income countries, 45.5 percent of adults with diabetes are undiagnosed.[22] We thus expanded the scope to capture the reality of T2D in Mexico, where structural barriers to healthcare access mean the condition often goes undiagnosed and untreated. Capturing a range of glycemic profiles, including participants with normal glycemic control, better represents the communities we worked in.

Depending on the participants' availability and resources, they either travelled to a local school for their initial study visit, or we travelled to their locations. These locations varied, such as in their home or in their place of work, namely, greenhouses. In our first visit, we gained informed consent and then helped participants complete a questionnaire consisting of three sections: (1) basic demographic data, (2) an Ecological Momentary Assessment (EMA — see Table 1 for what it measures), and (3) behavioural changes in extreme heat. After that, we attached the glucose and temperature monitors to the participants. We obtained further environmental data from the European Centre for Medium-Range Weather Forecasts ERA5-Land re-analysis data set.[23] This hourly climate data allowed us to complement participant-level wearable temperature measurements and characterize environmental conditions at the study location.

We conducted a final study visit to collect the sensors, conduct a final questionnaire, and evaluate the participants' experience of the study. The final questionnaire was adapted from Ferreira-Pêgo and colleagues and asked about fluid intake, including water and other beverages.[24] To deepen our understanding for study interpretation, we asked the participants informally about their time with the sensors and experience with diabetes and existing health systems.

22 Felix Teufel, Katherine Orgutsova, Irini Genitsaridi, et al., "Global, Regional, and National Estimates of Undiagnosed Diabetes in Adults: Findings From the 2025 IDF Diabetes Atlas," *Diabetes Care* 49, no. 3 (2026): 490–96.

23 "ERA5-Land Hourly Data from 1950 to Present," European Centre for Medium-Range Weather Forecasts.

24 Cíntia Ferreira-Pêgo, Mariela Nissensohn, Stavros Kavouras, et al., "Beverage Intake Assessment Questionnaire: Relative Validity and Repeatability in a Spanish Population with Metabolic Syndrome from the PREDIMED-PLUS Study," *Nutrients* 8, no. 8 (2016): 475.

Table 1. Description of data collected in our study

Method of data collection	Data collected	Description	Frequency of data collection
Questionnaire	Demographic data	Collects basic demographic data, such as age, sex, occupation, and whether their work requires them to work outside, inside, or a mix or both	Once; initial study visit
	EMA	The morning EMA measures sleep quality, restfulness, and nighttime temperature exposure. The daytime/evening EMA measures how participants felt throughout the day, including heat exposure, symptoms, mood, hydration, activity levels, and time spent outdoors in direct heat.	Once; initial study visit
	Heat-related symptoms and behavioural changes in extreme heat (adapted from Zander et al.)[25]	Measures participants' experience in extreme heat, including mental stress, physical symptoms (such as heavy sweating, poor sleep, and nausea), and behavioural changes (such as air conditioning use, soft drink consumption, and water consumption)	Once; initial study visit
	Typical fluid intake and consumption (adapted from Ferreira-Pêgo et al.)[26]	Evaluated typical beverage consumption per week and the typical time of day consumed, including water, juices, coffee, and sugar-sweetened beverages	Once; final study visit
Continuous glucose monitoring (CGM) sensor	Glucose data (mmol/L) Time (UTC-6)	The Freestyle Libre 2 (FL2) is an intermittently scanning CGM that collects glucose data every 15 minutes for 14 days. Applied directly on a person's upper arm via an adhesive, it is non-invasive and very safe[27] with an operating temperature of 10°C to 45°C, making it an ideal choice for this study.[28]	Every 15 minutes

25 Kerstin K. Zander, Supriya Mathew, and Sarah Carter, "Behavioural (Mal)Adaptation to Extreme Heat in Australia: Implications for Health and Wellbeing," *Urban Climate* 53 (2024): 101772.

26 Ferreira-Pêgo et al., "Beverage Intake Assessment Questionnaire."

27 Matteo Conti, Giulia Massari, Elena Meneghini, et al., "Effectiveness and Safety of the Intermittently Scanned Continuous Glucose Monitoring System FreeStyle Libre 2 in Patients with Type 2 Diabetes Treated with Basal Insulin or Oral Antidiabetic Drugs: An Observational, Retrospective Real-World Study," *Journal of Clinical Medicine* 13, no. 3 (2024): 642.

28 "What Is the Operating Temperature for the FreeStyle Libre 14 Day System?" FreeStyle Libre Support.

Method of data collection	Data collected	Description	Frequency of data collection
Body temperature sensor	Body temperature (°C) Time (UTC)	The TempU05 is worn on a lanyard around the neck and collects temperature data every 10 minutes for 14 days. Positioned at the body-environment interface, the sensor captures temperature influenced by both the participant and their immediate surroundings, providing a proxy for body-environment thermal conditions rather than core body temperature.	Every 10 minutes
ERA5-Land	2m air temperature: temperature of air at 2 metres above the surface of land, sea or in-land waters (K) 2m dew point temperature: temperature to which the air, at 2 metres above the surface of the Earth, would have to be cooled for saturation to occur, acting as a measure of humidity (K) The Earth's skin: temperature of the uppermost surface layer of the Earth (K) Time (UTC)	ERA5-Land is a public global climate data set that provides a consistent and high-resolution global view of various land variables in a complete and consistent data set.[29] Of 50 available variables, these three were picked specifically for their relevance to the study, and data extracted using a bounding box (a rectangular geographic boundary defined by specific latitude and longitude limits) surrounding Acatzingo, using coordinates (19.03–18.93°N, 97.84–97.73°W).	Hourly, taken to cover study period

29 "ERA5-Land Hourly Data from 1950 to Present," European Centre for Medium-Range Weather Forecasts.

Data Processing and Analysis

Data processing and analysis took place in multiple phases. First, the CGM, body temperature, and ERA5-Land data were independently cleaned, quality-checked, and formatted, before being standardized, aggregated, and merged. At the time of analysis, questionnaire data was not available and therefore excluded.

As part of the study design, we predefined commonly used CGM metrics to characterize glycemic control, including time in range (TIR), time below range (TBR), and time above range (TAR), adapted from the American Diabetes Association (ADA).[30] These metrics were used to describe participants' glycemic profiles and assess differences in glycemic control.

Table 2. Explanation of glucose metrics

Metric	Explanation	Target/Ideal
Number of days CGM is worn (days)	The ADA recommends that CGM monitors be worn for 14 days at a time, because 14 days of CGM data is found to correlate well with 3 months of CGM data.[31]	14 days
Percentage of time CGM is active (%)	Ideally, the CGMs would be active throughout all 14 days. However, in the case of mechanical failure, having 70% of CGM data (10 days) is still a reliable indicator of typical glucose patterns.[32]	70% (10 days)
Mean glucose (mmol/L)	The average glucose level (in mmol/L) throughout the whole period.	
Mean amplitude of glycemic excursion (MAGE) (mmol/L)	This measures glycemic variability as an arithmetic average of significant glucose fluctuations from mean glucose levels.	
Time above range (TAR) (%)	*Level 2:* The percentage of readings that the participant measures greater than 13.9 mmol/L.	<5%, or <1h 12m per day)
	Level 1: The percentage of readings that the participant measures between 10.1 and 13.9 mmol/L.	<25%, or <6h per day
Time in range (TIR) (%)	The percentage of readings and time that the participant measures between 3.9 and 10.0 mmol/L, which constitutes the healthy range.	>70%, or >16h 48m per day
Time below range (TBR) (%)	*Level 1:* The percentage of readings that the participant measures between 3.0 and 3.8 mmol/L.	<4%, or <1h per day
	Level 2: The percentage of readings that the participant measures under 3.0 mmol/L.	<1%, or <15m per day

30 Tadej Battelino, Thomas Danne, Richard M. Bergenstal, et al., "Clinical Targets for Continuous Glucose Monitoring Data Interpretation: Recommendations from the International Consensus on Time in Range," *Diabetes Care* 42, no. 8 (2019): 1593–603.

31 Richard M. Bergenstal, "Understanding Continuous Glucose Monitoring Data," in *Role of Continuous Glucose Monitoring in Diabetes Treatment*, ADA Clinical Compendia Series (Arlington, VA: American Diabetes Association, 2018).

32 Ibid.

Results

Analysis Data Set Overview

Each data source (CGM, body temperature sensors, ERA5-Land) was processed through a separate cleaning and aggregation pipeline in Python, with GitHub for version control, before being merged into a single hourly panel data set. Timestamps were converted to Puebla's time zone (UTC-6) before merging. Table 3 summarizes the original scope of each source relative to the final merged and analytic datasets.

