County-Level Assessment of United States Construction-Worker Exposure to Ambient Fine Particulate Matter ($PM_{2.5}$) Above the 24-Hour National Standard in 2023

A reproducible integration of U.S. EPA air-quality monitoring and BLS labor-market data

Abstract

Outdoor construction workers combine high physical exertion, elevated ventilation rates, and unavoidable outdoor placement, making them one of the working populations most exposed to ambient fine particulate matter ($PM_{2.5}$). The record-breaking 2023 Canadian wildfire season, whose smoke plumes repeatedly degraded air quality across the U.S. Midwest and Northeast, sharpened the need to know *where* the largest at-risk construction workforces coincide with hazardous air. We integrated the U.S. Environmental Protection Agency (EPA) Air Quality System (AQS) daily $PM_{2.5}$ record (parameter 88101) with the U.S. Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW) private-sector construction file (NAICS 23) for calendar year 2023, at the county level, to quantify construction worker-days and wage exposure occurring on days when the county-representative $PM_{2.5}$ concentration exceeded the EPA 24-hour primary standard of $35\,\mu g\,m^{-3}$. After deduplicating pollutant-standard records, aggregating monitors to a robust county-day median, and filling spatial and temporal monitoring gaps by principled interpolation, we joined 2,656 counties containing construction employment. Nationwide, an estimated 18.95 million construction worker-days (upper bound 26.13 million) coincided with exceedance days, corresponding to a potential wage exposure of roughly \$5.68 billion (upper bound \$7.85 billion) under a 260-working-day convention. Exposure was highly concentrated: the Gini coefficient of exposed worker-days across counties was 0.846, with the top 5% and top 10% of counties accounting for 58.4% and 75.8% of the national total, respectively. We combined exposure volume, economic weight, and pollution severity into an equally weighted Composite Vulnerability Index (CVI) and ranked all counties, recommending a targeted set of 20 counties—led by Cook (IL), Hennepin (MN), and Marion (IN)—for a prospective worker-protection study. We emphasize that our wage metric is a measure of *potential wage exposure* (an upper-bound, gross-flow accounting quantity), not *realized economic loss*, and we articulate the analytic gap between the two. The pipeline is fully reproducible from public data and provides an actionable, transparent basis for prioritizing occupational air-quality interventions.

Keywords: fine particulate matter; $PM_{2.5}$; occupational exposure; construction workers; wildfire smoke; air-quality standards; environmental justice; composite vulnerability index; exposure inequality

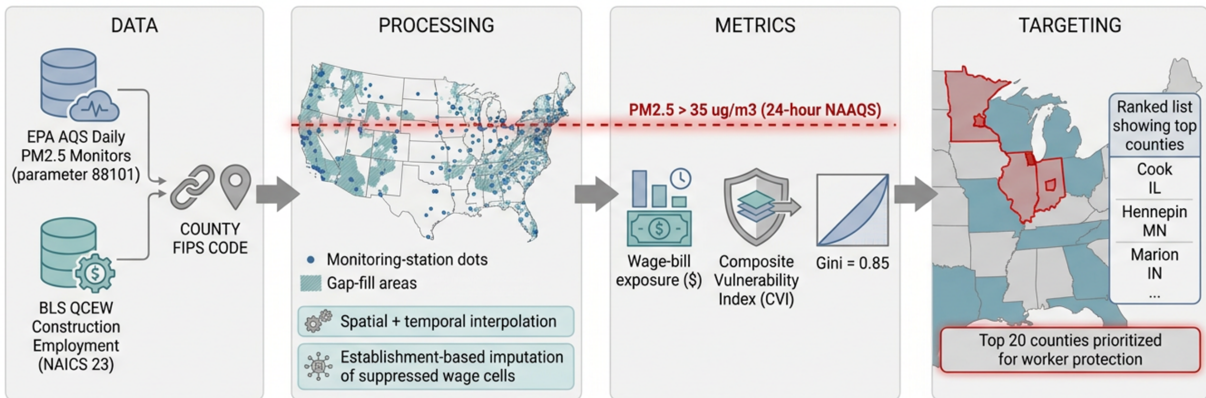

Figure 1: Graphical abstract. The analysis links EPA AQS daily $PM_{2.5}$ monitoring and BLS QCEW construction employment by county FIPS code, fills monitoring and reporting gaps through spatial/temporal interpolation and establishment-based imputation, quantifies exposed worker-days and wage-bill exposure on days exceeding the $35\,\mu g\,m^{-3}$ 24-hour standard, characterizes the concentration of exposure (Gini $= 0.85$), and prioritizes 20 counties for a worker-protection study.

1 Introduction

Ambient fine particulate matter with an aerodynamic diameter below $2.5\,\mu m$ ($PM_{2.5}$) is among the most thoroughly documented environmental threats to human health. Decades of cohort and time-series epidemiology have connected both long-term and short-term $PM_{2.5}$ exposure to increased cardiovascular and respiratory morbidity and to premature mortality [1, 2]. In the Medicare population, analyses spanning the entire continental United States found that each $10\,\mu g\,m^{-3}$ increment in annual $PM_{2.5}$ was associated with a measurable increase in all-cause mortality, with no evidence of a threshold below which risk disappears [3]. Short-term elevations likewise track closely with same-day and next-day hospital admissions for cardiovascular and respiratory disease [4]. At the global scale, ambient particulate pollution ranks among the leading modifiable contributors to the burden of disease, accounting for several million deaths annually [5]. These findings collectively motivate the regulatory architecture of the U.S. National Ambient Air Quality Standards (NAAQS), including the 24-hour primary standard for $PM_{2.5}$ of $35\,\mu g\,m^{-3}$ that anchors the present study [6].

