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Ambient $PM_{2.5}$ Air Pollution in Ouagadougou, Burkina Faso: Exposure, Attributable Health Burden, and Economic Cost

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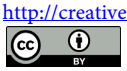

Abstract

Ambient fine particulate matter ($PM_{2.5}$) is among the leading environmental causes of premature death, and the highest population-weighted exposures now sit in rapidly urbanizing cities of sub-Saharan Africa. Ouagadougou combines heavy two-wheeler traffic, household biomass use, unpaved road dust, and recurrent Harmattan dust, yet the resulting health and economic losses have not been quantified. We estimate the mortality, disability, and economic costs attributable to ambient $PM_{2.5}$ exposure in Ouagadougou, and we evaluate the benefits of meeting World Health Organization (WHO) air-quality targets. Annual $PM_{2.5}$ concentrations were compiled from ground monitoring and satellite-derived datasets. Disease-specific relative risks came from the integrated exposure response (IER) functions used by the Global Burden of Disease (GBD) study. We computed population attributable fractions, attributable deaths, years of life lost (YLL), years lived with disability (YLD), and disability-adjusted life years (DALYs) for the five $PM_{2.5}$-related causes. Economic losses were valued with a cost-of-illness (COI) approach and a benefit-transferred value of a statistical life (VSL). A 10,000-iteration Monte Carlo simulation propagated parameter uncertainty. At a city mean of about 48 $\mu g \cdot m^{-3}$, roughly ten times the WHO guideline, ambient $PM_{2.5}$ was associated with approximately 980 deaths per year (95% CI: 660 to 1420) and 27,900 DALYs (95% CI: 19,000 to 40,000). Lower respiratory infection and stroke carried the largest share. The combined economic loss reached about US$102 million in 2024 values, near 1.8% of the metropolitan product. Meeting the WHO guideline would avoid close to 930 deaths each year. The avoidable burden is large relative to the size of the local economy. Cleaner two-wheeler fleets, a shift away

from solid cooking fuels, and dust control on unpaved roads would return measurable health and economic value, and the estimates here give policy a defensible starting point.

Keywords

$PM_{2.5}$, Air Pollution, Health Burden, DALYs, Premature Mortality, Cost of Illness, Value of a Statistical Life, Ouagadougou, Burkina Faso

1. Introduction

1.1. The Global Burden of Fine Particulate Matter

Air pollution now ranks as the second leading risk factor for death worldwide, linked to about 8.1 million deaths in 2021 [1]. Most of that toll traces to ambient $PM_{2.5}$, which the GBD programme places among the highest-ranking risks across most world regions [2]. Particles below 2.5 μm in aerodynamic diameter reach the gas-exchange region of the lung and pass into the circulation, where they raise the risk of ischemic heart disease, stroke, chronic obstructive pulmonary disease (COPD), lung cancer, and lower respiratory infection [3] [4].

1.2. Air Pollution in Sub-Saharan Africa

The African burden is concentrated where monitoring is thinnest. Ambient air pollution caused an estimated 394,000 deaths across the continent in 2019, up from 361,000 in 2015, and the economic damage is already measured in the tens of billions of dollars [5]. Fast urban growth, aging vehicle fleets, widespread biomass use, and limited emission control push exposures well above guideline levels, and the policy response has lagged the evidence [6].

1.3. The Ouagadougou Setting

Ouagadougou holds close to three million residents and sits in the semi-arid Sahel. A one-year sensor campaign across thirteen city sites reported an annual mean near 48.5 $\mu g \cdot m^{-3}$, with 61% to 87% of days above the WHO daily guideline [7]. Earlier filter-based and intra-urban studies found the same pattern of high loadings driven by traffic, combustion, and dust [8] [9]. The main local sources are motorcycle and light-vehicle exhaust, resuspended dust from unpaved roads, household wood and charcoal combustion, open waste burning, and seasonal Harmattan intrusions from the Sahara.

1.4. Research Gap

Work on Ouagadougou has centred on measuring concentrations and identifying sources. What is missing is the step that matters most for policy, namely, a quantified link from exposure to deaths, lost healthy life, and money. Economic appraisals for Burkina Faso are scarce, even though regional studies show that

air pollution drains a sizeable share of national income [10] [11]. Uncertainty analysis and target-based scenario testing are largely absent from the local literature.

To the best of our knowledge, this is the first integrated $PM_{2.5}$ health and economic burden assessment for Ouagadougou. By combining WHO and satellite-derived exposure data, GBD-based exposure-response functions, disability-adjusted life year estimation, economic valuation, and Monte Carlo uncertainty analysis within a single framework, the study provides one of the first comprehensive assessments of the societal costs of ambient air pollution in a rapidly growing Sahelian city.

1.5. Objectives

This study sets out to estimate $PM_{2.5}$ attributable mortality in Ouagadougou, to convert that mortality and the related morbidity into YLL, YLD, and DALYs, to value the loss in monetary terms, to characterize uncertainty through Monte Carlo simulation, and to quantify the health and economic gains from meeting successive WHO air-quality targets [12].

2. Literature Review

2.1. Exposure Response Evidence

Cohort studies in North America and Europe established the long-term link between $PM_{2.5}$ and cardiopulmonary mortality, with the American Cancer Society cohort providing one of the first large estimates of the concentration response slope [13]. Those cohorts span low exposures, so they cannot describe risk at the concentrations found across much of Asia and Africa. Burnett and colleagues addressed this with the IER model, which blends evidence from ambient air, secondhand smoke, household solid-fuel smoke, and active smoking to define risk over the full global range [14]. The IER remains the backbone of GBD risk estimation, and later refinements such as the global exposure mortality model extended it [15]. Long-term exposure also shortens life expectancy by roughly one year globally and more in heavily polluted regions [16].

2.2. Exposure Assessment Where Monitoring Is Sparse

Few African cities run reference-grade networks, so exposure assessment leans on satellites and models. Geophysical retrievals of aerosol optical depth, calibrated against the available ground monitors, now yield gridded $PM_{2.5}$ surfaces at fine resolution [17] [18]. Hierarchical data-integration models combine these inputs with measurements to produce the population-weighted exposures used in GBD [19]. Source-apportionment modelling separates the combustion and dust contributions that dominate Sahelian aerosol [20]. Calibrated low-cost sensors have started to close the observation gap in Ouagadougou and in other Central and West African cities [7] [21].