CGM readings, body temperature readings, and ERA5-Land climate variables were each aggregated to hourly means and merged on participant identifiers and timestamps, attaching the chosen atmospheric variables to every participant record, since climate conditions were shared across all participants at a given hour. The full merged data set included 5,867 hourly participant-observations across 14 participants (P01-P15, excluding P03 due to a documented device malfunction).

Missing data. Climate and body temperature data were available continuously across each participant's device-active period, with none missing for either variable. CGM data availability, by contrast, depended on whether the sensor remained adhered to the skin. Because many participants worked in greenhouse environments, sensor wear time ranged from 3 to 15 days per participant (including application and removal days). As a result, 3,462 of the 5,867 merged hourly observations (59%) lacked a glucose measurement. Analyses of the glucose-temperature association were restricted to observations with complete glucose and body temperature data, yielding a final analytic sample of 2,405 hourly observations.

Characteristics. Table 4 presents descriptive statistics for the 2,405 complete-case observations.

Table 3. Construction of the merged analysis data set

Data set	Observations	Time period
ERA5-Land	720 hourly observations	1–30 Jun 2026
CGM (FL2)	10,924 total readings across 15 participants	8–24 Jun 2026
Body temperature sensors (TempU05)	43,916 total readings across 15 participants	4–25 June 2026
Full merged data set	5,867 participant-hourly observations	4–25 June 2026
Final data set (complete cases)	2,405 hourly observations	8–24 June 2026

Table 4. Descriptive statistics for analytical variables (*N*=2,405 observations)

Variable	Mean ± SD	Range	Source
Hourly average glucose (mmol/L)	7.30 ± 3.58	3.38–24.95	FL2
Hourly average body temperature (°C)	27.99 ± 4.25	16.5–36.7	TempU05
Hourly air temperature, Acatzingo (°C)	16.89 ± 2.77	10.13–22.76	ERA5-Land
Hourly earth skin temperature, Acatzingo (°C)	19.00 ± 6.52	8.61–32.84	ERA5-Land
Hourly dew point, Acatzingo (°C)	13.46 ± 1.44	9.46–17.71	ERA5-Land

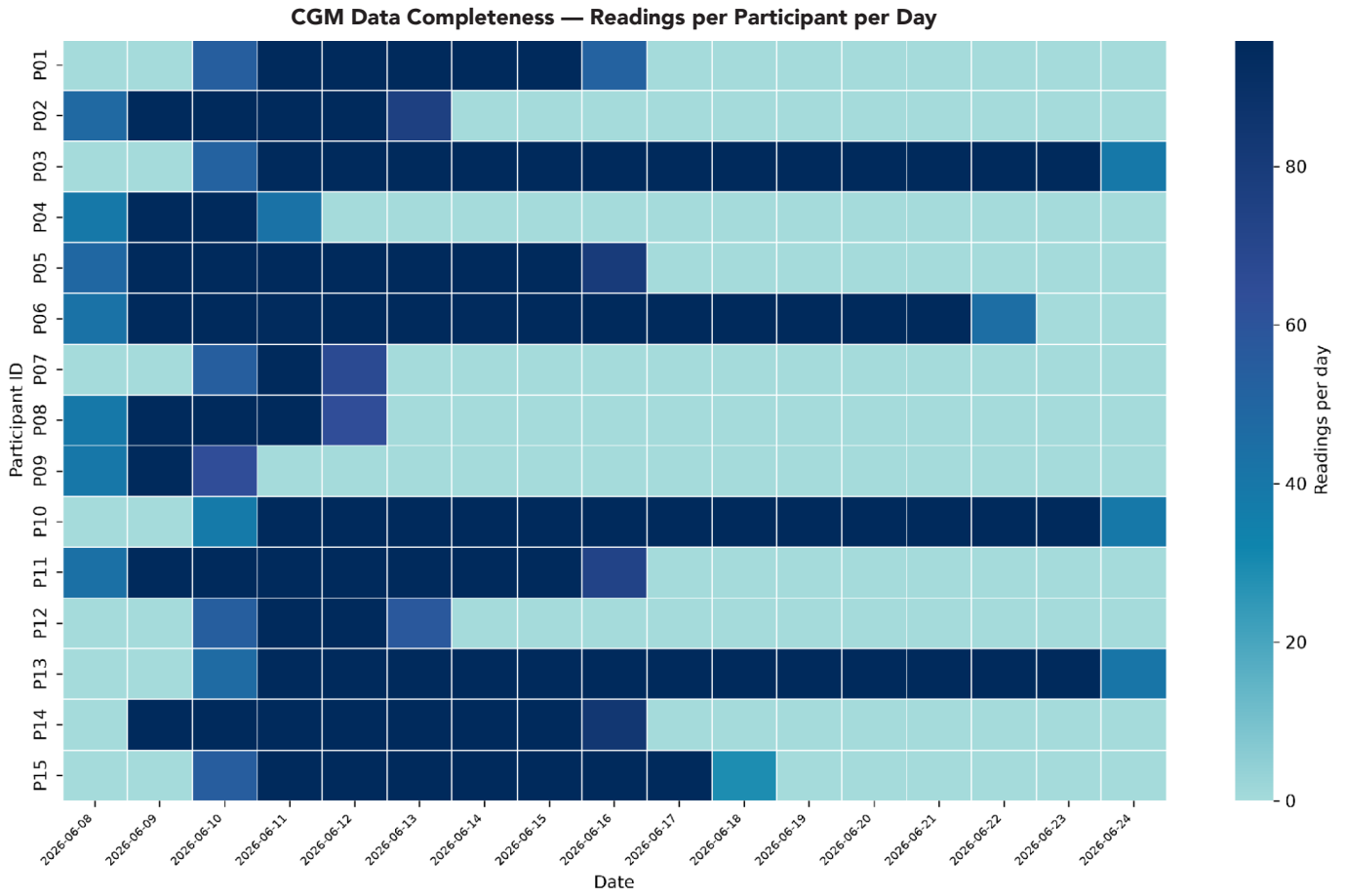


Figure 3. Heatmap of CGM data collected per participant

Participant contribution. Contribution to the analytic sample varied across the 14 participants, ranging from 50 hourly observations (P09) to 335 (P06, P13), reflecting differences in CGM sensor wear time. The median contribution was 168.5 hours (7 days) and the mean was 171.8 hours (7.2 days). Although the target wear time was 10 days, four participants (P03, P06, P10, P13) approached the full 14-day period, while the rest of the cohort had monitoring periods of fewer than 10 days. Given the resulting sample size at the observation-hour level (N = 2,405; median 7 days and mean 7.2 days of wear time per participant), and the use of mixed-effects models with participant-level random effects to account for unequal and clustered observation counts across individuals, we considered the data set adequate for the purposes of this exploratory, observational associative study. Unequal participant contribution is a recognized limitation of field-based wearable studies in occupational and agricultural settings, and we address it further in the section on the study's limitations.

Climate Characteristics

Since glucose and body temperature associations with climate could reflect either shared diurnal timing, meaning similar patterns of variation across the day, or genuine physiological response to ambient conditions, we characterized the temporal structure of the climate variables themselves.

As Figure 2 indicates, we observed a clear diurnal cycle, with mean air temperature increasing from approximately 13.1°C in the early morning (06:00) to a maximum of 21°C at 13:00–14:00, before declining throughout the evening. Earth skin temperature followed a similar daily pattern but showed a substantially larger range between its daytime and nighttime minimums, whereas dew point temperature remained comparatively stable throughout the day (12.1–13.8°C).

Air temperature and Earth skin temperature were strongly correlated (r = 0.95); given this collinearity,

we used air temperature as the primary climate predictor in subsequent regression models. Dew point temperature showed only weak correlation with both air temperature (r = 0.17) and skin temperature (r = 0.21), supporting its inclusion as an independent predictor and measure of absolute humidity and heat-stress conditions.

Together, these analyses allowed us to characterize the environmental conditions experienced during the study period, demonstrating meaningful temporal variation, and supporting the inclusion of these climate variables as supplementary information in subsequent analyses of glucose and body temperature.

