Scientia Psychiatrica
Vol. 7, No. 4, 2026, pp. 181–190 · e-ISSN 2715-9736 journal homepage: scientiapsychiatrica.com

ORIGINAL RESEARCH ARTICLE

Population-Weighted $PM_{2.5}$ and NO_2 Exposure and Global Depressive Disorder Burden: A Spatial Ecological Panel Study

Jasmila Tanjung[1], Theresia Putri Sinaga[2*]
[1]*Department of Environmental Engineering, CMHC Research Center, Palembang, Indonesia*
[2]*Department of Public Health, CMHC Research Center, Palembang, Indonesia*

ARTICLE INFO

Article history
Received: August 19, 2026
Revised: September 18, 2026
Accepted: October 10, 2026
Available online: October 27, 2026
Published: October 30, 2026

Keywords
Air pollution
Depressive disorders
Ecological study
Nitrogen dioxide
Particulate matter
Spatial epidemiology

***Corresponding author**
Theresia Putri Sinaga
E-mail: theresia.ps@cattleyacenter.id
ORCID: 0009-0009-9019-3689

DOI
10.37275/scipsy.v7i4.220

ABSTRACT

Background. Ambient air pollution has been associated with depression in individual-level studies, yet global comparisons are vulnerable to contextual confounding and rarely distinguish cross-national contrasts from within-country change.

Objective. To estimate associations of population-weighted fine particulate matter ($PM_{2.5}$) and tropospheric nitrogen dioxide (NO_2) with depressive-disorder years lived with disability (YLD), test persistence within countries, and quantify residual spatial dependence.

Methods. We conducted a spatial ecological panel study of 445 country-years from 153 countries (2019–2021). Depressive-disorder YLD per 100,000 were linked to annual population-weighted $PM_{2.5}$, satellite-derived tropospheric NO_2, gross domestic product per capita, urbanization, region, and year. Pollutants were scaled to interquartile ranges (IQR). The primary pooled model used country-clustered standard errors; fixed-effects, between-country, spatial-error, and sensitivity analyses evaluated robustness.

Results. In the pooled model, each $PM_{2.5}$ IQR (17.994 μg/m^3) was associated with −41.66 YLD per 100,000 (95% confidence interval [CI], −80.76 to −2.55; p = 0.037); NO_2 showed no statistically significant association (−14.24; 95% CI, −40.06 to 11.59; p = 0.280). The $PM_{2.5}$ estimate did not persist with country and year fixed effects (6.35; 95% CI, −61.97 to 74.67), balanced-panel fixed effects (10.78; 95% CI, −58.20 to 79.76), or first differences (−1.71; 95% CI, −88.83 to 85.41). Residual spatial autocorrelation was present (Moran's I = 0.134; permutation p = 0.008).

Conclusion. The inverse pooled $PM_{2.5}$ association reflected cross-national structure, not within-country change, and should not be read as protective or causal. NO_2 estimates were imprecise. Longer panels with individual-level linkage are needed to separate pollution effects from contextual determinants.

Copyright: © 2026 The Author(s). Published by HM Publisher in collaboration with CMHC Research Center on behalf of Scientia Psychiatrica. The authors retain copyright of their work.

Access licence: This is an open access article distributed under the terms of the Creative Commons Attribution–NonCommercial–ShareAlike 4.0 International Licence (CC BY-NC-SA 4.0), which permits non-commercial use, sharing, adaptation and reproduction in any medium, provided the original author and source are credited and any derivative work is distributed under the same licence.

1. Introduction

Depressive disorders are a leading source of nonfatal health loss. They interfere with social participation, schooling, work, and survival. How much burden each country records differs widely, because occurrence, recognition, treatment, and disability estimation all depend on social and health-system context. The coronavirus disease 2019 pandemic then added a sharp global shock, and the estimated prevalence and burden of depressive and anxiety disorders rose in many settings.[1] Country-level depressive-disorder years lived with disability (YLD) are therefore useful for health planning. As an epidemiological outcome, though, they are hard to handle.

Ambient air pollution is a plausible contributor to mental-health burden at the population level. Recent systematic reviews and meta-analyses mostly report higher risks of depressive or anxiety outcomes where particulate or gaseous exposure is greater, but they stress variation in exposure windows, study populations, and outcome ascertainment.[2–4] Fine particulate matter with an aerodynamic diameter of 2.5 μm or less ($PM_{2.5}$) can trigger systemic inflammation, oxidative stress, vascular dysfunction, and neuroimmune responses. Nitrogen dioxide (NO_2) arises from combustion and serves as a marker of traffic and

urban activity. Its respiratory, vascular, sleep-related, and inflammatory pathways could all bear on mood.

Recent adult studies support the association, although its size depends on design and setting. Prospective and retrospective cohorts in Europe, China, and the United States have tied long-term particulate or gaseous pollution to major mental disorders, depressive symptoms, psychological distress, and related outcomes.[5–13] Cross-sectional and longitudinal work adds that the link varies with socioeconomic position, coexposure to green space, pollutant composition, and the passage from adolescence into adulthood.[14,15] None of these outcomes equals modeled national YLD. That measure captures prevalent disability, not incident diagnosis or symptom severity.

Evidence across the life course is just as mixed. Longitudinal studies have followed pollution and noise from childhood to young adulthood, behavioral trajectories in late childhood, adolescent cognition and mental health, and the roles of sleep, physical activity, green space, and lifestyle susceptibility.[16–20] In perinatal research, prenatal pollution mixtures have been linked to persistent postpartum symptoms and later psychological functioning. Adolescent studies connect diesel-related particles and short-term pollution episodes with cortisol response or depressive symptoms.[21–25] These findings point to developmental susceptibility. They also show why a single national ecological coefficient cannot stand for every age and exposure window.

Clinical and short-term studies offer a different angle. Pollution exposure has been related to the severity of major depression, wildfire-related emergency visits, anxiety admissions, mental and behavioral hospital encounters, and emergency ambulance dispatches.[26–33] These designs give fine temporal resolution and clinically observed outcomes. What they estimate, however, are acute changes within particular service systems, not differences in national burden. Country-level estimates can support surveillance across settings. Yet they stay sensitive to diagnostic access, reporting practices, and the inputs used to model the outcome.

