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Co-exposure to CO_2 and heatwaves and the risk for diabetes: a multi-center spatial epidemiological study in China

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Abstract

Background Climate change, closely linked to the increasing CO_2 concentrations and heatwave events, may directly and indirectly affect the risk for diabetes, which has been a leading cause of disability worldwide. Using the baseline survey of a large multi-center cohort including 134,403 participants in China, this study for the first time examined the associations of CO_2 and heatwaves with the risks for diabetes/prediabetes at an individual level.

Methods The exposure to CO_2 and heatwaves was estimated at spatial resolutions of 10 km and 27 km, respectively. Multilevel logistic regression models with random intercepts at the community level were used to estimate the associations after adjusting for individual-level covariates. Subgroup and sensitivity analyses investigated the variations and robustness of the association, respectively, while mediation analysis estimated the mediation effect of body mass index (BMI) on the association.

Results Elevated fasting blood glucose levels were associated with higher CO_2 concentrations (β=0.09 [95% CI: 0.07, 0.12]) and increased heatwave frequency (β=0.22 [95% CI: 0.09, 0.35]), both of which were also associated with the increased risks for diabetes (CO_2: OR=1.14 [1.09, 1.19]; heatwaves: OR=1.48 [1.17, 1.89]). The association between CO_2 and diabetes was stronger among individuals with less than a high school education, those residing in rural areas, and those living in non-compact built environment. The association between heatwaves and diabetes was stronger among individuals consuming≥400 g/day of fruit and vegetable. Among those who experienced heatwaves, BMI mediated about 8.2% and 2.9% of the associations between CO_2 and diabetes and prediabetes, respectively; among those who did not experience heatwaves, BMI mediated about 11.5% of the association between CO_2 and prediabetes.

Conclusions Higher CO_2 concentrations and increased heatwave frequency were associated with a higher risk of diabetes in China, with BMI partially mediating CO_2-diabetes association among individuals who experienced heatwave events. This study would advance our understanding of the health effects of climate change and provide scientific evidence for climate change mitigation.

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Keywords Climate change · Carbon dioxide · Heatwave · Diabetes · Prediabetes · Body mass index

Background

Diabetes, a leading cause of disability worldwide and a well-known risk factor for cardiovascular diseases (CVDs), is a metabolic disorder that affects how the body turns food into energy and occurs when the body becomes resistant to insulin or does not make enough insulin. The prevalence of diabetes has been dramatically increasing over the past few decades, making it a pandemic of unprecedented magnitude [1]. As of 2021, about 1 in 10 (approximately 537 million) adults aged 20–79 worldwide lived with diabetes, which is expected to rise to 1 in 8 adults by 2024 [2]. Once diagnosed, diabetes can only be relieved by making permanent lifestyle changes rather than being cured, so preventing it in the early stage is vital, especially for those with prediabetes (having a higher blood sugar level than normal but not yet to be diagnosed as diabetes) who showed a high risk for cardiovascular events as those with diabetes [3]. The global prevalence of prediabetes was estimated to be about 9.1% in 2021 [4]. In addition to unhealthy lifestyles that could partially account for the increasing prevalences of diabetes and prediabetes (e.g., excessive calorie intake, smoking, high alcohol consumption, high sedentary and insufficient physical activity (PA) [5, 6]), some studies have revealed environmental risk factors of diabetes, mainly air pollutants including particulate matter less than 2.5 μm in diameter ($PM_{2.5}$), sulfur dioxide (SO_2), ozone (O_3), carbon monoxide (CO), and nitrogen dioxide (NO_2) [7–9]. However, although levels of those harmful air pollutants have been falling steadily in the past decade, the prevalence of diabetes remains and even is growing. Therefore, it is necessary to deepen the current investigation of environmental determinants of diabetes for its better control and prevention at a large scale.

Climate change, beyond air pollution and driven primarily by rising greenhouse gas concentrations, has been recognized as a more persistent risk factor of human health [10, 11]. Approximately 85% of the global population is suffering from the impacts of climate change [12]. As an important greenhouse gas that has warmed the planet, carbon dioxide (CO_2) is mainly produced from the extraction and burning of fossil fuels (e.g., coal, oil, and natural gas), wildfires, and natural processes (e.g., volcanic eruptions). According to the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Synthesis Report, the amount of CO_2 in the atmosphere has increased by more than 20% over the past four decades and is still increasing [13]. CO_2 could directly influence the risk for diabetes/prediabetes by directly affecting blood sugar, blood pH, and hormonal reactions, revealed in some early animal experiments [14–16], and by playing a potential role in developing obesity that may increase the risk for diabetes/prediabetes [17]. CO_2 could also affect the risk for diabetes/prediabetes through other pathways; for example, high concentrations of CO_2 could lower protein and micronutrient contents in plants, which may degrade diet quality [18]. Furthermore, such influences may vary by local climate zones that show urban climate, air quality, and temperature at local levels, which would affect intervention design and policy making for mitigating negative health impacts of the increasing CO_2 in different regions [19]. However, to the best of our knowledge, there has not been any epidemiological research on the effects of CO_2 on diabetes/prediabetes at an individual level.

In addition, as the concentration of CO_2 continues to rise, extreme heat events are becoming more frequent and severe. For example, heatwaves in 2019 have produced record temperatures and led to over 345,000 heat-related deaths globally [20]. A growing body of research has suggested that extreme heat exposure may elevate the risks for diabetes and associated comorbidities [21]. For example, some empirical and review studies reported that, on days during heatwaves, rates of diabetes-related hospital admissions and emergency department visits had both increased [22, 23]. Heat stress could induce dehydration, inflammation, and hormonal changes that may impair glucose control, and the heat-related effects on glucose metabolism have appeared particularly pronounced among older adults and other vulnerable groups [24, 25]. This may aggravate the influence of CO_2 on

the risk for diabetes. However, such combined influences, to the best knowledge of the authors, have not been investigated by any existing studies on the impact of heatwaves on diabetes-related outcomes.

Using the baseline survey of a large multi-center cohort including 134,403 participants in China, this study, for the first time, simultaneously examined the associations of atmospheric CO_2 and heatwaves with the risks for diabetes/prediabetes at an individual level. Subgroup analysis was conducted for investigating the variations of those associations, including geographic variations across local climate zones, and sensitivity analysis for assessing the robustness of the results. Also, mediation analysis was used to examine the mediation effect of body mass index on the CO_2–diabetes association, stratified by heatwaves. The findings would advance our understanding of health effects of climate change, provide scientific evidence for climate change mitigation, better estimate the disease burden of diabetes, and improve prevention strategies for diabetes and, more broadly, other chronic diseases.