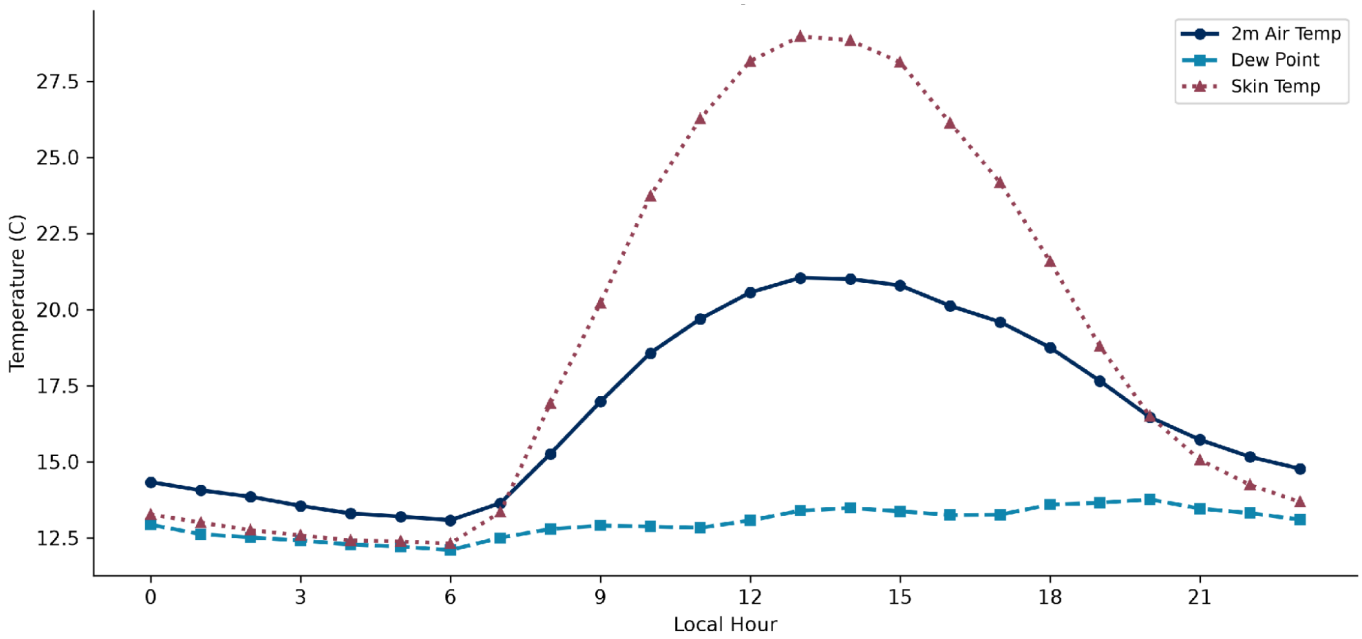


Figure 4. Mean diurnal profile during the study period in Acatzingo

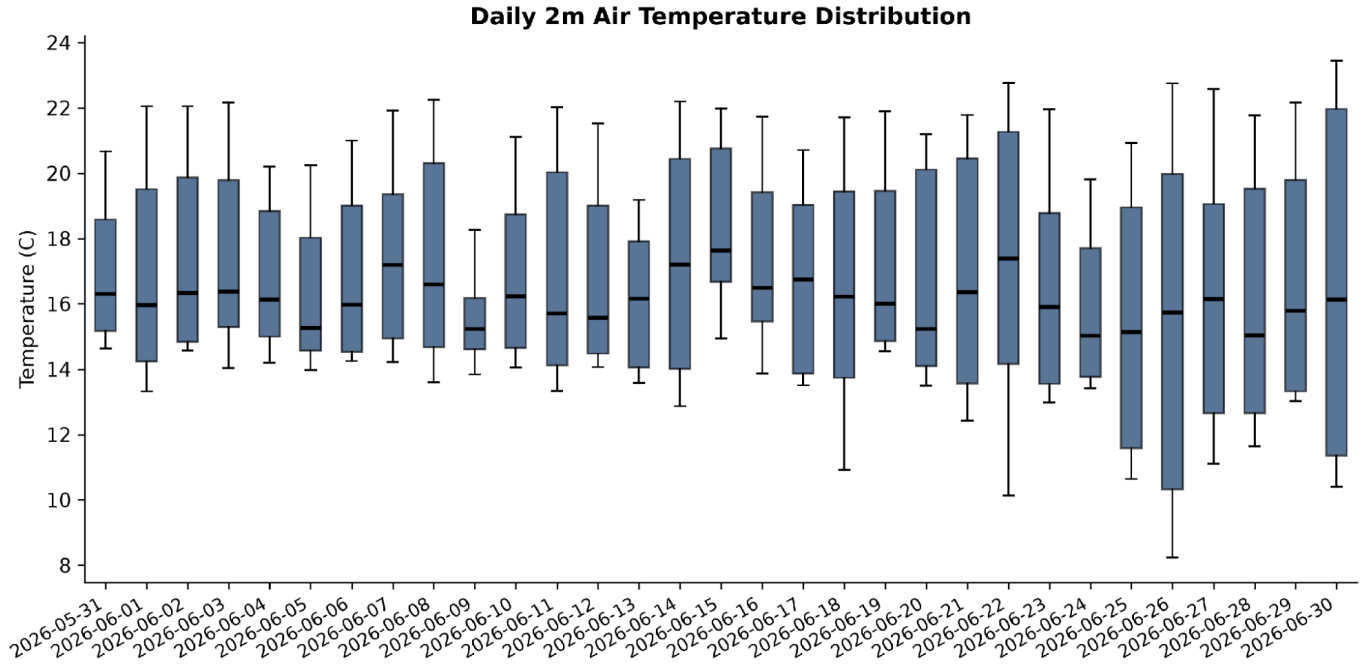


Figure 5. Daily air temperature during the study period in Acatzingo

Body Temperature Characteristics

Body temperature monitoring initially yielded 43,916 readings across 15 participants. A conservative threshold of three times the interquartile range was chosen to identify outliers, preserving the potential for genuine physiological variation in this exploratory, associative study. We then applied participant-level screening, which removed 104 extreme values within otherwise valid participant readings, leaving 43,812 observations. Separately, visual inspection of temperature recordings identified systematic, implausible measurements for participant P03, which we attributed to device failure. Thus, we excluded P03 from the analysis to avoid skewing results and introducing measurement errors. The final body temperature data set therefore includes 14 participants and 41,623 observations.

Across the 14 included participants, mean body temperature was 26.62°C (standard deviation (SD) 4.07°C; median 25.5°C), ranging from 14.3°C to 44.7°C. As Table 1 outlined, these values represent temperatures at the body–environment interface, and the relatively low and high values represent this proxy rather than physiological core temperature. Substantial between-participant variability was evident, with individual participant means ranging from 22.82°C (P09) to 31.19°C (P15) (Figure 6). This variability motivated the participant-level clustering analysis we present later.

At the cohort level, body temperature followed a clear daily pattern, broadly consistent with that of air temperature. Body temperature was lowest at 06:00 (mean 25.06°C) and highest at 15:00 (mean 28.11°C), giving an average daily difference of 3.05°C between the lowest and highest temperatures (Figure 5). Air temperature exhibited a larger daily difference of 7.96°C, with its peak occurring at 13:00 to 14:00, around one to two hours before body temperature peak. This is consistent with the fact that the human shell largely fluctuates along with the environment.[33]

Two participants were notable. P09 showed a markedly larger amplitude (10.03°C), driven by an unusually low trough temperature (18.77°C), which may reflect intermittent sensor contact loss rather than true physiological variation. P15 showed an inverted cycle, with peak temperature at 03:00 and trough at 19:00, the opposite timing of the cohort pattern. This may reflect participant-level factors, differences in activity or environmental exposure, or sensor artifacts, such as measurement distortions caused by the sensor itself; however, we couldn't distinguish these possibilities with the available data (see limitations section for further insight). Otherwise, daily mean body temperatures of the rest of the cohort remained

