Environment International 216 (2026) 110539

Contents lists available at ScienceDirect

Environment International

journal homepage: www.elsevier.com/locate/envint

Full length article

# Environmental exposures and mental health: longitudinal results from the German National Cohort (NAKO)

Yanding Wang [a,b,c,*], Susanne Breitner-Busch [a,b], Kathrin Wolf [a], Fiona Niedermayer [a,d], Nikolaos Nikolaou [a], Frank Padberg [e,f], Andrea Rachow [g,h,i], Fabian Bamberg [j], Stefanie Castell [k], Volker Harth [l], Antje Hebestreit [m], Michael Leitzmann [n], Wolfgang Lieb [o], Claudia Meinke-Franze [p], Dörthe Meyerdierks [k], Ilais Moreno Velásquez [q], Rajini Nagrani [m], Nadia Obi [l], Laura R. Pfrommer [r], Tobias Pischon [q,s,t], Christopher L. Schlett [j], Michael J. Stein [n], Stefan N. Willich [u], Thomas Keil [u], Rafael Mikolajczyk [v], Marie-Theres Huemer [a,1], Annette Peters [a,d,f,1]

[a] Institute of Epidemiology, Helmholtz Zentrum München, German Research Center for Environmental Health (GmbH), Ingolstädter Landstraße 1, 85764 Neuherberg, Germany
[b] Institute for Medical Information Processing, Biometry, and Epidemiology (IBE), Faculty of Medicine, LMU Munich, Pettenkofer School of Public Health, Munich, Germany
[c] Pettenkofer School of Public Health, Munich, Germany
[d] Chair of Epidemiology, Institute for Medical Information Processing, Biometry, and Epidemiology (IBE), Faculty of Medicine, Ludwig-Maximilians-University München, Munich, Germany
[e] Department of Psychiatry and Psychotherapy, LMU University Hospital Munich, Nussbaumstraße 7, Munich, Germany
[f] DZPG (German Center for Mental Health), Partner Site Munich-Augsburg, Munich, Germany
[g] Institute of Infectious Diseases and Tropical Medicine, LMU University Hospital, LMU Munich, Munich, Germany
[h] German Center for Infection Research (DZIF), Partner Site Munich, Munich, Germany
[i] Unit Global Health, Helmholtz Zentrum München, German Research Center for Environmental Health (HMGU), Neuherberg, Germany
[j] Department of Diagnostic and Interventional Radiology, Faculty of Medicine, University Medical Center Freiburg, University of Freiburg, Hugstetter Straße 55, Freiburg 79106, Germany
[k] Helmholtz Centre for Infection Research, Department of Epidemiology, Braunschweig, Germany
[l] Institute of Occupational and Maritime Medicine, University Medical Center Hamburg-Eppendorf, Hamburg, Germany
[m] Leibniz Institute for Prevention Research and Epidemiology - BIPS, Germany
[n] Dept. of Epidemiology and Preventive Medicine, University of Regensburg, Germany
[o] Institute of Epidemiology, Kiel University, Kiel, Germany
[p] Institute for Community Medicine, University Medicine Greifswald, Greifswald, Germany
[q] Max Delbrück Center for Molecular Medicine in the Helmholtz Association (MDC), Molecular Epidemiology Research Group, Berlin, Germany
[r] Institute for Medical Epidemiology, Biometry and Informatics (IMEBI), Interdisciplinary Centre for Health Sciences, Medical Faculty of the Martin Luther University Halle-Wittenberg, Halle (Saale), Germany
[s] Max Delbrück Center for Molecular Medicine in the Helmholtz Association (MDC), Biobank Technology Platform, Berlin, Germany
[t] Charité - Universitätsmedizin Berlin, Corporate Member of Freie Universität Berlin and Humboldt-Universität zu Berlin, Berlin, Germany
[u] Charité - Universitätsmedizin Berlin, Germany
[v] Institute for Medical Epidemiology, Biometrics and Informatics (IMEBI), Interdisciplinary Center for Health Sciences, Medical School of the Martin Luther University Halle-Wittenberg, Halle (Saale), Germany

A B S T R A C T

*Background:* Environmental exposures such as air pollution, population density, and climate-related stressors may influence mental health, yet large-scale longitudinal evidence is limited. This study examined associations of environmental exposures with depressive and anxiety symptoms, and stress in the German National Cohort (NAKO).

* Corresponding author at: Institute of Epidemiology, Helmholtz Zentrum München, German Research Center for Environmental Health (GmbH), Ingolstädter Landstraße 1, 85764 Neuherberg, Germany.
*E-mail address:* yanding.wang@helmholtz-munich.de (Y. Wang).

[1] Marie-Theres Huemer and Annette Peters contributed equally to this study.

https://doi.org/10.1016/j.envint.2026.110539
Received 11 March 2026; Received in revised form 18 September 2026; Accepted 22 September 2026
Available online 27 September 2026
0160-4120/© 2026 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).
Open access funding enabled and organized by Projekt DEAL.

*Methods:* We analyzed data of over 70,000 adults aged 19–74 years from the NAKO baseline (2014–2019), with repeated survey assessments in 2020 and 2022 of depressive symptoms (Patient Health Questionnaire-9), anxiety symptoms (Generalized Anxiety Disorder 7-item), and stress (Patient Health Questionnaire-stress) scores. The annual mean of environmental exposures, including nitrogen dioxide ($NO_2$), particulate matter (PM), black carbon, air temperature, precipitation, relative humidity, greenness (Normalized Difference Vegetation Index), and indicators of the built and social environment were assessed at the participants' residences at baseline and standardized with their interquartile range (IQR). Longitudinal associations of exposures with mental health outcomes were assessed using covariate-adjusted linear mixed models. Subgroup analyses were conducted stratifying by urbanization level, obesity, lung disease, and cardiovascular disease status.
*Findings:* Higher mean air temperature (per IQR) was associated with higher depressive symptom scores ($\beta = 0.07$, 95% CI: 0.03–0.12), anxiety symptom scores ($\beta = 0.05$, 95% CI: 0.01–0.09), and stress scores ($\beta = 0.05$, 95% CI: 0.01–0.09). Exposure to $NO_2$ was associated with higher depressive symptom scores ($\beta = 0.08$, 95% CI: 0.03–0.14). A higher population density within 100 m was associated with higher depressive, anxiety symptoms, and stress scores. In contrast, higher levels of greenness, precipitation, and relative humidity were associated with lower depressive symptom scores. Most of the associations with depressive or anxiety symptom scores were stronger in females, younger adults, people with obesity and those living in cities.
*Interpretation:* Improving air quality, enhancing urban green spaces, and implementing climate-adaptation strategies could help promote mental well-being, particularly in urban and vulnerable populations.

## Introduction

Mental health disorders, specifically depression and anxiety as well as related psychological conditions such as stress, are among the leading causes of global disability and disease burden, affecting hundreds of millions of people annually (GBD 2019 Mental Disorders Collaborators, 2022). These conditions are associated with elevated risks of chronic physical illnesses, premature mortality, and reduced quality of life (Zheng et al., 2020). Beyond psychological and socioeconomic determinants, environmental factors are increasingly recognized as significant contributors to mental health (Radua et al., 2024). Air pollution, particularly fine particulate matter ($PM_{2.5}$) and nitrogen dioxide ($NO_2$), have been consistently linked to an elevated risk of depression (Borroni et al., 2022). Additionally, meteorological exposures such as unfavorable ambient temperature and low humidity, as well as urban environmental stressors including lack of greenness and social deprivation, have been connected to mental distress (Chen et al., 2024; Terraneo 2021; Wahid et al., 2023). A cross-sectional study with UK Biobank data reported a 4% reduction in the odds of major depressive disorder per interquartile increase in residential greenness (Sarkar et al., 2018). Moreover, a recent nationwide population-based cross-sectional study from Nepal observed that long-term exposure to increased $PM_{2.5}$ and $PM_{10}$ concentrations was associated with elevated risk of depression and anxiety, while humidity showed a protective effect (Acharya et al., 2025).

However, prior studies have relied on cross-sectional designs, focused on only few environmental exposures, while large-scale longitudinal assessments are sparse. A difference-in-difference analysis of over 20,000 Chinese adults suggested that while higher air pollution levels and temperature variability were linked to deteriorating self-assessed mental health scores, mean temperature showed a weak and nonlinear association (Xue et al., 2019). The study further observed that lower residential greenness was associated with poorer mental health (Xue et al., 2019). Similarly, a nationally representative longitudinal study from Bangladesh observed an association between higher mean temperature and increased risk of anxiety, whereas no clear association was observed for depression alone (Wahid et al., 2023).