The health burden of $PM_{2.5}$, however, is not borne equally. A growing literature documents systematic disparities in exposure across income, race, and geography: lower-income communities and communities of color are, on average, exposed to higher concentrations and to particle mixtures of differing composition [7–9]. This distributional dimension has reframed air-quality management as a question not only of aggregate concentration but of *who* is exposed and *where*. Cumulative-burden screening tools, which combine pollution metrics with indicators of population vulnerability, have become a central instrument for translating this equity concern into administrative targeting decisions [10, 11]. The occupational dimension of this inequity, however, remains comparatively underexamined, even though a worker's job can be the single largest determinant of daily particulate dose.

Construction workers occupy a particularly exposed position within the labor market. Their work is overwhelmingly outdoors, physically strenuous, and conducted regardless of ambient air quality on most job sites; elevated minute ventilation during manual labor amplifies the inhaled dose of any given ambient concentration. A substantial body of occupational-health research has quantified the particulate burden of construction activity itself—from demolition, cutting, grinding, and earthmoving—and has linked it to respiratory impairment and elevated chronic-disease risk [12–14]. Longitudinal cohorts of construction workers show meaningfully elevated risks of chronic obstructive pulmonary disease relative to the general workforce [15], a pattern corroborated by meta-analysis [16]. Occupational exposure to particulate air pollution has, moreover, been associated with excess mortality from ischemic heart disease and cerebrovascular disease among heavily exposed male workers [17]. When ambient $PM_{2.5}$ is layered on top of these workplace sources, the total dose experienced by an outdoor construction worker on a hazardous-air day can substantially exceed that of the surrounding general population.

The salience of ambient exposure for outdoor workers escalated sharply in 2023. An extraordinary Canadian wildfire season burned more than an order of magnitude above the recent historical average and released record quantities of carbon and smoke [18]. Long-range transport of that smoke repeatedly degraded surface air quality across the U.S. Midwest, Great Lakes, and Northeast—regions not historically accustomed to wildfire-driven pollution—producing multi-day episodes in which 24-hour $PM_{2.5}$ concentrations far exceeded the NAAQS in major metropolitan areas [19]. This matters beyond the simple mass of particulate: emerging evidence indicates that wildfire-derived $PM_{2.5}$ may be more harmful per unit mass for respiratory outcomes than particulate from other sources [20], and reviews of wildfire-smoke health effects document consistent associations with respiratory and cardiovascular endpoints [21–23]. For outdoor workforces, the 2023 season was therefore not an abstraction but a large, acute, and geographically novel exposure event.

Beyond direct health endpoints, ambient particulate pollution imposes economic costs on the workforce through productivity and labor-supply channels. Field studies of manual and semi-manual labor have shown that elevated particulate concentrations measurably reduce output per worker [24, 25], and natural-experiment evidence links pollution episodes to reductions in labor supply [26]. Occupational heat-strain research provides an analogous and instructive template, quantifying how environmental stressors erode both worker health and productivity across large populations [27]. Recognition of these burdens has begun to translate into policy: several jurisdictions have adopted or proposed rules requiring employers to protect outdoor workers during wildfire-smoke events, for example through air-quality-index-triggered provision of respiratory protection or work modification [28]. Effective deployment of such protections, however, depends on knowing where the largest at-risk workforces are concentrated.

Despite the clear convergence of these literatures, there is no publicly reproducible, national, county-resolved accounting of *how much* construction labor coincides with hazardous ambient air, or of *where* that coincidence is greatest. The present study fills that gap. We integrate two authoritative, public federal datasets—the EPA AQS daily $PM_{2.5}$ record and the BLS QCEW construction-employment file—for calendar year 2023, and we estimate, at the county level, the number of construction worker-days and the magnitude of construction wages that were active on days when the county-representative $PM_{2.5}$ concentration exceeded $35\,\mu g\,m^{-3}$. We then characterize the striking geographic concentration of this exposure, combine exposure volume, economic weight, and pollution severity into a transparent Composite Vulnerability Index, and use it to recommend a defensible set of counties for a prospective worker-protection study. Throughout, we are careful to frame the wage metric as *potential wage exposure*—an upper-bound measure of the payroll operating under hazardous air—and to distinguish it explicitly from *realized economic loss*, which requires additional dose-response and behavioral modeling to estimate.

2 Methods

2.1 Overview and design

The analysis is a retrospective, observational integration of two federal data systems at the U.S. county level for calendar year 2023, organized as a five-stage reproducible pipeline (Figure 2). The unit of exposure is the *county-day*: for each county and each of the 365 days of 2023 we derive a representative ambient $PM_{2.5}$ concentration, flag it as an *exceedance day* when that concentration exceeds the EPA 24-hour primary standard of 35 µg m^{-3}, and multiply the number of exceedance days by the county's construction employment (and by its daily construction wage bill) to obtain exposed worker-days and wage-bill exposure. All processing used a fixed random seed for reproducibility, and an Earth radius of 6,371.008,8 km for geodesic distance calculations.