Methods

Study design and data

This study utilized the baseline data of a multi-center cohort established in the eastern (Fujian Province), central (Hubei Province), and western (Yunnan Province) regions of China. A multi-stage cluster random sampling method, adopted by the Chinese Center for Disease Prevention and Control to carry out the national Chronic Disease and Risk Factor Surveillance [26], was used to recruit participants from the general population in the selected communities, which were chosen from each of the districts/counties in the three provinces. Participants were invited to participate in the surveys if meeting all following inclusion criteria: (1) being aged≥18 years on the day of the survey; (2) living in the selected communities for more than three years; and (3) not having severe cognitive, psychiatric, or physical conditions that could impair their ability to provide informed consent or complete the study procedures. As a result, the Fujian Behavior and Disease Surveillance (FBDS) cohort was established during 2018–2020, recruiting 54,961 adults aged>18 years from 29 districts/counties of the province; the Hubei Behavior and Disease Surveillance (HBDS) cohort was established during 2018–2020, recruiting 27,962 adults aged>18 years from 10 districts/counties of the province; and the Yunnan Behavior and Disease Surveillance Cohort (YBDS) was established from January to August 2021, recruiting 51,480 adults aged>18 years from 35 districts/counties of the province [27]. Individual sociodemographic and behavioral information was collected by a structured questionnaire in face-to-face interviews, and anthropometric measurements included height, weight, and blood pressure. Venous blood samples were obtained after fasting overnight (at least 8 h) for clinical laboratory tests (e.g., routine blood tests, fasting blood glucose, and lipid levels).

In this study, participants were excluded if having missing information on basic sociodemographic and behavioral characteristics, fasting blood glucose (FBG), or home addresses. The 36,958 in FBDS, 18,398 in HBDS, and 49,799 participants in YBDS were included, resulting in a final sample of 105,155 participants. The study received ethical approval from the ethical review board of the National Center for Chronic and Non-Communicable Disease Control and Prevention, the Fujian Center for Disease Prevention and Control (2018001), and the Yunnan Center for Disease Prevention and Control (202017). Written informed consent was obtained from all participants prior to data collection, and the study was conducted in accordance with the principles of the Helsinki Declaration.

Outcome variables

According to the diagnostic criteria established by the American Diabetes Association in 2022, diabetes was defined as an FBG≥7.0 mmol/L or having a self-reported clinical diagnosis of diabetes. Prediabetes was defined as an FBG≥5.6 mmol/L and <7.0 mmol/L. A normal level of FBG (<5.6 mmol/L) was also referred to as normoglycemia.

Exposure variables

CO_2 exposure was defined as the mean annual atmospheric CO_2 concentration (ppm) at a 10 km spatial resolution over each participant's residential location for the calendar year immediately preceding the baseline survey (i.e., the most recent complete year of data available prior to each participant's survey date). Similarly, heatwave exposure was defined as the mean annual frequency of heatwave events (times/year) at a 27 km spatial resolution over the same calendar year and location. Annual concentrations of CO_2 over the three provinces were estimated at a spatial resolution of 10 km, using a light gradient boosting machine (LightGBM) algorithm on the basis of the OCO-2 (Orbiting Carbon Observatory 2 satellite) Level 2 bias-corrected XCO_2 dataset, CarbonTracker model-predicted CO_2 concentration, and other satellite-derived variables, including elevation, population density, land use, normalized difference vegetation index (NDVI), and meteorological conditions [28]. The accuracy of the resulting CO_2 products was assessed by the 10-fold validation, leading to an R^2 of 0.95 and a Root Mean Square Error (RMSE) of 0.91 ppm. The frequency of heatwave events (times/year) occurring over one's residence was calculated as the exposure to heatwaves, where a heatwave event was defined as three or more consecutive extreme heat days. To define the extreme heat day, a universal thermal climate index (UTCI) was derived from the ERA5 reanalysis (5th generation of the European Centre for Medium-Range Weather Forecasts Reanalysis) dataset, which, with a spatial resolution of 27 km, combines air temperature, relative humidity, ventilation, and radiation to indicate the temperature perceived by human body. Following the established practices in heat-health epidemiology [29, 30], the 99th percentile of the maximum UTCI for each summer day (May to September) during 1987–2017 (called a baseline period) was calculated, and an extreme heat day was defined as having the maximum UTCI being ≥38°C and falling within the 99th percentile of the maximum UTCI during the baseline period over one's residence.

Mediator variable

Elevated CO_2 concentration and heat stress may contribute to weight gain and obesity, as indicated by increased body mass index (BMI), through mechanisms such as appetite dysregulation, disrupted energy balance, and impaired body temperature regulation [17, 31]. This is particularly concerning, as an elevated BMI is associated with an increased risk of developing diabetes [21, 32]. Therefore, BMI was chosen as the potential mediators that connect CO_2 and heatwaves to the development of prediabetes and diabetes. BMI was defined as weight (kg) divided by the square of height (m) in this study.

Covariates

According to the existing literature, the covariates that may affect the risk for diabetes were selected to adjust in the models, including sociodemographic, lifestyle, and environmental factors. The socio-demographic factors included age (in year), sex (male, female), ethnicity (Han, minorities), marital status (married, unmarried/divorced/widowed), educational level (illiteracy, primary/junior high school, high school or above), occupation (farmer/worker, other employment, unemployed), and urbanicity (rural, urban). Lifestyle factors included alcohol drinking (yes, no), smoking (yes, no), sleep duration (in hours/day), sedentary time (in minutes/day), physical activity (PA, in MET hours/week), and daily intakes of vegetables, meat, grain, and fruit (in g/day). Physical activity was assessed as the Metabolic Equivalent of Task (MET) hours per week, where the MET values for moderate PA and vigorous PA were considered 4 and 8, respectively [33, 34]. The environmental factors included the annual concentrations of $PM_{2.5}$, O_3, CO, NO_2, and SO_2 (the five common air pollutants associated with the risk for diabetes) prior to the survey, estimated at a spatial resolution of 1 km by a newly developed multi-output LightGBM model, which has demonstrated better accuracy than all existing products [35].

Statistical analysis

The categorical variables of the participants were described as frequency and percentage (%), and continuous variables as means and standard deviation (SD). Comparisons of the characteristics between the participants with and without diabetes were presented and tested for group differences using a one-way analysis of variance (ANOVA) or a Pearson's χ^2 test. To account for potential clustering effects among participants within the same geographic areas, multilevel logistic regression models (also known as generalized linear mixed-effects models) were applied. These models included a random intercept for each community to evaluate the associations between CO_2/heatwaves and the risks for diabetes and prediabetes. Results are presented as odds ratios (ORs) with 95% confidence intervals (CIs), after adjusting for covariates in different models. Also, multi-level logistic regression models incorporating restricted cubic spline functions were used to estimate the exposure-response relationship between CO_2 concentrations and prediabetes/diabetes risk, stratified by heatwave and non-heatwave groups. Sensitivity analyses were conducted to assess the robustness of the results by excluding individuals with a family history of diabetes, those with self-reported coronary heart disease or diagnosed diabetes, by using 2-, 3-, and 4-year exposure windows, and by additionally controlling for city-level regions to account for potential geographical confounding. In these exposure windows, the CO_2 concentration and heatwave frequency were defined as the mean concentration and frequency over the 2, 3, or 4 calendar years immediately preceding the survey, respectively. Multicollinearity among all covariates and exposure variables was assessed using variance inflation factors (VIFs) in the fully adjusted logistic regression models. All VIFs were below 2, indicating low collinearity (Additional file 1: TableS1).

