

Doctoral Dissertation
Interuniversity Doctoral Program in
Urban and Regional Development (XXXVIII Cycle)

Air Pollution Impact on Health and its Economic Consequences: from Atmospheric Analysis to Global Burden Estimation.

SARA CIARLANTINI

Supervisor(s):

Prof. Alessandro Pezzoli, Supervisor
Dr Claudio A. Belis, Co-Supervisor
Prof. Vito Frontuto., Co-Supervisor

Doctoral Examination Committee:

Prof. Marta C. Bottero, Chair of the Examination Committee, Politecnico di Torino
Prof. Peter C. Roebeling, Referee, Universidade de Aveiro
Prof. Roberta Vecchi, Referee, Università degli Studi di Milano

Politecnico di Torino - Università degli Studi di Torino
February 4th, 2026

This thesis is licensed under a Creative Commons License, Attribution - Noncommercial - NoDerivative Works 4.0 International: see www.creativecommons.org. The text may be reproduced for non-commercial purposes, provided that credit is given to the original author.

I hereby declare that the contents and organisation of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

Sara Ciarlantini

Turin, February 4th, 2026

Abstract

Air pollution is one of the most pressing environmental health threats worldwide. Despite significant efforts to improve air quality, evidence indicates persistent adverse health consequences. Exposure to ambient and household air pollution is linked to a wide spectrum of effects in the general population, from subclinical conditions to premature death, with an estimated 7.9 million premature deaths in 2023. Quantitative assessment of these health effects is therefore essential. This dissertation aims to connect atmospheric mechanisms with economic valuation to enable policy makers and other stakeholders to design and implement more effective local, national, and global policies for reducing air pollution.

The first part of the dissertation examines how meteorology shapes pollutant concentrations. It analyses how temperature, relative humidity, wind speed, precipitation, and boundary layer height influence dispersion and dilution of particulate matter (PM₁₀) and sulfur dioxide (SO₂). The study focuses on Türkiye, a major economy with high population where concentrations frequently exceed international standards. Hourly summer and winter observations are analysed with a generalised additive model (GAM), complemented by a sensitivity analysis, to capture seasonal and regional heterogeneity. Projections for 2030 and 2050 under two IPCC scenarios are provided, assuming strong mitigation (RCP 4.5) and high emissions (RCP 8.5), to illustrate how changing atmospheric dynamics may alter pollution levels.

Air pollution is not only a critical public health issue but also a major economic burden. Beyond health expenditures, it imposes sizeable non-market costs through monetised welfare losses associated with mortality and morbidity.

To quantify the health costs of air pollution, policy assessment requires methods that balance the costs of risk reduction against expected benefits, measured as prevented premature deaths and preserved life expectancy. These benefits are captured by the Value of a Statistical Life (VSL), reflecting individuals' willingness to pay to reduce mortality risk, and the Value of a Life Year (VOLY), which accounts for impacts on life expectancy. Obtaining reliable VSL and VOLY is challenging because methods adopted in studies vary widely across, and even within, countries, and many lack robust country-specific estimates, limiting comparability in global assessments. To address this gap, the second part of the

dissertation develops an econometric model based on a meta-analysis of literature-derived VSL estimates related to air pollution only, tailoring VSL to country-specific economic, socio-economic, demographic, and health characteristics. A corresponding VOLY database is derived from the VSL-based estimates. The framework has global coverage and enables more consistent, country-specific application of VSL and VOLY in air pollution policy analysis, improving comparability of estimated benefits across countries and income groups.

The third part of the dissertation quantifies the health costs of air pollution, accounting for both mortality and years of life lost (YLL). To estimate country-level external annual costs attributable to PM_{2.5} and O₃, it applies the model developed in the above-mentioned meta-analysis. The study covers five years (2000, 2005, 2010, 2015, and 2019), yielding a dataset covering 108 countries that together represent 86% of the global population. Two complementary economic approaches are implemented: VSL combined with mortality, and VOLY combined with YLL.

The three parts of the dissertation, each corresponding to a scientific paper, provide a structured pathway from atmospheric mechanisms to economic valuation and global burden estimation. **Paper I** clarifies how meteorology modulates pollution levels and how these relationships may evolve under a changing climate, informing exposure pathways and the timing and targeting of interventions. **Paper II** develops an evidence-based econometric valuation model, with VSL and VOLY tailored to country context, harmonised at the global level to a) address comparability gaps and b) supply estimates for countries lacking them. **Paper III** applies the model developed in Paper II to produce internationally comparable trends of the economic costs of premature deaths due to air pollution. The combined evidence base supports more efficient resource allocation and the design of cost-effective policies that reduce exposure, prevent premature deaths, and limit long-term welfare losses.

Acknowledgments

This dissertation is the result of three challenging years of research and of both scientific and personal growth. The path was not always easy, but it has been an incredible experience, that I would totally do all over again.

First and foremost, I thank my supervisor and co-supervisors. I am deeply grateful to Prof. Alessandro Pezzoli for his constant support, valuable advices, strong expertise, and willingness to help me succeed, both professionally and personally. My gratitude also goes to Dr Claudio Belis, who welcomed and hosted me in his unit at the JRC, shared his expertise generously, and dedicated substantial time to my research. I also thank Prof. Vito Frontuto for his precious help and for inspiring me with his career, research, and knowledge.

I am grateful to the Chair of the Examination Committee, Prof. Bottero, and to the referees, Prof. Roebeling and Prof. Vecchi, for taking the time to read this dissertation and to make comments to improve it.

My thanks extend to the Politecnico di Torino and the Università degli Studi di Torino for the funding opportunity to undertake my studies, and to Prof. Santangelo, the PhD programme's chairman, for his patience throughout these past three years.

Special thanks go to the JRC Clean Air and Climate Unit—to all the brilliant scientists who are part of it and who welcomed me as a colleague—and, in particular, to Dr Ferenc Pekar, Head of Unit, and Dr Elisabetta Vignati, former Head of Unit, for making this invaluable experience possible.

I would like to thank my colleagues Ilaria, Andreas, Delia, and Francesco for their constant, daily support through the highs and lows of the PhD; it has been a pleasure to share these years with them.

I express my gratitude to all my friends around the world: I am so lucky to have them, always cheering me on. Their joy in my successes mean the world to me.

I am thankful to Luca, with his positive attitude towards everything and his motivation to make me improve. Nothing would have been the same without him.

Last but not least, I am extremely grateful to my family: they are everything to me.

Dedico tutto il mio lavoro alle persone più importanti della mia vita:

A mia mamma e mio papà,

A nonna Caterina,

Ai miei nonni lassù, nonno Alfonso, nonno Carmine e nonna Lucia,

A me.

Contents

Section A – Introduction and Methodology

1. Introduction	2
1.1 Air Pollution	5
1.2 Air Pollution – Atmosphere	10
1.3 Air Pollution – Health	14
1.4 Air Pollution – Economic Valuation	18
1.5 Research Objectives	22
1.6 Dissertation Outline	25
2. Methodological Framework	26
2.1 Atmospheric Analysis Methodology	26
2.2 Economic Analysis Methodology	33

Section B – Scientific papers

3. Air Pollution and Atmospheric Variables in Türkiye: A Comprehensive Analysis	43
4. Econometric Model Derived from Meta-Analysis to Estimate VSL and VOLY Associated to Air Pollution at a Global Level	82
5. Economic Valuation of Health Impacts Attributable to Air Pollution at a Country Level Worldwide	116

Section C – Discussion and Conclusions

6. Synthesis and Implications	148
6.1 Limitations	150
6.2 Future Research Directions	152
7. References	153
8. Appendix	177

List of Figures

Figure 1 – Schematic representation of this PhD dissertation’s steps and objectives.	4
Figure 2 – Key sources (natural and anthropogenic) of primary and secondary air pollutants. Arrows in the clouds indicate the photochemically-driven generation of secondary air pollutants from the primary ones (Antenozio, 2024).	7
Figure 3 – Different sources of pollutant emissions in the air (natural, area, stationary and mobile) (NPS.gov, 2018).	8
Figure 4 – Air pollutants chemical lifetime vs spatial scale (Seinfeld & Pandis, 2016).	9
Figure 5 – Climate and air quality interactions and direct and indirect effects on health (Orru et al., 2017).	11
Figure 6 – Thermal inversion vertical profile (EEA, 2020).	13
Figure 7 – Air pollution effects (including their magnitude and severity) and the proportion of population affected (US EPA, 2025).	15
Figure 8 – Schematic overview of the relative size of particulate pollution, PM ₁₀ and PM _{2.5} (US EPA, 2025).	17
Figure 9 – Mean Air Quality Index by month for PM10 concentrations (left panel) and SO2 concentrations (right panel), years 2015-2019.	28
Figure 10 – Seasonal PM10 (a) and SO2 (b) mean concentrations for i) the aggregated period 2015-2019 (black), ii) each single station (grey), iii) highlighting the most polluted stations (red).	29
Figure 11 – IPCC Representative Concentration Pathways (RCP) scenarios.	32
Figure 12 – Overview of methods 1 and 2 for adjusting for inflation. In these hypothetical examples, the year of the costing is 2006 and the base year of the analysis is 2016. In the example, USD are being used, but the same approach would be applicable to international dollars (Turner et al., 2019).	34
Figure 13 – Set of explanatory variables initially tested in the model.	35

Figure 14 – Zuur et al. (2010) protocol for data exploration and statistical model application.....36

Figure 15 – Scatterplots of VSL against the final explanatory variables included in the model (these include GDP, GINI, Population and number of Doctors).....37

Figure 16 – Years covered by the studies from the literature review conducted, serving as inputs for the meta-analysis.....39

List of Tables

Table 1 – PM ₁₀ concentrations Air Quality Index descriptive statistics (a) average (among all stations) of the days in the year with AQI ≥ 50 (%) (b) number of stations with more than half of the year with AQI ≥ 50 (%).....	28
Table 2 – PM ₁₀ and SO ₂ monthly average concentrations (ug/m ³), years 2015-2019.	29
Table 3 – Kahramanmaraş winter months polar plot (a), wind rose (b), daily precipitation (c), and BLH (d) scatterplots for PM ₁₀ concentrations.....	31
Table 4 – Mean VSL and VOLY (both in I\$) for all the continents, representing 186 countries.....	40

Nomenclature

Acronyms/Abbreviations

<i>AIC</i>	Akaike Information Criterion
<i>AP-HRA</i>	Air Pollution Health Risk Assessment
<i>BLH</i>	Boundary Layer Height
<i>COPD</i>	Chronic Obstructive Pulmonary Disease
<i>CPI</i>	Consumer Price Index
<i>DM</i>	Diabetes Mellitus
<i>ECMWF</i>	European Centre for Medium-Range Weather Forecasts
<i>EEA</i>	European Environment Agency
<i>FASST</i>	FAst Scenario Screening Tool
<i>GAM</i>	Generalized Additive Model
<i>GBD</i>	Global Burden of Disease
<i>GDP</i>	Gross Domestic Product
<i>GNI</i>	Gross National Income
<i>HDI</i>	Human Development Index
<i>HEI</i>	Health Effects Institute
<i>HIC</i>	High Income Countries
<i>IHME</i>	Institute for Health Metrics and Evaluation
<i>IPCC</i>	Intergovernmental Panel on Climate Change
<i>IHD</i>	Ischemic Heart Disease
<i>LMIC</i>	Low- and Middle-Income Countries
<i>LRI</i>	Lower Respiratory Airway Infections
<i>LC</i>	Lung Cancer

<i>LE</i>	Life Expectancy
<i>MAE</i>	Mean Absolute Error
<i>MCAR</i>	Missing Completely at Random
<i>MRM</i>	Meta-regression models
<i>NOAA</i>	National Oceanic and Atmospheric Administration
<i>OECD</i>	Organisation for Economic Co-Operation and Development
<i>PPP</i>	Purchasing Power Parity
<i>RCP</i>	Representative Concentration Pathways
<i>RR</i>	Relative Risk
<i>RMSE</i>	Root Mean Square Error
<i>SDG</i>	Sustainable Development Goals
<i>SDMA8h</i>	Seasonal Mean of Daily Maximum 8-Hour
<i>USD</i>	United States Dollar
<i>VIF</i>	Variance Inflation Factor
<i>VOLY</i>	Value of A Life Year
<i>VSL</i>	Value of A Statistical Life
<i>WHO</i>	World Health Organization
<i>WTP</i>	Willingness To Pay
<i>YLL</i>	Years of Life Lost

Pollutants Acronyms

<i>AVOC</i>	Anthropogenic VOCs
<i>BVOC</i>	Biogenic VOC
<i>CFC</i>	Chlorofluorocarbons
<i>CO</i>	Carbon Monoxide
<i>H₂SO₄</i>	Sulfuric Acid
<i>HM</i>	Heavy Metals

<i>HNO₃</i>	Nitric Acid
<i>NH₃</i>	Ammonia
<i>NM VOC</i>	Non-Methane Volatile Organic Compounds
<i>NO_x</i>	Nitrogen Oxides
<i>O₃</i>	Ground-Level Ozone
<i>PAH</i>	Polycyclic Aromatic Hydrocarbons
<i>PM</i>	Particulate Matter
<i>POP</i>	Persistent organic pollutants
<i>SLCP</i>	Short-lived climate pollutants
<i>SO₂</i>	Sulfur Dioxide
<i>SO_x</i>	Sulfur Oxides
<i>VIF</i>	Variance Inflation Factor
<i>VOC</i>	Volatile Organic Compounds

Section A

Introduction and Methodology

Ch. 1

Introduction

Air pollution is considered one of the most pressing environmental health threats worldwide. Although significant efforts have been made to improve air quality and promote human health, there is still scientific evidence indicating persistent negative health consequences. Moreover, air pollution is of increasing concern in many emerging countries where strict air quality regulations are absent, leading to hazardous air quality episodes, especially in urban areas (HEI, 2010). Consequently, obtaining quantitative assessments of the health effects of air pollution has become crucial, enabling policymakers and other stakeholders to design and implement more effective policies at local, national, and global levels.

Exposure to ambient and household air pollution has been officially associated with a wide range of adverse health effects in the general population by any health organization. These effects may range from minor subclinical diseases to premature death. Air pollution is the second leading fatal health risk worldwide (after high blood pressure), and it is considered responsible for 7.9 million annual premature deaths – more than 1 in 8 deaths worldwide, according to the State of Global Air 2025 (HEI, 2025).

Currently, 99% of the world's population breath unsafe air (UNEP, 2023), and 34% lives in areas that exceed even the least stringent WHO interim air quality targets (HEI, 2024). This issue is particularly crucial in low- and middle-income countries. Here, the majority of people depend on burning solid fuels in their homes for cooking and heating, thus increasing the exposure to indoor air pollution. Household fuel combustion, agriculture, and industrial coal combustion are among

the main sources affecting air quality in these countries. As a result, the health risks associated with air pollution are greater in developing countries, where populations living there are exposed to 1.3–4 times higher levels of ambient PM_{2.5} compared to other countries.

Compared with high-income countries, children under five in lower-income countries face more than 60 times the risk of death from air pollution (WHO, 2015). Air pollution is the second-largest risk factor after malnutrition, accounting for 709,000 deaths among children under five (HEI, 2024), with the greatest burden in Asia and Africa.”

Evidence from multiple studies suggests that health impacts constitute up to 95% of total calculable costs, and that mortality alone accounts for 90% or more of health-related costs (OECD, 2014; OECD, 2016; WHO & OECD, 2015). Beyond premature deaths and other negative health effects, air pollution also harms the built environment, animals and plants, lowers the productivity of agriculture and forestry, and damages wider ecosystems (OECD, 2016). These impacts fall outside the scope of this research.

To address the above mentioned challenges, this PhD research adopts an interdisciplinary approach to air pollution, treating it as a multifactorial, climate-sensitive phenomenon with profound health and economic consequences. As shown in Fig. 1, the research integrates atmospheric and climate science, epidemiology, and economics to: (i) characterise pollution patterns and their climatic drivers; (ii) quantify population health impacts; and (iii) monetise these impacts to estimate economic burdens.

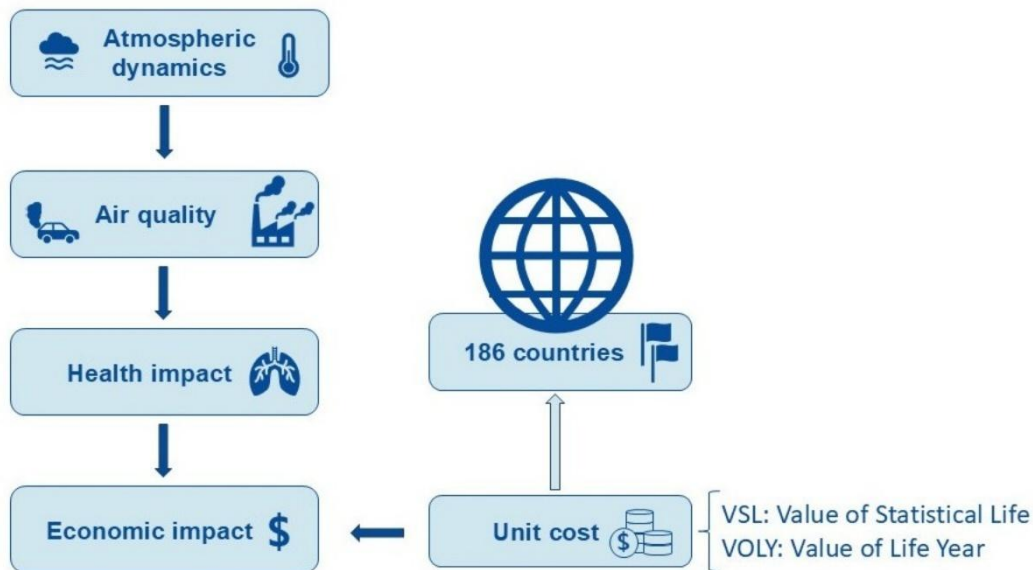


Figure 1 – Schematic representation of this PhD dissertation’s steps and objectives.

The objective of this research is to develop a comprehensive understanding of this complex phenomenon, which links atmospheric dynamics to air quality and the consequent health impacts and costs, and to provide evidence-based estimates and practical guidance. These outputs enable scientists, policymakers, and governments to: allocate resources, set priorities for clean-air action, prioritise cost-effective interventions, target vulnerable populations, and evaluate the returns to clean-air policies. This reinforces the urgency of well-designed pollution control as a public health and development priority and aligns this evidence with the broader aims of the Sustainable Development Goals (SDGs). By quantifying health impacts and monetising them, this research directly informs SDG 3 (Good Health and Well-being), notably the indicator on mortality from household and ambient air pollution. It also supports SDG 11 (Sustainable Cities and Communities, including urban PM_{2.5}) and SDG 7 (Affordable and Clean Energy, regarding access to clean cooking), while generates evidence relevant to SDG 13 (Climate Action) and SDG 10 (Reduced Inequalities) through cross-country analysis of exposure and economic burden. Human health and quality-of-life costs attributable to air pollution remain too high to be ignored.

1.1 Air Pollution

“Air pollution is contamination of the indoor or outdoor environment by any chemical, physical or biological agent that modifies the natural characteristics of the atmosphere” is the World Health Organization (WHO) definition. An air pollutant is, in general, any substance capable of harming people, animals, vegetation, or materials (Kampa and Castanas, 2008). From a health perspective, it is any substance that can increase mortality or serious illness or pose a present or potential danger to health.

Air pollutants differ in chemistry, reactivity, emission patterns, persistence, transport potential and health impacts, and they can be grouped into four broad classes (Kampa and Castanas, 2008):

1) Gaseous pollutants

Gaseous pollutants notably reshape atmospheric composition and largely stem from fossil-fuel combustion (Katsouyanni, 2003). Nitric oxide (NO) quickly oxidizes to NO₂, and in sunlight it reacts with volatile organic compounds (VOCs) to form ground-level ozone (O₃); traffic and stationary combustion are key sources. Carbon monoxide stems from incomplete combustion, with road transport the dominant contributor. Sulfur dioxide is mainly emitted by burning sulfur-containing fuels and by smelting, while natural sources (volcanoes, oceans) are responsible for a little portion of the total emissions.

2) Persistent organic pollutants

Persistent organic pollutants (POPs) are long-lived, toxic chemicals that bioaccumulate and biomagnify through food chains. Many POPs can enter the gas phase at ambient temperatures, volatilising from soils, vegetation, and water bodies. Because they resist degradation, they can undergo long-range transport and be re-deposited far from their original sources, often through repeated cycles of volatilisation and deposition (Jones, 1999). Among others, these pollutants mainly include pesticides, furans and dioxins.

3) Heavy metals

Heavy metals are natural, non-degradable elements that can be transported through air and water and enter the food supply. Beyond natural presence, these

metals enter the environment through emissions from combustion, waste water discharges, and industrial processes as well. In small amounts, they enter the human body and, as trace elements, support normal metabolic processes; however, at higher (even relatively low) concentrations they become toxic (Järup, 2003). The danger of many heavy metals stems from their tendency to bioaccumulate in human tissues. Examples of heavy metals are mercury, arsenic, lead, cadmium, nickel (all included in the EU Air Quality Directive).

4) Particulate matter

Particulate matter (PM) is a broad term for airborne pollution made up of complex, variable mixtures of solids and liquid droplets suspended in the breathing air. These particles differ in size and composition and arise from both natural and anthropogenic sources (e.g. road traffic, industry, waste incineration, construction, fires, and wind-blown dust) (Pöschl, 2005).

The size of the particles varies, and it is defined by the particles' aerodynamic diameter: for example, PM_{2.5} and PM₁₀ refer to particles smaller than 2.5 µm and 10 µm, respectively. Factors most relevant to health effects include particles size and surface, their number and their composition. In fact, substantial evidence indicates that smaller particles (called fine and ultrafine, according to their diameters) are more harmful than bigger ones (coarse particles), contributing to mortality and other diseases (see subsection 1.3). The particle size determines the site in the respiratory tract that they are more likely to deposit: PM₁₀ tends to settle in the upper airways, whereas finer and ultrafine fractions can penetrate to the alveoli.

Air pollutants are further grouped into two broad classes (see Fig. 2)—primary and secondary—to reflect whether they are emitted directly or formed in the atmosphere (EEA, 2021; Radaideh, 2017):

- (i) Primary pollutants are emitted directly from sources (e.g. industry, traffic and domestic activities) into the atmosphere. Primary air pollutants are also involved in various types of atmospheric processes like acid rain, greenhouse effect, global warming and photochemical smog (Sonwani and Saxena, 2016).
Examples include Particulate Matter (PM); Heavy Metals (HMs); Carbon Monoxide (CO); Nitrogen Oxides (NO_x); Sulfur Oxides (SO_x); Polycyclic

Aromatic Hydrocarbons (PAHs); Biogenic VOCs (BVOC); Anthropogenic VOCs (AVOC).

- (ii) Secondary pollutants form in the atmosphere through reactions among primary and other pollutants. The formation of secondary pollutants involves a variety of physical and chemical processes which can lead to the formation of thousands of compounds at the same time. Their production spans multiphase oxidation, gas-particle partitioning, nucleation, and ageing, involving thousands of intermediates simultaneously (Wang et al., 2023). Compared with primary species, they often exhibit greater toxicity. Examples of secondary pollutants include Particulate Matter (PM); Volatile Organic Compounds (VOCs); Ozone (O_3); Sulfuric Acid (H_2SO_4); Nitric Acid (HNO_3).

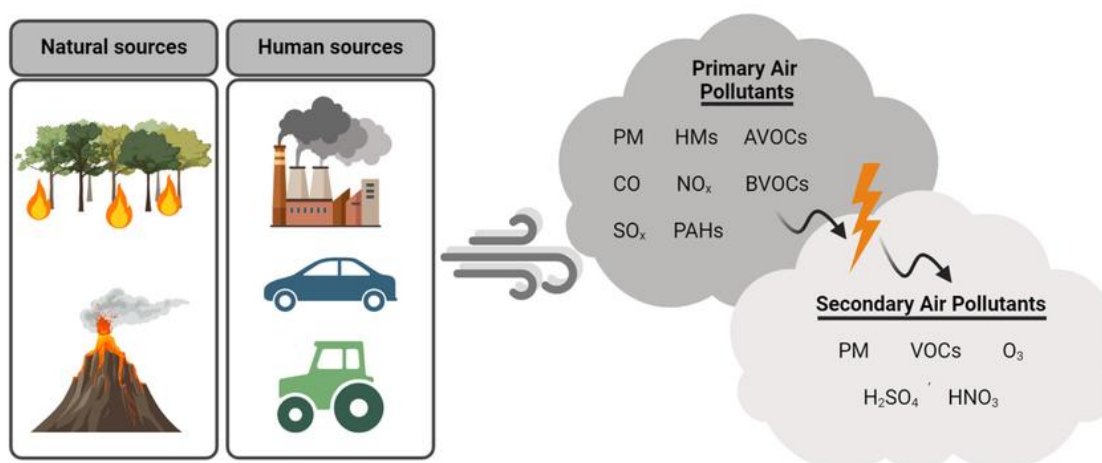


Figure 2 – Key sources (natural and anthropogenic) of primary and secondary air pollutants. Arrows in the clouds indicate the photochemically-driven generation of secondary air pollutants from the primary ones (Antenozio, 2024).

Air pollution arises from many sources, which can be natural or anthropogenic ones. As shown in Fig. 3, there are four main types of air pollution sources (NPS.gov, 2018):

- natural sources – such as wind-blown dust, wildfires, and volcanoes
- area sources – such as agricultural areas, cities, and wood burning fireplaces
- stationary sources – such as power plants, oil refineries, industrial facilities, and factories
- mobile sources – such as cars, buses, planes, trucks, and trains

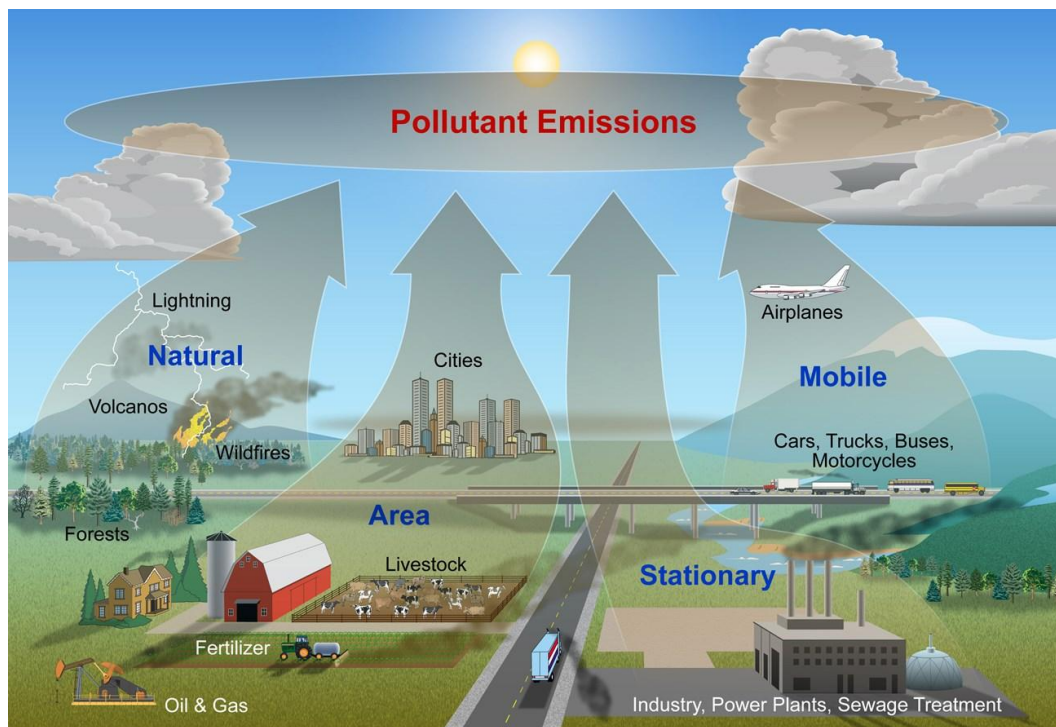


Figure 3 – Different sources of pollutant emissions in the air (natural, area, stationary and mobile) (NPS.gov, 2018).

The main sources of outdoor air pollution are associated with combustion processes, especially the use of solid fossil fuels and biomass for energy purposes, while indoor pollution derives from unvented cooking and heating and tobacco smoke. As people spend about 80% of their time indoors (Gov.UK, 2022), indoor air pollution is a major determinant of total exposure. This dissertation, however, is limited to outdoor air pollution. Because outdoor concentrations influence indoor levels and are easier to measure, outdoor measurements are considered a good proxy to estimate population exposure.

Pollutants span very different atmospheric lifetimes and therefore act on different spatial scales (Seinfeld & Pandis, 2016), as shown in Fig. 4. Short-lived climate pollutants (SLCPs) related processes are relevant from street to city scales and mainly reflect local emissions and boundary-layer dynamics. Owing to their high radiative efficiency and short lifetimes relative to CO_2 , these pollutants have large global-warming potential over short horizons (e.g., 20 years), and reducing emissions can yield near-term climate and health benefits (WHO Climate Change

and Health Unit, 2022). Indeed, comprehensive SLCP mitigation could cut the rate of global warming in half (about a 0.6 °C reduction) while preventing substantial pollution-related disease. By contrast, moderately long-lived species persist for hours to days, so observed concentrations blend local accumulation with regional transport. Long-lived species survive months to years: they become well mixed across hemispheres, and influence climate on global scales; some pollutants, such as the chlorofluorocarbons CFCs, have residence times from decades to centuries, so, even under global phase-outs, their atmospheric burdens decline only slowly. This lifetime–scale relationship explains why controls on short-lived species yield localised, near-term benefits, and consequently day-to-week species require regional coordination, while long-lived gases demand sustained international action (Seinfeld & Pandis, 2016).

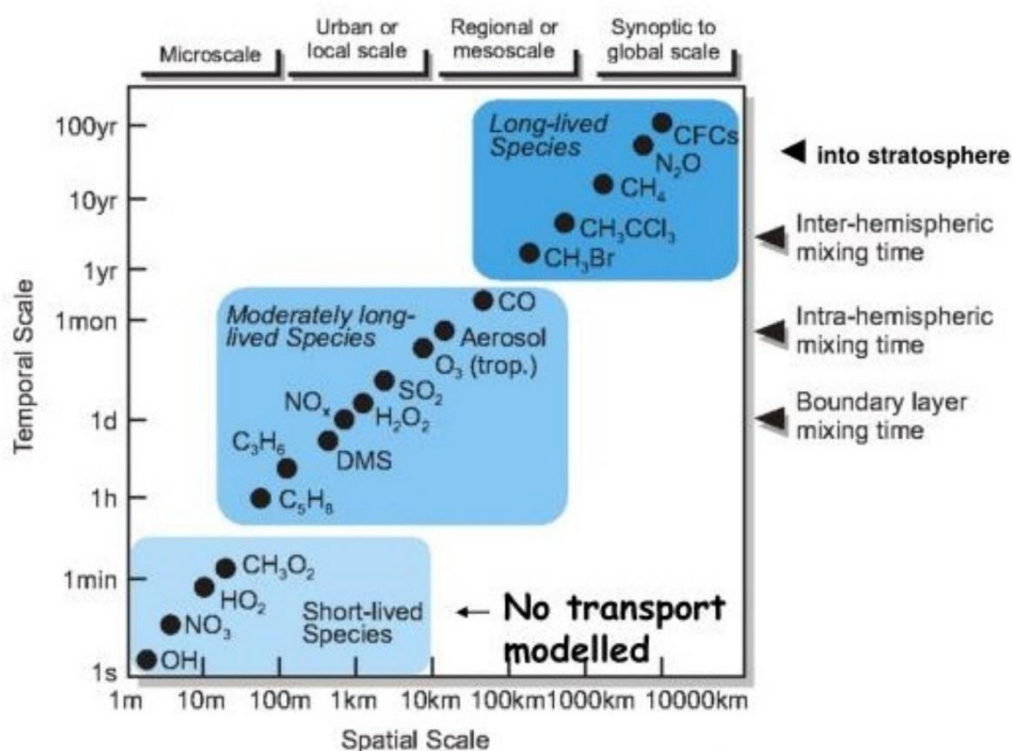


Figure 4 – Air pollutants chemical lifetime vs spatial scale (Seinfeld & Pandis, 2016).

These lifetimes translate into transport regimes: near-source accumulation for short-lived pollutants, regional advection for hours-to-days species, and hemispheric dispersion for long-lived species (Seinfeld & Pandis, 2016). As many episodes mix local build-up with inflow from elsewhere, effective control requires both local measures (e.g. traffic and combustion controls) and coordinated upwind action, a principle reflected in transboundary air-quality assessments under the UNECE Convention on Long-range Transboundary Air Pollution programme (UNECE, 2018).

Beyond this Convention, air-pollution governance combines international agreements with regional and national law. In the EU, the Ambient Air Quality Directive sets ambient standards and assessment methods, while the National Emissions reduction Commitments (NEC) Directive binds Member States to national reduction targets (EEA, 2025). These sit within the European Climate Law's 2050 climate-neutrality goal and the Zero Pollution ambition, with 2030 milestones (e.g. the Zero Pollution Action Plan and "Fit for 55") and a revised Ambient Air Quality Directive that tightens 2030 limit values and aligns more closely with WHO guidance. In the United States, the Clean Air Act establishes national ambient standards and regulates emissions from stationary and mobile sources (US EPA, 2007). Although not legally binding, the WHO Air Quality Guidelines serve as widely used scientific benchmarks that inform periodic updates to statutory standards (WHO, 2021).

1.2 Air Pollution – Atmosphere

Air quality is closely linked to the Earth's climate and ecosystems globally. Climate and air quality are tightly coupled through feedbacks that extend to health and ecosystems (see Fig. 5). Warming and associated shifts in meteorology negatively affect removal processes (weaker dispersion, altered precipitation) and intensify atmospheric chemistry, which tends to elevate secondary pollutants such as ozone and sulfate while shaping the burden of primary particles like soot (Fiore et al., 2015). In turn, these pollutant changes influence radiative forcing and biosphere–atmosphere exchanges, reinforcing climate feedbacks, while simultaneously amplifying heat- and pollution-related health risks and stressing crop productivity through reduced stomatal conductance, yield declines, and crop loss. In sum, climate affects air quality, air quality affects climate, and both directly and indirectly determine risks to human and ecological well-being (Orru et al., 2017).

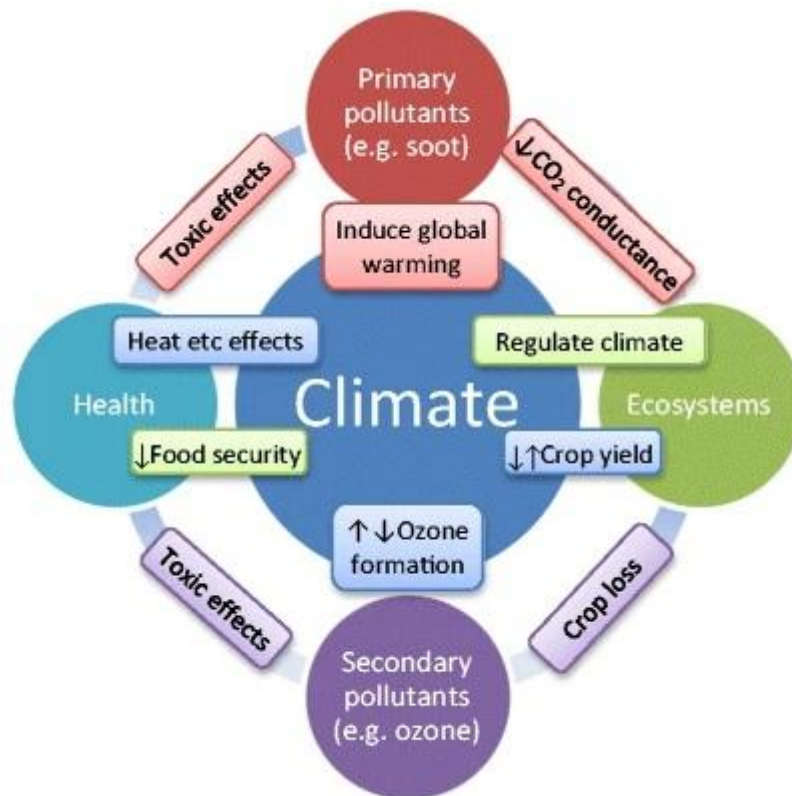


Figure 5 – Climate and air quality interactions and direct and indirect effects on health (Orru et al., 2017).

Many of the drivers of air pollution (i.e. combustion of fossil fuels) are also sources of greenhouse gas emissions. Policies to reduce air pollution, therefore, offer a win-win strategy for both climate and health, lowering the burden of disease attributable to air pollution, as well as contributing to the near- and long-term mitigation of climate change (Fiore et al., 2015). Climate and air quality are inextricably connected: the atmospheric state and its variability determine when, where, and how pollutants accumulate, transform, and disperse.

Atmospheric variables affecting air quality fall into two main classes (Latini et al., 2002):

- (i) variables that, through mechanical dispersion, influence the accumulation and spatial distribution of pollutants. Examples are temperature, precipitation, relative humidity, wind speed and

direction, and atmospheric stability, which can be described by mixing height, stability class, vertical temperature gradient, and solar radiation;

- (ii) variables affecting chemical transformations of pollutants, varying depending on the type of pollutant. For example, for ozone formation, temperature, humidity, and solar radiation are especially influential (Latini et al., 2002).

Meteorology governs emissions, transport, transformation, and deposition, so pollutant concentrations co-vary with wind speed and direction, temperature, and relative humidity; analyses should therefore consider multiple variables jointly rather than in isolation (Elminir, 2005; Gorai et al., 2015; Zhang, 2019). Because these variables are interrelated, their coupling shapes both chemical and physical processes: increased CO₂ enhances the greenhouse effect and raises temperature; high temperature with low wind speed can elevate pollutant levels; and stronger solar irradiance accelerates photochemical smog, increasing ozone (Hou and Xu, 2022).

Seasonal and diurnal atmospheric changes shape anthropogenic emission patterns and resulting pollution, necessitating attention to time-of-day and time-of-year variability (He et al., 2017; Qi et al., 2021). Seasonal differences reflect variations in emissions from heating, transport, and industrial activities that co-vary with weather, as well as shifts in energy-use behaviour. In particular settings, elevated winter concentrations correspond to the widespread use of coal for domestic heating and other fossil fuels, sometimes exacerbated by reliance on low-calorie, high-sulfur coal under low temperatures and specific socioeconomic conditions (Demir et al., 2014). Precipitation systematically reduces concentrations via wet deposition, notably through mechanical washout of PM₁₀ and dissolution-oxidation pathways for SO₂ (Yoo et al., 2014).

Moreover, colder months commonly exhibit higher concentrations because lower boundary-layer heights and frequent thermal inversions limit dispersion (Fig. 6), whereas warmer seasons generally show lower concentrations due to stronger mixing (Feng et al., 2020). Pollution episodes are more likely under temperature inversions associated with persistent high-pressure systems in winter: daytime solar heating warms the surface, but nocturnal radiative cooling chills air near the ground; a warmer overlying layer then caps the colder surface air, trapping emissions and progressively increasing near-surface concentrations until meteorological

conditions change (Feng et al., 2020). Low surface temperatures and high atmospheric pressure are often correlated with conditions favourable for inversions, reducing vertical mixing and elevating ground-level pollution.

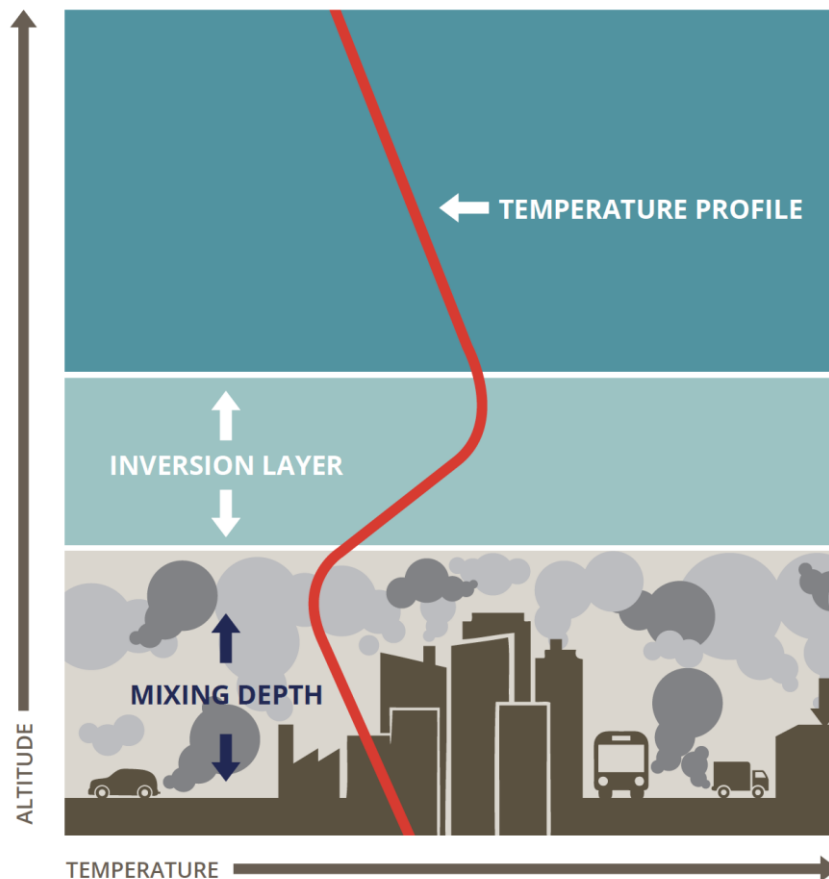


Figure 6 – Thermal inversion vertical profile (EEA, 2020).

Pollutant–meteorology relationships are pollutant-specific and should be interpreted as the joint action of interdependent drivers rather than single-factor associations (Gorai et al., 2015; Qi et al., 2021). For ozone, hot, sunny conditions enhance photochemical production, while humidity modulates reaction pathways. For PM_{10} , wind speed and boundary-layer dynamics govern dispersion: low winds and stable stratification suppress vertical mixing and favour surface accumulation, whereas stronger winds enhance dilution; wintertime inversions and shallow boundary layers are associated with higher near-surface concentrations, while precipitation reduces PM_{10} via washout and scavenging (Elminir, 2005; Feng et al.,

2020). For SO₂, higher temperatures can increase instability, contributing to lower concentrations in warmer conditions, while low wind speeds and stable boundary layers favour accumulation; rain events remove SO₂ through dissolution followed by oxidation (Hou and Xu, 2022; Yoo et al., 2014). For NO₂, a short-lived primary pollutant, concentrations tend to be higher under stagnant, stable conditions and decrease with stronger winds that enhance dispersion; precipitation episodes contribute to reductions via wet removal (Elminir, 2005; Yoo et al., 2014).

Because temperature, relative humidity, wind, precipitation, solar radiation, and mixing depth are interdependent, and because landscape and human activity patterns modulate emissions, the strength and even the sign of pollutant–meteorology associations can differ by location and season; robust assessments therefore examine multiple variables jointly and are tailored to local atmospheric regimes and topographic settings (Latini et al., 2002; Qi et al., 2021; Zyromski et al., 2014). Across this literature, some relationships are consistently observed—thermal inversion, wind speed, and precipitation exert clear and interpretable effects—while mixed evidence for temperature and humidity reflects pollutant specificity and contextual differences in atmospheric dynamics (Elminir, 2005; Yoo et al., 2014).

1.3 Air Pollution – Health

Air pollution is the main global environmental health hazard, with effects spanning from subclinical impacts to premature death (WHO, 2016; WHO, 2024). A health hazard is a source of risk to human health or well-being; here, the hazard of interest is air pollution (Department of Health, 2006).

The WHO 2021 Air Quality Guidelines underline that health harms can occur even at lower concentrations than previously understood (WHO, 2021). Beyond all-cause mortality, consistently implicated outcomes include stroke, ischaemic heart disease, chronic obstructive pulmonary disease (COPD), lung cancer (LC), type 2 diabetes, lower respiratory infections (e.g. pneumonia), and adverse birth outcomes; for household air pollution, cataract is also a recognised endpoint (WHO, 2025). In addition, outdoor air pollution and particulate matter (PM) are classified as carcinogenic to humans (Group 1), based on sufficient evidence in humans and strong mechanistic data (IARC, 2013). At population level, much of the impact arises from widespread morbidity—exacerbations of respiratory and cardiovascular

disease, greater medication use and healthcare demand, and lost school and work days—while the most severe outcomes (including myocardial infarction, stroke and lung cancer) drive the upper end of risk and long-term consequences (see Fig. 7).

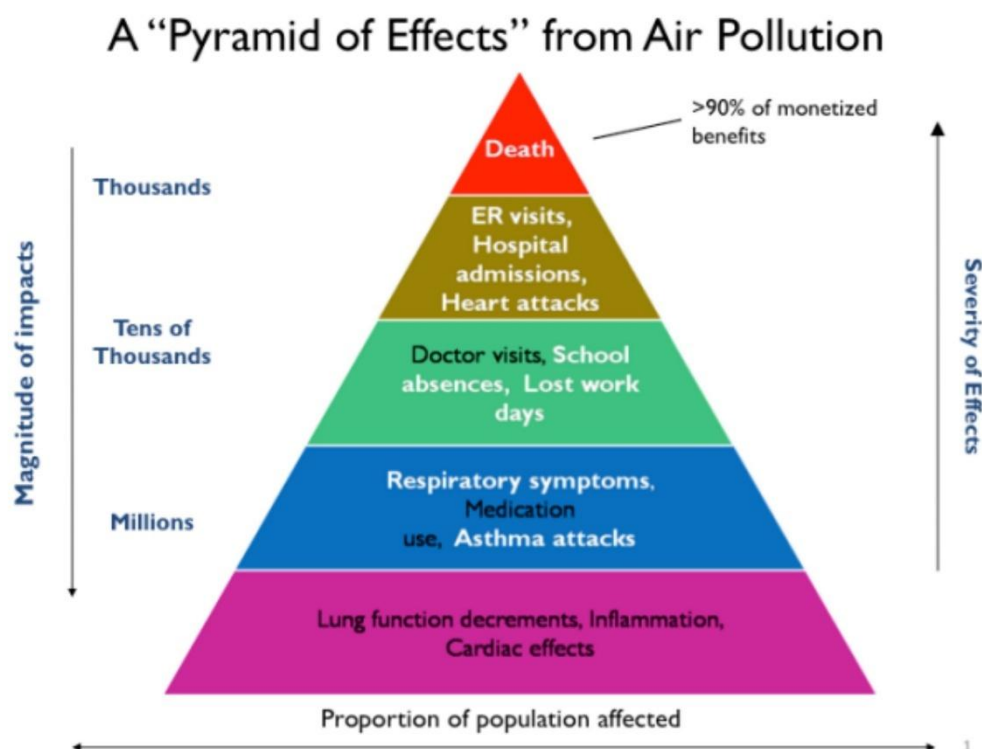


Figure 7 – Air pollution effects (including their magnitude and severity) and the proportion of population affected (US EPA, 2025).

For burden estimation and cost–benefit analysis, European guidance recommends including morbidity endpoints—beyond hospital admissions—to capture restricted-activity days and symptom days alongside mortality, thereby better reflecting the full public-health impact (Héroux et al., 2015; WHO HRAPIE, 2013). Recent European assessments likewise emphasise combining mortality and morbidity to account for healthcare use and productivity losses in addition to deaths (Soares et al., 2022). This dissertation refers to mortality only.

Impacts are unevenly distributed across the population. Pregnant people, infants and children, older adults, and those with pre-existing heart or lung disease, are more susceptible to given levels of exposure (HEI, 2025). Populations living in

poverty and historically marginalised groups face higher exposures due to socioeconomic disadvantage or ethnicity (HEI, 2020). Urban residents often encounter higher exposures because intensified economic activity raises concentrations in cities (EEA, 2023; World Bank and IHME, 2016). Globally, the heaviest burdens fall on South Asia and East, West, Central and Southern Africa (HEI, 2025).

Ambient air typically comprises complex pollutant mixtures. As a result, health effects attributed to a single pollutant in epidemiological analyses may reflect, in part, the broader mix. Commonly studied pollutants—PM, black carbon, ozone (O₃), nitrogen dioxide (NO₂), nitrogen oxides (NO_x), sulfur dioxide (SO₂), carbon monoxide, heavy metals, and black smoke—are often indicators for mixture exposure rather than isolated causal agents (WHO, 2016).

Particulate matter (especially PM_{2.5} from ambient and household sources) is the largest contributor to the global air-pollution disease burden, accounting for over 90% of total air-pollution-attributable mortality (HEI, 2025). Particle size determines where deposition occurs in the respiratory tract: PM₁₀ tends to settle in the upper airways, whereas fine and ultrafine particles can reach the alveoli (see PMs sizes in Fig. 8); components of fine PM can enter systemic circulation and exert organism-wide effects (HEI, 2024). The very small size and large surface area of PM_{2.5} favour long atmospheric residence times and transport. Upon inhalation, particles accumulate in the lungs, activate inflammatory cells, and trigger mediators and alveolar receptors, perturbing autonomic and neuroendocrine pathways. In the respiratory system, reactive oxygen and nitrogen species and oxidative stress initiate and propagate pulmonary inflammation with downstream illness risks; PM_{2.5} can infiltrate alveoli and enter the bloodstream (Thangavel et al., 2022). Notably, adverse effects persist at concentrations below many current standards, reinforcing the need for precautionary policy (WHO Regional Office for Europe, 2013; WHO, 2016).

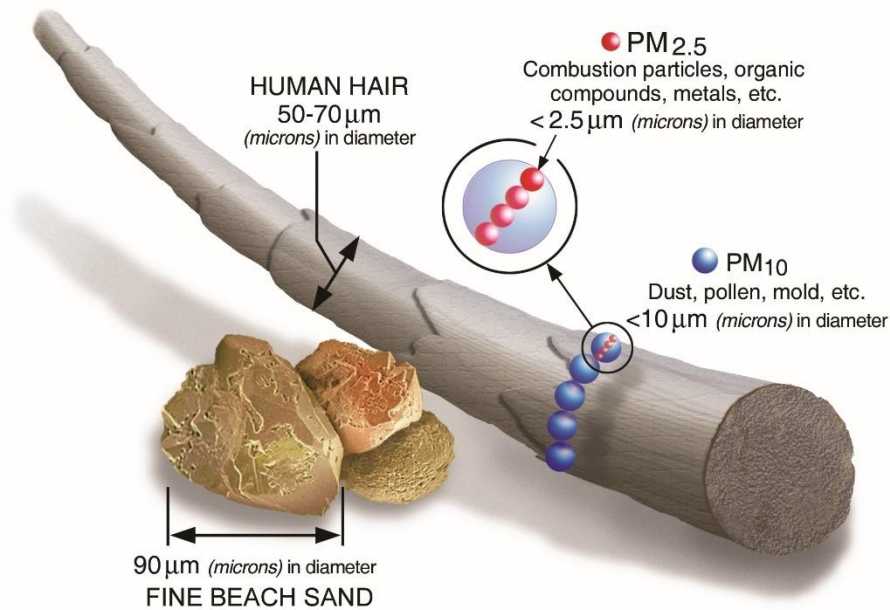


Figure 8 – Schematic overview of the relative size of particulate pollution, PM₁₀ and PM_{2.5} (US EPA, 2025).

Short-term (hours to days) increases in air-pollution levels can cause acute irritation of the eyes, nose, and throat—which generally diminishes as pollution levels fall—and can precipitate or worsen lower-respiratory conditions such as asthma, bronchitis, and COPD. In people with heart disease, short-term PM_{2.5} exposure may provoke arrhythmias, myocardial infarction, and even death. From a public-health standpoint, some of the most substantial harms arise from long-term exposures, which elevate risks of developing and dying prematurely from chronic heart, respiratory and metabolic diseases, lung infections and cancer, and they are associated with adverse birth outcomes (preterm birth and low birthweight) that raise infant morbidity and mortality. A growing body of evidence also implicates air pollution in brain-health outcomes (e.g. neurodevelopmental effects in children and neurodegenerative disease in adults), and overall reductions in life expectancy (HEI, 2020).

Air Pollution Health Risk Assessments (AP-HRAs) estimate health risks from past, current, or future exposures—and from exposure changes due to policies—by evaluating (i) pollutant concentrations, (ii) population exposure, and (iii) the resulting health risks to the exposed population. Assessments can be qualitative or

quantitative and are designed to inform decisions by policymakers and stakeholders (WHO, 2010; 2016). In practice, AP-HRAs quantify expected health benefits of air-quality policies across different policy, environmental, and socio-economic settings.

A common approach to estimate the health outcomes attributable to air pollution is based on the Relative Risk (RR). This concept apportions the share of a given endpoint attributable to the exposure to a specific pollutant on the basis of known exposure-response functions derived from epidemiological studies (e.g. Héroux et al., 2015; WHO HRAPIE, 2013)

Exposure assessment integrates pollution concentration fields with time-activity patterns, exposure duration and intensity, the proportion of susceptible subgroups, and pollutant properties (e.g. solubility, interaction with respiratory tissues). Once exposures are characterised, health-risk quantification draws on short- and long-term endpoints, which can be organised as follows (HEI, 2020; WHO, 2010; 2016):

- Short-term endpoints: all-cause and cause-specific mortality; emergency-department visits and hospital admissions for respiratory and cardiovascular diseases; restricted-activity days; school and work absences; and other acute symptoms (HEI, 2020).
- Long-term endpoints: mortality from cardiovascular and respiratory diseases; lung cancer; chronic incidence of respiratory or cardiovascular disease; declines in lung function and other physiologic measures; and adverse pregnancy outcomes (HEI, 2020; WHO, 2016).