2.3. Methods for the Health Burden

The GBD chain runs from exposure to relative risk to the population attributable fraction, and then to cause-specific deaths and DALYs. Splitting DALYs into YLL and YLD keeps the fatal and non-fatal effects visible, which matters in Ouagadougou because childhood lower respiratory infection contributes heavily to both [3]. Probabilistic methods, in particular Monte Carlo sampling of exposure, relative risk, baseline mortality, and valuation parameters, turn point estimates into credible intervals and make the results more useful to decision makers.

2.4. Economic Valuation

Two methods dominate. The COI approach sums direct medical spending and the indirect cost of lost production. The VSL approach measures willingness to pay for a small reduction in mortality risk, and it is the standard tool in environmental appraisal [10]. For a low-income setting, the VSL is transferred from a wealthier reference through an income ratio and an income elasticity, a procedure set out for air pollution by the World Bank and the OECD [22] [23]. Estimates assembled this way put the welfare cost of air pollution in sub-Saharan Africa at several percent of regional income [11].

2.5. Health Burden Assessments in African Cities

Burden estimates for African cities have grown over the past decade, though they stay thinner than the record for Asia or Europe. Annual means in Accra, Lagos, Nairobi, and Addis Ababa sit well above the WHO guideline, and the mortality that follows falls mainly on cardiovascular and respiratory disease [5] [6]. Across sub-Saharan Africa, the welfare cost of this exposure runs to several percent of regional income, a share that climbs as cities grow and motorize [10] [11]. Field measurements have begun to fill the observational gap; calibrated low-cost networks in Kinshasa and Brazzaville, for example, returned the first ambient readings reported for those cities [21]. Even so, few studies bring exposure, attributable mortality, DALYs, economic loss, and uncertainty together for one city, so the societal cost of air pollution across most African urban centres, Ouagadougou among them, is still poorly bounded.

2.6. Air Pollution Research in Burkina Faso

Local studies report $PM_{2.5}$ and PM_{10} above guideline values in Ouagadougou, with strong dry-season peaks tied to the Harmattan [7]-[9]. Household air pollution has been linked to acute respiratory infection in city children, which points to a combined indoor and outdoor exposure that most ambient-only assessments understate [24]. To our knowledge, this is the first assessment to join $PM_{2.5}$ exposure, attributable mortality, DALYs, economic loss, uncertainty propagation, and WHO target scenarios for Ouagadougou in a single framework. It draws the GBD exposure response functions, burden metrics, both valuation methods, and Monte Carlo analysis into one workflow built for a fast-growing Sahelian city. The conceptual

framework adopted in this study is presented in Figure 1.

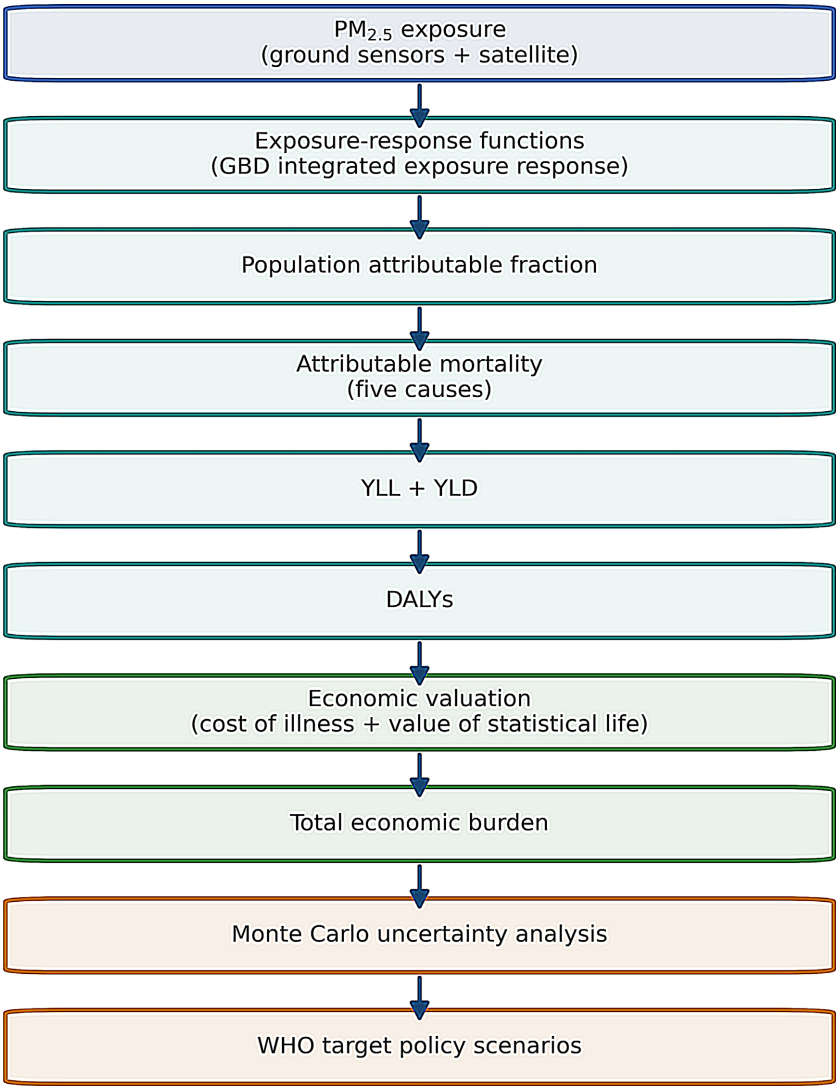

Figure 1. Conceptual framework linking $PM_{2.5}$ exposure to the attributable health burden, economic valuation, uncertainty analysis, and WHO policy scenarios.