Mechanistic work has pointed to candidate mediating proteins, tumor necrosis factor receptor pathways, dopaminergic disruption, systemic inflammation, brain-derived neurotrophic factors, and oxidative or endoplasmic-reticulum stress.[34–39] Studies of gene–environment interaction, Mendelian randomization, colocalization, and genetically stratified cohorts have asked whether inherited susceptibility modifies the observed associations or explains part of them.[40–43] Taken together, this evidence makes an inverse biological effect implausible. It does not, however, remove confounding or measurement differences from ecological comparisons.

This leaves a problem of scale unresolved. Countries differ in demographic profile, recognition of mental disorders, inputs to disease estimation, income, urban form, health-system capacity, and pollutant sources, and international comparisons mix all of these together. A negative cross-country coefficient may appear even when harmful individual-level effects exist, since less polluted countries may detect or record more disability. A positive coefficient may instead reflect disadvantage, not toxicity. Population weighting better represents where residents live. It does not turn a satellite measurement into personal exposure. Spatial dependence is a further complication, because neighboring countries share climate, emissions transport, economic history, diagnostic culture, regional shocks, and health-system traits.

This study combines population-weighted $PM_{2.5}$ and satellite-derived tropospheric NO_2 with World Health Organization (WHO) depressive-disorder YLD in a single global panel, and it directly contrasts pooled, between-country, within-country, first-difference, and spatial-error estimands. Our aims were to estimate associations of population-weighted $PM_{2.5}$ and NO_2 with depressive-disorder YLD across countries during 2019–2021, to test whether the associations held when identified from within-country change, and to quantify residual spatial dependence.

2. Methods

2.1. Study design and setting

We carried out an observational spatial ecological panel study. The setting was global, at the country level. It used country-year data for 2019, 2020, and 2021, and the country-year was the unit of analysis. The analytic frame joined modeled depressive-disorder burden, annual pollution exposures, macroeconomic and urbanization covariates, and geographic identifiers. The goal was comparison of complementary estimands. No single model was treated as causal. Reporting followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement.[44]

The window was chosen because harmonized outcome and exposure inputs overlapped in all three years. It includes the acute phase of the pandemic. Year indicators handled that period in every longitudinal specification, and a sensitivity analysis excluded 2020.

2.2. Participants

To enter the analytic sample, a country-year needed nonmissing depressive-disorder YLD, population-weighted $PM_{2.5}$, population-weighted NO_2, GDP per capita, urbanization, region, and geographic identifiers. Nothing was imputed. Of the potentially linkable observations, 445 complete country-years from 153 countries were kept. Of these countries, 144 contributed all three years.

2.3. Variables and instruments

Data sources. Depressive-disorder YLD estimates came from the World Health Organization Global Health Estimates country series. Annual mean $PM_{2.5}$ and gross domestic product (GDP) per capita came from World Bank indicator files. Urbanization was represented by urban population as a percentage of total population. Tropospheric NO_2 columns were derived from the

European Space Agency Climate Change Initiative and Sentinel-5P products. Population weights came from Gridded Population of the World version 4. Natural Earth country boundaries supported geographic matching and spatial weights.

Outcome. The outcome was depressive-disorder YLD per 100,000 population. YLD express nonfatal health loss by combining prevalence with disability weights. They are not a clinical diagnosis rate, a symptom score, or a treatment count. In the supplied series, depressive-disorder disability-adjusted life years (DALYs) equaled YLD. Mortality attributed directly to the disorder was zero in the modeled cause hierarchy. Analyses used the continuous YLD rate. A natural-log transformation was examined in sensitivity analysis.

Country-level YLD estimates follow the WHO estimation framework and depend on the information available in each setting. They can capture burden missing from treatment records. Uncertainty and reliance on surveillance inputs differ across countries, however. Observation-specific uncertainty intervals were absent from the analytic file. The regression models therefore took the published point estimates as outcomes, and results are interpreted with this measurement structure in mind.

Exposure. Annual $PM_{2.5}$ was expressed in $\mu g/m^3$. Annual NO_2 was the tropospheric vertical column density in molecules/cm^2. For both pollutants, gridded values were weighted by population within each country-year, so populated cells counted in proportion to residents and not to land area. One sensitivity analysis used an alternative area-mean NO_2 metric. Another kept only observations with at least 80% valid NO_2 population coverage.

$$\bar{X}_{ct}^{PW} = [\Sigma_g (x_{gct} \times P_{gc})] / [\Sigma_g P_{gc}]$$

We divided exposures by their analytic-sample interquartile ranges (IQRs): 17.994 $\mu g/m^3$ for $PM_{2.5}$ and 1.011×10^{15} molecules/cm^2 for NO_2. This makes coefficients comparable across pollutants and easier to read clinically. Each coefficient is the adjusted difference in YLD per 100,000 associated with an exposure one IQR higher, not the change per single measurement unit. $PM_{2.5}$ and NO_2 entered the models together. They capture different aspects of ambient pollution and were weakly correlated in this sample.

Covariates and conceptual model. GDP per capita was natural-log transformed to reduce right skew and to represent proportional differences in economic resources. Urbanization entered as a continuous percentage. World region and calendar year were categorical covariates in the pooled model. The adjustment set was specified before coefficients were interpreted. It addressed broad differences in economic development, settlement pattern, regional context, and common annual shocks, without conditioning on variables likely to result from pollution.

The ecological causal structure is only partly observed. Health-system access, diagnostic practice, conflict, social protection, educational distribution, climate, noise, green space, and pandemic response were not harmonized in the analysis file. The pooled coefficient therefore mixes residual between-country information with limited within-country information. Fixed-effects and first-difference models remove stable country characteristics. They cannot remove unmeasured factors that changed over time.

2.4. Data collection procedure

Data were assembled from public sources and linked at the country-year level. Country codes and names were harmonized before linkage, and duplicate country-year keys were prohibited. NO_2 pixels were screened with the source quality fields. They were aggregated annually, matched to population grids, and required valid population coverage. No individual records, clinical charts, survey microdata, or directly identifiable information were accessed.

2.5. Statistical analysis

Continuous variables were summarized by year as means and standard deviations. Medians and IQRs were examined during validation. Pairwise correlation described the relation between the two pollutants, and variance inflation factors assessed linear multicollinearity. Before modeling we checked plausible ranges, missingness, country-year uniqueness, balanced-panel membership, and the internal equality of YLD and the supplied depressive-disorder DALY field.