The burden of environmental risks is expected to increase further, especially amid accelerating climate change and extending urbanization, emphasizing the urgent need for large-scale, longitudinal studies that identify key environmental risk and protective factors of adverse mental health changes to guide targeted and effective prevention strategies. We therefore assessed data from over 70,000 participants of the prospective population-based German National Cohort (NAKO) to investigate the associations of long-term exposure to environmental factors—including air pollutants, meteorological variables, and built and social environment—with depressive symptoms, anxiety symptoms, and stress scores over three time points (baseline (2014–2019), 2020, and 2022). We further explored differential vulnerability in key subpopulations, including individuals with chronic diseases and those living in urban vs rural areas. To our knowledge, this is the first comprehensive, longitudinal assessment of multi-domain environmental exposures with mental health conducted in Germany, offering critical insights to inform mental health prevention strategies and environmental planning in a crucial phase of environmental change.

## 1. Methods

### 1.1. Study design and population

We analyzed data from participants enrolled in the German National Cohort (NAKO), a large-scale, population-based prospective cohort study initiated in 2014 (Peters et al., 2022). 205,415 participants aged 19–74 years were recruited at baseline in 2014–2019 from 16 study regions across Germany. In 2020, 160,227 individuals additionally completed a pandemic-related questionnaire via email or letter. In 2022, 110,375 individuals further completed an online survey including questionnaires on mental health (Mikolajczyk et al., 2024). For this study, we included more than 70,000 individuals who completed all mental health questionnaires across the baseline examination and the two follow-up questionnaires (baseline, 2020, and 2022), allowing for longitudinal linkage. The participant exclusions are illustrated in the Supplementary Fig. 1.

### 1.2. Mental health outcomes

Self-report mental health questionnaires were assessed at three time points (baseline, 2020, and 2022) using validated instruments. The depressive symptom score was measured using the Patient Health Questionnaire-9 (PHQ-9, range from 0 to 27), anxiety symptom score using the Generalized Anxiety Disorder 7-item (GAD-7, range from 0 to 21), and psychological stress score using the Patient Health Questionnaire-stress (PHQ-Stress, range from 0 to 20), in the Supplementary Methods.

### 1.3. Environmental exposure assessment

The environmental and social-built factors assessed in this study were obtained from a validated German spatiotemporal dataset, which assessed long-term exposure in different environments in the respective baseline year (2014–2019) of each participant. Environmental exposures were assigned to each NAKO participant based on their residential address in the participant's enrolment year and standardized using their interquartile ranges (IQR) to enable comparability across metrics. In the analysis, the baseline environmental exposures covered two environmental domains: (1) air pollutants and meteorological factors, and (2) social and built environmental factors. Data on ambient air pollution ($PM_{10}$, $PM_{2.5}$ and $NO_2$) was obtained from the German Environment Agency as gridded products based on chemical transport modelling with observational data assimilation (Nordmann et al., 2020). Black carbon

estimates from the ELAPSE project provided 2010 annual concentrations across Western Europe, derived using land-use regression models that integrated ground monitoring, satellite data, chemical transport models, and spatial predictors to produce country-wide maps at 100 m resolution. Greenness exposure was quantified using the Normalized Difference Vegetation Index (NDVI), derived from Sentinel-2 satellite imagery (DLR product) (Weigand et al., 2020). NDVI exposures were mainly assigned using 300 m and 1000 m residential buffers, reflecting different neighbourhood scales and corresponding to established walking-distance (Zare Sakhvidi et al., 2025). Meteorological variables covered air temperature (annual mean, standard deviation (SD), maximum, minimum, range, and seasonal temperature), precipitation, relative humidity, the number of frost days, and the number of heat days. The variables of social and built environment included imperviousness, NDVI within 300 m, 1000 m, and during the warm months (March to October), number of persons and buildings (in a 100 $m^2$ and 1000 $m^2$ grid cell), and the German index of socioeconomic deprivation (GISD index). The details for all environmental variables are listed in Supplementary Table 1.

### 1.4. Covariates

Covariates were derived from questionnaires on a touchscreen or during face-to-face interviews at baseline. Sociodemographic and socioeconomic characteristics included age, sex, education, marital status, net household income (in Euros/month), employment status, migration background, living alone, and the NAKO study region. Lifestyle factors included smoking status (never, former, current), alcohol consumption (g/day), and physical activity (min/week). Body mass index (BMI, kg/$m^2$) was additionally included as a covariate. Higher education included individuals with a university degree, a degree from a university of applied sciences, or a doctorate. Physical activity (minutes/week) was assessed by the Global Physical Activity Questionnaire (GPAQ) (Gottschalk et al., 2025). Urbanization levels were defined based on residential location and classified into cities, towns and suburbs, and rural areas (Supplementary Table 1). Further details on covariates and subgroup variables are available in the Supplementary Methods.

### 1.5. Statistical analyses

We applied a complete-case analysis approach for all primary analyses by excluding all participants with missing values for any outcome, exposure, and covariate at any of the three time points. Descriptive analyses were conducted to summarize baseline characteristics and exposure distributions. Based on normal distribution tests, continuous variables were reported as medians with interquartile range (IQR), and categorical variables as frequencies and percentages. To determine associations of environmental exposures with mental health across repeated assessments, we used linear mixed-effects (LME) models with random intercepts for individuals and fixed effect for time point and environmental exposures. Exposure pairs were concurrently entered into two-exposure models based on their single-exposure significance and the absence of high multicollinearity (Spearman $|r| < 0.7$; details in Supplementary Methods).

Three sequential models were fitted: The minimum model (model 1) adjusted for age and sex, the basic model (model 2) added socioeconomic covariates, and the main model (model 3) further adjusted for lifestyle factors and BMI. First, each exposure was modeled individually with its IQR-standardized values. Second, to explore whether the associations were sensitive to co-exposures, we constructed two-exposure models (Supplementary Methods). Subgroup analyses were conducted using the main adjusted (model 3) single-exposure model. Participants were stratified based on sex (female and male), age group (age <50 years and ≥50 years), urbanization level (cities vs. towns and suburbs vs. rural areas), presence of obesity, lung disease, and history of cardiovascular disease. In the sensitivity analysis, first, Generalized Additive Mixed Models (GAMMs) were employed to analyze potential nonlinear relationships between each environmental exposure and the three mental health scores. Second, we assessed alternate zones (e.g., 1000 m) of exposures, where available, seasonality of the temperature, and one-year lag effects of environmental exposures and meteorological measures (heat and frost days) using data from alternative sources, including the German Weather Service (DWD) (Supplementary Table 1) to test the main results for robustness. Third, false discovery rate (FDR) adjusted p-values were calculated for single-exposure models to confirm robustness against multiple testing in the main model. Fourth, we conducted linear regression models (with Model 3) for each time point of mental health assessment (baseline, 2020, 2022) individually to assess the influence of the data collection time point. Fifth, to assess the robustness of our findings with regard to multicollinearity and Type I error inflation in high-dimensional exposure settings, we implemented a two-step data-driven framework for each outcome measure. Specifically, we first applied Elastic Net regression for hyperparameter tuning to the baseline data to perform feature selection; subsequently, we conducted analyses using a longitudinal linear mixed model with multiple exposures, adjusted for each exposure factor and corrected for the Benjamini-Hochberg FDR. To verify the robustness of the study results with regard to spatial clustering effects, we constructed a multi-level random-effects sensitivity model. We introduced a random intercept for the 16 study regions to analyze the longitudinal effects of single-exposure pollutants on mental health. All analyses were conducted using R (V4.1.3). A two-tailed p-value $< 0.05$ indicated statistical significance.

## 2. Results

A total of 72,227 individuals were included in the analysis for the depressive symptom score, 72,909 for the anxiety symptom score, and 68,678 for the stress score. Mental health outcomes changed across the three time points (Table 1). The mean of the depressive symptom scores gradually increased from baseline to 2022, whereas anxiety and stress scores increased markedly until 2020 and then slightly decreased to 2022, while remaining higher than baseline. The distributional characteristics of environmental exposures are summarized in Supplementary Table 2. The correlation coefficients between environmental exposures are shown in the Supplementary Figs. 2-4.

In the baseline survey, sex was evenly distributed across the three outcome samples, with women comprising around 50%. The median age was also similar across outcome-specific samples: 50 years (IQR 42–58) for the depressive symptom score, 50 years (IQR 42–59) for the anxiety symptom score, and 49 years (IQR 42–58) for the stress score.

More than half of the participants had a university degree or higher education and were employed in a full-time job. Most participants were married and living together with their partner, representing approximately 60%, while around 27% were single, as shown in Table 2.