The results of an AP-HRA can also feed into economic valuation to estimate the health benefits of policy-driven air-quality improvements, which often depend on avoided premature mortality alongside substantial morbidity gains (US EPA, 2025; WHO, 2016).

1.4 Air Pollution – Economic Valuation

Air pollution is not only a health risk; it is also an economic burden (World Bank, 2016). By causing illness and premature death, pollution reduces quality of life, while lost productive work lowers output and household incomes. From an

economic valuation perspective, the burden operates through two main channels: the monetary value society places on avoiding disease and death, which is typically estimated with willingness-to-pay (WTP) methods, and the reduction in labour productivity (WHO, 2021) .

Within the WTP framework, avoided mortality risks are commonly measured in monetary terms using the value of a statistical life (VSL), while gains in statistical life expectancy are expressed as the value of a life year (VOLY). The VSL is the marginal value of a reduction in the risk of dying, defined as the rate at which people are prepared to trade off income for a small reduction in mortality risk (OECD, 2012). It is considered the value a given population places ex ante on avoiding the death of an unidentified individual. In practice, VSL is computed by first eliciting WTP for a specified risk reduction and then dividing WTP by the change in risk of dying (OECD, 2012):

$$VSL = \frac{\Delta WTP}{\Delta R}$$

Two main approaches are used to elicit WTP for specified reductions in mortality risk (or gains in longevity): stated preferences and revealed preferences (OECD, 2012):

- Stated preference methods (most commonly contingent valuation and choice experiments), are based on surveys in which individuals are asked to state their WTP to reduce the mortality risk in hypothetical markets for the mortality risk change (from which the VSL can then be derived).
- Revealed-preference methods elicit WTP from observed behaviour in markets where prices incorporate differences in mortality risk (e.g. labour markets, where wage premia reflect variation in workplace fatality risks) and from purchases of goods that prevent or reduce mortality risks (for example, buying bottled water to mitigate contamination risks, or motorcycle helmets to lower traffic-fatality risk).

Both stated-preference and revealed-preference approaches have recognised strengths and limitations, but there has been a growing emphasis on stated-preference methods in recent years. A key reason is that many environmental, transport and health policies mainly affect the youngest and the oldest, rather than workers in risky occupations on which wage-risk studies are based; moreover, mortality linked to pollution typically arises from long-term exposure and the

exacerbation of pre-existing conditions, not accidental workplace deaths (Alberini, 2005; OECD, 2012).

VOLY, which is a measure closely related to VSL, can also be quantified via WTP-based measures. Because VOLY weights the number of remaining life years, using VOLY rather than a single, age-invariant VSL can lead to different policy rankings when the age distribution of those affected differs (OECD, 2012).

Emplying WTP metrics enables to understand the magnitude of the welfare and income losses linked to air-pollution exposure. In 2019, exposure to ambient and household air pollution was associated with USD 8.1 trillion in global welfare losses, including mortality and morbidity (World Bank, 2022). These losses accounted for 5.9% of GDP in low-income countries and up to 8.9–9.0% in lower- and upper-middle-income countries.

Benefit transfer is commonly used to apply WTP-based measures in contexts where primary valuation is not feasible, so that pre-existing estimates must be used instead (Johnston et al., 2015). Usually, VSL and VOLY estimates are transferred from the available literature to a policy context where VSL/VOLY estimates are missing (OECD, 2012). Although in some applications a value from one country is transferred to another by adjusting only for GDP, this “naïve” approach risks bias if other determinants of WTP are ignored. In this PhD research, this issue is addressed by adjusting VSL and VOLY estimates from primary studies using economic, socioeconomic, demographic, and health characteristics.

There are two primary benefit transfer approaches: unit value transfers and value function transfers (Johnston et al., 2015). Unit value transfers involve taking a single number or a small set of numbers from prior studies, either “as is” or adjusted for differences in income, purchasing power and inflation, or according to expert judgement. Their advantages are transparency and low data demands; however, accuracy may suffer where differences exist between study and policy sites. Value-function transfers, instead, borrow an estimated WTP function, usually parametric, from previous research. The function may come from an original study, a meta-analysis that pools estimates across studies, or a preference-calibration exercise that specifies a structural utility model using evidence from two or more studies. Evidence generally indicates that function transfers outperform unit value transfers in terms of accuracy (Kaul et al., 2013; Rosenberger and Stanley, 2006).

Meta-analysis provides a foundation for many function transfers by quantifying how WTP varies systematically across studies and contexts. It is the quantitative

synthesis of evidence on a particular empirical outcome, drawing on prior primary studies (Nelson, 2015). In environmental economics, meta-analysis is most often implemented via meta-regression models (MRMs), estimated using classical or Bayesian methods. In MRMs, the dependent variable is a comparable outcome from the literature (e.g. VSL, VOLY, etc.), while moderator variables capture observable factors hypothesised to explain variation across observations, including study design (stated vs revealed preference; contingent valuation vs choice modelling; scope; payment vehicle; survey mode), economic context (income, PPP, price year), risk attributes (type, magnitude, baseline risk, latency) and population characteristics (age structure, health status) (Johnston et al., 2015). Observations may be drawn from both published and unpublished sources; precision weighting (e.g. inverse variance or sample size) and random-effects or hierarchical structures help address statistical reliability and unobserved heterogeneity. Meta-analysis increases the power of statistical tests, allows generalisation about the underlying distribution of effects, and enables evaluation of study quality (Nelson, 2015).

When used for benefit transfer, MRMs are applied to identify and test systematic influences of study, economic and resource attributes on WTP, to characterise the literature for specific non-market values, and to generate reduced-form benefit functions for direct transfer (Johnston et al., 2015). Evaluating a meta-analytic benefit function at policy-site covariates yields context-specific VSL or VOLY. Where policies primarily influence longevity rather than mortality risk per se, VOLY-based transfers are used. In fact, beyond mortality, other measures capture the air pollution-attributable burden that can be translated into economic outcomes.

In this PhD dissertation, apart from mortality, Years of Life Lost (YLL) are also considered. This measure summarises the years of potential life lost due to deaths occurring before a reference life expectancy, combining the frequency of deaths with the age at which they occur (EEA, 2024), offering a more comprehensive view of the impact of early mortality. Recent work also accounts for differences in age structure and gender when quantifying how different pollutant levels affect life expectancy (Liu et al., 2024). Higher concentrations of air pollution have shown to be correlated with increased YLL: a 10% rise in $PM_{2.5}$ results in a 16.7% increase in YLL (Juginović et al., 2021). Evidence from 72 Chinese cities further supports this relationship, estimating that each $10 \mu g/m^3$ increase in $PM_{2.5}$ corresponds to an additional 0.43 years of life lost (Qi et al., 2020).

While uncertainties remain around the precise disease burden and the determinants of WTP, the evidence consistently indicates millions of deaths, large losses of healthy life years, and trillions of dollars in annual costs; estimates vary with method, survey design, population sampled and baseline risk, and these uncertainties should be reflected in sensitivity analyses.

Moreover, VSL estimates are split according to the risk context in which they are calculated: almost half of the time they are elicited with respect to a change in a health-related mortality risk, and usually the other contexts are traffic (road accidents) and environment (OECD, 2012). Within this PhD dissertation, VSL and VOLY estimates considered are only related to the risk of air pollution.

1.5 Research Objectives

This doctoral research investigates the health and economic consequences of air pollution, with a focus on mortality and YLL, and their monetary valuation. The overall aim is to generate policy-relevant metrics, both epidemiological and economic, that can inform country-tailored pollution abatement and climate policies under a consistent, transparent framework.

This dissertation is built upon three main articles that constitute the outcome of the research developed during the PhD. To make the methodological framework and the logical, consequential links among the three works explicit, this dissertation begins with an overview of the state of the art of the topics interlinked and explored in my research: air pollution, its drivers, its impacts on health, and the associated economic costs. It then focuses on the methodologies employed to assess air-pollution drivers, to project them into the future, and to assess corresponding health impacts and costs. Concluding remarks and a discussion of results are presented in the final section.

Air pollution is a complex phenomenon and, before entering into the economic part, understanding what is behind it (especially in highly polluted countries) is a valid research question I have tried to answer by carrying out detailed research on the link between atmosphere and air pollution. Results are presented in **Paper I**.

Understanding, in monetary terms, how much air pollution costs different countries—and how better-performing countries can serve as exemplars for others—would be highly useful for policy-makers to allocate resources more

effectively and, above all, to prevent illness, years of life lost, and premature mortality. But, persistent gaps exist in the literature:

- most countries have insufficient and unreliable VSL and VOLY estimates;
- lack of country-specific data;
- lack of common methodology among existing studies;
- VSL and VOLY not tailored to air-pollution risk, often derived in aggregation with other risk categories.

To fill these gaps, this research creates a harmonised database, through a transparent meta-analytic procedure, for the development of an econometric model for global application, able to translate epidemiological impacts into economic terms (see **Paper II**). The resulting evidence enables cross-country comparisons of pollution-control and climate policies while preserving local relevance.

Once the econometric model is developed, I proceed with its application. Using two different methodologies to assess the economic burden of air pollution on health, I provide estimates for 108 countries—meeting the objective of having economic estimates for as many countries as possible, including those without prior valuations (see **Paper III**).

The more specific research objectives addressed in the three papers are as follows:

Objective 1 — Atmospheric Drivers of Air Quality.

The objective is to understand what drives air pollution from an atmospheric point of view. This is important, because high concentrations of air pollutants are not exclusively caused by abrupt increases in emissions, but atmospheric conditions significantly control the dispersion and the accumulation of pollutants, as well as favour their formation through chemical reactions. Therefore it is an important aspect to be considered when studying air pollution. The aim of this paper is to identify and quantify how atmospheric variables shape ambient concentrations of key pollutants, in the case study of Türkiye, which exemplifies a high polluted and densely populated country, and one of the largest economies worldwide. Using station-level observations, the analysis examines the role of temperature, relative humidity, wind speed, precipitation, and boundary layer height in driving concentration dynamics and periods of degraded air quality (**Paper I**).

Objective 2 — Global Monetisation Model for Mortality Risk.

The development of an econometric meta-analytic model able to estimate the VSL and the VOLY specifically for air-pollution risk is the second main objective of my PhD research. The goal is to fill the above mentioned gaps in the literature, and to provide transparent, policy-ready parameters and a practical workflow to translate health impacts into economic terms across different national contexts (**Paper II**).

Objective 3 — Economic Burden of Air-Pollution Mortality.

Quantify the economic impact of air-pollution-attributable mortality and YLL worldwide, with particular emphasis on countries lacking data. This is done by conducting a health impact assessment and applying the VSL/VOLY estimates derived in Paper II. The analysis covers the last two decades, in order to document mortality and YLL levels and trends, enabling comparison across countries under a common valuation framework (**Paper III**).

The papers presented are the result of three years of research under the careful supervision of the supervisor and co-supervisors. The work benefited from many experts' feedback during an 18-month visiting period at the European Commission Joint Research Centre (Ispra) and from presentations at international conferences and congresses. A side-objective was to create collaborative networks with experts in different fields: climatologists, epidemiologists, and economists. This objective is being achieved: the work has raised considerable interest, and several collaborations have been requested, with the aim of applying the econometric model developed within this PhD.

1.6 Dissertation Outline

This dissertation examines the relationships among air pollution, climate-related drivers, health impacts, and economic valuation. Section A presents the introduction and methodology framework. The introduction (Chapter 1) outlines the conceptual framework and research questions, while the methodology (Chapter 2) is presented in two chapters: one for **Paper I** (subsection 2.1) and another for **Paper II** and **Paper III** (subsection 2.2). These present the preparatory and advanced analyses undertaken for the preparation of the scientific articles.

Section B presents three scientific articles (Chapters 3–5) that examine the previously mentioned topics and their connections, with the aim of answering the research questions outlined in the subsection 1.5:

- **Paper I** — Chapter 3. Interaction between air quality and atmospheric variables in a specific case study (Türkiye).
- **Paper II** — Chapter 4. Development of an econometric model, derived from a meta-analysis, to estimate VSL and VOLY for global application.
- **Paper III** — Chapter 5. Economic quantification of air-pollution-related mortality and YLL at the country level, covering 108 countries across five continents and over 86% of the world's population.

Each chapter is designed to be read independently and includes its own set of references list presented at the end of this dissertation. **Paper I** is published in the *Atmospheric Pollution Research* journal; the published version is accessible via its DOI (<https://doi.org/10.1016/j.apr.2025.102826>). **Paper II** is published in the *Journal of Environmental Management*; the published version is accessible via its DOI (<https://doi.org/10.1016/j.jenvman.2025.124824>). **Paper III** is currently under review at the *Environmental and Resource Economics* journal.

Section C presents a discussion of the main findings and a conclusion. It examines limitations and applications, and outlines the research implications. A complete reference list is provided at the end of the dissertation.

Ch. 2

Methodological Framework

2.1 Atmospheric Analysis Methodology

This chapter outlines the methodological steps leading to the final paper on atmospheric variables and air pollution, whose definitive version appears as **Paper I** in Section B of this dissertation. It documents the steps undertaken prior to the definitive model, since each phase was essential to the robustness of the overall outcome, and provides a synthesis of the complex set of analyses undertaken to ensure that the results in the final paper have a solid theoretical and methodological basis.

Paper I investigates the relationships between atmospheric variables and air pollution across 42 monitoring stations in Türkiye (the rationale behind this study area's choice is presented in subsection 1.5; further details are provided in the paper – Chapter 3 of this dissertation). The analysis relies on high-resolution hourly data to capture temporal variations in summer and winter, and it employs a generalised additive model (GAM), complemented by a sensitivity analysis, to examine how temperature, relative humidity, wind speed, precipitation and boundary layer height influence pollutant concentrations, with attention to seasonal and regional differences.

Before presenting the final statistical model and the specific results discussed in the paper, a sequence of preliminary analyses was carried out on the full dataset. Although this chapter mainly reports PM₁₀ examples, the complete analysis was also performed for SO₂.

Air pollutants concentrations are sourced from the European Environment Agency (EEA). To assess the influence of climate on air quality, in-situ meteorological stations located within 5 km of the nearest air-quality monitoring site are selected to ensure cross-site consistency (Colston et al., 2018). The National Oceanic and Atmospheric Administration (NOAA) provides observations of:

- a) temperature ($^{\circ}\text{C}$)
- b) wind speed (m s^{-1})
- c) wind direction (degrees)
- d) sea-level pressure (hPa).

From these, two additional variables are derived:

- e) relative pressure (referenced to the mean atmospheric pressure over the preceding 30 years; hPa)
- f) relative humidity (computed from air and dew-point temperatures; %)

Not available from NOAA, two other variables are retrieved from ERA5 outputs (Hersbach et al., 2020), the fifth-generation reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF, 2024):

- g) precipitation (mm)
- h) boundary-layer height (BLH; m)

A comprehensive exploratory analysis is conducted station by station across the entire 2015–2019 period to identify evident patterns in the variables prior to modelling (see Appendix). Analysis are carried out at diurnal, monthly and annual levels, also differentiated by seasons, both for individual stations and in aggregated form.

Türkiye's Air-Pollution Levels (2015–2019)

National-level conditions are assessed for PM_{10} and SO_2 using data from the World's Air Pollution - Real-time Air Quality Index website (WAQI, 2023). The descriptive statistics in Table 1 refer to PM_{10} only, as SO_2 series display a high proportion of missing values. Table 1(a) reports, averaged across stations, the percentage of days per year exceeding the U.S. Environmental Protection Agency Air Quality Index threshold of 50—levels that may cause health problems in susceptible groups (US EPA, 2023b). Over 2015–2019, at least 25% of days each

year exceeded the threshold. Table 1(b) shows that from 2015 to 2017, about 16% of monitoring stations recorded more than half the year above AQI 50; the shares were 9.15% in 2018 and 14.37% in 2019 (US EPA, 2023b; WAQI, 2023). Days with the most severe pollution, indicated by higher AQI values, predominantly occur in colder months, as shown in Fig. 9 for PM₁₀ (left) and SO₂ (right).

Table 1 – PM₁₀ concentrations Air Quality Index descriptive statistics
(a) average (among all stations) of the days in the year with AQI ≥ 50 (%)
(b) number of stations with more than half of the year with AQI ≥ 50 (%)

	PM10				
	2015	2016	2017	2018	2019
(a)	28.49%	29.39%	29.47%	25.48%	26.76%
(b)	16.55%	16.13%	16.15%	9.15%	14.37%
Tot stations	139	155	161	164	167

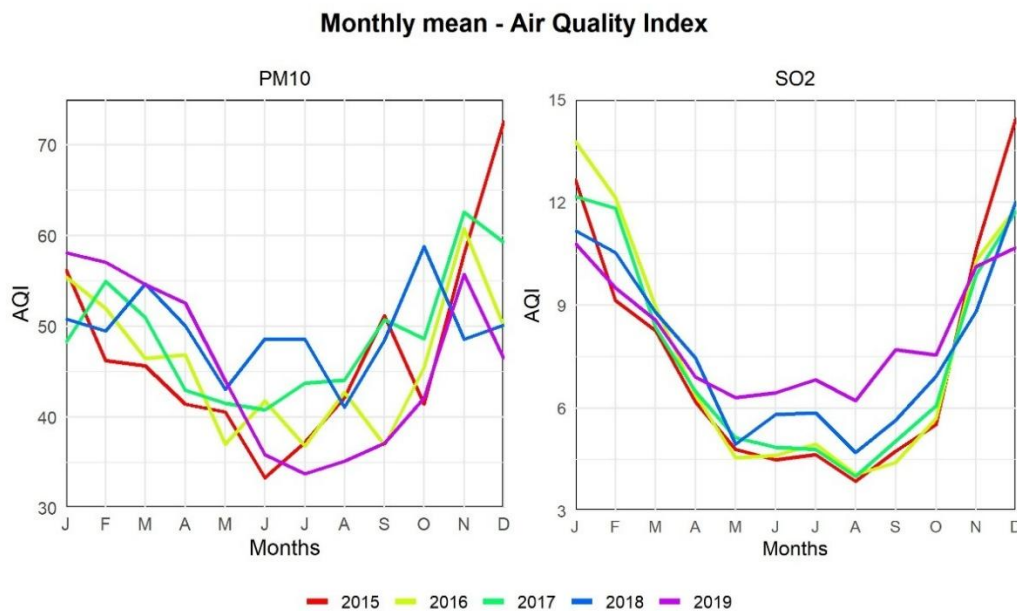


Figure 9 – Mean Air Quality Index by month for PM₁₀ concentrations (left panel) and SO₂ concentrations (right panel), years 2015-2019.

Identifying the Most Polluted Stations

Monthly PM₁₀ and SO₂ concentrations are used to identify stations that consistently exceed the monthly mean for 11 out of 12 months (see Table 2). These are labelled “most polluted stations” (red in Fig. 10a for PM₁₀ and Fig. 10b for SO₂).

Table 2 – PM₁₀ and SO₂ monthly average concentrations (ug/m³), years 2015-2019.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
PM ₁₀	53,76	53,09	48,90	44,28	39,91	37,01	38,39	43,31	46,08	51,86	62,12	58,89
SO ₂	22,15	18,81	13,16	9,00	5,58	4,79	5,34	5,06	6,13	7,63	16,34	22,53

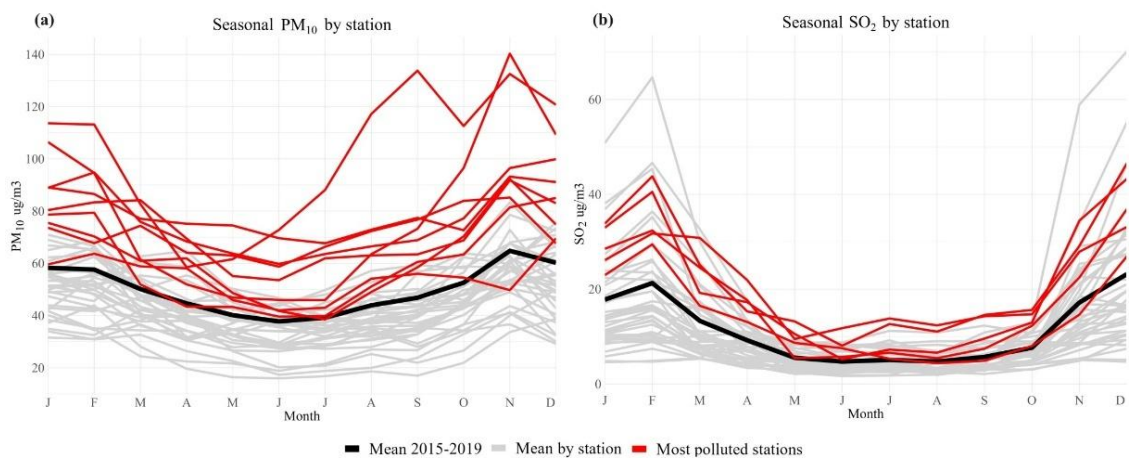


Figure 10 – Seasonal PM₁₀ (a) and SO₂ (b) mean concentrations for i) the aggregated period 2015-2019 (black), ii) each single station (grey), iii) highlighting the most polluted stations (red).

Regression Analysis on the Most Polluted Sites

An initial multivariate linear regression assesses the most polluted sites using climatic variables, seasonality and site-specific characteristics (e.g. land cover). To capture long-term trends and provide a baseline, the pollutant concentration from the same day of the previous year is included, allowing the influence of climatic variables to be distinguished from persistent pollution levels.

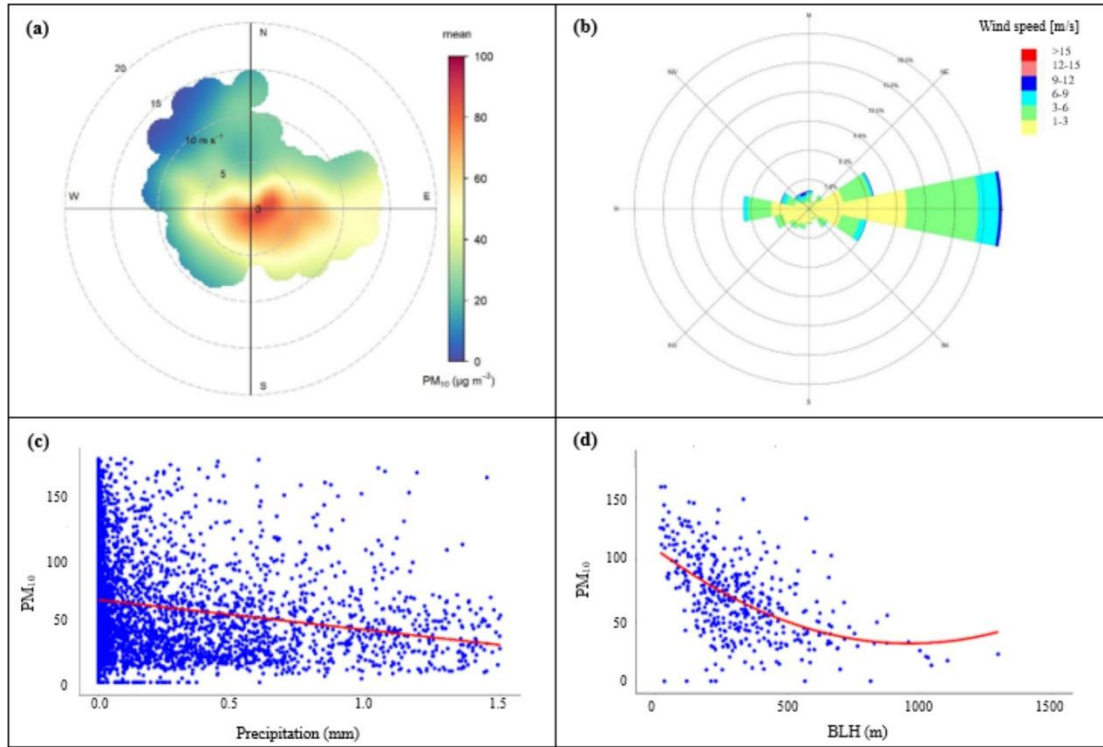
Multicollinearity is evaluated using variance inflation factors (Thompson et al., 2017). With a backward selection, the following variables are used: temperature, wind speed/direction, precipitation, humidity and BLH. A mixed-effects specification is then estimated with random effects nested by region and station, expressed as (1 | region/station), to account for variability attributable to both regional climate and local conditions. The general model equation can be expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + (1|region/station) + \varepsilon \quad (1)$$

where β_0 is the regression constant, β represents the regression coefficients, n denotes the number of explanatory variables included. The random effects are nested by region and station, specified in the model with the (1 | region/station) term. This structure accounts for variability in air pollution at both the regional and station levels, capturing differences in climatic conditions and local factors that influence pollution. The error term is ε .

Scatterplots and the Akaike Information Criterion indicate non-linear relationships between both precipitation and boundary layer height with PM_{10} and SO_2 ; second-degree polynomial terms for these variables are therefore included. The linear regression is further supported by wind roses (wind speed and direction) and seasonal polar plots linking pollution with wind regimes. Analyses are conducted for all seasons, with subsequent focus on summer (lowest pollution) and winter (highest pollution) across stations for 2015–2019, exemplified in Table 3 for Kahramanmaraş (polar plot, wind rose, precipitation, and BLH scatterplots).

Table 3 – Kahramanmaraş winter months polar plot (a), wind rose (b), daily precipitation (c), and BLH (d) scatterplots for PM_{10} concentrations.



Generalised Additive Models

Following this assessment, the multivariate linear approach proved limited in explaining the relationship between our variables. The switch to a GAM model provides more accurate results and a stronger basis for interpretation and discussion, including potential policy implications. GAMs are well-suited to analyse relationships between air pollutants and atmospheric variables, which are frequently non-linear (Lou Thompson et al., 2001; Pearce et al., 2011). Moreover, the underlying datasets are often non-normally distributed. For these reasons, the final model adopted in this research is GAM, which captures how atmospheric variables shape air-pollution patterns at national scale, using observations from 42 stations grouped by climatic region (Hastie and Tibshirani, 1990; Pearce et al., 2011; Thompson et al., 2001). GAMs extend traditional regression by replacing linear coefficients with smoothing terms that flexibly capture non-linear relationships (Hastie and Tibshirani, 1990).

The statistical approach using GAMs provides valuable insights complementary to process-based models such as chemical transport or dispersion models, which require extensive parametrisation and computational resources and may introduce uncertainties. Here, GAMs enable direct interpretation of complex atmospheric–pollution associations from observational data.

The final model is applied for both summer and winter, aggregating the 42 monitoring stations by climatic regions.

Future Scenarios

Using the GAM model, future scenarios for both pollutants are computed for summer and winter. Two representative IPCC climate pathways—RCP 4.5 and RCP 8.5—are considered (see details in Fig. 11). The idea is to explore potential impacts on PM₁₀ and SO₂ in 2030 and 2050, representing lower and higher levels of mitigation, respectively (CMCC, 2024). All methodological details are fully outlined in Paper I.

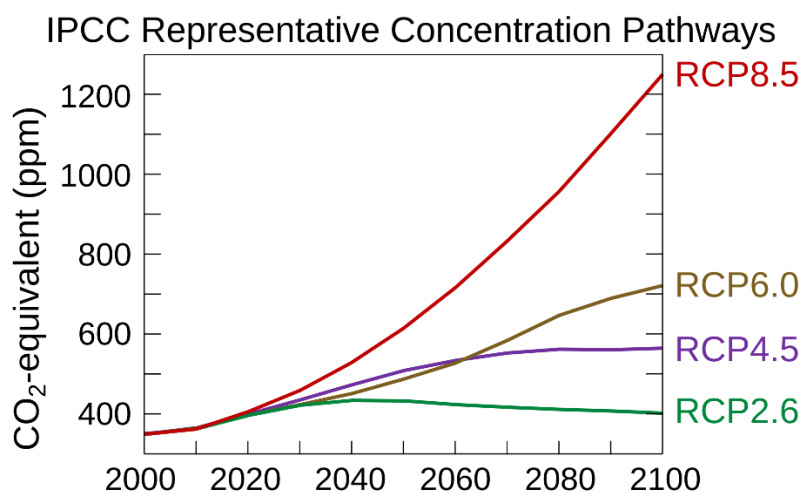


Figure 11 – IPCC Representative Concentration Pathways (RCP) scenarios.

2.2 Economic Analysis Methodology

This chapter sets out the methodological framework that underpins **Paper II** and **Paper III** in this dissertation. Where the theoretical background is already developed in subsection 1.4, it is only briefly recalled here as a bridge to the empirical implementation.

Overview and Motivation

Establishing reliable estimates of VSL and VOLY remains challenging because primary studies employ heterogeneous methods and data, often yielding divergent results even within the same country. For many countries, estimates are sparse or absent due to limited data on health and air pollution, and there is lack of country-specific valuation studies. To address these gaps, Paper II conducts a comprehensive meta-analysis to build an econometric model capable of predicting air-pollution-related VSL and VOLY at the country level worldwide. In contrast to earlier syntheses, the database is restricted to willingness-to-pay for reductions in all-cause mortality specifically attributable to air pollution.

Literature Search and Inclusion Criteria

The database for the meta-analysis combines peer-reviewed papers and technical reports identified through a systematic search conducted manually and independently by two researchers (a Master's student I supervised during my PhD and myself). The peer-reviewed stream comprises 621 English-language publications after de-duplication. Screening progressed through:

- titles/keywords (criterion 1)
- abstracts (criterion 2)
- full texts (criterion 3).
- only studies reporting monetary VSL/VOLY estimates for air pollution (criterion 4)
- estimates at the country level (criterion 5): about 45% of the final papers selected were conducted at city level.

This search yielded 23 peer-reviewed studies. In parallel, 24 reports from recognised agencies were gathered and filtered: for each organisation, the most recent report was selected, and only English-language reports providing country-level VSL/VOLY estimates were retained, leaving 11. The selection here might lead to some kind of biased, as the choice depended exclusively on the authors' choice, considering only international, authoritative and reliable reports.

Overall, 34 publications contribute with 504 value entries: 61 from peer-reviewed papers and 443 from reports.

Standardising Monetary Values

To make values comparable across contexts and over time, all VSL/VOLY figures are converted to 2019 purchasing power parity international dollars (PPP I\$). Each VSL from the literature is first expressed in the study country's local currency (for the relevant costing year), then adjusted for inflation using the country-specific Consumer Price Index (CPI), and finally converted to 2019 PPP I\$ using International Monetary Fund PPP exchange rates (method 2 in Fig. 12), an approach also adopted in OECD meta-analyses (2025).

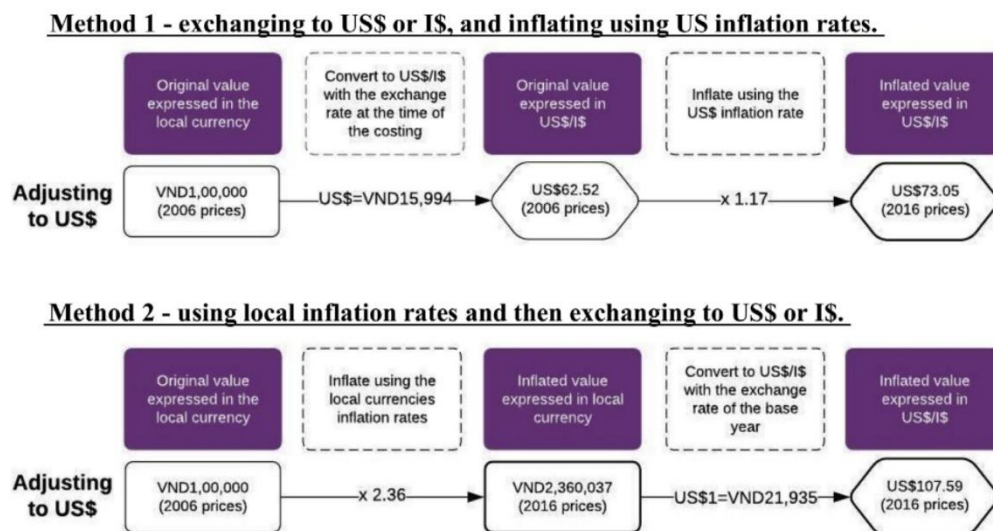


Figure 12 – Overview of two methods to adjust for inflation. In these hypothetical examples, the year of the costing is 2006 and the base year of the analysis is 2016. In the example, USD are being used, but the same approach would be applicable to international dollars (Turner et al., 2019).

Variables and Initial Model Specification

Benefit transfer is commonly used to apply VSL and VOLY estimates from literature to policy settings where original valuations are unavailable (Johnston et al., 2015; OECD, 2012). In practice, estimates from one country are often imported to another by adjusting for income, typically via GDP adjustments. This PhD research advances that approach by examining how factors beyond GDP (i.e. additional explanatory variables) account for cross-country variation in VSL, yielding innovative evidence on the determinants of these values on air pollution-related analysis. The initial set of explanatory variables covers economic, socio-economic, health and environmental domains (see Fig. 13).

Variables	Category
Gross Domestic product per capita (GDP)	economic
Consumer Price Index (CPI)	economic
Gross National Income per capita (GNI)	economic
Unemployment rate	economic
People living below the poverty line	economic
GINI index	economic
Income	economic
Population	demographic
Population density	demographic
Urban population	demographic
Number of megalopolis	demographic
Mean years of schooling	education
Life expectancy (LE)	health
Number of doctors per capita	health
Health expenditure	health
Human Development Index (HDI)	
PM2.5 concentrations	environment
O3 concentrations	environment
Nox concentrations	environment

Figure 13 – Set of explanatory variables initially tested in the model.

The data-exploration protocol of Zuur et al. (2010) is followed (see Fig. 14). An ordinary least squares (OLS) multiple linear regression is tested as a benchmark statistical model.

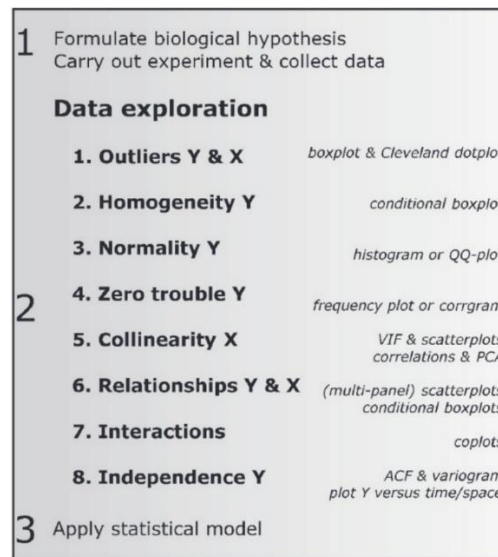


Figure 14 – Zuur et al. (2010) protocol for data exploration and statistical model application.

Observations with missing values (<5%) are omitted (this choice is made by me, in accordance with the other authors' and could lead to a bias). Potential outliers are identified via the interquartile range (IQR) rule; observations outside this interval [$Q1 - 1.5 \cdot IQR$, $Q3 + 1.5 \cdot IQR$] are flagged and excluded.

Assumptions of Multiple Linear Regression

- Linearity. Pearson correlations and scatterplots are examined to check for approximately linear relations between each predictor and the dependent variable (see Fig. 15). Where relationships are obviously non-linear, transformations (log, square-root, cubic-root) are considered. Variables such as unemployment rate, population density, PM_{2.5}, O₃ and CPI are dropped after transformations failed to recover linearity.

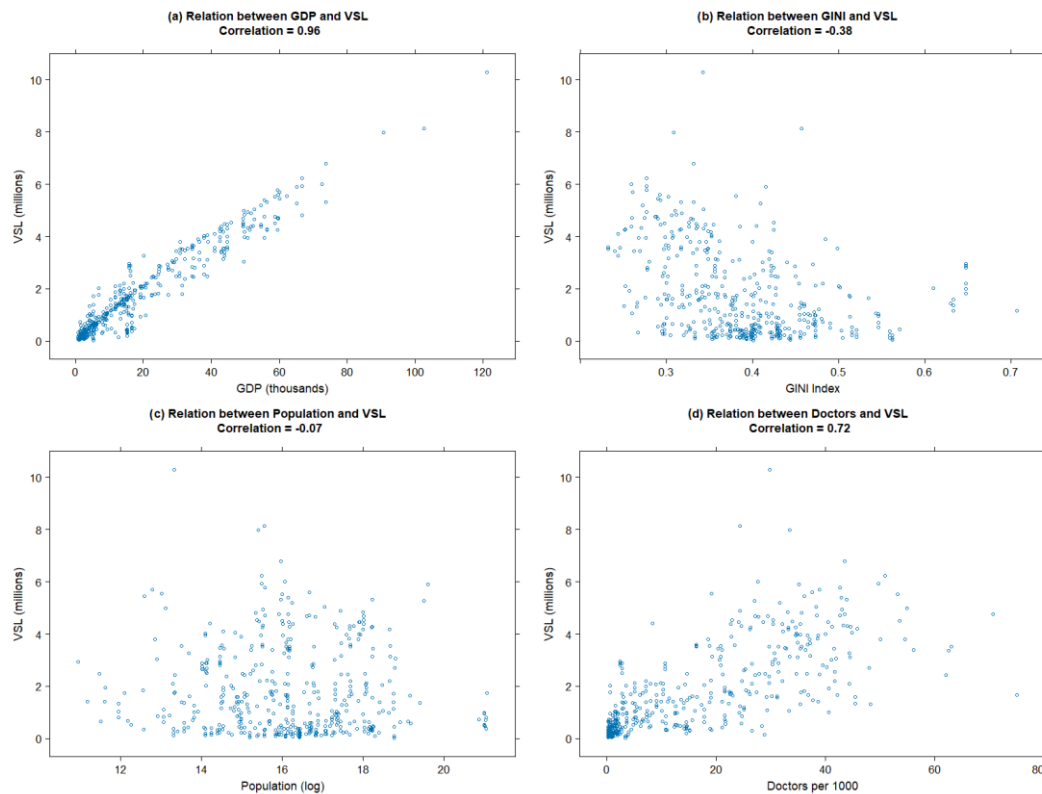


Figure 15 – Scatterplots of VSL against the final explanatory variables included in the model (these include GDP, GINI, Population and number of Doctors).

- Homoscedasticity. Residuals versus fitted values are inspected to verify constant variance and symmetry around zero. As a general principle, visual checks may be complemented by formal tests such as Breusch–Pagan or White tests, but the analysis relies on graphical diagnostics to avoid over-rejection in large samples.
- No multicollinearity. Variance inflation factors (VIFs) are computed for all predictors, with $VIF > 10$ indicating problematic collinearity. HDI, GDP, GNI, schooling and life expectancy are highly correlated—unsurprising given that HDI is constructed from life expectancy, education and GNI. To mitigate redundancy, HDI and related components are excluded while retaining GDP, which is conventional in VSL modelling and produces a higher adjusted R^2 .
- Independence. The Durbin–Watson statistic indicates residual autocorrelation, violating the independence assumption.

- Normality. The Kolmogorov–Smirnov test rejects residual normality. Given the presence of outliers and heavy tails, OLS estimates may be inefficient and sensitive to leverage points.

To address assumption violations and limit outlier leverage, a robust regression is adopted. This approach down-weights unreliable observations and is resilient to heavy-tailed errors. Roughly 5% of observations receive very low weights ($|w| \leq \text{threshold}$), implying negligible influence on the fitted model.

Model structure: the robust meta-regression is estimated with backward selection. Let the dependent variable be the mean air-pollution-related VSL in 2019 PPP I\$. Core covariates include GDP (economic scale), the Gini index (income inequality), the logarithm of population (ensuring comparability across countries), and physicians per 10,000 people (health-system capacity). An interaction between GDP and World Bank income groups is included to capture heterogeneous income–VSL gradients (income elasticity). The total population is dropped after causing instability and implausible predictions in very populous, lower-income settings; the log specification resolves this issue. Initially, total population is included as a covariate. However, for highly populous countries—particularly India—the specification produces implausible (negative) VSL estimates. This reflects the model’s structure in settings with very large populations, relatively low GDP, and few doctors per capita. To address this, the population variables are log-transformed.

Temporal Effects (Year Effects)

As a robustness check, the potential role of study year is examined, given that the database pools estimates produced at different points in time (as shown in Fig. 16). The analysis finds only a negligible year effect and therefore omits it from the final specification. This is consistent with meta-analytic evidence showing that once income (and related covariates) is controlled for, little residual temporal trend remains in VSL estimates; most of the apparent time variation is mediated through income growth rather than calendar time per se.

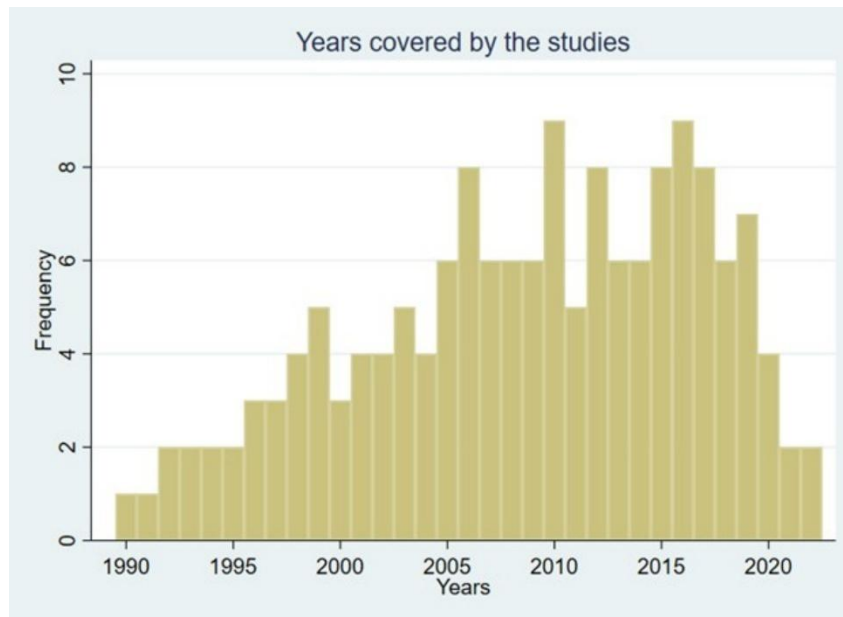


Figure 16 – Years covered by the studies from the literature review conducted, serving as inputs for the meta-analysis.

Global Sensitivity Analysis

Uncertainty is quantified with global sensitivity analysis (SIMLAB, Joint Research Centre), adopting moment-independent indices that assess the influence of inputs on the full output distribution. Two complementary implementations are used: a probability-density-based approach and a cumulative-distribution-based approach. Sensitivity experiments are repeated with and without outliers and across alternative income-group aggregations; to align with the robust regression, results excluding outliers and pooling income groups are retained.

Accounting for Non-Independence Across Studies

A common challenge in meta-analytic datasets is dependence among estimates reported within the same primary study and potential cross-study influence. To check for robustness, a mixed-effects specification that models within-study clustering (i-level) is fitted as a sensitivity analysis, acknowledging the hierarchical structure of the data.

Deriving VOLY from VSL

Air pollution tends to shorten life expectancy rather than causing instantaneous fatalities. Where mortality impacts involve small changes in remaining life years, VOLY is the appropriate monetary metric. Given the scarcity of direct air-pollution VOLY studies in the database (~2% of entries), VOLY is inferred from VSL under the assumption of a constant VOLY across remaining lifetime:

$$VOLY = \frac{VSL}{\left(\frac{1-(1+r)^{-n}}{r}\right)} \quad (2)$$

where n is the discount period (remaining expected life year), and r is the discount rate (Ananthapavan et al., 2021). The discount period n is determined by subtracting the median age of a country's population in the collection year from the corresponding life expectancy for that country in the same year. Because VSL elicitation methods vary and respondents may implicitly discount future payments, VOLY is calculated using $r = 3\%, 7\%, 10\%$. The final discount rate chosen is 3%, consistent with the most recent literature. The mean of VSL and VOLY for all continents, covering 186 countries, is outlined in Table 4.

Table 4 – Mean VSL and VOLY (both in I\$) for all the continents, representing 186 countries.

Continent	Mean VSL (I\$)	Mean VOLY (I\$)
Africa	737,670	34,537
Asia	1,552,518	62,806
Europa	3,489,625	152,695
Oceania	2,168,234	68,105
North America	2,362,474	109,511
South America	1,775,335	71,649
Total countries	186	

From VSL/VOLY to Country-Level Health Costs

The econometric VSL and derived VOLY feed into country-level estimates of the health costs attributable to ambient PM_{2.5} and O₃. To maximise coverage, gaps in Gini and physician density are imputed via short-range temporal interpolation (up to ± 2 years) and spatial interpolation using neighbouring countries with similar

socio-economic profiles; GDP and population are complete for all countries and years. Explanatory variables are compiled for 2000, 2005, 2010, 2015 and 2019. Countries with unresolved gaps after interpolation are excluded. The final dataset includes air-pollution cost estimates for 108 countries.

Costs are computed with two different methodologies: (i) premature deaths attributable to air pollution (Eq. 3) and (ii) YLL (Eq. 4), both derived following the GBD 2021 methodology presented in Paper III.

$$Cost_1 = VSL \cdot \Delta Mort \quad (3)$$

$$Cost_2 = VOLY \cdot \Delta YLL \quad (4)$$

The costs derived from the two methodologies are then compared, and a special focus is given on the four countries that account for the highest economic burden attributable to air pollution.

Section B

Scientific Papers

Ch. 3

Air Pollution and Atmospheric Variables in Türkiye: A Comprehensive Analysis

Sara Ciarlantini ^{a, b 1}, Claudio A. Belis ^b, Andreas Gavros ^c, Alessandro Pezzoli ^a

^a DIST—Interuniversity Department of Regional and Urban Studies and Planning, Polytechnic of Turin and University of Turin, Turin, Italy

^b European Commission, Joint Research Centre (JRC), Ispra, Italy

^c Fincons SPA, Vimercate, Italy

Published version available here: <https://doi.org/10.1016/j.apr.2025.102826>.

Abstract

This study examines particulate matter (PM₁₀) and sulfur dioxide (SO₂) concentrations in Türkiye, one of the world's 20 largest economies with a population of more than 86 million people. The analysis covers from 2015 to 2019, a period during which pollutant levels frequently exceeded international air quality

¹ Visiting scientist at the European Commission, Joint Research Centre (JRC), Ispra, Italy

standards. While anthropogenic emissions are significant contributors, atmospheric variables also play a crucial role in pollutant dispersion and dilution. The research investigates how temperature, relative humidity, wind speed, precipitation, and boundary layer height affect pollutant concentrations in this country. Using a generalized additive model (GAM) and conducting a sensitivity analysis, the study explores seasonal and regional variations in the influence of these atmospheric variables across Türkiye, offering a national, multivariable perspective. The analysis relies on hourly data to capture diurnal variations during summer and winter. Additionally, it provides projections of pollutant concentrations for 2030 and 2050 under two IPCC climate scenarios: one assuming strong mitigation measures (RCP 4.5) and the other representing high-emission conditions (RCP 8.5). The GAM outputs show that temperature, humidity, wind speed, and precipitation affect PM₁₀ and SO₂ differently across the country, with marked regional and seasonal variations. Winter PM₁₀ commonly peaks near ~10 °C, whereas in several regions summer concentrations decline once temperatures exceed ~30 °C; relative humidity is generally positively associated with PM₁₀ yet negatively with SO₂; and stronger winds and precipitation coincide with lower pollutant levels (with PM₁₀ highest at low winds < 5 m/s and notably reduced on days with ~25 mm rainfall). Coastal/maritime regions show the strongest wind- and rain-related reductions in concentrations; interior continental and semi-arid regions display a weaker precipitation signal with a tighter humidity–PM₁₀ association; and high-elevation basins and valleys are characterized by heightened sensitivity to boundary-layer stability. Sensitivity analysis indicates that boundary-layer height and wind are the primary atmospheric drivers for PM₁₀, whereas SO₂ shows a weaker overall sensitivity to atmospheric factors. Projections about the influence of atmospheric variables on pollution for 2030 and 2050 suggest that PM₁₀ levels will generally decline across both seasons, while SO₂ concentrations are expected to rise during summer. The study highlights the increasing influence of climate change on air pollution, stressing the importance of region-specific air quality management strategies. By integrating mitigation and adaptation measures, the findings offer valuable insights for policymakers aiming to improve air quality and reduce health risks across Türkiye.

1. Introduction

With over 99% of the world's population breathing unsafe air (UNEP, 2023), air pollution is one of the main environmental risks to public health (WHO, 2024).

Over the recent decades, particulate matter and sulfur dioxide (hereafter referred to as PM and SO₂, respectively) originated from the burning of fossil fuels have emerged as the main components of air pollution in many parts of the world (WHO, 2021), and their harmful effects on health and the environment are widely documented (HEI, 2025; World Bank and IHME, 2016).

Significant PM₁₀ anthropogenic sources include industrial activities, construction processes (especially during earthwork and foundation stages; Yan et al., 2023), agricultural practices, and road transport. The latter also encompasses automobile exhaust emissions and tyre abrasion (Lenschow, 2001). Furthermore, natural sources, such as sea salt and desert dust, also contribute to the formation of PM₁₀ (Ledoux et al., 2023). Within the group of sulfur oxide gases, SO₂ is the most prevalent in the atmosphere, and an increase in its concentrations leads to a higher risk of mortality (EPA, 2024b). The largest source of SO₂ emissions in the atmosphere is fossil fuel combustion in power plants and other industrial facilities (EPA, 2024b). Additionally, vehicles like locomotives, ships, and heavy equipment burning high sulfur content fuels contribute to these emissions. Natural sources, such as volcanoes, also play a role in releasing SO₂ into the atmosphere. The impact of these pollutants varies significantly across different geographical and socioeconomic contexts, with rapidly developing economies often facing particularly serious challenges in managing air quality (HEI, 2025). These challenges typically arise from the complex interplay between rapid industrialisation, urbanisation, and existing environmental regulations (IQAir, 2024). Understanding these dynamics is crucial for developing effective air quality management strategies, especially in countries experiencing significant economic growth while striving to maintain environmental standards. This context is particularly relevant for understanding the air pollution challenges in Türkiye, where the combination of rapid economic development, geographic location, and complex atmospheric conditions creates a unique set of air quality management challenges.

Türkiye, with a population of more than 86 million people, is one of the world's 20 largest economies (FAO, 2024) and is affected by severe air pollution annual levels (European Commission, 2023). From 2009 to 2019, Türkiye continuously reported the highest (although decreasing) share of deaths attributed to air pollution compared to all EU-27 countries, with an average of 10% of all-cause mortality (IHME - GHDx, 2019). According to The Right to Clean Air Platform, in this country air pollution is responsible each year for over 30,000 premature deaths due

to stroke, ischemic heart disease, lung cancer, and chronic respiratory diseases (THPP, 2024).

Europe's air quality status in 2021 reveals that Eastern European countries, particularly Türkiye, reported SO₂ concentrations exceeding the EU daily limit value of 50 µg/m³, and PM₁₀ levels surpassing the EU daily limit of 45 µg/m³—both established by Directive (EU) 2024/2881 and set to be enforced in 2030 (European Parliament and Council, 2024)—as well as the WHO daily guideline of 45 µg/m³ (EEA, 2023). In 2017, only 1 out of 81 Turkish cities had PM₁₀ levels below WHO guideline levels (THPP, 2024). Notably, in this country, daily average PM₁₀ levels often exceed 75 µg/m³, with concentrations generally stable except in specific provinces like Edirne and Kahramanmaraş, where air pollution has become a prominent issue (Aykaç and Yasin., 2021).

Episodes of high concentrations of air pollutants in urban and suburban areas are not exclusively caused by abrupt rises in emissions, but atmospheric conditions significantly control the dispersion and the accumulation of pollutants, as well as favour their formation through chemical reactions (e.g. photochemical formation of ozone; Han et al., 2015; Latini et al., 2002; Ma et al., 2021; Qi et al., 2021). Atmospheric variables impacting air quality fall into two main categories (Latini et al., 2002): (a) variables that, through mechanical dispersion, influence the accumulation and spatial distribution of pollutants, such as atmospheric stability, temperature, wind, precipitation, and relative humidity; and (b) variables that impact the chemical transformations of pollutants, varying depending on the type of pollutant. Rather than focusing on the role of a single atmospheric parameter in the accumulation and dispersion of air pollutants, it is essential to examine multiple atmospheric variables collectively, as their interplay has the most significant impact on air pollutant concentrations (Qi et al., 2021; Van Nieuwenhuyse et al., 2023). To do so, most analytical methods have traditionally relied on linear approaches (Ravindra et al., 2019), despite evidence that nonlinear statistical methods can more effectively capture the complex relationships between meteorological variables and air pollution (Thompson et al., 2001).

This study moves beyond traditional single-variable approaches by applying a harmonised, multivariable GAM framework to recent air-quality data across Türkiye. Prior research has typically focused on individual cities (e.g. ÇelİK and Kadi, 2007; İçağa and Sabah, 2009; Ulutaş et al., 2021) and on one or two atmospheric variables rather than a broader set of potentially influential atmospheric drivers (İçağa and Sabah, 2009; Tasdemir et al., 2005; Tayanç, 1997,

2000; Ulutaş et al., 2021); a national, multivariable perspective therefore offers a more comprehensive view of how atmospheric conditions may shape pollutant concentrations. Moreover, much of the existing literature relies on observations from the late 1990s and early 2000s, underscoring the need for updated datasets (Cuhadaroglu and Demirici, 1997; Kartal and Özer, 1998; Tayanç et al., 1997).

