The Economic Burden of Air Pollution's Health Impact.

Evaluating Single Businesses Value Chains on a Global Scale

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Authors' roles

This report was prepared by GIST's Natural Capital Research team led by Anupam Ravi with the core team members Smarika Kulshreshtha and Rahul Kumar Singh. The work is based on a previously built framework by Harsha Vardhan Murari, Sneha Phalke and Meghana Karod, led by Anupam Ravi. Chiara Gastaldi has collected and re-organised the material into the present paper. This work is done for GIST under the supervision of Pavan Sukhdev (CEO, GIST).

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Abstract

Air pollution is a major cause of morbidity and mortality. Since air pollution tends to concentrate around the emission point, its precise geographical assessment is particularly important. With the present work, we propose a new method to assess the impacts of any company's emissions on human health and the economy. We address the challenge of discovering, measuring, and managing the risks associated with externalities from air emissions. The methodology is accessible via the online tool for companies (Impact Valuation Engine). Our method allows spatially explicit analysis of the local impacts for each individual asset of the company; the outputs are specific at a resolution of $0.5° \times 0.5°$. For financial institutions, we provide the aggregated impacts embedded in their investment portfolios. Our analysis can help financial institutions reduce the overall footprint of their portfolios, meet sustainable investment targets, and comply with current regulations such as Sustainable Finance Disclosure Regulation and European Union Taxonomy.

1 Introduction

Air pollution is the world's fourth-leading risk factor for mortality, after high blood pressure, tobacco consumption, and dietary risks [1]. Exposure to air pollution significantly increases the chances of life-threatening diseases such as ischemic heart disease (IHD), lung cancer (LC), chronic obstructive pulmonary disease (COPD), cardiovascular diseases (CVD), stroke, and diabetes [2, 3]. Air pollution also plays a central role in deteriorating the quality of life and standards of urban cities worldwide [4]. Unfortunately, people of low-income socioeconomic status suffer the largest impact of air pollution, despite being directly the least responsible for it. This implies that poor people with the least means to address the health damages of air pollution often disproportionately carry the medical and economic burden [2]. Air pollution imposes a particularly heavy economic burden on the economies of low-middle-income countries (LMICs) and the global economy in general due to premature death, illness, lost earnings, and increased healthcare expenditures, all of which hinder productivity and economic growth [5–7]. For example, the global health cost of mortality and morbidity caused by air pollution in 2019 was estimated to be \$8.1 trillion, equivalent to 6.1% of the global GDP [2, 8], with over 95% of the 6.67 million premature deaths concentrated in low-income countries.

The UN's sustainable development goals (SDGs) strongly focus on reducing air pollution. Mitigating air pollution not only has a direct positive impact on SDGs related to the environment, such as SDG3 (good health and well-being) and SDG15 (life on land), but also significant connections to other SDGs, including SDG4 (quality education), SDG9 (industry, innovation and infrastructure), SDG12 (responsible consumption and production), SDG16 (peace, justice, and strong institutions), and SDG17 (global partnerships) [9].

In the literature, we can identify two main lines of studies. On the one hand, there is the estimation of air pollution and its effect (outcomes) in different geographies, which is a consolidated field, underlying that the chosen spatial resolution plays an important role [10–12]. This is particularly true when we want to assess the impact of pollution in densely inhabited areas, such as urban areas [13, 14]. There is a variety of tools to identify the geographical distribution of air pollution. On the other hand, we find several studies that use the impact pathway approach (IPA) to evaluate the impact of air pollution, Fig. 1 [15], and the methods to assess them [16]. With this approach, we can evaluate the impact of a pollution increment at a given location [17, 18]. Our approach bridges the two lines by using the IPA to assess the impact of air pollution of a company, with good geographical precision and leaving the possibility for the future to increase the geographical resolution.