### Single exposure models

We observed several associations of environmental exposures (per

**Table 1**
Mental health changes over three time points.

| Mental Health (mean ± SD) | Baseline | 2020 | 2022 | P-value[a] |
|---|---|---|---|---|
| Depressive symptom score | 3.59 ± 3.38 | 3.96 ± 3.81 | 4.06 ± 4.03 | <0.001 |
| Anxiety symptom score | 2.95 ± 2.96 | 3.32 ± 3.38 | 3.27 ± 3.52 | <0.001 |
| Stress score | 3.29 ± 2.84 | 4.44 ± 3.43 | 4.25 ± 3.61 | <0.001 |

[a] P-value was calculated using repeated measures ANOVA to compare the mental health scores across the three time points.

**Table 2**
Characteristics of the study population with available data for symptom scores of depressive symptom, anxiety symptom, and stress score at baseline.

| Characteristic[a] | Level or unit | Depressive symptom score (N = 72,227) (median [IQR])/N (%) | Anxiety symptom score (N = 72,909) (median [IQR])/N (%) | Stress score (N = 68,678) (median [IQR])/N (%) |
|---|---|---|---|---|
| Age | Years | 50 [42, 58] | 50 [42, 59] | 49 [42, 58] |
| Sex | Male | 35,778 (49.5) | 36,162 (49.6) | 34,568 (50.3) |
| | Female | 36,449 (50.5) | 36,747 (50.4) | 34,110 (49.7) |
| Marital status | Single | 19,619 (27.2) | 19,646 (26.9) | 18,707 (27.2) |
| | Married, living together | 43,250 (59.9) | 43,745 (60.0) | 41,544 (60.5) |
| | Divorced/ widowed/ separated | 9,358 (13.0) | 9,518 (13.1) | 8,427 (12.3) |
| Living alone | No | 59,186 (81.9) | 59,753 (82.0) | 56,932 (82.9) |
| | Yes | 13,041 (18.1) | 13,156 (18.0) | 11,746 (17.1) |
| Net household income | Euro/month | 2,267 [1,633, 2,935] | 2,262 [1,633, 2,935] | 2,267 [1,633, 3,050] |
| Education | Higher | 45,277 (62.7) | 45,699 (62.7) | 43,296 (63.0) |
| | Lower | 26,950 (37.3) | 27,210 (37.3) | 25,382 (37.0) |
| Employment status | Employed full-time | 41,222 (57.1) | 41,524 (57.0) | 39,930 (58.1) |
| | Employed part-time | 18,910 (26.2) | 19,050 (26.1) | 18,086 (26.3) |
| | Unemployed | 1,247 (1.7) | 1,272 (1.7) | 1,152 (1.7) |
| | Non-working population | 10,848 (15.0) | 11,063 (15.2) | 9,510 (13.8) |
| Physical activity | Minutes/week | 690 [300, 1,610] | 690 [300, 1,620] | 680 [300, 1,600] |
| Smoking | Non-smoker | 35,881 (49.7) | 36,209 (49.7) | 34,177 (49.8) |
| | Former smoker | 24,172 (33.5) | 24,416 (33.5) | 22,882 (33.3) |
| | Current smoker | 12,174 (16.9) | 12,284 (16.8) | 11,619 (16.9) |
| Alcohol amount | g/day | 5.20 [1.68, 13.79] | 5.20 [1.68, 13.85] | 5.24 [1.73, 13.87] |
| BMI | $kg/m^2$ | 25.4 [22.8, 28.5] | 25.4 [22.9, 28.6] | 25.4 [22.8, 28.5] |
| Obesity | No | 59,422 (82.3) | 59,948 (82.2) | 56,625 (82.4) |
| | Yes | 12,805 (17.7) | 12,961 (17.8) | 12,053 (17.6) |
| CVD | No | 50,187 (69.5) | 50,586 (69.4) | 48,171 (70.1) |
| | Yes | 22,040 (30.5) | 22,323 (30.6) | 20,507 (29.9) |
| Lung disease | No | 64,199 (88.9) | 64,818 (88.9) | 61,127 (89.0) |
| | Yes | 8,028 (11.1) | 8,091 (11.1) | 7,551 (11.0) |
| Urbanization | Cities | 52,805 (73.1) | 53,258 (73.0) | 50,102 (73.0) |
| | Towns and suburbs | 11,675 (16.2) | 11,822 (16.2) | 11,114 (16.2) |
| | Rural areas | 7,747 (10.7) | 7,829 (10.7) | 7,462 (10.9) |

[a] Continuous variables are shown as median (IQR), and categorical variables as counts (N) and percentages. Abbreviations: BMI = body mass index, CVD = cardiovascular disease, IQR = interquartile range.

IQR) with mental health scores for depressive symptoms, anxiety symptoms, and stress in the main model (Fig. 1).

Among air pollutants, each IQR increase in $NO_2$ exposure was associated with a 0.08-point higher depressive symptom score (95% CI: 0.03, 0.14). Higher mean air temperature (β = 0.07, 95% CI: 0.03, 0.12), maximum temperature (β = 0.06, 95% CI: 0.02, 0.10), and minimum temperature (β = 0.06, 95% CI: 0.01, 0.11) were further associated with higher depressive symptom scores; as were higher annual SD of air temperature (β = 0.07, 95% CI: 0.04, 0.11), higher annual SD of air temperature range (mean: β = 0.04, 95% CI: 0.01, 0.07), and number of heat days (max > 30 °C) (β = 0.04, 95% CI: 0.01, 0.08) (Fig. 1A, Supplementary Excel Files 1–3). Additionally, population density within a 100 m grid (β = 0.06, 95% CI: 0.03, 0.09) was positively associated with higher depressive symptom scores. In contrast, an IQR increase in NDVI during warm months (β = -0.05, 95% CI: −0.08, −0.01) was associated with a 0.05-point lower depressive symptom score. Similarly, IQR increases in annual sum of monthly precipitation (β = -0.07, 95% CI: −0.12, −0.02) and relative humidity (β = -0.07, 95% CI: −0.11, −0.04) also showed an inverse association with depressive symptom scores.

For anxiety symptom scores (Fig. 1B), we observed similar, though fewer, statistically significant associations with environmental exposures. Higher mean temperature (β = 0.05, 95% CI: 0.01, 0.09) and annual SD of temperature (β = 0.05, 95% CI: 0.02, 0.08) were positively associated with anxiety symptoms. Increased population density within 100 m (β = 0.04, 95% CI: 0.01, 0.06) was also associated with higher anxiety symptom scores. In contrast, an IQR increase in relative humidity (β = -0.04, 95% CI: −0.07, −0.01) was linked with lower anxiety symptom scores.

Regarding stress scores (Fig. 1C), results were consistent with those for depressive and anxiety symptoms, though fewer associations reached statistical significance. At the nominal significance level, the mean (β = 0.05, 95% CI: 0.01, 0.09), minimum temperature (β = 0.05, 95% CI: 0.001, 0.09) and population density within 100 m (β = 0.04, 95% CI: 0.02, 0.07) were positively associated with stress scores, while higher precipitation (β = -0.04, 95% CI: −0.09, upper CI slightly below zero) was inversely associated. After FDR correction, only the positive association with population density within 100 m remained statistically significant.

### *Subgroup analyses*

The longitudinal impact of $NO_2$ on depression was highly robust and consistent across both males (β = 0.10, 95% CI: 0.04, 0.16) and females (β = 0.09, 95% CI: 0.03, 0.15). However, females displayed broader vulnerability to meteorological variations (precipitation: β = -0.08 and temperature: β = 0.08) for anxiety scores, whereas the adverse effect of $NO_2$ on stress was manifest in males (β = 0.08, 95% CI: 0.03, 0.13), see Fig. 2. Regarding age, environmental hazards (such as $NO_2$ and black carbon) exhibited robust at the nominal significance level, detrimental longitudinal impacts on depression and anxiety scores predominantly among younger participants (<50 years), while these associations were largely attenuated in the elder (Fig. 3).

The association between air temperature and mental health remained robust only in individuals living in cities for depression symptom scores (SD air temperature β = 0.07, 95% CI: 0.03, 0.11) and anxiety symptom scores (SD air temperature β = 0.06, 95% CI: 0.02, 0.09), see Supplementary Fig. 5–7. We also found a significant inverse association of relative humidity with depressive symptom score in cities.