Subgroup analyses were conducted by age (<60, ≥60 years), sex (male, female), ethnicity (Han, minorities), marital status (married, unmarried/divorced/widowed), educational level (below high school, high school and above), urbanicity (rural, urban), occupation (employed, unemployed), alcohol drinking (yes, no), smoking (yes, no), sleep duration (<7, ≥7 h/day), sedentary time (below median, median and above), physical activity (<10, ≥10 MET hours/week), and fruit/vegetable intake (<400, ≥400 g/day). The significance of the differences in the associations between subgroups was examined using a Z-test based on the fixed-effect estimates and their corresponding standard errors from the multilevel logistic models. Also, variations of the associations between CO_2/heatwaves and diabetes/prediabetes were examined in different local climate zones, which were classified based on the levels of urbanization, vegetation, and land cover [19], and then combined into compact (including compact high-rise, compact mid-rise, compact low-rise), open (including open high-rise, open mid-rise, open low-rise), large low-rise, sparsely built, and nature-oriented (including dense trees, scattered trees, bush/scrub, low plants, bare rock/paved, bare soil/sand, and water) arrangements.

The mediation analysis was conducted to examine the mediating effect of BMI on the association between CO_2 and diabetes/prediabetes in both heatwave and non-heatwave groups, by estimating the proportion of the indirect effect through BMI over the total effect of CO_2 on diabetes/prediabetes [36].

All statistical analyses were performed using R software, version 4.3.1, with the lme4, stats, rms, and mlma packages.

Results

Characteristics of the participants

The mean age of the 105,155 participants included in the analysis was 53.9 ± 13.8 years, with 56.8% (59,755) of them being female and 77.5% (81,536) being Hans (Table 1). The majority of them were married (89.1%), employed (72.3%), and lived in rural areas (76.6%). The 46.7% of them received primary or junior high school education, with only 14.4% receiving high school education and above. The prevalences of diabetes and prediabetes among them were 7.8% and 23.3%, respectively. The mean concentration of atmospheric CO_2 and mean

Table 1 Characteristics of the study participants

Variables	Number (%) or Mean ± SD				*p* value[a]
	All (*n* = 105,155)	Normoglycemia (*n* = 72,523)	Prediabetes (*n* = 24,473)	Diabetes (*n* = 8,159)	
Age (year)	53.9 ± 13.8	52.5 ± 14.0	56.1 ± 12.8	59.4 ± 11.6	< 0.001
Sex					< 0.001
Male	45,400 (43.2)	30,743 (42.4)	10,828 (44.2)	3,829 (46.9)	
Female	59,755 (56.8)	41,780 (57.6)	13,645 (55.8)	4,330 (53.1)	
Ethnicity					< 0.001
Han	81,536 (77.5)	54,716 (75.4)	20,119 (82.2)	6,701 (82.1)	
Minorities	23,619 (22.5)	17,807 (24.6)	4,354 (17.8)	1,458 (17.9)	
Marital status					0.200
Married	93,662 (89.1)	64,590 (89.1)	21,848 (89.3)	7,224 (88.5)	
Unmarried/divorced/widowed	11,493 (10.9)	7,933 (10.9)	2,625 (10.7)	935 (11.5)	
Educational level					< 0.001
Illiteracy	40,898 (38.9)	27,634 (38.1)	9,756 (39.9)	3,508 (43.0)	
Primary/junior high school	49,133 (46.7)	34,379 (47.4)	11,114 (45.4)	3,640 (44.6)	
High school/college and above	15,124 (14.4)	10,510 (14.5)	3,603 (14.7)	1,011 (12.4)	
Occupation					< 0.001
Farmer/worker	52,652 (50.1)	36,866 (50.8)	12,020 (49.1)	3,766 (46.2)	
Other employment	23,344 (22.2)	16,504 (22.8)	5,318 (21.7)	1,522 (18.7)	
Unemployed	29,159 (27.7)	19,153 (26.4)	7,135 (29.2)	2,871 (35.2)	
Urbanicity					< 0.001
Rural	80,548 (76.6)	55,845 (77.0)	18,856 (77.0)	5,847 (71.7)	
Urban	24,607 (23.4)	16,678 (23.0)	5,617 (23.0)	2,312 (28.3)	
Alcohol drinking					0.008
Yes	33,693 (32.0)	23,221 (32.0)	7,967 (32.6)	2,505 (30.7)	
No	71,462 (68.0)	49,302 (68.0)	16,506 (67.4)	5,654 (69.3)	
Smoking					< 0.001
Yes	31,242 (29.7)	21,678 (29.9)	7,046 (28.8)	2,518 (30.9)	
No	73,913 (70.3)	50,845 (70.1)	17,427 (71.2)	5,641 (69.1)	
Sleep duration (hours/day)	7.6 ± 1.7	7.6 ± 1.6	7.5 ± 1.7	7.5 ± 1.8	< 0.001
Sedentary time (minutes/day)	242.4 ± 153.3	243.3 ± 154.2	238.1 ± 150.5	246.6 ± 153.5	< 0.001
Physical activity (MET hours/week)	117.8 ± 151.0	123.3 ± 155.4	109.1 ± 142.6	94.6 ± 130.5	< 0.001
Diet (g/day)					
Vegetables	359.1 ± 295.8	351.2 ± 298.6	381.1 ± 288.0	364.2 ± 290.1	< 0.001
Meat	118.9 ± 172.3	124.2 ± 179.4	106.9 ± 149.4	107.6 ± 169.0	< 0.001
Grain	373.9 ± 344.1	380.0 ± 347.9	360.7 ± 352.5	359.0 ± 276.0	< 0.001
Fruit	96.0 ± 179.3	100.7 ± 194.5	87.3 ± 138.7	79.2 ± 140.3	< 0.001
Local climate zones					< 0.001
Compact arrangement	6,505 (6.2)	4,406 (6.1)	1,428 (5.8)	671 (8.2)	
Open arrangement	26,509 (25.2)	18,756 (25.9)	5,718 (23.4)	2,035 (24.9)	
Large low-rise arrangement	8,151 (7.8)	5,497 (7.6)	1,873 (7.7)	781 (9.6)	
Sparsely built arrangement	35,961 (34.2)	23,397 (32.3)	9,683 (39.6)	2,881 (35.3)	
Nature-oriented arrangement	28,029 (26.7)	20,467 (28.2)	5,771 (23.6)	1,791 (22.0)	
Environmental factors					
CO_2 (ppm)	412.3 ± 1.3	412.3 ± 1.2	412.4 ± 1.5	412.3 ± 1.4	< 0.001
Heatwaves (times/year)	0.1 ± 0.2	0.1 ± 0.2	0.1 ± 0.3	0.1 ± 0.3	
$PM_{2.5}$ (μg/m^3)	24.3 ± 7.1	24.4 ± 7.3	24.0 ± 6.5	24.3 ± 7.3	< 0.001
O_3 (μg/m^3)	92.7 ± 8.1	93.0 ± 8.2	91.7 ± 7.8	92.5 ± 8.3	< 0.001
CO (mg/m^3)	0.7 ± 0.1	0.7 ± 0.1	0.7 ± 0.1	0.7 ± 0.1	< 0.001
NO_2 (μg/m^3)	16.7 ± 5.5	16.7 ± 5.6	16.5 ± 5.1	16.8 ± 5.4	< 0.001
SO_2 (μg/m^3)	8.7 ± 1.6	8.6 ± 1.6	8.9 ± 1.5	8.8 ± 1.5	< 0.001
FBG (mmol/L)	5.5 ± 1.6	4.8 ± 0.5	6.1 ± 0.4	9.6 ± 3.1	< 0.001
BMI (kg/m^2)	24.0 ± 3.6	23.7 ± 3.5	24.6 ± 3.6	25.4 ± 3.7	< 0.001