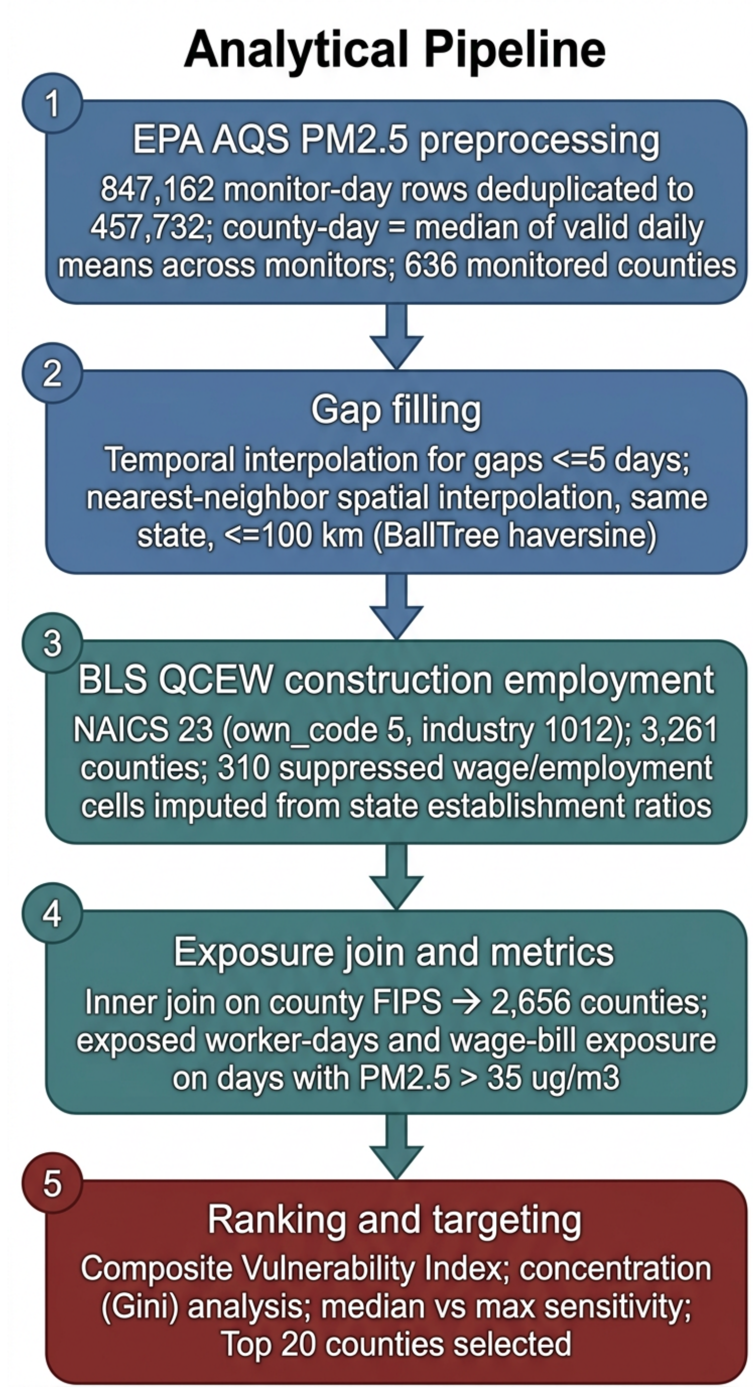

Figure 2: Analytical pipeline. Five sequential stages transform raw EPA AQS and BLS QCEW records into county-level exposure metrics and a prioritized county list. Counts shown are the principal quality-control quantities reported in the text.

2.2 Air-quality data: EPA AQS daily $PM_{2.5}$

Ambient concentrations were drawn from the EPA AQS daily summary file for $PM_{2.5}$ Local Conditions (parameter code 88101) for 2023. Because a single monitor-day can appear multiple times in the AQS daily file—once for each pollutant standard against which the measurement is evaluated—direct aggregation would double-count observations. We therefore first deduplicated to unique monitor-days. Of 847,162 monitor-day rows, 389,430 were redundant pollutant-standard duplicates; retaining the primary “PM25 24-hour 2012” standard record yielded 457,732 unique monitor-days. No rows with a null daily mean were present. Negative daily means (n = 2,990; overall minimum $-5.96\ \mu g\, m^{-3}$) were retained as measured rather than truncated at zero, in order to preserve the unbiased statistical mean of low-concentration measurements; truncation would introduce a small positive bias.

To obtain a single representative concentration per county-day, monitors within a county were aggregated using the *median* of their valid daily means across distinct monitors. The median was chosen over the mean for its robustness to a single anomalous monitor and its insensitivity to the retained negative values. This step produced 203,450 directly observed county-days across 636 monitored counties.

2.3 Filling monitoring gaps: temporal and spatial interpolation

Monitoring networks are sparse in both time (missed sampling days) and space (unmonitored counties), so a county-day panel built only from observations would be badly incomplete. We filled gaps using two principled, conservative procedures. First, *temporal interpolation* filled short within-county gaps of at most five consecutive days by linear interpolation between bracketing observed county-days, on the rationale that ambient $PM_{2.5}$ is temporally autocorrelated over a few days; this recovered 19,434 county-days. Second, *spatial interpolation* filled remaining gaps using nearest-neighbor transfer from the closest monitored county, subject to two constraints: the neighbor had to lie within 100 km (great-circle distance, computed with a BallTree on haversine distances) and had to be in the *same state*, so that transferred values respect broad meteorological and regulatory regions. The choice of nearest-neighbor transfer, rather than inverse-distance or kriging surfaces, keeps the imputed value physically interpretable as “the nearest representative monitor” and avoids smoothing away the short, sharp episodes (such as wildfire-smoke days) that drive exceedances; the trade-offs among interpolation methods for air-quality surfaces are well characterized [29]. Spatial interpolation filled 5,581 within-monitored-county gap-days and extended coverage to 2,038 otherwise unmonitored counties (732,169 county-days). A residual 554 counties had no qualifying neighbor within 100 km in the same state and were left unresolved (15,376 unresolved county-days), a deliberately transparent limitation rather than an aggressive extrapolation. The resulting panel comprised 2,674 distinct counties.