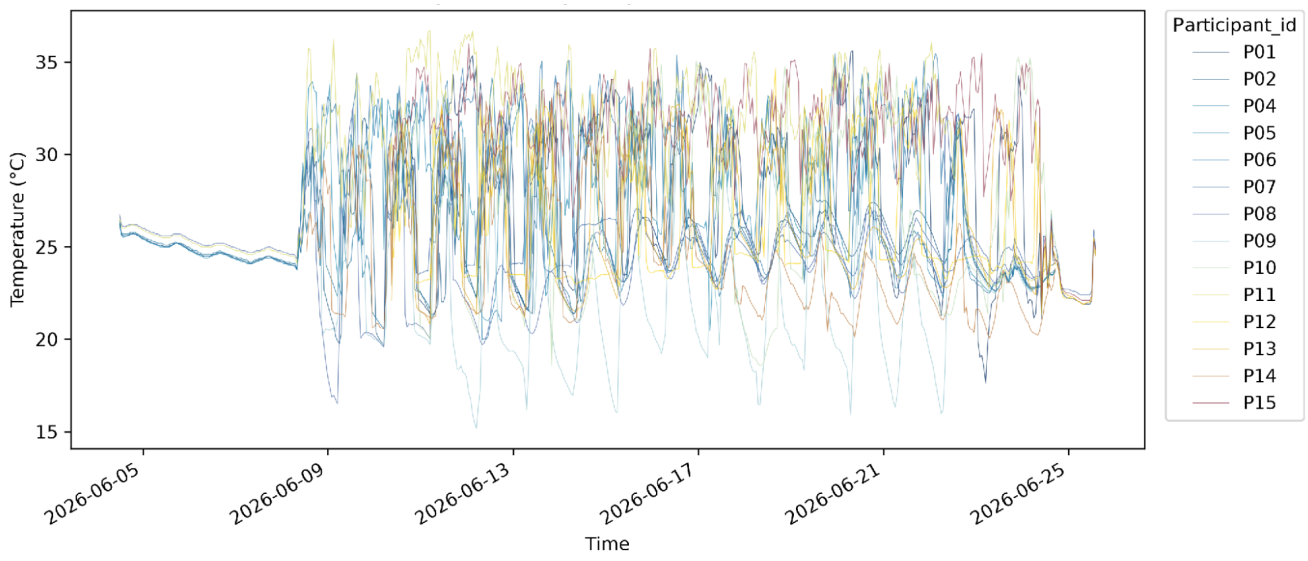


Figure 6. Hourly mean body temperature over time

33 Chan Lek Tan and Zachary A. Knight, "Regulation of Body Temperature by the Nervous System," *Neuron* 98, no. 1 (2018): 31–48.

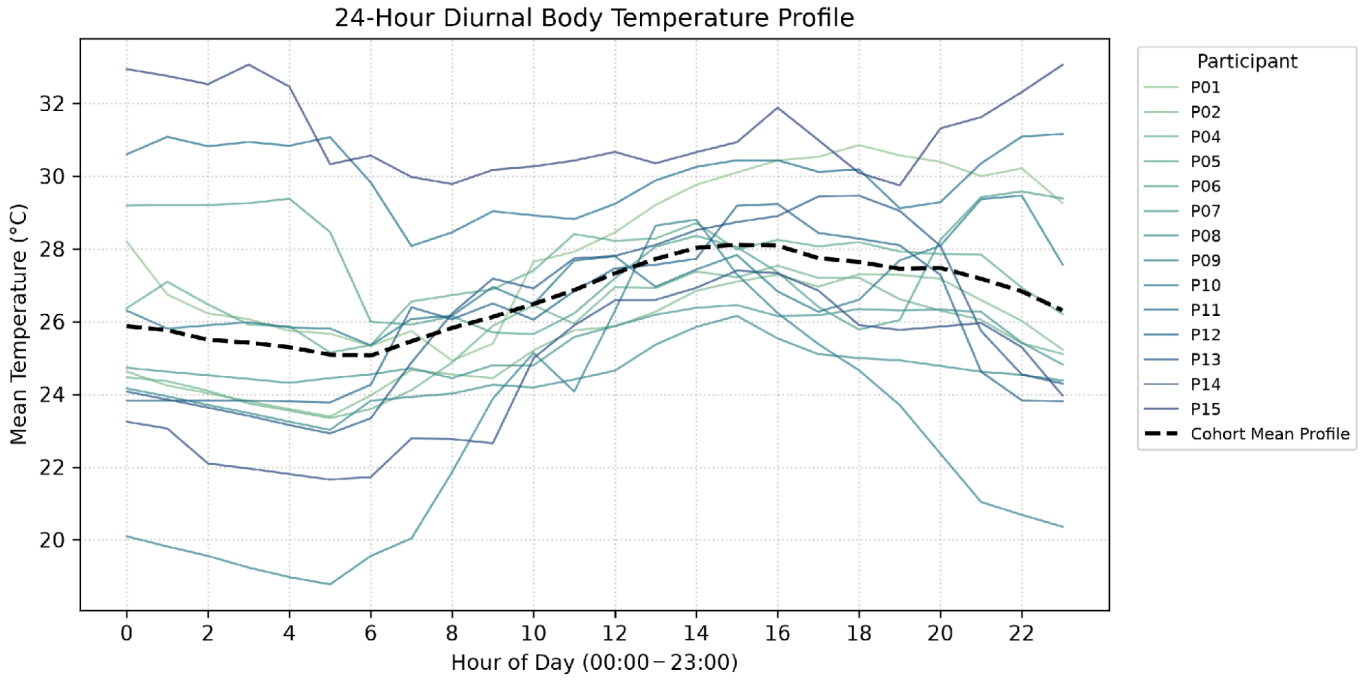


Figure 7. Diurnal profile of the cohort

relatively stable throughout the monitoring period, with no evidence that sensor readings systematically increased or decreased over time.

CGM Characteristics

CGM monitoring yielded 10,924 raw glucose readings across 15 participants. One sparse day-window with fewer than 11 readings was excluded to ensure sufficient data for calculating daily glucose measures, removing eight readings and leaving a final analytic CGM data set of 10,916 readings across 15 participants, spanning 8 to 24 June 2026. Monitoring duration per participant ranged from approximately 2 to 14 days, reflecting variation in sensor adhesion and wear time.

Cohort-level glycemic control. Across all readings, mean glucose was 7.81 mmol/L (SD 3.82; median 6.3 mmol/L; coefficient of variation 48.9%), ranging from 2.9 to 25.3 mmol/L. Using standard CGM range metrics outlined in Table 2, participants spent 77.1 per cent of time in range (TIR), 1.1 per cent of time below range (TBR), and 21.9 per cent of time above range (TAR) across the monitoring period.

Between-participant variability. Glycemic control varied substantially across participants. At one extreme, P02 exhibited sustained severe hyperglycemia (mean 16.33 mmol/L; SD 3.52; TAR 99.4%), spending virtually the entire monitoring period above range. P01, P03, and P15 similarly showed elevated means (13.78, 11.43, and 9.38 mmol/L respectively) with substantial time above range (TAR 80.72%, 62.73%, 33.99%). At the other extreme, P04 (mean 5.54 mmol/L; SD 0.73; TIR 100%) and P05, P06, P07, P09, P10 maintained consistently well-controlled glucose throughout monitoring, with TIR at or near 100 per cent. This range, from near-continuous hyperglycemia to tightly regulated normoglycemia within the same cohort, suggests considerable heterogeneity in underlying glycemic status. This potentially includes undiagnosed or unmanaged dysregulation, independent of any climate association.

Daily glucose pattern. At the cohort level, mean glucose followed a clear pattern across the day, from a trough overnight (00:00–06:00, mean 6.9 mmol/L), through morning (06:00–12:00, mean 7.4 mmol/L) and afternoon (12:00–18:00, 8.19 mmol/L) to a peak in the evening window (18:00–23:00, mean 8.83 mmol/L). Notably, this peak occurred several hours later than the daily peaks observed for air

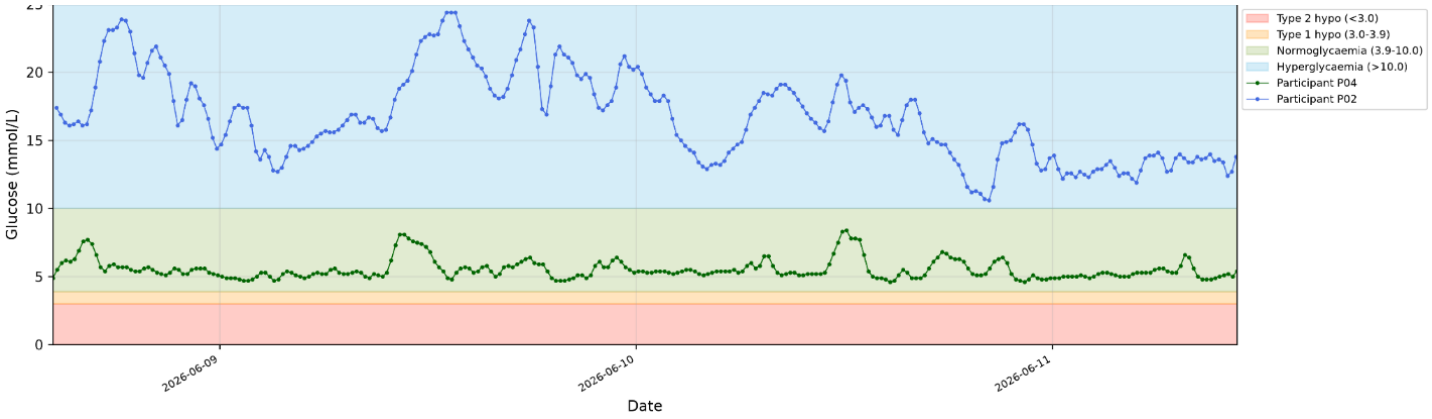


Figure 8. Glucose timeline comparison between P04 (well-controlled) and P02 (hyperglycemia)