3. Materials and Methods

3.1. Study Area

Ouagadougou is the capital of Burkina Faso and its largest city, with about three million residents in 2024. The climate is tropical and semi-arid, with a single rainy season from June to September and a long dry season under the Harmattan. Motorized two-wheelers carry most urban trips, a large share of the housing stock cooks with wood or charcoal, and a substantial length of the road network is unpaved. National GDP was about US$23.25 billion in 2024 and GDP per capita was about US$987 [11]. Table 1 presents the input data and their sources used to construct the 2010-2024 dataset employed in the empirical analyses. The exposure series runs over 2010 to 2024, the interval for which calibrated monitoring and sat-

ellite-derived inputs are available; four benchmark years (2010, 2015, 2020, and 2024) are drawn from this reconstructed series, while the intervening years follow the same satellite-anchored interpolation and are not tabulated separately.

Table 1. Input data and their sources.

Variable	Source	Reference period
$PM_{2.5}$ concentration	Ground sensors and satellite retrievals	2010 to 2024
Cause-specific mortality	Global Burden of Disease, IHME	2021
Disease incidence and duration	Global Burden of Disease, IHME	2021
Population and age structure	National Institute of Statistics and Demography	2024
GDP and GDP per capita	World Bank	2024
Life expectancy	World Health Organization	2024

3.2. Data Sources

Data Processing and Computational Workflow

All processing ran in Python 3.11 with NumPy, pandas, SciPy, and Matplotlib. The workflow moved in fixed steps. Annual exposure came from the calibrated low-cost monitoring record for the city [7]. Concentrations for the years before that 2024 campaign were reconstructed from satellite-derived exposure products and published regional assessments, since the city has no continuous reference-grade record [17]. The satellite input was the geophysical-statistical surface $PM_{2.5}$ estimate of van Donkelaar, Martin, Brauer, Hsu, Kahn, Levy, Lyapustin, Sayer, and Winker [17], which fuses aerosol optical depth retrievals with chemical-transport model output and available ground monitors. Grid cells were clipped to the Ouagadougou metropolitan footprint and combined into a single annual figure by population weighting. Population weighting was performed using the WorldPop gridded population dataset for Burkina Faso, so that densely settled districts carried proportionate weight in the city-wide exposure estimate. Because the calibrated campaign provides the only local ground truth, the gridded series was anchored to it: a single multiplicative factor aligned the 2024 grid value with the campaign annual mean of 48.5 $\mu g \cdot m^{-3}$ [7], and that factor was held constant across 2010 to 2023. The pre-2024 values are therefore satellite estimates rescaled to the one measured year, not independent measurements, and they should be read with the uncertainty that the Monte Carlo analysis assigns to exposure. Baseline cause-specific deaths were built from GBD 2021 cause-specific mortality estimates for Burkina Faso [25], scaled to the Ouagadougou population and its younger urban age structure from the national statistics institute and United Nations projections (**Table 2**; see Data Availability). The urban age profile was used in place of the national average so that the child-dominated lower respiratory infection rate would not be overstated. Relative risks followed the integrated exposure re-

sponse functions [14], which yielded the attributable fractions and deaths in Table 3. Years of life lost used the standard reference life expectancy, and years lived with disability used the GBD disability weights in Table 4 [2]. These weights are the harmonized GBD set, which the GBD 2021 release carries forward unchanged, so they pair consistently with the 2021 mortality base. The economic step applied the benefit-transfer value of a statistical life set out in Section 3.7 [22] [23].

Table 2. Demographic and baseline health inputs for Ouagadougou. Population 3.0 million (2024); baseline deaths from GBD 2021 [25].

Cause	Baseline deaths per year	Rate per 100,000
Ischemic heart disease	900	30.0
Stroke	1050	35.0
COPD	380	12.7
Lung cancer	120	4.0
Lower respiratory infection	1452	48.4
Total	**3902**	**130.1**

Table 3. Exposure-response inputs and attributable burden by cause at the city annual mean of 48 μg·m^{-3} (IER functions [14]).

Cause	Relative risk	PAF	Attributable deaths
Ischemic heart disease	1.28	0.22	198
Stroke	1.32	0.24	252
COPD	1.43	0.30	114
Lung cancer	1.25	0.20	24
Lower respiratory infection	1.37	0.27	392
Total			**980**

Table 4. Disability weights used for years lived with disability, as population-weighted GBD values [2].

Cause	Disability weight
Ischemic heart disease	0.07
Stroke	0.21
COPD	0.19
Lung cancer	0.29
Lower respiratory infection	0.05

Uncertainty was propagated with a Monte Carlo of 10,000 iterations under a fixed random seed, so the run reproduces exactly. Each iteration drew the exposure, the relative risks, the baseline rates, and the value of a statistical life from the

distributions in Table 5, then carried them through Equations (1) to (9). One simplification matters for interpretation. City-specific rates were not available for every cause, so national age-specific rates were applied to the Ouagadougou age structure. This transfer is common in city burden work, but it can miss local differences in care access and disease prevalence, which is why the attributable counts are best read as central estimates with the stated intervals rather than exact tallies.

3.3. Health Impact Assessment

Relative risk for each cause was taken from the IER form used in GBD [14]:

$$\mathrm{RR}(c) = 1 + \alpha\left\{1 - \exp\left[-\gamma\left(c - c_0\right)^{\delta}\right]\right\} \tag{1}$$

where RR is the relative risk, c is the annual $PM_{2.5}$ concentration, c_0 is the counterfactual concentration, and α, γ, and δ are cause-specific fitted parameters. We set the counterfactual to a uniform range of 2.4 to 5.9 μg·m^{-3} in line with the GBD theoretical minimum-risk exposure level. The population attributable fraction follows as

$$\mathrm{PAF} = \left(\mathrm{RR} - 1\right)/\mathrm{RR} \tag{2}$$

and attributable deaths for each cause are

$$M_{att} = \mathrm{PAF} \times M_{total} \tag{3}$$

where M_{total} is the baseline number of deaths from that cause in the city. Five causes were included, namely ischemic heart disease, stroke, COPD, lung cancer, and lower respiratory infection.