The various valuation methods or approaches have their strengths and limitations, which sometimes leads to uncertainty or scepticism about the accuracy of the results [18, 19]. For example, the *willingness to pay* (WTP) approach is adopted as a standard practice in high-income countries to evaluate the health cost due to air pollution. Still, it has its limitations: a) it may not accurately reflect individuals' true willingness to pay, b) it can be criticized as being insensitive to income or wealth distribution, and c) its results may be influenced by the design and structure of the survey used to elicit WTP [20]. Hence, in the present study, we present a pragmatic approach for air pollution impact assessment and valuation based on IPA, which can be used for site-specific, regional, or global impact analysis. Although sufficient literature is available for certain industries, such as transportation [21], there is currently a lack of a comprehensive approach to assess the impact of the entire value chain of a generic business. With this work, we aim to provide such a tool, which estimates both the health and economic impact of air pollution from a generic business, and we apply it to a specific study case of a steel manufacturing plant in India in the Results section.

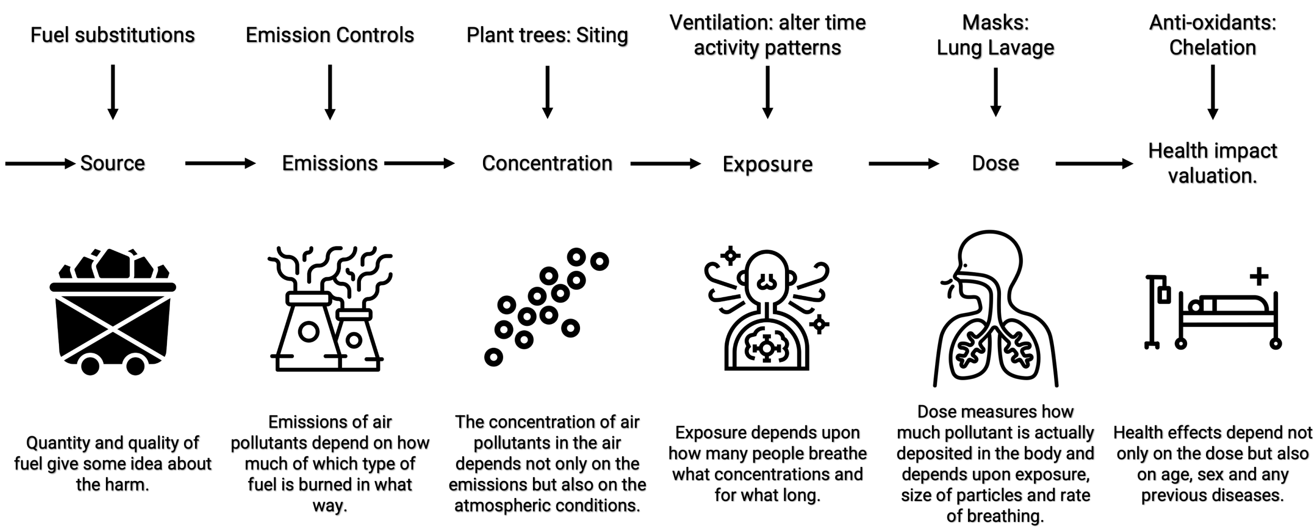

Figure 1: Air pollution impact pathway from source to effect (adapted from [15]).

In the method section, we present our novel approach to apply IPA framework at each grid, including dispersion modeling, exposure modeling, health impact quantification, and economic impact quantification. This novel approach allows for the calculation of the cost of a marginal change in the quantity of released pollutants in each of the 67,420 grid boxes. Using this granular approach, we could work back the cost factors for larger regional units such as cities, states, countries, and regions. The approach is flexible and adaptable to the level of data disclosure provided by a company. In cases a company's pollutant release data is disclosed at the country level, we use the country-level average cost factors to compute the impacts. Impacts are expressed in terms of the monetary estimates of the health impact cost of 1 tonne of increase of three air pollutants (marginal cost in dollar terms). Also, we performed a sensitivity analysis to evaluate uncertainties by changing one parameter at a time and analyzing its effect on the final output. In addition, the most sensitive parameter was selected for the range estimate of minimum, mean, and maximum total cost per tonne of pollutants.