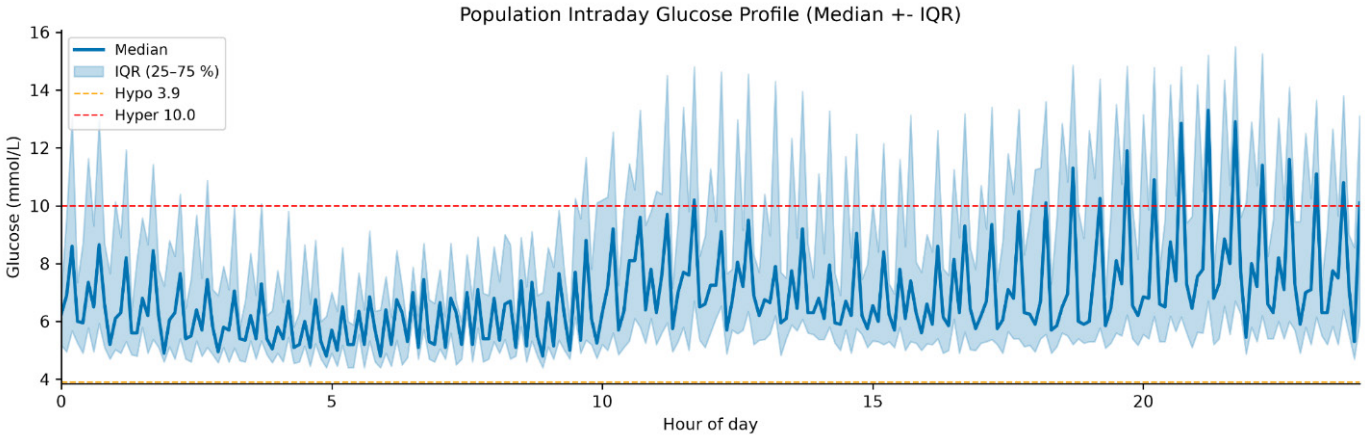


Figure 9. Population intraday glucose profiles show peaks at midday and in the later evening, coinciding with mealtimes

temperature (13:00–14:00) and body temperature (15:00), consistent with glucose being driven primarily by meal timing and activity patterns rather than directly tracking ambient thermal conditions. This timing offset is an important consideration for interpreting the glucose–temperature associations we present: any observed association is unlikely to simply reflect two variables independently following the same daily clock.

To illustrate cohort heterogeneity, we plotted individual trajectories for P02 and P04 in Figure 6 illustrating the contrast between sustained hyperglycemia and well-controlled glycemia across the study period. Participant-level associations with body temperature and climate exposure are examined further after that.

Associations Between Body Temperature, Glucose, and Environmental Conditions

Figure 10 shows hourly mean glucose concentration, body temperature, and ambient air temperature over the monitoring period for participant P01 (individual correlation r = 0.35), which we selected as an illustrative example close to the cohort mean (r=0.217, SD=0.189). All three variables show visually synchronized troughs and peaks across the daily cycle, with a midday peak, but with both physiological variables (body temperature and glucose) showing greater fluctuation magnitudes and variability than the comparatively smooth, low-amplitude air temperature signal. This pattern is consistent with an underlying association between the three variables, though visual synchrony alone cannot establish its strength or direction at the population level, motivating our use of further analyses.

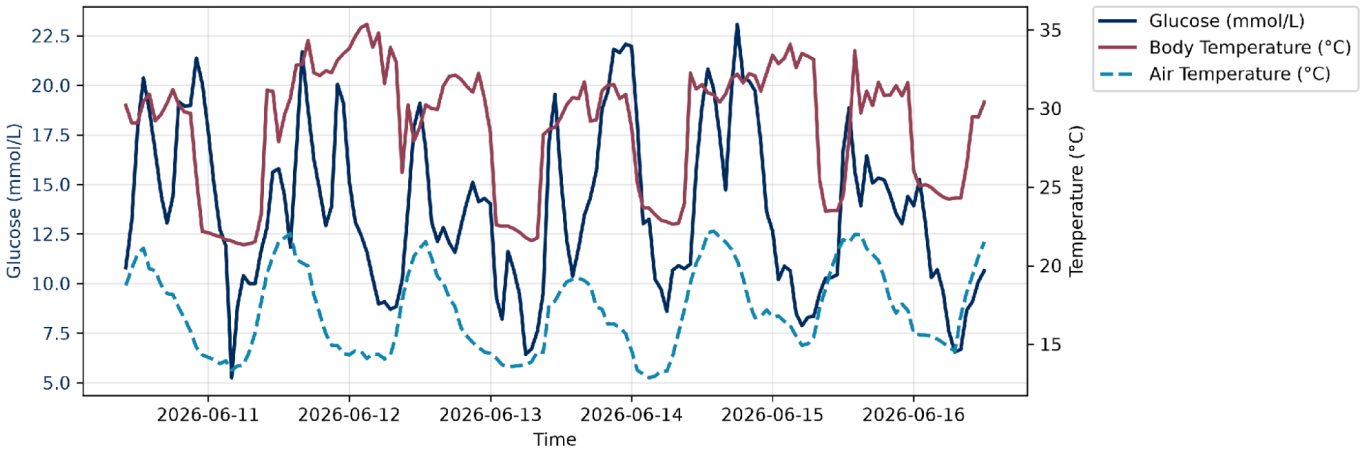


Figure 10. Hourly glucose, body temperature, and air temperature for P01, showing synced troughs and peaks

Cohort-level correlations. Pearson correlation analysis across all hourly observations (N=2,405) showed weak positive associations between glucose and each climate/body temperature variable: body temperature (r=0.083, 95% CI: 0.043–0.123), air temperature (r=0.110, 95% CI: 0.070–0.149), dew point temperature (r=0.137, 95% CI: 0.098–0.176), and earth skin temperature (r=0.099, 95% CI: 0.059–0.139). Body temperature was more strongly correlated with air temperature (r=0.232, 95% CI: 0.194–0.269) than with glucose, consistent with body/earth skin temperature responding more directly to ambient thermal conditions.

Notably, dew point, a measure for absolute humidity and combined heat-humidity stress, showed the strongest correlation with glucose among the climate variables, which may be more physiologically relevant given the humid greenhouse conditions that many participants worked in. Air temperature and Earth skin temperature remained highly collinear (r=0.93), consistent with the EDA findings we presented earlier, and supported the exclusion of Earth skin temperature from primary regression models.

Participant-level correlations. Correlating hourly glucose and body temperature within each participant, rather than pooling across the cohort, yielded a mean correlation of r=0.217 (SD=0.189), which is more than double the pooled cohort-level estimate (r=0.083) (Figure 11). Thirteen of fourteen participants showed positive within-participant correlations, ranging from r=0.016 (P06) to r=0.570 (P02), with P12 (r=0.529) also showing a notably strong positive association. This divergence between pooled and within-participant estimates is characteristic of clustered, repeated-measures data: because participants differ systematically in their baseline glucose and body temperature levels, a naive pooled correlation can understate and distort the true within-person relationship between two variables. This finding motivates the use of mixed-effects regression models with participant-level random effects as the primary analytical approach, since mixed models can separate within-participant associations from between-participant differences in baseline levels.

The substantial heterogeneity in within-participant correlations (from near-zero/slightly negative to r=0.57) further suggests that the glucose-body temperature relationship is not uniform across the cohort, but varies by individuals, which motivated further exploration in a cluster analysis done later. The correlation from P02, who exhibits the highest average glucose in the cohort and poorest TIR (being more than double that of the cohort average) provides evidence that those with the poorest control of their glucose may experience higher sensitivity to changes in temperature. This is compounded by the fact the second-highest correlation is P12, who exhibited the highest TBR in the cohort at 4.28 per cent.