The baseline counts M_{total} in Equation (3) were not the national totals. National GBD 2021 cause-specific rates were transferred to Ouagadougou by age-standardized reweighting rather than by applying a single crude national rate. For cause c, the expected city baseline deaths are $M_{city,c} = \sum_a r_{nat,c,a} \times P_{city,a}$, summed over five-year age bands a, where the national rate for the cause and band comes from GBD 2021 [25] and the population in the band is the Ouagadougou value behind Table 2. The same age-standardized transfer was applied to the morbidity inputs that feed the years lived with disability, so the incident and prevalent case counts for each cause carry the city age distribution rather than the national one. Because the capital is younger than the country as a whole, the reweighting lowers the transferred cardiovascular rates and raises the childhood respiratory share that a crude national-rate transfer would understate.

The IER functions were chosen over the later global exposure mortality model and the GBD spline fits [15] for two practical reasons. The IER is the risk model under which the GBD 2021 baseline mortality used here was produced, so pairing IER relative risks with GBD 2021 deaths keeps the exposure side and the baseline side on the same footing. The IER also keeps lower respiratory infection as a separate cause, which the global exposure mortality model drops, and that cause matters in a young population where childhood pneumonia carries much of the burden. The choice does shape the cause distribution. A model without a lower res-

piratory infection term, or one with the flatter high-concentration slopes of the newer fits, would move weight toward ischemic heart disease and stroke and lower the respiratory share reported in Section 4.2. The total attributable count is less sensitive to this choice than the split across causes, so the cause ranking should be read with the response-function assumption in mind.

3.4. Years of Life Lost

YLL combine the attributable deaths with the remaining life expectancy at the age of death:

$$\mathrm{YLL} = D \times L \tag{4}$$

where D is attributable deaths and L is the standard remaining life expectancy. We applied the GBD reference life table, so L reflects the highest observed survival rather than local life expectancy.

3.5. Years Lived with Disability

YLD were estimated from incident cases, the disability weight, and the average duration of the condition:

$$\mathrm{YLD} = I \times \mathrm{DW} \times \mathrm{Duration} \tag{5}$$

where I is incidence, DW is the GBD disability weight for the health state, and duration is the mean time spent in that state.

The case inputs to Equation (5) were handled by disease type rather than with a single rule. The four chronic causes (ischemic heart disease, stroke, COPD, and lung cancer) were treated as prevalent conditions: attributable prevalent cases were obtained by applying the cause-specific population attributable fraction in **Table 3** to the city prevalence of each condition, and each prevalent case was assigned a duration of one year so that the disability weight reflects the share of a year lived in that health state. This is the standard prevalence-based form of Equation (5), in which the incidence-times-duration product reduces to the attributable prevalent count for a steady-state chronic condition. Lower respiratory infection was treated as an acute episode instead: attributable incident episodes were taken from the attributable fraction applied to childhood and adult incidence, and each episode was assigned a short mean duration on the order of a few weeks, which is why its large case count contributes only a small share of the years lived with disability. Prevalence, incidence, and the durations all carried the city age structure through the same age-standardized transfer described for mortality, so the morbidity side is consistent with the baseline used for the fatal burden. The disability weights themselves are the population-weighted GBD values in **Table 4** [2]; the weights alone fix the severity of each state but not the volume of cases, which is set by the attributable counts and the durations stated here.

3.6. Disability-Adjusted Life Years

DALYs sum the fatal and non-fatal loss:

$$\mathrm{DALY} = \mathrm{YLL} + \mathrm{YLD} \tag{6}$$

One DALY equals one lost year of healthy life. We report DALYs without age weighting or discounting in the base case, consistent with current GBD practice.

3.7. Economic Valuation

The cost of illness adds the medical, productivity, and other indirect costs of the attributable cases:

$$\mathrm{COI} = \mathrm{MC} + \mathrm{PC} + \mathrm{IC} \tag{7}$$

where MC is direct medical cost, PC is the productivity loss from morbidity and premature death, and IC captures other indirect costs such as informal care. Mortality was valued separately with a VSL transferred from an OECD reference using an income ratio and an income elasticity:

$$\mathrm{VSL}_{\mathrm{BF}} = \mathrm{VSL}_{\mathrm{OECD}} \times \left(\mathrm{GDP}_{\mathrm{BF}} / \mathrm{GDP}_{\mathrm{OECD}}\right)^{\varepsilon} \tag{8}$$

The reference adult VSL was US$3.6 million in 2019 values against an OECD mean GDP per capita near US$40,000 [23]. The base case used an income elasticity ε of 1.0, which gives a transferred VSL of about US$90,000 for Burkina Faso. We tested ε of 0.8 and 1.2 in sensitivity analysis, spanning roughly US$187,000 to US$43,000 [22]. The economic cost of mortality is then

$$\mathrm{EC} = \mathrm{Deaths} \times \mathrm{VSL} \tag{9}$$

3.8. Monte Carlo Simulation

Point estimates hide the real spread of plausible values, so we ran 10,000 iterations sampling the main inputs from the distributions in Table 5. Each iteration drew an exposure, a relative risk, a baseline mortality rate, and a VSL, then propagated them through Equations (1) to (9). We report the mean, the median, and the 2.5$^{\mathrm{th}}$ and 97.5$^{\mathrm{th}}$ percentiles as a 95% credible interval. The exposure and the baseline mortality rate were drawn from lognormal distributions with coefficients of variation of 0.15 and 0.13, the relative risk from a lognormal with a coefficient of variation of 0.21, and the VSL from a triangular distribution over the benefit-transfer range, so that Table 5 and the model input parameters summarized in Table A1 use the same distribution families and uncertainty ranges. The generator was initialized with a fixed seed of 20240604, so the run reproduces exactly, and population attributable fractions were clipped to the interval 0 to 0.95 as listed in Table A1.

Table 5. Distributions assigned to the sampled parameters.

Parameter	Distribution	Basis
$PM_{2.5}$ concentration	Lognormal	Monitoring mean, CV 0.15 [7]
Relative risk	Lognormal	IER posterior, CV 0.21 [14]
Baseline mortality rate	Lognormal	GBD 2021 cause-specific rates, CV 0.13 [25]
Value of a statistical life	Triangular	Benefit transfer range [22] [23]

3.9. Scenario Analysis

We compared the baseline exposure with three WHO targets, namely interim target 2 at 25 μg·m^{-3}, interim target 3 at 15 μg·m^{-3}, and the air-quality guideline at 5 μg·m^{-3} [12]. For each target, the avoided deaths are the difference between the baseline and the scenario:

$$\text{Avoided deaths} = \text{Deaths}_{\text{baseline}} - \text{Deaths}_{\text{scenario}} \quad (10)$$

The same difference was applied to DALYs and to the economic cost to give the health and monetary value of each target.