More generally, externalities are directly linked with future risks (operational, reputational, market, or regulatory) for the company, and therefore we propose a tool to expand the horizon of the performance measurement from only looking at the financial performance of the companies to including third-party impacts. The use case is not limited to companies; it also applies to financial institutions as they can be exposed to these risks directly and indirectly via their investments in these companies. We are providing a mechanism through which the risk assessment of publicly listed company can be done using a limited set of data. To this end, we have demonstrated the application of the same by calculating the outputs of 12,000 companies for multiple years, on the Impact's Impact Valuation Engine (IVE). By using IVE, companies can gain insights into their activities' economic and social implications and make informed decisions to reduce their negative impact. Ultimately, the tool can help companies move towards more sustainable and responsible business practices while improving their bottom line.

2 Methods

Our approach is based on top-down life cycle impact evaluation models, specifically the eco-indicator 99 [22] and the impact pathway approach [23]. An outline of the framework adopted for evaluating impacts from air pollutants is shown in Fig. 2. *Drivers* for releasing air pollutants include multiple activities across a company's value chain. Activities like the use of fossil fuels in boilers, process emissions, transportation of raw material and finalised

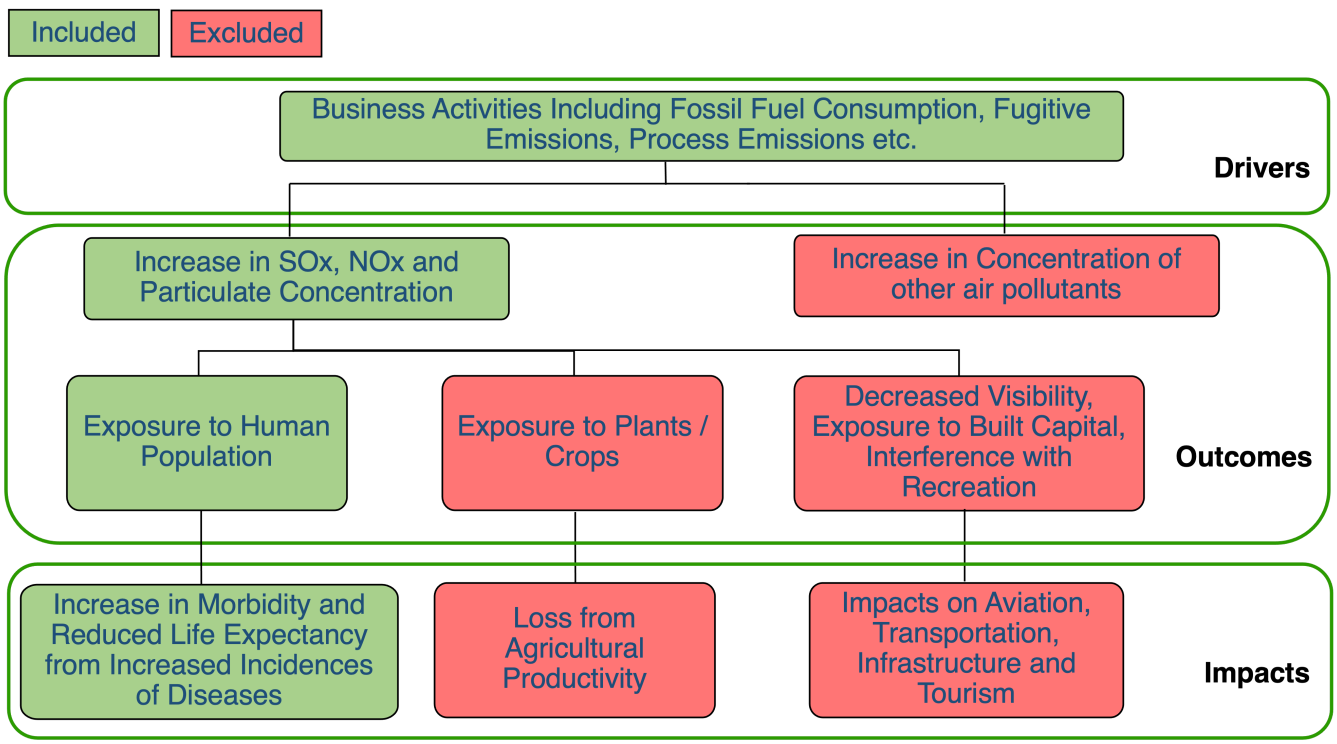

Figure 2: Air pollution evaluation framework.

products, fugitive emissions during handling of raw material and road transportation etc. lead to the release of air pollutants. Therefore each activity causes the marginal increase in the concentration of air pollutants in local environment which we call primary *outcome*. Net change in concentration of pollutants can be estimated through air dispersion modelling. Increased concentration of pollutants leads to multiple secondary outcomes such as exposure to human population, exposure to plants or crops, decreased visibility, exposure to buildings, and hampers recreational activities. Finally, these outcomes lead to *impacts* such as increase in morbidity or mortality from increased incidences of diseases, loss of agricultural productivity, impacts on aviation, transportation, infrastructure and tourism. In current assessment, only human health impacts are considered as they contribute as much as ∼95% of total impacts from air pollutants [24].