In the CVD and lung disease subgroup analyses, associations among individuals without CVD or lung disease were largely consistent with the main findings, with mean air temperature, relative humidity and population density still being significantly associated with depressive and anxiety symptom scores (Supplementary Figs. 5-6). Nominal associations were observed between $NO_2$ and both depressive (β = 0.11, 95% CI: 0.004, 0.22) and anxiety (β = 0.10, 95% CI: 0.01, 0.20) symptom scores in persons with CVD. Among participants with obesity, several

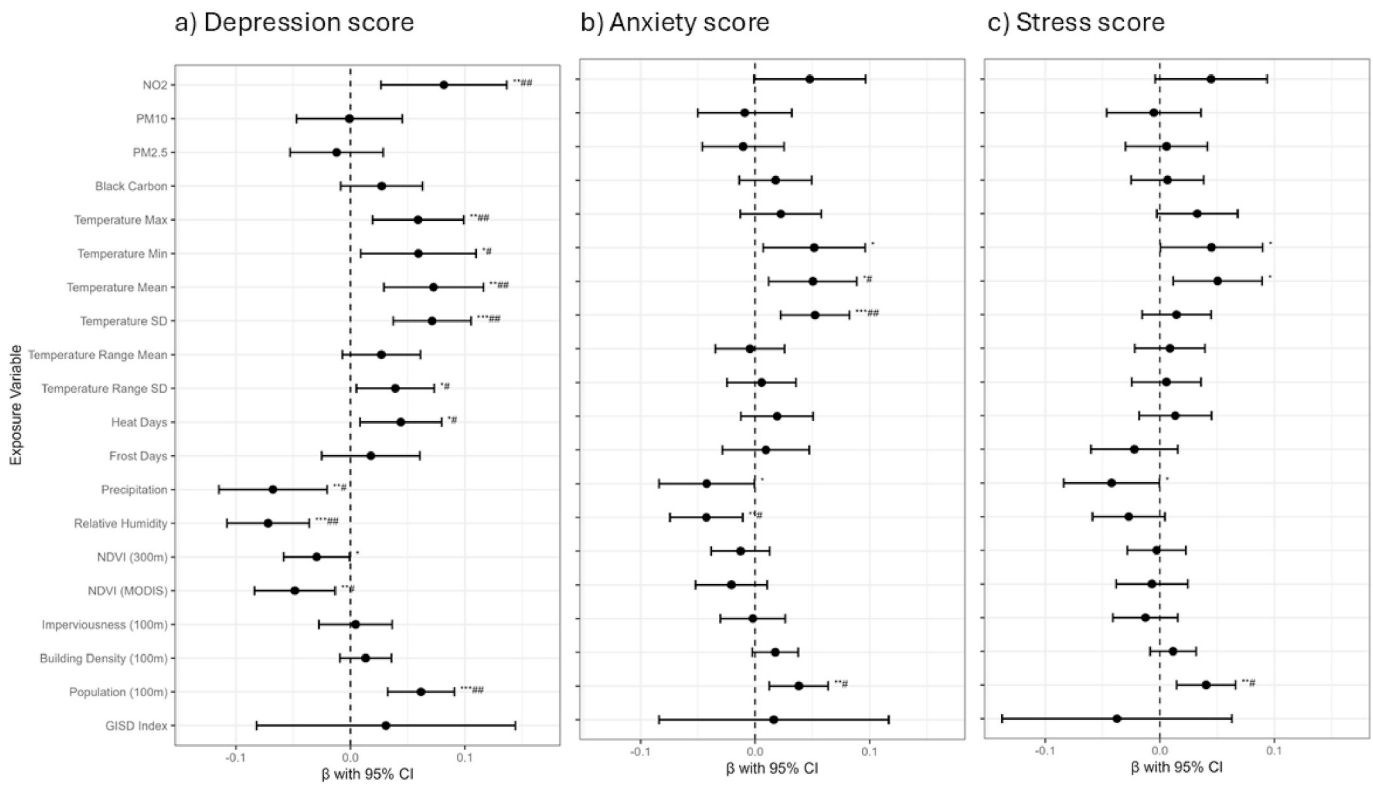


**Fig. 1.** Associations between environmental exposures and (a) depressive symptoms, (b) anxiety symptoms and (c) stress scores based on linear mixed-effects models. Effect estimates (β) and 95% confidence intervals (CI) are shown for each exposure in the adjusted single-exposure model 3. All exposures were standardized by interquartile range (IQR) to enable comparability across variables. Nominal significance is indicated by asterisks: $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***). Hash symbols indicate statistical significance after Benjamini–Hochberg false discovery rate (FDR) correction: FDR-adjusted $p < 0.05$ (#), FDR-adjusted $p < 0.01$ (##), and FDR-adjusted $p < 0.001$ (###). Model 3 was adjusted for sex, age, marital status, income, migration background, living alone, employment status, education, study region, weekly physical activity, alcohol consumption, smoking status, and body mass index (BMI). Abbreviations: CI = confidence interval; GISD = German index of socioeconomic deprivation; NDVI (MODIS) = normalized difference vegetation index during the warm months (March to October); SD = standard deviation.

strengthened associations emerged. $NO_2$, and NDVI in warm months had stronger associations with depression and anxiety symptom scores compared to those without obesity.

*Two-exposure models*

In the two-exposure models, most environmental exposures remained significantly associated with mental health outcomes after adjustment for a second exposure (Supplementary Table 3). Higher mean air temperature consistently emerged as a risk factor for higher depressive symptom scores and higher population density for depressive symptoms, anxiety symptoms, and stress scores. In contrast, higher relative humidity was robustly associated with reduced depressive symptoms. Notably, higher NDVI (greenness within 1000 m) only remained significantly associated with lower depressive symptoms after adjustment for precipitation, whereas additional adjustment for $NO_2$, relative humidity, heat days, mean air temperature, and population density attenuated the association between NDVI and depressive symptom scores.

*Sensitivity analysis*

Sensitivity analyses for (1) 1000 m spatial resolution of NDVI, imperviousness, building density, and population density, (2) mean and SD values of four seasonal temperatures, and (3) the lag effects of air pollutants and seasonal temperature demonstrated consistent findings (*Supplementary Fig. 8*). For instance, NDVI within 1000 m had a significant association with lower depressive symptom scores ($\beta = -0.04$, 95% CI: −0.08, −0.006), consistent with the findings of the main analysis . The number of heat days based on DWD data (max >= 30 °C) also showed a similar positive association with depressive symptom scores ($\beta = 0.04$, 0.01, 0.08) compared to the number of heat days (max > 30 °C) in the main analysis.

Additionally, the one-year lag effect of $NO_2$ was associated with higher depressive symptom ($\beta = 0.09$, 95% CI: 0.03, 0.14), anxiety symptom ($\beta = 0.06$, 95% CI: 0.01, 0.11) and stress scores ($\beta = 0.05$, 95% CI: 0.002, 0.10). Most air temperature-related exposures, especially the mean and one-year lag of summer temperature, were positively associated with depressive symptom, anxiety symptoms and stress scores, further supporting the relation of seasonal air temperature with mental health.

Detailed results, including FDR-adjusted p-values for the single-exposure models, are provided in Supplementary Excel Files 1–3. After FDR correction, the overall pattern of associations in single exposure results remained consistent. Furthermore, GAMM analysis revealed nonlinear relationships between some environmental factors and mental health (Supplementary Figs. 9–11). The maximum and minimum of air temperature displayed a slightly U-shaped relationship with depression and anxiety symptoms ($p < 0.01$). Additionally, $PM_{10}$ ($p = 0.067$) and $PM_{2.5}$ ($p = 0.076$) showed an inverted U-shaped relationship with depressive symptom scores. NDVI in warm months ($p < 0.01$) and the number of frost days ($p = 0.054$) had a slightly inverted U-shape relationship with depressive. In separate analyses for each time point of outcome assessment (baseline, 2020, 2022), significant associations of environmental exposures with mental health scores were largely missing for mental health at baseline. However, associations of baseline