For all the mentioned reasons, this study aims to: (i) analyse recent (since 2015) air pollutant concentration time series across Türkiye, assessing the combined influence of different atmospheric variables on PM₁₀ and SO₂ levels, and examining regional differences in air quality using a generalized additive model (GAM) combined with a sensitivity analysis framework; and (ii) evaluate how future climatic conditions may affect pollutant concentrations in 2030 and 2050, assuming all other variables remain constant, under two contrasting climate scenarios—one reflecting strong mitigation efforts and the other representing an extreme case. The innovative strength of this research lies in combining multiple analytical techniques to capture the dynamics of air pollution in relation to historical trends and projected climatic scenarios, though the use of a nonlinear statistical approach.

2. Methodology

2.1 Data resources

Hourly concentrations of PM₁₀ (µg/m³) and SO₂ (µg/m³) are obtained from the European Environment Agency platform (EEA, 2024). These two pollutants are selected because they provide the most complete temporal and spatial coverage across national monitoring stations, as they serve as suitable indicators for assessing meteorological influences on air quality, whereas other pollutants, such as NO₂, are less responsive to meteorological variability (EEA, 2025). Background stations are chosen as they can capture integrated contributions from various sources while excluding traffic and industrial stations (DEFRA, 2023). The final selection includes 42 air quality monitoring stations, located in urban, suburban, and rural areas.

To examine the impact of climate on air pollution levels, in-situ meteorological stations located within 5 km of the nearest air quality monitoring station are selected to ensure consistency across sites (Colston et al., 2018). This approach ensures paired hourly meteorology for each air-quality station, overcoming slight

differences in air pollution data caused by the geographical distribution of monitoring stations (Hou and Xu, 2022). The National Oceanic and Atmospheric Administration database (NOAA, 2024) provides hourly observations of: (a) temperature ($^{\circ}\text{C}$), (b) wind speed (m/s), (c) wind direction (degree), (d) sea level pressure (hPa). Through an elaboration of these variables, the following ones are also calculated: (e) relative pressure (measured against the average atmospheric pressure of the preceding 30 years; hPa), and (f) relative humidity (calculated from air and dewpoint temperatures measurements; %). Hourly data observations of total precipitation (mm) and boundary layer height (hereafter BLH; m) are unavailable from the NOAA database. Thus, they are retrieved from the outputs of ERA5 (Hersbach et al., 2018), i.e. the fifth generation reanalysis produced by ECMWF. Combining past observations with models, ERA5 outputs are produced hourly at a horizontal resolution of 31 km. The total number of meteorological stations is 39, as three different air quality monitoring stations (namely Alsancak, Bayrakli, and Sirinyer) share a common NOAA station within 5 km.

The selection of monitoring stations follows a rigorous multi-step process to ensure data quality and representativeness: (i) continuous coverage for consecutive years; (ii) $\geq 75\%$ annual completeness; and (iii) spatial representativeness across all Türkiye's climatic regions. Although a five-year window is shorter compared to some climatological studies, several factors support the validity and relevance of our results: (i) the high temporal resolution (hourly measurements) enables detailed analyses of diurnal and seasonal cycles and their relationships with atmospheric variables; and (ii) the broad spatial coverage, with stations distributed across all Turkey's seven climatic regions, provides geographical robustness.

Data for future climate projections are obtained from the Copernicus Climate Data Store (Copernicus, 2024). The dataset provides daily projections of temperature, relative humidity, precipitation, and wind speed for the years 2030 and 2050 at a 25 km resolution (see Supplementary section – Part 1a). These variables are selected under two different future Intergovernmental Panel on Climate Change (IPCC) scenarios, based on Representative Concentration Pathways (RCPs): RCP 4.5 and RCP 8.5. Future yearly mean concentrations are derived from the hourly data of pollutants and atmospheric variables, following a similar approach to Çapraz et al. (2016).

2.2 Study area

The location of the 42 air quality monitoring stations and 39 meteorological stations is shown in Fig. 1. More information about the stations (e.g. coordinates, elevation, distance) can be found in Table S1 in the Supplementary content.

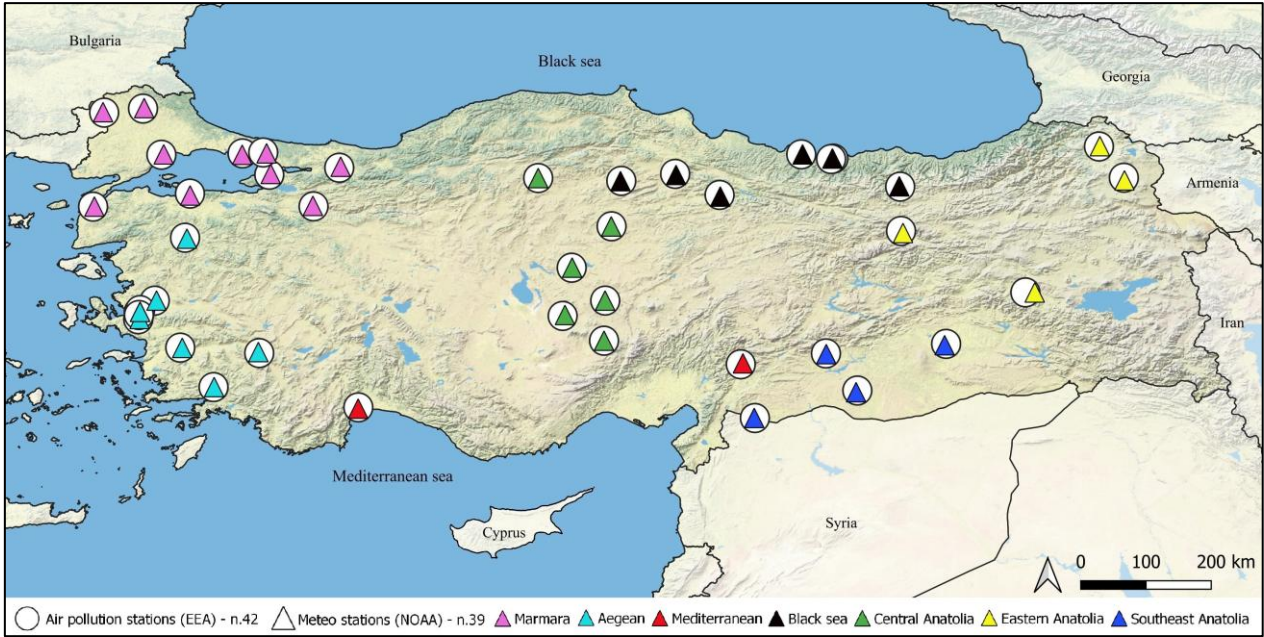


Figure 1. Elevation map of the study area with the location of the 42 air quality monitoring stations (white circles) and the 39 meteorological stations (triangles coloured according to the climatic region of belonging) across Türkiye.

Türkiye has been conventionally divided into seven climatic zones (Erinç, 1984 in Sahin and Cigizoglu, 2012): (1) Marmara, around the Sea of Marmara bordering Greece and Bulgaria; (2) Aegean, on the west coast; (3) Mediterranean, Türkiye's southern shore; (4) Black Sea, Türkiye's Black Sea coast; (5) Central Anatolia, the vast inland plateau in the centre; (6) Eastern Anatolia, at east adjacent to Iran and the Caucasus countries; and (7) Southeastern Anatolia, bordering Syria and Iraq. These seven climatic regions are shown in Fig. 2. The climate of Türkiye is heavily influenced by its physiographic features, such as mountain chains and surrounding seas, with the latter acting as natural passages for frontal cyclones moving from west to east (Türkeş, 1996). Large-scale atmospheric circulation patterns also play a crucial role in shaping Türkiye's atmospheric conditions (Deniz et al., 2011). During winter, the influence of the polar front and cold air masses from the Balkans

is associated frontal passages and lower temperatures. In contrast, the polar front shifts northward during summer, leading to weaker frontal passages and increased maritime influences. Anticyclonic pressure patterns, such as the Azores high-pressure system in summer and the Siberian anticyclone in winter, further impact Türkiye's climate dynamics.



Figure 2. Türkiye's seven climatic regions.

2.3 Study design

2.3.1 Missing data management

A conservative approach is adopted regarding missing data, where results are based solely on observed data, avoiding imputation techniques to prevent the introduction of potential biases (Alwateer, 2024; Donders et al., 2006). Instead, we focused on the careful selection of stations with high data completeness, ensuring the integrity of the analysis.

The missing data analysis reveals slightly different patterns across stations and variables. For air quality data, the percentage of missing values over the 5-year period ranged from 0.77% to 15%, depending on the station, with average missing rates of 4.45% for PM₁₀ and 3.3% for SO₂. For atmospheric variables, data completeness is generally higher than for air quality data. Precipitation and BLH

are 100% complete across all stations, while temperature, relative humidity, and wind speed have occasional missing values, with the highest percentage reaching 1.15% at some stations. A detailed overview of missing data for each station and variable can be found in Table S2 of the Supplementary content.

Temporal analysis of missing data reveals no clear seasonality or trends, indicating that data are missing completely at random (MCAR), rather than being influenced by environmental or operational factors (Little, 2012). In the few cases where data are missing, logistic regression analyses could not be performed due to the rarity of missing values, reinforcing the assumption of randomness.

2.3.2 Climate normals

To ensure that the climate data in the analysis aligns with the long-term climate, it is necessary to compare the 2015-2019 statistics with the climatological normal, i.e. the monthly averages computed for a prolonged period of at least 30 consecutive years. Such comparison helps verify that there have not been significant changes in the climate over time (WMO, 2017) and ensures that the years used in the analysis are not “exceptional” (for example, extremely cold or warm) compared to the “normal” climate.

This study uses the 30-year 1985-2014 period to calculate the temperature, sea level pressure, and relative humidity climate normals, following the World Meteorological Organization's 2017 guidelines (WMO, 2017). Despite some discrepancies between the 2015-2019 and the 1985-2014 distributions, also considering the rise in temperature over recent decades, such differences are statistically insignificant, meaning that the data of this study for the limited 5-year period is not unusual or drawn from exceptional atmospheric conditions (according to the Kolmogorov-Smirnov, Mann-Whitney U and Kruskal-Wallis statistical tests - Berger and Zhou, 2014; MacFarland and Yates, 2016; McKight and Najab, 2010; see Fig. S3).

2.3.3 Statistical measures for comparison

This study applies GAMs to better capture how atmospheric variables influence air pollution patterns at a national scale. GAMs are an extension of traditional

regression models, where smoothing splines replace linear coefficients for covariates (Hastie and Tibshirani, 1990). They provide a more flexible and effective framework than conventional linear models for analysing relationships between air pollutants and atmospheric variables, which are often nonlinear and not normally distributed (Pearce et al., 2011; Thompson et al., 2001). The GAM analyses are conducted separately for winter and summer in each of Türkiye's climatic regions, with seasonal classification based on a 24-month dataset corresponding to northern hemisphere seasons. Additional details on the GAM methodology, including equations and references, are provided in the Supplementary section (Part 1b).

The GAM approach adopted in this study offers advantages in terms of data-driven analysis, ability to capture non-linear relationships, and direct interpretation of complex atmospheric-pollution associations from observational data. This statistical methodology has been successfully applied in numerous air quality studies (Thompson et al., 2001; Pearce et al., 2011; Hou and Xu, 2022), providing a robust framework for analysing complex environmental relationships, while acknowledging that it represents these relationships statistically rather than mechanistically.

A sensitivity analysis is also conducted to evaluate variables' contribution to uncertainty of the predicted PM₁₀ and SO₂ concentrations. The adopted SIMLAB software (Joint Research Centre) employs moment-independent sensitivity indices derived from both the probability density function method (Plischke et al., 2013) and the cumulative density function method (Pianosi and Wagener, 2015). The former examines how the complete probability distribution of the model outputs changes in response to variations in input parameters, while the latter focuses on the accumulated effects of parameter variations across their entire range of values. The resulting sensitivity indices quantify the relative contribution of each atmospheric variable to the model's uncertainty, providing crucial information for understanding which parameters most strongly influence pollutant concentrations in different regions and seasons.

2.3.4 Model selection and validation

In this study, two models are tested: a linear model and a GAM. Both models use PM₁₀ or SO₂ concentrations as the response variable (Y) and four atmospheric

variables (temperature, relative humidity, wind speed, and precipitation) as predictors (X).

The comparative evaluation of the models is conducted through four quantitative performance metrics: (i) explained deviance measures the proportion of variability in the data captured by the model (Hastie and Tibshirani, 1990); (ii) the Akaike Information Criterion (AIC) assesses the balance between goodness of fit and model complexity, with lower values indicating better models (Akaike, 1974); (iii) Root Mean Square Error (RMSE) and (iv) Mean Absolute Error (MAE) quantify the average magnitude of prediction errors, where smaller values represent better predictive performance (Chai & Draxler, 2014).

3. Results and Discussion

3.1 Air quality seasonal trends

To analyse the seasonal differences in air pollutant concentrations, the seasonal cycles of both PM₁₀ and SO₂ are plotted in Fig. 3. For both pollutants, higher concentrations are recorded during colder months (from November to February) compared to warmer months (from May to August). This seasonal pattern aligns with those observed for PM₁₀ in 81 Turkish cities (Kabatas et al., 2014), SO₂ in 50 Turkish sites (Bozkurt et al., 2018), and both pollutants in 75 Turkish city centres (Güneş, 2005). High levels of PM₁₀ during winter are expected due to significant local and regional pollution sources (Kabatas et al., 2014). The atmospheric conditions in winter, such as lower BLH, do not favor the dispersion of pollutants, leading to elevated PM₁₀ levels. In contrast, PM₁₀ concentrations are generally lower during warm seasons, reflecting the reduced pollution sources and more favorable atmospheric conditions for dispersion. Additionally, during the transition seasons, particularly spring and autumn, Saharan dust outbreaks can contribute to spikes in PM₁₀ levels (Kabatas et al., 2018). These dust events, originating from the Sahara desert, may impact air quality in Türkiye, explaining the occasional high PM₁₀ measurements even during typically lower-pollution seasons. Similarly, SO₂ levels follow a seasonal trend, with higher concentrations observed in winter compared to other seasons (Bozkurt et al., 2018). This increase primarily corresponds to the widespread use of coal and other fossil fuels for heating, greater traffic intensity, and atmospheric conditions like reduced mixing height, as described above.

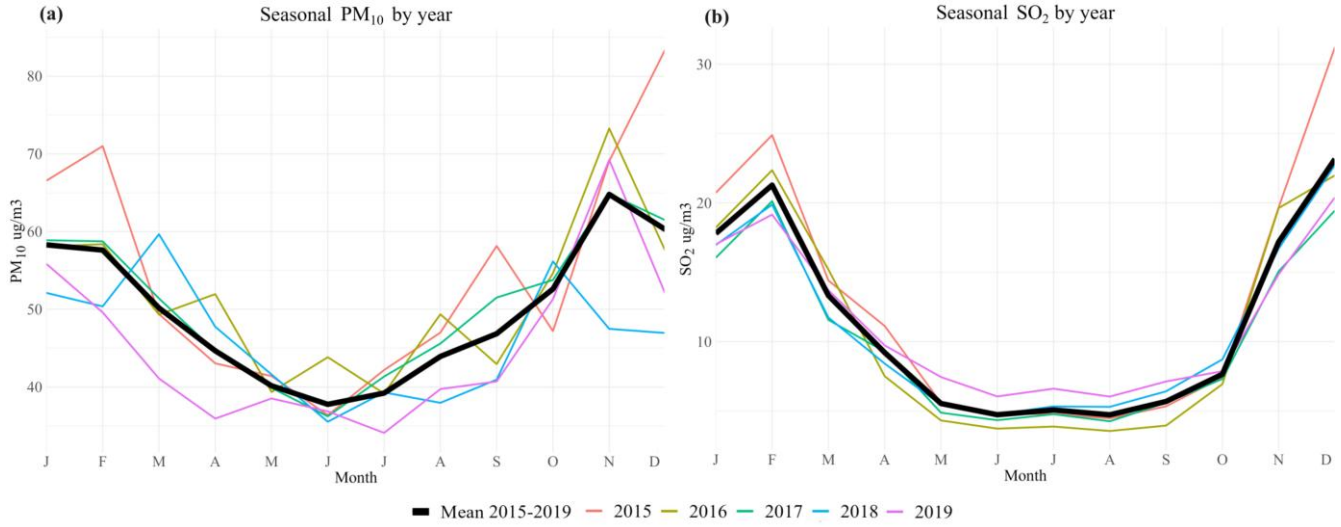


Figure 3. Mean (i.e. averaged over all 42 monitoring stations) seasonal cycle of PM₁₀ (a) and SO₂ (b) concentrations for 2015-2019 (black line) and each year of the 2015-2019 period (coloured lines).

Figure 4 illustrates the spatial variability of mean PM₁₀ (a–b) and SO₂ (c–d) concentrations across Türkiye during winter and summer, aggregated over the period 2015–2019.

For PM₁₀, concentrations during winter reach up to 100 $\mu\text{g}/\text{m}^3$ (Fig. 4a), whereas in summer they generally remain below 25 $\mu\text{g}/\text{m}^3$, with mean values not exceeding 75 $\mu\text{g}/\text{m}^3$ (Fig. 4b). Higher PM₁₀ seasonal levels are observed in the Marmara, Aegean, and Eastern Anatolia regions compared to other regions, while the Black Sea region records lower concentrations. This latter pattern likely reflects the area's consistent year-round precipitation, which contributes to improved air quality (Sensoy and Demircan, 2016; see Fig. 2 for climatic region divisions).

SO₂ concentrations exhibit a marked seasonal contrast (Fig. 4c–d). In winter, elevated levels are observed across all regions, with averages exceeding 50 $\mu\text{g}/\text{m}^3$ in the Marmara, Aegean, and Central Anatolia regions (Fig. 4c). During summer, mean SO₂ concentrations drop to 10 $\mu\text{g}/\text{m}^3$ (or lower) at most stations (Fig. 4d). Notable exceptions include Muğla, in the Aegean region—likely due to emissions from three coal-fired power plants located in the area—and Ardahan, in Eastern Anatolia, where low temperatures and socio-economic variables contribute to reliance on inexpensive, low-calorie coal with high sulfur content (Demir et al., 2014).

Overall, the Marmara and Aegean regions are identified as highly polluted for both PM₁₀ and SO₂. Compared to other regions, Eastern Anatolia experiences relatively higher PM₁₀ concentrations, while Central Anatolia shows higher SO₂ levels.

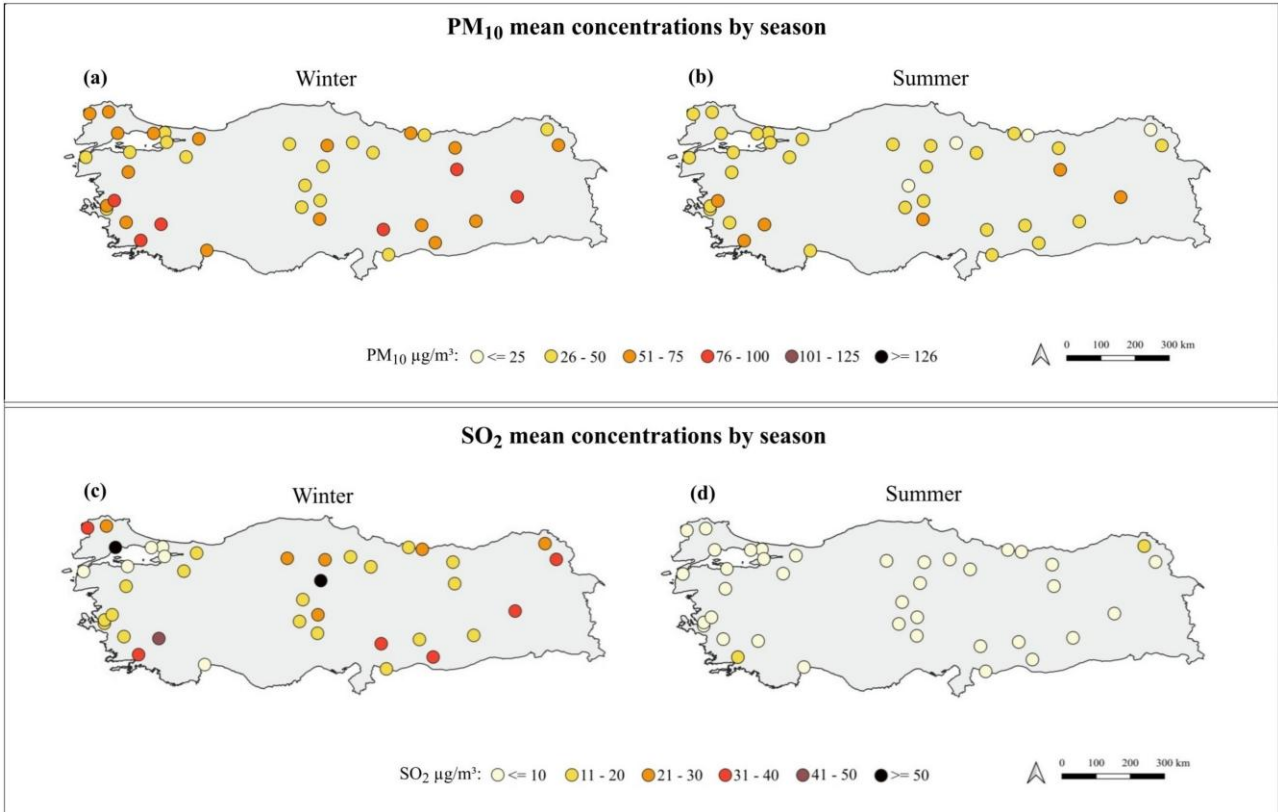


Figure 4. Spatial distribution of the seasonal mean concentrations of observed PM₁₀ for winter (a) and summer (b), and SO₂ for winter (c) and summer (d), across 42 monitoring stations during the period 2015–2019.

3.2 Atmospheric variables trends

The mean seasonal cycles of temperature, relative humidity, precipitation, and wind speed from the monitoring stations are presented in Fig. 5. As expected, considerable climatic differences emerge among the seven regions of the country. Eastern Anatolia stands out as the coldest region year-round, with average minimum temperatures frequently falling below 0°C, with the highest average

monthly temperature of 23.5°C in August. At the other extreme, Southeast Anatolia records the highest average temperatures in Türkiye, especially during summer. In this season, mean temperatures regularly exceed those of the Mediterranean region (Türkiye's second hottest area) by several degrees Celsius. This highlights Southeast Anatolia's distinctly arid and hot summer conditions. Coastal regions such as the Mediterranean and Aegean also experience high summer temperatures, though moderated by their proximity to the sea. In terms of humidity, the Black Sea region displays a distinctly moist climate. It is the only region in Türkiye that receives consistent precipitation year-round (Sensoy and Demircan, 2016), maintaining relative humidity levels above 50% in all seasons. In contrast, Southeast Anatolia experiences the lowest relative humidity levels, particularly in summer, when values drop below 30% due to its arid conditions and high temperatures. The Marmara region maintains the highest relative humidity levels throughout the year, consistently above 60%. Wind speed patterns show distinct seasonal cycles. The strongest winds are recorded in summer, driven by significant temperature differences between land and sea (Şahin and Türkeş, 2013). Conversely, autumn sees the weakest winds as temperature gradients and pressure differences diminish following the end of summer. The highest wind speeds occur in coastal regions, particularly in the Aegean and Mediterranean areas. In the Aegean region, strong summer winds are largely due to the Etesian winds—persistent northerly flows that prevail over the Aegean Sea during summer and early autumn (Şahin and Türkeş, 2020). Precipitation patterns also vary significantly. Eastern and Central Anatolia, the second coldest region, receive low precipitation throughout the year due to the blocking effects of the South and North Anatolian mountain chains, which run parallel to the Mediterranean and Black Sea coasts, respectively (Deniz et al., 2011). Conversely, the Black Sea region again stands out as the wettest area, while the coastal regions—Marmara, Aegean and Mediterranean—experience wetter winters and hot, dry summers. These dry summer conditions are often associated with persistent anticyclonic systems over the central and eastern Mediterranean Basin (Türkeş, 1996).

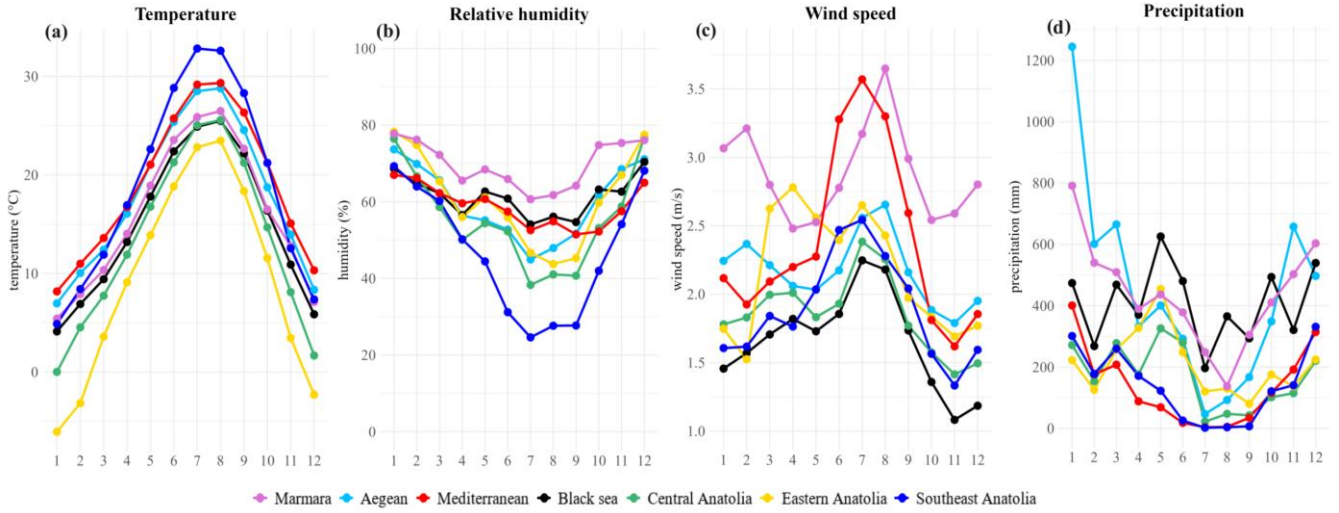


Figure 5. Mean seasonal cycle of temperature (a), relative humidity (b), wind speed (c), and precipitation (d) over each Türkiye's climatic region for 2015-2019.

3.3 Impact of atmospheric variables on air quality

Changes in pollutants levels are influenced not only by seasonal meteorological variations but also by other atmospheric variables (Kayes et al., 2019; Manju et al., 2018). This section examines how such variables influence pollutant concentrations during winter and summer, which represent the periods of highest and lowest levels, respectively, for the two studied pollutants (Figs. 3–4) using GAM, as it consistently outperforms the linear model across all metrics and climate regions (see Supplementary section – Part 1c).

For both seasons and across each of Türkiye's seven climatic regions, the dependencies of PM_{10} and SO_2 on temperature, relative humidity, wind speed, and precipitation are illustrated in Fig. 6 for PM_{10} and Fig. 7 for SO_2 . Each figure presents two panels: 1) The upper panel shows the estimated smoother for each variable derived from the GAMs (Y-axis); 2) The lower panel displays the corresponding fitted values (Y-axis). To calculate the fitted values, the estimated smoother was combined with the model's intercept (Zuur, 2012). It is important to note that these atmospheric variables are naturally interdependent; for example, temperature and relative humidity often vary together. This correlation among predictors complicates the attribution of effects to individual variables, as their influences on pollutant concentrations may not be entirely separable. However, the

analysis of these interdependencies is beyond the scope of this study. Moreover, it should be noted that the model assumes that stations within the same climatic region share similar characteristics, which may not account for local topographical or microclimatic variations.

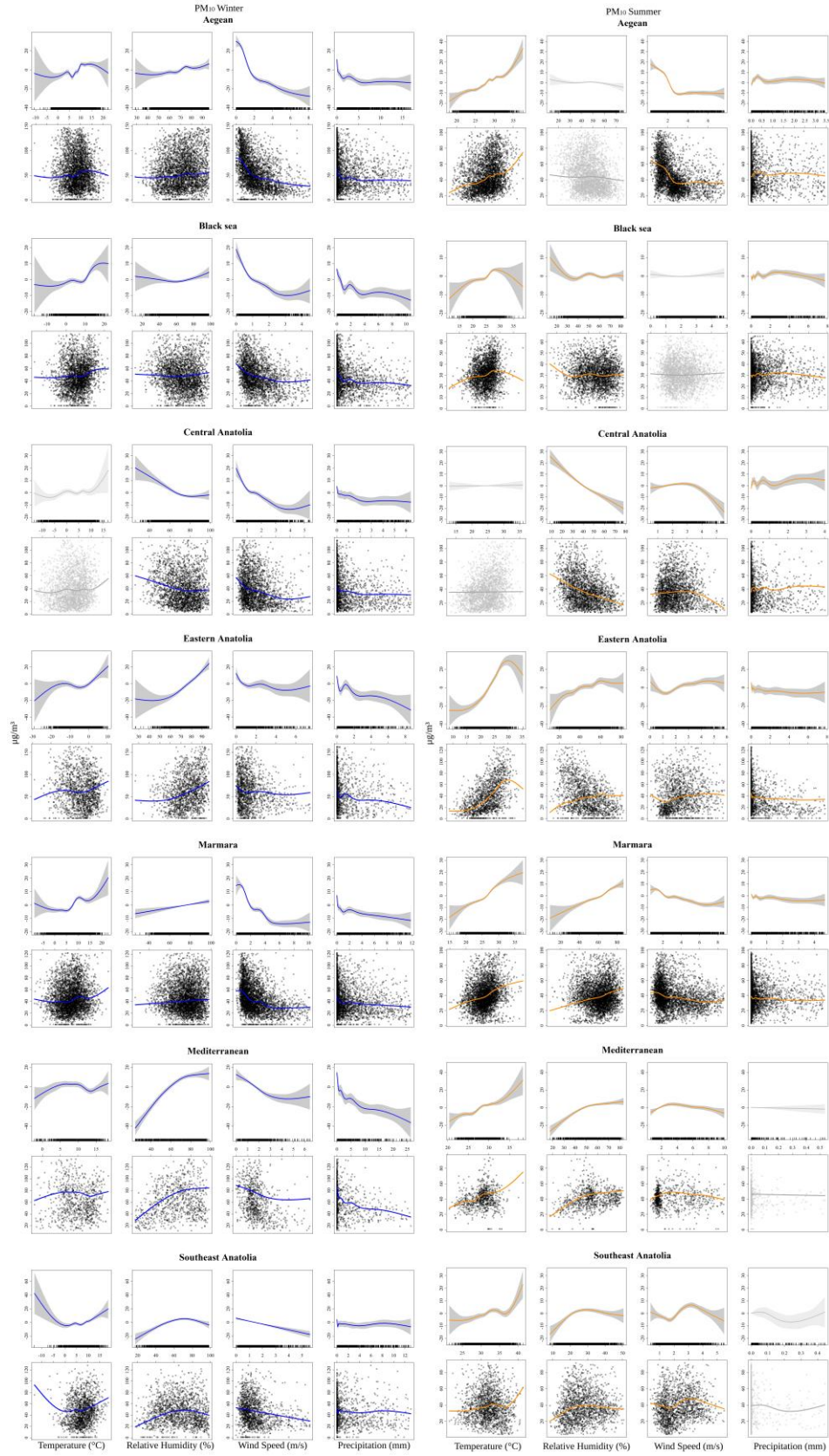


Figure 6. PM₁₀ GAM outputs for each of the 7 climatic regions in summer and winter.

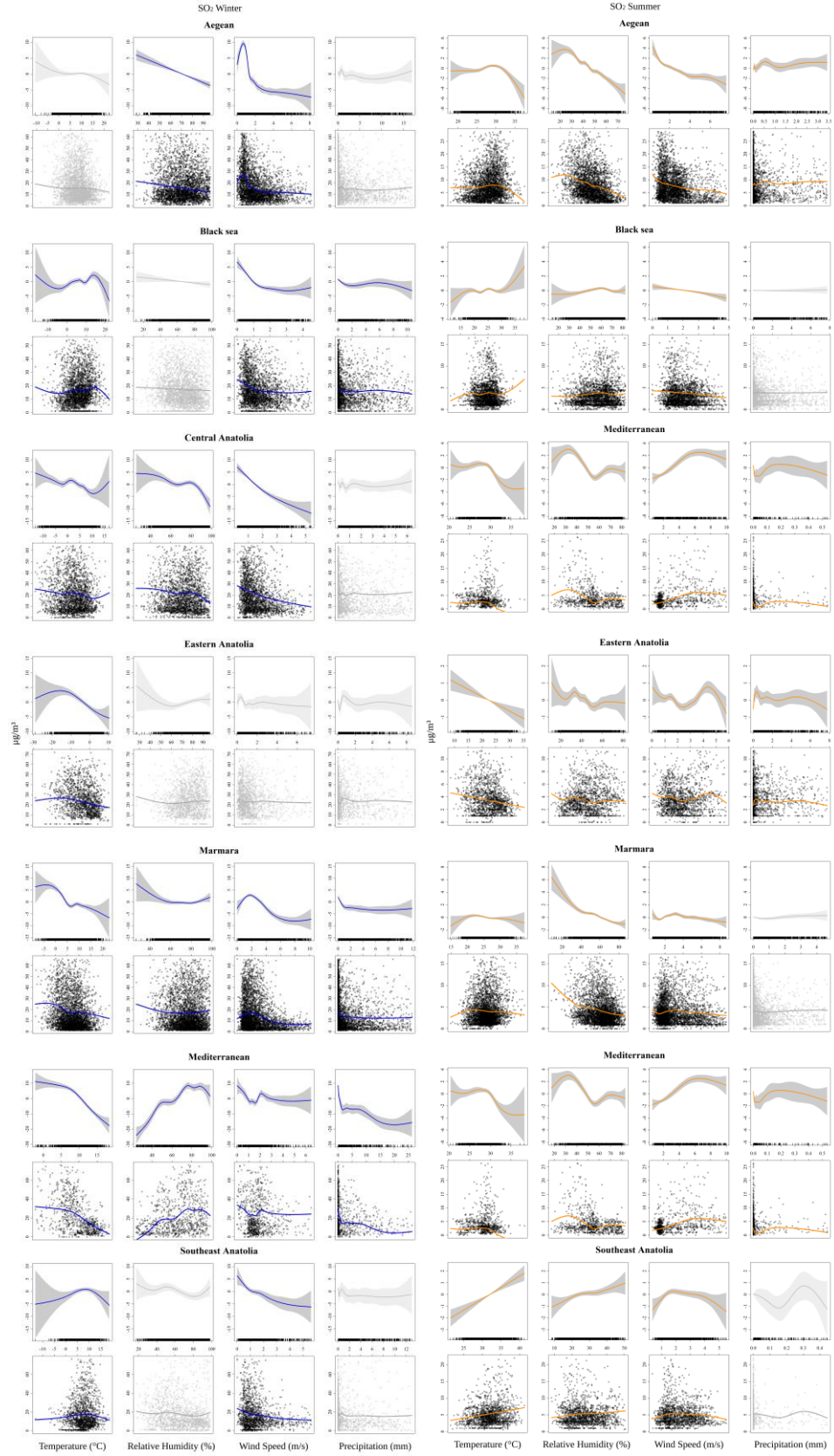


Figure 7. SO₂ GAM outputs for each of the 7 climatic regions in summer and winter.

The GAM outputs reveal a complex interplay between **temperature** and PM₁₀ concentrations across Turkish regions. In winter, PM₁₀ levels typically peak around 10°C, yet the subsequent trend differs by region: while concentrations decline with increasing temperature in the Aegean, Marmara, and Mediterranean regions, they continue to rise in the Black Sea, Eastern Anatolia, and Southeast Anatolia. While our dataset includes only surface measurements and does not contain direct observations of vertical temperature profiles, previous studies have shown that low surface temperatures and high atmospheric pressure in winter are often correlated with conditions favourable for thermal inversions (Feng et al., 2020). Under such conditions, vertical air mixing can be reduced, potentially contributing to higher pollutant concentrations near the ground. However, we emphasize that our statistical associations do not demonstrate the actual presence of inversion layers. During summer, a generally weak positive temperature dependency is observed, yet in the Black Sea, Eastern Anatolia, and Southeast Anatolia, PM₁₀ levels begin to drop when temperatures exceed 30°C. In contrast, SO₂ exhibits a predominantly negative relationship with temperature in both seasons (except in the Black Sea and Southeast Anatolia, where the patterns become more complex with temperature variations). This may be because high temperatures could enhance the instability of SO₂ (Hou and Xu, 2022). It is important to note that the temperature measurements used in this study represent surface-level observations at individual meteorological stations and not vertical temperature profiles. While our analysis identifies statistical associations between these surface measurements and pollutant concentrations, we cannot directly observe atmospheric thermal stratification or boundary layer dynamics from these data alone.

Relative **humidity** also plays a significant role in modulating pollutant levels. In winter, most regions show a positive correlation between PM₁₀ concentrations and relative humidity, meaning higher humidity coincides with increased pollutant levels—Central Anatolia being the only exception, where higher humidity is associated with lower concentrations. A similar pattern emerges in summer, with the majority of regions exhibiting positive dependencies between PM₁₀ and humidity; however, in Central Anatolia the dependence remains negative, while in the Black Sea region PM₁₀ levels initially decrease at relative humidity levels below 40% before stabilizing. Unlike PM₁₀, SO₂ generally maintains a negative dependency on relative humidity in both winter (albeit moderately) and summer (particularly pronounced in the Aegean and Marmara). Our analysis reveals a significant association between increased relative humidity and decreased SO₂ concentrations. While this pattern is consistent with the physical process of SO₂

dissolution in water droplets described by Hou and Xu (2022), our statistical approach cannot confirm this as the actual mechanism. Other factors that covary with humidity might also contribute to the observed pattern. Exceptions include the Mediterranean region in winter, where an overall positive correlation is observed, and Southeast Anatolia in summer, where a clear positive relationship emerges, as well as the Black Sea region, where a moderate positive dependency is noted.

Wind speed emerges as another key factor, inversely associated with PM_{10} concentrations, with relationships observed between wind patterns and dispersion through turbulence and horizontal transport. This relationship is particularly pronounced during winter, notably in coastal areas—such as the Aegean, Marmara, Mediterranean, and Black Sea—where higher wind speeds correlate with notable reductions in PM_{10} . Wind speed is also linked to SO_2 dispersion patterns, particularly in winter, where negative dependencies are observed across most regions. In the Aegean and Marmara, SO_2 concentrations peak at low wind speeds (1 m/s and 2 m/s, respectively) before declining as wind speed increases. Moreover, station-level polar plot analyses indicate that periods of low wind speed (<5 m/s), with high frequencies close to the origin, are associated with the highest pollution levels (see Fig. S4). Additionally, analysis of the BLH suggests a statistical relationship between BLH values and pollutant concentrations (see Fig. S5). However, it is important to note that these reanalysis-derived BLH values represent model outputs that incorporate multiple atmospheric variables and should not be interpreted as direct observations of atmospheric mixing processes. The statistical associations we observe between BLH and pollutant concentrations should be considered as indications of potential relationships rather than demonstrations of physical causal mechanisms. This pattern is especially noticeable in valleys, where downslope cold air flow appears connected to boundary layer stability. Overall, the GAM results indicate that PM_{10} shows stronger statistical relationships with wind-driven dispersion than SO_2 . This difference may be associated with the relative proximity of PM_{10} sources to monitoring stations, in contrast to SO_2 sources, such as power plants, which are typically more distant.

Precipitation further shows relationships with pollutant dynamics through wet deposition processes. In winter, a strong negative dependency is evident for PM_{10} , especially in regions like the Mediterranean where daily rainfall can reach 25 mm; here, higher rainfall corresponds to lower PM_{10} levels. Southeast Anatolia, however, displays a relatively flat relationship, potentially connected to its arid climate and the region's limited rainfall. In summer, when rainfall is generally lower across all regions compared to winter, this dependency weakens. Nonetheless, PM_{10}

concentrations still peak under very low precipitation and decline as rainfall increases, although less markedly than in winter. The relationship between precipitation and SO₂ concentrations remains weakly negative in both seasons, with regions such as Southeast Anatolia displaying little to no dependency. Overall, these patterns are consistent with a correlation between wet deposition—through mechanical washout for PM₁₀ and chemical dissolution and subsequent oxidation for SO₂—and reduced atmospheric pollutant levels.

The sensitivity analysis quantifies the importance of each atmospheric variable, reinforcing our findings and highlighting the key contributors to the model's uncertainty. For PM₁₀ in winter, BLH consistently shows the highest sensitivity indices across all stations, indicating its statistical association with pollutant dispersion and vertical mixing patterns. In most regions, precipitation is the second most influential factor, followed by wind speed. Notably, in the Aegean, Marmara, and Southeast Anatolia regions, wind speed emerges as more influential than precipitation. Greater regional variation emerges in summer: wind speed is the primary driver in coastal areas, temperature in the Black Sea and Eastern Anatolia regions, and precipitation in Central and Southeast Anatolia. For SO₂ concentrations, atmospheric variables contribute less—or not at all—to the model's uncertainty compared to PM₁₀. In winter, wind speed is the predominant factor in most regions, except in Eastern Anatolia and the Mediterranean, where temperature is more influential, and in Southeast Anatolia, where relative humidity plays a larger role. In summer, precipitation is generally the most influential variable, except in the Black Sea and Eastern Anatolia regions, where relative humidity has the greatest impact.

The statistical relationships identified in this study should be interpreted with consideration of several potential confounding factors that are not explicitly included in our model. These include:

- Seasonal variations in emissions from heating, transportation, and industrial activities that may covary with meteorological conditions
- Land use patterns and topographical features that influence both local climate and pollution dispersion
- Regional and transboundary pollution transport patterns
- Changes in energy consumption behaviour that may correlate with temperature and other weather conditions

- Policy interventions and regulatory activities during the study period

These factors may create apparent statistical associations between atmospheric variables and pollutant concentrations that do not reflect direct physical relationships. While our statistical approach helps identify patterns, it cannot fully disentangle these complex interactions.

Furthermore, even the relationships we have identified should be interpreted within the context of atmospheric system complexity. For example, the apparent relationship between wind speed and pollutant concentrations represents a statistical association that simplifies numerous underlying processes, including turbulent mixing, horizontal transport, and the interaction between local and synoptic meteorological conditions. Similarly, temperature-pollution relationships may reflect not only direct physical effects but also indirect pathways through altered emissions patterns, chemical reaction rates, and boundary layer dynamics.

3.4 Future scenarios

This section evaluates future climatic conditions under two contrasting climate scenarios to assess their potential impact on PM₁₀ and SO₂ concentrations in Türkiye for the years 2030 and 2050. The analysis focuses on the sensitivity of air quality to climate change, holding all other conditions constant. The climate scenarios are based on the IPCC Representative Concentration Pathways (RCPs): RCP 4.5 and RCP 8.5, which represent moderate and high greenhouse gas emissions pathways with different levels of mitigation efforts, respectively (CMCC, 2024).

1. RCP 4.5 (Strong Mitigation Scenario): This low emissions scenario, often referred to as "Strong Mitigation," assumes the implementation of stringent measures to control GHG emissions. It represents a stabilization pathway, where emissions peak mid-century and subsequently decline, leading to stabilized atmospheric GHG concentrations by the end of the century. Under this scenario, global temperatures are expected to rise at a slower pace, with a reduced intensity and frequency of extreme weather events.
2. RCP 8.5 (Extreme Climate Change Scenario): The high emissions scenario, commonly associated with the term "Business-as-usual" or "No Mitigation," assumes a continued growth in GHG emissions at current rates. This

scenario leads to significant global warming, characterized by more frequent and severe heatwaves, altered precipitation patterns, and changes in atmospheric pressure.

The GAM analysis of the period 2015-2019 is used to estimate the effects of changes in temperature, relative humidity, wind speed, and precipitation on pollutant concentrations in 2030 and 2050 according to the mentioned climate scenarios. The results are shown in Fig. 8, with yearly averages of PM₁₀ and SO₂ concentrations by region and season. These visual representations highlight the regional variations in pollutant levels, showing the potential shifts in air pollution under both RCP 4.5 and RCP 8.5 scenarios due to the influence of atmospheric variables.

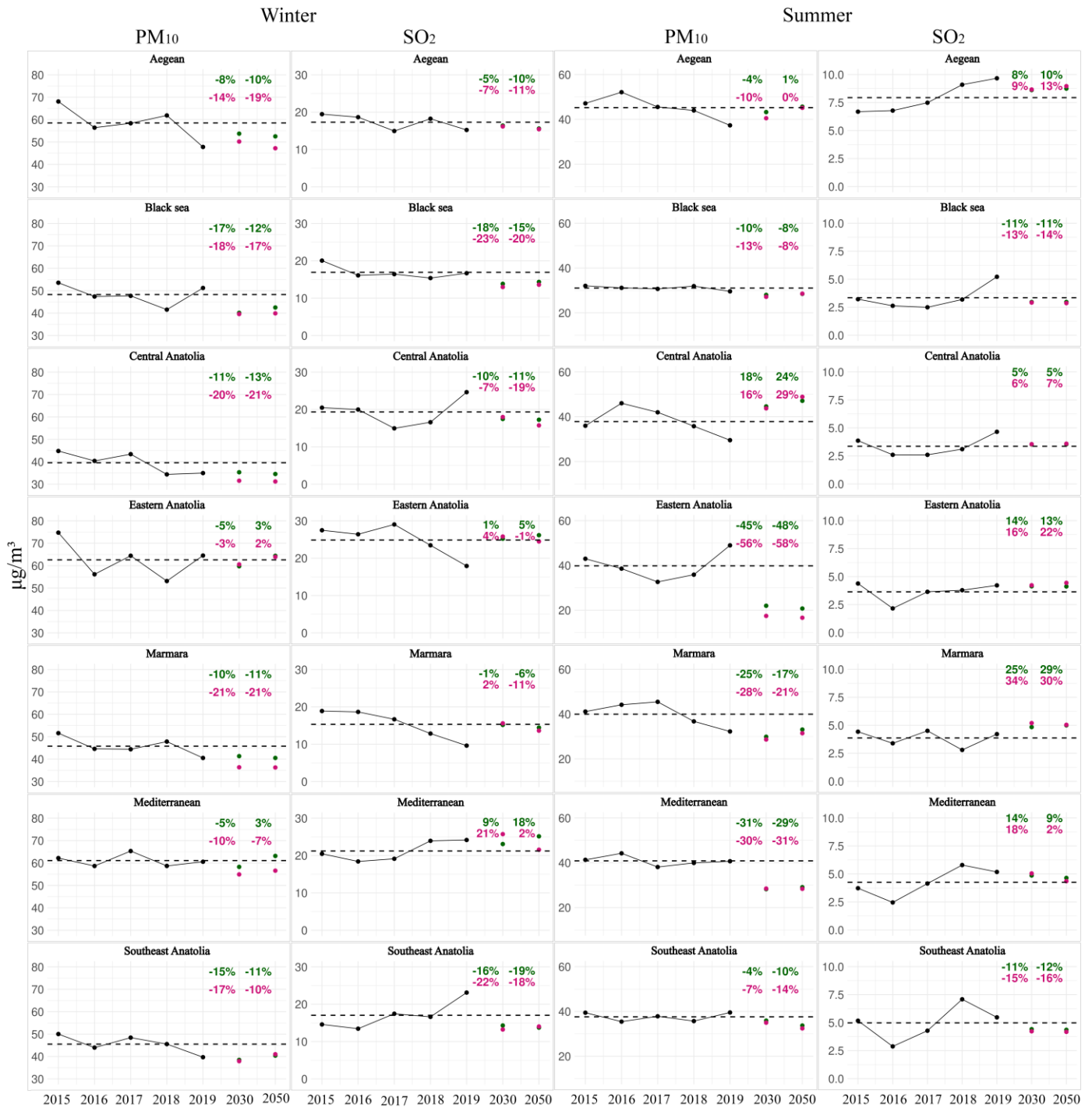


Figure 8. Projected yearly averages of PM₁₀ and SO₂ concentrations by region and season for 2030 and 2050 under RCP 4.5 (green) and RCP 8.5 (fuchsia) scenarios. Predictions are based on the generalized additive model.

Winter projections generally indicate a potential decline in PM₁₀ concentrations across all climatic regions and scenarios for both 2030 and 2050 compared to the 2015–2019 annual averages (hereafter: this is the reference period used to assess future changes). However, two exceptions emerge: in Eastern Anatolia concentrations are projected to decrease under both scenarios in 2030 but potentially increase in 2050, while in the Mediterranean region PM₁₀ levels are forecasted to decline in 2030 and may rise by 2050 under RCP 4.5, whereas the models suggest they would continue to decrease under RCP 8.5 in both years. Among all the seven climatic regions, Eastern Anatolia is projected to exhibit the smallest change in PM₁₀ concentrations relative to the reference period, while Central Anatolia is forecasted to show the most significant deviation. Specifically, in Central Anatolia under RCP 4.5, concentrations are projected to decrease by approximately 11% in 2030 and 13% in 2050, while under RCP 8.5, the models suggest reductions could reach 20% and 21%, respectively. In summer, both scenarios predict a general decrease in PM₁₀ concentrations across all regions, with the exception of Central Anatolia where an increase is projected, with concentrations potentially rising by 18% in 2030 and 24% in 2050 under RCP 4.5, and by 16% and 29% under RCP 8.5. In the same season, Eastern Anatolia is projected to see the most pronounced decline, with potential reductions of 45% in 2030 and 48% in 2050 under RCP 4.5, and potentially even sharper decreases of approximately 56% and 58% under RCP 8.5. These model outputs suggest that seasonal differences could be significant in future projections, with summer months appearing to show more pronounced variations compared to winter.

SO₂ concentrations are projected to generally increase across most regions in summer, with the exception of the Black Sea and Southeast Anatolia, where levels are forecasted to decrease. The projected reduction in Southeast Anatolia might be associated with its high summer temperatures, which could potentially relate to increased photochemical reactions that convert SO₂ into other compounds, such as sulphate aerosols, corresponding with lower concentrations in projections (Eatough et al., 1994). In the Black Sea region, persistent year-round precipitation, likely contributes to SO₂ removal through wet deposition, possibly contributing to its projected lower levels. Among all regions, Marmara is projected to have the most pronounced increase relative to the baseline, with SO₂ concentrations rising by 25% in 2030 and 29% in 2050 under RCP 4.5, and by 34% in 2030 and 30% in 2050 under RCP 8.5. Conversely, SO₂ concentrations during winter are generally projected to decrease compared to the 2015–2019 average, though some exceptions emerge. Notably, the Mediterranean region is forecasted to show an increase in SO₂

concentrations compared to the reference period: a potential rise of 9% in 2030 and 18% in 2050 under RCP 4.5, and 21% in 2030 and 2% in 2050 under RCP 8.5. This represents what appears to be the most notable difference between the two years within the same scenario across all seven regions in the projections.

These findings emphasize the critical role that future climate conditions may play in shaping air quality across Türkiye, under the assumption that emissions evolve according to the pathways defined by the selected RCP scenarios, without incorporating additional changes or external sources beyond those already considered. The results show significant variations across regions and scenarios, with notable differences between pollutants and seasons. PM₁₀ concentrations are generally projected to decrease compared to the 2015–2019 average, suggesting that, if the emission trajectories and contributing factors remain as specified in the climatic scenarios, particulate matter may become a less pressing concern in many areas.

The model's outcomes show that the more extreme climate scenario (RCP 8.5) is often associated with greater reductions in PM₁₀ concentrations compared to RCP 4.5 across all regions and seasons. This trend may be attributed to climate-driven changes such as higher boundary layer heights, increased wind speeds, and more frequent or intense precipitation events, all of which can enhance pollutant dispersion and removal. Additionally, warmer temperatures projected under future scenarios, particularly under RCP 8.5, may reduce the demand for residential heating in winter, leading to lower local emissions. However, the reductions presented here are based on the assumption that emissions follow the RCP scenario pathways without any unforeseen alterations. While climate conditions under RCP 8.5 may favour lower PM₁₀ concentrations in some cases, the broader consequences of this high-emission scenario (such as more severe climate impacts) should not be overlooked. In contrast, SO₂ concentrations are projected to rise across nearly all regions in summer and decrease in winter in most regions (though not all). Unlike PM₁₀, SO₂ is closely tied to fixed emission sources such as industrial activities and power generation, and it appears less influenced by meteorological variables that promote dispersion.

3.4.1 Uncertainties in climate projections

Air pollution projections based on climate models are characterized by multiple sources of uncertainty that require careful consideration when interpreting results.

Climate model uncertainty stems from the intrinsic variability among different global (GCM) and regional (RCM) models, each with their own parameterisations and representations of physical processes. Closely related is the downscaling uncertainty, as the reduction of scale from global to regional projections often involves simplifications and approximations that affect the accuracy of results at the local scale. In recent years, climate model experiments have increasingly aimed to support local and regional adaptation to the expected impacts of anthropogenic climate change, thereby magnifying the role of downscaling. While downscaling enables finer-scale analysis, it introduces an additional source of uncertainty. For example, a study in the southeastern United States found that downscaling accounted for approximately 20% of the total uncertainty in precipitation projections and around 30% for extreme heat days ($>35^{\circ}\text{C}$), depending on the completeness of the downscaled ensemble used (Wootten et al., 2017).