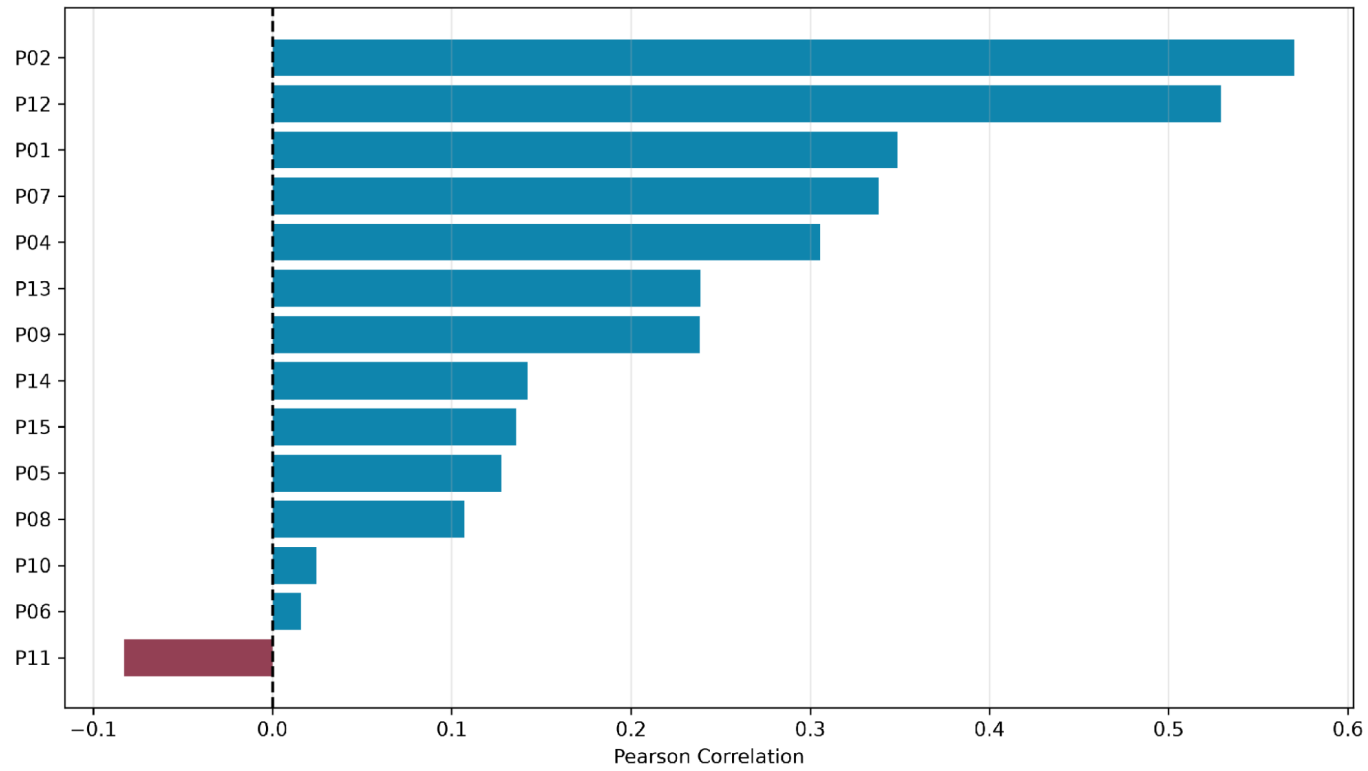


Figure 11. Bar plot showing participant-level correlation between body temperature and glucose

Regressions

To formally test the associations we identified, mixed-effects regression models were fit to the complete-case hourly data set (n=2,405 observations; 14 participants), with glucose (raw and natural-log transformed) as the outcome, and body temperature, air temperature, and dew point temperature as fixed-effect predictors. Earth skin temperature was excluded as previously justified. Each model included a random intercept for participant, allowing baseline glucose levels to vary by individual and directly accounting for the between-participant heterogeneity we mentioned earlier. We applied natural log transformations to reduce skewness and assess the robustness of the associations to outcome scale and allow for interpretation in relative rather than absolute terms.

Model results. In the raw-scale model, body temperature, air temperature, and dew point were each significantly and positively associated with glucose (Table 5). A one-degree Celsius increase in body temperature was associated with a 0.068 mmol/L increase in glucose (95% confidence interval (CI): 0.048–0.088, p<0.001); a one-degree increase in air temperature with a 0.094 mmol/L increase (95% CI: 0.067–0.122, p<0.001); and a one-degree increase in dew point with a 0.172 mmol/L increase (95% CI: 0.119–0.225, p<0.001). In practical terms, glucose tended to be higher when participants experienced warmer body and environmental conditions, with dew point showing the largest estimated association.

The log-transformed model showed the same pattern of significant, positive associations at a proportionally smaller scale: body temperature (0.006, 95% CI: 0.004–0.008), air temperature (0.012, 95% CI: 0.009–0.015), and dew point (0.021, 95% CI: 0.015–0.027), all p<0.001 (Table 6), which suggests that the observed relationships were not driven by scale or distribution of the glucose measurements.

The model also showed substantial differences in baseline glucose between participants. In other words, participants tended to have different underlying glucose levels even after accounting for

Table 5. Mixed effects linear regression results for mean glucose levels

Variable	Coef.	Std.Err.	z	P>|z|	[0.025,	0.975]
Intercept	1.733	1.013	1.712	0.087	-0.252	3.719
Body temperature	0.068	0.010	6.568	0.000	0.048	0.088
Air temperature	0.094	0.014	6.797	0.000	0.067	0.122
Dew point	0.172	0.027	6.368	0.000	0.119	0.225
Group Var	11.867	2.652				

Note: Model fitted via REML. No. observations: 2,405. No. groups: 14. Group size: min = 50, max = 335, mean = 171.8. Log-likelihood = -4826.6731. Scale: 3.1066. Model successfully converged.

differences in temperature and dew point, which highlights the need to consider individual differences when examining climate-glucose relationships.

Across both models, dew point showed the largest standardized association with glucose among the three predictors, consistent with our correlation findings, where dew point also showed the strongest pooled correlation with glucose (r=0.137) among the climate variables. This suggests that ambient humidity, not just ambient heat, may be relevant to the observed glucose–climate association. This has physiological grounding, since combined heat and humidity exposure worsens heat stress by reducing sweat evaporation, and is increasingly important as climate change raises temperature and humidity levels, intensifying both extremes.[34]

> “Combined heat and humidity exposure worsens heat stress by reducing sweat evaporation, and is increasingly important as climate change raises temperature and humidity levels, **intensifying both extremes.**

It is also important to note that ERA5-Land data reflects regional ambient atmospheric conditions rather than the microclimate directly experienced by participants, many of whom worked in greenhouse environments known to trap heat and humidity beyond ambient levels (some workers grew cucumbers in greenhouses, which need humidity levels of 60 to 70 per cent). Thus, if participants’ true thermal-humidity exposure while working indoors exceeded the ambient conditions captured by ERA5, the associations reported here may represent a conservative approximation of the true glucose-thermal stress relationship for our cohort. This is a limitation of the available climate data, but analyses

34 Jane W. Baldwin, Tarik Benmarhnia, Kristie L. Ebi, Ollie Jay, Nicholas J. Lutsko, and Jennifer K. Vanos, “Humidity’s Role in Heat-Related Health Outcomes: A Heated Debate,” *Environmental Health Perspectives* 131, no. 5 (2023): 55001.

Table 6. Log mixed effects regression results for log glucose levels

Variable	Coef.	Std.Err.	z	P>|z|	[0.025,	0.975]
Intercept	1.277	0.107	11.891	0.000	1.067	1.488
Body temperature	0.006	0.001	5.320	0.000	0.004	0.008
Air temperature	0.012	0.001	7.856	0.000	0.009	0.015
Dew point	0.021	0.003	7.221	0.000	0.015	0.027
Group Var	0.132	0.274				

Note: Model fitted via REML. No. observations: 2,405. No. groups: 14. Group size: min = 50, max = 335, mean = 171.8. Scale: 0.0362. Model successfully converged.

here still provide a foundation for uncovering such an association.

These results are consistent with, and strengthen, the pattern we identified before, where within-participant correlations between glucose and body temperature (mean r=0.217) and the mixed-effect coefficients reported here similarly account for participant-level baseline differences. These methods represent a more statistically appropriate quantification of how temperature changes impact each participant personally.

As with any hourly time-series data, residuals in these models are likely to retain some degree of within-participant temporal autocorrelation; we address this further in the limitations section.

To illustrate these effects in practical terms: the mean daily range in air temperature observed in Acatzingo during the study period was approximately 4 to 8°C. Applying the mixed-effects model coefficient, this daily temperature swing corresponds to an estimated 0.48 to 0.88 mmol/L increase in glucose, roughly 5 to 10 per cent of the cohort's overall mean glucose level (7.30 mmol/L). This is a modest but potentially clinically relevant shift when compounded with existing glycemic burden in participants who are already experiencing elevated glucose, like P02, or those in extremely low glucose, like P12.

Clustering

K-means clustering is an unsupervised machine-learning method that groups data by similarity. It is useful to uncover time-dependent metabolic relationships and reveal specific patterns across a 24-hour period, allowing us to further investigate whether glucose measurements occurred within distinct temperature–time patterns. We performed the analysis using the same hourly aggregated data set from the regressions, but with cyclically encoded local hour of day using sin/cosine transformations. We determined the optimal number of four clusters by using a silhouette analysis (Figure 12) which indicated that four groups provided the clearest separation between observations. We then used a principal component analysis (PCA) to visualize these groups (Figure 13), demonstrating that observations can be grouped into distinct combinations of glucose, temperature, and time-of-day characteristics.