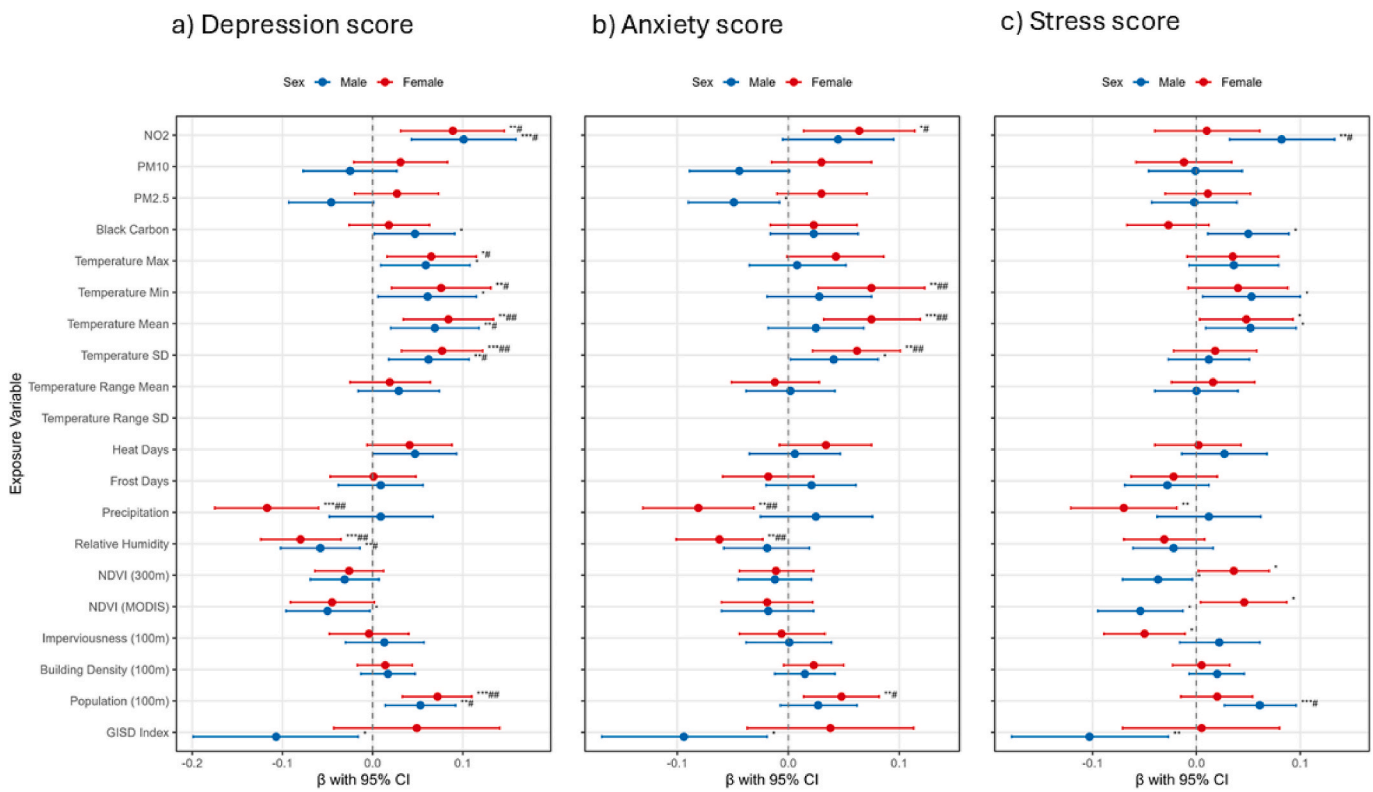


**Fig. 2.** The longitudinal effects of environmental exposures on depression, anxiety, and stress scores, stratified by sex (Male vs. Female). Effect estimates (β) and 95% confidence intervals (CI) are shown for each exposure in the adjusted single-exposure model 3. All exposures were standardized by interquartile range (IQR) to enable comparability across variables. Nominal significance is indicated by asterisks: $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***). Hash symbols indicate statistical significance after Benjamini–Hochberg false discovery rate (FDR) correction: FDR-adjusted $p < 0.05$ (#), FDR-adjusted $p < 0.01$ (##), and FDR-adjusted $p < 0.001$ (###). Model 3 was adjusted for sex, age, marital status, income, migration background, living alone, employment status, education, study region, weekly physical activity, alcohol consumption, smoking status, and body mass index (BMI). Abbreviations: CI = confidence interval; GISD = German index of socioeconomic deprivation; NDVI (MODIS) = normalized difference vegetation index during the warm months (March to October); SD = standard deviation.

environmental exposures with mental health at 2020 and 2022 were mostly consistent with the main results (*Supplementary Fig. 12–14*). The implemented variable-selection approach reduced the initial exposure matrix into 12, 7, and 11 core environmental predictors at baseline for depression, anxiety, and stress, respectively (Supplementary Fig. 15–17). In subsequent mutually-adjusted multi-exposure LMM, key independent risk factors (e.g., $NO_2$, $PM_{10}$ and population density for depression; population density for stress) remained highly robust under strict FDR control, while providing conservative joint variance partitioning for anxiety and stress trajectories (Supplementary Tables S4–S6). When the 16 study regions were modelled as random effects, the result yielded highly robust longitudinal associations (Supplementary Tables S7–S9).

## 3. Discussion

In this large-scale population-based study using longitudinal data from the NAKO, we identified that higher mean air temperature and population density were associated with increased depressive symptom, anxiety symptom, and stress scores across follow-up. Further environmental stressors such as $NO_2$ and heat days were positively associated with adverse depressive symptom scores, while higher levels of precipitation, relative humidity, and greenness (during warm months) were linked with reduced depressive symptom scores. Subgroup analyses identified that most associations were stronger among females, younger adults, individuals living in urban areas and among people with obesity. This study extends prior research on the relationship between environmental exposures and mental health changes by large-scale, prospective data with multiple environmental factors (air pollutants, social and built environment, and climate-related factors).

We observed that higher $NO_2$, air temperature, the number of heat days, and population density were associated with increased depressive symptom scores, whereas relative humidity, greenness, and precipitation emerged as protective factors of adverse mental health scores, particularly for depressive symptoms. While cross-sectional studies have linked various environmental exposures to mental health outcomes, long-term population-based evidence on how air quality, temperature patterns, greenness, and social and built environment are associated with changes in depressive symptom, anxiety symptom, and stress is limited, both in Germany and globally. Previous longitudinal research from China indicated that the mean temperature was not associated with changes in self-rated mental health scores (Xue et al., 2019). In contrast, our study provides robust evidence that multiple dimensions of air temperature exposure—including mean, minimum, and maximum temperature, temperature variability (SD), and their one-year lagged exposures—were significantly associated with changes in mental health, particularly in relation to depressive and anxiety symptom scores. This is further supported by a nationally representative cohort study from Bangladesh, which found that a 1 °C increase in mean temperature over a two-month period was associated with a 21% increase in the odds of GAD-7-defined anxiety (1.21 [1.00–1.47]) (Wahid et al., 2023). Additionally, our findings for depressive symptom scores based on the general population align with results from women during postpartum of a large retrospective cohort study from Southern California, which identified that postpartum temperature exposure was significantly associated with increased risks of postpartum depression, particularly for higher mean and maximum temperatures and greater diurnal temperature variability (Sun et al., 2024). The findings suggest that focusing