We quantify the health impacts cause by an increase in air pollutant concentration in terms of the marginal increase of the attributable morbidity and mortality. Next, the financial cost of morbidity and mortality is valued using the hybrid *human capital approach* (HCA) [25]. The HCA approach is a method used for impact valuation that aims to estimate the economic value of human capital development, particularly in terms of its impact on productivity and income. It has two components: the *cost of illness* (COI)[1], which includes direct costs, such as medical costs; and the *disability adjusted life years* (DALYs), which count the indirect costs, and it is equivalent to the number of productive days lost due to illness (including the reduced life expectancy) [25].

Based on an extensive meta-analysis of multiple research papers, relative risk values are selected for PM_{10}, SO_x, and NO_x [26–33]. The selection process involved analyzing a large body of scientific literature, evaluating the quality of the studies, and synthesizing the results to arrive at the most accurate and reliable estimates of relative risk. We used the mortality and morbidity rates due to $PM_{2.5}$ exposure from the Global Burden of Disease Study 2019 (GBD) [34], which assesses mortality and disability from numerous diseases, injuries, and risk factors. For SO_x and NO_x mortality and morbidity rates we use the data from [35, 36].

According to the GBD 2019 study, globally, ischemic heart disease and stroke account for 53% of deaths from $PM_{2.5}$; respiratory illnesses for 35%, including COPD, LRI, and lung cancer; neonatal disorders for 6 percent; diabetes for 5%; and other diseases for less than 1 percent [34]. In this report, the valuation is done in terms of the health impacts of the following disease endpoints: ischemic heart disease (IHD) and cardiovascular diseases (CVD), lung cancer, chronic obstructive pulmonary disease (COPD), stroke, lower respiratory infections, and diabetes.

The costs of health impacts due to a marginal increase in air pollution is calculated in five steps below.

2.0.1 Step 1: Sources classification

Fine particulate matter (PM_{10}), nitrogen oxides (NO_x), and sulfur oxides (SO_x) are among the most commonly monitored air pollutants, due to their negative impact on human health and the environment. The current work aims to provide the monetary estimates of the health impact cost of 1 ton of increase of three air pollutants (marginal cost in dollar terms), viz., PM_{10}, SO_x and NO_x emitted from three different sources viz, line, area and point all over the world divided into more than 67420 grid boxes of $0.5^\circ \times 0.5^\circ$ resolution.