Emission scenarios constitute a major source of uncertainty, as projections can differ markedly when additional pathways beyond the two RCPs considered in this study are included. For example, Zhu et al. (2019) found that differences between RCPs accounted for up to 50% of the total uncertainty in runoff projections during certain months, while contributing less than 30% in most others. This highlights the seasonal variability of scenario-related uncertainty and its frequent interplay with model-related uncertainty. Moreover, the inherent variability of the climate system (especially at decadal scales) can mask or amplify anthropogenic signals, further complicating the detection of significant trends.

All the above mentioned factors suggest that the results of our projections should be interpreted as indications of possible future trends rather than precise forecasts, highlighting the importance of developing multi-model methods and probabilistic approaches to better quantify uncertainty in future research on air quality in a changing climate.

4. Conclusions

This study contributes to the understanding of statistical relationships between atmospheric conditions and air pollution in Türkiye, by investigating the relationship between atmospheric variables and PM_{10} and SO_2 concentrations for the 2015-2019 period. It examines how variables such as temperature, humidity, wind speed, precipitation, and BLH can influence air quality across regions and seasons, using a GAM with sensitivity analysis. Projections for 2030 and 2050

under two climate scenarios—one with strong mitigation efforts and one with extreme GHG emissions—are also presented.

The relationships identified through GAM analysis reveal significant correlational patterns, but these do not necessarily imply direct causal relationships. These statistical relationships reflect fundamental physical processes governing air pollutants, such as vertical mixing, horizontal transport, and removal mechanisms, which interact to produce the complex patterns observed in the data.

The GAM outputs reveal that in winter, PM₁₀ levels exhibit mixed behaviour, typically peaking around 10°C, with thermal inversions being associated with increased pollutant accumulation—particularly in the Black Sea, Eastern Anatolia, and Southeast Anatolia regions. In summer, PM₁₀ shows weak positive temperature dependence, while SO₂ is negatively associated with temperature in both seasons. Relative humidity correlates positively with PM₁₀ in most regions, while SO₂ generally decreases with higher humidity, especially in colder months. Higher wind speed is associated to lower PM₁₀ and SO₂ levels, especially along coastal areas, with PM₁₀ more responsive to wind-driven dispersion than SO₂. Precipitation is generally associated with reduced PM₁₀ levels, especially in winter, while its association with SO₂ remains surprisingly weak.

The projected changes in PM₁₀ and SO₂ concentrations associated with atmospheric variables under RCP 4.5 and RCP 8.5 scenarios underscore the importance of adapting air quality strategies to regional and seasonal variations. While meteorological conditions are generally linked to reductions in PM₁₀ levels across most areas and both seasons, their relationship with SO₂ suggests potential increases during summer, highlighting the need for targeted mitigation measures.

While this study provides valuable insights, some limitations should be acknowledged. A significant limitation is that the study relies on surface meteorological measurements to draw inferences about complex vertical atmospheric processes. Without direct measurements of vertical temperature profiles, our interpretations regarding thermal inversions and boundary layer dynamics remain speculative. Additionally, there is a lack of validation against process-based atmospheric models, which explicitly represent atmospheric dynamics. To address these methodological limitations, future research should: (1) incorporate radiosonde data, lidar measurements, or other vertical profiling techniques; and (2) compare statistical findings with mechanistic approaches to evaluate consistency. Additionally, future research in Türkiye should adopt quasi-

experimental designs or analyses of policy interventions to better isolate causal relationships between atmospheric variables and air pollution. The integration of longer-term studies, high-resolution satellite data, and the extension of the analysis to additional pollutants and seasonal periods would allow for a deeper understanding of pollutant variability and its determinants. Additionally, pollutant concentrations are also influenced by several factors not addressed in this study, such as variations in emission sources (patterns in traffic and industrial activity), changes in energy consumption behaviour, agricultural activities, and episodic events (i.e. wildfires, dust storms). Transboundary pollution transport also remains an important external contributor. To better understand source attribution, enhanced models that incorporate emission inventories, land-use data, and sector-specific activity patterns are essential (Belis et al., 2020; Belis et al., 2021).

The results of this study suggest that national air quality strategies may not be universally effective, emphasizing the need for region-specific mitigation efforts—particularly in areas where both PM₁₀ and SO₂ levels are projected to rise.

Meteorologically driven pollution dynamics can significantly influence economic policy decisions by enabling more cost-effective and targeted regulatory strategies. For instance, the OECD employs thermal inversions as an instrumental variable in a two-stage estimation approach, first using weather patterns to predict pollution, then linking it to economic outcomes (Dechezleprêtre et al., 2019)—showing how climate signals can be translated into actionable policy levers. In Türkiye, where evidence-based policymaking is urgent given current climate and air-quality governance gaps (European Commission, 2024), including persistent coal-based emissions, limited alignment with EU standards, and the absence of a long-term emission-reduction strategy, this study’s findings are especially relevant. The results provide a practical basis to implement or update policies already in force, including meteorology-based episode plans and tighter fuel-quality and stack-emission enforcement under Environment Law No. 2872 (2022). They also supply an evidence base for voluntary alignment with the UNECE Gothenburg Protocol framework—Türkiye has not signed or ratified—by prioritizing emission-ceiling-style measures, thereby advancing convergence with the EU air-quality acquis and helping policymakers target resources for measurable health gains at lower cost. In this context, the insights offered by this study provide a practical foundation for strengthening environmental governance and guiding more targeted, forward-looking policy action for sustainable development and improved public well-being.

Supplementary material

Part 1

- (a) Processing and extraction of future climate projections data
- (b) Generalised Additive Model (GAM)
- (c) GAM vs Linear models

Part 2

Lists of tables

- Table S1. Information about selected stations, both air quality monitoring stations and meteorologic stations, with the distance (km) between them.
- Table S2. Percentage of missing values for each station across the 2015-2019 period for each variable.

Lists of figures

- Figure S3. Distribution of temperature (a), sea level pressure (b), and relative humidity (c) for 1985-2014 vs. 2015-2019.
- Figure S4. Polar plots for the winter months of PM₁₀ (top panel) and SO₂ (bottom panel) for three example stations.
- Figure S5. BLH against hourly PM₁₀ concentrations in (a) and SO₂ concentrations in (b) in two examples stations.

Part 1

(a) Processing and extraction of future climate projections data

The following describes the methodology applied to process the NetCDF files containing future climate projections. The goal was to generate consistent and high-resolution datasets suitable for station-based analysis.

The NetCDF files containing future climate projections were acquired from the Copernicus Climate Data Store (Copernicus, 2024). To enhance the spatial accuracy of the extracted values relative to the station locations, datasets with the highest available spatial resolution were selected. However, in cases where datasets with matching high resolution were unavailable, lower-resolution files were remapped to the target resolution of $0.25^\circ \times 0.25^\circ$ (latitude/longitude). This remapping process was performed using Climate Data Operators (CDO), employing a conservative remapping technique to preserve data integrity.

Following the harmonization of spatial resolution across all datasets, additional preprocessing steps were undertaken. Climate variables were converted to the appropriate units (e.g. temperatures were converted from Kelvin to Celsius), and temporal aggregation was applied where necessary. Specifically, temperature and wind speed data, originally provided in three-hour intervals, were processed to generate daily averages. Subsequently, the daily layers corresponding to the target years of 2030 and 2050 were extracted.

For the station-specific data extraction, the geographic coordinates (latitude and longitude) of each monitoring station were used to identify the closest grid point within the remapped datasets. The grid cell with the minimum distance to each station was selected, and the relevant climate data were extracted accordingly.

All data processing and extraction procedures were implemented using the R programming language. The final output was a structured dataset in tabular form, comprising columns for each climate variable (temperature, relative humidity, precipitation and wind speed), the two years of analysis (2030 and 2050), and the two RCPs scenarios (RCP 4.5 and RCP 8.5). In total, the resulting dataset included 16 columns of climate information for 39 monitoring stations.

(b) Generalised Additive Model (GAM)

Generalized Additive Models, first proposed by Hastie and Tibshirani (1986), represent an evolution of Generalized Linear Models (GLMs). While GLMs extend multiple linear regression by allowing the response variable Y (pollutants concentrations) to follow exponential family distributions with various link functions, GAMs take this flexibility further by replacing linear predictors with smooth functions of explanatory variables (atmospheric variables). The GAMs are estimated using the ‘mgcv’ package in R (Wood, 2006). Cubic regression splines are employed as smooth functions, and the smoothing parameter (λ) is optimized via Generalized Cross Validation (GCV). Knots are placed at selected quantiles of the distribution of each atmospheric variable.

For a response variable Y , the GAM can be mathematically expressed as:

$$g(E(Y|\mathbf{X})) = a + \sum_{j=1}^p f_j(X_j) \quad (1)$$

Where:

- $g(\cdot)$ represents a monotonic link function
- a is the intercept term
- f_j denotes the smooth function of the j -th explanatory variable X_j
- $\mathbf{X}$ is a matrix whose columns correspond to a set of p explanatory variables

The key advantage of GAMs over GLMs is their ability to model non-linear relationships between the response variable and each of the explanatory variables.

Each smooth function f_j can be constructed as a linear combination of k basis functions $b_{ji}(x)$:

$$f_j(x) = \sum_{i=1}^k \beta_{ji} b_{ji}(x), \quad (2)$$

where β_{ji} are smoothing coefficients. The smooth functions in GAMs are typically estimated using splines—curves formed by connecting piecewise polynomial functions at points called knots. The literature describes various spline types (cubic, P-splines, B-splines, etc.). Traditional regression splines require careful selection of knot positions and quantities. However, penalized splines offer more flexibility as their performance depends primarily on smoothing parameters

rather than specific knot configurations. Natural cubic splines interpolate each data point, but this can lead to overfitting. A solution involves optimizing the penalized log-likelihood (Wood, 2008):

$$l_p(\boldsymbol{\beta}) = l(\boldsymbol{\beta}) - \frac{1}{2} \sum_{j=1}^p \lambda_j \boldsymbol{\beta}' \mathbf{S}_j \boldsymbol{\beta} \quad (3)$$

Where:

- $l(\boldsymbol{\beta})$ is the log-likelihood function
- $\boldsymbol{\beta}$ represents the coefficients vector with $\boldsymbol{\beta}'$ as its transpose
- λ_j is the smoothing parameter of the j -th smooth function f_j
- $\mathbf{S}_j$ is a matrix of known coefficients

The smoothing parameter λ_j ranges from 0 (unpenalized case) to 1 (completely smoothed case), allowing for control over the trade-off between model fit and function smoothness. For a given set of smoothing parameters $\boldsymbol{\lambda}$, the function $l_p(\cdot)$ is maximized using the penalized iteratively reweighted least squares method (Wood, 2004). These parameters are determined iteratively based on criteria such as generalized cross-validation (GCV; Wahba, 1985), unbiased risk estimator (Craven and Wahba, 1978), or maximum likelihood.

References

1. Craven, P., Wahba, G.: Smoothing noisy data with spline functions, *Numer. Math*, 31, 377–403, <https://doi.org/10.1007/BF01404567>, 1978.
2. Hastie, T., Tibshirani, R.: Generalized Additive Models, *Stat. Sci*, 1(3), 297–318, 1986.
3. Wahba, G.: A Comparison of GCV and GML for Choosing the Smoothing Parameter in the Generalized Spline Smoothing Problem, *The Annals of Statistics*, 13, 1378–1402, <https://doi.org/10.1214/aos/1176349743>, 1985.
4. Wood, S.N.: Stable and Efficient Multiple Smoothing Parameter Estimation for Generalized Additive Models, *Journal of the American Statistical Association*, 99, 673–686, <https://doi.org/10.1198/016214504000000980>, 2004.
5. Wood, S.N.: Fast Stable Direct Fitting and Smoothness Selection for Generalized Additive Models, *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 70, 495–518, <https://doi.org/10.1111/j.1467-9868.2007.00646.x>, 2008.

(c) GAM vs Linear models

The GAM consistently outperforms the linear model across all metrics and climate regions. For explained deviance, the GAM shows substantial improvements, with increases of up to 84% for PM_{10} and 56% for SO_2 in winter compared to the linear model. Even more dramatic improvements are observed in summer, with explained deviance increasing by up to 254% for PM_{10} and 174% for SO_2 . These substantial improvements indicate that the non-linear relationships captured by the GAM are critically important for understanding pollutant behaviour. While the AIC values are consistently lower with the GAM model for both pollutants in both seasons, the reductions are modest, averaging less than 1% across all climate regions. However, more substantial differences are observed for RMSE and MAE. With the GAM, RMSE values in winter decrease by up to 9.50% and 13% for PM_{10} and SO_2 , respectively. In summer, RMSE values are approximately 8% lower with the GAM compared to the linear model for both pollutants. Similarly, MAE values from the GAM are approximately 12% lower than the linear model in winter for both pollutants, and in summer, approximately 12% lower for PM_{10} and 7% lower for SO_2 .

It is important to emphasize that the GAM approach used in this study identifies statistical relationships, not causal mechanisms. GAMs excel at capturing non-linear associations between variables but cannot establish causality. The relationships we describe between atmospheric variables and pollutant concentrations represent statistical correlations that may be indicative of underlying physical processes; however, they should not be interpreted as direct evidence of causal pathways. Multiple confounding factors, including emissions patterns, transportation activities, and industrial operations, likely influence these relationships but are not captured in our model. Furthermore, air pollution dynamics represent a complex system with numerous feedbacks and interactions across multiple spatial and temporal scales that cannot be fully captured by any single modelling approach, regardless of its statistical sophistication.

Part 2

N. station	Air quality stations (EEA)	Longitude	Latitude	Elevation (m)	Meteo stations (NOAA)	Longitude	Latitude	Elevation (m)	Distance (km)
1	ADYAMAN	38.2783	37.7606	675	ADYAMAN	38.2833	37.7500	672	1.24
2	AKSARAY	34.0133	38.3680	966	AKSARAY	34.0500	38.3833	961	2.82
3	AMASYA	35.8355	40.6675	397	AMASYA	35.8500	40.6500	412	2.29
4	ANTALYA	30.7028	36.8876	50	ANTALYA BOLGE	30.7000	36.8667	47	2.33
5	ARDAHAN	42.7011	41.1108	1807	ARDAHAN	42.7167	41.1167	1829	1.46
6	AYDIN	27.8180	37.8544	76	AYDIN	27.8500	37.8500	56	2.85
7	BALIKESIR	27.8959	39.6339	142	BALIKESIR	27.9260	39.6193	104	3.04
8	BALIKESIR BANDIRMA	27.9750	40.3479	38	BANDIRMA	27.9777	40.3180	52	3.33
9	BILECIK	29.9778	40.1411	534	BILECIK	29.9667	40.1500	539	1.38
10	CANAKKALE	26.4058	40.1369	9	CANAKKALE	26.4268	40.1377	7	1.79
11	CANKIRI	33.6169	40.5997	731	CANKIRI	33.6167	40.6000	751	0.05
12	CORUM	34.9631	40.5542	828	CORUM	34.9500	40.5500	776	1.19
13	DENIZLI BAYRAMYERI	29.0971	37.7664	408	DENIZLI	29.0833	37.7833	425	2.25
14	DIYARBAKIR	40.2250	37.9153	676	DIYARBAKIR	40.2010	37.8939	686	3.17
15	EDIRNE	26.5850	41.6592	41	EDIRNE	26.5667	41.6667	51	1.74
16	ERZINCAN	39.4950	39.7430	1201	ERZINCAN	39.5270	39.7102	1153	4.54
17	GIRESUN	38.3620	40.9072	13	GIRESUN	38.3833	40.9167	37	2.09
18	GIRESUN GEMILERCEKEGI	38.3986	40.9144	38	GIRESUN	38.3833	40.9167	37	1.3
19	GUMUSHANE	39.4809	40.4608	1199	GUMUSHANE	39.4667	40.4667	1219	1.38
20	ISTANBUL UMRANIYE	29.1622	41.0136	162	SAMANDIRA	29.2167	41.0000	122	4.81
21	ISTANBUL YENIBOSNA	28.8267	40.9989	31	ATATURK	28.8211	40.9769	50	2.48
22	IZMIR ALSANCAK	27.1444	38.4322	11	IZMIR GUZELYAL	27.1667	38.4333	29	1.95
23	IZMIR BAYRAKLI	27.1667	38.4622	5	IZMIR GUZELYAL	27.1667	38.4333	29	3.2
24	IZMIR GAZIEMIR	27.1373	38.3144	141	GAZIEMIR	27.1594	38.3191	132	2
25	IZMIR SIRINYER	27.1483	38.3825	64	IZMIR GUZELYAL	27.1667	38.4333	29	3.2
26	KAHRAMANMARAS	36.8985	37.5849	692	KAHRAMANMARAS	36.9333	37.6000	572	3.49
27	KARS	43.1045	40.6050	1762	KARS	43.1150	40.5622	1795	4.83
28	KILIS	37.1271	36.7152	646	KILIS	37.1167	36.7167	638	0.95
29	KIRKLARELI	27.2145	41.7245	208	KIRKLARELI	27.2333	41.7333	232	1.85
30	KIRSEHIR	34.1593	39.1484	989	KIRSEHIR	34.1667	39.1500	1007	0.66
31	MANISA	27.4048	38.6153	71	MANISA	27.4333	38.6167	71	2.48
32	MUGLA MUSLUHITTIN	28.3572	37.2158	647	MUGLA	28.3667	37.2167	646	0.84
33	MUS	41.5095	38.7486	1314	MUS	41.6612	38.7478	1267	1.8
34	NEVSEHIR	34.7025	38.6160	1254	NEVSEHIR	34.7000	38.6167	1260	0.24
35	NIGDE	34.6833	37.9667	1220	NIGDE	34.6833	37.9667	1210	0.27
36	ORDU STADYUM	37.8784	40.9834	9	ORDU	37.9000	40.9833	4	1.82
37	SAKARYA	30.3939	40.7668	31	ADAPAZARI	30.4167	40.7833	30	2.66
38	SANLIURFA	38.7870	37.1604	550	SANLIURFA	38.7667	37.1333	549	3.51
39	TEKIRDAG	27.5127	40.9764	26	TEKIRDAG	27.5500	40.9833	3	3.23
40	TOKAT	36.5552	40.3263	608	TOKAT	36.5667	40.3000	608	3.07
41	YALOVA	29.2600	40.6533	5	YALOVA	29.2833	40.6667	4	2.46
42	YOZGAT	34.8057	39.8189	1288	YOZGAT	34.8000	39.8167	1298	0.53

Table S1. Information about selected stations, both air quality monitoring stations and meteorologic stations, with the distance (km) between them.

Station	PM10	SO2	Temperature	Rel. humidity	Wind speed	Precipitation	BLH
ADIYAMAN	4.83%	0.77%	0.01%	0.16%	0.08%	0.00%	0.00%
AKSARAY	3.20%	3.37%	0.00%	0.01%	0.00%	0.00%	0.00%
AMASYA	5.76%	1.01%	0.00%	0.03%	0.00%	0.00%	0.00%
ANTALYA	1.63%	1.30%	0.01%	0.27%	0.00%	0.00%	0.00%
ARDAHAN	4.00%	14.79%	0.00%	0.00%	0.01%	0.00%	0.00%
AYDIN	3.85%	1.92%	0.02%	0.03%	0.00%	0.00%	0.00%
BALIKESIR	2.18%	0.90%	0.08%	0.19%	0.01%	0.00%	0.00%
BALIKESIR BANDIRMA	1.62%	1.46%	0.00%	0.05%	0.00%	0.00%	0.00%
BILECIK	1.70%	1.37%	0.17%	1.15%	0.00%	0.00%	0.00%
CANAKKALE	3.71%	5.02%	0.01%	0.13%	0.62%	0.00%	0.00%
CANKIRI	3.22%	4.38%	0.00%	0.02%	0.00%	0.00%	0.00%
CORUM	5.86%	5.18%	0.01%	0.28%	0.00%	0.00%	0.00%
DENIZLI BAYRAMYERI	4.50%	1.24%	0.00%	0.04%	0.00%	0.00%	0.00%
DIYARBAKIR	7.85%	0.98%	0.00%	0.20%	0.00%	0.00%	0.00%
EDIRNE	3.22%	4.15%	0.00%	0.05%	0.00%	0.00%	0.00%
ERZINCAN	4.27%	0.78%	0.00%	0.02%	0.00%	0.00%	0.00%
GIRESUN	5.82%	6.58%	0.00%	0.02%	0.00%	0.00%	0.00%
GIRESUN GEMILERCEKEGI	4.82%	4.10%	0.00%	0.03%	0.00%	0.00%	0.00%
GUMUSHANE	3.17%	6.51%	0.00%	0.09%	0.00%	0.00%	0.00%
ISTANBUL UMRANIYE	4.45%	2.74%	0.22%	0.22%	0.00%	0.00%	0.00%
ISTANBUL YENIBOSNA	2.20%	1.84%	0.00%	0.01%	0.02%	0.00%	0.00%
IZMIR ALSANCAK	2.48%	3.18%	0.00%	0.02%	0.00%	0.00%	0.00%
IZMIR BAYRAKLI	2.77%	1.84%	0.00%	0.01%	0.00%	0.00%	0.00%
IZMIR GAZIEMIR	4.09%	7.18%	0.00%	0.00%	0.04%	0.00%	0.00%
IZMIR SIRINYER	2.65%	2.18%	0.00%	0.02%	0.00%	0.00%	0.00%
KAHRAMANMARAS	3.88%	2.34%	0.00%	0.17%	0.00%	0.00%	0.00%
KARS	4.80%	2.97%	0.01%	0.04%	0.00%	0.00%	0.00%
KILIS	9.35%	3.27%	0.01%	0.05%	0.00%	0.00%	0.00%
KIRKLARELI	4.80%	2.05%	0.00%	0.01%	0.00%	0.00%	0.00%
KIRSEHIR	4.00%	3.74%	0.03%	0.05%	0.01%	0.00%	0.00%
MANISA	6.61%	4.53%	0.00%	0.01%	0.00%	0.00%	0.00%
MUGLA MUSLUHITTIN	6.08%	5.18%	0.00%	0.00%	0.00%	0.00%	0.00%
MUS	10.87%	3.52%	0.00%	0.00%	0.12%	0.00%	0.00%
NEVSEHIR	3.02%	1.96%	0.00%	0.04%	0.00%	0.00%	0.00%
NIGDE	7.02%	4.34%	0.01%	0.03%	0.00%	0.00%	0.00%
ORDU STADYUM	3.79%	1.03%	0.00%	0.03%	0.00%	0.00%	0.00%
SAKARYA	4.02%	1.86%	0.00%	0.01%	0.00%	0.00%	0.00%
SANLIURFA	3.69%	2.99%	0.01%	0.09%	0.01%	0.00%	0.00%
TEKIRDAG	3.80%	3.78%	0.00%	0.02%	0.00%	0.00%	0.00%
TOKAT	10.25%	6.05%	0.00%	0.12%	0.00%	0.00%	0.00%
YALOVA	1.13%	2.54%	0.00%	0.17%	0.03%	0.00%	0.00%
YOZGAT	5.90%	2.12%	0.00%	0.03%	0.00%	0.00%	0.00%

Table S2. Percentage of missing values for each station across the 2015-2019 period for each variable.

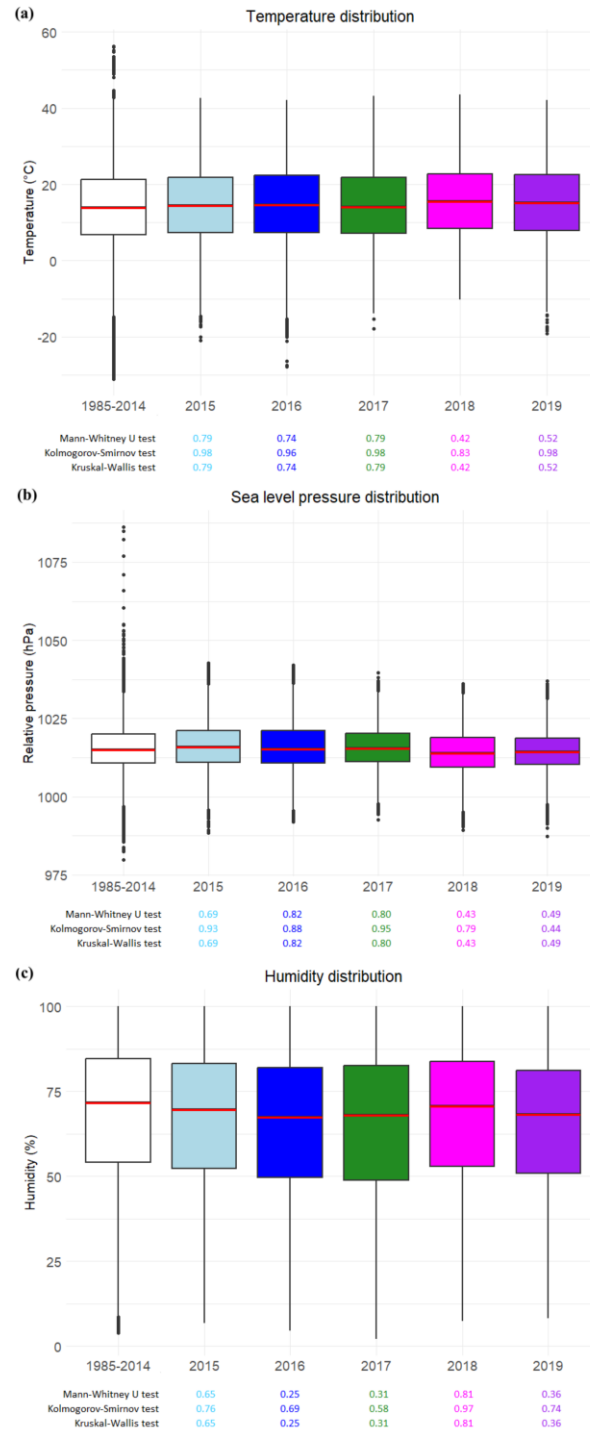


Figure S3. Distribution of temperature (a), sea level pressure (b), and relative humidity (c) for 1985-2014 vs. 2015-2019, with p-values from the Mann-Whitney U Test, Kolmogorov-Smirnov Test, and Kruskal-Wallis Test. The null hypothesis for these tests states that there are no significant differences between the distributions being compared. The high p-values confirm the null hypothesis.

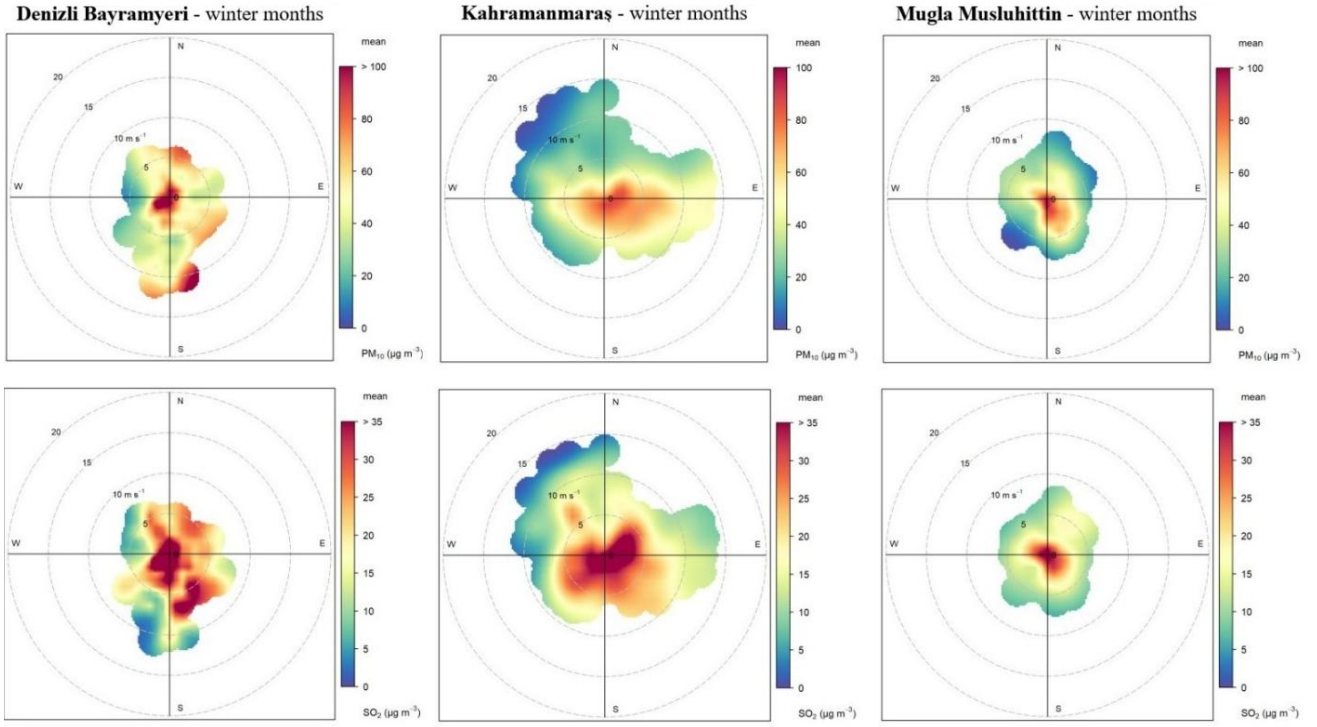


Figure S4. Polar plots for the winter months of PM₁₀ (top panel) and SO₂ (bottom panel) for three example stations. Data is aggregated for the period 2015-2019 for the winter months.

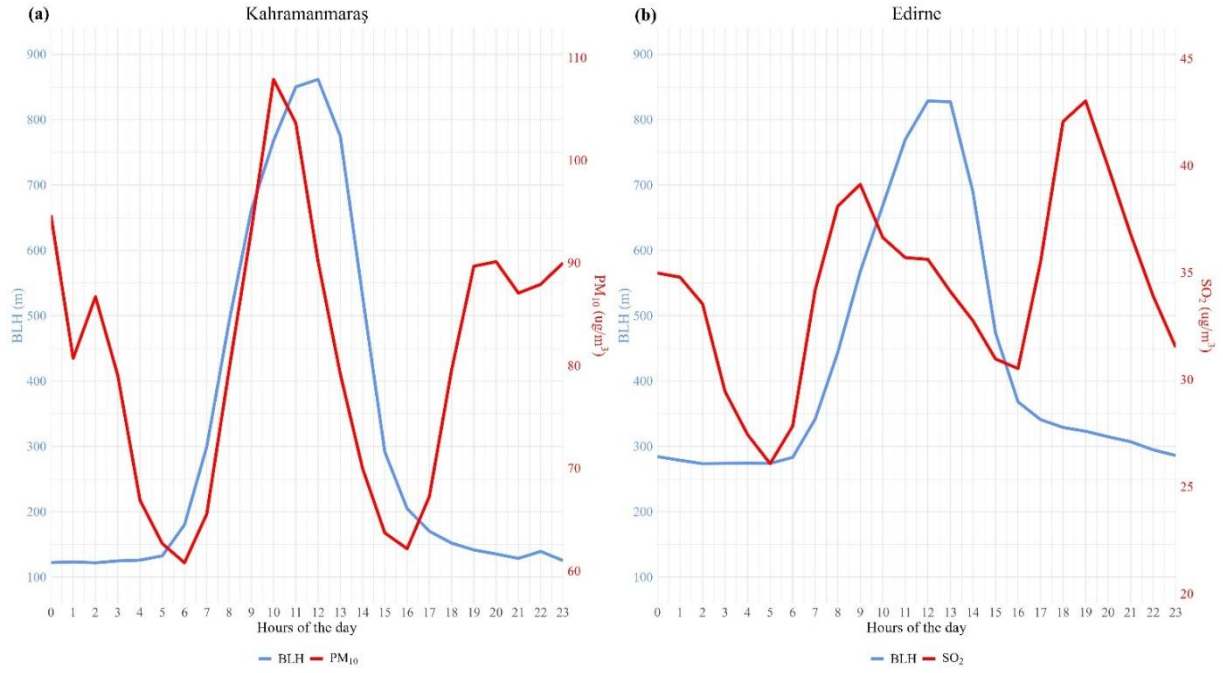


Figure S5. BLH against hourly PM₁₀ concentrations in (a) and SO₂ concentrations in (b) in two examples stations. Data is aggregated for 2015-2019 for the winter months.

Ch. 4

Econometric Model Derived from Meta-Analysis to Estimate VSL and VOLY Associated to Air Pollution at a Global Level

Sara Ciarlantini ^{a, b}, Vito Frontuto ^c, Alessandro Pezzoli ^a, Andreas Gavros ^d,
Claudio A. Belis ^b

^a DIST—Interuniversity Department of Regional and Urban Studies and Planning, Polytechnic of Turin and University of Turin, Turin, Italy

^b European Commission, Joint Research Centre (JRC), Ispra, Italy

^c EST—Economics and Statistics Department, University of Turin, Turin, Italy

^d Fincons SPA, Vimercate, Italy

Published version available here: <https://doi.org/10.1016/j.jenvman.2025.124824>.

Abstract

Air pollution is a key determinant of health, with numerous studies linking it to a range of adverse health effects in the general population, from minor subclinical impacts to premature mortality. Addressing policy questions on the health impacts of air pollution requires methods that balance the costs of risk reduction with the

expected benefits, measured in terms of prevented premature deaths. These benefits can be quantified through the Value of a Statistical Life (VSL), representing individuals' willingness to pay for reduced mortality risk, and the Value of a Life Year (VOLY), which accounts for pollution's impact on life expectancy. However, obtaining reliable VSL and VOLY values is challenging, as methodologies vary widely across—and even within—countries, and many lack robust, country-specific data. This inconsistency affects the comparability between countries in global assessments. To address this gap, a database of 494 air pollution-related VSL estimates was compiled from the literature, covering 186 countries across all continents. Using these estimates, a meta-analysis was conducted to integrate them into a specific econometric model assessing only the share of health costs attributable to air pollution worldwide. The model incorporates economic, socio-economic, demographic, and health proxies to tailor VSL estimates to each country's characteristics. This approach, new in air pollution analysis, enables a more specific application of VSL in policy contexts specific to each country. Additionally, a corresponding VOLY database was developed, derived from VSL-based estimates. This work aims to improve quantitative and comparable estimates of the economic benefits associated with air pollution abatement policies and the consequent reduction in premature deaths worldwide.

1. Introduction

Air pollution is a key determinant of health. Numerous studies have identified an association between air pollution and negative health effects in the general population (Burnett et al., 2018; Juginović et al., 2021; WHO, 2024). These negative consequences range in severity from minor subclinical effects to premature death (WHO, 2016). Exposure to air pollution is now the second-largest risk factor of deaths worldwide, accounting for 8.1 million deaths in 2021 (HEI, 2024). The major cost within the air pollution control context is the impact on human health (Alberini and Scasny, 2011; Lindhjem et al., 2011). Premature deaths due to exposure to both ambient and household air pollution cost the global economy approximately USD 5.11 trillion in welfare losses (World Bank and IHME, 2016). Although assigning a monetary value to human life may be controversial from an ethical standpoint (OECD, 2012), it provides crucial information for public interventions aimed at reducing premature deaths linked to air pollution.

The Value of a Statistical Life (VSL) and the Value of a Life Year (VOLY) are important metrics in this domain as they quantify the economic value of human life. They represent what individuals are willing to pay for a death risk reduction or an increase in their life expectancy (Viscusi and Aldy, 2003). Specifically, the VSL is an economic parameter that reflects individuals' willingness to trade wealth for a lower risk of mortality. It captures society's collective willingness to pay (WTP) for a marginal reduction in the risk of premature death (Miller, 2000). VSL is derived from aggregating individuals' WTP, typically assessed through surveys, to secure this reduced risk (OECD, 2016). The VOLY refers to the monetized value of a one-year increase in life expectancy. Unlike the VSL, which quantifies the value of reducing the risk of premature death, VOLY provides an economic assessment of life years lost due to early mortality (Lattarulo and Plechero, 2005).

VSL and VOLY values referring to different causes of death can vary significantly (Hammit, 2006). In fact, these metrics provide policymakers with a quantitative framework to assess the costs and benefits of proposed interventions across various policy fields, including healthcare, transportation, environment, and occupational safety. Air pollution-related valuations take into account a range of contextual factors, such as pollutant type, exposure duration, and demographic characteristics of affected populations, providing a more suitable estimate. It is important, therefore, to focus on a context-specific VSL and VOLY quantification: in this study, VSL represents the value of preventing a premature death caused by exposure to air pollution, while VOLY refers to the change in life expectancy associated with air pollution.

However, establishing reliable VSL and VOLY estimates is challenging due to variations in the methods used across different studies and even within countries. Furthermore, many countries have insufficient and unreliable estimates of VSL and VOLY due to limited data collection on health and air pollution, as well as a lack of studies specific to those regions. The absence of country-specific data and a common methodology makes it difficult to assess climate policy on a global scale. This study seeks to address this gap by conducting a comprehensive meta-analysis of existing literature, with the aim of developing an econometric model to estimate air pollution-related VSL and VOLY at a country level worldwide. This approach is intended for the estimation of health costs due to air pollution, even in countries where VSL and VOLY studies have not been conducted. Unlike other VSL/VOLY meta-analyses in the literature, this study exclusively focuses on the willingness to pay for reductions in all-cause mortality associated with air pollution.

The remainder of this paper is organized as follows: Section 2 details the development of the database, including the systematic literature review process, the inclusion criteria, and the variables used in the meta-analysis. Section 3 outlines the model specification and the statistical methods employed for the analysis. Section 4 presents the database used for the meta-analysis, along with the results and a discussion. Section 5 introduces a method for converting VSL into VOLY values as an alternative parameter for quantifying the health costs of air pollution. Section 6 concludes the paper.

2. VSL and VOLY database development

2.1 Literature search and inclusion criteria

The final database used for the meta-analysis includes monetary assessments of VSL/VOLY, sourced from an extensive and systematic literature review. To avoid any form of bias, the literature review was conducted simultaneously by two researchers. This review was divided into two parts. The first part focused exclusively on peer-reviewed academic papers to ensure the quality of primary valuation studies. The second part reviewed technical reports published by globally recognized authoritative agencies and organizations, aiming to achieve broader global coverage and enhance the review's comprehensiveness.

Peer-reviewed literature was searched using publicly accessible search engines, such as Web of Science (<https://www.webofscience.com>), Scopus (<https://www.scopus.com>), and PubMed (<https://pubmed.ncbi.nlm.nih.gov>). The initial phase involved searching for relevant studies published in English up to June 2023. The search strings used were:

(({VSL} OR "Value of Statistical Life") OR ({VOLY} OR "Value of Life Year") AND "air pollution") OR (({VSL} OR "Value of Statistical Life") OR ({VOLY} OR "Value of Life Year") AND ({WTP} OR "Willingness to pay"))

A flowchart diagram summarising the studies selection process is shown in Figure 1(a). After excluding duplicates, and papers not published in English, 621 peer-reviewed publications remained. The first two steps involved scanning titles and keywords (inclusion criterion 1) and the papers' abstracts (inclusion criterion 2). Afterwards, the full-text documents were downloaded for an in-depth evaluation

(inclusion criterion 3). Unlike other meta-analyses found in the literature, this study exclusively considers VSL and VOLY estimates related to air pollution: all papers containing other types of VSL and VOLY estimates were excluded. Furthermore, only studies providing a monetary estimation of VSL and VOLY were retained (inclusion criterion 4). The final criterion was to include only country-level VSL and VOLY estimates, excluding those at the city level (inclusion criterion 5). The final number of peer-reviewed papers in the database is 23.

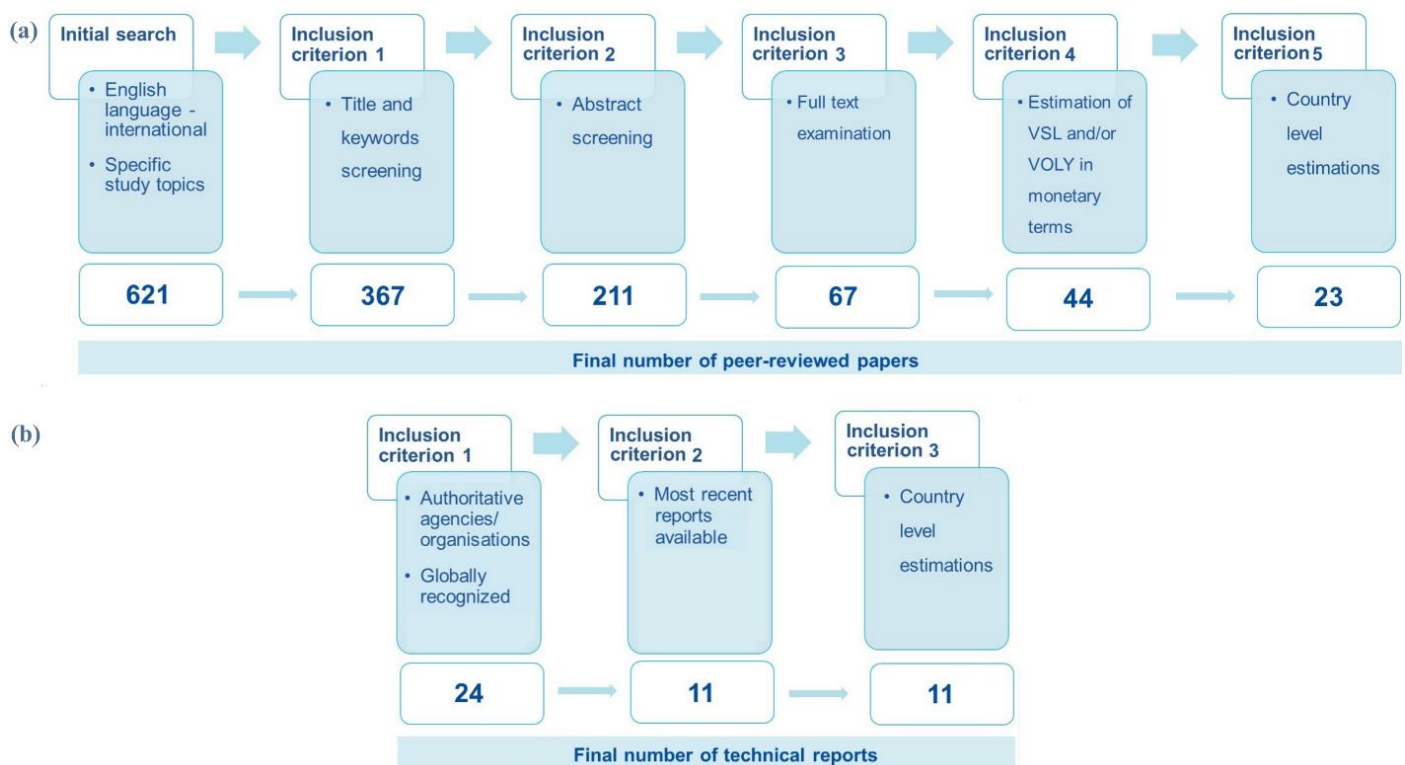


Figure 1. Systematic literature review flowchart for the selection of peer-reviewed papers (a) and technical reports (b).

The selection process regarding technical reports is summarised in Figure 1(b). Estimates of VSL and VOLY related to air pollution in technical reports were identified through Google searches and on the websites and platforms of authoritative agencies and bodies (e.g. DEFRA, European Commission, OECD, US EPA, WHO, World Bank). Additionally, cross-references from primary peer-reviewed articles were checked. Conference abstracts, newspaper articles and dissertations were excluded. Validity of the source was the initial selection criterion (inclusion criterion 1). This thorough search yielded 24 reports, which were further

filtered based on the publication date to include only the most recent reports from each agency/body (inclusion criterion 2). Reports not published in English or lacking VSL/VOLY estimates were excluded. The final number of technical reports in the database is 11. This final selection includes outcomes from CLIMAQ-H (Climate Change Mitigation, Air Quality and Health), a tool developed by WHO/Europe for quantifying the health impacts of air pollution (WHO, 2023). As for the peer-reviewed papers, only reports with country-level VSL and VOLY estimates are included in the final database.

After the comprehensive review and application of inclusion criteria, 34 publications were selected, yielding 504 value entries: 61 from peer-reviewed papers and 443 from technical reports. Among these, 10 entries exclusively estimate VOLY, all derived from two peer-reviewed papers. Other two papers provide estimates for both VSL and VOLY, namely Desaigues et al. (2007) for France and Orru et al. (2009) for Estonia. Given that VOLY estimates represent only about 2% of the total entries, they are excluded from the regression analysis, which focuses solely on VSL entries from 32 publications. Instead, VOLY values for each country are derived computationally based on VSL values (see Section 5). The practice of computing VOLY from VSL values in the air pollution context is supported by the literature (OECD, 2010; Hurley et al., 2005). Thus, the final database includes 494 value entries from 32 publications, with 51 entries from peer-reviewed papers and 443 from technical reports. Multiple VSL observations for the same country or from the same study are kept if they correspond to different years, methodologies employed or WTP elicitation formats. Refer to Appendix A for the complete list of selected studies and technical reports.

2.2 Variables used in the meta-analysis

In this meta-analysis, the dependent variable is the monetary value of the Value of a Statistical Life (VSL). When studies report both maximum and minimum VSL values, the average of these values is considered.

To compare costs and cost-effectiveness data across various countries and years, adjustments for inflation are necessary to account for changes in currency value. These adjustments are essential for systematic literature reviews, allowing for meaningful comparisons of economic evaluations conducted at different times and in different countries (Kumaranayake, 2000). To standardize the dependent

variable across studies, it was converted to 2019 International Dollars (I\$). International dollars are preferred over US dollars for cross-country comparisons, as they adjust for variations in location rather than in time (Turner et al., 2019).

Therefore, the dependent variable was first converted to the local currency of the respective country for the year of the analysis (if not already presented in local currency). Subsequently, costs were adjusted for inflation using the country's consumer price index (CPI). Then, conversion to 2019 international dollars was achieved using the purchasing power parity (PPP) exchange rates, which are relatively stable over time, offering an additional advantage of using international dollars (Turner et al., 2019). Both CPI and PPP values were taken from the International Monetary Fund World Economic Outlook Database (April 2023 Edition, accessible at: <http://www.imf.org/external/ns/cs.aspx?id=28>).

The explanatory variables used in the initial model encompass various categories: economic, socio-economic, health, and environmental variables. These variables, along with their codes (used hereafter in the text), their units of measurement and sources, are detailed in Table 1.

Table 1

Explanatory variables used for developing the econometric model and their corresponding coding, categories, units of measurement and sources.

Variable	Code	Category	Units	Source
Gross Domestic Product per capita (*)	GDP	economic	PPP (current I\$)	International Monetary Fund
Gross National Income per capita (*)	GNI	economic	PPP (current I\$)	World Bank
Consumer Price Index (*)	CPI	economic	points	International Monetary Fund
Income category (*)	income_LM-L	economic	categorical variable	World Bank
	income_HM-H			

Unemployment rate	unemp	socio-economic	% of total labor force	World Bank
GINI Index	GINI	socio-economic	0-1	World Bank
Mean years of schooling	school	socio-economic	years	UN Development Programme
Human Development Index	HDI	socio-economic	0-1	UN Development Programme
Life expectancy	LE	demographic	years	UN Development Programme
Population	pop	demographic	millions	International Monetary Fund
Population density	pop_den	demographic	persons per km ²	UN Population Division
Urban population	pop_urb	demographic	% of total population	UN Population Division
Number of doctors per capita	doctors	health	n./10,000 people	World Health Organization
Current health expenditure	exp_GDP	health	% of GDP	World Health Organization
Current health expenditure per capita(*)	exp_capita	health	PPP (US\$)	World Health Organization
PM _{2.5} concentrations	PM _{2.5}	environment	ug/m ³	See Appendix B
O ₃ concentrations	O ₃	environment	ug/m ³	See Appendix B

NO₂
concentrations

NO₂

environment

ug/m³

See Appendix B

Notes: The variables marked with (*) were collected for 2019, the baseline year. All other variables were collected for the respective year in which the VSL was estimated.

3. Statistical methods

The comprehensive review of articles and reports revisits established methodologies for quantifying air pollution-related all-cause mortality, resulting in a wide-ranging database of empirical data on VSL. Using this updated database, an econometric model was developed, considering each country's distinct characteristics.

3.1 Model specification of the meta-regression

The methodological approach adopted for this meta-analysis is an ordinary least square multiple linear regression model. All the statistical tests and analysis were conducted using R software (version 2023.12.1+402). Data exploration was conducted following the protocol described by Zuur et al. (2010) prior to performing the multiple linear regression analysis. Missing values, which constitute less than 5% of the total observations, were excluded from the final database. The presence of outliers was investigated using the Interquartile Range (IQR) method, where all points falling outside the interval $[Q1 - 1.5 \text{ IQR}; Q3 + 1.5 \text{ IQR}]$ were classified as potential outliers and, as such, excluded (Hubert and Vandervieren, 2008; Schwertman et al., 2004).

The initial model is structured as follows:

$$VSL_{ij} = \beta_0 + \beta^E X_{ij}^E + \beta^{SE} X_{ij}^{SE} + \beta^D X_{ij}^D + \beta^H X_{ij}^H + \beta^{ENV} X_{ij}^{ENV} + \varepsilon_{ij} \quad (1)$$

Where the dependent variable VSL_{ij} represents the mean Value of Statistical Life expressed in 2019 PPP International Dollars (I\$). The subscript i takes values from 1 to the number of studies (32), while the subscript j denotes the observation level, ranging from 1 to 494 as the total number of observations is $N = 494$.

The variables used in the model are grouped into matrices based on economic, socio-economic, demographic, health, and environmental characteristics (refer to Table 1). The vector $\mathbf{X}^E$ includes economic characteristics, namely GDP, GNI and CPI. Additionally, a categorical variable representing income categories is included to capture differences in income elasticities among countries. This variable is included to examine how the WTP for reducing the risk of premature mortality varies with different income levels across countries. These categories are grouped into two based on the World Bank's GNI per capita classification: income_LM-L, which combines lower-middle-income and low-income countries, and income_UM-H, which includes upper-middle-income and high-income countries. Socio-economic variables, such as unemployment rate, GINI index, mean years of schooling, life expectancy and HDI index, are contained in vector $\mathbf{X}^{SE}$. The vector $\mathbf{X}^D$ refers to demographic characteristics, such as population, population density, and urban population. The vector $\mathbf{X}^H$ contains health variables, such as the number of doctors per capita and current health expenditure (both as a percentage of GDP and per capita). Finally, $\mathbf{X}^{ENV}$ includes environmental variables, namely the concentrations of PM_{2.5}, O₃, and NO₂. The error term, represented by ϵ_j , is the residual for the j -th observation.

3.2 Multiple linear regression assumptions

The linear relationship between each predictor variable and the response variable was evaluated using the Pearson correlation coefficients and illustrated with scatterplots. For predictor variables that do not exhibit a linear relationship with the response variable, nonlinear transformations—such as logarithmic, square root, and cubic root transformations—were applied. Unemployment rate, population density, PM_{2.5}, O₃, and CPI were excluded from the analysis because after transformation no linear relationship with the response variable was observed (CPI example is illustrated in Fig. S1).

To verify homoskedasticity, residuals were plotted against fitted values to ensure constant variance, with residuals showing consistent dispersion around zero (Zuur, 2012). This assumption holds for the model employed in our analysis, as illustrated in Fig. S2.

Multicollinearity was assessed by calculating the variance inflation factor (VIF) for each predictor variable to ensure that predictor variables were not highly

correlated. A $VIF > 10$ was considered indicative of multicollinearity (O'Brien, 2007). Unsurprisingly, GDP, GNI, school, LE and HDI were correlated, since HDI is composed of life expectancy, education (mean years of schooling) and GNI indices (UNDP, 2022). As a result, these three variables were excluded from the analysis. There was a positive correlation between HDI and GDP (Ulas and Keskin, 2017), with a mutually influential relationship between them (Elistia, 2018). Table S1 presents the VIF values for each explanatory variable initially selected. Further VIF analysis confirmed this interdependence, leading to the exclusion of one of these variables from the model. HDI was excluded and GDP was retained for two reasons: studies on VSL values typically account for GDP, and the model showed a higher adjusted R-squared with this variable.

The Durbin-Watson test was used to check for autocorrelation in the residuals (and thus the variables), and the results indicated a violation of the independence assumption. The normality assumption was also violated (see Fig. S3). The Kolmogorov-Smirnov test confirmed this with a very low p-value, rejecting the null hypothesis of normality.

To overcome the non-compliance of the multiple linear regressions assumptions and the outliers leverage effect, a robust regression was employed (R package Robustbase). This regression technique, designed to withstand heavy-tailed errors and outliers, assigns lower weights to less reliable data, thereby minimizing the influence of outliers (Bellavance et al., 2009; Lambert-Lacroix and Zwald, 2011). About 5% of the observations were identified as outliers, with weights having absolute values less than or equal to 4.6×10^{-7} . This indicates that these observations had negligible influence on the regression model due to their very low weights.