The primary model was a pooled ordinary least-squares regression with both IQR-scaled pollutants, log GDP per capita, urbanization, region indicators, and year indicators. Standard errors were clustered by country, which allows arbitrary serial correlation and heteroskedasticity within countries. The model estimates the adjusted association across all country-years. Most exposure variation lay between countries. Cross-national contrasts were therefore expected to dominate it.

A country and year fixed-effects model removed all time-invariant country characteristics and common annual shocks. Its coefficients were therefore identified only from deviations around each country's own mean. A between-country model regressed each country's 2019–2021 mean outcome on mean exposures and covariates, which isolates the stable cross-sectional component. For 2021 we fitted a maximum-likelihood spatial-error model. It used row-standardized, symmetrized four-nearest-neighbor weights built from country centroids. Residual Moran's I was evaluated with 999 permutations before the spatial modeling.

Sensitivity analyses comprised fixed effects restricted to the 144 balanced countries; a 2019–2021 first-difference model; separate year-specific cross-sections; single-pollutant models; alternative NO_2 exposure construction; restriction to ≥80% NO_2 population coverage; exclusion of 2020; quadratic pollutant terms; a log-YLD model; heteroskedasticity-consistent HC3 covariance; and influence analysis. Cook's distance flagged observations with comparatively high leverage or residual influence, and each influential country was then left out in turn and the models re-estimated. We

read sensitivity analyses by direction, magnitude, and interval compatibility, not by a binary significance threshold.

We report two-sided p values and 95% confidence intervals (CIs). Statistical significance was set at $p < 0.05$ for the prespecified primary coefficients. Sensitivity analyses received no multiplicity correction, since they served to assess robustness and not to generate independent confirmatory claims. Analyses were run in Python with pandas, NumPy, SciPy, statsmodels, and spatial-analysis routines. An independent validation script reproduced the primary coefficients to machine precision.

2.6. Ethical approval

Ethical approval was granted by the CMHC Research Center Ethics Committee Indonesia (No. 2026/027). The study used aggregated, publicly available country-level data without personal identifiers; informed consent was therefore not applicable. Data permissions and licenses for each source were respected independently of the ethics determination.

3. Results

3.1. Study sample and descriptive findings

The complete-case panel contained 445 country-year observations from 153 countries; 144 countries contributed observations in all three years. The yearly sample comprised 147 observations in 2019, 152 in 2020, and 146 in 2021. Mean depressive-disorder YLD per 100,000 increased from 650.1 (standard deviation [SD], 168.0) in 2019 to 741.6 (SD, 196.2) in 2020 and 762.8 (SD, 205.3) in 2021, as detailed in Table 1. Mean $PM_{2.5}$ was comparatively stable, whereas mean NO_2 declined in 2020 and partially recovered in 2021; these annual patterns are visualized in Figure 1.

$PM_{2.5}$ and NO_2 were weakly correlated ($r = 0.035$). Variance inflation factors were 1.36 for $PM_{2.5}$, 1.34 for NO_2, 2.75 for log GDP per capita, and 2.16 for urbanization, providing no indication that pollutant collinearity drove coefficient instability. No duplicate country-year keys or missing required analytic values remained after complete-case selection.

Table 1. Year-specific characteristics of the analytic panel.

Year	n	YLD/100,000	$PM_{2.5}$, μg/m³	NO_2, ×10¹⁵ molecules/cm²
2019	147	650.1 (168.0)	24.1 (13.4)	1.54 (1.13)
2020	152	741.6 (196.2)	23.6 (13.9)	1.44 (0.98)
2021	146	762.8 (205.3)	24.6 (14.5)	1.48 (0.98)

Notes: Values are mean (SD) unless stated. NO_2, nitrogen dioxide; $PM_{2.5}$, particulate matter ≤2.5 μm; SD, standard deviation; YLD, years lived with disability.

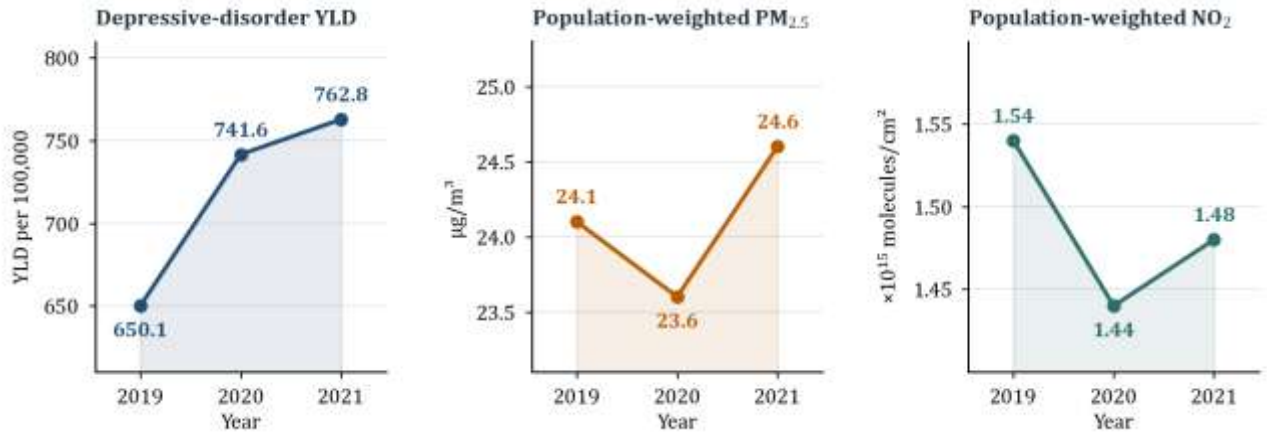


Figure 1. Annual means of depressive-disorder YLD and population-weighted pollutants, 2019–2021. Points are country-year means and correspond exactly to Table 1. NO_2, nitrogen dioxide; $PM_{2.5}$, particulate matter ≤2.5 μm; YLD, years lived with disability.