[a]*p* values were calculated by the one-way analysis of variance (ANOVA) for continuous variables, and by the Pearson's χ^2 test for categorical variables. BMI, body mass index; FBG, fasting blood glucose; ppm, part per million; SD, standard deviation

frequency of heatwave events over the participants' residence were 412.3 ppm (ranging from 408.0 to 414.7) and 0.1 times/year (ranging from 0 to 1), respectively (Additional file 1: Fig. S1).

Associations of CO_2 and heatwaves with diabetes/prediabetes

In single-exposure models, after adjusting for all covariates, the FBG levels were positively associated with CO_2 concentration ($\beta = 0.08$ [95% CI: 0.06, 0.11]) (Fig. 1d). Each 1 ppm increase in CO_2 concentration was associated with a 12% increase in the risk for diabetes (OR = 1.12 [1.08, 1.17]) and a 19% increase in the risk for prediabetes (OR = 1.19 [1.13, 1.25]). Additionally, each additional heatwave event was associated with a 27% higher risk for diabetes (OR = 1.27 [1.00, 1.61]). The results from two-exposure models were consistent with those from the single-exposure models but showed stronger associations with FBG, diabetes, and prediabetes (Fig. 1e). Specifically, FBG levels were associated with both CO_2 ($\beta = 0.09$ [95% CI: 0.07, 0.12]) and heatwave frequency ($\beta = 0.22$ [95% CI: 0.09, 0.35]). Each 1 ppm increase in CO_2 was associated with a 14% increased risk of diabetes (OR = 1.14 [1.09, 1.19]) and a 20% increased risk of prediabetes (OR = 1.20 [1.14, 1.27]). For heatwaves, each additional event was associated with a 48% increase risk of diabetes (OR = 1.48 [1.17, 1.89]).

The nonlinear relationships between CO_2 concentration and diabetes/prediabetes risks were fitted under different scenarios of heatwave exposure (i.e., whether heatwave events were experienced)(Fig. 2). For individuals who did not experience heatwave events, the risks for both diabetes and prediabetes exhibited a U-shaped association with CO_2 concentrations. For example, the risk for diabetes initially decreased, reaching a nadir at approximately 411.0 ppm, and then began to increase significantly after surpassing the threshold of 413.0 ppm. A similar pattern was observed for prediabetes, where the ORs remain below 1.0 between 408.5 and 413.5 ppm, followed by a sharp upward trend as CO_2 concentrations continued to rise. In contrast, among individuals who experienced heatwave events, the risk for diabetes increased steadily with rising CO_2 concentrations. However, the risk for prediabetes exhibited a reverse U-shaped association with CO_2 concentrations: the risk peaked at approximately 412.0 ppm and then slightly declined, although the ORs remained consistently and significantly above 1.0.

Heterogeneities and robustness of the associations of CO_2 and heatwaves with diabetes/prediabetes

There were heterogeneities in the associations of CO_2 and heatwaves with diabetes/prediabetes among subgroups (Figs. 4 and 3). For example, the association between CO_2 and diabetes was stronger among individuals with an educational level below high school (OR = 1.15 [1.10, 1.21]) than among those with an educational level of high school or above (OR = 1.13 [1.05, 1.22]), and stronger among those residing in rural areas (OR = 1.16 [1.10, 1.23]) than those residing in urban areas (OR = 1.07 [0.99, 1.16]). Regarding heatwaves, the risk for diabetes was modified by fruit and vegetable intake ($p = 0.012$), with individuals consuming ≥ 400 g/day (OR = 1.78 [1.36, 2.34]) having a higher risk than those consuming < 400 g/day (OR = 1.43 [1.10, 1.86]). The association between heatwaves and prediabetes was stronger among those aged < 60 years (OR = 1.37 [1.01, 1.86]) than those aged ≥ 60 years (OR = 1.36 [1.04, 1.78]). Additionally, compared to the individuals living in built environments with compact arrangements, those living in nature-oriented environments exhibited stronger associations of CO_2 with diabetes (OR = 1.20 [1.08, 1.34]) and prediabetes (OR = 1.34 [1.18, 1.53]), as well as stronger associations of heatwaves with prediabetes (OR = 3.85 [1.72, 8.61]).

The associations of CO_2 and heatwaves with diabetes/prediabetes were robust after excluding those with family history of diabetes, those with self-reported coronary heart diseases, and those with self-reported diabetes (Fig. 5). The associations between CO_2 and diabetes/prediabetes were also robust after varying the exposure period to two (diabetes: OR = 1.09 [1.04, 1.14]; prediabetes: OR = 1.12 [1.07, 1.17]), three (diabetes: OR = 1.09 [1.04, 1.15]; prediabetes: OR = 1.14 [1.08, 1.20]), and four years (diabetes: OR = 1.10 [1.05, 1.16]; prediabetes: OR = 1.15 [1.10, 1.22]). The associations between CO_2 and diabetes/prediabetes also remained robust after additionally controlling for city-level regions (diabetes: OR = 1.15 [1.09, 1.20]; prediabetes: OR = 1.14 [1.08, 1.20]).