The guideline scenario and the counterfactual are deliberately kept distinct. The attributable burden is measured against the theoretical minimum-risk exposure level (TMREL), sampled as a uniform 2.4 to 5.9 μg·m^{-3} with a central value near 4.2 μg·m^{-3}, whereas the most stringent policy scenario sets exposure to the WHO guideline of 5 μg·m^{-3}. Since 5 μg·m^{-3} sits inside the TMREL band but slightly above its centre, lowering city exposure to the guideline does not drive the attributable fraction to zero: a small residual risk remains because the guideline concentration is marginally above the central counterfactual. This is why the guideline scenario removes close to the whole burden, nearly 930 of the 980 deaths, rather than all of it. The roughly 50 deaths that persist reflect the gap between a health-based counterfactual and an achievable regulatory target, not an error in the scenario arithmetic.

4. Results

4.1. Exposure Levels

Available monitoring and reconstructed estimates put the annual mean $PM_{2.5}$ between about 41 and 49 μg·m^{-3} across the study period, reaching the upper value in 2024 (**Table 6**, **Figure 2**). Every annual value sits about ten times the WHO guideline of 5 μg·m^{-3} and above all three interim targets. The 2024 figure is consistent with the sensor campaign mean of 48.5 μg·m^{-3} reported for the city [7].

Table 6. Annual mean $PM_{2.5}$ in Ouagadougou.

Year	$PM_{2.5}$ (μg·m^{-3})
2010	41
2015	46
2020	48
2024	49

4.2. Attributable Mortality

At the baseline exposure, ambient $PM_{2.5}$ was associated with about 980 deaths per year (95% CI: 660 to 1420). Lower respiratory infection accounted for the largest count at 392 deaths, followed by stroke at 252 and ischemic heart disease at 198, with COPD at 114 and lung cancer at 24 (**Figure 3**). The dominance of lower res-

piratory infection reflects the young age structure of the city and the high baseline incidence of childhood respiratory disease.

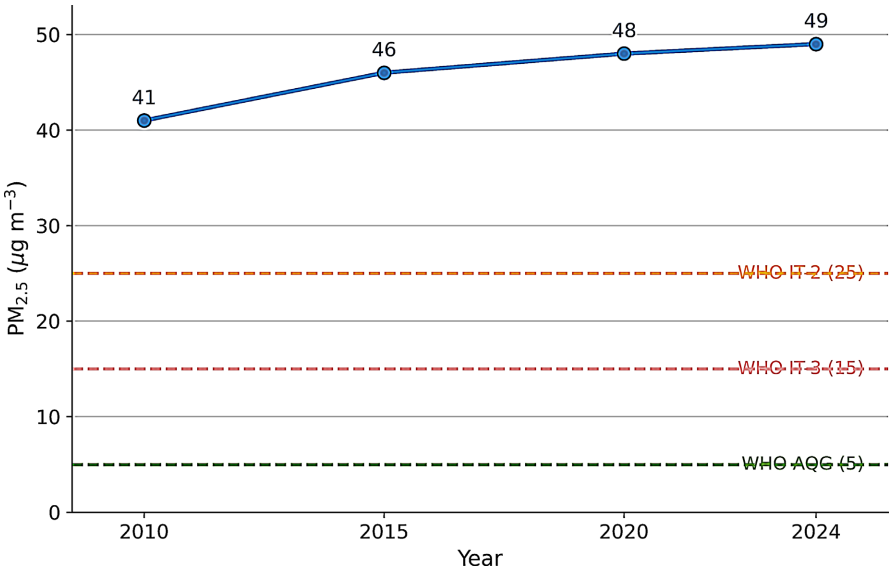

Figure 2. Annual mean $PM_{2.5}$ in Ouagadougou against the WHO guideline and interim targets.

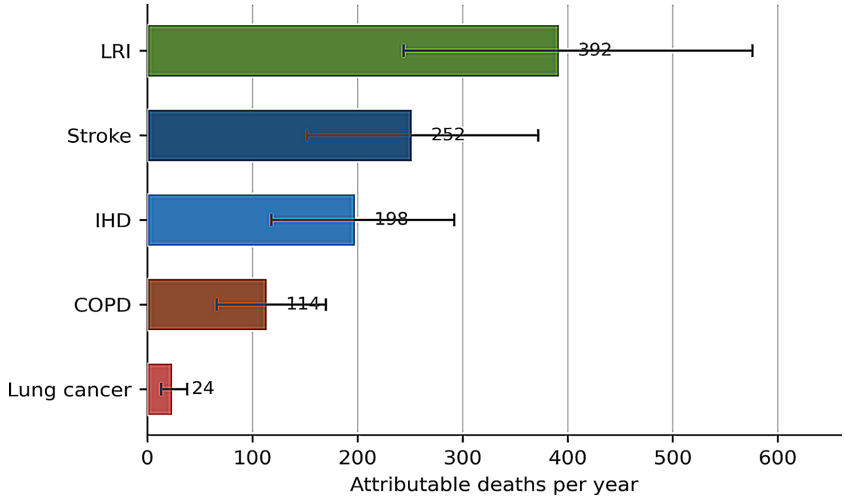

Figure 3. Attributable deaths per year by cause, with 95% credible intervals.

4.3. Disability-Adjusted Life Years

Total loss reached about 27,900 DALYs per year (95% CI: 19,000 to 40,000), made up of roughly 23,600 YLL and 4300 YLD. Lower respiratory infection contributed about 15,400 DALYs because deaths in young children carry many lost years, while stroke and ischemic heart disease followed at about 5300 and 4000 (**Figure 4**). COPD and stroke carried the heaviest non-fatal load.