3.2. Primary and complementary models

In the pooled region- and year-adjusted model, one $PM_{2.5}$ IQR was associated with 41.66 fewer depressive-disorder YLD per 100,000 (95% CI, −80.76 to −2.55; $p = 0.037$). The corresponding NO_2 coefficient was −14.24 YLD per 100,000 (95% CI, −40.06 to 11.59; $p = 0.280$). The model explained 43.9% of observed outcome variation, but this value includes the explanatory contribution of regional, temporal, economic, and urbanization terms and does not establish causal attribution to either pollutant. The full set of primary and complementary estimates is detailed in Table 2.

The country and year fixed-effects estimates differed from the pooled $PM_{2.5}$ result. Within the same country over time, the $PM_{2.5}$ coefficient was 6.35 (95% CI, −61.97 to 74.67; $p = 0.855$) and the NO_2 coefficient was −18.69 (95% CI, −68.66 to 31.28; $p = 0.463$). The wide intervals reflect limited year-to-year exposure movement and a three-year observation window. The between-country $PM_{2.5}$ coefficient was −39.81 (95% CI, −86.04 to 6.42; $p = 0.091$), close in magnitude to the pooled coefficient, whereas NO_2 remained imprecise.

Pooled-model residuals retained geographic clustering (Moran's I = 0.134; expected value, −0.0069; permutation p = 0.008). In the 2021 spatial-error model, the spatial error coefficient was 0.306 (95% CI, 0.068 to 0.543; p = 0.012). After modeling that dependence, $PM_{2.5}$ was −40.97 (95% CI, −87.84 to 5.90; p = 0.087) and NO_2 was −11.16 (95% CI, −45.11 to 22.80; p = 0.520). The cross-model pattern is shown in Figure 2: the inverse $PM_{2.5}$ estimate was concentrated in specifications dominated by cross-country contrast.

Table 2. Associations of population-weighted pollutants with depressive-disorder YLD.

Model	Pollutant	Difference in YLD per 100,000 per IQR (95% CI)	p
Pooled panel	$PM_{2.5}$	−41.66 (−80.76 to −2.55)	0.037
Pooled panel	NO_2	−14.24 (−40.06 to 11.59)	0.280
Country/year FE	$PM_{2.5}$	6.35 (−61.97 to 74.67)	0.855
Country/year FE	NO_2	−18.69 (−68.66 to 31.28)	0.463
Between-country	$PM_{2.5}$	−39.81 (−86.04 to 6.42)	0.091
Between-country	NO_2	−15.11 (−44.46 to 14.25)	0.313
Spatial error, 2021	$PM_{2.5}$	−40.97 (−87.84 to 5.90)	0.087
Spatial error, 2021	NO_2	−11.16 (−45.11 to 22.80)	0.520

Notes: Estimates are YLD per 100,000 per study IQR. Pooled and fixed-effects models use country-clustered standard errors. CI, confidence interval; FE, fixed effects; IQR, interquartile range.

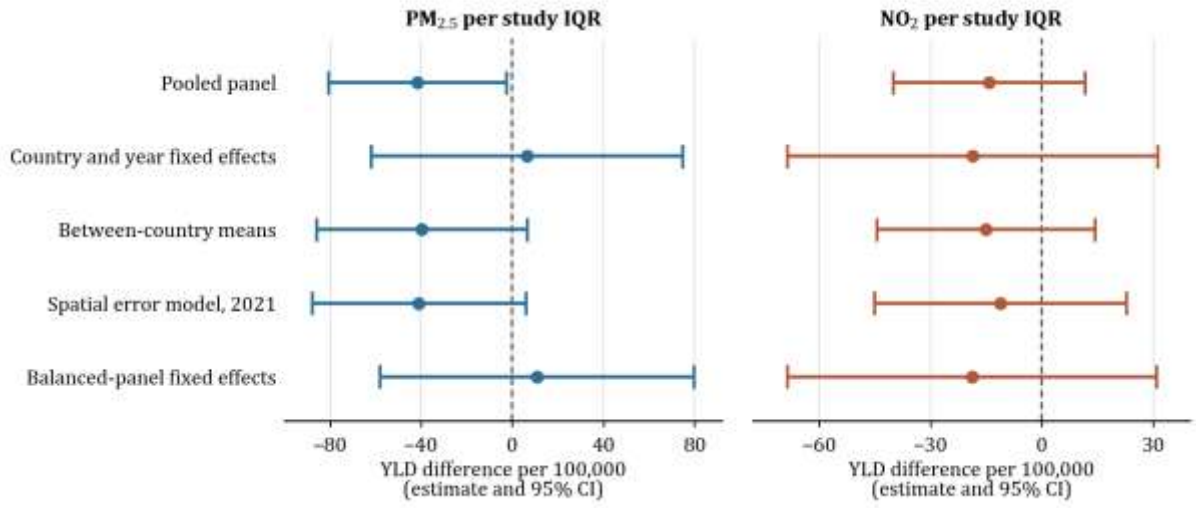


Figure 2. Associations across complementary model specifications. Points show adjusted differences in depressive-disorder YLD per 100,000 per pollutant IQR; bars show 95% CIs. The dashed line marks no association. CI, confidence interval; IQR, interquartile range; NO_2, nitrogen dioxide; $PM_{2.5}$, particulate matter ≤2.5 μm; YLD, years lived with disability.

3.3. Sensitivity and influence analyses

Restricting the fixed-effects analysis to 144 balanced countries produced a $PM_{2.5}$ coefficient of 10.78 (95% CI, −58.20 to 79.76; p = 0.759) and an NO_2 coefficient of −18.85 (95% CI, −68.62 to 30.91; p = 0.458). The 2019–2021 first-difference estimates were −1.71 for $PM_{2.5}$ (95% CI, −88.83 to 85.41; p = 0.969) and −4.63 for NO_2 (95% CI, −66.65 to 57.38; p = 0.884). Neither analysis supported a stable association between within-country exposure change and YLD change, as detailed in Table 3.

Year-specific $PM_{2.5}$ coefficients were −36.53 in 2019 (95% CI, −78.44 to 5.38), −39.01 in 2020 (95% CI, −86.65 to 8.62), and −50.33 in 2021 (95% CI, −100.63 to −0.03). The $PM_{2.5}$ interval for 2021 only just excludes zero. NO_2 coefficients were compatible with no association in every year. In the log-outcome model, one $PM_{2.5}$ IQR corresponded to an estimated −5.40% difference in YLD (95% CI, −10.57% to 0.06%; p = 0.053), and NO_2 corresponded to −1.49% (95% CI, −5.03% to 2.18%; p = 0.420).