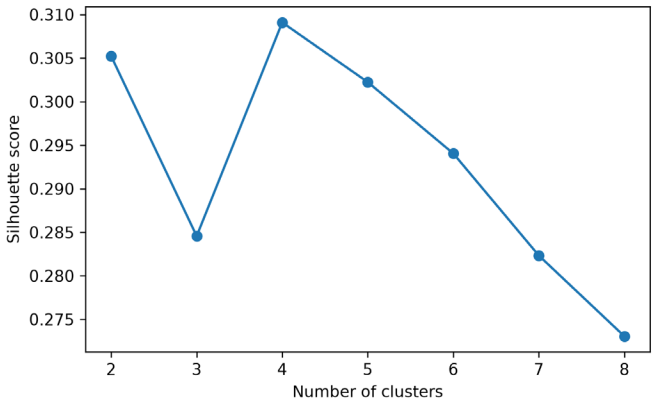


Figure 12. Silhouette analysis to determine the optimal number of clusters

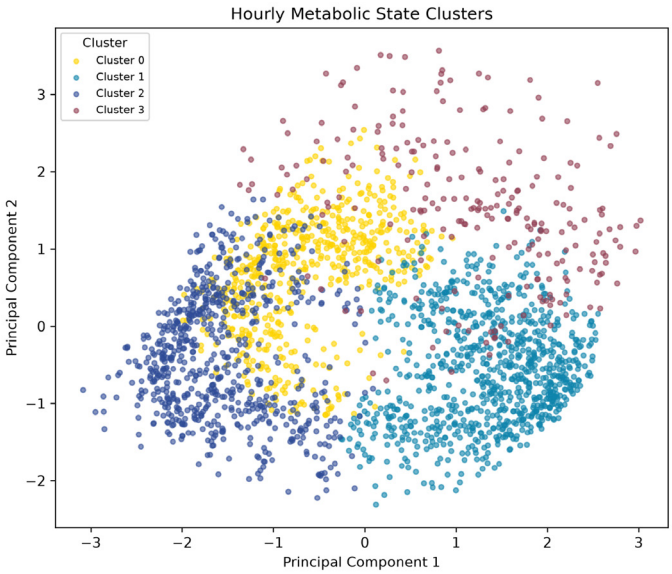


Figure 13. PCA analysis

Three of four clusters represented normoglycemic conditions with very similar mean glucose concentrations around 6.34 to 6.40mmol/L, despite large differences in mean body temperature and environmental temperatures (Table 7). Cluster 0 was characterized by having the highest mean body temperature (31.69°C) and predominantly occurred around 20:00. Cluster 1 in contrast exhibited the warmest environmental temperatures (19.69°C) and consistent with previous findings, occurred at 14:00. Cluster 2 represents the coolest physiological state at 23.35°C at 06:00. Together, these clusters indicate that similar glucose levels were observed across a range of thermal conditions, suggesting that the temperature measured at the body-environment interface does not on its own define distinct glycemic states. In contrast, cluster 3 was characterized by glucose levels more than double that of the other clusters (mean 15.80mmol/L), while exhibiting body and air temperature comparable to those observed in cluster 1 (mean body temperature: 29.36°C versus 28.86°C; mean air temperature: 17.97°C versus 19.69°C). The fact that elevated glucose levels were observed under thermal conditions similar to that of normoglycemic conditions suggests that factors beyond thermal exposure contribute to glucose variations. Temperature therefore appears to be one component of a more complex relationship rather than a stand-alone explanation for hyperglycemia.

The temporal distribution of clusters demonstrated a clear daily pattern. Cluster 2 is predominant during the early morning hours, specifically between 4:00 and 8:00 am, cluster 1 during midday (11:00–16:00), and cluster 0 during the evening (20:00–22:00). The hyperglycemic cluster 3 occurred most frequently in a small window between 17:30 and 19:30. Together, these findings suggest that time of day contributes

Table 7. Cluster summary

Cluster	Number of observations	Mean glucose	SD of glucose	Mean body temperature	Mean air temperature	Dominant hour
0	583	6.359634	1.937749	31.69008	15.07968	20
1	882	6.343528	1.702651	28.85968	19.68584	14
2	701	6.397682	2.384885	23.34591	14.50989	6
3	239	15.79728	3.522699	29.35662	17.96565	18

to the organization of glucose–temperature observations and may influence glucose regulation independently of ambient temperature, most likely and seemingly due to the typical timings of meals.

Furthermore, participant-level analysis revealed substantial inter-individual heterogeneity, as we saw in our prior analyses. The hyperglycemic cluster 3 was largely composed of observations from P01 and P02, who accounted for 72.38 per cent of all observations assigned to the cluster. P01 had a mean glucose concentration of 13.77 mmol/L, with 57.8 per cent of observations assigned to the hyperglycemic cluster, while P02 had the highest overall mean glucose concentration and 69.3 per cent of observations assigned to cluster 3. In contrast, most remaining participants exhibited no observations within the hyperglycemic cluster, despite comparable body and environmental temperatures.

Overall, this clustering analysis indicates that glucose observations form distinct time-dependent patterns, but these patterns are not explained by temperature alone. Instead, the clusters, combined with the correlations and regressions, point to the fact that individual physiological differences represent an important source of variability, with individuals who have the lowest TIR exhibiting higher sensitivity to glucose changes as temperature changes.

Impact: From Climate and Health to Community Action

Our research began with a literature review examining how climate change may affect type 2 diabetes (T2D), from glycemic control to the number of new cases. We then designed a field study combining wearable sensors and climate data to investigate these relationships directly in rural Acatzingo. Our findings have implications for how climate exposure is measured, which populations may be most vulnerable, and how climate-health research can be translated into community action.

Climate exposure is multidimensional. Glucose was positively associated with body temperature, air temperature, and dew point in both correlation and mixed-effects analyses. In the mixed-effects model, dew point showed the largest estimated association with glucose (β=0.172, 95% CI 0.119–0.225), followed by air temperature (β=0.094, 95% CI 0.067–0.122) and body temperature (β=0.068, 95% CI 0.048–0.088). This suggests that humidity-related exposure warrants greater attention in future climate–glycemic research, rather than treating temperature as a stand-alone measure of environmental exposure.

The most vulnerable may be the most climate sensitive. Participants with poorer glycemic control appeared to show greater sensitivity to temperature changes. This raises the possibility that people already experiencing poorer glycemic control may be particularly vulnerable to environmental stress. During informal conversations, participants described rising food prices and the increasing difficulty of maintaining a healthy diet. While these observations were not quantitatively assessed, they highlighted how economic constraints can compound diabetes and climate vulnerability, particularly when the impacts of climate change and food insecurity are disproportionately experienced by economically disadvantaged populations.[35]

These findings represent early evidence that climate change deserves greater attention in glycemic health research, especially in high-risk populations. Hard-to-reach populations, like those in Acatzingo, are of particular importance as climate changes exacerbate existing inequalities by making it more difficult to have healthy food, stay out of the sun, and mitigate other environmental health risks.

CGM-based methods open new possibilities for climate–health research. To the best of our knowledge, this study is among the first to use

35 Sarah Butler, "Rising Food Prices Driven by Climate Crisis Threaten World's Poorest, Report Finds," *The Guardian*, 21 July 2025.

CGMs to investigate the association between climate data and glucose control, particularly at an hourly level. Prior work has largely examined associations between static glucose measurements or diabetes prevalence to mean ambient temperatures, and the use of CGM-based approaches remains relatively rare. While conducting this research, we identified one recent comparable study by Daultrey and colleagues, which used retrospective CGM data from those with T1D in the UK, reporting that increasing ambient temperatures were associated with a higher short-term risk of hypoglycemia.[36]

Our findings report the opposite: rising temperatures were associated with higher glucose. We interpret this as reflecting population and clinical context rather than inconsistency. Our cohort was a rural agricultural population with evidence of substantial undiagnosed or unmanaged hyperglycemia and no confirmed insulin use. Together, these contrasting findings suggest that the direction of climate–glucose relationships may depend on diabetes type, treatment status, and environmental context, rather than following a universal pattern. This is consistent with the heterogeneity observed between participants in our cohort.

By combining CGMs with wearable temperature sensors and high-resolution climate data, our study demonstrates the feasibility of examining climate-glycemic relationships at much higher temporal resolution. Together, combined with previous work, our findings suggest that CGM-based approaches could help investigate these relationships across different diabetes types and environmental settings.