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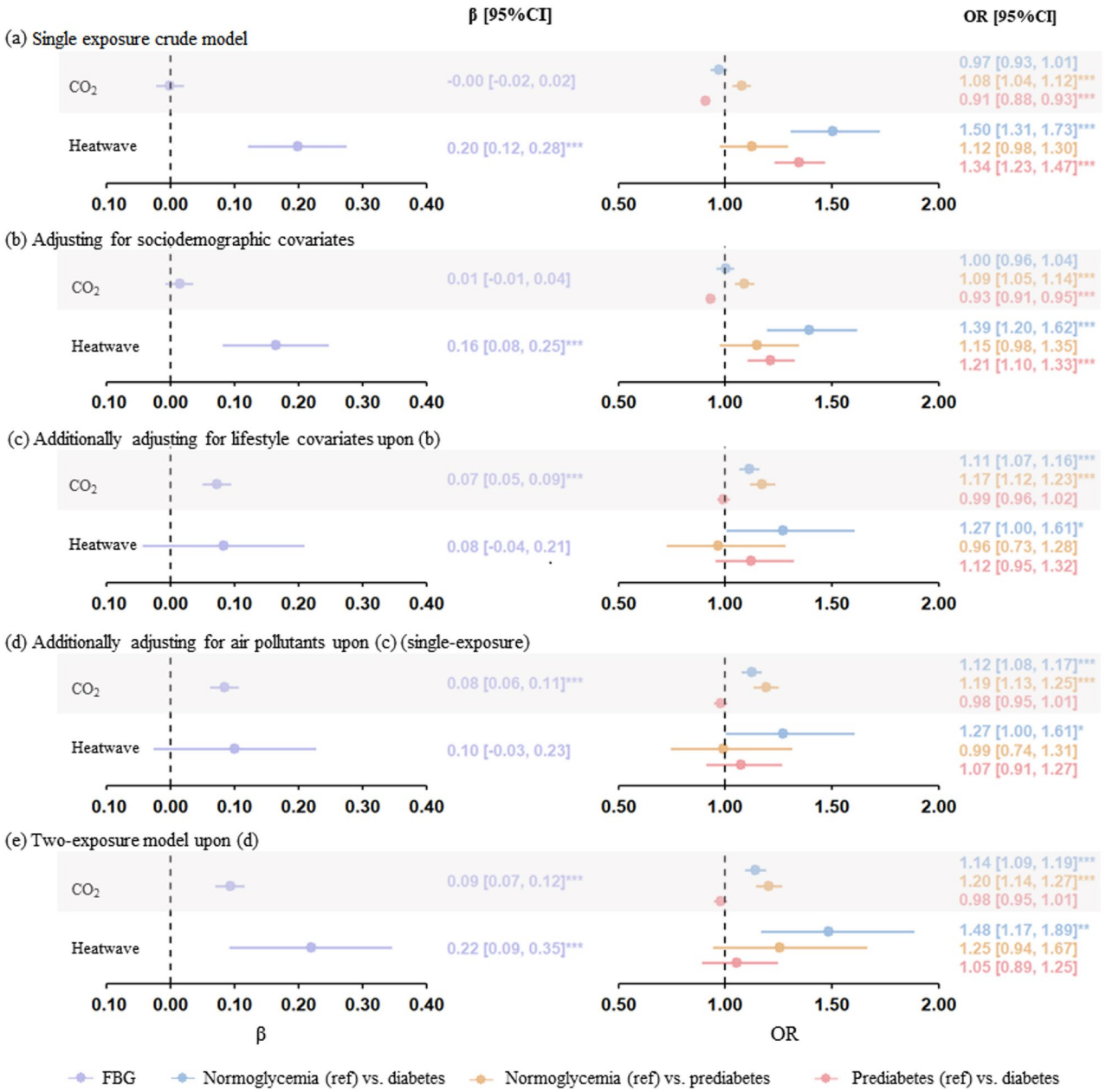


Fig. 1 Associations of CO_2 and heatwaves with the risks for diabetes/prediabetes. **a** Single-exposure crude models; (**b**) single-exposure models adjusting for age, sex, ethnicity, marital status, educational level, occupation, and urbanicity; (**c**) single-exposure models additionally adjusting for alcohol drinking, smoking, sleep duration, sedentary time, physical activity, and diet upon (**b**); (**d**) single-exposure models additionally adjusting for $PM_{2.5}$, O_3, CO, NO_2, and SO_2 upon (**c**); (**e**) two-exposure models adjusting for all covariates in (**d**). CI, confidence interval; FBG, fasting blood glucose; OR, odds ratio. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