The pooled $PM_{2.5}$ estimate remained inverse in single-pollutant, area-mean NO_2, high-NO_2-coverage, and 2020-exclusion models. Quadratic terms were not supported. The maximum Cook's distance was 0.051. Sixteen countries met the prespecified influence-screening threshold; when each was omitted in turn, $PM_{2.5}$ estimates ranged from −53.80 to −35.15 YLD per 100,000 and NO_2 estimates from −20.76 to −11.40. This stability of the pooled coefficient to single-country omission did not resolve the discrepancy between cross-national and within-country estimands. Multicollinearity, spatial-dependence, and influence diagnostics are consolidated in Table 4.

Table 3. Sensitivity analyses emphasizing within-country information.

Analysis	Pollutant	Difference in YLD per 100,000 per IQR (95% CI)	p
Balanced-panel FE	$PM_{2.5}$	10.78 (−58.20 to 79.76)	0.759
Balanced-panel FE	NO_2	−18.85 (−68.62 to 30.91)	0.458
First difference	$PM_{2.5}$	−1.71 (−88.83 to 85.41)	0.969
First difference	NO_2	−4.63 (−66.65 to 57.38)	0.884
Log outcome	$PM_{2.5}$	−5.40% (−10.57% to 0.06%)	0.053
Log outcome	NO_2	−1.49% (−5.03% to 2.18%)	0.420

Notes: First-difference estimates use 2019–2021 changes. Log-outcome estimates are percentage differences. CI, confidence interval; FE, fixed effects; NO_2, nitrogen dioxide; $PM_{2.5}$, particulate matter ≤2.5 μm.

Table 4. Model diagnostics and influence analysis.

Diagnostic	Statistic	Value
Pollutant correlation	Pearson r ($PM_{2.5}$, NO_2)	0.035
Multicollinearity	VIF: $PM_{2.5}$ / NO_2	1.36 / 1.34
Multicollinearity	VIF: log GDP / urbanization	2.75 / 2.16
Spatial dependence	Moran's I (expected); permutation p	0.134 (−0.0069); 0.008
Spatial-error model	λ (95% CI); p	0.306 (0.068 to 0.543); 0.012
Observation influence	Maximum Cook's distance	0.051
Country influence	Countries above 4/n	16
Leave-one-country-out	$PM_{2.5}$ coefficient range	−53.80 to −35.15
Leave-one-country-out	NO_2 coefficient range	−20.76 to −11.40

Notes: The influence threshold was Cook's distance >4/n. CI, confidence interval; GDP, gross domestic product; NO_2, nitrogen dioxide; $PM_{2.5}$, particulate matter ≤2.5 μm; VIF, variance inflation factor.

4. Discussion

4.1. Principal findings

This global ecological panel produced three linked findings. First, higher population-weighted $PM_{2.5}$ was associated with lower recorded depressive-disorder YLD in the pooled model. NO_2 showed no statistically significant association. Second, the $PM_{2.5}$ association vanished in country and year fixed-effects, balanced-panel, and first-difference analyses. Third, geographic dependence remained in the residuals after conventional adjustment, and it was material in the 2021 spatial-error model. Together, the results indicate that the inverse pooled coefficient is mainly a cross-national pattern. It is not evidence that $PM_{2.5}$ lowers depression burden.

The distinction matters. A pooled estimate asks whether country-years with higher pollution differ from other country-years once measured covariates are adjusted. A fixed-effects estimate asks something else. Does a country's burden change when its pollution moves away from its own average? The two questions need not share an answer. Here, pooled and between-country coefficients are close, and the within-country coefficients are near null. That points to contextual structure. It does not point to a reproducible short-term exposure-response relation.

4.2. Comparison with existing evidence

The inverse pooled $PM_{2.5}$ coefficient runs against meta-analytic evidence that greater long-term pollution exposure raises the risk of depression or anxiety.[2–4] It also departs from individual-level studies that tie particulate or gaseous pollution to incident disorders, depressive symptoms, psychological distress, or depression-related health encounters.[5–15] This is not necessarily a contradiction. Individual studies compare people within fairly homogeneous institutional settings. Our analysis compares national burden estimates drawn from surveillance, treatment, demographic, economic, and cultural environments that differ greatly.

Recent investigations underline the importance of scale and susceptibility. Studies of children, adolescents, perinatal populations, and adults report heterogeneity by developmental timing, sex, socioeconomic position, coexposure, physical activity, sleep, and other dimensions of vulnerability.[16–25] Country aggregates cannot test these modifiers. Nor can they test the mechanisms. They do explain how a global ecological coefficient might conceal effects in susceptible subpopulations.

The NO_2 intervals are consistently wide. They fit both modest harmful and modest inverse associations. Reviews report mixed NO_2 findings, and cohort results vary with exposure window and outcome definition.[2–5,7,12,18,20] Our exposure was a population-weighted tropospheric column, not a calibrated near-surface concentration. That improves global coverage, but it may respond differently to vertical mixing, meteorology, retrieval quality, and emission height. The null estimates therefore do not show that ground-level, traffic-related NO_2 has no mental-health effect.

The pandemic-era window matters too. Mean YLD rose from 650.1 to 762.8 per 100,000 between 2019 and 2021 (about 17%, in samples that differ by year), while $PM_{2.5}$ stayed fairly stable and NO_2 dipped temporarily. A global analysis documented increased depressive and anxiety burden during the pandemic, with larger

changes where infection rates and mobility reductions were greater.[1] Year indicators absorb a common global shift. They cannot capture country-specific lockdown intensity, mortality, income support, service interruption, or reporting. Excluding 2020 kept the pooled $PM_{2.5}$ pattern. The short panel, though, could not separate lagged environmental effects from these simultaneous shocks.

4.3. Interpretation and plausible mechanisms

An inverse causal effect of $PM_{2.5}$ on depression is biologically unlikely. Human biomarker and experimental studies point instead to inflammatory signaling, proteomic mediators, dopaminergic disruption, altered neurotrophic factors, and oxidative or endoplasmic-reticulum stress as candidate pathways from particulate exposure to mood disturbance.[34–39] Genetic-interaction, Mendelian-randomization, and colocalization studies add evidence on susceptibility and causal structure, though that evidence depends on design.[40–43] Pollution may also affect sleep, physical activity, social interaction, and perceived neighborhood quality. The pooled coefficient should be read through bias structure. It is not a rival protective mechanism.