Research can double as a direct community benefit. This study generated direct benefits for participants and the surrounding community, consistent with the understanding that improving health literacy and access to care is one of the most effective methods of addressing the growing burden of T2D, especially in rural settings.

For many participants, involvement in this study provided the first opportunity to see their own glucose data and discuss it directly with medical experts, enabling more proactive health engagement for participants with limited prior exposure to glucose regulation. Several participants also discovered previously unrecognized elevated blood pressure, along with an understanding of diabetes and high blood pressure's many health implications and practical management tools.

Alongside the core research, we delivered multiple scientific communication workshops in local primary and secondary schools under the guidance of Laura Andres Rodriguez. These workshops taught children practical health literacy skills, including reading nutrition labels, estimating sugar content in everyday snacks and drinks, and identifying health priorities relevant to their own community, alongside age-appropriate explanations of diabetes and its risks. Parents also attended, extending our reach beyond the immediate participant group and creating an opportunity for knowledge to spread further through the community.



Figure 14. Responses to a scientific communication workshop in an elementary school in Acatzingo, Puebla (photo by Laura Andres Rodriguez)

Toward climate-resilient diabetes care. Together, our findings highlight the need for diabetes research and management to become increasingly climate aware. This means moving beyond temperature alone, identifying populations already experiencing greater metabolic vulnerability, and recognizing the socioeconomic conditions that shape people's ability to adapt to environmental stress. We also highlight

36 Harriet E. Daultrey, Nick S. Oliver, Ali J. Chakera, Arturo De La Cruz Libardi, Collins C. Iwuji, and Antonio Gasparrini, "The Association Between Ambient Temperature and Hypoglycemia in People Living with Type 1 Diabetes: A Case Time Series Analysis Using Real-Time Continuous Glucose Monitoring," *Diabetes Care* 49, no. 8 (2026): 1323–29.

the importance of pairing scientific research with direct, tangible benefits to both participants and the wider communities involved.

As climate change continues to reshape the conditions under which vulnerable populations live and work, understanding and responding to its effects on chronic disease management will be essential to closing rather than widening existing health inequities.

> “As climate change continues to reshape the conditions under which vulnerable populations live and work, understanding and responding to its effects on chronic disease management will be **essential to closing rather than widening existing health inequities.**

Limitations

Devices

- The largest limitation of our study is that 73.33 per cent of CGM monitors stopped working before the expected requirement of at least 10 days. This was unsurprising because many participants worked in physically demanding occupations, including greenhouse workers and physical education, where prolonged sweating may have reduced adhesive integrity. We were unable to reapply the CGM monitors due to logistical constraints: the FL2 monitors are for single use and we had insufficient field time to redo data collection.[37]
- The TempU05 logger measured temperature at the body-environment interface rather than core body temperature. It therefore captured the combined influence of the participant’s body and their immediate surroundings but did not directly measure local microclimatic conditions that participants experienced. In particular, we could not quantify conditions within settings like greenhouses, including relative humidity, radiant heat, or air movement. We therefore used ERA5-Land reanalysis data to approximate ambient environmental conditions. Although ERA5-Land provides regional estimates of air temperature and dew point, it cannot capture the highly localized thermal environment that individual participants experienced.

Study Design

- As an observational study, the analyses identified associations between glucose, body-environment temperature, and climate data but cannot establish causal relationships. Although several physiological mechanisms may plausibly explain the observed associations, alternative explanations, including residual confounding and bidirectional interactions between variables, cannot be excluded. Longitudinal studies with more comprehensive physiological measurements and, where feasible, controlled experimental designs are required to determine whether changes in environmental temperature directly influence glucose regulation.
- The study did not measure several important confounding variables, including dietary intake, physical activity, insulin regimen, occupation-specific heat exposure, and time spent indoors versus outdoors. Although participant surveys and body temperature measurements were collected, these were not available at the time of analyses and provided only indirect evidence of daily routines. Consequently, between-participant differences in environmental exposure could not be evaluated directly and may partially explain the observed heterogeneity.
- This study focused on ambient temperature as one pathway linking climate and glucose

37 “Your FreeStyle Libre 14 Day System,” FreeStyle Libre.

regulation. Climate change may also influence T2D through food insecurity, reduced physical activity, disruption of healthcare access, and heat-induced insulin degradation, none of which we examined here.

Sample and Generalizability

- Only 14 participants contributed to the analysis data set. Recruitment in rural Acatzingo was challenging because of medical mistrust and concerns regarding wearable devices.
- Monitoring lasted approximately two weeks, capturing acute temperature-glucose relationships but not seasonal or interannual variation. Consequently, these findings may not generalize to populations living in different climates or environmental settings.

Statistical Limitations

- Unequal participant contribution is a recognized limitation of field-based wearable studies conducted under real-world conditions. Participants contributed substantially different monitoring periods, resulting in varying numbers of observations and differing exposure to environmental conditions. Consequently, participant-specific associations may be estimated with differing levels of precision.

- Although mixed-effects models account for repeated observations through participant-specific random intercepts, they do not explicitly account for the fact that measurements taken close together in time are likely to be more similar to one another than measurements taken further apart. Consequently, some residual temporal correlation may remain, potentially underestimating standard errors and slightly overstating statistical significance. However, this was not deemed to be problematic because the consistency of associations across models and their small p-values suggests that the main findings are unlikely to be explained by this limitation.



Figure 15. A participant getting his blood pressure taken for the study (photo by Rania Harryanto)

Lessons Learned

Beyond our findings, this study offered several lessons about conducting climate-health fieldwork in rural, hard-to-reach settings.

Fieldwork rarely follows protocol. Unexpected complications, such as participant attrition and equipment-related issues, required the team to adapt the protocol in response to circumstances, highlighting the importance of building flexibility into plans.

Informal conversation revealed what quantitative data could not. Conversations with participants outside the formal questionnaires provided important contextual information, including reports on rising food costs. These observations helped contextualize patterns and inconsistencies in quantitative data that may otherwise have been difficult to interpret.



Figure 16. The UCL Mexico Reach Alliance team in front of the Acatzingo sign (from left to right: Rania Harryanto, Jose Luis Flores-Guerrero, Adrian Khan; photo by Laura Andres Rodriguez)

Community trust had to be built before data was collected. Participants were understandably cautious about sharing personal information and engaging with an unfamiliar research team. Trust was strengthened through collaboration with local partners, repeated visits, clear communication, and transparency about the purpose of the research. Meaningful community engagement is not merely an addition to data collection, but a prerequisite for it.

In recent years, the Mexican government has introduced measures to promote healthier nutrition in response to the growing burden of noncommunicable diseases, including type 2 diabetes (T2D). Mexico's 2024 *Ley general de Alimentación Adecuadea y Sostenible* (General Law on Adequate and Sustainable Nutrition) represents a framework for radically transforming the food system and promoting food sovereignty.[38] However, two years after its passage, it remains unimplemented.[39] While national policy is important, our experience demonstrates the continued value of community-level engagement, particularly in rural communities where the benefits of policy sometimes take time to reach. From CGM data collection to community workshops, this study demonstrates that research and engagement around climate-related influences on glucose regulation can begin at the community level, through sustained relationships with local communities, regardless of any national policy implementation.

38 Elisa Pineda, Mauricio Hernández-F, Ana G. Ortega-Avila, Alexandra Jones, and Juan A. Rivera, "Mexico's Bold New Law on Adequate and Sustainable Nutrition," *The Lancet* 405, no. 10481 (2025): 764–67.

39 Danielle Resnick and Fiorella Espinosa de Candido, "Two Steps Forward, One Step Back? Champions and Roadblocks for Mexico's General Law on Adequate and Sustainable Food," The International Food Policy Research Institute (IFPRI), 2026.

Research Team



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Jose Luis Flores-Guerrero studied medicine at the Autonomous University of Puebla (Mexico, 2013). He earned a master's degree in medical sciences diabetes from the University of Glasgow (UK, 2016) and a PhD in medical sciences from the University of Groningen (The Netherlands, 2021). Jose Luis worked as a research assistant at the University of Helsinki in Finland and completed a postdoctoral fellowship at the Institute of Cardiovascular Sciences, University College London. His work focuses on the study of digital and molecular biomarkers of cardiometabolic diseases, including their interaction with the central nervous system and the microbiota. He has published more than 40 articles in international journals, and his work has received over 1,300 citations. He has presented at more than 20 international conferences and has received several awards and distinctions. For example, he was invited to the Nobel Prize ceremony in Stockholm, Sweden. He has received the award for the most impactful article from the American Heart Association (2019) and the award for best presentation from the European Society of Endocrinology (2020). He was recently appointed member of the Global Young Academy (2026–2031).

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