The meta-analysis was conducted using a robust meta-regression technique with a backward selection process. The resulting model is:

$$VSL_{ij} = \beta_0 + \beta_1 GDP_{ij} + \beta_2 GINI_{ij} + \beta_3 pop_{ij} + \beta_4 doctors_{ij} + \varepsilon_{ij} \quad (2)$$

4. Results and discussion

The final database includes observations from publications estimating VSL values from 1999 to 2020. These years were selected as reference for currency conversion and inflation adjustments. It is important to note that these reference years do not necessarily align with the coverage period of the studies, which is the actual timeframe during which the research was conducted. For survey-based studies, the coverage period refers to the years in which interviews were conducted, while for other types of studies, it pertains to the period during which pollutant concentrations were measured.

Table 2 shows the number of countries covered in each continent and the total number of VSL estimates associated to them. An extensive list of all covered countries is provided in Appendix C. After applying the robust linear regression, the VSL observation for Qatar was excluded because considered an outlier, resulting in a database that covers 185 countries, represented in Figure 2.

Table 2

Number of countries included in the database and total number of VSL estimates, by continent.

Continent	Countries	VSL Estimates
Africa	52	199
Asia	44	105
Europa	42	131
Oceania	14	16
North America	23	30
South America	11	13
Total	186	494

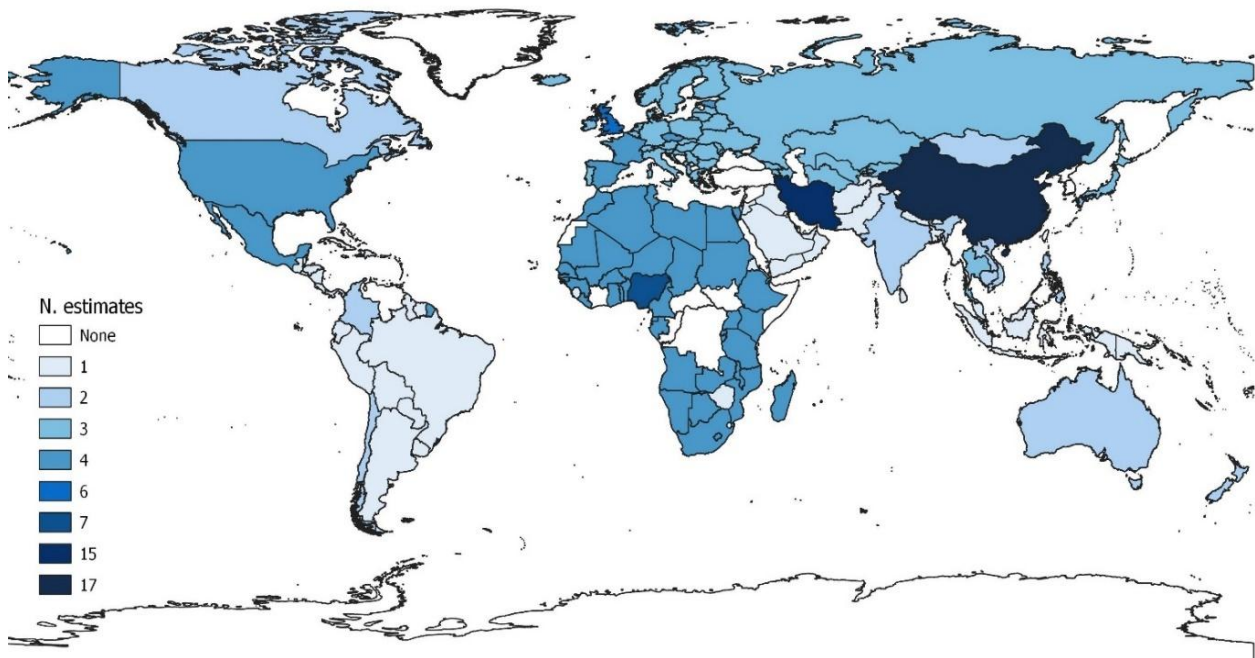


Figure 2. Countries included in the database. Different colours correspond to the number of VSL estimates collected for each country.

Table 3 presents the mean VSL values in 2019 PPP I\$ by continent. Africa presents the lowest mean VSL value (737,670 I\$), whereas Europe holds the highest (3,489,625 I\$). The variation in VSL values across continents may reflect differences in economic conditions, public health investments and cost of living.

Following the removal of outliers through robust regression techniques, the VSL in the database ranges between a minimum of 17,715 PPP I\$ (2019) for Nigeria and a maximum of 10,273,480 PPP I\$ (2019) for Luxembourg. The median is 1,239,917 PPP I\$, with a mean of 1,797,465 PPP I\$ (standard deviation of 1,697,635), suggesting a right-skewed distribution.

Table 3
Mean VSL (in 2019 PPP I\$) values by continent.

Continent	Mean VSL (I\$)
Africa	737,670
Asia	1,552,518
Europa	3,489,625
Oceania	2,168,234
North America	2,362,474
South America	1,775,335
Total	186

The final model is outlined in Eq.(3):

$$VSL_{ij} = \beta_0 + \beta_1 GDP_{ij} + \beta_2 GINI_{ij} + \beta_3 \log(pop_{ij}) + \beta_4 doctors_{ij} + \beta_5 GDP_{ij} income_{ij} + \varepsilon_{ij} \quad (3)$$

The model includes GDP, as an indicator of economic growth and the GINI index, as a measure of economic inequality. Additionally, the model incorporates the total population of the country and the number of doctors per capita (every 10,000 people). Starting from the model in Eq.(2), interactions across variables were introduced. The interaction between GDP and GINI allows to investigate how the effect of GDP on VSL varies depending on different levels of inequality within a country. Furthermore, the interaction between GDP and income category captures the different behaviors of countries based on their income level regarding their WTP for reducing the risk of premature death. This concept is equivalent to income elasticity (Narain and Sall, 2016).

As a robustness check, the potential impact of a year effect on the outcome was examined. The results confirmed the presence of a negligible year effect that was not included in the final model. The final model resulting from the meta-analysis is presented in Table 4.

Table 4

Final model. It is the result of a backward selection through a robust regression linear model.

***, **, *, stands for statistical significance at the 0%, 0.1% and 1% level, respectively.

Final model			
	Coeff.	Std. err	
(Intercept)	361,098.65	231,845.70	
GDP	101.23	7.08	***
GINI	702,603.13	292,758.39	*
pop	-37,632.67	10,871.18	***
doctors	8,145.65	1,882.33	***
GDP : income (UM-H)	-18.30	6.53	**
Multiple R ²	0.9528		
Adjusted R ²	0.9523		
Robust res. Std. err	324.300		

Notes: The coefficients are rounded to the second decimal figure; “pop” refers to the natural logarithm of the “population” variable.

The outcome of the meta-analysis reveals a positive correlation between the dependent variable, VSL, and GDP. This indicates that individuals in countries with higher economic growth assign a greater value to preventing premature mortality due to air pollution, reflecting a higher willingness to pay for safety improvements. Miller's research highlights the use of per capita GDP as a measure of income to explain variations in VSL (Miller, 2000, in Mrozek & Taylor, 2002). Consequently, VSL tends to increase with higher income levels (Hammitt, 2000; Viscusi & Aldy, 2003). This positive relationship may be attributable to the fact that safety is considered a normal good (Viscusi, 1978, in Viscusi & Aldy, 2003). As countries experience economic growth and per capita income rises, individuals have more resources to invest in safety measures and risk reduction. Thus, in wealthier nations with greater disposable income, the perceived value of reducing risks due to air pollution also increases.

The higher GDP coefficient (101.23) in low- and lower-middle income countries shows that VSL grows proportionally or more quickly when income increases in this category of countries compared to those with middle to high-income, reflecting that even a small GDP rise leads to relatively large increases in

WTP for risk reductions. While GDP rises, people in low-income countries place greater value on health and safety due to pressing survival concerns and lack of social safety nets (Robinson and Hammitt, 2009; Cropper and Sahin, 2009). In this context—where health risks are higher, and social protections are weaker—the income elasticity of WTP is heightened compared to wealthier countries. Conversely, in upper-middle- and high-income countries, a lower GDP coefficient (82.93) suggests that as GDP grows, VSL rises at a slower rate, indicating a diminishing marginal utility of health and safety investments (OECD, 2016; WHO Regional Office for Europe, OECD, 2015). This trend reflects literature findings that WTP for risk reduction rises more sharply with income growth in low-income countries (Hammitt and Robinson, 2011; Narain and Sall, 2016). Consequently, GDP changes have a more pronounced effect on VSL in lower-income regions.

Moreover, the results indicate a positive relationship between VSL and the GINI coefficient, a measure of income inequality where 0 represents perfect equality and 1 maximum inequality, suggesting that as income inequality increases, the VSL tends to rise. The logarithm of country population shows a negative relationship with VSL, therefore every 1% increase in population, VSL decreases by approximately 376 I \$. This slight decrease in VSL may suggest that in countries with larger populations, the average VSL tends to be lower. One potential reason for this relationship is that more populous countries often experience relatively lower GDP per capita (Lianos et al., 2023). Consequently, lower average income levels in these countries can contribute to a reduced average VSL. In contrast, the number of doctors per capita presents a positive relationship with VSL. This indicates that better health conditions contribute to a greater willingness to pay for preventing mortality. This relationship reinforces the notion that as health infrastructure improves and more resources are available, individuals are more inclined to invest in measures that reduce mortality risks.

Including results from different studies for each country in the VSL database implies that VSL variations may occur even within the same countries. This is attributed to the methodological choices each study's authors made, either in the data collection or in data elaboration. These studies may suffer from issues such as sample bias and variations in the choice of the risk variable, as discussed by Bellavance (2009). These varying choices can significantly influence the results and likely account for the wide variability in the published VSLs. Additionally, the results presented in this study are influenced by the choices made by the authors regarding the selection of explanatory variables. A sensitivity analysis was performed to assess the model's uncertainty, using SIMLAB software (Joint

Research Centre). Moment-independent sensitivity indices were applied, using both the probability density function method (Plischke et al., 2013) and the cumulative density function method (Pianosi and Wagener, 2015). Since the model variables are correlated, the analysis shows that all variables, with the exception of population, contribute to its uncertainty. GDP stands out as the first one in the variables rank, followed by income and the number of doctors. GINI also affects the uncertainty, though to a lesser extent. Although the parameters that most influence the output distribution are not always those that most impact the variance (Borgonovo, 2007), in this case, their relevance aligns. The variance-based BSPCE method (Shao et al., 2017) reveals that GDP alone accounts for about 37% of the model's uncertainty, while interactions between GDP and the other variables explain 57%.

Moreover, a crucial methodological issue in the meta-analysis literature is the non-independence of estimates across primary studies. This arises because individual studies often yield multiple values, leading to potential within-study correlation among observations (Nelson and Kennedy, 2009). Furthermore, the primary studies may also influence each other, indicating the presence of between-study autocorrelation. In fact, meta-data often include a hierarchical structure, which means that observations can be clustered or nested at some level, such as the study level (*i*) in this case. For the sake of robustness check, a mixed-model that accounts for this correlation among the same studies was used. The results of the mixed-model are outlined in Appendix D. Although some significance is lost in the population and income variables, the output confirms the results of the robust model presented in Table 4.

Studies have consistently shown a positive relationship between VSL and GDP, even in contexts unrelated to air pollution, such as cancer risk, accident risk, and wage-risk (OECD, 2010; Milligan et al., 2014; Miller, 2000). However, in the air pollution context, there is no prior evidence in the literature regarding the relationship between VSL and the other variables included in this model which are essential to better grasp the variability between countries. This work is innovative in that it explores how factors beyond GDP can explain variations in VSL, providing new insights into the determinants of VSL values.

5. Deriving VOLY from VSL

Air pollution does not directly cause death but worsens pre-existing conditions, resulting in a reduction in life expectancy and a higher risk of premature death. In cases involving small reductions in life expectancy, such as chronic exposure to air pollution, VOLY is often preferred over VSL (Martinez et al., 2018). This measure is particularly valuable for assessing public health interventions and quantifying the economic impact of mortality linked to air pollution (Bickel, 2005). The VOLY is to be applied in combination with the estimation of years of life lost (YLL). The advantage of this approach compared with VSL is that it considers the age of the subject at death giving more emphasis to younger subjects.

Given the limited number of studies directly reporting VOLY estimates in the air pollution context—in this study's final database representing only about 2% of the total entries (12 out of 504)—it is considered more appropriate to estimate VOLY from VSL values. This approach is well-supported by the literature, both within the air pollution context (Andersen, 2017; OECD, 2010; Hurley et al., 2005; Lattarulo and Plechero, 2005) and in other fields (Abelson, 2003; Ananthapavan et al., 2021). In this study, VOLY values were computed using the following formula (Ananthapavan et al., 2021):

$$VOLY = \frac{VSL}{\left(\frac{1-(1+r)^{-n}}{r}\right)} \quad (4)$$

The discount period n was determined by subtracting the median age of a country's population in the collection year from the corresponding life expectancy for that country in the same year. Country's specific median age was downloaded from the WHO. Given the diverse methodologies employed in deriving VSL across different studies, along with the necessity to account for respondents' perceptions of payment timing (Desaigues et al., 2011), the selection of an appropriate discount rate r is not straightforward. For this reason, VOLY estimates were calculated using three different discount rates: 3%, 7%, and 10%.

The result shows VOLY values consistent with the literature (Abelson P., 2008; US EPA (2003) in Hurley et al., 2005). At a 3% discount rate, on average VSL values are about 23 times higher than VOLY. This ratio is approximately 13 times higher with a 7% discount rate and about 10 times higher with a 10% discount rate. The discount rate used for the final VOLY database construction is 3% because these results are aligned with existing literature in the air pollution context. Belis et

al. (2023), using this same discount rate, report VSL values that are 23 times greater than VOLY values for both Czechia and OECD countries. Similarly, VSL values are found to be approximately 20 times greater than VOLY in France (Desaigues et al., 2007) and about 26 times greater in Estonia (Orru et al., 2009). Moreover, a city-level study conducted for Skopje reports a VSL value approximately 25 times higher than the corresponding VOLY (Martinez et al., 2018). Additionally, the European Commission's NewExt study (Friedrich et al., 2004), which analyses different risk scenarios across three countries (UK, Italy, and France), shows that VSL values are, on average, 20 times greater than VOLY.

The approach adopted in the present study led to a worldwide database with 494 country-specific VOLY values derived from VSL estimates. However, this approach is widely debated in the literature because estimating VOLY from VSL is not straightforward; the risks valued in the solicitation of VOLY and VSL differ, contributing to significant uncertainty in the VOLY estimates. Consequently, the monetary valuation carries a high degree of uncertainty (Leksell and Rabl, 2001; Hein et al., 2016). Another challenge with VOLY is the variability in estimates, depending on the methods used (Ananthapavan et al., 2021), particularly regarding the selection of discount rates and discount periods.

6. Conclusion

The methodology adopted in this study is fit for the purpose of developing a comprehensive worldwide database, including 494 country-specific VSL estimates related to air pollution from 186 countries. These estimates were used to develop an econometric model that accounts not only for economic variability across countries, represented by GDP, but also for other key country specific socio-economic, demographic and healthcare factors. Specifically, the model incorporates the GINI index and income categories, based on the World Bank GNI per capita classification, to capture income inequality. It also includes population size as a demographic factor, and the number of doctors per 10,000 people as a proxy for healthcare access. This approach enables the estimation of health costs associated with air pollution, with country detail, at a global level, even in countries without available or up-to-date VSL estimates.

The literature review conducted in this work builds up on prior reviews and meta-analyses (Jaafar et al., 2018; Hein et al., 2016; OECD, 2012). However, unlike

previous studies, this model focuses exclusively on air pollution-related VSL estimates and accounts for country-specific differences beyond GDP alone. While GDP remains a key factor, the model shows that other variables also play a role in shaping VSL. Specifically, individuals in countries with higher economic growth (GDP) place a greater value on preventing premature mortality due to air pollution, reflecting a higher willingness to pay for safety improvements. As economies grow and per capita income rises, individuals in wealthier nations are more likely to invest in risk reduction and safety measures, resulting in a higher perceived value of reducing air pollution risks. However, the income elasticity, incorporated in the model through the classification of countries into different income categories, indicates that GDP has a greater impact on VSL in lower-middle-income and low-income countries than in upper-middle-income and high-income countries. The model also highlights the role of income inequality. Although the GINI coefficient, which measures income inequality, is not statistically significant on its own, its significant interaction with GDP suggests that economic growth has a more pronounced effect on VSL in countries with higher income inequality. Furthermore, the analysis reveals that countries with larger populations tend to have a lower average VSL, likely due to a greater income inequality associated with a lower average income levels. Lastly, better access to healthcare increases the willingness to pay for mortality risk reduction, emphasizing that improved health conditions lead to a higher value placed on preventing air pollution-related deaths.

Additionally, a VOLY database was developed specifically for the context of air pollution. All estimates in this database have been derived from VSL estimates to address the limited number of direct VOLY studies. The resulting database comprising 494 VOLY values (with a discount rate of 3%), represents a valuable alternative tool for assessing health costs associated with air pollution while considering each country's median population age and life expectancy.

While the model presented in this paper does not directly calculate the health impacts of air pollution, it provides unitary costs at the country level, based on the input variables that are available at this scale. Our model was designed with an international scope, aiming to be applicable to as many countries as possible. An upcoming study will apply this model to quantify the economic costs of air pollution-related mortality, accounting for variations in pollution exposure across the countries analysed, thereby demonstrating its practical application. However, the model can also be downscaled to specific regional or local contexts, provided that data at this level of detail is available.

The VSL/VOLY databases and the econometric model developed in this study offer a valuable tool for both researchers and policymakers. Researchers gain access to two comprehensive global databases focused exclusively on air pollution studies. For policymakers, the model's outputs are essential for forecasting the financial burden of air pollution on health, facilitating more informed decisions on resource allocation to reduce premature mortality associated with air pollution.

Appendix A

Table A.1

Complete list of selected peer-reviewed papers (21) and technical reports (11).

N. study	Type	Title of publication	Year of publication	Authors	Journal/Organisation	N. VSL estimates
1	paper	The economic cost of particulate air pollution on health in Singapore	2003	Quah E. and Boon T.L.	Journal of Asian Economics	1
2	paper	Health Burden and economic impacts attributed to PM _{2.5} and O-3 in China from 2010 to 2050 under different representative concentration pathway scenarios	2021	Wang, Y. et al.	Resources, Conservation & Recycling	1
3	paper	Cost-Benefit Analysis of Reducing Premature Mortality Caused by Exposure to Ozone and PM _{2.5} in East Asia in 2020	2015	Chen, F. et al.	Water, Air, & Soil Pollution	10
4	paper	What is the health cost of haze pollution? Evidence from China	2019	Hao, Y.; Zhao, M.; Lu, Z.	The International Journal of Health Planning and Management	1
5	paper	Priming and the value of a statistical life: A cross country comparison	2023	Andersson, H. and Ouyard, B.	Journal of Behavioral and Experimental Economics	2
6	paper	An Economic Analysis of the Environmental Impact of PM _{2.5} Exposure on Health Status in Three Northwestern Mexican Cities	2021	Becerra-Perez, L. A. et al.	Sustainability	1

7	paper	Health impact and related cost of ambient air pollution in Tehran	2019	Bayat, R. et al.	Environmental Research	1
8	paper	The value of a statistical life in Mexico	2020	De Lima, M.	Journal of Environmental Economics and Policy	1
9	paper	Monetary value of a life expectancy gain due to reduced air pollution: Lessons from a contingent valuation in France	2007	Desaigues, B. et al.	Revue d'économie politique	1
10	paper	The Economic Value of Air-Pollution-Related Health Risks in China: A Contingent Valuation Study	2006	Hammitt, J. K. and Zhou, Y.	Environmental & Resource Economics	1
11	paper	Estimating Mortality and Economic Costs of Particulate Air Pollution in Developing Countries: The Case of Nigeria	2012	Yaduma, N.; Kortelainen, M.; Wossink, A.	Environmental & Resource Economics	3
12	paper	Health and economic impacts of ambient air particulate matter (PM _{2.5}) in Karaj city from 2012 to 2019 using BenMAP-CE	2022	Kianizadeh, F. et al.	Environmental Monitoring and Assessment	8
13	paper	A health impact assessment of long-term exposure to particulate air pollution in Thailand	2021	Mueller, W. et al.	Environmental Research Letters	1
14	paper	Health impact assessment of particulate pollution in Tallinn using fine spatial resolution and modeling techniques	2009	Orru, H. et al.	Environmental Health	1

15	paper	Estimating health co-benefits of climate policies in China: An application of the Regional Emissions-Air quality-Climate-Health (REACH) framework	2020	Qu, C. et al.	Climate Change Economics	1
16	paper	The economic benefits of fulfilling the World Health Organization's limits for particulates: A case study in Algeciras Bay (Spain)	2019	Roman-Collado, R. and Jimenez de Reyna, J.	Journal of the Air & Waste Management Association	1
17	paper	Health impact assessment and evaluation of economic costs attributed to PM _{2.5} air pollution using BenMAP-CE	2022	Safari, Z. et al.	International Journal of Biometeorology	1
18	paper	Valuation of Mortality Risk Attributable to Climate Change: Investigating the Effect of Survey Administration Modes on a VSL	2012	Ščasný, M. and Alberini, A.	International Journal of Environmental Research and Public Health	1
19	paper	Estimation of economic costs of air pollution caused by motor vehicles in Iran (Isfahan)	2021	Soleimani, M. et al.	Environmental Science and Pollution Research	1
20	paper	Health benefits of improving air quality in Taiyuan, China	2014	Tang, D. et al.	Environment International	10
21	paper	Economic valuation of air pollution health impacts in the Tehran area, Iran	2008	Karimzadegan, H. et al.	Iranian Journal of Public Health	3
22	report	Valuation of Health Benefits Associated with Reductions in Air Pollution	2004	Chilton, S. Covey et al.	Department for Environment, Food and Rural Affairs (Defra)	2

23	report	The cost of air pollution in Africa	2016	Roy, R.	OECD	144
24	report	The Cost of Air Pollution	2014	-	OECD	36
25	report	Economic cost of the health impact of air pollution in Europe	2015	-	WHO/OECD	23
26	report	Western Balkans Regional AQM - Western Balkans Report – AQM in Bosnia and Herzegovina	2019	-	World Bank	1
27	report	Western Balkans Regional AQM - Western Balkans Report – AQM in North Macedonia	2019	-	World Bank	1
28	report	Western Balkans Regional AQM - Western Balkans Report – AQM in Kosovo	2019	-	World Bank	1
29	report	Environmental Health Costs in Colombia: The Changes from 2002 to 2010	2014	Golub, E. et al.	World Bank	1
30	report	Policy Assessment for the Review of the Particulate Matter National Ambient Air Quality Standards	2011	-	U.S. Environmental Protection Agency (U.S. EPA)	1

31	report	Mortality, morbidity and welfare cost from exposure to environment-related risks	2023	OECD Data Explorer	OECD	185
32	report	Climate Change Mitigation, Air Quality and Health (CLIMAQ-H)	2023	WHO Regional Office for Europe, European Centre for Environment and Health (ECEH)	CLIMAQ-H WHO	48

Appendix B

PM_{2.5}, O₃ and NO₂ concentrations calculation.

We calculated the country weighted averages for the following pollutants: PM_{2.5}, NO₂ and O₃. In order to calculate the timeseries needed for our analysis, we made use of widely acknowledged air pollution datasets. For PM_{2.5} we analysed the annual Gridded mean PM_{2.5} concentrations dataset from Atmospheric Composition Analysis Group. The data are available at $0.01^\circ \times 0.01^\circ$ resolution for the years 1998-2022 and were obtained by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, SeaWIFS, and VIIRS with the GEOS-Chem chemical transport model by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, SeaWIFS, and VIIRS with the GEOS-Chem chemical transport model (Shen et al., 2024).

For NO₂ we analysed the Nitrogen Dioxide Surface-Level Annual Average Concentrations V1 (SFC_NITROGEN_DIOXIDE_CONC) dataset, which provides annual global NO₂ surface values (ppb) at a very high resolution of $0.0083^\circ \times 0.0083^\circ$ for every year since 2000. The values of this dataset were obtained through the use of a Land Use Regression (LUR) model (based on 5220 NO₂ monitors in 58 countries) for the years 2010-2012 (Anenberg, 2023). For the O₃ analysis we used the TROPES Chemical Reanalysis dataset provided by NASA. The spatial resolution of this dataset is significantly lower compared to the other two datasets ($1.125^\circ \times 1.125^\circ$) but we considered that the available resolution is sufficient for the needs of this study. The data are available in two-hour format for each year (2005-2021), so this added an additional step of calculation since we created the annual average of the hourly values for each available year (Miyazaki, 2024).

All the air quality files that were used in the analysis were in the form of ncdf4.

Population-Land weighted values calculation

The population weighted values were calculated in the following way. For each grid cell of the map we multiplied the population value and the pollutant concentration value. We then took the sum of the of all these calculations for a single country and we divided the result with the total population for this country:

$$\text{Population Weighted Pollutant Conc.} = \frac{\sum \text{grid population} \times \text{grid pollution concentration}}{\text{Total country population}} \quad \text{Eq.(B.1)}$$

For the land weighted values we applied the same logic, replacing the population with the land surface value:

$$\text{Land Weighted Pollutant Conc.} = \frac{\sum \text{grid land surface} \times \text{grid pollution concentration}}{\text{Total country land surface}} \quad \text{Eq.(B.2)}$$

Appendix C

Table C.1

List of countries included in the final database and the corresponding number of studies conducted in each.

Country	N. studies	Country	N. studies	Country	N. studies	Country	N. studies
Afghanistan	1	Dominican Republic	1	Liberia	4	Saint Lucia	1
Albania	3	Ecuador	1	Libya	4	Saint Vincent and the Grenadines	1
Algeria	4	Egypt	4	Lithuania	3	Samoa	1
Angola	4	El Salvador	1	Luxembourg	3	San Marino	1
Antigua and Barbuda	1	Equatorial Guinea	4	Madagascar	4	Sao Tome and Principe	4
Argentina	1	Eritrea	1	Malawi	4	Saudi Arabia	1
Armenia	3	Estonia	4	Malaysia	1	Senegal	4
Australia	2	Eswatini	4	Maldives	1	Serbia	3
Austria	3	Ethiopia	4	Mali	4	Seychelles	4
Azerbaijan	3	Fiji	1	Malta	3	Sierra Leone	1
Bahamas	1	Finland	3	Marshall Islands	1	Singapore	2
Bahrain	1	France	4	Mauritania	4	Slovakia	3
Bangladesh	1	Gabon	4	Mauritius	4	Slovenia	3
Barbados	1	Gambia	4	Mexico	4	Solomon Islands	1
Belarus	3	Georgia	3	Micronesia	1	South Africa	4
Belgium	3	Germany	3	Moldova	3	South Korea	3
Belize	1	Ghana	4	Mongolia	2	Spain	4
Benin	4	Greece	3	Montenegro	3	Sri Lanka	1
Bhutan	1	Grenada	1	Morocco	4	Sudan	4
Bolivia	1	Guatemala	1	Mozambique	4	Suriname	1
Bosnia and Herzegovina	4	Guinea	4	Myanmar	2	Sweden	3
Botswana	4	Guinea-Bissau	4	Namibia	4	Switzerland	3
Brazil	1	Guyana	1	Nauru	1	Tajikistan	1
Brunei	1	Haiti	1	Nepal	1	Tanzania	4

Bulgaria	3	Honduras	1	Netherlands	3	Thailand	3
Burkina Faso	4	Hungary	3	New Zealand	2	Timor-Leste	1
Burundi	4	Iceland	3	Nicaragua	1	Togo	4
Cabo Verde	4	India	2	Niger	4	Tonga	1
Cambodia	2	Indonesia	1	Nigeria	7	Trinidad and Tobago	1
Cameroon	4	Iran	15	North Macedonia	4	Tunisia	4
Canada	2	Iraq	1	Norway	3	Turkmenistan	3
Central African Republic	4	Ireland	3	Oman	1	Tuvalu	1
Chad	4	Israel	2	Pakistan	1	Türkiye	3
Chile	2	Italy	3	Palau	1	Uganda	4
China	17	Jamaica	1	Panama	1	Ukraine	3
Colombia	2	Japan	3	Papua New Guinea	1	United Arab Emirates	1
Comoros	4	Jordan	1	Paraguay	1	United Kingdom	6
Congo	4	Kazakhstan	3	Peru	1	United States	4
Costa Rica	1	Kenya	4	Philippines	2	Uruguay	1
Croatia	3	Kiribati	1	Poland	3	Uzbekistan	3
Cyprus	3	Kosovo*	1	Portugal	3	Vanuatu	1
Czechia	4	Kuwait	1	Puerto Rico	1	Vietnam	2
Côte d'Ivoire	4	Kyrgyzstan	3	Qatar**	1	Yemen	1
Democratic Republic of the Congo	1	Laos	2	Romania	3	Zambia	4
Denmark	3	Latvia	3	Russia	3	Zimbabwe	1
Djibouti	4	Lebanon	1	Rwanda	4		
Dominica	1	Lesotho	4	Saint Kitts and Nevis	1	Total	494

Notes: *This designation is without prejudice to positions on status, and is in line with UNSCR 1244 and the ICJ Opinion on the Kosovo declaration of independence, as on the official website of the European Union.

**Qatar is the only country excluded, considered an outlier, after applying the robust regression model.

Appendix D

Table D.1

Mixed-model's output used as robustness check for within-study correlation among observations.

***, **, * , stands for statistical significance at the 0%, 0.1% and 1% level, respectively.

	Mixed-model		
	Coeff.	Std. err	
(Intercept)	-920,479.35	239,150.31	***
GDP	86.24	6.05	***
GINI	634,328.06	249,391.22	*
pop	6,743.59	9,935.98	
doctors	11,161.20	1,787.62	***
GDP : income (UM-H)	-3.62	5.58	

Notes: The coefficients are rounded to the second decimal figure; “pop” refers to the natural logarithm of the “population” variable.

Supplementary material

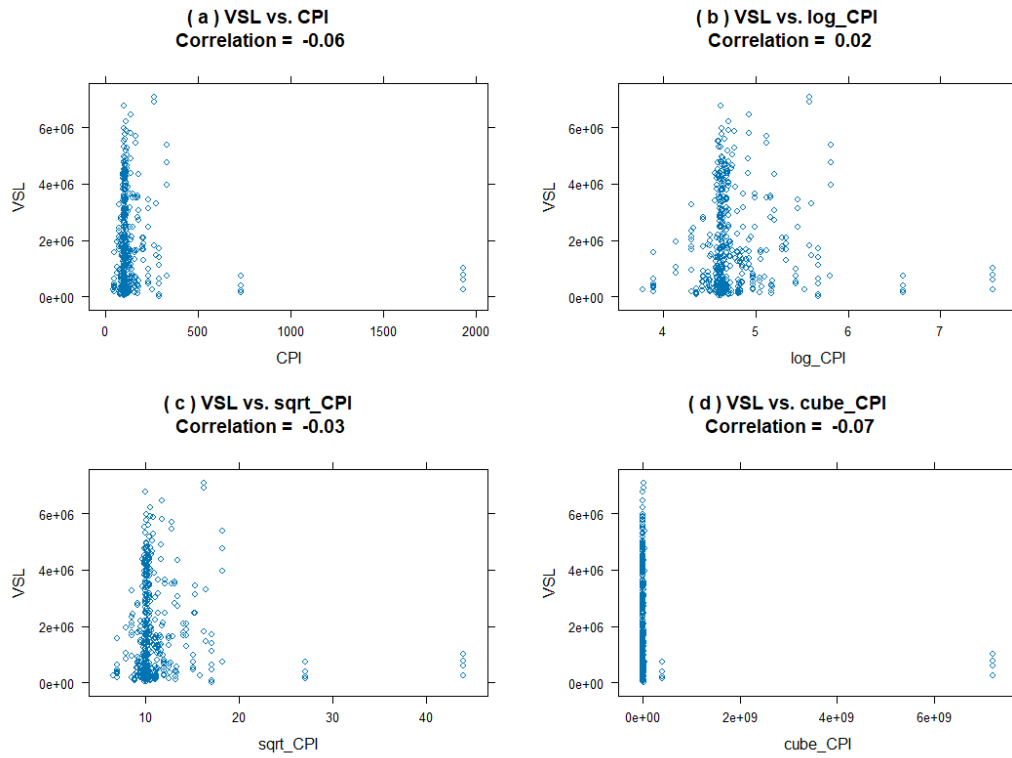


Figure S1. Scatterplots of VSL against CPI (a), log CPI (b), square root CPI (c) and cubic CPI (d) and the related Pearson correlation coefficients.

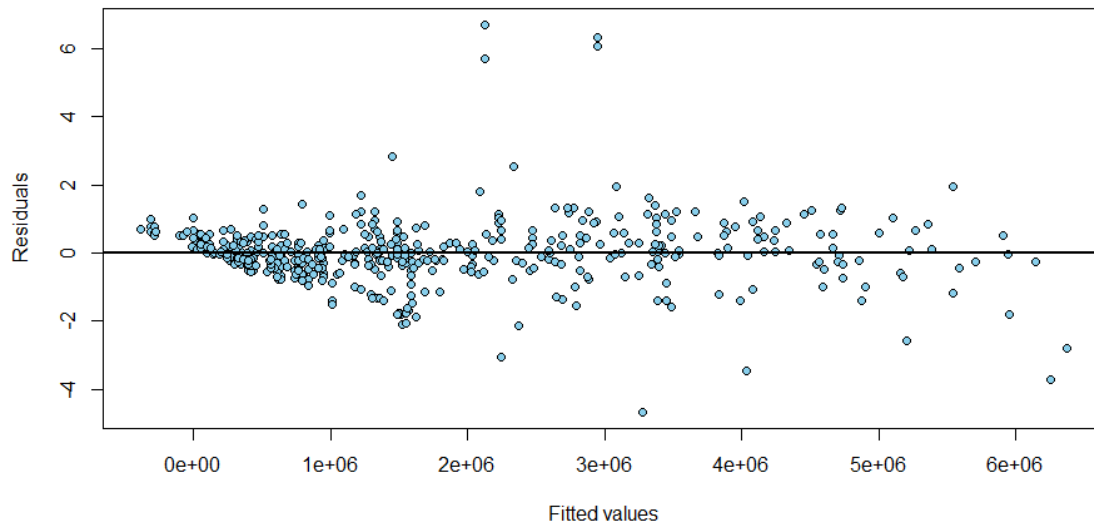


Figure S2. Plotted standardized residuals versus fitted values to assess homoskedasticity.

Table S1. Variables initially selected and the corresponding VIF values.

Variable	VIF value
GDP	85.94
GNI	100.28
GINI	1.83
pop_urb	2.60
school	14.55
LE	12.53
doctors	4.38
exp_GDP	2.20
exp_capita	7.54
HDI	52.00
NO2	2.05

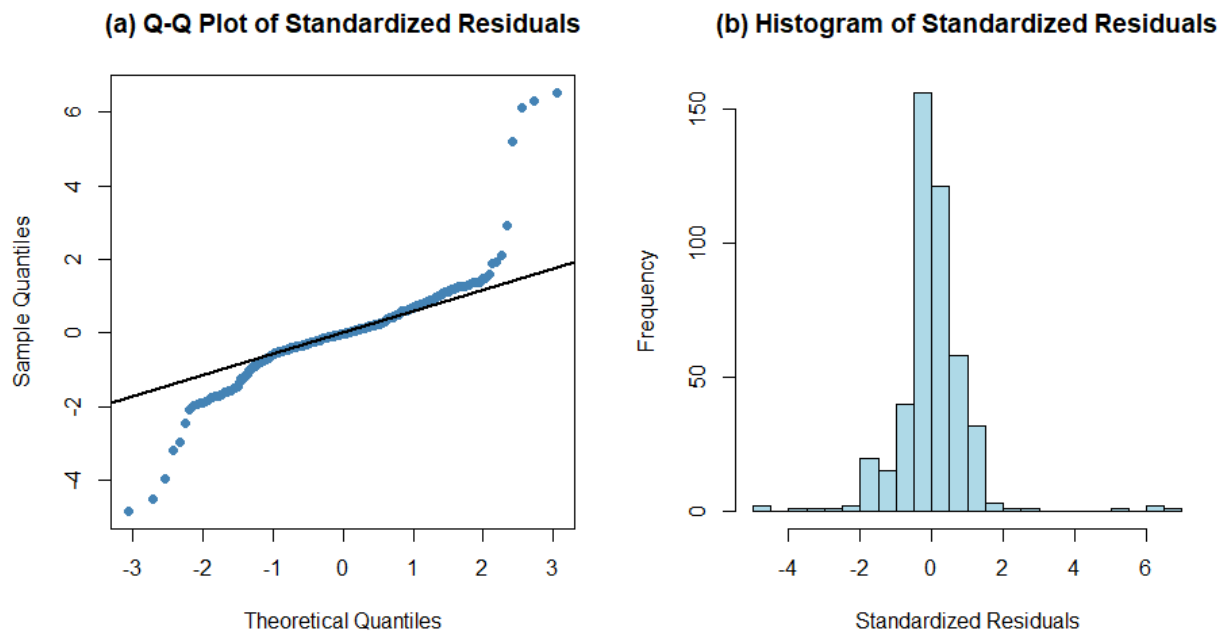


Figure S3. Quantile-quantile plot (a) and histogram (b) of the standardized residuals.

Ch. 5

Economic Valuation of Health Impacts Attributable to Air Pollution at a Country Level Worldwide

Sara Ciarlantini ^{a, b}, Vito Frontuto ^c, Alessandro Pezzoli ^a, Andreas Gavros ^d,
Claudio A. Belis ^b

^a DIST—Interuniversity Department of Regional and Urban Studies and Planning, Polytechnic of Turin and University of Turin, Turin, Italy

^b European Commission, Joint Research Centre (JRC), Ispra, Italy

^c EST—Economics and Statistics Department, University of Turin, Turin, Italy

^d Fincons SPA, Vimercate, Italy

Abstract

Air pollution is among the most pressing environmental health threats worldwide. Despite sustained efforts to improve air quality, scientific evidence continues to show substantial adverse health impacts, from subclinical conditions to premature death, with an estimated 7.9 million premature deaths each year. Air pollution is not only a critical public health issue but also a major economic burden. Beyond health expenditures, it imposes sizeable non-market costs through

monetised welfare losses associated with mortality and morbidity. This paper quantifies those costs for PM_{2.5} and O₃, valuing both premature mortality and years of life lost (YLL). The quantification is based on an econometric model that estimates country-specific values of a statistical life (VSL) and a value of a life year (VOLY)—both attributable to air pollution—by tailoring them to countries' economic, socio-economic, demographic, and health characteristics. The analysis covers 108 countries, representing about 86% of the global population, across five benchmark years (2000, 2005, 2010, 2015, 2019). Costs are computed through two complementary approaches: VSL multiplied by mortality, and VOLY multiplied by YLL. Across 2000–2019, VSL–mortality estimates exceed VOLY–YLL, while cross-country patterns are consistent. The largest burdens fall on China, India, and the United States, reflecting very large exposed populations despite progress in emission reductions. Russia also records high costs despite medium–low pollution levels due to its population size. O₃-attributable costs are roughly 98–99% lower than PM_{2.5}, consistent with markedly lower O₃-related mortality and YLL. Monetising premature mortality and YLL attributable to PM_{2.5} and O₃ indicates costs of about 5% of world GDP when valuing mortality and 4% when valuing YLL, underscoring that cleaner air delivers substantial and timely welfare gains. These results provide decision-relevant evidence for prioritising air-quality management, especially in highly populated countries, with the objective of supporting more efficient resource allocation and the design of cost-effective policies that reduce exposure, prevent premature deaths, and limit long-term welfare losses.

1. Introduction

Air pollution represents one of the most pressing environmental health threats worldwide. Over 99% of the global population is exposed to air quality levels that exceed internationally recognized safety thresholds (UNEP 2025; WHO, 2024). These effects are particularly severe in densely populated urban areas, where air pollution contributes to a significant burden of disease, including premature mortality and chronic conditions (OECD, 2016).

In 2023, air pollution ranked as the second leading risk factor for early mortality globally, surpassed only by high blood pressure (HEI, 2025). It was associated with 7.9 million deaths, more than one in every eight worldwide, underscoring its critical impact on public health.

This burden is largely driven by exposure to fine particulate matter (PM_{2.5}) and ozone (O₃), which together accounted for about 13% of global deaths in 2023 (HEI, 2025). Ambient and household PM_{2.5} was responsible for over 90% of this burden, with ambient PM_{2.5} alone linked to an estimated 4.9 million [95% UI: 3.9–6.1] deaths. Ozone contributed to around 470,000 (95% UI: 108,000–800,000) deaths annually, primarily through its association with chronic obstructive pulmonary disease (COPD).

The burden of air pollution is unevenly distributed across the globe. Low- and middle-income countries (LMICs) bear the greatest health impacts, driven by rising pollution levels in rapidly urbanizing, densely populated regions (World Bank, 2022). Since the 1990s, exposure to ambient air pollution has increased in most non-high-income countries, contributing to a widening health gap between LMICs and high-income countries (HICs) (Burnett and Cohen, 2020). Currently, LMICs host about 80% of the global population and account for 95% of deaths and nonfatal illnesses linked to air pollution each year (World Bank, 2022).

Air pollution is not only a critical public health issue but also a major economic burden. Beyond healthcare expenditures, it imposes substantial non-market costs. These mainly consist of the monetized welfare losses associated with premature mortality and morbidity (OECD, 2016). Such welfare losses are difficult to capture within standard economic models, as they are not directly reflected in market transactions or measurable outputs. In 2019, exposure to ambient and household air pollution led to an estimated USD 8.1 trillion in global welfare losses, including both mortality and morbidity (World Bank, 2022). This substantial figure underscores both the urgent need for comprehensive strategies to mitigate air pollution and the importance of updated assessments to capture its current and far-reaching costs. Building on this need, the present study aims to quantify the external annual costs (hereafter, costs) associated with the health impacts of air pollution, specifically focusing on mortality linked to PM_{2.5} and O₃ exposure at a country level worldwide.

To this end, the analysis applies a methodology developed by Ciarlantini et al. (2025), which accounts for cross-country differences in economic structures, demographic profiles, healthcare access, and broader socio-economic conditions. These factors allow the assessment of disparities between low- and high-income countries.

Given the substantial number of deaths attributable to air pollution each year, estimating the economic value of these losses provides a powerful tool for understanding the scale of the problem. Assigning monetary values to premature mortality not only underscores the urgency of mitigation but also supports governments in navigating competing development priorities. By revealing the economic burden of inaction, these estimates can guide more efficient resource allocation and inform the design of cost-effective air quality management policies.

2. Material and methods

2.1 Air pollutant-related impacts on health

To compute global air pollutant-related impacts on human health, the FAsT Scenario Screening Tool (FASST) is used. This tool is a reduced-form air quality source-receptor model that takes as inputs annual pollution emission data aggregated at the national or regional level (Van Dingenen et al., 2018). FASST defines 74 emission source regions, with concentrations and impacts initially calculated on a $0.5^\circ \times 0.5^\circ$ global grid (0.1×0.1 for Europe) and subsequently downscaled to estimate population exposure. The model incorporates anthropogenic emissions assuming constant meteorological conditions (based on the year 2015). As a result, it does not account for climate feedbacks on factors such as photolysis rates, precursor residence times, or deposition rates. Consequently, natural emissions—such as volatile organic compounds (including natural CH_4), NO_x , and natural $\text{PM}_{2.5}$ —are treated as fixed, constant contributors.

The exposure metrics are the population-weighted $\text{PM}_{2.5}$ annual concentrations and the seasonal mean of daily maximum 8-hour O_3 average (SDMA8h). Mortality attributable to outdoor air pollution is estimated according to the Global Burden of Disease (Brauer et al., 2024; IHME 2021). This approach calculates the number of annual premature mortalities from six causes of death: COPD, lung cancer (LC), lower respiratory airway infections (LRI), diabetes mellitus (DM), ischemic heart disease (IHD), and stroke. Cause-specific excess mortality is determined at the grid cell level using the population-attributable fraction approach (Murray et al., 2003):

$$\Delta Mort = m_0 \cdot AF \cdot pop \quad (1)$$

$$AF = \frac{(RR-1)}{RR} \quad (2)$$

where m_0 is the cause-specific all-risk mortality rate (deaths per capita) for the exposed population POP, AF is the fraction of total mortalities attributable to air pollution, and RR is the relative risk of death attributable to a change in population-weighted mean pollutant concentration. For $PM_{2.5}$ exposure, RR is calculated from the curves developed by Brauer et al. (2024). Mortality caused by COPD attributable to O_3 exposure is based on a log- linear exposure-response function (IHME 2021). A complete description and validation of the FASST model can be found in Belis et al. (2022), Sampedro et al. (2022), and Van Dingenen et al. (2018).

The Years of Life Lost (YLL) metric estimates the burden of premature mortality by incorporating both the frequency of deaths and the age at which they occur, offering a more comprehensive view of the impact of early mortality. Same as mortality, the YLL values are computed according to the GBD 2021 methodology described above.

2.2 Air pollutant-related unit costs

With the aim of estimating health costs attributable to air pollution worldwide, VSL and VOLY values are computed at the country level using a meta-analytic value transfer approach that considers, in addition to GDP, a number of socio-economic predictors (Ciarlantini et al., 2025). This approach is intended for the estimation of health costs due to air pollution, even in countries where VSL and VOLY studies are not available. Through a robust regression technique, this model focuses exclusively on air pollution-related VSL estimates and accounts for differences among countries represented by GDP and other socio-economic, demographic and healthcare proxies:

$$VSL_{ij} = \beta_0 + \beta_1 GDP_{ij} + \beta_2 GINI_{ij} + \beta_3 \log(pop_{ij}) + \beta_4 doctors_{ij} + \beta_5 GDP_{ij} income_{ij} + \varepsilon_{ij} \quad (3)$$

As shown in equation (3), the model incorporates the GINI index and income categories, based on the World Bank GNI per capita classification, to capture income inequality. It also includes the logarithm of the country population as a demographic factor, and the number of doctors per 10,000 people as a proxy for healthcare access.

From these VSL estimates, it is possible to derive the VOLY, an indicator reported in the literature both within the air pollution context (Andersen, 2017; Hurley et al., 2005; Lattarulo and Plechero, 2005; OECD, 2010) and across other fields (Abelson, 2003; Ananthapavan et al., 2021). VOLY is often preferred over VSL in cases involving small reductions in life expectancy, such as those caused by chronic exposure to air pollution (Martinez et al., 2018), since air pollution typically does not cause death directly but worsens existing health conditions, leading to reduced life expectancy and a higher risk of premature death. In this study, VOLY was computed according to (Ananthapavan et al., 2021):

$$VOLY = \frac{VSL}{\left(\frac{1-(1+r)^{-n}}{r}\right)} \quad (4)$$

The discount period (n) is determined by subtracting the median age of a given country's population in the collection year from its corresponding life expectancy (UNDP, 2022). A discount rate (r) of 3% is applied in the construction of the final VOLY database, consistent with the values suggested by the European Commission in its Economic Appraisal Vademecum for 2021–2027 (European Commission, 2021) and aligned with recent valuation of air pollution impacts on health (Belis et al., 2023).

To maximize country coverage, missing GINI and doctors' data are filled in by temporal and spatial interpolation (GDP and population data were available at country level for all the years for all the countries). Temporal interpolation assumes a linear change between the observed years, and it is done for a maximum of two years before and two years after the missing value to be found. Spatial interpolation is performed using data from neighboring countries with comparable socio-economic and demographic characteristics (e.g. GDP per capita, income inequality, and population structure).

The explanatory variables for the model are retrieved for five years spanning the two first decades of the century: 2000, 2005, 2010, 2015, and 2019. The year 2019 is chosen instead of 2020 to avoid the impact of the COVID-19 pandemic (2020–2021), which significantly altered mortality outcomes (HEI, 2024). Countries are excluded from the analysis if data for any explanatory variable were missing in one or more study years, even after interpolation. The final dataset contains air pollution-related costs in 108 countries across all continents, representing 86% of the world population in 2019. The countries included in the dataset are shown in Fig. 1 (further details can be found in Table S1). Coverage is

lowest in Africa and the Arab Peninsula due to the lack of proxy data for equation (3).

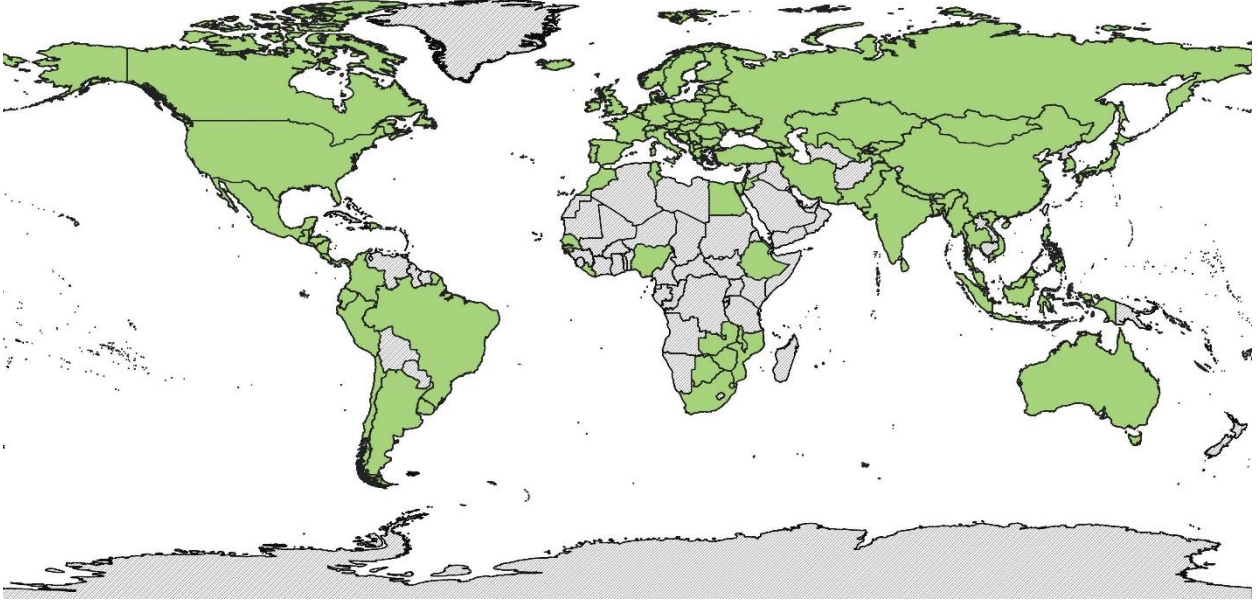


Figure 1. Countries (108) included in the database of air pollution-related mortality unit costs.

The VSL and VOLY estimates are used to assess the monetary value of a reduction in mortality risk at the country level, both in terms of premature deaths (Eq. 5) and years of life lost (i.e. the economic cost associated with reduced life expectancy (Eq. 6)). All the values are provided in purchasing power parity international dollars I\$ (2019 PPP).

$$Cost_1 = VSL \cdot \Delta Mort \quad (5)$$

$$Cost_2 = VOLY \cdot \Delta YLL \quad (6)$$

3. Results

3.1 VSL and VOLY

Between 2000 and 2019, the VSL rankings across countries reveal a striking and persistent disparity between the highest and lowest values. Luxembourg holds the top position throughout the period, with VSLs ranging from I\$10.3 million in 2000 (95% CI: I\$10,033,328–I\$10,615,414) to I\$10.4 million in 2019 (95% CI: I\$10,093,368–I\$10,653,846) while Ireland and Switzerland remain close behind in second and third place. In sharp contrast, the lowest VSL values are observed in African countries: Malawi, Liberia, and Ethiopia. Their VSLs range from approximately I\$160,000 to I\$235,000, resulting in a disparity from 44- to 65-fold compared to the top-ranked countries. Cross-country differences in VSL reflect disparities in economic development, public health expenditures, and living costs. While VSLs rise moderately over 2000–2019, the relative gap between the highest and lowest values remains substantially unchanged. Consistent with this interpretation, VSL values largely mirror differences in the model covariates (income, GDP per capita, and number of doctors) which are proxies for national wealth and institutional robustness (Ferretti et al., 2023; OECD, 2025; Sunstein, 2023). The VSL values for each country between 2000 and 2019 are illustrated in Fig. 2.

On average, VOLY is about 4.2% of the corresponding VSL for the same year and country, which aligns with previous findings in the literature (Desaigues et al., 2007; Martinez et al., 2018; Orru et al., 2009). The VOLY values range from about 5.5% the VSL in countries such as Eswatini, Zimbabwe, and Russia, to nearly 3.7% the VSL in the Maldives, Jordan, and Israel.

In the first two decades of the century, VOLY estimates range from I\$437,275 in Luxembourg (95% CI: I\$424,948–I\$449,601) to I\$6,242 in Malawi (95% CI: I\$3,552–I\$8,933). As expected, the geographical patterns of VOLY are the same as those of VSL (see S1).