Differential measurement of depressive burden is one likely contributor. Higher-income countries, which are often less polluted, may have denser epidemiological data, better recognition of mental disorders, longer survival with disability, and fuller health-system contact. Lower-resource countries may carry substantial symptoms yet have sparse surveys, treatment gaps, competing mortality, or culturally different help-seeking and reporting. Modeled YLD methods try to harmonize these inputs. Residual differences can persist. They may track pollution and GDP even after adjustment.

Unmeasured contextual confounding is a second explanation. Governance, education, inequality, conflict, social protection, health expenditure, climate, urban green space, noise, and occupational structure can shape both pollution and depression burden. GDP and urbanization are broad proxies for these pathways. They cannot replace them. Region indicators reduce some clustering. Even so, the significant Moran's I and spatial-error coefficient show that geographically patterned determinants remained.

Temporal mismatch is a third. Depression can develop after prolonged exposure. YLD, moreover, reflects prevalent disability and not incident onset. Three annual pollution means may miss cumulative or latency-sensitive exposure, and fixed-effects estimates rest on relatively small short-term movements. Wide within-country confidence intervals thus signal limited information about change, not proof of no long-term effect. Longer panels with distributed lags and historically reconstructed exposures are needed. None of these three explanations was tested directly in the present data.

4.4. Implications for practice and policy

The pooled $PM_{2.5}$ estimate, approximately 42 YLD per 100,000 per IQR, would matter for populations if it were causal. Its direction and model dependence rule that reading out. Significance in one specification does not outweigh inconsistency across estimands. The fixed-effects intervals are wide enough to include changes that could matter for public health. They offer no precise reassurance. The right conclusion is uncertainty about the global ecological association. It is neither evidence of benefit nor evidence of no harm.

Policy should keep relying on the broader evidence for air-quality improvement, which includes well-established cardiopulmonary benefits and a growing body of mental-health evidence. This study adds a methodological warning for global mental-health surveillance. Population weighting and spatial modeling improve the exposure and error structure. They leave differential outcome measurement and ecological confounding untouched. Where panel data allow, international comparisons should report between- and within-unit estimates together.

Future studies should link gridded pollution to individual-level or subnational longitudinal mental-health data. They should use repeated validated symptom or diagnostic measures and define relevant exposure windows in advance. Harmonized information on health-system access, treatment coverage, conflict, inequality, green space, noise, heat, and pandemic policies would tighten confounding control. Surface-calibrated NO_2 products and multipollutant or mixture models should be compared against tropospheric-column metrics.

Global burden programs could ease environmental linkage by publishing machine-readable uncertainty draws and clearer country-year metadata on input quality. Analysts could then carry outcome uncertainty through their models. Treating point estimates as error-free would no longer be necessary. Hierarchical models might separate sampling uncertainty, regional borrowing, spatial transport, and country-specific trajectories. Negative-control outcomes or exposures, quasi-experimental policy changes, and triangulation across designs would test causal explanations further.

The spatial dependence we observed has operational implications. Regional clusters may share data infrastructure as well as environmental sources. Cross-border pollution control and regional mental-health surveillance could therefore be evaluated jointly. Still, spatial correlation should not be mistaken for pollution transport alone. Reporting maps, residual diagnostics, and spatially robust intervals can guard against overconfidence in conventional national regressions.

A sensible next step is a coordinated multicountry protocol. It would keep individual-level information comparable while allowing locally valid measurement. A common core could harmonize repeated symptom instruments, diagnostic interviews in validation subsamples, treatment access, residential histories, time activity, and geocoded exposure. Country-specific

models could then be combined hierarchically, which makes heterogeneity visible instead of forcing one ecological coefficient to represent every setting. Prespecified subgroup analyses should prioritize developmental stage, sex, socioeconomic position, cardiometabolic vulnerability, urbanicity, and exposure mixture, with adequate power and clear multiplicity control. The design would also allow absolute-risk translation. Services would find that more useful than an ecological difference in modeled YLD alone.

4.5. Strengths and limitations

Strengths include a globally broad sample, population-weighted exposure construction, joint evaluation of two pollutants, explicit separation of estimands, country-clustered inference, spatial diagnostics, independent replication of coefficients, and an extensive sensitivity program. The complete dataset held unique country-year keys. No primary analytic fields were missing after selection. The low correlation between pollutants lessened concern about unstable joint coefficients. Leave-one-country-out checks showed that no single influential country explained the pooled result.

The ecological design is the central limitation. Associations between national averages cannot be transferred to individuals. Only three years were available, which limited within-country variation, lag analysis, and power. Complete-case selection may affect geographic representation. WHO YLD estimates are modeled and their precision varies with source data, and the regressions could not incorporate outcome uncertainty draws. GDP, urbanization, region, and year cannot capture every cross-national determinant of depression or pollution.

Exposure limitations deserve attention as well. $PM_{2.5}$ and NO_2 products carry retrieval and model uncertainty. Population weighting represents residential location, not personal mobility. A tropospheric NO_2 column is not equivalent to ground-level inhaled concentration. Country centroids and four-nearest-neighbor weights simplify complex transport and connectivity. The spatial-error model covered only 2021, so its results may depend on the weights definition. Finally, the many sensitivity analyses were descriptive and uncorrected for multiplicity. Interpretation therefore rests on the pattern across models and not on isolated p values.

5. Conclusion

Across 153 countries in 2019–2021, population-weighted $PM_{2.5}$ was inversely associated with depressive-disorder YLD in a pooled model. That association did not reappear when identified from within-country change. Population-weighted tropospheric NO_2 showed no precise association. Residual spatial dependence remained. The evidence supports a contextual cross-national reading, not a protective or causal effect of $PM_{2.5}$. Estimating pollution-related mental-health effects will take longer harmonized panels and individual-level linkage, and it must account for surveillance quality, socioeconomic context, latency, and spatial structure.

Declarations

Use of Generative Artificial Intelligence. The authors declare that no generative artificial intelligence tool was used in the conception, research, analysis, drafting, revision or preparation of this manuscript.