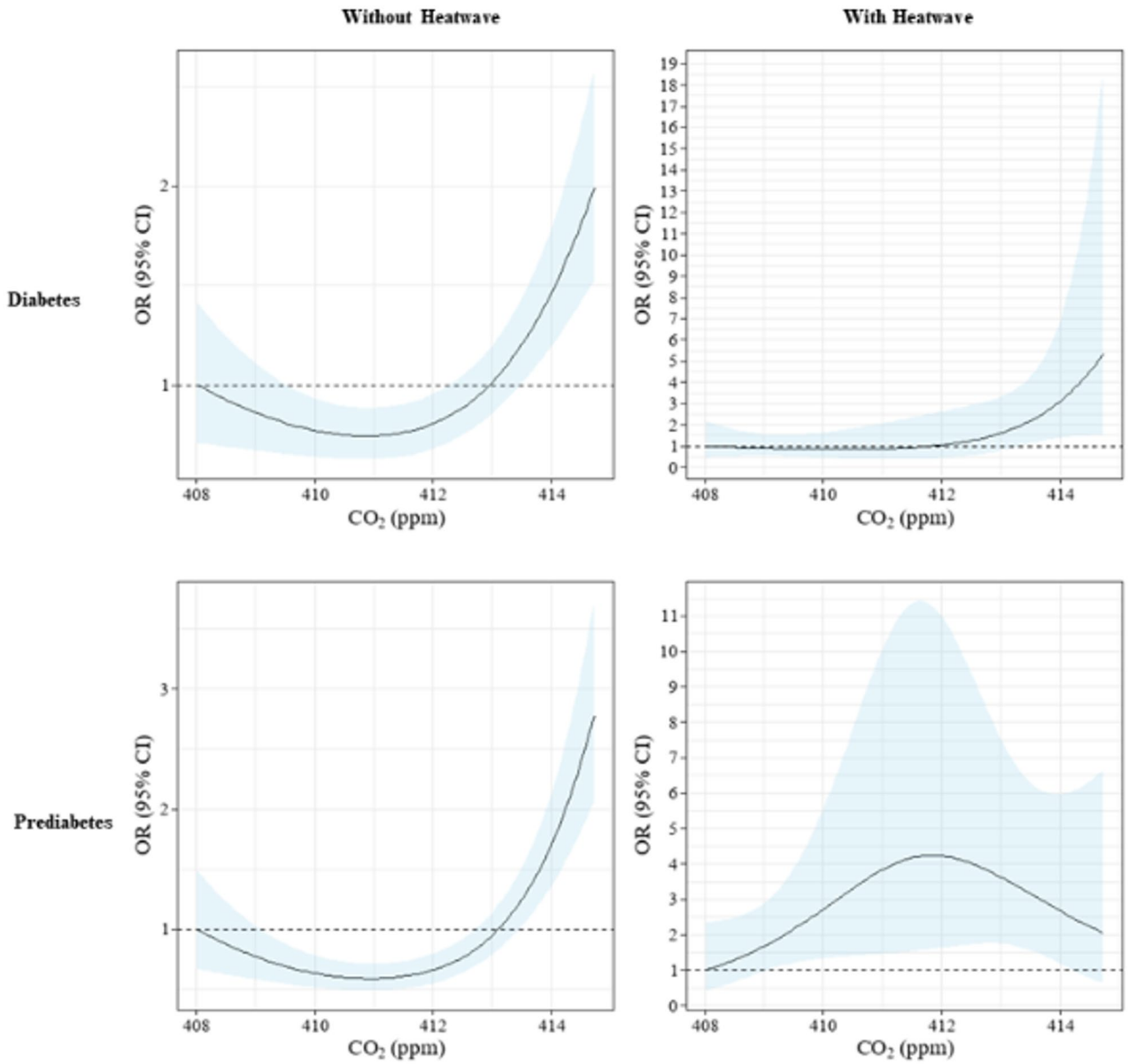


Fig. 2 Exposure-response curves of the associations between CO_2 and diabetes/prediabetes, stratified by heatwaves. Shadows indicate the 95% confidence intervals. OR, odds ratio

The associations between heatwaves and diabetes remained robust over a 4-year exposure period (OR = 1.18 [1.06, 1.30]) and additionally controlling for city-level regions (OR = 1.31 [1.03, 1.66]). The association between heatwaves and prediabetes remained robust over a 4-year exposure period (OR = 1.13 [1.02, 1.27]).

Mediation analyses

The mediation analyses revealed distinct patterns in the mediating role of BMI in the association between CO_2 and diabetes/prediabetes, stratified by heatwaves (Fig. 6). Among individuals who did not experience heatwave events, BMI mediated 11.5% [8.2%, 14.2%] of the association between CO_2 and prediabetes. Among those exposed to heatwave events, BMI mediated 8.2% [5.8%, 11.8%] of the association between CO_2 and diabetes, and 2.9% [1.9%, 4.1%] of the association between CO_2 and prediabetes.



Fig. 3 Associations between CO_2/heatwaves and prediabetes among subgroups. All models were two-exposure models adjusting for age, sex, ethnicity, marital status, educational level, occupation, urbanicity, alcohol drinking, smoking, sleep duration, sedentary time, physical activity, diet, $PM_{2.5}$, O_3, CO, NO_2, and SO_2. CI, confidence interval; MET, Metabolic Equivalent of Task; OR, odds ratio. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Discussion

This is the first individual-level, large-sample spatial epidemiological study to investigate the associations of climate change—measured by CO_2 concentration and the frequency of heatwave events—and the risks for diabetes and prediabetes. It was found that each 1 ppm increase in CO_2 concentration was associated with a 14% increase in diabetes risk and a 20% increase in prediabetes risk, while each additional heatwave event was linked to a 48%



Fig. 4 Associations between CO_2/heatwaves and diabetes among subgroups. All models were two-exposure models adjusting for age, sex, ethnicity, marital status, educational level, occupation, urbanicity, alcohol drinking, smoking, sleep duration, sedentary time, physical activity, diet, $PM_{2.5}$, O_3, CO, NO_2, and SO_2. CI, confidence interval; MET, Metabolic Equivalent of Task; OR, odds ratio. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

increase in the risk for diabetes. The association between CO_2 and diabetes was stronger among individuals with less than a high school education, those residing in rural areas, and those living in nature-oriented built environments. The heatwave-diabetes association was stronger among individuals consuming≥400 g/day of fruits and vegetables. Additionally, among those who experienced heatwave events, BMI played a mediating role in the associations between CO_2 and diabetes/prediabetes.

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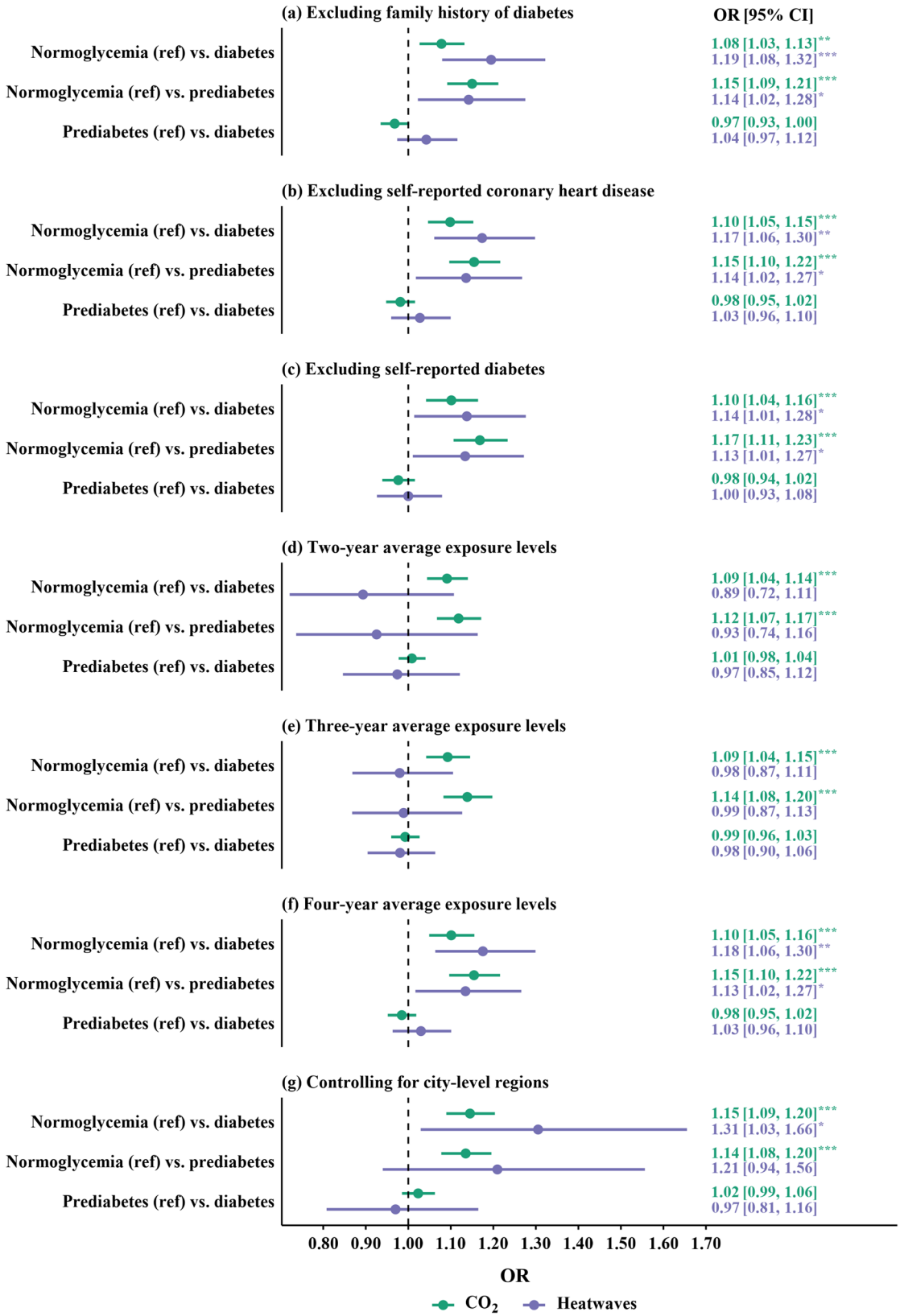