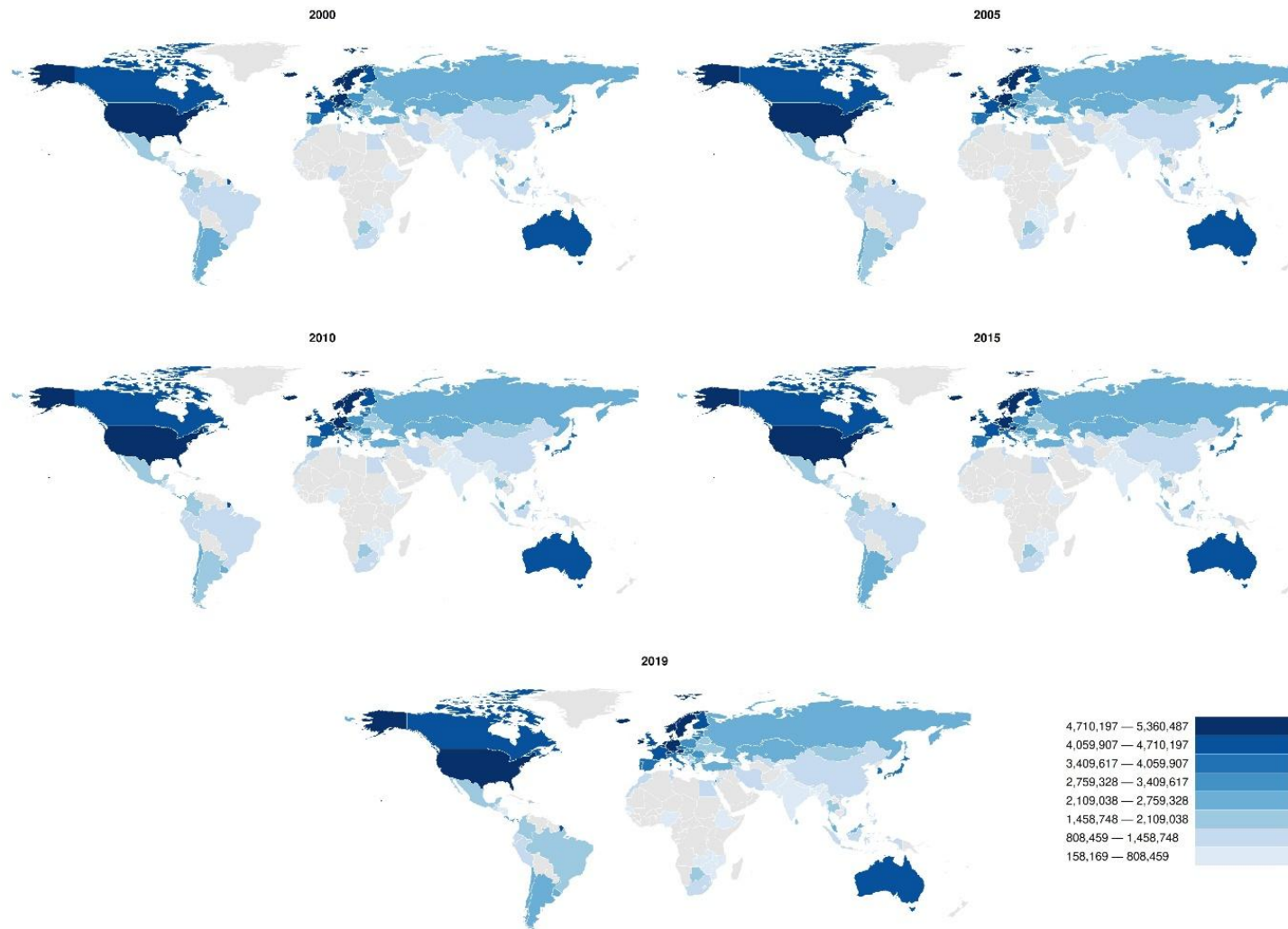


Figure 2. VSL values by country in the first two decades of the XXI century (from 2000 to 2019)

3.2 Mortality and YLL attributable to air pollution

3.2.1 PM_{2.5}

This section synthesises the global patterns of mortality and YLL attributable to air pollution, focusing on fine particulate matter (PM_{2.5}) and ground-level ozone (O₃). Unless otherwise specified, all values refer to rates per 100,000 inhabitants. The EuroVoc regional definitions² are adopted throughout the analysis.

Across regions and over 2000–2019, mortality and YLL attributable to PM_{2.5} show closely aligned dynamics. Mortality and YLL global maps are shown in Figures S4 and S5, respectively. Central and Eastern European countries persistently rank among the most affected ones. In 2000, the highest mortality rates are observed in Ukraine, Belarus, and Bulgaria, all exceeding 190 deaths per 100,000 inhabitants. Ukraine ranks among the countries with highest mortality rate also during the 2010s decade, while countries such as Kosovo and Serbia also emerge with similarly high burdens. By 2015 and 2019, the highest mortality levels are found in Kosovo, North Macedonia, Serbia, and Armenia. Although a general decline is observed over time (from above 230 deaths in 2000 to around 150–160 in 2019) these countries continue to experience a disproportionately high burden of PM_{2.5}-related health impacts compared to other European countries³, registering mortality levels about 70% higher than the European average.

PM_{2.5}-attributable YLL mirrors the mortality picture. During 2000–2019, YLL values range from approximately 2,707 to 4,448. In the early 2000s, the highest YLL values are observed in Central and Eastern Europe (notably Ukraine, Bulgaria, Serbia, Kosovo, North Macedonia, and Belarus). These findings align with previous evidence identifying Central and Eastern Europe among the areas with the highest PM_{2.5}-related YLL burdens (EEA, 2023; Juginović et al., 2021). However, from 2010 onward, Egypt increasingly ranks among the countries with the highest YLL values, with an average YLL of 3,359 over the period, averaging more than three times higher than the African continent mean.

² The EuroVoc regional definitions are accessible here: <https://lex.europa.eu/browse/eurovoc.html>

³ The countries considered are Albania, Austria, Belgium, Bosnia and Herzegovina, Belarus, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kosovo, Latvia, Lithuania, Luxembourg, Malta, Moldova, Montenegro, the Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, the Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Ukraine, and the United Kingdom.

This outcome may be attributed to the persistently high levels of PM_{2.5} pollution in these countries, as previous studies have demonstrated a strong positive association between mortality/YLL and PM_{2.5} exposure (Juginović et al., 2021, Qi et al., 2020). In fact, Bosnia and Herzegovina (34.6 µg/m³), North Macedonia (32.4 µg/m³), Bulgaria (25.5 µg/m³), Kosovo (23.5 µg/m³), and Serbia (23.3 µg/m³) rank among the top five European countries in terms of annual mean PM_{2.5} concentrations, according to the 2019 World Air Quality Report (IQAir, 2019).

A major driver of the elevated PM_{2.5} burden in Central and Eastern Europe is the persistent use of solid fuels, particularly for household heating and industrial activities (Almeida et al, 2020; Belis et al., 2019; Gu et al., 2023). In addition, the continued reliance on coal and other high-emission fuels in power generation and heavy industry contributes substantially to pollutant levels in the region (Crippa et al., 2019), along with obsolete industrial infrastructure, aging vehicle fleets, ammonia-intensive agricultural practices, and inadequate waste management systems (Andersen et al., 2025). These environmental challenges are deeply rooted in long-standing socioeconomic constraints, including the legacy of the Soviet era, the destabilizing effects of the 1990s civil war in former Yugoslavia and surrounding Balkan regions have hindered progress toward cleaner energy transitions and sustainable development (Andersen et al., 2025). Moreover, the domestic availability of cheap and low quality lignite fuel represented an obstacle to the penetration of renewables in this region (e.g. Balkans, Southern Poland). However, renewables could be largely financed by markets revenues by introducing carbon pricing mechanisms to account for externalities (Enervis, 2021).

South Asia, including India, sustains high but comparatively lower PM_{2.5} burdens—roughly one-third of those observed in Central and Eastern Europe—remaining stable across the two decades. Medium-to-high burdens are also observed in Russia, Far East Asia, and Africa, but with downward trends over time. In Russia, both mortality and YLL fall substantially (by 60% and 66%, respectively); in Far East Asia, China registers marked declines over the two decades analysed: a decrease of 130% in mortality rates and 109% in YLL rates. In the African continent, mortality decreases by about 4%, while YLL drops by about 27% over the two decades. Since YLL reflects not only the number of deaths but also the age at which they occur, this larger reduction suggests a shift away from premature deaths, with a greater share occurring at older ages. By contrast, North America and Southern Europe show comparatively low burdens with decreasing trends, while South America remains at low, largely stable levels.

3.2.2 O₃

Overall, O₃-attributable mortality and YLL rates remain substantially lower than that of PM_{2.5} by a factor of 7 to 25, aligning with previous findings (Cohen et al., 2017; HEI, 2024; Lelieveld et al., 2023; Pozzer et al., 2023). Global maps can be found in Figs. S6 and S7, for mortality and YLL rates, respectively.

Mortality and YLL rates attributable to O₃ are more prominent in South, South East and Far East Asia (particularly Nepal, India, Kyrgyzstan, and Bhutan), regions where the disease burden linked to ozone exposure increases over the 2010s, while in other parts of the world it remains stable or slightly declines (HEI, 2025). Over the 20-year period, the countries most affected by O₃-related mortality show relatively little variation, ranging between 7 and 15 deaths. Nepal persistently reports the highest mortality, rising from 14 to 23 deaths. China also presents a high rate of deaths and YLL attributable to ozone, although a decrease of about 40% is observed over the two decades analysed. Conversely, India experiences high increases in ozone-related mortality and YLL over time, by 107% and 82% respectively. In particular, India's trend is linked to the country's growing and aging population, which heightens vulnerability to ozone exposure (Conibear et al., 2018).

The elevated burden found in these Asian countries is driven by a combination of intense precursor emissions and high population exposure. In Southeast Asia, biogenic volatile organic compounds (VOCs) released by extensive natural vegetation significantly contribute to ozone formation, accounting for 30% to 64% of ozone-related deaths in some countries (Gu et al., 2024). At the same time, densely populated urban regions experience high NO_x emissions from road transport, which amplify ozone formation and public exposure. The convergence of abundant natural and anthropogenic precursor sources, meteorological conditions favourable to ozone formation, and large exposed populations explains the growing health burden from ozone in this region. Since the O₃ formation is driven by solar UV radiation, the concentrations of this pollutant are higher in sites located at high altitude compared to low altitude (for comparable emission levels). Moreover, in this area, a significant share of ozone-related health impacts may be attributed not only to local emissions, but also to transboundary air pollution among countries of the region (Gu et al., 2024; Monks et al., 2015).

Even though substantially lower than the above mentioned Asian countries, O₃-attributable mortality and YLL are also present in North America and in Central

and Eastern Europe (even if their rates decrease over 2000–2019). In Central and Eastern Europe, the YLL attributable to O₃ exposure is, on average, about 75 times lower than that associated with PM_{2.5} during the same period, reflecting comparatively lower ozone pollution in the region. In this area, high levels of deaths and YLL can be associated to persistent dependence on high-emission fuels, outdated industrial systems, and long-standing socioeconomic barriers that continue to delay environmental improvements. By contrast, South America and Southern Europe show lower values than these regions but increasing trends across the two decades. Finally, Africa records low O₃-attributable mortality and YLL with an overall stable trend over 2000–2019.

3.3 Air pollution costs

Throughout the 2000–2019 period and across the 108 countries included in the analysis, China, India, Russia and the United States are the ones with the greatest air pollution economic burden for both PM_{2.5} and O₃. This reflects their large economic output, high industrial activity, and dense populations, all of which are heavily exposed to harmful pollutants such as PM_{2.5} and O₃.

This sections outlines the main results derived with the two methodologies adopted: the one combining VSL and mortality (Eq. 5) and the one combining VOLY and YLL (Eq. 6). All costs are expressed in I\$ (PPP 2019).

3.3.1 PM_{2.5}

For PM_{2.5}-related costs, China incurs the largest burden, far exceeding the levels observed in the United States, Russia and India. This outcome is consistent within the two methodologies, and the results are outlined in Table 1 for VSL–mortality and Table 2 for VOLY–YLL (their global maps can be found in Figs. S2 and S3, respectively).

Between 2000 and 2005, several European countries, including Germany, the United Kingdom, and Italy, also report comparatively high costs. These elevated costs are not explained by high mortality, as their air pollution–attributable deaths are lower than those in China, India, or Russia, but instead by their relatively high VSL (Fig. 2). For instance, during 2000–2005, India’s average VSL is

approximately seven times lower than Italy's, eight times lower than the United Kingdom's, and nine times lower than Germany's. Similarly, VSL values in China and Russia are also below those of Central and Eastern European countries.

At the same time, countries in Central and Eastern Europe report very high mortality and YLL rates associated with air pollution (see Section 3.2), but they do not appear among the regions with the highest costs. This apparent paradox is explained by their low absolute number of deaths due to their modest population density. These findings highlight how population size is a critical determinant of aggregated health and economic burdens from air pollution (Burnett et al., 2018).

In terms of absolute changes, both China and India record increases in PM_{2.5}-related costs between 2000 and 2019, with India experiencing the most pronounced growth. These increases cannot be attributed to changes in the VSL and VOLY, which increase only modestly over the two decades, but rather to a combination of factors: high pollution levels, population growth and sharp increases in PM_{2.5}-attributable mortality and YLL, both in absolute terms and per 100,000 inhabitants (see Tables 1 and 2).

By contrast, the United States and Russia experience cost reductions of around 62% over the same period. Such downward trends are explained by substantial decreases in air pollution-attributable deaths and years of life lost, while VSL and VOLY values remain relatively stable (see Tables 1 and 2). In the United States, this decline reflects the success of stringent air quality regulations and pollution control measures (US EPA, 2025 a-b). In Russia, such reductions are consistent with evidence of declining mortality linked to improvements in air quality and public health interventions in the decades following the post-Soviet era.

Table 1. Differences in PM_{2.5}-attributable costs, VSL and mortality rates for the highest economic burden countries in the sample. Costs are calculated using the “VSL x mortality” approach. Costs are given in I\$ (2019 PPP); ‘b’ stands for billion, ‘t’ for trillion. Data is from 2000-2019.

	Cost		Cost % change	VSL % change	Mortality % change
	2000	2019			
China	907 b	2.5 t	+ 163%	+ 5%	+ 150%
India	169 b	562 b	+ 233%	+ 4%	+ 220%
Russia	618 b	236 b	– 62%	=	– 61%
United States	658 b	249 b	– 62 %	=	– 63%

Table 2. Differences in PM_{2.5}-attributable costs, VOLY and YLL rates for the highest economic burden countries in the sample. Costs are calculated using the “VOLY x YLL” approach. Costs are given in I\$ (2019 PPP); ‘b’ stands for billion, ‘t’ for trillion. Data is from 2000-2019.

	Cost		Cost % change	VOLY % change	YLL % change
	2000	2019			
China	834 b	1.88 t	+ 126%	+ 8%	+ 109%
India	245 b	574 b	+ 134%	=	+ 131%
Russia	692 b	210 b	– 70%	– 10%	– 66%
United States	495 b	190 b	– 62%	=	– 62%

3.3.2 O₃

Ozone-related costs for 2000–2019 derived using two methodologies are shown in Fig. 3 (VSL–mortality) and Fig. 4 (VOLY–YLL). As expected, O₃ costs are substantially smaller than those for PM_{2.5}: under the VSL approach they average about 1/48 of PM_{2.5} costs, and under the VOLY approach about 1/82.

Similar to PM_{2.5} costs outcomes, and common to both methodologies, China leads global O₃ related costs, followed by the United States during the 2000s decade, and by India in the 2010s. The cost gap between China and the United States widens in the 2000s decade (delta 115–154%) and narrows down during the 2010s decade. At the same time, the gap between the United States and India decreases considerably over time, driven not only by a reduction in United States costs but especially by the rapid increase in India’s O₃-related costs, which rise much faster than those of the United States.

With the VSL–mortality approach, in the 2000s decade, O₃-attributable costs in both China and the United States increase reflecting rising mortality rates. In the subsequent decade, however, although VSL values continue to rise, O₃-related mortality declines, resulting in overall reductions in costs. By 2019, China’s O₃-attributable costs falls by approximately 17% compared with 2000 levels, while the United States register a reduction of about 12%. Conversely, India experiences the steepest increase: its O₃-related costs rise by around 180% over the two decades, driven partly by a modest rise in VSL (+4%) but primarily by a dramatic increase in O₃-attributable mortality (+170% in absolute terms compared to 2000).

Similarly, using the VOLY–YLL approach, China’s costs peak in 2005 at nearly I\$175 billion but decline steadily thereafter, reaching around I\$107 billion in 2019, about 27% lower than in 2000. This reduction is consistent with a 32% decline in O₃-attributable YLL, which helps explaining the downward trend in costs despite continuing growth in population and income levels. India, by contrast, experiences a dramatic increase in costs over the same period. O₃-related economic losses rise from approximately I\$39 billion in 2000 to more than I\$96 billion in 2019, showing a 142% increase. This rise is largely attributable to a 139% increase in YLL, reflecting both worsening air quality and rising mortality impacts, while VOLY plays a comparatively minor role. The United States show a more moderate pattern, with O₃-attributable costs decreasing gradually from about I\$66 billion in 2000 to I\$57 billion in 2019 (approximately 13% less). Although costs slightly fluctuate in intermediate years, the overall trend reflects a 14% decline in O₃-related YLL, consistent with the country’s long-standing regulatory efforts and improvements in air quality (US EPA, 2025 a-b).

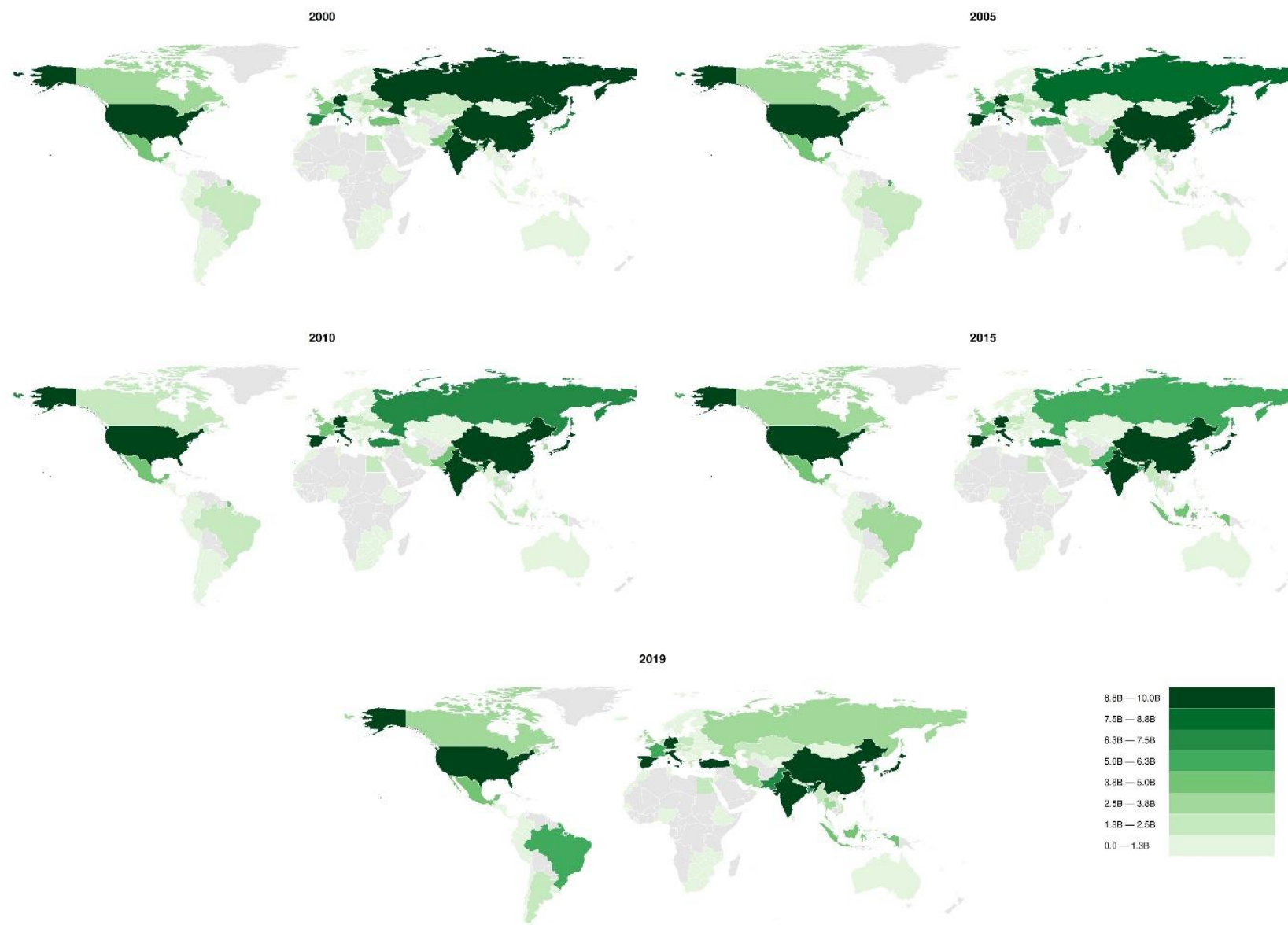


Figure 3. O₃ air pollution costs in IS\$ (mortality) by country for 5 different years, ranging from 2000 to 2019.

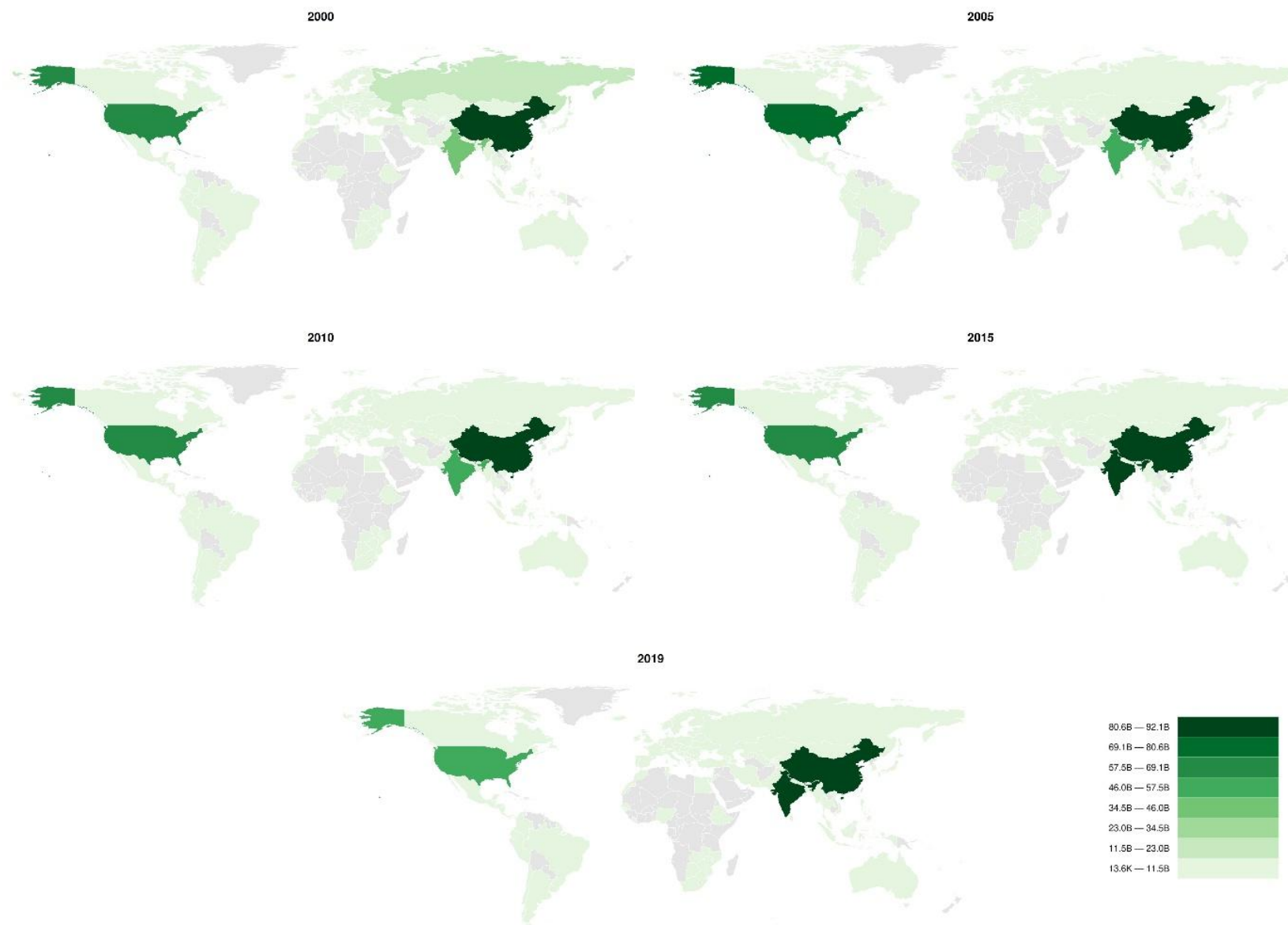


Figure 4. O₃ air pollution costs in IS (YLL) by country in the first two decades of the XXI century (from 2000 to 2019).

4. Discussion

In this study, the health and economic burden attributable to PM_{2.5} and O₃ exposure are estimated at the country level worldwide every five years between 2000 and 2019, applying two alternative approaches to cost valuation. Specifically, results are compared between a methodology based on the VSL combined with projected mortality and one based on the VOLY combined with YLL. Our results confirm that the choice of valuation method substantially affects the estimated economic costs of air pollution (Jakubowska, 2023). Consequently, comparison of methods and sensitivity analysis should be taken into account in this kind of studies.

At the global level (108 countries), both PM_{2.5} and O₃ costs rise between 2000 and 2019. Costs attributable to PM_{2.5}, with the VSL–mortality method totalise I\$ 6.06 trillion in 2019, which is 15% higher than 2000 (I\$ 5.28 trillion), while the VOLY–YLL method shows a modest 2% rise (from I\$ 4.95 to I\$ 5.05 trillion). These results are consistent with previous estimates of global welfare losses (World Bank, 2022). O₃ costs are smaller but follow the same trend: I\$ 526 billion in 2019 with VSL–mortality (+19% from I\$ 442 billion in 2000) and I\$ 370 billion with VOLY–YLL (+9% from I\$ 339 billion) in the same period.

PM_{2.5}-attributable global costs represent 4.46% and 3.72% of the world's GDP in 2019 (I\$ PPP), using the VSL–mortality and the VOLY–YLL method, respectively—both below the World Bank (2022) estimate of 6.1%, which also includes morbidity costs. By contrast, O₃-attributable costs are much smaller: 0.39% under VSL–mortality and 0.27% under VOLY–YLL. When referring to world, only the countries included in our analysis are considered. In lower-middle-income and low-income countries⁴, PM_{2.5}-attributable costs are from 22 to 25% of their 2019 GDP (according to the methodology employed), while it goes from 19 to 23% in upper-middle-income and high-income countries. This share of GDP is much smaller when accounting for O₃ costs, that represents 2-3% of GDP of lower-middle-income and low-income countries, and 1-2% of GDP in upper-middle-income and high-income countries. These latter countries, in 2019, account for 80% of global PM_{2.5} costs and 72% of O₃ costs (China alone represent about 38% of PM_{2.5} costs and 30% of O₃ costs). This pattern persists across the other years analysed, as deaths are monetised using VSL that rises with income. Consequently,

⁴ Income categories grouped into the World Bank's GNI per capita classification (World Bank Open Data).

identical health impacts yield larger monetary losses in richer economies (Hammitt, 2000; OECD, 2025; Viscusi & Aldy, 2003).

In general, comparing the two methods, costs derived using the VSL–mortality approach are higher than those obtained with the VOLY–YLL approach for both pollutants. The difference arises from the higher detail incorporated in YLL about the age at which the death occurs compared to VSL which considers all deaths in the same way (Eq. 4) (US EPA, 2024). According to our results (Section 3.1), differences are much larger when deaths occur at older ages because fewer years of life are lost leading to lower costs under the VOLY approach. Nevertheless, the VOLY–YLL approach could be also affected by the higher uncertainty associated with inaccuracies in the quantification of the average lifespan and median age. Moreover, differences between $PM_{2.5}$ and O_3 could be a consequence of the different causes of death associated with each of them that may affect different ages (e.g. COPD is a chronic disease that affects only adults) and consequently affect VOLY–YLL estimations for each pollutant differently.

In our study, the VOLY–YLL approach exceeds the VSL–mortality estimates in a 33% of $PM_{2.5}$ cases and a 10% of O_3 cases. High VOLY–YLL cost are more frequent in specific regions like Pacific island states (e.g. Fiji, Kiribati, Solomon Islands) and is especially pronounced in most African countries, where the VOLY–YLL approach produces higher costs than the VSL–mortality in about 90% of the countries for $PM_{2.5}$ and 40% for O_3 .

Figure 5 compares the two methods in the four countries with the highest $PM_{2.5}$ - and O_3 -related economic burdens over the two decades. China and the United States present higher VSL–mortality costs compared VOLY–YLL, while India and Russia present mixed results. In India, the VOLY–YLL method yields from 2% to 32% higher $PM_{2.5}$ -related costs than those from the VSL–mortality approach. In Russia the VOLY–YLL method yields higher costs than the VSL–mortality method between 2000 and 2010 for both pollutants. The pattern reverses in 2015 and 2019, with VSL-based estimates exceeding VOLY-based ones. Such difference reflects the combined effect of medium to high air pollution with socioeconomic variables (mainly GDP per capita) and demography (i.e. low average lifespan and median age).

Country-specific differences are also notable. In China, the discrepancy between methods varies substantially by pollutant, averaging 19% for $PM_{2.5}$ and nearly 43% for O_3 , suggesting that ozone-related impacts are particularly sensitive

to the choice of methodology. By contrast, in the United States, differences between methods are more consistent across pollutants, with an average gap of about 32% for PM_{2.5} and 41% for O₃.

Overall, these findings underscore that the choice of valuation framework (VSL vs. VOLY), along with other methodological choices, substantially affects the magnitude of air pollution cost estimates, leading to variation across countries and pollutants. This highlights the need for methodological transparency and harmonization to ensure that results remain comparable across studies and can reliably inform policy evaluation.

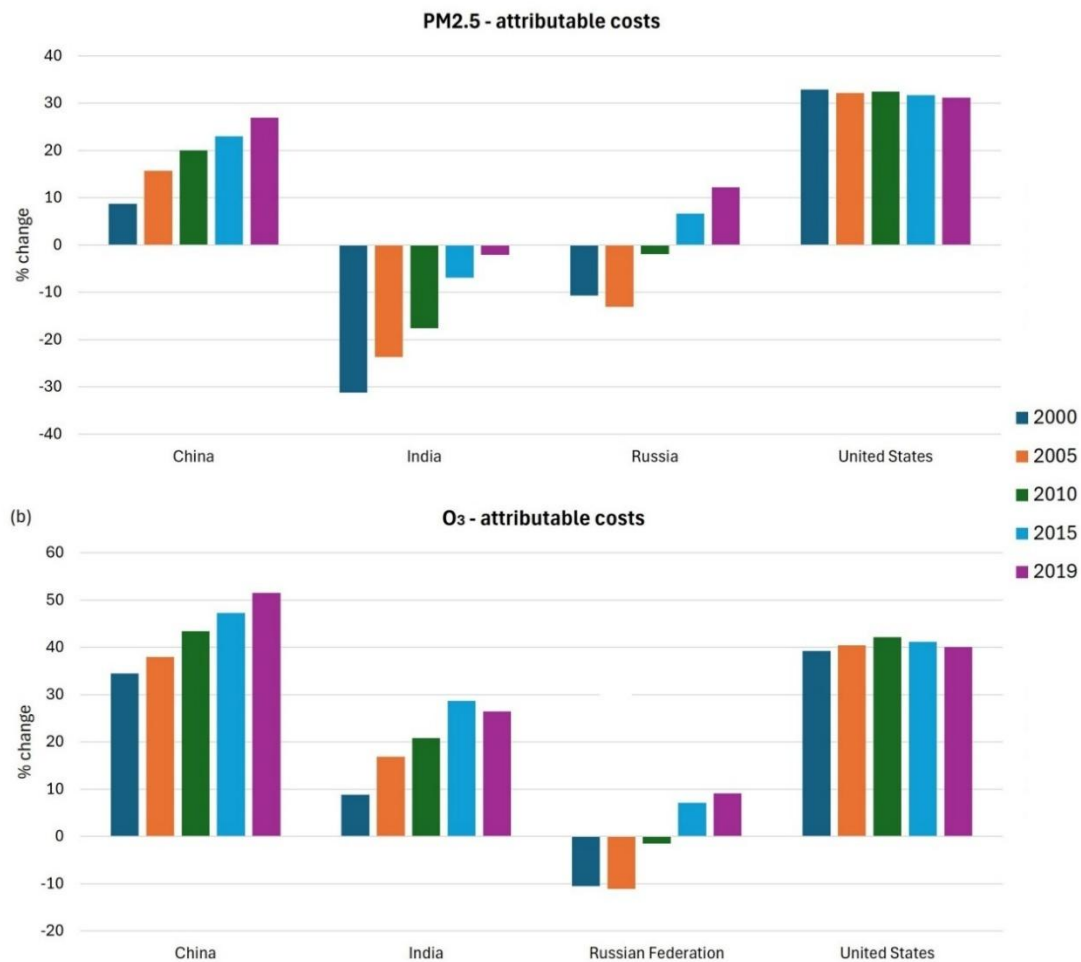


Figure 5. Percentage difference between cost estimates derived from VSL–mortality and VOLY–YLL for PM_{2.5} (panel a) and O₃ (panel b), displayed for the four highest economic burden countries in the sample.

The economic burden estimates associated with air pollution obtained in this study are generally higher than those reported in the literature that employed either mortality or YLL. Our estimates are between 1 and 6.4 times higher than those reported in the literature (Deryugina et al., 2019; Ginsberg et al., 2016; Hanigan et al., 2021; Petrou et al., 2024). Such gap likely reflects differences in methodological assumptions, scope of analysis, and aggregation choices across studies.

5. Conclusions

This study provides country-level estimates of the economic costs of mortality attributable to PM_{2.5} and O₃ for 108 countries, covering about 86% of the global population (in 2019) during the first two decades of this century. The approach accounts for cross-country heterogeneity in economic structures, demographic profiles, healthcare access, and wider socio-economic conditions, which leads to more meaningful comparisons across income groups and regions compared to previous work.

Economic costs are calculated using two complementary methods: (i) VSL multiplied by mortality; and (ii) VOLY multiplied by years of life lost. In this study, VSL, VOLY, mortality, and YLL are exclusively attributable to air pollution (Ciarlantini et al., 2025).

Overall, estimates derived from the VSL–mortality approach exceed those from VOLY–YLL, yet cross-country patterns and rankings are consistent. Across 2000–2019, the largest economic costs fall on China, India, and the United States. Although there were improvements in reducing emissions during the two decades examined, particularly in the United States and to a lesser extent in China, the number of individual exposed to medium-high pollution remained high because these are the world’s three most populous countries. Despite its medium-low pollution levels, Russia also presents high air pollution-attributable costs due to its large population. Moreover, O₃-attributable costs are roughly 98–99% lower than PM_{2.5} costs, consistent with the lower O₃-attributable mortality and YLL compared to PM_{2.5}.

Several choices were necessary to construct a consistent, globally scaled dataset, and alternative assumptions could have yielded different results. VOLY values are derived from VSL using a 3% discount rate; using different rates would

have changed the resulting estimates. Some explanatory variables required temporal and spatial interpolation to fill gaps for certain countries and years in order to achieve broad coverage, which adds further uncertainty. Temporal interpolation can smooth over real, abrupt shifts (e.g. policy changes or shocks), while spatial interpolation from similar neighbors can carry over country-specific idiosyncrasies and regional measurement biases. These issues are most pronounced for Africa and the Arabian Peninsula, where gaps are larger; results for these areas should therefore be interpreted with extra caution.

The successful application of our methodology in this study opens the door for application in other contexts and different purposes. Scenario-based projections would help policymakers assessing the consequences of different policy choices and allocate resources more efficiently. The framework can also be extended to additional pollutants to provide a more comprehensive picture of air-quality-related economic costs.

Monetising premature mortality and years of life lost attributable to PM_{2.5} and O₃ puts the scale of the problem in economic perspective. On this basis, PM_{2.5}- and O₃-attributable costs amount to about 5% of world GDP when valued mortality and 4% when valued years of life lost (PPP, 2019). By setting the costs of inaction alongside the benefits of cleaner air, these estimates can guide timely and cost-effective air-quality management. Reducing air pollution is both a public health need and a long-term economic investment: early action delivers immediate health gains, while yielding enduring welfare benefits across countries.

Supplementary material

Table S1. Number of countries (and respective % share by continent) in the dataset of unit costs (VSL and VOLY).

Continent	n. of countries	% of countries
Africa	16	15%
Asia	29	25%
Europe	40	37%
Oceania	4	4%
North America	12	11%
South America	7	6%
Total	108	100%

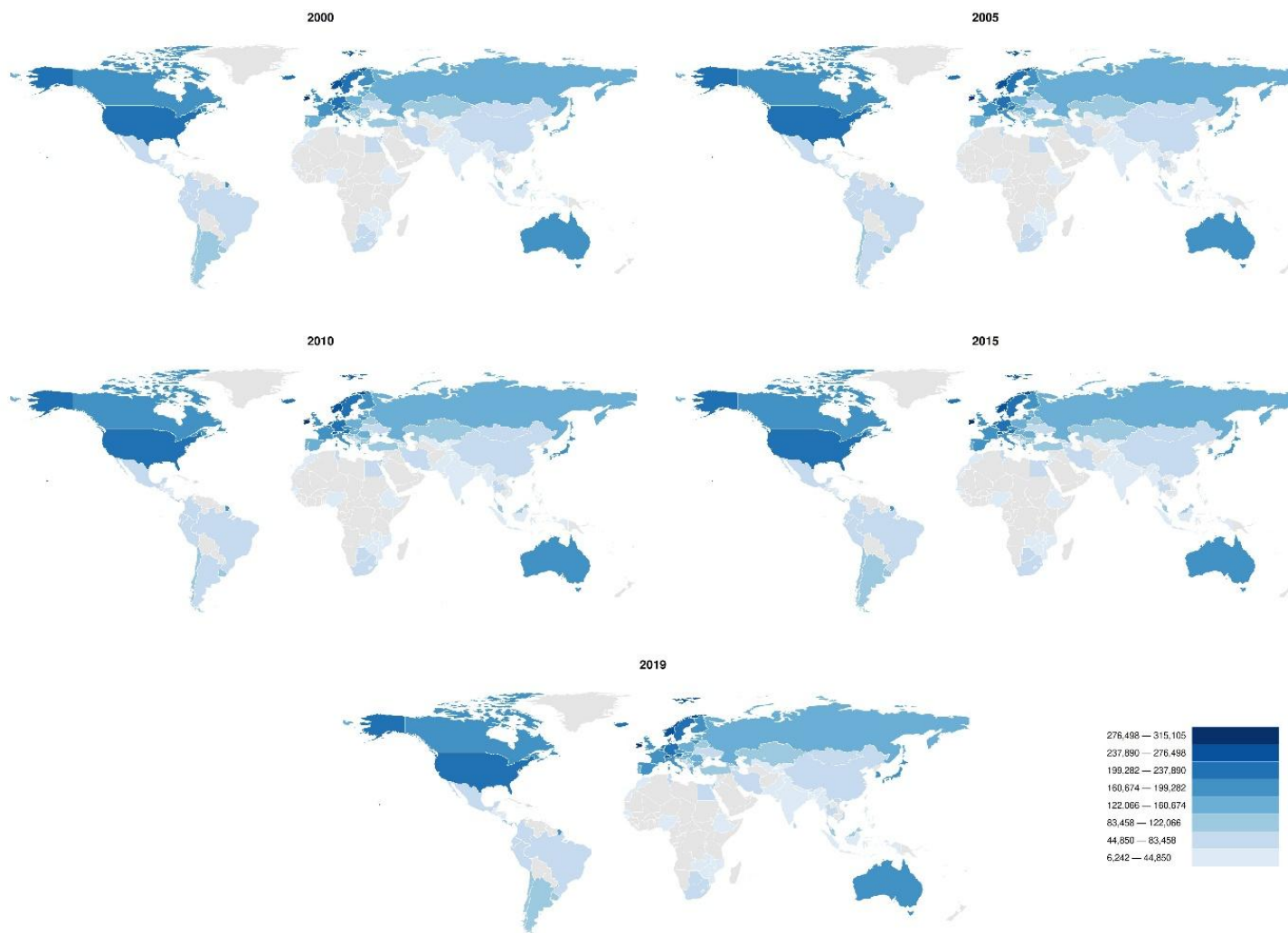


Figure S1. VOLY values by country in the first two decades of the XXI century (from 2000 to 2019).

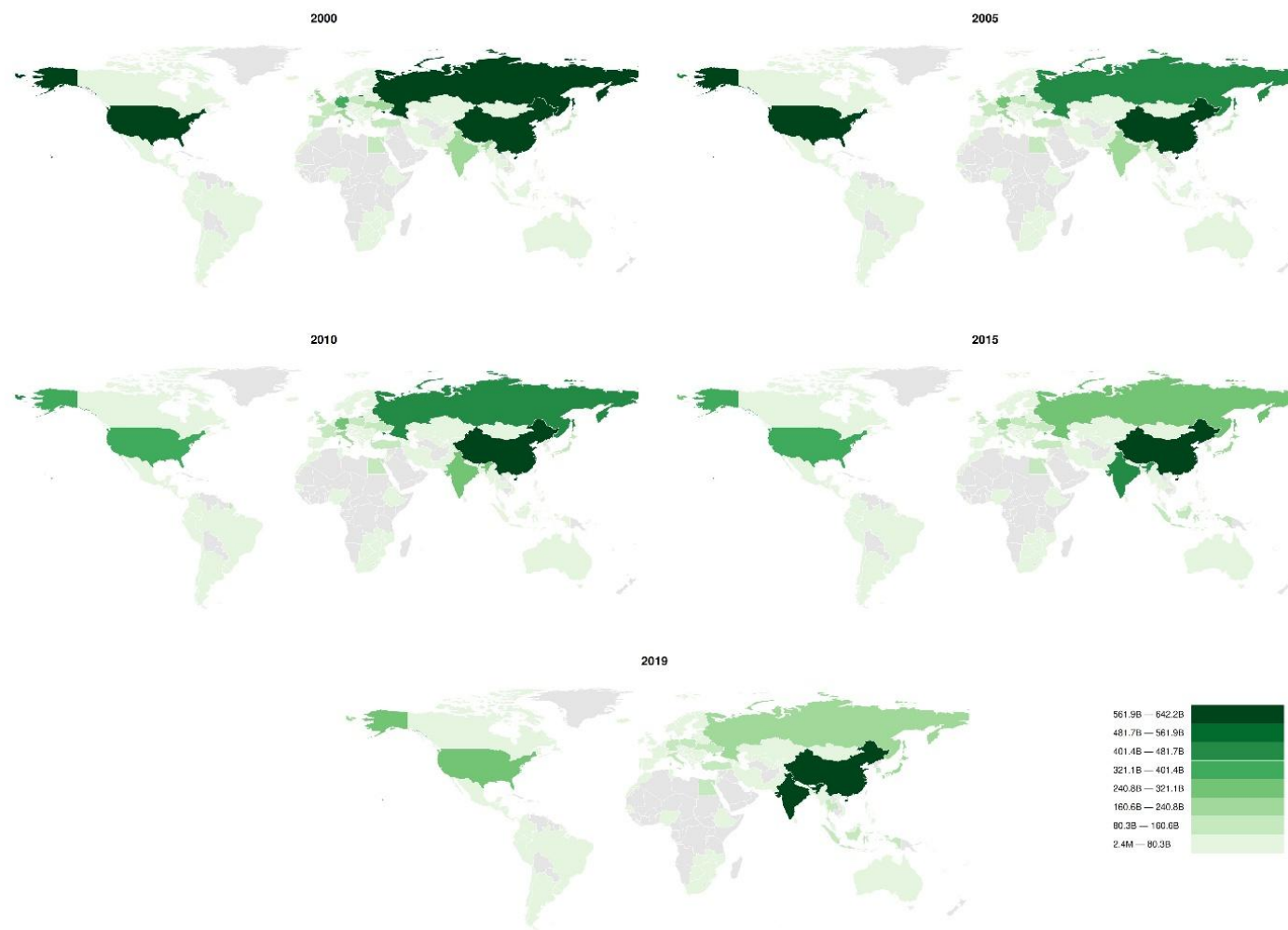


Figure S2. PM_{2.5} air pollution costs in IS\$ (mortality) by country in the first two decades of the XXI century (from 2000 to 2019)

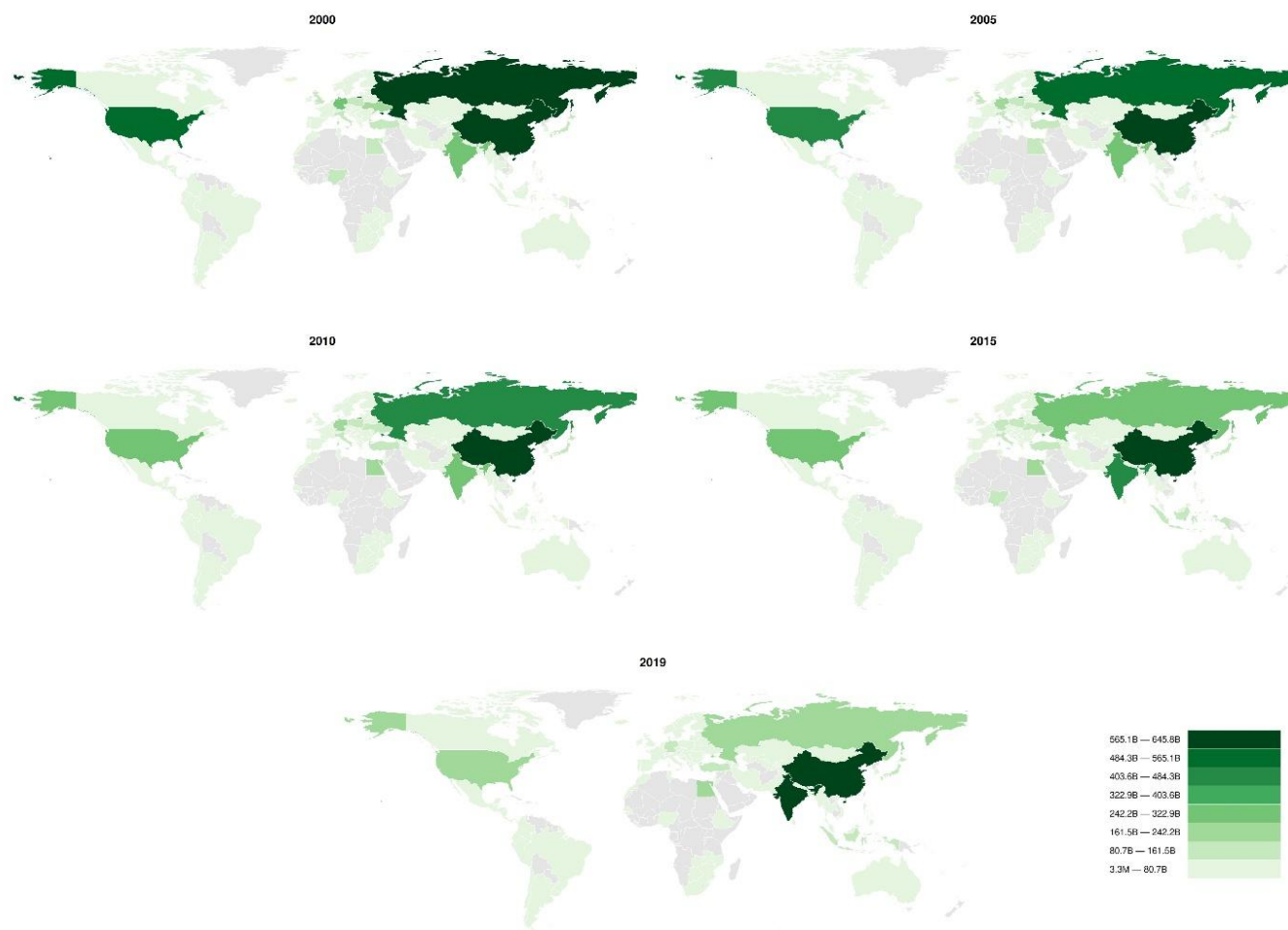


Figure S3. PM_{2.5} air pollution costs in I\$ (YLL) by country in the first two decades of the XXI century (from 2000 to 2019).

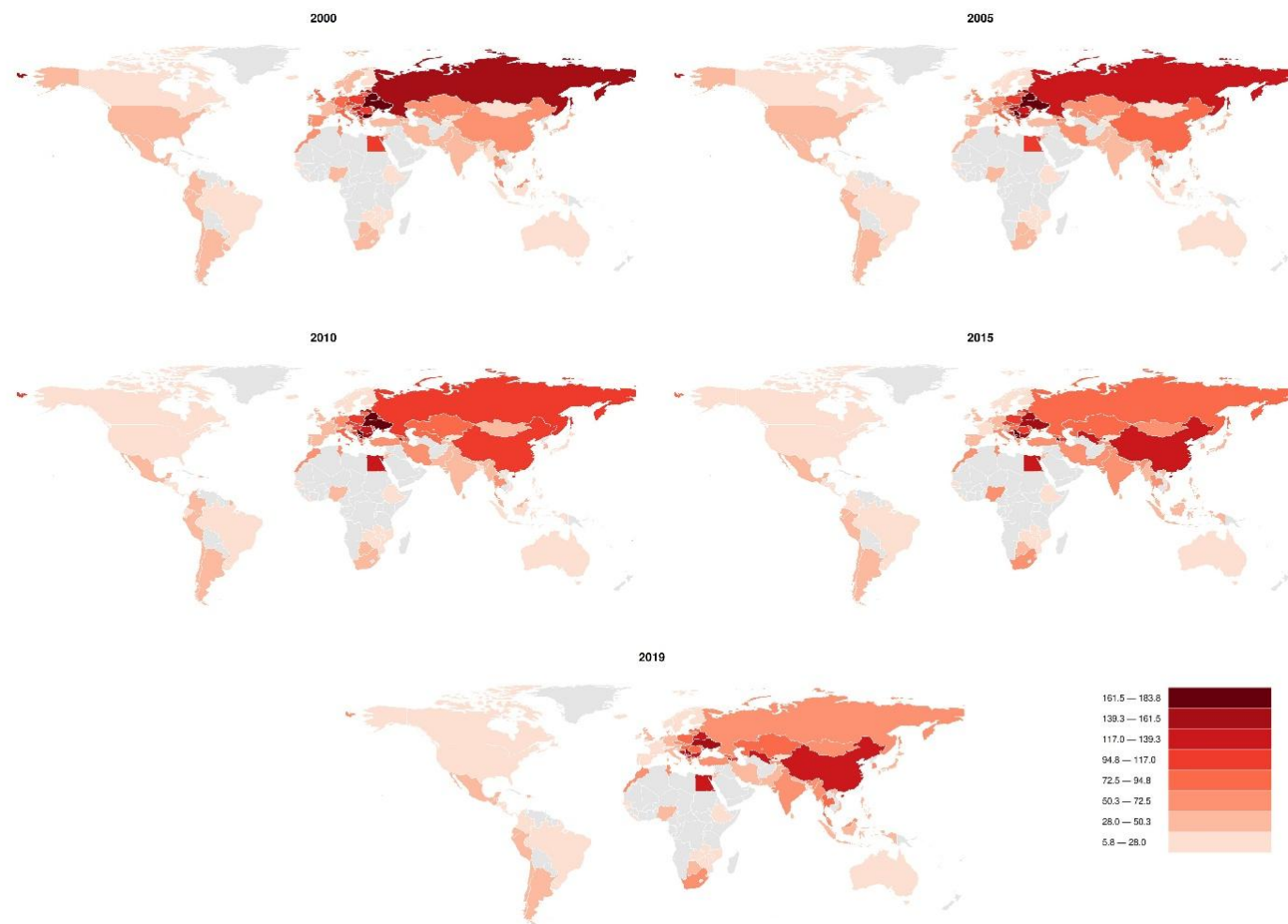


Figure S4. PM_{2.5}-attributable mortality rates every 100,000 people.