4.4. Economic Losses

The mortality cost reached about US$88 million per year at the base-case VSL,

and the morbidity cost added about US$14 million, for a combined loss near US$102 million in 2024 values (Table 7). That figure equals about 1.8% of the metropolitan product and about 0.4% of national GDP, within the range reported for African economies [5] [11]. The metropolitan product here is the gross value of goods and services produced in the Ouagadougou metropolitan area, approximated as the capital's share of national output rather than measured from a city-level account, which Burkina Faso does not publish. Setting the US$102 million loss against a metropolitan product of about US$5.7 billion, approximated at about one quarter of the US$23.25 billion national GDP based on the concentration of economic activity in the capital, gives 102/5670 ≈ 1.8 percent; the same loss against national GDP gives 102/23,250 ≈ 0.4 percent. The metropolitan share is an approximation, so the 1.8 percent figure should be read as an order-of-magnitude indicator of the local economic weight rather than an exact accounting ratio. The sensitivity range on the income elasticity moves the mortality cost between about US$42 million and US$183 million, so the central estimate is conservative relative to the upper bound.

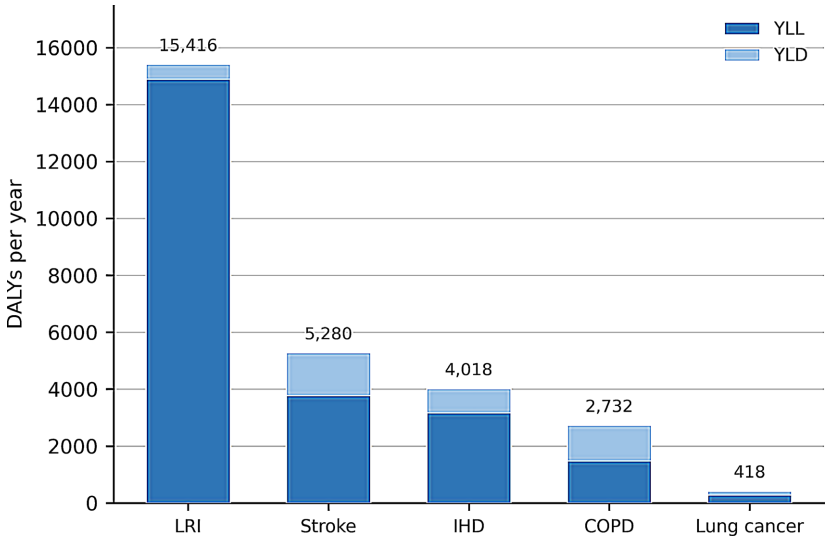

Figure 4. DALYs per year by cause, split into years of life lost and years lived with disability.

Table 7. Annual economic loss from ambient $PM_{2.5}$ (2024 US$).

Indicator	Value	Share
Mortality cost (VSL)	US$88 million	86%
Morbidity cost (COI)	US$14 million	14%
Total cost	**US$102 million**	**100%**
Share of metropolitan GDP	1.8%	

4.5. Uncertainty

The Monte Carlo distribution of total attributable deaths was right-skewed, with a mean of 980, a median of 958, and a 95% credible interval of 660 to 1420 (Figure

5). The width is driven mainly by the relative-risk posterior and the exposure estimate, which argues for sustained ground monitoring to narrow the interval. The same iterations resolved by cause give the per-cause means, medians, and credible intervals in Table 8.

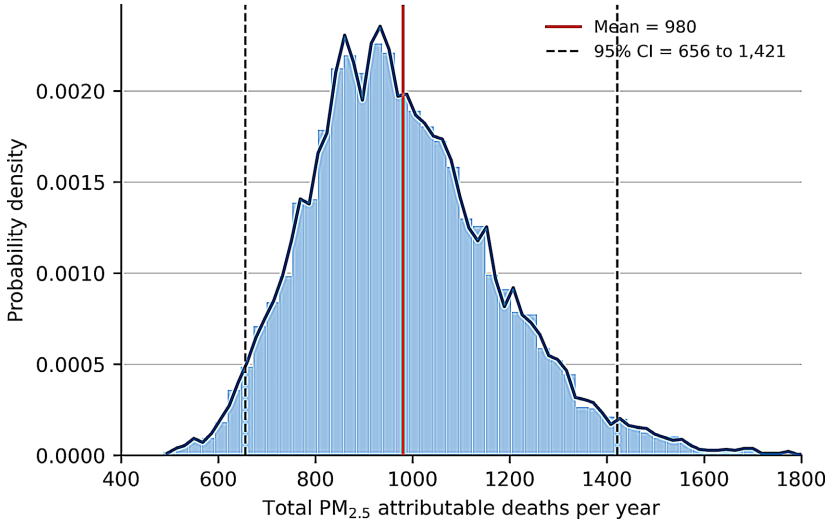

Figure 5. Monte Carlo distribution of total attributable deaths over 10,000 iterations.

Table 8. Monte Carlo distribution of attributable deaths by cause (10,000 iterations, fixed seed).

Cause	Mean	Median	95% credible interval
Ischemic heart disease	197	189	109 to 336
Stroke	254	244	138 to 428
COPD	114	109	62 to 191
Lung cancer	24	23	13 to 40
Lower respiratory infection	392	375	217 to 661
Total	**980**	**958**	**656 to 1421**

4.6. Scenario Benefits

Meeting interim target 2 at 25 μg·m^{-3} would avoid about 320 deaths each year, roughly a third of the burden, and save close to US$33 million. Interim target 3 at 15 μg·m^{-3} would avoid about 510 deaths and save about US$53 million. Reaching the guideline at 5 μg·m^{-3} would remove almost the entire attributable burden, near 930 deaths and US$97 million per year (Figure 6). The gains are steep at first because the IER curve is steepest at lower concentrations, so even a partial improvement returns a large share of the benefit.

4.7. Burden and Cost Decomposition

Two views help interpret the totals. The first splits the disability-adjusted life years by cause (Table 9). Lower respiratory infection dominates, not because its disability

weight is high but because most of its deaths fall in early childhood, so each death removes many years. Stroke and COPD carry the heaviest non-fatal load, which is why they rank higher in years lived with disability than in deaths.