2.4 Labor data: BLS QCEW construction employment

Construction employment and wages were drawn from the BLS QCEW 2023 annual single-file, restricted to private-sector construction (ownership code 5, industry code 1012, corresponding to NAICS sector 23). This yielded records for 3,261 counties, none with zero establishments. QCEW suppresses employment and wage cells that could disclose information about individual establishments—a standard statistical-disclosure-control practice [30]; 310 county cells were suppressed for both employment and wages. Rather than dropping these counties—which would bias the national accounting downward and could omit high-exposure areas—we imputed the suppressed cells hierarchically using establishment-based ratios. For each state we computed the ratio of employment to establishments and of wages to establishments among its non-suppressed counties, and applied that state ratio to the (non-suppressed) establishment count of each suppressed county; where a state ratio was unavailable we fell back to the national ratio (national employment-per-establishment = 8.57; national wages-per-establishment = \$661,476). In practice all 310 suppressed cells were resolved at the state level, with no county requiring the national fallback. Imputation raised total construction employment from 7,882,825 (reported) to 8,035,601 and total wages from \$605.9 billion to \$617.3 billion, closely bracketing the national reported totals (7,950,260 jobs; \$613.5 billion).

The daily construction wage bill for each county was derived by dividing annual construction wages by an assumed number of working days. We report results primarily under a 260-day convention (a five-day work-week year) and provide a 365-day (calendar-day) convention for comparison; nationally these imply daily construction wage bills of \$2.37 billion and \$1.69 billion, respectively.

2.5 Exposure join and metric construction

The county $PM_{2.5}$ panel and the county construction file were combined by an inner join on the five-digit county FIPS code, matching 2,656 counties. Eighteen $PM_{2.5}$-only counties (typically EPA special/tribal monitor codes with no QCEW county record) and 605 QCEW-only counties (more than 100 km from any monitor and thus not spatially imputable) were dropped. These drops are scientifically appropriate—worker-days cannot be estimated where either employment or a representative concentration is absent—and correspond to join rates of 99.3% relative to the $PM_{2.5}$ panel and 81.4% relative to the QCEW panel.

For each matched county we counted *exceedance days* (county-days with representative $PM_{2.5}$ $> 35\,\mu\mathrm{g\,m^{-3}}$) and computed:

$$\text{Exposed worker-days} = (\text{annual average construction employment}) \times (\text{exceedance days}), \quad (1)$$

$$\text{Wage-bill exposure} = (\text{daily construction wage bill}) \times (\text{exceedance days}). \quad (2)$$

Because the number of exceedance days depends on how multiple monitors within a county are reconciled, we computed two bounding versions of every metric: a *median* convention (county-day concentration is the median across monitors, as above) and a *max* convention (county-day concentration is the maximum across monitors, which flags a county-day as an exceedance if *any* monitor exceeds the standard). The median convention is our primary, conservative estimate; the max convention provides a plausible upper bound.

2.6 Concentration (inequality) analysis

To characterize how unevenly exposure is distributed across the country, we ranked counties by exposed worker-days in descending order and constructed a concentration (Lorenz-type) curve of the cumulative share of national exposed worker-days against the cumulative share of counties. We summarized the curve with the Gini coefficient and with the exposure shares held by the top 5% and top 10% of counties. This framing parallels the exposure-inequality literature, which increasingly uses concentration metrics to describe the distribution of particulate burden across populations [7, 8].

2.7 Composite Vulnerability Index (CVI)

To translate multiple exposure dimensions into a single prioritization score, we constructed an equally weighted Composite Vulnerability Index from three components (Figure 3): a *volume* component (exposed worker-days, median convention), a *weight* component (wage-bill exposure, median convention, 260-day basis), and a *severity* component (the 90th percentile of the county's 2023 $PM_{2.5}$ distribution, capturing how intense the worst air-quality days were). Each component was rescaled to the unit interval by min–max normalization across all 2,656 matched counties,

$$x_i^{\text{norm}} = \frac{x_i - \min_j x_j}{\max_j x_j - \min_j x_j}, \quad (3)$$

and the CVI was defined as the unweighted mean of the three normalized components,

$$\mathrm{CVI}_i = \tfrac{1}{3}\left(x_i^{\mathrm{vol,norm}} + x_i^{\mathrm{wt,norm}} + x_i^{\mathrm{sev,norm}}\right). \tag{4}$$

Equal weighting is a deliberate, transparent default that avoids embedding contestable value judgments about the relative importance of workforce size, economic magnitude, and pollution intensity; it is the same design philosophy underlying widely used cumulative-burden screening indices [10, 11]. Counties were ranked by CVI, and the 20 highest-scoring counties were recommended as the target set for a prospective worker-protection study.