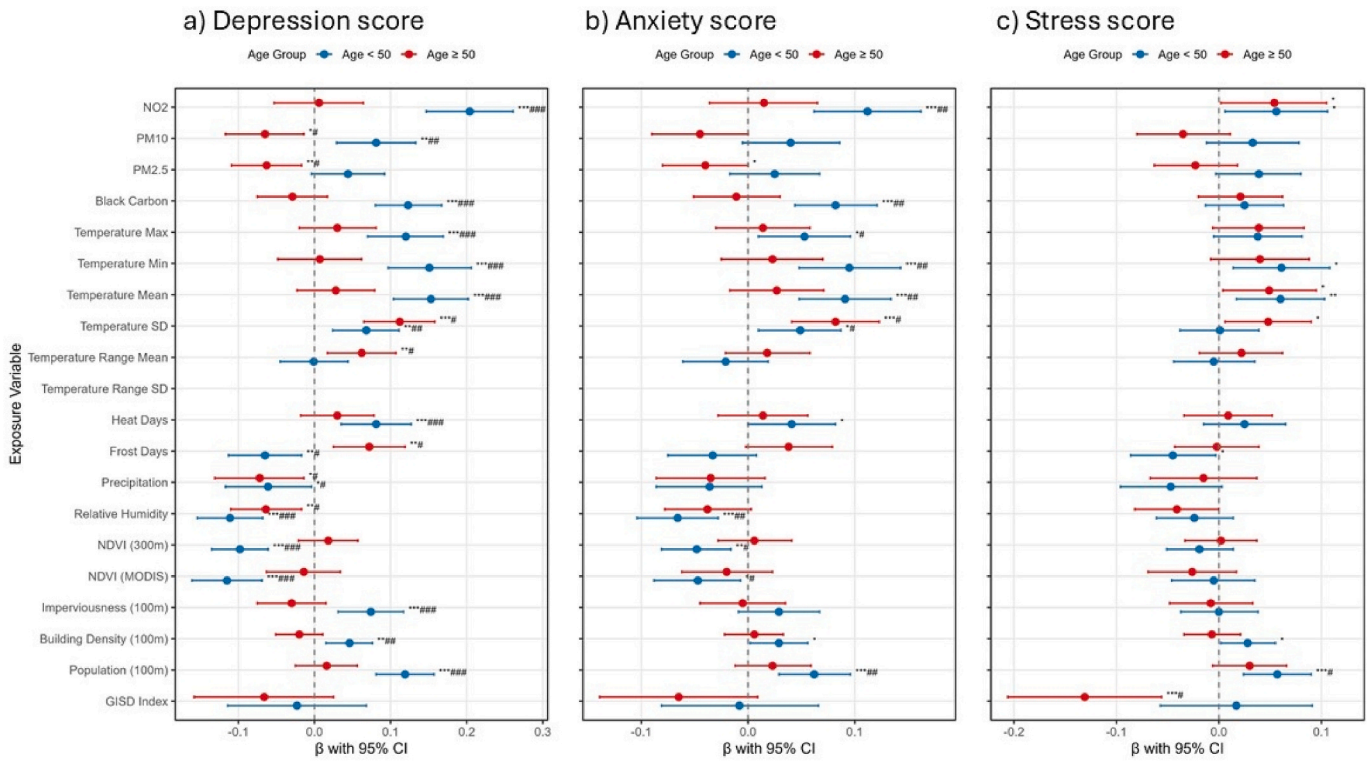


**Fig. 3.** The longitudinal effects of environmental exposures on depression, anxiety, and stress scores, stratified by age (<50 years vs. >= 50 years). Effect estimates (β) and 95% confidence intervals (CI) are shown for each exposure in the adjusted single-exposure model 3. All exposures were standardized by interquartile range (IQR) to enable comparability across variables. Nominal significance is indicated by asterisks: $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***). Hash symbols indicate statistical significance after Benjamini–Hochberg false discovery rate (FDR) correction: FDR-adjusted $p < 0.05$ (#), FDR-adjusted $p < 0.01$ (##), and FDR-adjusted $p < 0.001$ (###). Model 3 was adjusted for sex, age, marital status, income, migration background, living alone, employment status, education, study region, weekly physical activity, alcohol consumption, smoking status, and body mass index (BMI). Abbreviations: CI = confidence interval; GISD = German index of socioeconomic deprivation; NDVI (MODIS) = normalized difference vegetation index during the warm months (March to October); SD = standard deviation.

solely on mean temperature may underestimate the full scope of temperature-related mental health risks. By incorporating a broader range of temperature metrics, our study supports the evidence base linking key climatic factors to adverse mental health outcomes. The U-shaped relationship between depression and anxiety highlights the existence of a 'thermal comfort zone'. Once this comfort zone is deviated from, extreme thermal environments act as systemic stressors, thereby triggering alterations in sleep architecture, neuroendocrine pathways, cognitive function, and thermoregulatory mechanisms (Thompson et al., 2023). Mechanistically, severe hyperthermia leads to structural brain damage, characterised by cerebral oedema and neuronal swelling accompanied by nuclear disintegration, ultimately resulting in irreversible neurological dysfunction. Furthermore, heat stress induces changes in emotional state and cognition by overactivating the hypothalamic–pituitary–adrenal (HPA) axis and altering the dynamic balance of hypothalamic dopamine (Chauhan et al., 2017; Lõhmus 2018).

Furthermore, our findings on $NO_2$ exposure and depression symptom scores are consistent with growing evidence linking ambient air pollution to common mental health disorders. In a longitudinal cohort study with data from the UK Biobank involving around 390,000 participants recruited between 2006 and 2010 and followed for a median of 10.9 years, long-term exposure to multiple pollutants, including $NO_2$, was associated with a significantly increased risk of incident depression and anxiety (Yang et al., 2023a). Those findings are further supported by a prospective, US-based cohort study, which found that long-term $NO_2$ exposure and temperature were adversely associated with generalized anxiety disorder (Mehta et al., 2025). However, the present study only observed an association between baseline $NO_2$ and anxiety symptom scores at the time point 2020 but not in the overall LMM. Among participants with cardiovascular disease and obesity in the present study, we observed stronger associations of higher $NO_2$ with increases in depressive and anxiety symptom scores, suggesting a heightened vulnerability of those subgroups. Individuals with obesity or CVD may be more susceptible due to lipid abnormalities (Kim et al., 2019) and pre-existing endothelial dysfunction, impaired thermoregulation, and systemic chronic inflammation (Brook et al., 2004). Chronic exposure to air pollutants has been shown to trigger oxidative stress and neuroinflammatory processes, which in turn may disrupt neurotransmitter pathways, impair cerebrovascular integrity, and activate the HPA axis—mechanisms implicated in the onset and progression of depression and anxiety (Block and Calderón-Garcidueñas 2009; Lundberg and Weitzberg 2022; Yao et al., 2025). These biological processes can cumulatively increase the risk of cerebrovascular and neuropsychiatric disorders, as highlighted in a recent review (Hahad et al., 2020).

We further observed that higher precipitation and relative humidity were associated with reduced depressive and anxiety symptom scores. This may appear counterintuitive compared to studies on extreme weather events (Jiang et al., 2022; Wahid et al., 2023), yet several mechanisms may explain our findings. Of note, we observed that those associations were stronger in cities compared to rural areas and towns/suburbs. In urban areas, precipitation and humidity may mitigate urban heat island effects and air pollution (Guo et al., 2016), two key environmental stressors linked to adverse mental health. Additionally, these conditions during warm seasons may contribute to enhanced urban greenness, providing additional health benefits. Similarly, the observation that higher population density was associated with adverse mental health aligns with Chen et al (Chen et al., 2015), who demonstrated that elevated population density is a robust, significant predictor of elevated Depression Scale scores in China.

Our findings suggesting a protective effect of NDVI on mental health

are in line with previous research showing that greater residential greenness is associated with a lower risk of depression and anxiety (Mehta et al., 2025; Perrino et al., 2019). A large US-based study among Medicare beneficiaries reported that older adults living in the greenest neighborhoods had 16% lower odds of depression compared with those in the least green areas, even after adjusting for comorbidities and socioeconomic status (Perrino et al., 2019). A Canadian study also observed that greater residential greenness was associated with lower odds of poor self-rated mental health and reduced psychological distress, particularly among residents in urban cores (Crouse et al., 2021). Similar protective associations between residential greenness and reduced depression risk have also been reported in longitudinal studies from China and Finland (Chen et al., 2024; Gonzales-Inca et al., 2022). The mechanisms by which greenness supports mental health are multifaceted. As reviewed by Yang et al., residential green spaces offer biophysical benefits including evaporative cooling, shading, and humidity regulation, which mitigate the physiological burden of heat exposure (Yang et al., 2023b). Meanwhile, green infrastructure facilitates physical activity, fosters social cohesion, and provides restorative environments that promote psychological well-being. Taken together, these pathways suggest that urban vegetation not only mitigates environmental stressors, such as extreme temperatures, but also reinforces individual and community-level mental resilience. The findings support the integration of greenness promotion into climate-adaptive urban health strategies.

These findings underscore the importance of greater awareness for the association between environmental factors and mental health. Our study further supports the importance of embedding environmental stressors in mental health surveillance and early warning systems. With the world facing climate change, targeted adaptations will be critical for mental health resilience.

## 4. Strengths and limitations

The key strengths of this study include the large, population-based cohort with repeated assessments of mental health, enabling longitudinal analyses. Our exposure assessment was based on high-resolution environmental data covering multiple domains, including air pollutants, meteorological conditions, and built and social environments. A methodological strength is the systematic analysis of handling the variability in follow-up time among NAKO participants by assessing and adjusting for the time effect in linear mixed-effects models, comparing the performance of different settings to ensure the robustness of our findings.

However, several limitations should be acknowledged. First, mental health status was evaluated using self-report questionnaires, which may be subject to reporting bias or underdiagnosis, especially in population-based samples. Second, environmental exposures were assigned based on the residential address and may not account for individual mobility patterns, time spent indoors, or variations in personal exposures. Third, our environmental exposure metrics were restricted to the baseline wave due to data availability. Fourth, relevant covariates such as income, employment, social factors, BMI, and physical activity were captured at baseline but may have changed during the 2020 and 2022 follow-up within the COVID-19 pandemic. Moreover, NAKO participants tend to be healthier and higher educated than the general population, potentially underestimating associations due to limited variability in exposures or endpoints (Rach et al., 2025). While our study leveraged longitudinal outcomes across three time points, we were unable to capture lifetime or early-life exposure histories, which may have long-term implications for mental health.