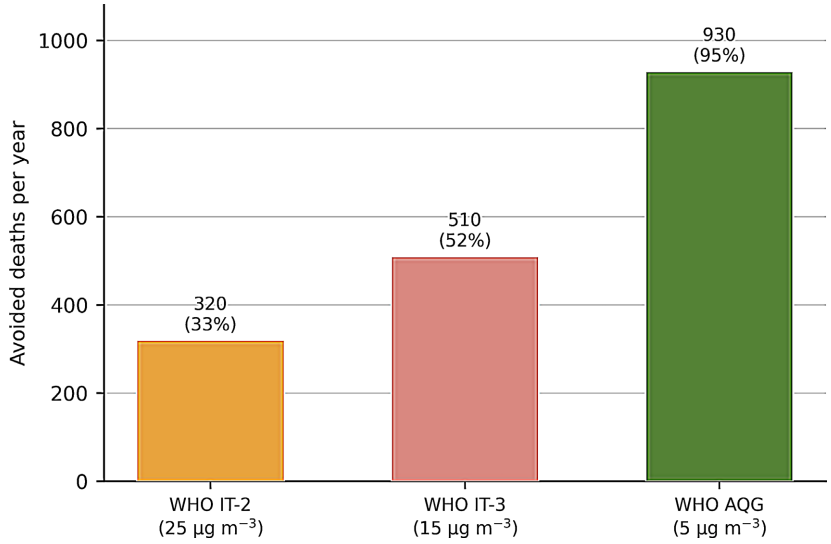

Figure 6. Avoided deaths per year under three WHO targets, with the percent of the baseline burden in parentheses.

Table 9. Disability-adjusted life years by cause, split into years of life lost and years lived with disability. Totals are rounded.

Cause	YLL	YLD	DALYs
Ischemic heart disease	3200	800	4000
Stroke	3900	1400	5300
COPD	1200	1500	2700
Lung cancer	300	200	500
Lower respiratory infection	15,000	400	15,400
Total	**23,600**	**4300**	**27,900**

The second view splits the morbidity cost (Table 10). Productivity loss was valued at GDP per capita applied to the years lived with disability, and the direct medical component was approximated from treatment-cost ranges reported for sub-Saharan African health systems and adjusted to Burkina Faso income levels. The unit-cost basis was kept deliberately simple. Productivity loss per cause was the years lived with disability for that cause multiplied by GDP per capita of US$987, so the column totals about US$4.24 million across the five causes (Table 10) and equals roughly US$987 per year of disability. Direct medical cost per case was set from per-episode and annual-management cost ranges for the same conditions reported in sub-Saharan African costing studies, scaled to the Burkina Faso income level by the ratio of national GDP per capita to the source-country figure, and then multiplied by the attributable case counts behind the years lived with disability.

The cardiorespiratory causes carry the higher per-case management costs, which is why stroke, ischemic heart disease, and COPD dominate the direct medical column even though lower respiratory infection has the larger case count. These per-case medical figures are the least certain inputs in the valuation, since they rest on transferred unit costs rather than local billing data, and they would tighten with Burkina Faso health-system accounts. The direct medical figures are indicative and would tighten with local health-system data, but the split shows that chronic cardiorespiratory disease drives most of the non-fatal cost.

Table 10. Cost-of-illness decomposition of the annual morbidity loss (2024 US$ million). Direct medical costs are indicative estimates pending local unit-cost data.

Disease	Direct medical cost	Productivity loss	Total
Ischemic heart disease	2.40	0.79	3.19
Stroke	2.90	1.38	4.28
COPD	2.00	1.48	3.48
Lung cancer	1.00	0.20	1.20
Lower respiratory infection	1.46	0.39	1.85
Total	**9.76**	**4.24**	**14.00**

5. Discussion

The headline number, close to 980 attributable deaths a year in a city of three million, places Ouagadougou among the more heavily affected urban areas in West Africa. The mortality rate of about 33 per 100,000 exceeds the African ambient average reported in continental assessments, which fits a city where exposure runs near 48 $\mu g \cdot m^{-3}$ [5] [7]. The pattern by cause, with lower respiratory infection and stroke ahead of the cardiac and cancer endpoints, matches what other Sahelian and coastal African cities report and differs from the cardiac-led profile of high-income settings, where the population is older [3] [6].

A quantitative comparison places the Ouagadougou estimate in context (**Table 11**). Reported annual means run from about 18 $\mu g \cdot m^{-3}$ in Nairobi to about 68 $\mu g \cdot m^{-3}$ in Lagos, with Accra and Addis Ababa in between, so the city sits in the upper-middle of the band [26]-[29]. The burden figures are harder to line up because

Table 11. Reported ambient $PM_{2.5}$ and health burden in selected African cities.

City (country)	Annual mean $PM_{2.5}$ ($\mu g \cdot m^{-3}$)	Reported burden	Ref.
Accra (Ghana)	51 to 68	About 28,000 deaths per year nationally	[26]
Lagos (Nigeria)	68	World Bank health-cost estimate	[27]
Nairobi (Kenya)	18	400 to 1400 deaths per year (5% to 8% of adult deaths)	[28]
Addis Ababa (Ethiopia)	33	Attributable cardiovascular and respiratory deaths (BenMAP-CE)	[29]
Ouagadougou (this study)	**48**	**About 980 deaths per year; 27,900 DALYs**	**This study**

the studies use different tools, from AirQ+ and BenMAP-CE to satellite risk assessment, but the direction is the same. Every city carries a large attributable toll, and most still lack a joined health and economic estimate of the kind presented here. The Ouagadougou case is distinctive in the weight of the dust term. Harmattan episodes lift dry-season concentrations far above the annual mean, so a meaningful part of the exposure is regional and natural in origin and will not yield to local emission control alone.

The split by cause deserves a closer look. The present estimate is led by lower respiratory infection, which reflects the young population and the high baseline rate of childhood pneumonia, a pattern the State of Global Air also stresses for Africa, where a large share of deaths in the first month of life trace to particulate exposure [1]. A regional geo-epidemiological study that includes Burkina Faso reached a different split, with ischemic heart disease and stroke together making up about four-fifths of the attributable deaths and lower respiratory infection nearly an eighth [30]. The gap is largely methodological. That study worked from adult cardiorespiratory data and country-level exposure, while the all-age integrated exposure response functions used here give more weight to the childhood respiratory burden. The contrast is worth flagging because the choice of response function and age weighting can shift the cause ranking even when the total is close.