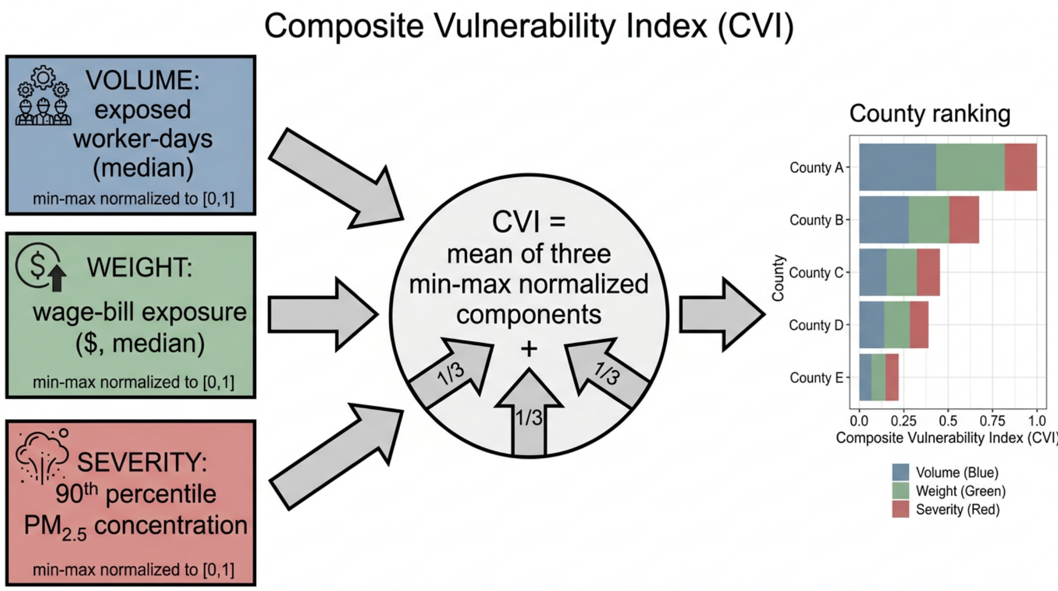

Figure 3: Construction of the Composite Vulnerability Index (CVI). Three min–max-normalized components—exposure volume (exposed worker-days), economic weight (wage-bill exposure), and pollution severity (90th-percentile $PM_{2.5}$)—are averaged with equal weight to yield a single county score used for ranking.

2.8 Interpretation guardrail: potential exposure versus realized loss

A central methodological commitment of this study is that the wage metric is a measure of *potential wage exposure*—the dollar value of construction payroll that was active and paid in geographies experiencing hazardous air—and *not* a measure of realized economic damage. Potential wage exposure is an upper-bound, gross-flow accounting quantity: it answers "how large is the payroll of the workforce operating under hazardous air-quality conditions?" It deliberately does not encode whether workers were outdoors, whether output or hours changed, or any downstream health cost. We formalize this distinction, and its consequences for policy interpretation, in the Discussion.

3 Results

3.1 National magnitude of construction-worker $PM_{2.5}$ exposure

Across the 2,656 matched counties, an estimated 18,952,962 construction worker-days coincided with $PM_{2.5}$ exceedance days in 2023 under the primary (median) convention, rising to 26,127,413 worker-days under the max convention. The corresponding potential wage exposure was approximately

\$5.68 billion (median convention, 260-day basis; \$4.05 billion on a 365-day basis) and up to \$7.85 billion under the max convention. Exceedances were geographically widespread rather than confined to a few localities: a median of 1,991 counties (up to 2,073 under the max convention) recorded at least one exceedance day during the year, consistent with the broad footprint of transported wildfire smoke described for the 2023 season [18, 19].

Because monitoring coverage is incomplete, a meaningful share of the national total rests on interpolation. Decomposing exposed worker-days by data provenance, 66.7% derived from directly observed county-days and 33.3% from imputation (29.1% spatial, 4.3% temporal) under the median convention; the observed share rose to 72.5% under the max convention. Thus roughly two-thirds of the estimated national exposure is anchored in direct measurement, with the remainder transparently attributable to conservative gap-filling—an accounting we report explicitly rather than folding into an undifferentiated total.

3.2 Exposure is highly concentrated geographically

Construction-worker $PM_{2.5}$ exposure is strikingly unequal across counties (Figure 4). The concentration curve of exposed worker-days departs sharply from the line of perfect equality, yielding a Gini coefficient of 0.846. The top 5% of counties account for 58.4% of all exposed worker-days nationally, and the top 10% account for 75.8%. In other words, three-quarters of the national construction-worker exposure burden is concentrated in roughly one-tenth of counties. This degree of concentration exceeds what is typically observed for ambient concentration alone and reflects the compounding of two spatial gradients: construction employment is agglomerated in populous metropolitan counties, and the 2023 exceedance days were themselves regionally clustered. The practical implication is that a geographically targeted intervention reaching a small number of counties could address the large majority of the national exposure burden—a pattern that directly motivates the prioritization exercise below.

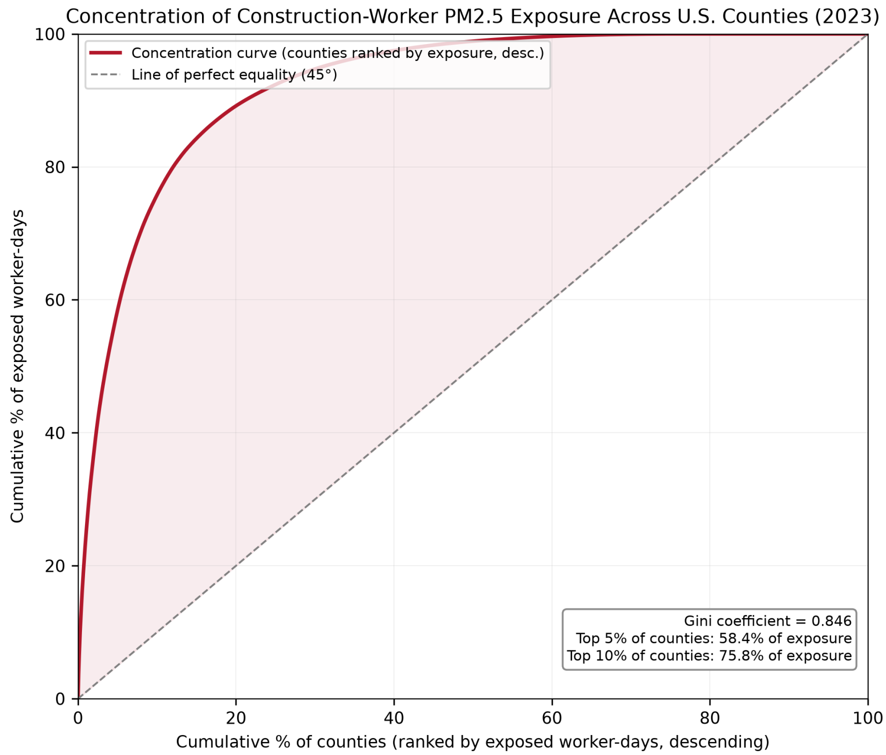

Figure 4: Concentration of construction-worker $PM_{2.5}$ exposure across U.S. counties (2023). Counties are ranked by exposed worker-days in descending order (horizontal axis) against the cumulative share of national exposed worker-days (vertical axis). The pronounced departure from the 45° line of perfect equality corresponds to a Gini coefficient of 0.846; the top 5% and top 10% of counties hold 58.4% and 75.8% of national exposure, respectively.