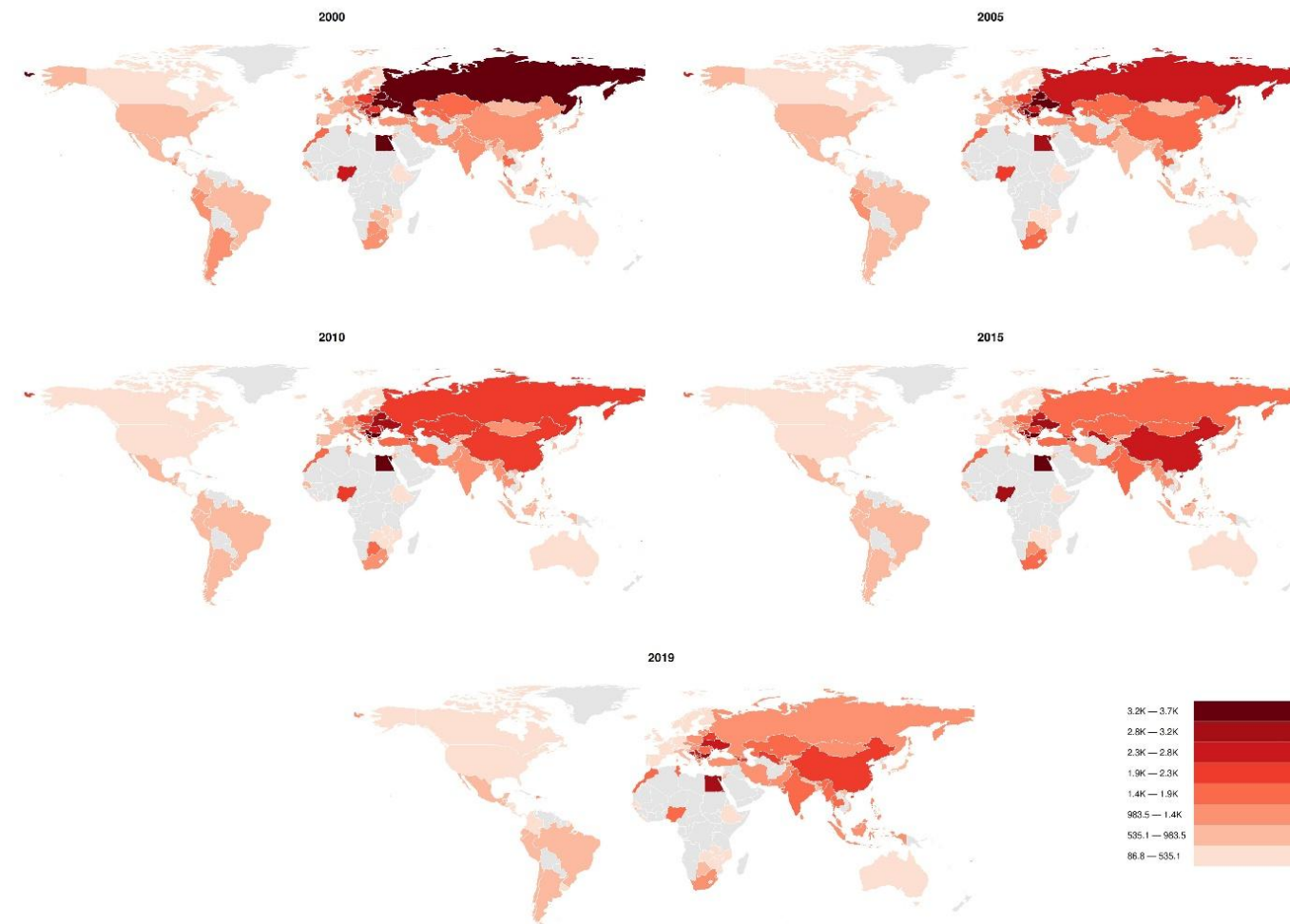


Figure S5. PM_{2.5}-attributable YLL rates every 100,000 people.

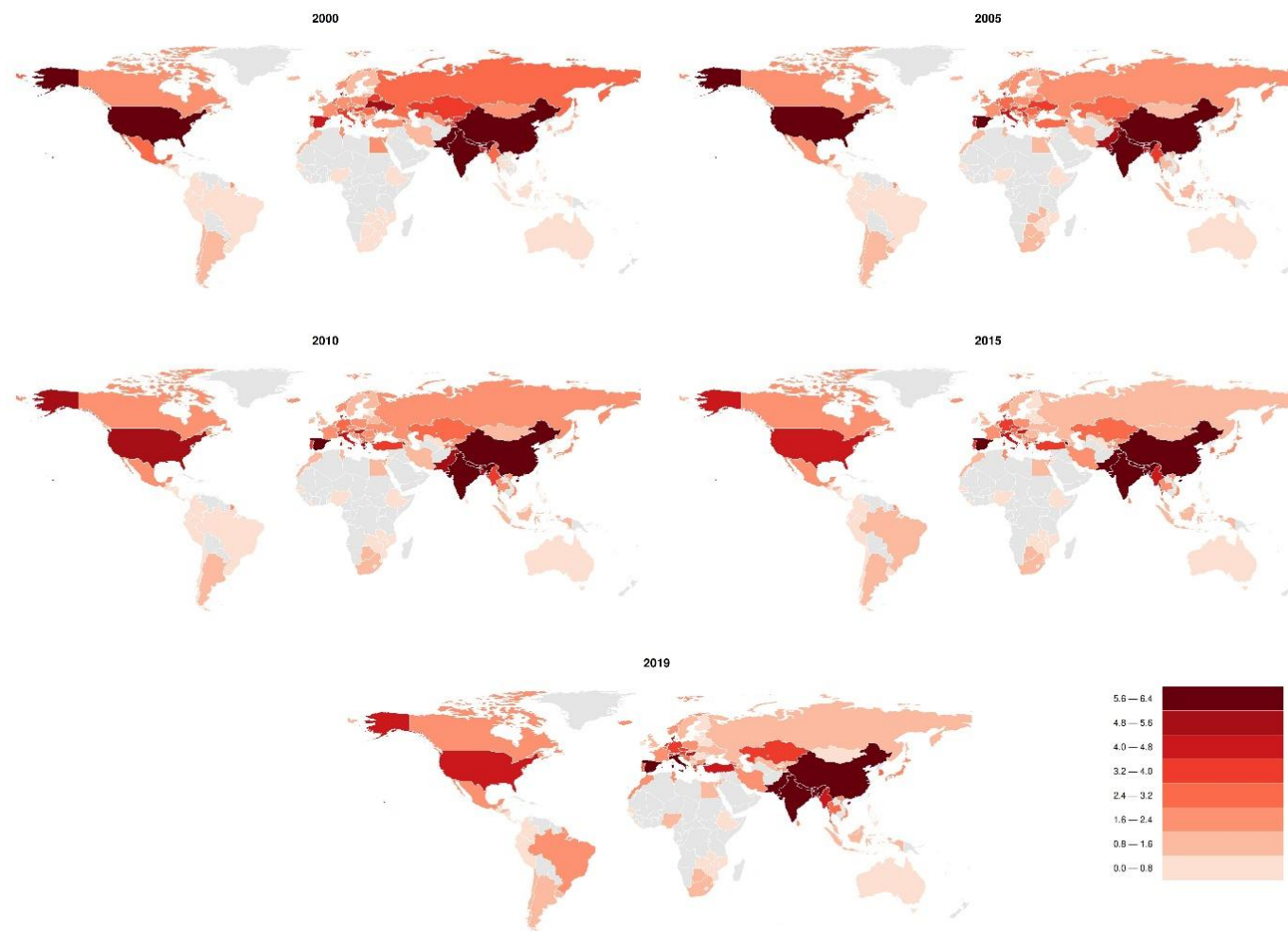


Figure S6. O₃-attributable mortality rates every 100,000 people.

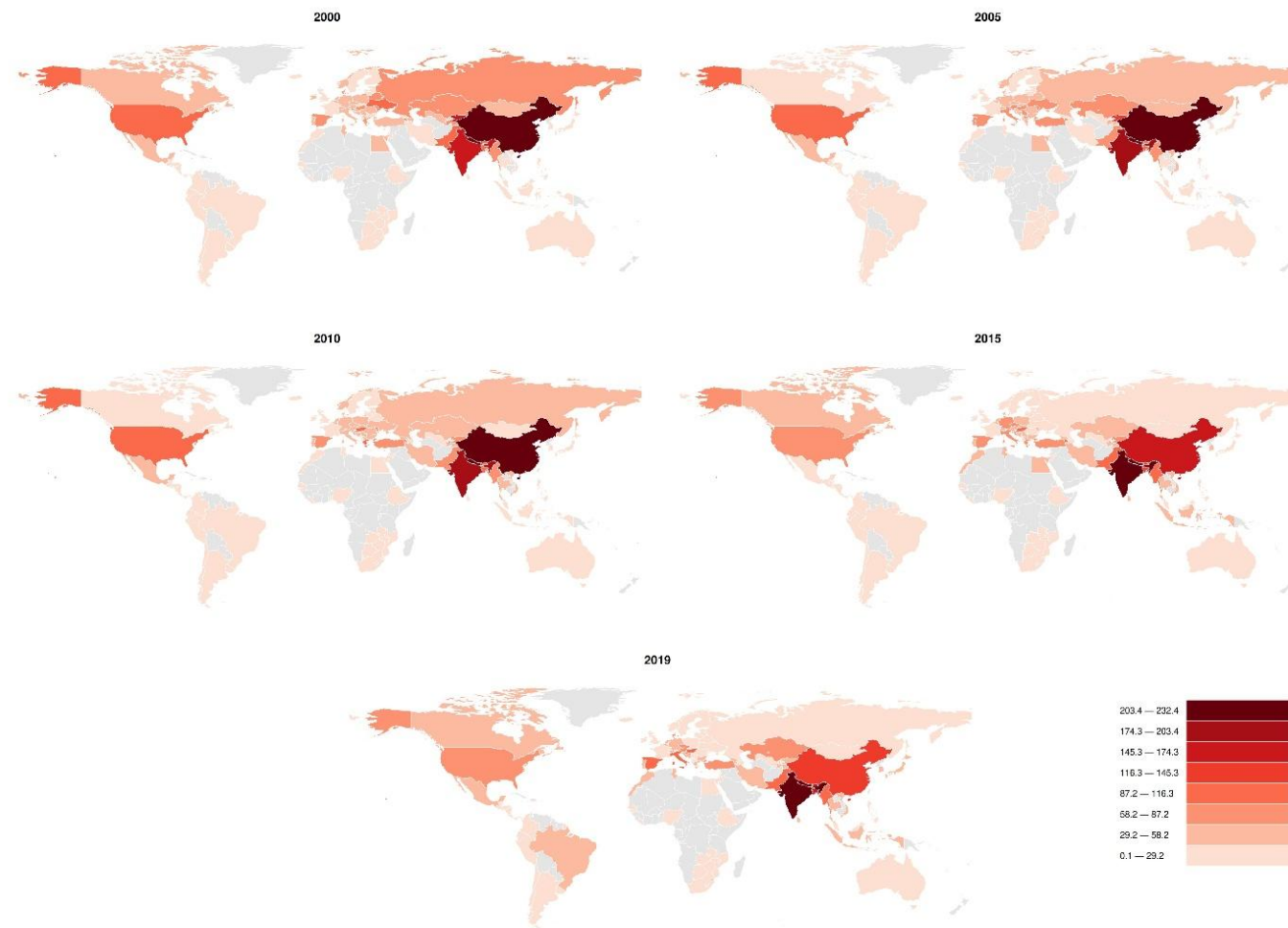


Figure S7. O₃-attributable YLL rates every 100,000 people.

Section C

Discussion and Conclusions

Ch. 6

Synthesis and Implications

This dissertation advances the understanding of how atmospheric dynamics shape air quality and how those changes translate into health-related economic costs. Taken together, the three articles offer a coherent line of argument, progressing from physical process to economic quantification: (i) meteorology and boundary-layer processes structure short-term and seasonal variability in particulate and gaseous pollutants; (ii) valuing premature mortality attributable to air pollution benefits from country-specific economic and social detail (which is beyond the sole GDP-transfer); and (iii) combining epidemiological evidence with context-sensitive valuation yields policy-relevant estimates of the economic burden across a large share of the world's population.

The first study, focusing on the complex atmospheric system in Türkiye, reveals that atmospheric conditions—temperature, relative humidity, wind speed, precipitation, and boundary-layer height—are systematically associated with PM₁₀ and SO₂ concentrations. The correlational structure captured by the GAM aligns with fundamental physical mechanisms: vertical mixing and horizontal transport disperse pollutants; wet deposition reduces particulate matter; and thermal inversions are associated with pollutant accumulation, particularly in the cold season. Crucially, the response to these drivers is highly modulated by seasonality and geography. Particulate responses to temperature and mixing differ between cold and warm periods, while SO₂ responses do not show a clear seasonality as it generally declines with both temperature and higher ambient moisture. Projections for 2030 and 2050 under contrasting climate IPCC pathways, such as the strongly

mitigated RCP 4.5 and the extreme RCP 8.5, indicate meteorologically-linked reductions in PM_{10} in many Turkish climatic regions, alongside potential summertime increases in SO_2 . The results demonstrate that effective air-quality management requires explicit consideration of meteorological and climatic conditions alongside emissions control. The strong seasonal and regional modulation of pollutant responses implies that uniform national measures may be inefficient, supporting the adoption of geographically differentiated and season-specific strategies. The identification of stagnation events, shallow boundary layers, and wintertime inversions as key contributors to high concentrations provides a scientific basis for forecast-based early-warning systems and short-term interventions during high-risk episodes. Moreover, the projected differences in pollutant trajectories under alternative climate pathways highlight the importance of integrating air-quality objectives into climate-adaptation planning and reinforce the potential co-benefits of emissions mitigation for future exposure reduction.

The second study addresses a critical gap in the existing literature, by developing a global, air-pollution-specific VSL and VOLY database. An econometric model is created to explain cross-country variation in VSL, incorporating GDP alongside income inequality (GINI index), population size, and healthcare access. The results indicate that willingness to pay for mortality risk reduction rises with income, but exhibits higher elasticities in lower-income contexts, demonstrating the importance of disaggregating by income category. The derived VOLY database, created using a 3% discount rate and accounting for country-specific median population age and life expectancy, provides an alternative unit value where YLL are employed, rather than mortality. These tools enable consistent, country-level cost valuations for air pollution even where primary valuation studies are absent. This allows policymakers to design and prioritise air-quality interventions based on country-specific economic, demographic and health conditions, supporting more efficient and evidence-based resource allocation.

Building on the previous step, the third study applies this robust, context-sensitive econometric model to estimate the country-level economic costs of mortality attributable to $PM_{2.5}$ and O_3 for 108 countries over the period 2000–2019. Using both the VSL * mortality and VOLY * YLL approaches, consistent cross-country patterns emerge, with the highest totals concentrated in the largest, most populous economies (China, India, and the United States). The analysis confirms that O_3 -attributable costs are markedly lower than those for $PM_{2.5}$, reflecting the lower O_3 -related mortality and YLL. Expressed relative to the world output, the

burden is substantial: it accounts for approximately 4–5% of global GDP, making the costs of inaction economically significant, and providing a clear rationale for timely air-quality management. Framing health damages in monetary terms clarifies the scale of benefits available from targeted action, promoting the view of emission reduction as a critical economic investment for the future. These findings provide policymakers with evidence to prioritise interventions, integrate health-damage valuations into development and climate strategies, and align short-term air-quality measures with long-term economic and environmental goals.

Viewed as a whole, the dissertation connects atmospheric process signals detected in monitoring data to valuation instruments which accounts for socio-economic heterogeneity, and finally to comparative cost estimates worldwide. This structure supports evidence-based prioritisation: interventions that reduce stagnant conditions and emissions during high-risk periods, paired with policies informed by country-specific unit values, can yield sizeable and immediate welfare gains while aligning with longer-term climate objectives. By linking environmental, health, and economic evidence, it provides a practical framework for policymakers to allocate resources efficiently and design strategies that maximise both societal and environmental benefits.

6.1 Limitations

Some methodological and conceptual limitations should be recognised across the three studies.

In the atmospheric analysis, the strong intrinsic interdependence between meteorological parameters makes the task of isolating the effects of individual variables highly complex. The statistical modelling approach (GAM) may be reductionist when applied to highly non-linear, multi-scale atmospheric systems; while the correlations observed are consistent with physical mechanisms, they should not be read as direct causal effects. External validation of these statistical findings against process-based chemical transport models remains limited. Additionally, while the GAM may account for major atmospheric influences, emission sources also shape pollutant concentrations. These sources are beyond the scope of the current research, although atmospheric variables and pollution sources are likely interrelated. Specifically, without these sources, PM₁₀ and SO₂ concentrations would likely be lower. Conversely, if source emissions remained

constant, atmospheric variables would account for all variability, since it would be only a matter of concentration diffusion. Consequently, the analysis underscores the important interaction between the timing and intensity of emissions from various sources and the influence of atmospheric conditions on their dispersion.

Additional temporal and spatial limitations should be acknowledged. The five-year analysis period may not capture long-term trends or extreme events that occur with lower frequency. Moreover, the uneven spatial distribution of monitoring stations, particularly in rural and complex terrain areas, limits comprehensive coverage and representativeness. Furthermore, while the focus is on PM₁₀ and SO₂, other pollutants such as PM_{2.5}, NO₂, and O₃ may exhibit different relationships with atmospheric conditions. The increasing role of climate change may alter circulation, boundary-layer dynamics, and precipitation regimes, potentially affecting future pollution patterns and the transferability of the estimates.

For the development of the econometric model, and for the economic valuation, key assumptions fundamentally influence the resulting estimates and their cross-country comparability. For example, the estimation of VOLY from VSL is directly dependent on the choice of the discount rate: alternative rates would yield different derived values. Currency conversion, PPP adjustments, income classification, and the income elasticity used for benefit transfer also affect cross-country comparability. Owing to data availability, only PM_{2.5}- and O₃-attributable costs are calculated. This differs from the atmospheric analysis, which includes SO₂ and PM₁₀. Although using an identical pollutant set throughout would have improved internal consistency, data completeness and comparability were prioritised.

To ensure broad geographical and temporal coverage, some socio-economic and health variables required temporal and spatial interpolation to fill gaps by country and year, which introduce additional uncertainty. Temporal interpolation can smooth over abrupt, policy-driven or shock-related changes, while spatial interpolation may impute country-specific idiosyncrasies and regional measurement biases. These issues are most pronounced for Africa and the Arabian Peninsula, where data gaps are larger, and results should therefore be interpreted with particular caution.

Further limitations arise from VSL elicitation and WTP methods. Stated-preference evidence can be affected by hypothetical bias, scope insensitivity, the framing of small risks, and sample-selection issues (Alberini, 2005). Revealed-preference estimates, instead, often reflect specific labour-market settings that do

not generalise. More broadly, valuing small risk reductions is intrinsically difficult: respondents are not used to work with probabilities, and survey design (or inadequate risk communication) can yield poor response quality, including completely random answers to the payment questions or protest payments. In addition, benefit transfer propagates any errors present in the original value estimates (Johnston et al., 2015). Beyond these imported errors (called measurement errors), transfers also face generalisation errors arising from the transfer process itself (e.g. mismatched contexts or scaling). Although accuracy assessments often emphasise generalisation error—on the assumption that original research is unbiased, or that biased studies have been eliminated through quality screening—both error sources should be borne in mind when interpreting the valuation results.

6.2 Future Research Directions

Future work can address these constraints and strengthen the policy relevance of the findings. To deepen understanding of atmospheric processes, research should incorporate direct vertical profiling (e.g. radiosondes) to characterise mixing regimes and validate boundary-layer interpretations. Given the interdependence of meteorological variables, advanced statistical and machine-learning methods can help isolate variable-specific effects. Robustness should be assessed by comparing data-driven estimates with process-based chemical transport models and with source-apportionment studies. Longer-term analyses integrating high-resolution meteorological and satellite data, expanding the scope to include additional pollutants, and enhanced statistical models that incorporate emission inventories and land-use information would improve source attribution.

From an economic perspective, the valuation framework can be broadened to include non-fatal outcomes (morbidity), which currently lack a single, standardised economic metric, to capture total health costs more fully. Costing should also be expanded to additional pollutants and, where data permit, downscaled to sub-national levels, especially in contexts with scarce data or missing data. The econometric model could also be applied for future plausible economic and demographic pathways, integrating different IPCC scenarios trajectories of emissions, population change, and prospective improvements in healthcare access (this work is already in progress by the authors and myself).

References

1. Abelson, P., 2003. The Value of Life and Health for Public Policy. *Economic Record*, 79 (Special Issue). <https://doi.org/10.1111/1475-4932.00087>.
2. Abelson, P., 2008. Establishing a Monetary Value for Lives Saved: Issues and Controversies. Working papers in cost-benefit analysis. Office of Best Practice Regulation Department of Finance and Deregulation.
3. Alberini, A., 2005. What Is a Life Worth? Robustness of VSL Values from Contingent Valuation Surveys. *Risk Analysis*, 25(4), 783–800. <https://doi.org/10.1111/j.1539-6924.2005.00646.x>.
4. Alberini, A., Ščasný, M., 2011. Context and the VSL: Evidence from a Stated Preference Study in Italy and the Czech Republic. *Environmental and Resource Economics*, 49, 511–538. <https://doi.org/10.1007/s10640-010-9444-8>.
5. Almeida, S. M., Manousakas, M., Diapouli, E., Kertesz, Z., Samek, L., Hristova, E., Šega, K., Alvarez, R. P., Belis, C. A., & Eleftheriadis, K., 2020. Ambient particulate matter source apportionment using receptor modelling in European and Central Asia urban areas. *Environmental Pollution*, 266, 115199. <https://doi.org/10.1016/j.envpol.2020.115199>.
6. Ananthapavan, J., Moodie, M., Milat, A. J., & Carter, R., 2021. Systematic Review to Update ‘Value of a Statistical Life’ Estimates for Australia. *International Journal of Environmental Research and Public Health*, 18(11), 6168. <https://doi.org/10.3390/ijerph18116168>.
7. Andersen, M.S., 2017. Co-benefits of climate mitigation: Counting statistical lives or life-years? *Ecological Indicators*, 79, 11–18. <https://doi.org/10.1016/j.ecolind.2017.03.051>.
8. Andersen, Z. J., Badyda, A., Tzivian, L., Dzhambov, A. M., Paunovic, K., Savic, S., Jacquemin, B., & Dragic, N., 2025. Air pollution inequalities in Europe: A deeper understating of challenges in Eastern Europe and pathways forward towards closing the gap between East and West. *Environmental Epidemiology*, 9(3), e383. <https://doi.org/10.1097/EE9.0000000000000383>.
9. Andersson, H., Ouyard, B., 2023. Priming and the value of a statistical life: A cross country comparison. *Journal of Behavioral and Experimental Economics*, 104, 102013. <https://doi.org/10.1016/j.socec.2023.102013>.
10. Anenberg, S.C., 2023. Nitrogen Dioxide Surface-Level Annual Average Concentrations. <https://doi.org/10.5067/J99FI2U38YRN>.

11. Antenzio, M. L., Caissutti, C., Caporusso, F. M., Marzi, D., & Brunetti, P., 2024. Urban Air Pollution and Plant Tolerance: Omics Responses to Ozone, Nitrogen Oxides, and Particulate Matter. *Plants*, 13(15), 2027. <https://doi.org/10.3390/plants13152027>.
12. Aykaç N, Yasin Y., 2021. Persistent ambient air pollution in Turkey: A 4-year analysis, *Turkish Thoracic Journal.*, 22, 482-488. <https://doi.org/10.5152/TurkThoracJ.2021.21121>.
13. Baumgardner, D., Varela, S., Escobedo, F. J., Chacalo, A., & Ochoa, C., 2012. The role of a peri-urban forest on air quality improvement in the Mexico City megalopolis. *Environmental Pollution*, 163, 174–183. <https://doi.org/10.1016/j.envpol.2011.12.016>.
14. Bayat, R., Ashrafi, K., Shafiepour Motlagh, M., Hassanvand, M.S., Daroudi, R., Fink, G., Künzli, N., 2019. Health impact and related cost of ambient air pollution in Tehran. *Environmental Research*, 176, 108547. <https://doi.org/10.1016/j.envres.2019.108547>.
15. Becerra-Pérez, L.A., Ramos-Álvarez, R.A., DelaCruz, J.J., García-Páez, B., Páez-Osuna, F., Cedeño-Laurent, J.G., Boldo, E., 2021. An Economic Analysis of the Environmental Impact of PM_{2.5} Exposure on Health Status in Three Northwestern Mexican Cities. *Sustainability*, 13, 10782. <https://doi.org/10.3390/su131910782>.
16. Belis, C. A., Matkovic, V., Ballocci, M., Jevtic, M., Millo, G., Mata, E., & Van Dingenen, R., 2023. Assessment of health impacts and costs attributable to air pollution in urban areas using two different approaches. A case study in the Western Balkans. *Environment International*, 182, 108347. <https://doi.org/10.1016/j.envint.2023.108347>.
17. Belis, C. A., Pisoni, E., Degraeuwe, B., Peduzzi, E., Thunis, P., Monforti-Ferrario, F., & Guizzardi, D., 2019. Urban pollution in the Danube and Western Balkans regions: The impact of major PM_{2.5} sources. *Environment International*, 133, 105158. <https://doi.org/10.1016/j.envint.2019.105158>.
18. Belis, C. A., Van Dingenen, R., Klimont, Z., & Dentener, F., 2022. Scenario analysis of PM_{2.5} and ozone impacts on health, crops and climate with TM5-FASST: A case study in the Western Balkans. *Journal of Environmental Management*, 319, 115738. <https://doi.org/10.1016/j.jenvman.2022.115738>.
19. Belis, C.A., Pernigotti, D., Pirovano, G., Favez, O., Jaffrezo, J.L., Kuenen, J., Denier Van Der Gon, H., Reizer, M., Riffault, V., Alleman, L.Y., Almeida, M., Amato, F., Angyal, A., Argyropoulos, G., Bande, S., Beslic, I., Besombes, J.-L., Bove, M.C., Brotto, P., Calori, G., Cesari, D., Colombi, C., Contini, D., De Gennaro, G., Di Gilio, A., Diapouli, E., El Haddad, I., Elbern, H., Eleftheriadis,

- K., Ferreira, J., Vivanco, M.G., Gilardoni, S., Golly, B., Hellebust, S., Hopke, P.K., Izadmanesh, Y., Jorquera, H., Krajsek, K., Kranenburg, R., Lazzeri, P., Lenartz, F., Lucarelli, F., Maciejewska, K., Manders, A., Manousakas, M., Masiol, M., Mircea, M., Mooibroek, D., Nava, S., Oliveira, D., Paglione, M., Pandolfi, M., Perrone, M., Petralia, E., Pietrodangelo, A., Pillon, S., Pokorna, P., Prati, P., Salameh, D., Samara, C., Samek, L., Saraga, D., Sauvage, S., Schaap, M., Scotto, F., Sega, K., Siour, G., Tauler, R., Valli, G., Vecchi, R., Venturini, E., Vestenius, M., Waked, A., Yubero, E., 2020. Evaluation of receptor and chemical transport models for PM10 source apportionment, *Atmospheric Environment: X*, 5, 100053. <https://doi.org/10.1016/j.aeaoa.2019.100053>.
20. Belis, C.A., Pirovano, G., Villani, M.G., Calori, G., Pepe, N., Putaud, J.P., 2021. Comparison of source apportionment approaches and analysis of non-linearity in a real case model application. *Geoscientific Model Development*, 14, 4731–4750. <https://doi.org/10.5194/gmd-14-4731-2021>.
21. Bellavance, F., Dionne, G., Lebeau, M., 2009. The value of a statistical life: A meta-analysis with a mixed effects regression model. *Journal of Health Economics*, 28, 444–464. <https://doi.org/10.1016/j.jhealeco.2008.10.013>.
22. Berger, V.W., Zhou, Y., 2014. Kolmogorov–Smirnov Test: Overview. *Wiley StatsRef: Statistics Reference Online*, John Wiley & Sons Ltd. <https://doi.org/10.1002/9781118445112.stat06558>.
23. Bickel, P., Europäische Kommission, 2005. ExternE: externalities of energy: methodology 2005 update, Sustainable energy systems. Office for Official Publications of the European Communities, Luxembourg.
24. Borgonovo, E., 2007. A new uncertainty importance measure. *Reliability Engineering & System Safety*, 92, 771–784. <https://doi.org/10.1016/j.res.2006.04.015>.
25. Bozkurt, Z., Üzmez, Ö. Ö., Döğeroğlu, T., Artun, G., and Gaga, E. O., 2018. Atmospheric concentrations of SO₂, NO₂, ozone and VOCs in Düzce, Turkey using passive air samplers: Sources, spatial and seasonal variations and health risk estimation. *Atmospheric Pollution Research*, 9, 1146–1156. <https://doi.org/10.1016/j.apr.2018.05.001>.
26. Brauer, M., Roth, G. A., Aravkin, A. Y., Zheng, P., Abate, K. H., Abate, Y. H., Abbafati, C., Abbasgholizadeh, R., Abbasi, M. A., Abbasian, M., Abbasifard, M., Abbasi-Kangevari, M., Abd ElHafeez, S., Abd-Elsalam, S., Abdi, P., Abdollahi, M., Abdoun, M., Abdulah, D. M., Abdullahi, A., Gakidou, E., 2024. Global burden and strength of evidence for 88 risk factors in 204 countries and 811 subnational locations, 1990–2021: A systematic analysis for the Global

- Burden of Disease Study 2021. *The Lancet*, 403(10440), 2162–2203. [https://doi.org/10.1016/S0140-6736\(24\)00933-4](https://doi.org/10.1016/S0140-6736(24)00933-4).
27. Burnett, R., & Cohen, A., 2020. Relative Risk Functions for Estimating Excess Mortality Attributable to Outdoor PM_{2.5} Air Pollution: Evolution and State-of-the-Art. *Atmosphere*, 11(6), 589. <https://doi.org/10.3390/atmos11060589>.
 28. Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C. A., Apte, J. S., Brauer, M., Cohen, A., Weichenthal, S., Coggins, J., Di, Q., Brunekreef, B., Frostad, J., Lim, S. S., Kan, H., Walker, K. D., Thurston, G. D., Hayes, R. B., Spadaro, J. V., 2018. Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proceedings of the National Academy of Sciences*, 115(38), 9592–9597. <https://doi.org/10.1073/pnas.1803222115>.
 29. Cekim, H. O., 2020. Forecasting PM₁₀ concentrations using time series models: a case of the most polluted cities in Turkey. *Environmental Science and Pollution Research*, 27, 25612–25624. <https://doi.org/10.1007/s11356-020-08164-x>.
 30. Çelik, M. B., Kadi, I., 2007. The Relation Between Meteorological Factors and Pollutants Concentrations in Karabük City, G.U. *Journal of Science*, 20, 87-95.
 31. Chen, F., Yamashita, K., Kurokawa, J., Klimont, Z., 2015. Cost–Benefit Analysis of Reducing Premature Mortality Caused by Exposure to Ozone and PM_{2.5} in East Asia in 2020. *Water, Air, & Soil Pollution*, 226, 108. <https://doi.org/10.1007/s11270-015-2316-7>.
 32. Chilton, S., Covey, J., Jones-Lee, M., Loomes, G., Metcalf, H., 2004. Valuation of health benefits associated with reductions in air pollution. Final report. Department for Environment, Food and Rural Affairs, London.
 33. Ciarlantini, S., Frontuto, V., Pezzoli, A., Gavros, A., & Belis, C. A., 2025. Econometric model derived from meta-analysis to estimate VSL and VOLY associated to air pollution at a global level. *Journal of Environmental Management*, 379, 124824. <https://doi.org/10.1016/j.jenvman.2025.124824>.
 34. CMCC, 2024. Scenari climatici per l'Italia: <https://www.cmcc.it/it/scenari-climatici-per-litalia>, last access: 17 March 2025.
 35. Cohen, A. J., Brauer, M., Burnett, R., Anderson, H. R., Frostad, J., Estep, K., Balakrishnan, K., Brunekreef, B., Dandona, L., Dandona, R., Feigin, V., Freedman, G., Hubbell, B., Jobling, A., Kan, H., Knibbs, L., Liu, Y., Martin, R., Morawska, L., Forouzanfar, M. H., 2017. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: An analysis of data from the Global Burden of Diseases Study 2015. *The Lancet*, 389(10082), 1907–1918. [https://doi.org/10.1016/S0140-6736\(17\)30505-6](https://doi.org/10.1016/S0140-6736(17)30505-6).

36. Colston, J. M., Ahmed, T., Mahopo, C., Kang, G., Kosek, M., De Sousa Junior, F., Shrestha, P. S., Svensen, E., Turab, A., & Zaitchik, B., 2018. Evaluating meteorological data from weather stations, and from satellites and global models for a multi-site epidemiological study. *Environmental Research*, 165, 91–109. <https://doi.org/10.1016/j.envres.2018.02.027>.
37. Conibear, L., Butt, E. W., Knotte, C., Spracklen, D. V., & Arnold, S. R., 2018. Current and Future Disease Burden From Ambient Ozone Exposure in India. *GeoHealth*, 2(11), 334–355. <https://doi.org/10.1029/2018GH000168>.
38. Copernicus, 2024. Climate Data Store: <https://cds.climate.copernicus.eu/datasets?q=projections>, last access: 28 February 2025.
39. Craven, P., Wahba, G., 1978. Smoothing noisy data with spline functions, *Numerische Mathematik*, 31, 377–403. <https://doi.org/10.1007/BF01404567>.
40. Crippa, M., Janssens-Maenhout, G., Guizzardi, D., Van Dingenen, R., & Dentener, F., 2019. Contribution and uncertainty of sectorial and regional emissions to regional and global PM_{2.5} health impacts. *Atmospheric Chemistry and Physics*, 19(7), 5165–5186. <https://doi.org/10.5194/acp-19-5165-2019>.
41. Cropper, M.L., Sahin, S., 2009. Valuing Mortality And Morbidity In The Context Of Disaster Risks, Policy Research Working Papers. World Bank. <https://doi.org/10.1596/1813-9450-4832>.
42. Cuhadaroglu, B. and Demirci, E., 1997. Influence of some meteorological factors on air pollution in Trabzon city. *Energy and Buildings*, 25, 179–184. [https://doi.org/10.1016/S0378-7788\(96\)00992-9](https://doi.org/10.1016/S0378-7788(96)00992-9).
43. Cui Hong, Ma Ruiqing, and Gao Feng, 2018. Relationship between meteorological factors and diffusion of atmospheric pollutants. *Chemical Engineering Transactions*, 71, 1417–1422. <https://doi.org/10.3303/CET1871237>.
44. De Lima, M., 2020. The value of a statistical life in Mexico. *Journal of Environmental Economics and Policy*, 9, 140–166. <https://doi.org/10.1080/21606544.2019.1617196>.
45. Dechezleprêtre, A., Rivers, N., Stadler, B., 2019. The economic cost of air pollution: evidence from Europe economics department working papers No. 1584, OECD.
46. DEFRA, UK Air, 2023. Site environment types: <https://uk-air.defra.gov.uk/networks/site-types>, last access: 13 November 2024.
47. Demir, M., Dindaroğlu, T., & Yılmaz, S., 2014. Effects of forest areas on air quality; Aras Basin and its environment. *Journal of Environmental Health Science and Engineering*, 12(1), 60. <https://doi.org/10.1186/2052-336X-12-60>.

48. Deniz, A., Toros, H., and Incecik, S., 2011. Spatial variations of climate indices in Turkey. *International Journal of Climatology*, 31, 394–403. <https://doi.org/10.1002/joc.2081>.
49. Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J., 2019. The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction. *The American Economic Review*, 109(12), 4178–4219. <https://doi.org/10.1257/aer.20180279>.
50. Desaiques, B., Ami, D., Bartczak, A., Braun-Kohlová, M., Chilton, S., Czajkowski, M., Farreras, V., Hunt, A., Hutchison, M., Jeanrenaud, C., Kaderjak, P., Máca, V., Markiewicz, O., Markowska, A., Metcalf, H., Navrud, S., Nielsen, J.S., Ortiz, R., Pellegrini, S., Rabl, A., Riera, R., Scasny, M., Stoeckel, M.-E., Szántó, R., Urban, J., 2011. Economic valuation of air pollution mortality: A 9-country contingent valuation survey of value of a life year (VOLY). *Ecological Indicators*, 11, 902–910. <https://doi.org/10.1016/j.ecolind.2010.12.006>.
51. Desaiques, B., Rabl, A., Ami, D., Boun My, K., Masson, S., Salomon, M.-A., & Santoni, L., 2007. Monetary Value of a Life Expectancy Gain due to Reduced Air Pollution: Lessons from a Contingent Valuation in France. *Revue d'économie Politique*, 117(5), 675–698. <https://doi.org/10.3917/redp.175.0675>.
52. Eatough, D.J., Caka, F.M., Farber, R.J., 1994. The Conversion of SO₂ to Sulfate in the Atmosphere. *Israel Journal of Chemistry*, 34, 301–314. <https://doi.org/10.1002/ijch.199400034>.
53. ECMWF, 2024. Climate Data Store: <https://cds.climate.copernicus.eu/>, last access: 13 November 2024.
54. EEA, 2021. Europe's air quality status 2021- update: <https://www.eea.europa.eu/publications/air-quality-in-europe-2021/air-quality-status-briefing-2021>, last access: 10 January 2024.
55. EEA, 2023(a). Burden of disease 2023: <https://www.eea.europa.eu/publications/harm-to-human-health-from-air-pollution/table-3>.
56. EEA, 2023(b). Europe's air quality status 2023: <https://www.eea.europa.eu/publications/europes-air-quality-status-2023/europes-air-quality-status2023>, last access: 22 August 2024.
57. EEA, 2024. <https://www.eea.europa.eu/en>, last access: 13 November 2024.
58. EEA, 2025. National Emission reduction Commitments Directive: <https://www.eea.europa.eu/en/topics/in-depth/air-pollution/necd>.
59. Elistia, E., Syahzuni, B.A., 2018. The correlation of the Human Development Index (HDI) towards economic growth (GDP per capita) in 10 Asean member

- countries. *JHSS*, 2, 40–46. <https://doi.org/10.33751/jhss.v2i2.949>.
60. Elminir, H. K., 2005. Dependence of urban air pollutants on meteorology. *Science of The Total Environment*, 350(1–3), 225–237. <https://doi.org/10.1016/j.scitotenv.2005.01.043>.
 61. EMEP/EEA, 2023. Air pollutant emission inventory guidebook: <https://www.eea.europa.eu/en/analysis/publications/emep-eea-guidebook-2023> last access: 02 October 2023.
 62. Enervis, 2021. The Future of Lignite in the Western Balkans. Scenarios for a 2040 Lignite Exit: <https://www.agora-energiewende.org/publications/the-future-of-lignite-in-the-western-balkans>.
 63. Environment Law No. 2872, 2022. <https://www.ecolex.org/details/legislation/environment-law-no-2872-lex-faoc007700/>, last access: 24 October 2025.
 64. EPA, 2024(a). Particulate Matter (PM) Basics: <https://www.epa.gov/pm-pollution/particulate-matter-pm-basics>, last access: 12 November 2024.
 65. EPA, 2024(b). Sulfur Dioxide Basics: <https://www.epa.gov/so2-pollution/sulfur-dioxide-basics>, last access: 12 November 2024.
 66. European Commission, 2023. Türkiye 2023 Report Accompanying the document Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. Communication on EU Enlargement policy, 696 final, Brussels.
 67. European Commission, Directorate-General for Regional and Urban Policy, 2021. Economic appraisal vademecum 2021–2027: General principles and sector applications. Publications Office of the European Union. <https://doi.org/10.2776/182302>.
 68. European Commission: Commission staff working document, 2024. Türkiye 2024 Report, 696, Brussels.
 69. European Parliament and Council, 2024. Directive (EU) 2024/2881 on ambient air quality and cleaner air for Europe, Official Journal of the European Union.
 70. EuroVoc—EUR-Lex: <https://eur-lex.europa.eu/browse/eurovoc.html?params=72%2C7226%2C2848>, last access: 16 September 2025.
 71. FAO, 2024. FAO in Türkiye, Türkiye at a glance: <https://www.fao.org/turkiye/fao-in-turkiye/turkey-at-a-glance/en/>, last access: 13 November 2024.
 72. Feng, X., Wei, S., & Wang, S., 2020. Temperature inversions in the atmospheric boundary layer and lower troposphere over the Sichuan Basin, China: Climatology and impacts on air pollution. *Science of The Total Environment*,

- 726, 138579. <https://doi.org/10.1016/j.scitotenv.2020.138579>.
73. Ferretti, F., Mariani, M., & Sarti, E., 2023. Physician density: Will we ever close the gap? *BMC Research Notes*, 16, 84. <https://doi.org/10.1186/s13104-023-06353-8>.
 74. Fiore, A. M., Naik, V., and Leibensperger, E. M., 2015. Air Quality and Climate Connections. *Journal of the Air & Waste Management Association*, 65, 645–685. <https://doi.org/10.1080/10962247.2015.1040526>.
 75. Friedrich, R., Rabl, A., Hirschberg, S., Desaiques, B., Markandya, A., De Nocker, L., 2004. New Elements for the Assessment of External Costs from Energy Technologies. Publishable Report to the European Commission, DG Research, Technological Development and Demonstration (RTD).
 76. Ginsberg, G. M., Kaliner, E., & Grotto, I., 2016. Mortality, hospital days and expenditures attributable to ambient air pollution from particulate matter in Israel. *Israel Journal of Health Policy Research*, 5, 51. <https://doi.org/10.1186/s13584-016-0110-7>.
 77. Golub, E., Klytchnikova, I., Martinez, S. G., Belausteguigoitia, J.C., 2014. Environmental Health Costs in Colombia. The Changes from 2002 to 2010. International Bank for Reconstruction and Development. World Bank, Washington DC.
 78. Gorai, A. K., Tuluri, F., Tchounwou, P. B., & Ambinakudige, S., 2015. Influence of local meteorology and NO₂ conditions on ground-level ozone concentrations in the eastern part of Texas, USA. *Air Quality, Atmosphere, & Health*, 8(1), 81–96. <https://doi.org/10.1007/s11869-014-0276-5>.
 79. Gov.UK, 2022. Air pollution: Applying All Our Health: <https://www.gov.uk/government/publications/air-pollution-applying-all-our-health/air-pollution-applying-all-our-health>.
 80. Gu, Y., Fang, T., & Yim, S. H. L., 2024. Source emission contributions to particulate matter and ozone, and their health impacts in Southeast Asia. *Environment International*, 186, 108578. <https://doi.org/10.1016/j.envint.2024.108578>.
 81. Gu, Y., Henze, D. K., Nawaz, M. O., Cao, H., & Wagner, U. J., 2023. Sources of PM_{2.5}-Associated Health Risks in Europe and Corresponding Emission-Induced Changes During 2005–2015. *GeoHealth*, 7(3), e2022GH000767. <https://doi.org/10.1029/2022GH000767>.
 82. Güneş, M., 2005. A Simple Evaluation of SO₂ and PM Data on Ambient Air Quality. *Energy Sources*, 27, 729-740. <https://doi.org/10.1080/00908310490450449>.
 83. Hammitt, J. K., 2000. Valuing Mortality Risk: Theory and Practice.

- Environmental Science & Technology*, 34(8), 1396–1400.
<https://doi.org/10.1021/es990733n>.
84. Hammitt, J.K., Robinson, L.A., 2011. The Income Elasticity of the Value per Statistical Life: Transferring Estimates between High and Low Income Populations. *Journal of Benefit-Cost Analysis*, 2, 1–29.
<https://doi.org/10.2202/2152-2812.1009>.
 85. Hammitt, J.K., Zhou, Y., 2006. The Economic Value of Air-Pollution-Related Health Risks in China: A Contingent Valuation Study. *Environmental and Resource Economics*, 33, 399–423. <https://doi.org/10.1007/s10640-005-3606-0>.
 86. Han, L., Zhou, W., Li, W., Meshesha, D. T., Li, L., and Zheng, M., 2015. Meteorological and urban landscape factors on severe air pollution in Beijing, *Journal of the Air & Waste Management Association*, 65, 782–787.
<https://doi.org/10.1080/10962247.2015.1007220>.
 87. Hanigan, I. C., Broome, R. A., Chaston, T. B., Cope, M., Dennekamp, M., Heyworth, J. S., Heathcote, K., Horsley, J. A., Jalaludin, B., Jegasothy, E., Johnston, F. H., Knibbs, L. D., Pereira, G., Vardoulakis, S., Vander Hoorn, S., & Morgan, G. G., 2021. Avoidable Mortality Attributable to Anthropogenic Fine Particulate Matter (PM_{2.5}) in Australia. *International Journal of Environmental Research and Public Health*, 18(1), 254.
<https://doi.org/10.3390/ijerph18010254>.
 88. Hao, Y., Zhao, M., Lu, Z., 2019. What is the health cost of haze pollution? Evidence from China. *Health Planning & Management*, 34, 1290–1303.
<https://doi.org/10.1002/hpm.2791>.
 89. Hastie, T., Tibshirani, R., 1986. Generalized Additive Models, *Statistical Science*, 1(3), 297–318.
 90. Hastie, T., Tibshirani, R., 1990. Generalized Additive Models.
 91. Hastie, T.J., 2017. Generalized Additive Models, Routledge, New York.
<https://doi.org/10.1201/9780203753781>.
 92. He, J., Gong, S., Yu, Y., Yu, L., Wu, L., Mao, H., Song, C., Zhao, S., Liu, H., Li, X., & Li, R., 2017. Air pollution characteristics and their relation to meteorological conditions during 2014–2015 in major Chinese cities. *Environmental Pollution*, 223, 484–496.
<https://doi.org/10.1016/j.envpol.2017.01.050>.
 93. HEI, 2020. Annual Report. Valuing Science Informing Decisions.
 94. HEI, 2024. State of Global Air 2024. Special Report. Boston, MA: Health Effects Institute.
 95. HEI, 2025. State of Global Air 2025: A Report on Air Pollution and Its Role in the World's Leading Causes of Death. Boston, MA: Health Effects Institute.

96. Hein, L., Roberts, P., Gonzalez, L., 2016. Valuing a Statistical Life Year in Relation to Clean Air. *Journal of Environmental Assessment Policy and Management*, 18, 1650025. <https://doi.org/10.1142/S1464333216500253>.
97. Héroux, M.-E., Anderson, H. R., Atkinson, R., Brunekreef, B., Cohen, A., Forastiere, F., Hurley, F., Katsouyanni, K., Krewski, D., Krzyzanowski, M., Künzli, N., Mills, I., Querol, X., Ostro, B., & Walton, H., 2015. Quantifying the health impacts of ambient air pollutants: Recommendations of a WHO/Europe project. *International Journal of Public Health*, 60(5), 619–627. <https://doi.org/10.1007/s00038-015-0690-y>.
98. Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Thépaut, J., 2020. The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730), 1999–2049. <https://doi.org/10.1002/qj.3803>.
99. Hou, K. and Xu, X., 2022. Evaluation of the influence between local meteorology and air quality in Beijing using Generalized Additive Models. *Atmosphere*, 13(1), 24. <https://doi.org/10.3390/atmos13010024/>.
100. Hubert, M., Vandervieren, E., 2008. An adjusted boxplot for skewed distributions. *Computational Statistics & Data Analysis*, 52, 5186–5201. <https://doi.org/10.1016/j.csda.2007.11.008>.
101. Hurley, F., Hunt, A., Cowie, H., Holland, M., Miller, B., Pye, S., Watkiss, P., 2005. Methodology for the Cost-Benefit analysis for CAFE. Health Impact Assessment 2.
102. IARC, 2013. Outdoor air pollution a leading environmental cause of cancer deaths: <https://www.iarc.who.int/news-events/iarc-outdoor-air-pollution-a-leading-environmental-cause-of-cancer-deaths>.
103. İçağa, Y. and Sabah, E., 2009. Statistical Analysis of Air Pollutants and Meteorological Parameters in Afyon, Turkey, *Environmental Modeling & Assessment*, 14, 259–266. <https://doi.org/10.1007/s10666-008-9139-5>.
104. IHME - GHDx, 2019. GBD Results: <https://vizhub.healthdata.org/gbd-results>, last access: 22 January 2024.
105. IHME - GHDx, 2021. Global Burden of Disease Study 2021 (GBD 2021): <https://ghdx.healthdata.org/gbd-2021>.
106. ILOSTAT - International Labour Organization. ILO Modelled Estimates and Projections database: <https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS>, last access: 25 January 2024.

107. Ilten, N. and Selici, A. T., 2008. Investigating the impacts of some meteorological parameters on air pollution in Balıkesir, Turkey, *Environmental Monitoring & Assessment*, 140, 267–277. <https://doi.org/10.1007/s10661-007-9865-1>.
108. International Monetary Fund (IMF), 2023. World Economic Outlook Database – April 2023 Edition: <https://www.imf.org/en/Publications/WEO/weo-database/2023/April>, last access 01 March 2024.
109. IQAir, 2019. 2019 World Air Quality Report: Region & City PM2.5 ranking (Version 8). IQAir.
110. IQAir, 2024. World Air Quality Report. Region & City PM2.5 Ranking.
111. Jaafar, H., Razi, N.A., Azzeri, A., Isahak, M., Dahlui, M., 2018. A systematic review of financial implications of air pollution on health in Asia. *Environmental Science and Pollution Research*, 25, 30009–30020. <https://doi.org/10.1007/s11356-018-3049-0>.
112. Jakubowska, A., 2023. The Burden of Air Pollution: A Perspective on Global Health Inequalities. *Pollutants*, 3(3), 419–436. <https://doi.org/10.3390/pollutants3030029>.
113. Järup, L., 2003. Hazards of heavy metal contamination. *British Medical Bulletin*, 68(1), 167–182. <https://doi.org/10.1093/bmb/ldg032>.
114. Johnston, R. J., Rolfe, J., Rosenberger, R. S., & Brouwer, R., 2015. Introduction to Benefit Transfer Methods in R. J. Johnston, J. Rolfe, R. S. Rosenberger, & R. Brouwer (Eds.), *Benefit Transfer of Environmental and Resource Values: A Guide for Researchers and Practitioners* (pp. 19–59). Springer Netherlands. https://doi.org/10.1007/978-94-017-9930-0_2.
115. Joint Research Centre. SIMLAB reference manual POLIS-JRC ISIS: <https://web.jrc.ec.europa.eu/rapps/pub/simlab/>.
116. Jones, K. C., & de Voogt, P., 1999. Persistent organic pollutants (POPs): State of the science. *Environmental Pollution*, 100(1), 209–221. [https://doi.org/10.1016/S0269-7491\(99\)00098-6](https://doi.org/10.1016/S0269-7491(99)00098-6).
117. Juginović, A., Vuković, M., Aranza, I., & Biloš, V., 2021. Health impacts of air pollution exposure from 1990 to 2019 in 43 European countries. *Scientific Reports*, 11(1), 22516. <https://doi.org/10.1038/s41598-021-01802-5>.
118. Kabatas, B., Pierce, R. B., Unal, A., Rogal, M. J., Lenzen, A., 2018. April 2008 Saharan dust event: Its contribution to PM10 concentrations over the Anatolian Peninsula and relation with synoptic conditions. *Science of the Total Environment*, 633, 317–328. <https://doi.org/10.1016/j.scitotenv.2018.03.150> " _blank" \o "Persistent link using digital object identifier.

119. Kabatas, B., Unal, A., Pierce, R. B., Kindap, T., and Pozzoli, L., 2014. The contribution of Saharan dust in PM₁₀ concentration levels in Anatolian Peninsula of Turkey. *Science of The Total Environment*, 488–489, 413–421. <https://doi.org/10.1016/j.scitotenv.2013.12.045>.
120. Kampa, M., & Castanas, E., 2008. Human health effects of air pollution. *Environmental Pollution*, 151(2), 362–367. <https://doi.org/10.1016/j.envpol.2007.06.012>.
121. Karimzadegan, H., Rahmatian, M., Farhud, D., Yunesian, M., 2008. Economic Valuation of Air Pollution Health Impacts in the Tehran Area, *Iran*, 37.
122. Kartal, S. and Özer, U., 1998. Determination and Parameterization of Some Air Pollutants as a Function of Meteorological Parameters in Kayseri, Turkey. *Journal of the Air & Waste Management Association*, 48, 853–859. <https://doi.org/10.1080/10473289.1998.10463738>.
123. Katsouyanni, K., 2003. Ambient air pollution and health. *British Medical Bulletin*, 68, 143–156. <https://doi.org/10.1093/bmb/ldg028>.
124. Kaul, S., Boyle, K. J., Kuminoff, N. V., Parmeter, C. F., & Pope, J. C., 2013. What can we learn from benefit transfer errors? Evidence from 20 years of research on convergent validity. *Journal of Environmental Economics and Management*, 66(1), 90–104. <https://doi.org/10.1016/j.jeem.2013.03.001>.
125. Kayes, I., Shahriar, S.A., Hasan, K., Akhter, M., Kabir, M.M., Salam, M.A., 2019. The relationships between meteorological parameters and air pollutants in an urban environment. *Global Journal of Environmental Science and Management*, 5. <https://doi.org/10.22034/GJESM.2019.03.01>.
126. Kianizadeh, F., Godini, H., Moghimbeigi, A., Hassanvand, M.S., 2022. Health and economic impacts of ambient air particulate matter (PM_{2.5}) in Karaj city from 2012 to 2019 using BenMAP-CE. *Environmental Monitoring and Assessment*, 194, 847. <https://doi.org/10.1007/s10661-022-10489-8>.
127. Kumaranayake, L., 2000. The real and the nominal? Making inflationary adjustments to cost and other economic data. *Health Policy and Planning*, 15, 230–234. <https://doi.org/10.1093/heapol/15.2.230>.
128. Lambert-Lacroix, S., Zwald, L., 2011. Robust regression through the Huber's criterion and adaptive lasso penalty. *Electronic Journal of Statistics*, 5. <https://doi.org/10.1214/11-EJS635>.
129. Latini, G., Grifoni, R. C., and Passerini, G., 2002. Influence of meteorological parameters on urban and suburban air pollution, *Air Pollution X*.
130. Lattarulo, P., Plechero, M., 2005. Traffico e inquinamento: i danni per la salute dell'uomo e i costi sociali. IRPET (Istituto Regionale Programmazione

Economica Toscana).