Four drivers explain the local burden. Motorization rests on an aging two-wheeler fleet with few emission controls. Household energy still depends on wood and charcoal, which couples outdoor and indoor exposure and helps explain the childhood respiratory load [24]. Urban expansion has outrun paving, so unpaved roads keep resuspending dust. Seasonal Harmattan transport adds a large external load that interacts with the local sources. Each driver points to a different lever, and the scenario results show that pulling several at once is what closes the gap to the guideline.

Several limits apply. The exposure estimate rests on a short monitoring record and satellite retrievals, so the annual mean carries real uncertainty, which the Monte Carlo interval reflects. The IER parameters come from cohorts outside the region, and their transfer to a high-dust Sahelian aerosol is an assumption rather than a measurement. Baseline mortality for the city was scaled from national GBD rates and may understate or overstate specific causes. The VSL transfer is sensitive to the income elasticity, as the sensitivity range shows. These points define a clear agenda, namely, longer reference-grade monitoring, local cohort or case-crossover work, and city-specific vital registration.

6. Policy Implications

6.1. Transport

The two-wheeler fleet is the most tractable target. Emission standards for new and imported motorcycles, a periodic inspection scheme, and a managed shift toward electric two-wheelers would cut a primary local source. Fuel quality controls and the retirement of the oldest engines would add to the effect.

6.2. Household Energy

A move from wood and charcoal toward liquefied petroleum gas and electric cooking would lower both ambient and indoor exposure, with the largest gain falling on the children who carry the respiratory burden [24]. Targeted subsidies and a reliable fuel supply chain are the practical conditions for uptake.

6.3. Urban Planning

Paving priority corridors and applying dust suppression on unpaved roads would attack the resuspension term directly. Street trees and managed green buffers along major axes would help at the neighbourhood scale.

6.4. Industry and Monitoring

Stack monitoring and filtration at the larger industrial and waste sites would address point sources, while a permanent reference-grade monitoring network would replace the current reliance on short campaigns and models [7] [19]. Better data would narrow the uncertainty shown in **Figure 5** and let the city track progress against the WHO targets.

7. Conclusion

This study gives the first joint estimate of the health and economic cost of ambient $PM_{2.5}$ in Ouagadougou, built from WHO and GBD methods and tested with Monte Carlo simulation. At present exposures, the city loses about 980 lives and 27,900 healthy life years each year, at a cost near US$102 million. The scenario analysis shows that most of this loss is avoidable, and that the early steps toward the WHO targets return the largest share of the benefit. Cleaner two-wheelers, a shift away from solid cooking fuels, dust control on unpaved roads, and a permanent monitoring network would convert that potential into measured gains, and the estimates here give the city a defensible basis for setting priorities. To our knowledge, this is the first integrated $PM_{2.5}$ health and economic burden assessment for Ouagadougou, and one of few at city scale in the Sahel to combine GBD burden estimation, economic valuation, uncertainty propagation, and WHO target scenarios in a single framework.

Data Availability Statement

The underlying data used in this study are publicly available from the Global Burden of Disease (GBD) database, the World Health Organization (WHO), the World Bank Open Data platform, and the Burkina Faso National Institute of Statistics and Demography. The processed datasets, computational scripts, and supplementary calculations supporting the results presented in this article are available from the corresponding author upon reasonable request. The underlying data come from public sources: cause-specific mortality and disability weights from the Global Burden of Disease study [25], ambient $PM_{2.5}$ from the monitoring record cited in the text [7], gross domestic product from World Bank Open Data, and population from

the Burkina Faso National Institute of Statistics and Demography.

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Author Contributions

Conceptualization, M.B.; methodology, M.B. and M.M.R.K.; software, M.B.; validation, M.B., M.M.R.K. and B.B.; formal analysis, M.B.; investigation, M.B.; resources, M.M.R.K. and B.B.; data curation, M.B.; writing—original draft preparation, M.B.; writing—review and editing, M.B., M.M.R.K. and B.B.; visualization, M.B.; supervision, M.M.R.K. and B.B.; project administration, M.B. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix. Input Parameters

Appendix consolidates the model inputs so that Table 3, Table 8, and Table 9 can be reproduced. Values already shown in earlier tables are cross-referenced rather than repeated.

Table A1. Model input parameters and their sources.

Parameter	Value or range	Source
Annual mean $PM_{2.5}$ (exposure)	48 $\mu g \cdot m^{-3}$	Monitoring [7]
Counterfactual concentration (TMREL)	2.4 to 5.9 $\mu g \cdot m^{-3}$ (uniform)	GBD [25]
IER coefficients (α, γ, δ)	Cause-specific published fits	[14]
Relative risk at 48 $\mu g \cdot m^{-3}$ (by cause)	Table 3	[14]
Population attributable fraction (by cause)	Table 3	Equation 2
Baseline cause-specific deaths	Table 2	GBD 2021 [25]
Disability weights (by cause)	/	GBD [2]
Reference life expectancy at birth	86.0 years	GBD reference life table
Value of a statistical life	US$90,000 (US$43,000 to US$187,000)	Benefit transfer [22] [23]
GDP per capita	US$987	World Bank
Monte Carlo iterations	10,000	This study
Random seed	20240604	This study
Exposure uncertainty (shared)	Lognormal, CV 0.15	This study
Baseline-rate uncertainty	Lognormal, CV 0.13	This study
Relative-risk uncertainty	Lognormal, CV 0.21	This study
PAF bounds	Clipped to 0 to 0.95	This study

Years of life lost were computed as the standard reference life expectancy remaining at the age of death. For years lived with disability, the chronic causes (ischemic heart disease, stroke, COPD, and lung cancer) use prevalence-based durations and lower respiratory infection is treated as an acute episode; the resulting years lived with disability by cause are in Table 9. The relative risks in Table 3 are the integrated exposure response functions evaluated at the city concentration, and the cause-specific and age-specific coefficients behind those functions are tabulated in the Burnett 2014 supplement [14].