3.3 Sensitivity to the monitor-aggregation convention

The choice of within-county aggregation convention affects the magnitude but not the ranking of exposure (Figure 5). Across all 2,656 counties, county-level exposed worker-days under the median and max conventions are strongly correlated (Pearson $r = 0.809$), and the max estimate exceeds the median estimate for essentially every county, as expected because the max convention flags an exceedance whenever any single monitor exceeds the standard. The gap between conventions is largest in multi-monitor metropolitan counties where monitors disagree on a given day—for example, Cook County (IL) and Allegheny County (PA) show substantially higher exposure under the max convention—whereas single-monitor counties are identical under both conventions. Crucially, the relative ordering of the highest-exposure counties is preserved across conventions, indicating that the prioritization is robust to this analytic choice. We therefore report the median convention as our primary estimate and treat the max convention as an upper bound.

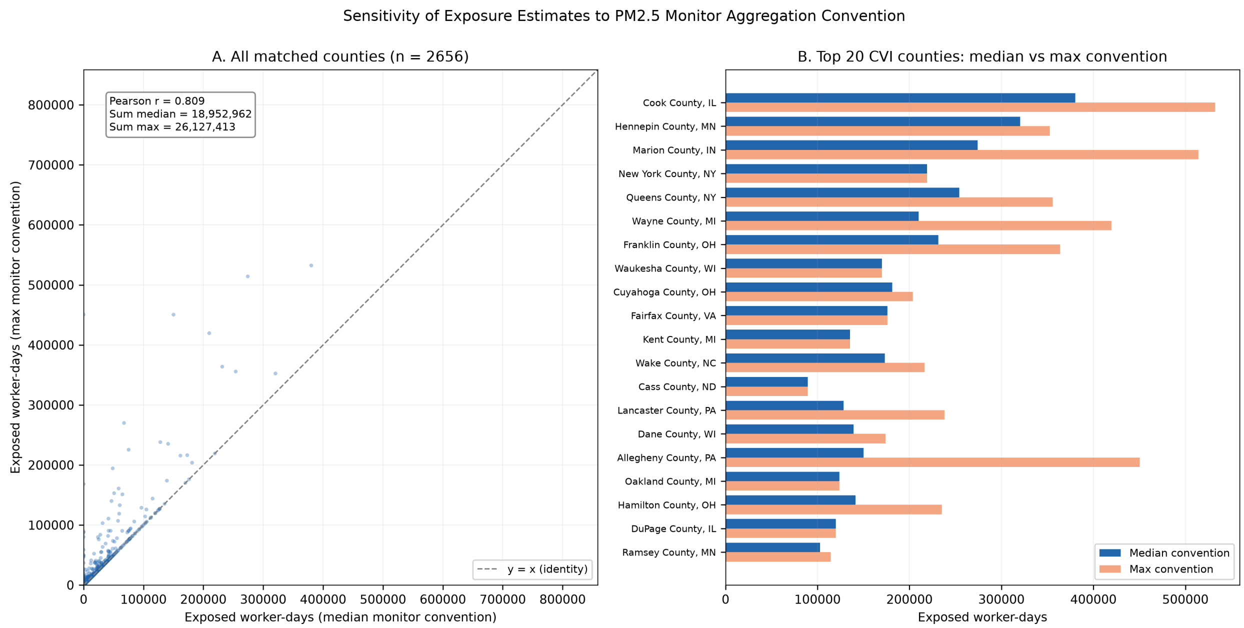

Figure 5: Sensitivity of exposure estimates to the $\mathbf{PM_{2.5}}$ monitor-aggregation convention. (A) County-level exposed worker-days under the median versus max convention for all 2,656 matched counties; points lie on or above the identity line, and the two conventions are strongly correlated ($r = 0.809$). (B) Median versus max exposed worker-days for the top 20 CVI counties; the ranking is preserved while the absolute magnitude shifts upward under the max convention, most notably for multi-monitor metropolitan counties.

3.4 County rankings and the recommended study set

Ranking all 2,656 counties by the Composite Vulnerability Index (mean CVI = 0.193; range 0 to 0.919) produced a clear hierarchy of priority counties (Table 1). Cook County, Illinois, ranks first with a near-maximal CVI of 0.919, driven by the largest construction workforce in the sample (annual average of 76,056 construction jobs) combined with five exceedance days, yielding 380,280 exposed worker-days and $138 million in potential wage exposure. Hennepin County, Minnesota (CVI 0.851), ranks second, notable for a high severity component: its ten exceedance days and elevated 90th-percentile concentration ($19.75\,\mu\mathrm{g\,m^{-3}}$) reflect intense, repeated smoke intrusion over the upper Midwest. Marion County, Indiana (CVI 0.744), ranks third, with the highest severity among the leading counties (90th-percentile $PM_{2.5}$ of $20.36\,\mu\mathrm{g\,m^{-3}}$).