Author Contributions. J.T. — conceptualization, methodology, software, formal analysis, data curation, visualization, writing — original draft. T.P.S. — conceptualization, validation, investigation, supervision, project administration, writing — review and editing.

Funding. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of Interest. The authors declare no competing interests.

Ethical Approval. Ethical approval was granted by the CMHC Research Center Ethics Committee Indonesia (No. 2026/027).

Informed Consent. Not applicable. The study analyzed aggregated, publicly available country-level data without personal identifiers.

Data Availability. The source data are available from the World Health Organization, World Bank, European Space Agency Climate Change Initiative/Sentinel-5P, NASA Gridded Population of the World, and Natural Earth under their respective terms. The harmonized analytic dataset, validation outputs, and analysis code are available from the corresponding author on reasonable request.

Acknowledgements. None.

References

1. Santomauro DF, Mantilla Herrera AM, Shadid J, et al. Global prevalence and burden of depressive and anxiety disorders in 204 countries and territories in 2020 due to the COVID-19 pandemic. Lancet. 2021;398(10312):1700-1712. doi:10.1016/S0140-6736(21)02143-7
2. Borroni E, Pesatori AC, Bollati V, et al. Air pollution exposure and depression: a comprehensive updated systematic review and meta-analysis. Environ Pollut. 2022;292(Pt A):118245. doi:10.1016/j.envpol.2021.118245
3. Cao T, Tian M, Hu H, et al. The relationship between air pollution and depression and anxiety disorders: a systematic evaluation and meta-analysis of a cohort-based study. Int J Soc Psychiatry. 2024;70(2):241-270. doi:10.1177/00207640231197941
4. Zundel CG, Ryan P, Brokamp C, et al. Air pollution, depressive and anxiety disorders, and brain effects: a systematic review. Neurotoxicology. 2022;93:272-300. doi:10.1016/j.neuro.2022.10.011
5. Pan C, Cheng B, Cheng S, et al. Long-term ambient air pollution and the risk of major mental disorder: a prospective cohort study. Eur Psychiatry. 2024;68(1):e1. doi:10.1192/j.eurpsy.2024.1809
6. Burrows K, Luo J, Cai Y, et al. Long-term $PM_{2.5}$ exposure and mental health disparities: a prospective analysis of the All of Us Research Program. Environ Res. 2025;285(Pt 5):122691. doi:10.1016/j.envres.2025.122691
7. Werder E, Lawrence K, Deng X, et al. Residential air pollution, green space, and adverse mental health outcomes in the U.S. Gulf Long-term Follow-up Study. Sci Total Environ. 2024;946:174434. doi:10.1016/j.scitotenv.2024.174434
8. Lyons S, Nolan A, Carthy P, et al. Long-term exposure to $PM_{2.5}$ air pollution and mental health: a retrospective

cohort study in Ireland. Environ Health. 2024;23(1):54. doi:10.1186/s12940-024-01093-z

9. Motoc I, Ginos BNR, Goncalves Soares A, et al. Examining associations of air pollution and green space with depressive symptoms in adults: a LongITools cross-cohort analysis. Environ Res. 2025;264(Pt 1):120321. doi:10.1016/j.envres.2024.120321
10. Wu H, Liu J, Conway E, et al. Fine particulate matter components associated with exacerbated depressive symptoms among middle-aged and older adults in China. Sci Total Environ. 2024;946:174228. doi:10.1016/j.scitotenv.2024.174228
11. Liu X, Li Y, Xie W, et al. Long-term effects of fine particulate matter components on depression among middle-aged and elderly adults in China: a nationwide cohort study. J Affect Disord. 2024;361:720-727. doi:10.1016/j.jad.2024.06.066
12. Zhou Y, Wang K, Wang X, et al. Gaseous air pollution exposure and depression in middle-aged and elderly adults: evidence from a Chinese cohort. Environ Sci Process Impacts. 2025;27(5):1472-1481. doi:10.1039/d5em00187k
13. Canning T, Richards M, Hansell AL, et al. Association of ambient air pollution exposure with psychological distress in mid and later adulthood: a 26-year prospective cohort study. PLoS One. 2025;20(3):e0320332. doi:10.1371/journal.pone.0320332
14. Cao T, Tian M, Hu H, et al. Do social economic status modify the association between air pollution and depressive or anxiety symptoms? a big sample cross-sectional study from the rural areas of Central China. J Affect Disord. 2024;362:502-509. doi:10.1016/j.jad.2024.07.063
15. Yu W, Thurston G, Shao Y, et al. Ambient air pollution and depressed mood in the National Longitudinal Study of Adolescent to Adult Health (Add Health) wave 4. Am J Epidemiol. 2025;194(4):975-983.