Fig. 5 Robustness of the associations between CO_2/heatwaves and diabetes/prediabetes after (**a**) excluding the family history of diabetes; (**b**) excluding self-reported coronary heart disease; (**c**) excluding self-reported diabetes; (**d**) assuming the 2-year average exposure levels of CO_2 and heatwaves; (**e**) assuming the 3-year average exposure levels of CO_2 and heatwaves; (**f**) assuming the 4-year average exposure levels of CO_2 and heatwaves; (**g**) additionally controlling for city-level regions. All models were two-exposure models adjusting for age, sex, ethnicity, marital status, educational level, occupation, urbanicity, alcohol drinking, smoking, sleep duration, sedentary time, physical activity, diet, $PM_{2.5}$, O_3, CO, NO_2, and SO_2. CI, confidence interval; OR, odds ratio. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

The positive association between CO_2 and diabetes found in this study echoed a recent review that concluded that the risk for non-communicable diseases may increase when exposed to climate change (under a rising level of CO_2) [37]. On one hand, the elevated level of atmospheric CO_2 may increase individuals' exposure through inhalation both outdoors and indoors, which could directly affect blood sugar, blood pH, hormonal reactions, and thus the risk for diabetes. On the other hand, lasting exposure to the high concentration of CO_2 may cause other adverse health outcomes, such as inflammation, kidney calcification, and physiological stress [37–39], which may be a predisposition to metabolic syndrome and further diabetes [40, 41]. The high concentration of CO_2 could also lower protein and micronutrient contents of plants, potentially degrading dietary quality and thereby influencing diabetes/prediabetes through diet-related pathways [18]. However, it should be noted that the extent to which locally elevated CO_2 leads to individual-level changes may be limited in areas where food is sourced from diverse geographic regions. Therefore, this pathway should be interpreted with caution. The potential links between certain aspects of climate change and diabetes have been discussed, such as extreme heat, extreme cold, and heatwaves [23, 42–44], although few individual-level epidemiological evidence existed. This study elucidated the associations of CO_2 and heatwaves with diabetes/prediabetes after teasing out the influences of individual-level covariates, emphasizing the importance of fighting the climate crisis from a public health perspective. This, together with the considerable contribution of CO_2 to the risk for diabetes, implies the necessity of enhancing resilience to climate change through policies that could not only address the vulnerability to global climate change, but also curb CO_2 emissions.

Heatwaves may affect individuals with diabetes by directly exacerbating acute health risks and contributing to long-term complications. For example, heatwaves could elevate hospitalization and mortality risks for diabetes by about 3% and 10%, respectively [45]. Heatwaves may worsen glycemic control through several mechanisms, including heat-related insulin instability, degradation of medications (e.g., reduced effectiveness of insulin pens when exposed to high temperatures), and metabolic dysregulation—particularly when dehydration could aggravate hyperglycemia and obscure symptoms of hypoglycemia [46]. Additionally, the elevated CO_2 concentration could increase the frequency and duration of heatwaves via greenhouse forcing, prolonging exposure to extreme temperatures that may further disrupt glucose homeostasis and impair insulin sensitivity [47].

The stronger association between heatwaves and diabetes observed among individuals with higher fruit and vegetable intake (≥400 g/day) may seem paradoxical, given the generally protective role of a high-quality diet against diabetes. One possible explanation is that individuals who consume more fruits and vegetables may spend more time engaged in outdoor activities such as gardening, farming, or food preparation, thereby increasing their exposure to heat during heatwave events [48, 49]. This behavioral pathway, rather than diet itself, may account for the observed effect modification. Notably, our study population was predominantly rural, where outdoor agricultural activities are common, which further supports this interpretation. These explanations remain speculative and warrant further investigation in future studies with more detailed data on outdoor exposure time and healthcare-seeking behavior.

The stronger associations of CO_2 and heatwaves with diabetes and prediabetes in the areas with a nature-oriented arrangement (e.g., rural areas) compared to areas with a compact arrangement may reflect multiple, non-mutuality exclusive pathways. One possibility is that residents in less compact, nature-oriented areas often rely more on personal vehicles for transportation, potentially increasing their exposure to traffic-related combustion products, for which CO_2 serves as a proxy. In this situation, it is important to emphasize that CO_2 is

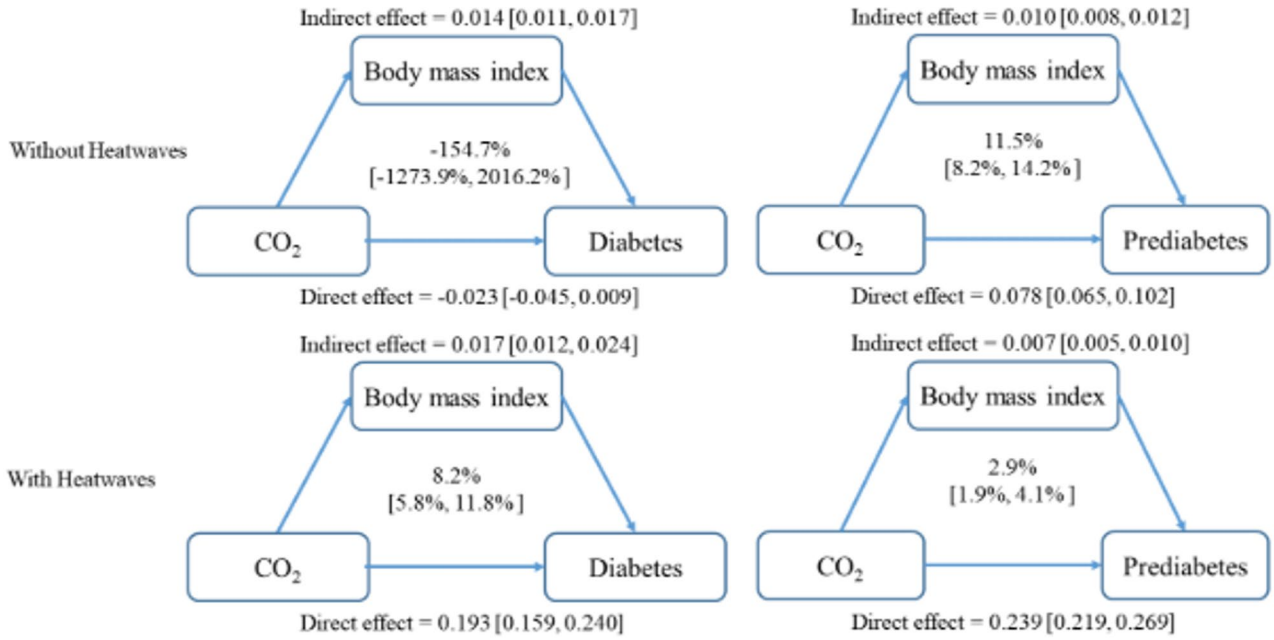


Fig. 6 Percentages mediated by body mass index in the associations between CO_2 and diabetes/prediabetes, stratified by heatwaves