The recommended set of 20 counties is dominated by industrial and rapidly growing metropolitan areas of the Midwest, Great Lakes, and Northeast—precisely the regions most affected by transported Canadian wildfire smoke in 2023. New York (NY) and Queens (NY) counties (ranks 4–5) contribute large, dense construction workforces; the Ohio counties of Franklin, Cuyahoga, and Hamilton (ranks 7, 9, 18) and the Michigan counties of Wayne, Kent, and Oakland (ranks 6, 11, 17) recur prominently, as do the Wisconsin counties of Waukesha and Dane (ranks 8, 15). The list also captures counties whose selection is driven predominantly by severity rather than sheer size: Cass County, North Dakota (rank 13), enters the top 20 despite a comparatively modest workforce (8,948 jobs) because its 90th-percentile $PM_{2.5}$ of $22.35\,\mu\mathrm{g\,m^{-3}}$—the highest severity component in the entire top 20 (normalized severity 0.99)—and ten exceedance days signal exceptionally intense episodic pollution. This heterogeneity in the drivers of ranking illustrates the value of the composite design: the CVI surfaces both the large-workforce metropolitan counties and the smaller, acutely affected counties that a purely volume-based ranking would miss.

Table 1: Top 20 counties recommended for a construction-worker $PM_{2.5}$ protection study, ranked by Composite Vulnerability Index (CVI). Exposed worker-days and wage-bill exposure are shown under the primary (median) convention; wage-bill exposure uses the 260-working-day basis. "Exc. days" is the median number of $PM_{2.5}$ exceedance days; "$PM_{2.5}$ p90" is the 90th-percentile daily concentration (µg m^{-3}); "Constr. jobs" is the annual-average construction employment.

Rank	County (State)	CVI	Exposed worker-days	Wage-bill exp. ($M)	Exc. days	$PM_{2.5}$ p90	Constr. jobs
1	Cook (IL)	0.919	380,280	138.4	5	18.06	76,056
2	Hennepin (MN)	0.851	320,450	119.3	10	19.75	32,045
3	Marion (IN)	0.744	274,240	87.4	8	20.36	34,280
4	New York (NY)	0.650	219,162	104.2	6	15.55	36,527
5	Queens (NY)	0.645	254,085	86.1	5	15.96	50,817
6	Wayne (MI)	0.627	209,844	69.0	9	19.46	23,316
7	Franklin (OH)	0.626	231,525	74.7	7	17.56	33,075
8	Waukesha (WI)	0.544	170,109	54.8	9	18.68	18,901
9	Cuyahoga (OH)	0.544	181,192	54.9	8	18.10	22,649
10	Fairfax (VA)	0.502	175,980	62.2	7	15.05	25,140
11	Kent (MI)	0.490	135,240	40.4	7	19.26	19,320
12	Wake (NC)	0.474	173,068	54.0	4	14.71	43,267
13	Cass (ND)	0.470	89,480	25.9	10	22.35	8,948
14	Lancaster (PA)	0.470	128,170	36.5	7	19.02	18,310
15	Dane (WI)	0.470	139,128	43.3	8	17.56	17,391
16	Allegheny (PA)	0.463	150,165	46.1	5	16.25	30,033
17	Oakland (MI)	0.457	123,900	43.0	4	17.64	30,975
18	Hamilton (OH)	0.456	141,162	41.6	6	16.92	23,527
19	DuPage (IL)	0.454	120,064	43.8	4	17.55	30,016
20	Ramsey (MN)	0.446	102,816	37.0	9	18.86	11,424

4 Discussion

4.1 Principal findings

This study provides the first publicly reproducible, national, county-resolved accounting of the coincidence between U.S. construction labor and hazardous ambient $PM_{2.5}$ in 2023. Three findings stand out. First, the aggregate magnitude is substantial: on the order of 19 million construction worker-days—and roughly $5.7 billion of active construction payroll—were operating on days when the county-representative $PM_{2.5}$ exceeded the 24-hour national standard, with upper bounds of 26 million worker-days and $7.9 billion. Second, this exposure is extraordinarily concentrated: with a Gini coefficient of 0.846 and three-quarters of the burden falling in one-tenth of counties, exposure is far more spatially concentrated than ambient concentration alone, because it compounds the agglomeration of construction employment with the regional clustering of 2023 smoke episodes. Third, the counties bearing the greatest burden are overwhelmingly in the industrial Midwest, Great Lakes, and Northeast—regions historically insulated from wildfire smoke but heavily affected by long-range transport from the record 2023 Canadian fire season [18, 19].

4.2 Why construction workers warrant specific attention

The concentration of exposure identified here is consequential precisely because construction workers are physiologically and occupationally predisposed to high effective doses. Outdoor placement removes the building-envelope protection that attenuates indoor exposure for most workers, and the elevated ventilation of heavy manual labor increases the volume of contaminated air inhaled per hour. These ambient exposures are superimposed on the substantial particulate burden generated by construction activity itself, which is independently associated with respiratory impairment and elevated chronic-disease risk [12–16]. The health stakes are amplified further by the composition of 2023's dominant particulate source: wildfire-derived $PM_{2.5}$ appears to be disproportionately harmful for respiratory outcomes relative to particulate from other sources [20], and the broader wildfire-smoke literature documents consistent respiratory and cardiovascular effects [21–23]. Taken together, the workforce we identify is one for whom a given ambient concentration likely translates into an above-average health burden, strengthening the case for targeted protection.