## 5. Conclusion

Based on longitudinal, large-scale data from the German National Cohort (NAKO), we observed that sustained exposure to higher mean temperatures, greater temperature variability, higher population density, and higher $NO_2$ was associated with decreased mental health, foremost depressive symptoms. Greenness, precipitation, and relative humidity appeared as protective factors for mental health changes. These findings underscore the need to incorporate mental health considerations into climate adaptation policy and support the integration of environmental metrics into routine public mental health planning.

## CRediT authorship contribution statement

**Yanding Wang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Susanne Breitner-Busch:** Writing – review & editing, Supervision, Resources, Project administration, Data curation, Conceptualization. **Kathrin Wolf:** Writing – review & editing, Resources, Methodology, Data curation. **Fiona Niedermayer:** Writing – review & editing, Resources, Conceptualization. **Nikolaos Nikolaou:** Writing – review & editing, Resources. **Frank Padberg:** Writing – review & editing, Supervision. **Andrea Rachow:** Writing – review & editing, Supervision. **Fabian Bamberg:** Writing – review & editing, Resources, Conceptualization. **Stefanie Castell:** Writing – review & editing, Resources, Conceptualization. **Volker Harth:** Writing – review & editing, Resources, Conceptualization. **Antje Hebestreit:** Writing – review & editing, Resources. **Michael Leitzmann:** Writing – review & editing, Resources. **Wolfgang Lieb:** Writing – review & editing, Resources. **Claudia Meinke-Franze:** Writing – review & editing, Resources. **Dörthe Meyerdierks:** Writing – review & editing, Resources. **Ilais Moreno Velásquez:** Writing – review & editing, Resources. **Rajini Nagrani:** Writing – review & editing, Resources, Conceptualization. **Nadia Obi:** Writing – review & editing, Resources, Conceptualization. **Laura R. Pfrommer:** Writing – review & editing, Resources, Conceptualization. **Tobias Pischon:** Writing – review & editing, Resources. **Christopher L. Schlett:** Writing – review & editing, Resources, Conceptualization. **Michael J. Stein:** Writing – review & editing, Resources. **Stefan N. Willich:** Writing – review & editing, Resources. **Thomas Keil:** Writing – review & editing, Resources. **Rafael Mikolajczyk:** Writing – review & editing, Resources, Methodology, Data curation. **Marie-Theres Huemer:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Annette Peters:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

## Ethics declaration

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place.

This study was conducted in accordance with Declaration of Helsinki of 1975 (in the current, revised version) and applicable national law.

This study was approved by the Bavarian Medical Association (Bayerische Landesärztekammer, BLÄK).

(Approval No. 13023).

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgments

This project was conducted with data (Application No. NAKO-807)

from the German National Cohort (NAKO) (www.nako.de). The NAKO is funded by the Federal Ministry of Education and Research (BMBF) [project funding reference numbers: 01ER1301A/B/C, 01ER1511D, 01ER1801A/B/C/D and 01ER2301A/B/C], federal states of Germany and the Helmholtz Association, the participating universities and the institutes of the Leibniz Association. This work was also supported by a scholarship under the State Scholarship Fund by the China Scholarship Council (File No. 202308210125).

## Appendix A. Supplementary data

Supplementary material includes supplementary methods, tables, figures, and additional model outputs for depressive symptom, anxiety symptom, and stress analyses. Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2026.110539.

## Data availability

The data underlying this article were provided by NAKO e.V. by permission. Data will be shared on request to the corresponding author with permission of NAKO e.V.

## References

Acharya, S.R., Bhatta, J., Timilsina, D., Ray, N., Pahari, S., 2025. Long-term exposure to air pollutants, meteorological factors, and mental health status: a nationwide population-based study with multilevel regression analysis. Arch. Public Health 83, 81.

Block, M.L., Calderón-Garcidueñas, L., 2009. Air pollution: mechanisms of neuroinflammation and CNS disease. Trends Neurosci. 32, 506–516.

Borroni, E., Pesatori, A.C., Bollati, V., Buoli, M., Carugno, M., 2022. Air pollution exposure and depression: a comprehensive updated systematic review and meta-analysis. Environ. Pollut. 292, 118245.

Brook, R.D., Franklin, B., Cascio, W., Hong, Y., Howard, G., Lipsett, M., Luepker, R., Mittleman, M., Samet, J., Smith Jr., S.C., Tager, I., 2004. Air pollution and cardiovascular disease: a statement for healthcare professionals from the Expert Panel on Population and Prevention Science of the American Heart Association. Circulation 109, 2655–2671.

Chauhan, N.R., Kapoor, M., Prabha Singh, L., Gupta, R.K., Chand Meena, R., Tulsawani, R., Nanda, S., Bala Singh, S., 2017. Heat stress-induced neuroinflammation and aberration in monoamine levels in hypothalamus are associated with temperature dysregulation. Neuroscience 358, 79–92.

Chen, J., Chen, S., Landry, P.F., 2015. Urbanization and mental health in China: linking the 2010 population census with a cross-sectional survey. Int. J. Environ. Res. Public Health 12, 9012–9024.

Chen, Z., Wu, F., Shi, Y., Guo, Y., Xu, J., Liang, S., Huang, Z., He, G., Hu, J., Zhu, Q., Yu, S., Yang, S., Wu, C., Tang, W., Dong, X., Ma, W., Liu, T., 2024. Association of residential greenness exposure with depression incidence in adults 50 years of age and older: findings from the cohort Study on Global AGEing and Adult Health (SAGE) in China. Environ. Health Perspect. 132, 67004.

Crouse, D.L., Pinault, L., Christidis, T., Lavigne, E., Thomson, E.M., Villeneuve, P.J., 2021. Residential greenness and indicators of stress and mental well-being in a Canadian national-level survey. Environ. Res. 192, 110267.

GBD 2019 Mental Disorders Collaborators, 2022. Global, regional, and national burden of 12 mental disorders in 204 countries and territories, 1990–2019: A systematic analysis for the Global Burden of Disease Study 2019. Lancet Psychiatr. 9 (2), 137–150. https://doi.org/10.1016/S2215-0366(21)00395-3.

Gonzales-Inca, C., Pentti, J., Stenholm, S., Suominen, S., Vahtera, J., Käyhkö, N., 2022. Residential greenness and risks of depression: Longitudinal associations with different greenness indicators and spatial scales in a Finnish population cohort. Health Place 74, 102760.

Gottschalk, S., König, H.H., Weber, A., Leitzmann, M.F., Stein, M.J., Peters, A., Flexeder, C., Krist, L., Willich, S.N., Nimptsch, K., Pischon, T., Gastell, S., Steindorf, K., Herbolsheimer, F., Ebert, N., Michels, K.B., Dorrn, A., Harth, V., Obi, N., Karch, A., Teismann, H., Völzke, H., Meinke-Franze, C., Klimeck, L., Seum, T.L., Dams, J., 2025. Costs associated with insufficient physical activity in Germany: cross-sectional results from the baseline examination of the German national cohort (NAKO). Eur. J. Health Econ. 26, 117–128.

Guo, L.C., Zhang, Y., Lin, H., Zeng, W., Liu, T., Xiao, J., Rutherford, S., You, J., Ma, W., 2016. The washout effects of rainfall on atmospheric particulate pollution in two Chinese cities. Environ. Pollut. 215, 195–202.

Hahad, O., Lelieveld, J., Birklein, F., Lieb, K., Daiber, A., Münzel, T., 2020. Ambient air pollution increases the risk of cerebrovascular and neuropsychiatric disorders through induction of inflammation and oxidative stress. Int. J. Mol. Sci. 21.

Jiang, G., Ji, Y., Chen, C., Wang, X., Ye, T., Ling, Y., Wang, H., 2022. Effects of extreme precipitation on hospital visit risk and disease burden of depression in Suzhou, China. BMC Public Health 22, 1710.

Kim, J.S., Chen, Z., Alderete, T.L., Toledo-Corral, C., Lurmann, F., Berhane, K., Gilliland, F.D., 2019. Associations of air pollution, obesity and cardiometabolic health in young adults: the Meta-AIR study. Environ. Int. 133, 105180.

Lõhmus, M., 2018. Possible biological mechanisms linking mental health and heat-a contemplative review. Int. J. Environ. Res. Public Health 15.

Lundberg, J.O., Weitzberg, E., 2022. Nitric oxide signaling in health and disease. Cell 185, 2853–2878.

Mehta, U.V., Wilt, G.E., Roscoe, C., Okereke, O.I., Coull, B.A., James, P., Laden, F., Iyer, H.S., Yanosky, J.D., Kaufman, J., Fiffer, M.R., DeVille, N.V., Holland, I., Hart, J. E., 2025. The association between multiple environmental exposures and symptoms of generalized anxiety disorder in a prospective, US-based cohort study. Environ. Health Perspect. 133, 67008.