    doi:10.1093/aje/kwae314
16. Newbury JB, Heron J, Kirkbride JB, et al. Air and noise pollution exposure in early life and mental health from adolescence to young adulthood. JAMA Netw Open. 2024;7(5):e2412169. doi:10.1001/jamanetworkopen.2024.12169
17. Smolker HR, Reid CE, Friedman NP, et al. The association between exposure to fine particulate air pollution and the trajectory of internalizing and externalizing behaviors during late childhood and early adolescence: evidence from the Adolescent Brain Cognitive Development (ABCD) study. Environ Health Perspect. 2024;132(8):87001. doi:10.1289/EHP13427
18. Thompson R, Stewart G, Vu T, et al. Air pollution, traffic noise, mental health, and cognitive development: a multi-exposure longitudinal study of London adolescents in the SCAMP cohort. Environ Int. 2024;191:108963. doi:10.1016/j.envint.2024.108963
19. Yuan W, Yang T, Chen L, et al. Sufficient sleep and physical activity can relieve the effects of long-term exposure to particulate matter on depressive symptoms among 0.31 million children and adolescents from 103 counties in China. J Affect Disord. 2024;364:116-124. doi:10.1016/j.jad.2024.08.026
20. Li S, Liu Y, Li R, et al. Association between green space and multiple ambient air pollutants with depressive and anxiety symptoms among Chinese adolescents: the role of physical activity. Environ Int. 2024;189:108796. doi:10.1016/j.envint.2024.108796
21. Hu Y, Niu Z, Eckel SP, et al. Prenatal exposure to ambient air pollution and persistent postpartum depression. Sci Total Environ. 2024;953:176089. doi:10.1016/j.scitotenv.2024.176089
22. Chiu YM, Coull BA, Wilson A, et al. Air pollution mixture exposure during pregnancy and postpartum psychological functioning: racial/ethnic- and fetal sex-specific associations. J Expo Sci Environ Epidemiol. 2025;35(4):548-556. doi:10.1038/s41370-024-00726-2
23. Uy JP, Shin K, Buthmann JL, et al. Exposure to diesel-related particulate matter, cortisol stress responsivity, and depressive symptoms in adolescents. Psychoneuroendocrinology. 2025;171:107214. doi:10.1016/j.psyneuen.2024.107214
24. Wang F, Lian X, Wang Y, et al. Short-term exposure to $PM_{2.5}$ and high pollution events on depressive symptoms among adolescents. J Hazard Mater. 2025;492:138131. doi:10.1016/j.jhazmat.2025.138131
25. Hu J, Hu W, Xu Z, et al. Joint effect of exposure to fine particulate matter and lifestyle risk factors on depression and anxiety among Chinese adolescents: a national school-based study in China. Epidemiol Psychiatr Sci. 2025;34:e55. doi:10.1017/S2045796025100292
26. Borroni E, Buoli M, Nosari G, et al. Impact of air pollution exposure on the severity of major depressive disorder: results from the DeprAir study. Eur Psychiatry. 2024;67(1):e61. doi:10.1192/j.eurpsy.2024.1767
27. Jung YS, Johnson MM, Burke M, et al. Fine particulate matter from 2020 California wildfires and mental health-related emergency department visits. JAMA Netw Open. 2025;8(4):e253326. doi:10.1001/jamanetworkopen.2025.3326
28. Fu P, Jiang W, Tan X, et al. Short-term attributable risk and economic burden of hospital admissions for anxiety disorders due to air pollution: a multicity time-stratified case-crossover study. Environ Health. 2025;24(1):4. doi:10.1186/s12940-025-01157-8
29. Zhong X, Guo T, Zhang J, et al. Short-term effect of air pollution on daily hospital visits for anxiety disorders in southern China with low pollution concentrations. Toxics. 2025;13(1):45. doi:10.3390/toxics13010045
30. Ruiz-Páez R, López-Bueno JA, Padrón-Monedero A, et al. Short-term effects of fine particulate matter from biomass combustion and Saharan dust intrusions on emergency hospital admissions due to mental and behavioural disorders, anxiety and depression in Spain. Sci Total Environ. 2024;946:174316.

    doi:10.1016/j.scitotenv.2024.174316
31. Xu R, Luo L, Yuan T, et al. Association of short-term exposure to ambient fine particulate matter and ozone with outpatient visits for anxiety disorders: a hospital-based case-crossover study in South China. J Affect Disord. 2024;361:277-284. doi:10.1016/j.jad.2024.06.007
32. Chen YH, Zhang WW, Liu JW, et al. [Impact of ambient air pollution on hospital visits for mental and behavioral disorders among residents in an industrial area in Henan Province from 2016 to 2021]. Zhonghua Yu Fang Yi Xue Za Zhi. 2025;59(1):39-52. Chinese. doi:10.3760/cma.j.cn112150-20241022-00833
33. Tian YC, Yin ZM, Wang P, et al. The impact of air pollutants on emergency ambulance dispatches due to mental and behavioral disorders in Shenzhen, China. BMC Public Health. 2025;25(1):673. doi:10.1186/s12889-025-21781-w
34. Wang M, Ma Y, Zheng Y, et al. Proteomic biomarkers as mediators in the association between air pollution and incident depression and anxiety: evidence from the UK Biobank. Depress Anxiety. 2025;2025:3984517. doi:10.1155/da/3984517
35. Pan C, Qi X, Yang X, et al. Large-scale plasma proteomics uncovers novel targets linking ambient air pollution and depression. Mol Psychiatry. 2025;30(8):3650-3659. doi:10.1038/s41380-025-02953-x

36. Chang TY, Zhuang TY, Yang YC, et al. The increased risk of exposure to fine particulate matter for depression incidence is mediated by elevated TNF-R1: the Healthy Aging Longitudinal Study. Environ Health Prev Med. 2025;30:49. doi:10.1265/ehpm.25-00106
37. Ji S, Guo Y, Yan W, et al. $PM_{2.5}$ exposure contributes to anxiety and depression-like behaviors via phenyl-containing compounds interfering with dopamine receptor. Proc Natl Acad Sci U S A. 2024;121(21):e2319595121. doi:10.1073/pnas.2319595121
38. Li H, Guo X, Li P, et al. Particulate matter induces depression-like behavior through systemic inflammation and brain-derived neurotrophic factors. Environ Int. 2024;194:108883. doi:10.1016/j.envint.2024.108883
39. Kim HJ, Kim JH, Lee S, et al. $PM_{2.5}$ exposure triggers hypothalamic oxidative and ER stress leading to depressive-like behaviors in rats. Int J Mol Sci. 2024;25(24):13527. doi:10.3390/ijms252413527
40. Meng P, Pan C, Qin X, et al. A genome-wide gene-environmental interaction study identified novel loci for the relationship between ambient air pollution exposure and depression, anxiety. Ecotoxicol Environ Saf. 2024;285:117121. doi:10.1016/j.ecoenv.2024.117121
41. Fan H, Li J, Dou Y, et al. Linking ambient air pollution to mental health: evidence based on the two-sample Mendelian randomization and colocalization study. Transl Psychiatry. 2024;14(1):489. doi:10.1038/s41398-024-03196-0
42. Zhou J, Lu Z, Xu K, et al. Air pollution is the risk factor for psychiatric disorders: a two-step Mendelian randomization study. J Affect Disord. 2025;388:119475. doi:10.1016/j.jad.2025.119475
43. Yao XI, Sun S, Yang Q, et al. Associations between multiple ambient air pollutants, genetic risk, and incident mental disorders: an interaction study in the UK population. Sci Total Environ. 2025;973:179137. doi:10.1016/j.scitotenv.2025.179137
44. von Elm E, Altman DG, Egger M, et al. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: guidelines for reporting observational studies. Lancet. 2007;370(9596):1453-1457. doi:10.1016/S0140-6736(07)61602-X