131. Ledoux, F., Roche, C., Delmaire, G., Roussel, G., Favez, O., Fadel, M., Courcot, D., 2023. Measurement report: A 1-year study to estimate maritime contributions to PM₁₀ in a coastal area in northern France. *Atmospheric Chemistry and Physics*, 23, 8607–8622. <https://doi.org/10.5194/acp-23-8607-2023>.
132. Leksell, I., Rabl, A., 2001. Air Pollution and Mortality: Quantification and Valuation of Years of Life Lost. *Risk Analysis*, 21, 843–843. <https://doi.org/10.1111/0272-4332.215156>.
133. Lelieveld, J., Haines, A., Burnett, R., Tonne, C., Klingmüller, K., Münzel, T., & Pozzer, A., 2023. Air pollution deaths attributable to fossil fuels: Observational and modelling study. *BMJ*, 383, 077784. <https://doi.org/10.1136/bmj-2023-077784>.
134. Lenschow, P., 2001. Some ideas about the sources of PM₁₀. *Atmospheric Environment*, 35, 23–33. [https://doi.org/10.1016/S1352-2310\(01\)00122-4](https://doi.org/10.1016/S1352-2310(01)00122-4).
135. Lindhjem, H., Navrud, S., Braathen, N.A., Biaisque, V., 2011. Valuing Mortality Risk Reductions from Environmental, Transport, and Health Policies: A Global Meta-Analysis of Stated Preference Studies. *Risk Analysis*, 31, 1381–1407. <https://doi.org/10.1111/j.1539-6924.2011.01694.x>.
136. Liu, Y., Yang, S., Li, C., Fang, Q., Han, C., Cheng, C., Cao, Y., Cui, F., & Li, X., 2024. Changes in years of life lost and life expectancy by reducing air pollution. *Air Quality, Atmosphere & Health*, 17(1), 89–102. <https://doi.org/10.1007/s11869-023-01430-0>.
137. Lou Thompson, M., 2001. A review of statistical methods for the meteorological adjustment of tropospheric ozone. *Atmospheric Environment*, 35(3), 617–630. [https://doi.org/10.1016/S1352-2310\(00\)00261-2](https://doi.org/10.1016/S1352-2310(00)00261-2).
138. Ma, S., Shao, M., Zhang, Y., Dai, Q., and Xie, M., 2021. Sensitivity of PM_{2.5} and O₃ pollution episodes to meteorological factors over the North China Plain. *Science of The Total Environment*, 792, 148474. <https://doi.org/10.1016/j.scitotenv.2021.148474>.
139. MacFarland, T.W., Yates, J.M., 2016. Mann–Whitney U Test, Introduction to Nonparametric Statistics for the Biological Sciences Using R. Springer, Cham, 103–132. https://doi.org/10.1007/978-3-319-30634-6_4.
140. Manju, A., Kalaiselvi, K., Dhananjayan, V., Palanivel, M., Banupriya, G.S., Vidhya, M.H., Panjakumar, K., Ravichandran, B., 2018. Spatio-seasonal variation in ambient air pollutants and influence of meteorological factors in Coimbatore, Southern India. *Air Quality, Atmosphere and Health*, 11, 1179–1189. <https://doi.org/10.1007/s11869-018-0617-x>.

141. Martinez, G., Spadaro, J., Chapizanis, D., Kendrovski, V., Kochubovski, M., & Mudu, P., 2018. Health Impacts and Economic Costs of Air Pollution in the Metropolitan Area of Skopje. *International Journal of Environmental Research and Public Health*, 15(4), 626. <https://doi.org/10.3390/ijerph15040626>.
142. McKight, P.E., Najab, J., 2010. Kruskal-Wallis Test, *The Corsini Encyclopedia of Psychology*, John Wiley & Sons, Ltd. <https://doi.org/10.1002/9780470479216.corpsy0491>.
143. Miller, T.R., 2000. Variations between Countries in Values of Statistical Life. *Journal of Transport Economics and Policy*, 34, 169-188.
144. Milligan, C., Kopp, A., Dahdah, S., Montufar, J., 2014. Value of a statistical life in road safety: A benefit-transfer function with risk-analysis guidance based on developing country data. *Accident Analysis & Prevention*, 71, 236–247. <https://doi.org/10.1016/j.aap.2014.05.026>.
145. Miyazaki, K., 2024. TROPESS Chemical Reanalysis Surface NO 2-Hourly 2-dimensional Product: <https://doi.org/10.5067/HY54CQO7ZTHY>.
146. Monks, P. S., Archibald, A. T., Colette, A., Cooper, O., Coyle, M., Derwent, R., Fowler, D., Granier, C., Law, K. S., Mills, G. E., Stevenson, D. S., Tarasova, O., Thouret, V., von Schneidemesser, E., Sommariva, R., Wild, O., & Williams, M. L., 2015. Tropospheric ozone and its precursors from the urban to the global scale from air quality to short-lived climate forcer. *Atmospheric Chemistry and Physics*, 15(15), 8889–8973. <https://doi.org/10.5194/acp-15-8889-2015>.
147. Mrozek, J. R., Taylor L.O., 2002. What Determines the Value of Life? A Meta-Analysis. *Journal of Policy Analysis and Management*, 21, 253-270.
148. Mueller, W., Vardoulakis, S., Steinle, S., Loh, M., Johnston, H.J., Precha, N., Kliengchuay, W., Sahanavin, N., Nakhapakorn, K., Sillaparassamee, R., Tantrakarnapa, K., Cherrie, J.W., 2021. A health impact assessment of long-term exposure to particulate air pollution in Thailand. *Environmental Research Letters*, 16, 055018. <https://doi.org/10.1088/1748-9326/abe3ba>.
149. Murray, C. J., Ezzati, M., Lopez, A. D., Rodgers, A., & Vander Hoorn, S., 2003. Comparative quantification of health risks conceptual framework and methodological issues. *Population Health Metrics*, 1(1). <https://doi.org/10.1186/1478-7954-1-1>.
150. Narain, U., Sall, C., 2016. Methodology for Valuing the Health Impacts of Air Pollution. World Bank, Washington DC. <https://doi.org/10.1596/24440>.
151. Nelson, J. P., 2015. Meta-analysis: Statistical Methods. In R. J. Johnston, J. Rolfe, R. S. Rosenberger, & R. Brouwer (Eds.), *Benefit Transfer of Environmental and Resource Values: A Guide for Researchers and Practitioners*

- (pp. 329–356). Springer Netherlands. https://doi.org/10.1007/978-94-017-9930-0_15.
152. Nelson, J.P., Kennedy, P.E., 2009. The Use (and Abuse) of Meta-Analysis in Environmental and Natural Resource Economics: An Assessment. *Environmental and Resource Economics*, 42, 345–377. <https://doi.org/10.1007/s10640-008-9253-5>.
 153. NOAA, 2024. National Centers for Environmental Information (NCEI): <https://www.ncei.noaa.gov/>, last access: 13 November 2024.
 154. Nowak, D. J., Crane, D. E., & Stevens, J. C., 2006. Air pollution removal by urban trees and shrubs in the United States. *Urban Forestry & Urban Greening*, 4(3), 115–123. <https://doi.org/10.1016/j.ufug.2006.01.007>.
 155. NPS.gov., 2018. Where Does Air Pollution Come From? - Air (U.S. National Park Service: <https://www.nps.gov/subjects/air/sources.html>, last access: 04 October 2025.
 156. O’Brien, R.M., 2007. A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity*, 41, 673–690. <https://doi.org/10.1007/s11135-006-9018-6>.
 157. OECD, 2010. The Value of Statistical Life: a Meta-Analysis. Working Party on National Environmental Policies. Environment Directorate Environment Policy Committee. OECD, Paris.
 158. OECD, 2012. Mortality Risk Valuation in Environment, Health and Transport Policies. OECD, Paris: <https://doi.org/10.1787/9789264130807-en>.
 159. OECD, 2014. The Cost of Air Pollution: Health Impacts of Road Transport. OECD, Paris: <https://doi.org/10.1787/9789264210448-en>.
 160. OECD, 2016. The Economic Consequences of Outdoor Air Pollution. OECD, Paris: <https://doi.org/10.1787/9789264257474-en>.
 161. OECD, 2023. Data Explorer: Archive - Mortality, morbidity and welfare cost from exposure to environment-related risks: [https://data-explorer.oecd.org/vis?tenant=archive&df\[ds\]=DisseminateArchiveDMZ&df\[id\]=DF_EXP_MORSC&df\[ag\]=OECD&dq=....&lom=LASTNPERIODS&lo=5&to\[TIME_PERIOD\]=false](https://data-explorer.oecd.org/vis?tenant=archive&df[ds]=DisseminateArchiveDMZ&df[id]=DF_EXP_MORSC&df[ag]=OECD&dq=....&lom=LASTNPERIODS&lo=5&to[TIME_PERIOD]=false), last access 12 January 2024.
 162. OECD, 2025. Mortality Risk Valuation in Policy Assessment: A Global Meta-Analysis of Value of Statistical Life Studies. OECD, Paris: <https://doi.org/10.1787/76ca89a2-en>.
 163. Orru, H., Ebi, K. L., & Forsberg, B., 2017. The Interplay of Climate Change and Air Pollution on Health. *Current Environmental Health Reports*, 4(4), 504–513. <https://doi.org/10.1007/s40572-017-0168-6>.
 164. Orru, H., Teinmaa, E., Lai, T., Tamm, T., Kaasik, M., Kimmel, V., Kangur,

- K., Merisalu, E., & Forsberg, B., 2009. Health impact assessment of particulate pollution in Tallinn using fine spatial resolution and modeling techniques. *Environmental Health*, 8(1), 7. <https://doi.org/10.1186/1476-069X-8-7>.
165. Pearce, J. L., Beringer, J., Nicholls, N., Hyndman, R. J., & Tapper, N. J., 2011. Quantifying the influence of local meteorology on air quality using generalized additive models. *Atmospheric Environment*, 45(6), 1328–1336. <https://doi.org/10.1016/j.atmosenv.2010.11.051>.
 166. Petrou, I., Psistaki, K., Kassomenos, P. A., Dokas, I. M., & Paschalidou, A. K., 2024. Studying the economic burden of premature mortality related to PM_{2.5} and O₃ exposure in Greece between 2004 and 2019. *Atmospheric Pollution Research*, 15(2), 101978. <https://doi.org/10.1016/j.apr.2023.101978>.
 167. Pianosi, F., Wagener, T., 2015. A simple and efficient method for global sensitivity analysis based on cumulative distribution functions. *Environmental Modelling & Software*, 67, 1–11. <https://doi.org/10.1016/j.envsoft.2015.01.004>.
 168. Plischke, E., Borgonovo, E., Smith, C.L., 2013. Global sensitivity measures from given data. *European Journal of Operational Research*, 226, 536–550. <https://doi.org/10.1016/j.ejor.2012.11.047>.
 169. Pöschl, U., 2005. Atmospheric Aerosols: Composition, Transformation, Climate and Health Effects. *Angewandte Chemie International Edition*, 44(46), 7520–7540. <https://doi.org/10.1002/anie.200501122>.
 170. Pozzer, A., Anenberg, S. C., Dey, S., Haines, A., Lelieveld, J., & Chowdhury, S., 2023. Mortality Attributable to Ambient Air Pollution: A Review of Global Estimates. *GeoHealth*, 7(1), e2022GH000711. <https://doi.org/10.1029/2022GH000711>.
 171. Qi, J., Ruan, Z., Qian, Z. M., Yin, P., Yang, Y., Acharya, B. K., Wang, L., & Lin, H., 2020. Potential gains in life expectancy by attaining daily ambient fine particulate matter pollution standards in mainland China: A modeling study based on nationwide data. *PLoS Medicine*, 17(1), e1003027. <https://doi.org/10.1371/journal.pmed.1003027>.
 172. Qi, X., Mei, G., Cuomo, S., Liu, C., & Xu, N., 2021. Data analysis and mining of the correlations between meteorological conditions and air quality: A case study in Beijing. *Internet of Things*, 14, 100127. <https://doi.org/10.1016/j.iot.2019.100127>.
 173. Qu, C., Yang, X., Zhang, D., Zhang, X., 2020. Estimating health co-benefits of climate policies in China: An application of the Regional Emissions-Air quality-Climate-Health (REACH) framework. *Climate Change Economics*, 11, 2041004. <https://doi.org/10.1142/S2010007820410043>.
 174. Quah, E., Boon, T.L., 2003. The economic cost of particulate air pollution

- on health in Singapore. *Journal of Asian Economics*, 14, 73–90. [https://doi.org/10.1016/S1049-0078\(02\)00240-3](https://doi.org/10.1016/S1049-0078(02)00240-3).
175. Radaideh, J. A., 2017. Effect of Meteorological Variables on Air Pollutants Variation in Arid Climates. *Journal of Environmental & Analytical Toxicology*, 07(04). <https://doi.org/10.4172/2161-0525.1000478>.
 176. Ravindra, K., Rattan, P., Mor, S., Aggarwal, A.N., 2019. Generalized additive models: Building evidence of air pollution, climate change and human health, *Environment International*, 132, 104987. <https://doi.org/10.1016/j.envint.2019.104987>.
 177. Robinson L.A., Hammitt J.K., 2009. The Value of Reducing Air Pollution Risks in Sub-Saharan Africa. Final Report. Prepared for: Eleodoro Mayorga-Alba The World Bank Sub-Saharan Africa Refinery Study.
 178. Román-Collado, R., Jiménez De Reyna, J., 2019. The economic benefits of fulfilling the World Health Organization's limits for particulates: A case study in Algeciras Bay (Spain). *Journal of the Air & Waste Management Association*, 69, 438–449. <https://doi.org/10.1080/10962247.2018.1544178>.
 179. Rosenberger, R. S., & Stanley, T. D., 2006. Measurement, generalization, and publication: Sources of error in benefit transfers and their management. *Ecological Economics*, 60(2), 372–378. <https://doi.org/10.1016/j.ecolecon.2006.03.018>.
 180. Rowe, L., 2020. Pollution and Atmosphere in Post-Soviet Russia: <https://books.apple.com/us/book/pollution-and-atmosphere-in-post-soviet-russia/id1542102497>.
 181. Roy, R., 2016. The cost of air pollution in Africa. Working Paper No. 333. OECD, Paris.
 182. Safari, Z., Fouladi-Fard, R., Vahedian, M., Mahmoudian, M.H., Rahbar, A., Fiore, M., 2022. Health impact assessment and evaluation of economic costs attributed to PM2.5 air pollution using BenMAP-CE. *International Journal of Biometeorology*, 66, 1891–1902. <https://doi.org/10.1007/s00484-022-02330-1>.
 183. Sahin, S. and Kerem Cigizoglu, H., 2012. The sub-climate regions and the sub-precipitation regime regions in Turkey. *Journal of Hydrology*, 450–451, 180–189. <https://doi.org/10.1016/j.jhydrol.2012.04.062>.
 184. Sahin, S. and Türkeş, M., 2013. Contemporary surface wind climatology of Turkey. *Theoretical and Applied Climatology*, 113, 337–349. <https://doi.org/10.1007/s00704-012-0789-5>.
 185. Şahin, S. and Türkeş, M., 2020. Assessing wind energy potential of Turkey via vectoral map of prevailing wind and mean wind of Turkey. *Theoretical and Applied Climatology*, 141, 1351–1366. <https://doi.org/10.1007/s00704-020->

[03276-3.](#)

186. Sampedro, J., Khan, Z., Vernon, C. R., Smith, S. J., Waldhoff, S., & Dingenen, R. V., 2022. Rfasst: An R tool to estimate air pollution impacts on health and agriculture. *Journal of Open Source Software*, 7(69), 3820. <https://doi.org/10.21105/joss.03820>.
187. Ščasný, M., Alberini, A., 2012. Valuation of Mortality Risk Attributable to Climate Change: Investigating the Effect of Survey Administration Modes on a VSL. *International Journal of Environmental Research and Public Health*, 9, 4760–4781. <https://doi.org/10.3390/ijerph9124760>.
188. Schwertman, N.C., Owens, M.A., Adnan, R., 2004. A simple more general boxplot method for identifying outliers. *Computational Statistics & Data Analysis*, 47, 165–174. <https://doi.org/10.1016/j.csda.2003.10.012>.
189. Seinfeld, J. H., & Pandis, S. N., 2016. Atmospheric Chemistry and Physics: From Air Pollution to Climate Change. John Wiley & Sons.
190. Sensoy, S., Demircan, M., 2016. Climate of Turkey.
191. Shao, Q., Younes, A., Fahs, M., Mara, T.A., 2017. Bayesian sparse polynomial chaos expansion for global sensitivity analysis. *Computer Methods in Applied Mechanics and Engineering*, 318, 474–496. <https://doi.org/10.1016/j.cma.2017.01.033>.
192. Shen, S., Li, C., van Donkelaar, A., Jacobs, N., Wang, C., Martin, R.V., 2024. Enhancing Global Estimation of Fine Particulate Matter Concentrations by Including Geophysical a Priori Information in Deep Learning. *ACS EST Air*, 1, 332–345. <https://doi.org/10.1021/acsestair.3c00054>.
193. Soares, J., Ortiz, A. G., Gsella, A., Horálek, J., Plass, D., & Kienzler, S., 2022. Health Risk Assessment of Air Pollution and the Impact of the New WHO Guidelines. ETC HE Report 2022/10: <https://doi.org/10.5281/zenodo.7405988>.
194. Soleimani, M., Akbari, N., Saffari, B., Haghshenas, H., 2021. Estimation of economic costs of air pollution caused by motor vehicles in Iran (Isfahan). *Environmental Science and Pollution Research*, 28, 66535–66555. <https://doi.org/10.1007/s11356-021-13504-6>.
195. Sunstein, C. R., 2023. Inequality and the Value of a Statistical Life. *Journal of Benefit-Cost Analysis*, 14(1), 1–7. <https://doi.org/10.1017/bca.2023.7>.
196. Tang, D., Wang, C., Nie, J., Chen, R., Niu, Q., Kan, H., Chen, B., Perera, F., 2014. Health benefits of improving air quality in Taiyuan, China. *Environment International*, 73, 235–242. <https://doi.org/10.1016/j.envint.2014.07.016>.
197. Tasdemir, Y., Cindoruk, S.S., Esen, F., 2005. Monitoring of Criteria Air Pollutants in Bursa, Turkey. *Environmental Monitoring and Assessment*, 110,

- 227–241. <https://doi.org/10.1007/s10661-005-7866-5>.
198. Tayanç, M., Karaca, M., and Yenigün, O., 1997. Annual and seasonal air temperature trend patterns of climate change and urbanization effects in relation to air pollutants in Turkey. *Journal of Geophysical Research*, 102, 1909–1919. <https://doi.org/10.1029/96JD02108>.
199. Thangavel, P., Park, D., & Lee, Y.-C., 2022. Recent Insights into Particulate Matter (PM_{2.5})-Mediated Toxicity in Humans: An Overview. *International Journal of Environmental Research and Public Health*, 19(12), 7511. <https://doi.org/10.3390/ijerph19127511>.
200. Thompson, M., 2001. A review of statistical methods for the meteorological adjustment of tropospheric ozone. *Atmospheric Environment*, 35, 617–630. [https://doi.org/10.1016/S1352-2310\(00\)00261-2](https://doi.org/10.1016/S1352-2310(00)00261-2).
201. THPP. Right to Clean Air Platform, 2024. Dark Report. Air Pollution And Health Impacts: <https://temizhavahakki.org/en/dark-report-2024/>.
202. Türkeş, M., 1996. Spatial and temporal analysis of annual rainfall variations in Turkey. *International Journal of Climatology*, 16, 1057–1076. [https://doi.org/10.1002/\(SICI\)1097-0088\(199609\)16:9<1057::AID-JOC75>3.0.CO;2-D](https://doi.org/10.1002/(SICI)1097-0088(199609)16:9<1057::AID-JOC75>3.0.CO;2-D).
203. Turner, H. C., Lauer, J. A., Tran, B. X., Teerawattananon, Y., & Jit, M., 2019. Adjusting for Inflation and Currency Changes Within Health Economic Studies. *Value in Health*, 22(9), 1026–1032. <https://doi.org/10.1016/j.jval.2019.03.021>.
204. Ulas, E., Keskin, B., 2017. Is There a Relation Between HDI and Economic Performances?, in: Procházka, D. (Ed.), *New Trends in Finance and Accounting*. Springer International Publishing, Cham, pp. 61–70. https://doi.org/10.1007/978-3-319-49559-0_6.
205. Ulutaş, K., Abujayyab, S. K. M., and Abu Amr, S., 2021. Evaluation of the major air pollutants levels and its interactions with meteorological parameters in Ankara. *Mühendislik Bilimleri ve Tasarım Dergisi*, 9, 1284–1295. <https://doi.org/10.21923/jesd.939724>.
206. UNDP, 2022. Human Development Report 2021/2022: Uncertain Times, Unsettled Lives: Shaping our Future in a Transforming World: https://hdr.undp.org/system/files/documents/global-report-document/hdr2021-22reportenglish_0.pdf.
207. UNDP, 2022. Human Development Report 2021/2022: Uncertain Times, Unsettled Lives: Shaping our Future in a Transforming World: https://hdr.undp.org/system/files/documents/global-report-document/hdr2021-22reportenglish_0.pdf.

208. UNECE, 2018. <https://unece.org/environmental-policy-1/air>.
209. UNEP, 2023. World must band together to combat air pollution, which kills 7 million a year: <https://www.unep.org/news-and-stories/story/world-must-band-together-combat-air-pollution-which-kills-7-million-year>, last access: 10 January 2024.
210. UNEP, 2025. Air Pollution Note – Data you need to know: <https://www.unep.org/interactives/air-pollution-note>.
211. UNEP, 2025. Air. UNEP - UN Environment Programme: <http://www.unep.org/explore-topics/air>.
212. United Nations, Department of Economic and Social Affairs, Population Division, 2022. World Population Prospects 2022, Online Edition: <https://population.un.org/wpp/>, last access 24 January 2024.
213. United Nations, Department of Economic and Social Affairs, Population Division, 2018. World Urbanization Prospects: The 2018 Revision, Online Edition: <https://population.un.org/wpp/>, last access 08 March 2024.
214. US EPA (a), 2025. Regulatory and Guidance Information by Topic: Air: <https://www.epa.gov/regulatory-information-topic/regulatory-and-guidance-information-topic-air>.
215. US EPA (b), 2025. Accomplishments and Successes of Reducing Air Pollution from Transportation in the United States: <https://www.epa.gov/transportation-air-pollution-and-climate-change/accomplishments-and-successes-reducing-air>.
216. US EPA (c), 2025. Air Pollution: Current and Future Challenges: <https://www.epa.gov/clean-air-act-overview/air-pollution-current-and-future-challenges>.
217. US EPA, 2007. The Plain English Guide to the Clean Air Act: <https://www.epa.gov/sites/default/files/2015-08/documents/peg.pdf>.
218. US EPA, 2023. AQI Basics | AirNow.gov: <https://www.airnow.gov/aqi/aqi-basics>.
219. US EPA, 2024. Guidelines for preparing economic analyses (3rd ed.; EPA-240-R-24-001): <https://www.epa.gov/environmental-economics/guidelines-preparing-economic-analyses-3rd-edition>.
220. Van Dingenen, R., Dentener, F., Crippa, M., Leitao, J., Marmer, E., Rao, S., Solazzo, E., & Valentini, L., 2018. TM5-FASST: A global atmospheric source–receptor model for rapid impact analysis of emission changes on air quality and short-lived climate pollutants. *Atmospheric Chemistry and Physics*, 18(21), 16173–16211. <https://doi.org/10.5194/acp-18-16173-2018>.
221. Van Nieuwenhuyse, J., Van Schaeybroeck, B., Caluwaerts, S., De Deyn, J.,

- Delcloo, A., De Troch, R., Hamdi, R., Termonia, P., 2023. Air-stagnation episodes based on regional climate models part I: evaluation over Europe. *Climate Dynamics*, 61, 2121–2138. <https://doi.org/10.1007/s00382-023-06665-2>.
222. Viscusi, W.K., 1978. Labor market valuations of life and limb: empirical evidence and policy implications. *Public Policy*, 26, 359–386.
223. Viscusi, W.K., Aldy, J.E., 2003. The Value of a Statistical Life: a critical review of market estimates throughout the world. Working Paper 9487. National Bureau of Economic Research, Cambridge, MA. <http://www.nber.org/papers/w9487>.
224. Wahba, G., 1985. A Comparison of GCV and GML for Choosing the Smoothing Parameter in the Generalized Spline Smoothing Problem. *The Annals of Statistics*, 13, 1378–1402. <https://doi.org/10.1214/aos/1176349743>.
225. Wang, Y., & Ge, Q., 2023. The positive impact of the Omicron pandemic lockdown on air quality and human health in cities around Shanghai. *Environment, Development and Sustainability*. <https://doi.org/10.1007/s10668-023-03071-w>.
226. Wang, Y., Hu, J., Zhu, J., Li, J., Qin, M., Liao, H., Chen, K., Wang, M., 2021. Health Burden and economic impacts attributed to PM_{2.5} and O₃ in China from 2010 to 2050 under different representative concentration pathway scenarios. *Resources, Conservation and Recycling*, 173, 105731. <https://doi.org/10.1016/j.resconrec.2021.105731>.
227. WAQI, 2023. World's Air Pollution: Real-time Air Quality Index: <https://waqi.info/>.
228. WHO HRAPIE, 2013. Health risks of air pollution in Europe – HRAPIE project. Recommendations for concentration–response functions for cost–benefit analysis of particulate matter, ozone and nitrogen dioxide: <https://iris.who.int/items/1fb731e8-0100-4020-8a09-873dcd100c08>.
229. WHO Regional Office for Europe, 2013. Review of evidence on health aspects of air pollution – REVIHAAP Project: Technical Report: <http://www.ncbi.nlm.nih.gov/books/NBK361805/>.
230. WHO Regional Office for Europe, 2016. Health risk assessment of air pollution – general principles. WHO Regional Office for Europe, Copenhagen.
231. WHO Regional Office for Europe, 2023. Achieving health benefits from carbon reductions. Manual for use of the climate change mitigation, air quality and health tool. WHO Regional Office for Europe, Copenhagen: [https://www.who.int/europe/tools-and-toolkits/climate-change-mitigation-air-quality-and-health-\(climaq-h\)](https://www.who.int/europe/tools-and-toolkits/climate-change-mitigation-air-quality-and-health-(climaq-h)), last access 10 March 2024.

232. WHO Regional Office for Europe, OECD, 2015. Economic cost of the health impact of air pollution in Europe: Clean air, health and wealth. WHO Regional Office for Europe, Copenhagen.
233. WHO, 2021. WHO global air quality guidelines. Particulate matter (PM_{2.5} and PM₁₀), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide, Geneva: <https://www.who.int/news-room/questions-and-answers/item/who-global-air-quality-guidelines>.
234. WHO, 2022. Policy Brief: Short-lived Climate Pollutants (SLCPs): [https://www.who.int/publications/m/item/who-policy-brief--short-lived-climate-pollutants-\(slcps\)](https://www.who.int/publications/m/item/who-policy-brief--short-lived-climate-pollutants-(slcps)).
235. WHO, 2024 (b). The Global Health Observatory: [https://www.who.int/data/gho/data/indicators/indicator-details/GHO/medical-doctors-\(per-10-000-population\)](https://www.who.int/data/gho/data/indicators/indicator-details/GHO/medical-doctors-(per-10-000-population)), last access 15 February 2024.
236. WHO, 2024. Ambient (outdoor) air pollution: [https://www.who.int/news-room/fact-sheets/detail/ambient-\(outdoor\)-air-quality-and-health](https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health), last access 05 November 2024.
237. WHO, 2024. Global Health Expenditure Database: <https://apps.who.int/nha/database/Select/Indicators/en>, last access: 18 March 2024.
238. WHO, 2025. Maternal, newborn, child and adolescent health and ageing Data portal: [https://platform.who.int/data/maternal-newborn-child-adolescent-ageing/indicator-explorer-new/MCA/median-age-\(years\)](https://platform.who.int/data/maternal-newborn-child-adolescent-ageing/indicator-explorer-new/MCA/median-age-(years)), last access: 11 September 2024.
239. WHO. (2025). Air quality, energy and health. <https://www.who.int/teams/environment-climate-change-and-health/air-quality-energy-and-health/health-impacts>.
240. WHO: Health risk assessment of air pollution – General principles, Copenhagen, 2016.
241. WMO, 2017. WMO Guidelines on the Calculation of Climate Normals (WMO-No. 1203), Geneva.
242. Wood, S., 2006. Generalized Additive Models: An Introduction with R. Chapman and Hall/CRC Press, London.
243. Wood, S.N., 2004. Stable and Efficient Multiple Smoothing Parameter Estimation for Generalized Additive Models. *Journal of the American Statistical Association*, 99, 673–686. <https://doi.org/10.1198/016214504000000980>.
244. Wood, S.N., 2008. Fast Stable Direct Fitting and Smoothness Selection for Generalized Additive Models. *Journal of the Royal Statistical Society Series B*:

- Statistical Methodology*, 70, 495–518. <https://doi.org/10.1111/j.1467-9868.2007.00646.x>.
245. Wootten, A., Terando, A., Reich, B.J., Boyles, R.P., Semazzi, F., 2017. Characterizing Sources of Uncertainty from Global Climate Models and Downscaling Techniques. *Journal of Applied Meteorology and Climatology*, 56(12), 3245–3262. <https://doi.org/10.1175/JAMC-D-17-00871>.
 246. World Bank and IHME, 2016. The Cost of Air Pollution: Strengthening the Economic Case for Action. World Bank, Washington DC.
 247. World Bank, 2019(a). Western Balkans Regional AQM - Western Balkans Report – AQM in Bosnia and Herzegovina. World Bank, Washington DC.
 248. World Bank, 2019(b). Western Balkans Regional AQM - Western Balkans Report – AQM in North Macedonia. World Bank, Washington DC.
 249. World Bank, 2019(c). Western Balkans Regional AQM - Western Balkans Report – AQM in Kosovo. World Bank, Washington DC.
 250. World Bank, 2022. The Global Health Cost of PM2.5 Air Pollution: A Case for Action Beyond 2021. International Development in Focus. Washington, DC: World Bank. License: Creative Commons Attribution CC BY 3.0 IGO. <https://documents.worldbank.org/curated/en/455211643691938459>.
 251. World Bank, 2024. Country and Lending Groups - historical classification by income: <https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups>, last access: 19 September 2024.
 252. World Bank, 2024. Poverty and Inequality Platform (version 20240326_2017_01_02_PROD: <https://pip.worldbank.org/poverty-calculator>, last access 24 January 2024.
 253. Wu, J., Li, J., Peng, J., Li, W., Xu, G., & Dong, C., 2015. Applying land use regression model to estimate spatial variation of PM2.5 in Beijing, China. *Environmental Science and Pollution Research*, 22(9), 7045–7061. <https://doi.org/10.1007/s11356-014-3893-5>.
 254. Xu, L. J., Zhou, J. X., Guo, Y., Wu, T. M., Chen, T. T., Zhong, Q. J., Yuan, D., Chen, P. Y., and Ou, C. Q., 2017. Spatiotemporal pattern of air quality index and its associated factors in 31 Chinese provincial capital cities. *Air Quality, Atmosphere & Health*, 10, 601–609. <https://doi.org/10.1007/s11869-016-0454-8>.
 255. Yaduma, N., Kortelainen, M., Wossink, A., 2012. Estimating Mortality and Economic Costs of Particulate Air Pollution in Developing Countries: The Case of Nigeria. *Environmental and Resource Economics*, 54, 361–387. <https://doi.org/10.1007/s10640-012-9598-7>.

256. Yan, H., Li, Q., Feng, K., and Zhang, L., 2023. The characteristics of PM emissions from construction sites during the earthwork and foundation stages: an empirical study evidence. *Environmental Science and Pollution Research*, 30, 62716–62732. <https://doi.org/10.1007/s11356-023-26494-4>.
257. Yoo, J.-M., Lee, Y.-R., Kim, D., Jeong, M.-J., Stockwell, W. R., Kundu, P. K., Oh, S.-M., Shin, D.-B., & Lee, S.-J., 2014. New indices for wet scavenging of air pollutants (O₃, CO, NO₂, SO₂, and PM₁₀) by summertime rain. *Atmospheric Environment*, 82, 226–237. <https://doi.org/10.1016/j.atmosenv.2013.10.022>.
258. Zhang, H., Wang, Z., and Zhang, W., 2016. Exploring spatiotemporal patterns of PM_{2.5} in China based on ground-level observations for 190 cities. *Environmental Pollution*, 216, 559–567. <https://doi.org/10.1016/j.envpol.2016.06.009>.
259. Zhang, Y., 2019. Dynamic effect analysis of meteorological conditions on air pollution: A case study from Beijing. *Science of The Total Environment*, 684, 178–185. <https://doi.org/10.1016/j.scitotenv.2019.05.360>.
260. Zhou, H., Yu, Y., Gu, X., Wu, Y., Wang, M., Yue, H., Gao, J., Lei, R., and Ge, X., 2020. Characteristics of Air Pollution and Their Relationship with Meteorological Parameters: Northern Versus Southern Cities of China. *Atmosphere*, 11, 253. <https://doi.org/10.3390/atmos11030253>.
261. Zhu, X., Zhang, A., Wu, P., Qi, W., Fu, G., Yue, G., Liu, X., 2019. Uncertainty Impacts of Climate Change and Downscaling Methods on Future Runoff Projections in the Biliu River Basin. *Water*, 11, 2130. <https://doi.org/10.3390/w11102130>.
262. Zuur, A. F., Ieno, E. N., & Elphick, C. S., 2010. A protocol for data exploration to avoid common statistical problems: Data exploration. *Methods in Ecology and Evolution*, 1(1), 3–14. <https://doi.org/10.1111/j.2041-210X.2009.00001.x>.
263. Zuur, A.F., 2012. A Beginner's Guide to Generalized Additive Models with R. Highland Statistics Ltd., Newburgh - United Kingdom.
264. Zuur, A.F., Ieno, E.N., Elphick, C.S., 2010. A protocol for data exploration to avoid common statistical problems: Data exploration. *Methods in Ecology and Evolution*, 1, 3–14. <https://doi.org/10.1111/j.2041-210X.2009.00001.x>.
265. Żyromski, A., Biniak-Pieróg, M., Burszta-Adamiak, E., & Zamiar, Z., 2014. Evaluation of Relationship Between Air Pollutant Concentration and Meteorological Elements in Winter Months. *Journal of Water and Land Development*, 22(1), 25–32. <https://doi.org/10.2478/jwld-2014-0019>.

Appendix

Atmospheric Analysis Methodology

This subsection outlines the exploratory analyses conducted prior to the model selection. All work covers PM₁₀ and SO₂ for 2015–2019. Analyses were performed at diurnal, monthly, and annual levels, and also disaggregated by season, both for individual stations and in aggregated form. Analyses were carried out for all available stations, but only a single illustrative station is shown in this subsection. Selected outcomes from these preliminary analyses are presented below.

Preliminary analysis

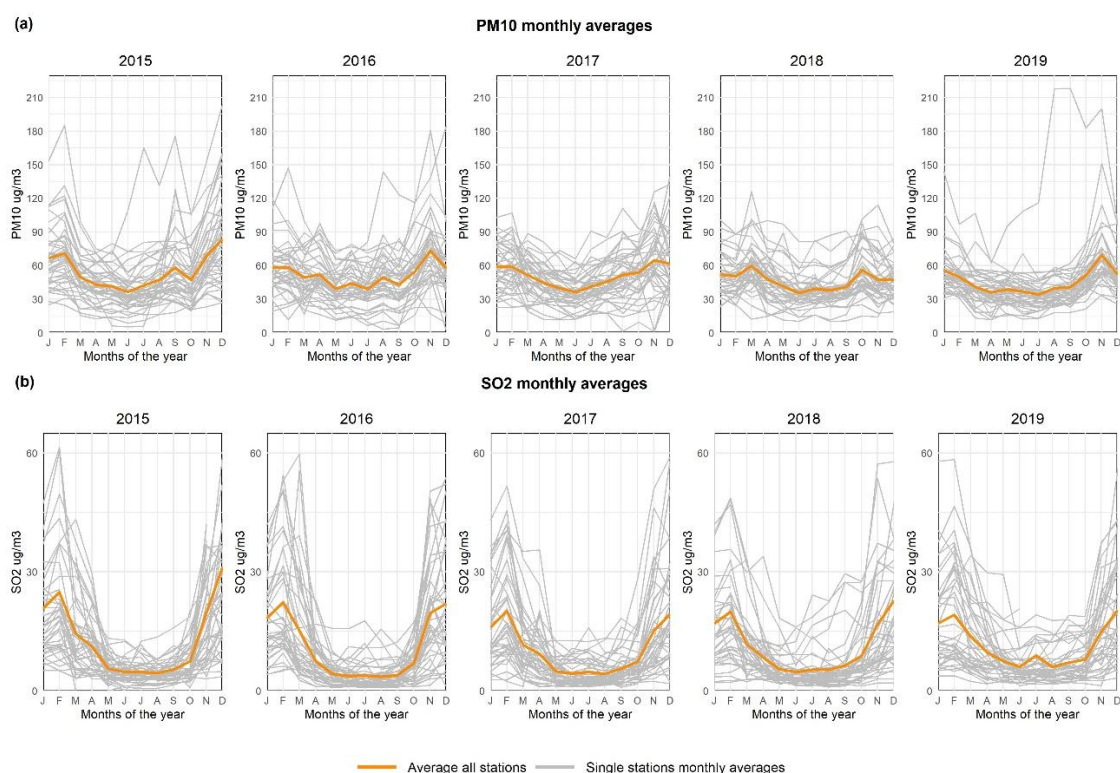


Figure A1 – Monthly averages for each single available station (grey) and monthly mean values (orange) for PM₁₀ concentrations (panel a) and SO₂ concentrations (panel b).

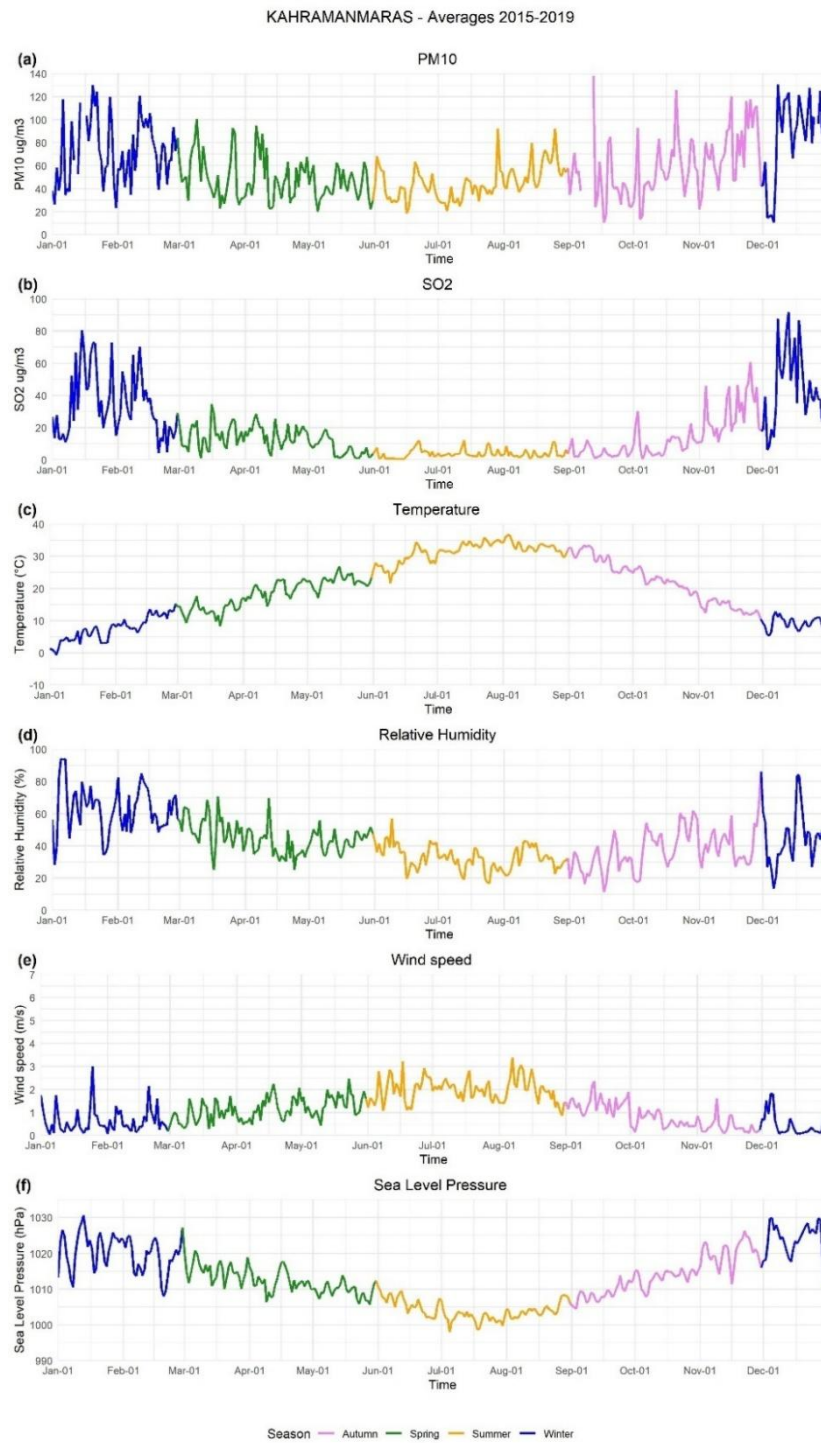


Figure A2 – Kahramanmaraş data analysis, for 2015-2019, for PM₁₀, SO₂, Temperature, Relative Humidity, Wind Speed and Sea Level Pressure, differentiating by season.

PM₁₀ diurnal cycle averages
2015-2019

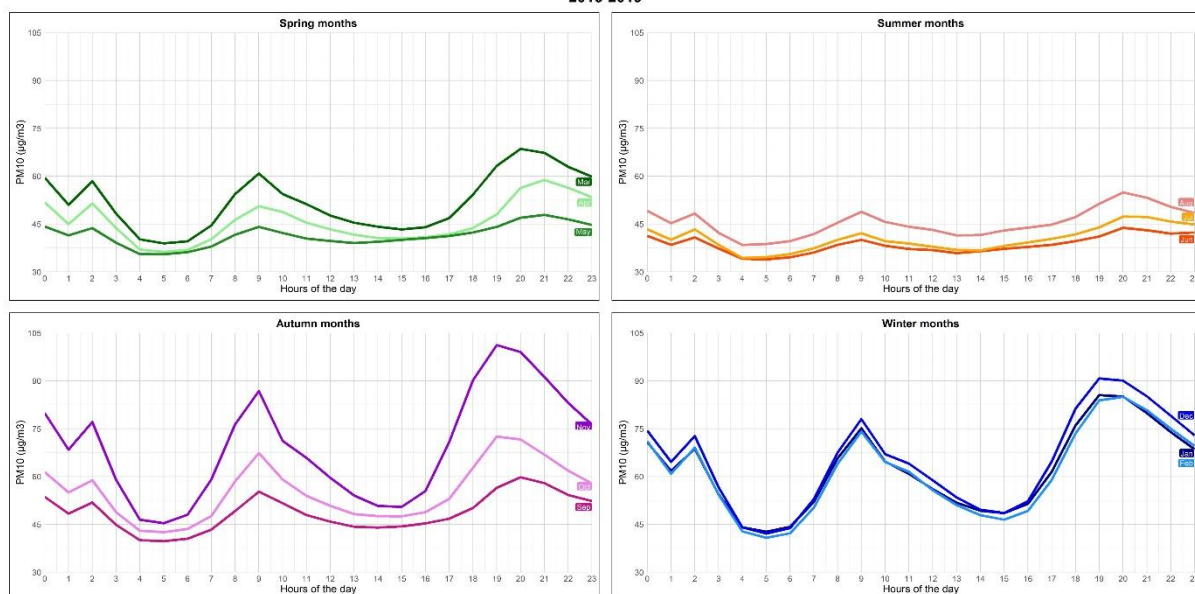


Figure A3 – PM₁₀ diurnal cycle averages aggregated by season for the period 2015-2019.

SO₂ diurnal cycle averages
2015-2019

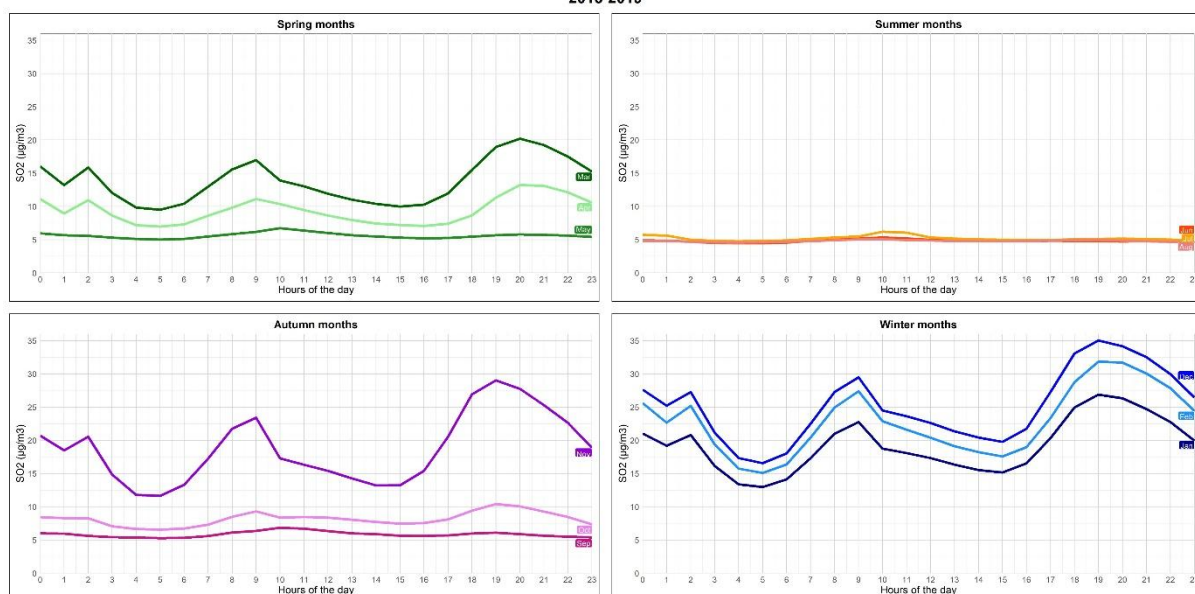


Figure A4 – SO₂ diurnal cycle averages aggregated by season for the period 2015-2019.

Topography

Each monitoring site's topographic context was examined to identify locations where higher pollution might have been expected or where peculiar settings may have influenced dispersion. For example, in valley locations (where downslope cold-air flows are related to boundary-layer stability) statistical associations between boundary layer height and pollutant concentrations should be interpreted as indicative relationships rather than demonstrations of physical causal mechanisms.

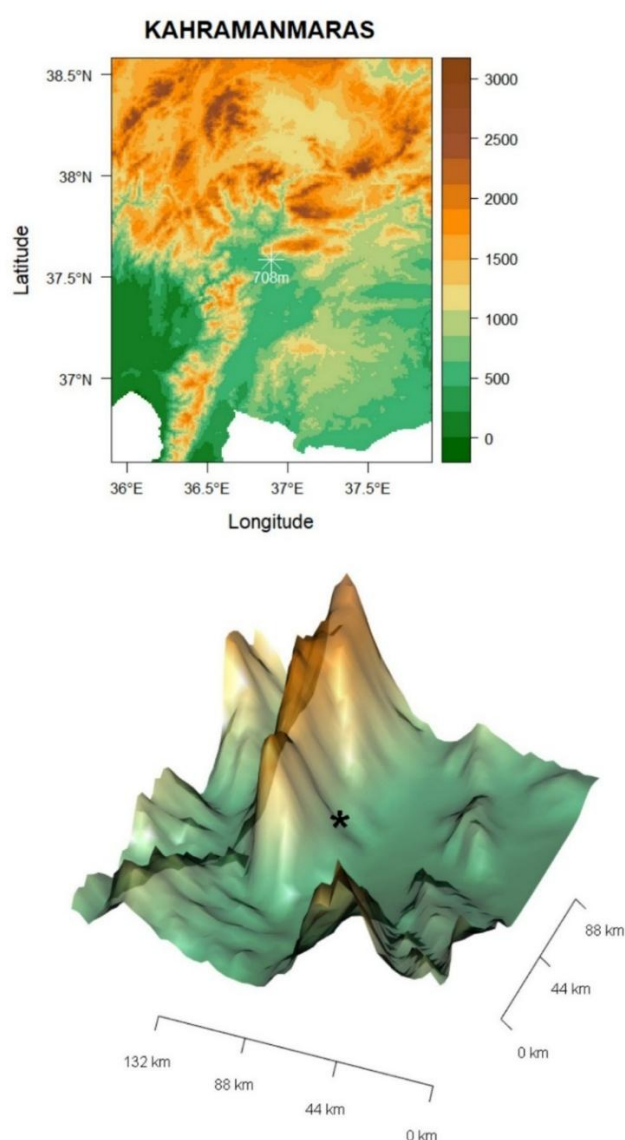


Figure A5 – Kahramanmaraş station location and its topographic profile.

Climate Normals

To ensure that the 2015–2019 study period is representative of the long-term climate and not characterised by exceptional atmospheric conditions, a climate-normals check was performed following the World Meteorological Organization’s guidance (WMO, 2017). This study adopts the standard 30-year period 1985–2014 to compute climatological normals for key variables, thereby providing a benchmark to assess whether 2015–2019 is unusual or drawn from extreme conditions. Non-parametric tests were used to compare the 2015–2019 distributions with the 1985–2014 climatology—specifically the Kolmogorov–Smirnov, Mann–Whitney U and Kruskal–Wallis tests—confirming that the study period is consistent with the long-term statistics.

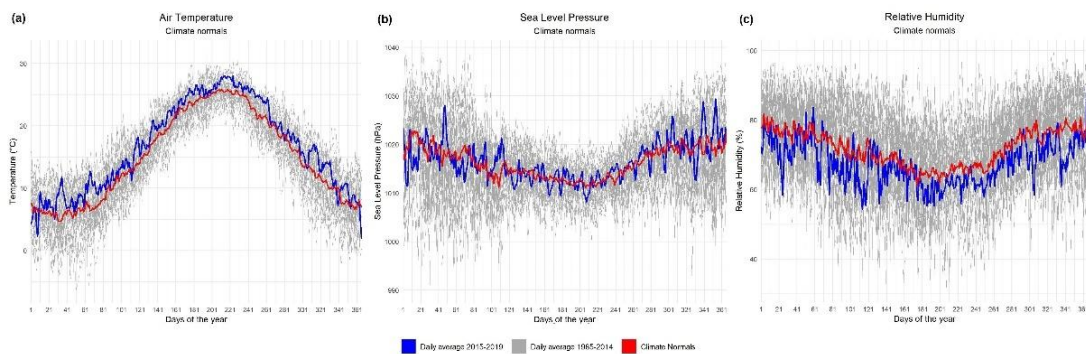


Figure A6 – Climate normals for Ataturk meteorological station.

Land Cover

Land cover can also influence pollution concentrations not only by contributing to pollution sources (though this is outside the scope of this study) (Wu et al., 2015), but also by affecting the dispersion and removal of pollutants through physical and biological processes (Baumgardner, 2012; Nowak, 2006). Land cover variables are constructed by dividing a 5 km square area around each station into a 5x5 grid and calculating the percentage of each of the four land cover categories for each grid—water bodies, green spaces, agricultural land and built-up areas. (land cover categories are simplified into four from the Copernicus Corine Land Cover).

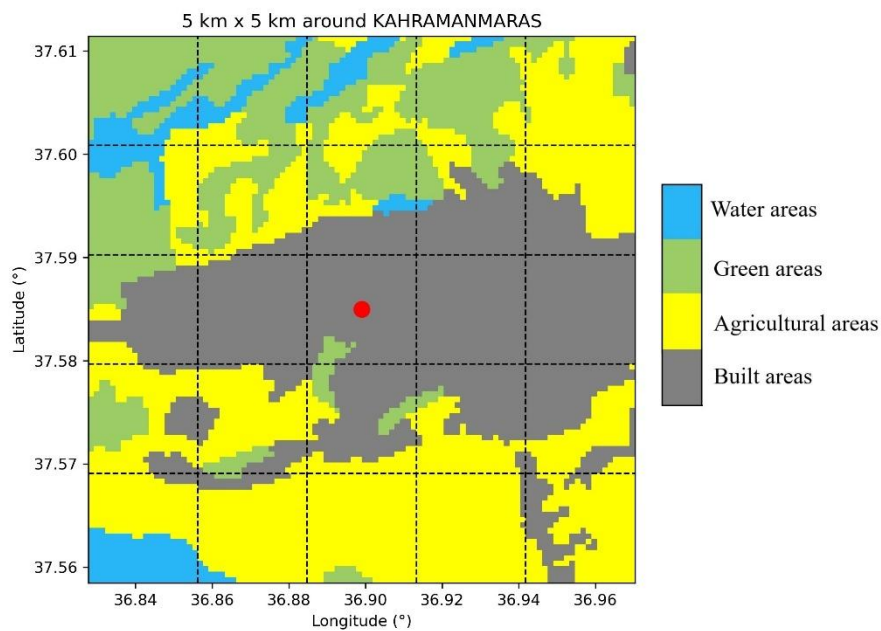


Figure A7 – 5 km square area for Kahramanmaraş station classified into four: Water, Green, Agriculture, and Built areas.