Mikolajczyk, R., Diexer, S., Klee, B., Pfrommer, L., Purschke, O., Fricke, J., Ahnert, P., Gabrysch, S., Gottschick, C., Bohn, B., Brenner, H., Buck, C., Castell, S., Gastell, S., Greiser, K.H., Harth, V., Heise, J.K., Holleczek, B., Kaaks, R., Keil, T., Krist, L., Leitzmann, M., Lieb, W., Meinke-Franze, C., Michels, K.B., Velásquez, I.M., Obi, N., Panreck, L., Peters, A., Pischon, T., Schikowski, T., Schmidt, B., Standl, M., Stang, A., Völzke, H., Weber, A., Zeeb, H., Karch, A., 2024. Likelihood of Post-COVID Condition in people with hybrid immunity; data from the German National Cohort (NAKO). J. Infect. 89, 106206.

Nordmann, S., Mues, A., Feigenspan, S., 2020. Evaluation of area-related air quality data in Germany from chemistry-transport modelling. Gefahrstoffe - Reinhalt. Luft 80, 281–290.

Perrino, T., Lombard, J., Rundek, T., Wang, K., Dong, C., Gutierrez, C.M., Toro, M., Byrne, M.M., Nardi, M.I., Kardys, J., Szapocznik, J., Brown, S.C., 2019. Neighbourhood greenness and depression among older adults. Br. J. Psychiatry 215, 476–480.

Peters, A., Peters, A., Greiser, K.H., Göttlicher, S., Ahrens, W., Albrecht, M., Bamberg, F., Bärnighausen, T., Becher, H., Berger, K., Beule, A., Boeing, H., Bohn, B., Bohnert, K., Braun, B., Brenner, H., Bülow, R., Castell, S., Damms-Machado, A., Dörr, M., Ebert, N., Ecker, M., Emmel, C., Fischer, B., Franzke, C.W., Gastell, S., Giani, G., Günther, M., Günther, K., Günther, K.P., Haerting, J., Haug, U., Heid, I.M., Heier, M., Heinemeyer, D., Hendel, T., Herbolsheimer, F., Hirsch, J., Hoffmann, W., Holleczek, B., Hölling, H., Hörlein, A., Jöckel, K.H., Kaaks, R., Karch, A., Karrasch, S., Kartschmit, N., Kauczor, H.U., Keil, T., Kemmling, Y., Klee, B., Klüppelholz, B., Kluttig, A., Kofink, L., Köttgen, A., Kraft, D., Krause, G., Kretz, L., Krist, L., Kühnisch, J., Kuß, O., Legath, N., Lehnich, A.T., Leitzmann, M., Lieb, W., Linseisen, J., Loeffler, M., Macdonald, A., Maier-Hein, K.H., Mangold, N., Meinke-Franze, C., Meisinger, C., Melzer, J., Mergarten, B., Michels, K.B., Mikolajczyk, R., Moebus, S., Mueller, U., Nauck, M., Niendorf, T., Nikolaou, K., Obi, N., Ostrzinski, S., Panreck, L., Pigeot, I., Pischon, T., Pschibul-Thamm, I., Rathmann, W., Reineke, A., Roloff, S., Rujescu, D., Rupf, S., Sander, O., Schikowski, T., Schipf, S., Schirmacher, P., Schlett, C.L., Schmidt, B., Schmidt, G., Schmidt, M., Schöne, G., Schulz, H., Schulze, M.B., Schweig, A., Sedlmeier, A.M., Selder, S., Six-Merker, J., Sowade, R., Stang, A., Stegle, O., Steindorf, K., Stübs, G., Swart, E., Teismann, H., Thiele, I., Thierry, S., Ueffing, M., Völzke, H., Waniek, S., Weber, A., Werner, N., Wichmann, H.E., Willich, S.N., Wirkner, K., Wolf, K., Wolff, R., Zeeb, H., Zinkhan, M., Zschocke, J., 2022. Framework and baseline examination of the German National Cohort (NAKO). Eur. J. Epidemiol. 37, 1107–1124.

Rach, S., Sand, M., Reineke, A., Becher, H., Greiser, K.H., Wolf, K., Wirkner, K., Schmidt, C.O., Schipf, S., Jöckel, K.-H., 2025. The baseline examinations of the German National Cohort (NAKO): recruitment protocol, response, and weighting. Eur. J. Epidemiol. 1–15.

Radua, J., De Prisco, M., Oliva, V., Fico, G., Vieta, E., Fusar-Poli, P., 2024. Impact of air pollution and climate change on mental health outcomes: an umbrella review of global evidence. World Psychiat. 23, 244–256.

Sarkar, C., Webster, C., Gallacher, J., 2018. Residential greenness and prevalence of major depressive disorders: a cross-sectional, observational, associational study of 94 879 adult UK Biobank participants. Lancet Planet Health 2, e162–e173.

Sun, Y., Headon, K.S., Umer, W., Jiao, A., Slezak, J.M., Avila, C.C., Chiu, V.Y., Sacks, D. A., Sanders, K.T., Molitor, J., Benmarhnia, T., Chen, J.C., Getahun, D., Wu, J., 2024. Association of postpartum temperature exposure with postpartum depression: a retrospective cohort study in Southern California. Environ. Health Perspect. 132, 117004.

Terraneo, M., 2021. The effect of material and social deprivation on well-being of elderly in Europe. Int. J. Health Serv. 51, 167–181.

Thompson, R., Lawrance, E.L., Roberts, L.F., Grailey, K., Ashrafian, H., Maheswaran, H., Toledano, M.B., Darzi, A., 2023. Ambient temperature and mental health: a systematic review and meta-analysis. Lancet Planet Health 7, e580–e589.

Wahid, S.S., Raza, W.A., Mahmud, I., Kohrt, B.A., 2023. Climate-related shocks and other stressors associated with depression and anxiety in Bangladesh: a nationally representative panel study. Lancet Planet Health 7, e137–e146.

Weigand, M., Staab, J., Wurm, M., Taubenböck, H., 2020. Spatial and semantic effects of LUCAS samples on fully automated land use/land cover classification in high-resolution Sentinel-2 data. Int. J. Appl. Earth Obs. Geoinf. 88, 102065.

Xue, T., Zhu, T., Zheng, Y., Zhang, Q., 2019. Declines in mental health associated with air pollution and temperature variability in China. Nat. Commun. 10, 2165.

Yang, T., Wang, J., Huang, J., Kelly, F.J., Li, G., 2023a. Long-term exposure to multiple ambient air pollutants and association with incident depression and anxiety. JAMA Psychiat. 80, 305–313.

Yang, Y., Zhang, Y., Sheng, S., 2023b. Residential greenness for mitigating impacts of extreme heat events on depression and supporting mental health. Front. Public Health 11, 1310410.

Yao, X.I., Sun, S., Yang, Q., Tong, X., Shen, C., 2025. Associations between multiple ambient air pollutants, genetic risk, and incident mental disorders: an interaction study in the UK population. Sci. Total Environ. 973, 179137.

Zare Sakhvidi, M.J., Browning, M., Samuelsson, K., Labib, S.M., Psyllidis, A., Amegah, A. K., Astell-Burt, T., Bach, A., Jerrett, M., Bratman, G.N., van den Bosch, M., de Hoogh, K., de Vries, S., Dzhambov, A.M., Fallah Madvari, R., Feng, X., Fernandes, A., Fuertes, E., Giannico, V., Gouveia, N., Hartig, T., Heinrich, J., Hystad, P., Ibarluzea, J., Jacquemin, B., James, P., Jashni, M., Knibbs, L.D., Knobel, P., Kogevinas, M., Lertxundi, A., Markevych, I., Mehrparvar, A., Miri, M., Mitchell, R., Nawrot, T.S., Nieuwenhuijsen, M.J., O'Callaghan-Gordo, C., Pearce, J., Plusquin, M., Sanesi, G., Su, J.G., Triguero-Mas, M., Ubalde-Lopez, M., Valentin, A., White, M.P., Yang, B.Y., Yang, J., Zhang, J., Zhao, T., Helbich, M., Dadvand, P., 2025. Methodological guidance for selecting buffers in greenspace-health studies. Lancet Planet Health 9, 101370.

Zheng, K., Abraham, C., Bruzzese, J.M., Smaldone, A., 2020. Longitudinal relationships between depression and chronic illness in adolescents: an integrative review. J. Pediatr. Health Care 34, 333–345.