not a conventional air pollutant but rather a marker of combustion sources. Another explanation is the "adaptation hypothesis", which suggests that individuals residing in an environment with better air quality may be less resistant to pollutants [50]. The areas with a nature-oriented arrangement typically feature dense vegetation (e.g., forests, scattered trees, bushes) or the proximity to natural water bodies, often with a lower level of CO_2 concentration, cooler temperatures, and better air quality compared to areas with a compact arrangement (usually in cities) [51]. Therefore, according to the hypothesis, each unit increase in CO_2 concentration and heatwave frequency may result in more adverse health impacts in areas with lower levels of CO_2 and heatwaves. Such varying impacts of CO_2 and heatwaves across local climate zones and sociodemographic subgroups underscore the importance of tailoring public health interventions to specific populations and areas.

Obesity has been considered a primary risk factor for diabetes [52]. Our study revealed that BMI partially mediated the CO_2-diabetes association under non-heatwave conditions, which was substantially attenuated under heatwave exposure. The increased CO_2 exposure through inhalation could decrease the pH of blood and transfer a signal to the hypothalamus, which could regulate appetite and wakefulness [53]. The nerve cells in the hypothalamus are extremely sensitive to pH, and their activities may double for every 0.1 decrease in pH [54]. The increased acidic load caused by the higher CO_2 concentration could potentially result in higher appetite and increased energy intake while reducing energy expenditure simultaneously, which could thus lead to obesity [17]. This points to the complex interplay between environments and behaviors, which suggests that efforts to mitigate health impacts of climate change should consider initiatives to promote healthy lifestyles, especially among populations at higher risk.

Several limitations in this study should be noted. First, it adopts a cross-sectional study design, which may have a limited capacity for establishing a causal relationship. However, this limitation may be compensated by the large number of participants and the robustness of the results. The future follow-ups of the cohort would further strengthen the evidence from this study by providing potentially stronger causality. Second, only outdoor concentrations of CO_2 were estimated. People may spend considerable time indoors in their residential neighborhoods, which may cause uncertainties when estimating the individual-level CO_2 exposure. However, the changing trends of indoor and outdoor CO_2 concentrations may be consistent in general [55, 56]. Future efforts

may utilize auxiliary data to capture more building-related attributes, such as occupant density and ventilation dynamics, to estimate CO_2 exposure in different scenarios [57, 58]. Third, because the satellite-derived data from the OCO-2 mission have only been available since 2015, the exposure window for CO_2 concentrations and heatwaves in this study was relatively short, which may not fully capture the long-term environmental influences relevant to the development of diabetes and prediabetes. Future longitudinal studies with longer-term exposure data are needed to better characterize the cumulative effects of CO_2 and heatwaves on diabetes risk. Fourth, the CO_2 product used in this study, although demonstrating good accuracy in the 10-fold validation, may not well match the high-quality health survey data of the participants due to the relatively coarse spatiotemporal resolution and the limited ground-truthing observations for validation purpose. However, the advanced methods of estimating air pollutants hold potential to generate CO_2 products with the higher spatiotemporal resolution [35]. Fifth, this study cannot entirely exclude the possibility that the observed associations between heatwaves and diabetes partly reflect a higher likelihood of incidental diabetes diagnoses among individuals who sought medical care for heat-related conditions, such as dehydration. Although our standardized, population-based survey approach and sensitivity analyses mitigate this concern, future prospective studies should investigate whether heat exposure influences the rates of new diabetes diagnoses through healthcare utilization pathways. Finally, the results may be affected by some unmeasured or unknown potential confounders, such as indoor exposure to air pollutants (e.g., solid fuel used for cooking), which should be better measured and considered in future efforts.

Conclusions

This study provides the first individual-level evidence that climate change—related exposures—specifically, ambient CO_2 concentration and heatwave frequency—are associated with risk for diabetes among adults in China. BMI partly mediated CO_2-diabetes association among individuals who exposed to heatwaves. Our findings suggest that climate change may exacerbate the diabetes epidemic, thus mitigating greenhouse gas emissions and reducing extreme heat exposure could curb the development of diabetes and yield significant public health co-benefits.

Abbreviations

ANOVA	Analysis of variance
BMI	Body mass index
CI	Confidence interval
CO	Carbon monoxide
CO_2	Carbon dioxide
CVD	Cardiovascular disease
FBDS	Fujian Behavior and Disease Surveillance
FBG	Fasting blood glucose
HBDS	Hubei Behavior and Disease Surveillance
IPCC	Intergovernmental Panel on Climate Change
LightGBM	Light gradient boosting machine
MET	Metabolic equivalent of task
NDVI	Normalized difference vegetation index
NO_2	Nitrogen dioxide
O_3	Ozone
OCO-2	Orbiting Carbon Observatory 2
OR	Odds ratio
PA	Physical activity

$PM_{2.5}$	Particulate matter less than 2.5 μm in diameter
RMSE	Root mean square error
SD	Standard deviation
SO_2	Sulfur dioxide
UTCI	Universal thermal climate index
VIF	Variance inflation factor
YBDS	Yunnan Behavior and Disease Surveillance Cohort

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Author contributions PJ conceived the study and secured the funding. LZ, XL, YS, and YYS prepared the data for the study. ML, LZ and YYS analyzed the data, drafted the manuscript and revised it. YYS, LZ, SHY, KQ, ZW, CL, BY, SD, SJY and CY substantially contributed to the manuscript by providing review comments and edits. All authors read and approved the final manuscript.

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Data availability The datasets from this study are held in coded form, and legal data sharing agreements prohibit the authors from making the dataset publicly available. Access to individual deidentified participant data (including data dictionaries) may be granted to those who send a reasonable request with specific data needs, analysis plans, and dissemination plans to Prof. Peng Jia (e-mail: jiapengff@hotmail.com). The authors will give feedback within 30 days. However, individual identification information may not be available for public use.

Declarations

Ethics approval and consent to participate The study received ethical approval from the ethical review board of the National Center for Chronic and Non-Communicable Disease Control and Prevention, the Fujian Center for Disease Prevention and Control (2018001), and the Yunnan Center for Disease Prevention and Control (202017). Written informed consent was obtained from all participants prior to data collection, and the study was conducted in accordance with the principles of the Helsinki Declaration

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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