4.3 Potential wage exposure is not realized economic loss

A crucial interpretive point concerns what the wage metric does and does not represent. Our wage-bill exposure quantifies *potential wage exposure*: the dollar value of construction payroll that was active and paid in geographies experiencing hazardous air. It is an upper-bound, gross-flow accounting quantity that answers a scale question—how large is the at-risk payroll?—and it deliberately excludes whether workers were actually outdoors, whether output or hours changed, and any downstream health cost. It must not be read as an estimate of the economic damage caused by pollution.

Realized economic loss, by contrast, is a net, welfare-relevant quantity: the actual reduction in economic value plus incremental costs attributable to the exposure. Its components include productivity decline (reduced output per hour under high-$PM_{2.5}$ conditions, an effect documented for manual and semi-manual labor [24, 25]); increased absenteeism from pollution-triggered respiratory and cardiovascular symptoms; medical and health-system costs, including the monetized value of morbidity and mortality risk; behavioral labor-supply responses, whereby workers reduce hours or exit outdoor tasks and wage premia are required to retain labor [26]; and work stoppages and schedule disruption arising from air-quality-index-triggered stop-work rules or voluntary halts. Each of these channels converts only a fraction of the exposed payroll into actual loss, and the size of that fraction is governed by dose-response functions and behavioral adjustment that lie outside the scope of a purely accounting-based exposure study. Formally, realized loss can be expressed schematically as potential wage exposure multiplied by a productivity/absenteeism loss fraction, plus external health and disruption costs, minus losses averted by adaptation—so that potential wage exposure is an upper bound on, and generally much larger than, realized loss.

This distinction is not merely semantic; it dictates correct use of the two quantities. Potential wage exposure and the CVI are the right instruments for *targeting*: they identify where the largest at-risk workforces are concentrated and therefore where protective interventions (monitoring, respiratory protection, stop-work thresholds, schedule modification) should be prioritized. Realized economic loss is the right instrument for *cost–benefit analysis* of those interventions, but it must be estimated separately with health and productivity models. Reporting potential wage exposure as if it were realized loss would substantially overstate damages; reporting realized loss without the exposure context would obscure the scale of the population needing protection. We therefore present the former as a transparent prioritization tool and explicitly defer the latter to downstream modeling.

4.4 Policy implications

The pronounced geographic concentration of exposure carries a direct and encouraging policy corollary: because roughly three-quarters of the national burden falls in about one-tenth of counties, a targeted program reaching a modest number of jurisdictions could address most of the exposure. The 20-county set in Table 1 offers a defensible, data-driven starting point for such a program, and for a prospective field study to measure realized health and productivity effects. Concretely, the findings support extending to interior and eastern states the kinds of outdoor-worker smoke protections already adopted in more fire-prone jurisdictions—for instance, air-quality-index-triggered provision of respiratory protection, acclimatization and work-modification rules, and real-time site-level monitoring [28]. The recurrence of severity-driven counties such as Cass County, North Dakota, further argues for protections keyed to episodic intensity (the number and magnitude of exceedance days) and not solely to workforce size, so that smaller but acutely affected communities are not overlooked. More broadly, situating occupational exposure within the cumulative-burden and environmental-justice framework [7–11] highlights that outdoor workers constitute a distinct, policy-relevant axis of exposure inequality that general population-weighted metrics do not capture.

4.5 Strengths and limitations

The principal strengths of this work are its reproducibility from public federal data, its transparent treatment of missing data, and its explicit separation of exposure accounting from loss estimation. Several limitations temper interpretation. First, roughly one-third of the national exposure estimate rests on spatial and temporal interpolation; although we report the observed-versus-imputed decomposition explicitly and constrain interpolation to same-state neighbors within 100 km, imputed county-days carry more uncertainty than measured ones, and 554 counties could not be resolved at all [29]. Second, exposure is assigned at the county level using ambient monitor data; it does not capture within-county spatial heterogeneity, micro-environmental factors, or whether individual workers were outdoors, and city-to-city differences in exposure characteristics can modulate the concentration–health relationship [31]. Third, employment is treated as static annual-average construction employment applied uniformly across exceedance days, which does not reflect seasonal or day-to-day variation in the active workforce. Fourth, the wage-bill exposure depends on the assumed number of working days per year; we address this by reporting both 260- and 365-day conventions. Fifth, the CVI's equal weighting, while transparent, is a value choice, and alternative weightings would shift specific ranks even though the strong concentration of exposure makes the broad composition of the priority set robust. Finally, as emphasized above, the study measures potential exposure, not realized health or economic outcomes, which require separate dose-response and behavioral modeling.

4.6 Future directions

Three extensions follow naturally. First, the potential-exposure estimates here can be paired with epidemiological dose-response functions and productivity/labor-supply models [24–27] to convert potential wage exposure into ranges of realized economic loss for cost–benefit analysis of interventions. Second, incorporating source-apportioned or satellite-derived $PM_{2.5}$ would allow the wildfire-smoke fraction to be isolated and weighted by its apparently greater per-mass toxicity [18, 20]. Third, a prospective field study in the recommended counties—combining personal exposure monitoring, health surveillance, and time-use data on outdoor work—would validate the county-level assignments and directly measure the outcomes this accounting can only bound.

4.7 Conclusion

Integrating EPA air-quality monitoring with BLS labor data reveals that construction-worker exposure to hazardous ambient $PM_{2.5}$ in 2023 was large in aggregate and extraordinarily concentrated geographically, with the industrial Midwest and Northeast bearing the brunt of a historic wildfire-smoke year. By quantifying potential wage exposure and combining it with pollution severity in a transparent Composite Vulnerability Index, we provide an actionable, reproducible basis for prioritizing worker-protection efforts—while carefully distinguishing the scale of the at-risk workforce from the realized economic loss that remains to be modeled. The 20 recommended counties offer a concrete target for policy and for the prospective research needed to close that gap.

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