The sources of air pollution are generally categorized as point, area, and mobile or line sources described as follows:

Point sources: typically industry and heating, they release pollutants into the air through a single well-defined point of emission. An example of a point source is a large industrial facility such as a coal-fired power plant or a chemical manufacturing plant. In Europe, around 60% of sulfur oxides come from energy production and distribution [35]. In the US, stationary fuel combustion sources like electric utilities and industrial boilers are responsible for 73.2% of sulfur dioxide pollution [36].

Line sources: refers to pollution sources that are linear or elongated in nature, such as highways or railroads. These sources emit pollutants over a long, narrow area. An example of a line source of air pollution is a major highway that runs through a densely populated urban area. More than 40% of NO_x and almost 40% of primary $PM_{2.5}$ emissions in Europe are linked to road transport. In the United States, 35.8% of CO and 32.8% of NO_x stem from road transport [36].

Area sources: typically from agriculture, area sources are widely dispersed and cover a large geographic area. They can be made up of multiple small sources, including residential and commercial buildings, agriculture, and landfills.

[1] The cost of illness (COI) method provides an estimate of the economic impact of a disease by calculating the direct costs associated with medical expenses such as pharmaceuticals, diagnostics, treatments, and hospitalizations, as well as the indirect costs such as lost income or reduced social output. This approach essentially provides a lower bound estimate of the value of health damage caused by the disease.

2.1 Step 2: Quantification of Pollutant Emission

The first step is to quantify all the relevant air pollution emissions within the geographical grid for a given time. Using onsite air emissions data, if available, would best for quantifying the impacts, however it is very difficult and rarely possible for a company to measure this data across entire value chain. So, the drivers of air pollution used in business activity (Ex: Fossil fuels) can be used to estimate emissions indirectly based on emission factors (e.g., compilation of air emissions factors [37]). Various modelling techniques based on life cycle assessment (E.g., GaBi Database, ecoinvent, etc. [38, 39]) and Environmentally - Extended Input Output (EEIO) analysis [40] (Ex: Exiobase [41]).

For global coefficients calculations, the globe is divided into 67,420 grid boxes of $0.5° \times 0.5°$ and a pollution source with unit emission (1gm/sec) is considered at the center of each grid. To provide a comprehensive understanding of the impacts of air pollution on human health and the environment, the global air pollution coefficients were calculated by dividing the world landscape into 67,420 grid boxes of $0.5° \times 0.5°$ (based on [42]) with unit emission (1gm/sec) pollution source considered at the centre of each grid running all stages for dispersion modeling, exposure modeling, health impact quantification, and economic impact quantification on these grid boxes. This approach allows for the calculation of the cost of releasing one ton of a pollutant in each of these 67,420 grid boxes (assuming that the centroid of that grid represents the dispersion profile of whole grid box).

Table 1 shows the details of 4 types of pollution sources considered at the center of the grid box as a representative of point, line, and area sources discussed in the previous section. These sources are close approximations to the available stack characteristics from businesses. Of the two stack heights (30m and 65m), the appropriate one can be based on the business sector of the source, e.g., a 65m stack is used in the case of utilities, cement manufacturing, etc. We have defined the emission per year as the emission rate the conversion factor of second to year (3600 s $\times$ 24 h $\times$ 365 d), divided by the conversion factor of grams to tonnes (10^6).

Source Type:	**Point Source - 65 meters stack**	**Point Source - 30 meters stack**	**Line source**	**Area Source**
Source Definition	Grid centroid coordinates	Grid centroid coordinates	Line source of 1 km $\times$ 15 m passing through Grid centroid coordinates	Area source of 1 km^2 with centroid as Grid centroid coordinates
Emission rate	1 g/s	1 g/s	1 g/s/m2	1 g/s/m2
Release height	65 m	35 m	0.5 m	10m
Gas exit temperature	423 Kelvin	385 Kelvin	-	-
Gas exit velocity	10 m/s	7 m/s	-	-
Stack inside diameter	4 m	1.5 m	-	-

Table 1: Characteristics of the four pollutant source types used for impact assessment

The dispersion model that quantifies the change (ΔC) of the concentration of the pollutant in the atmosphere, is described in Step 2.

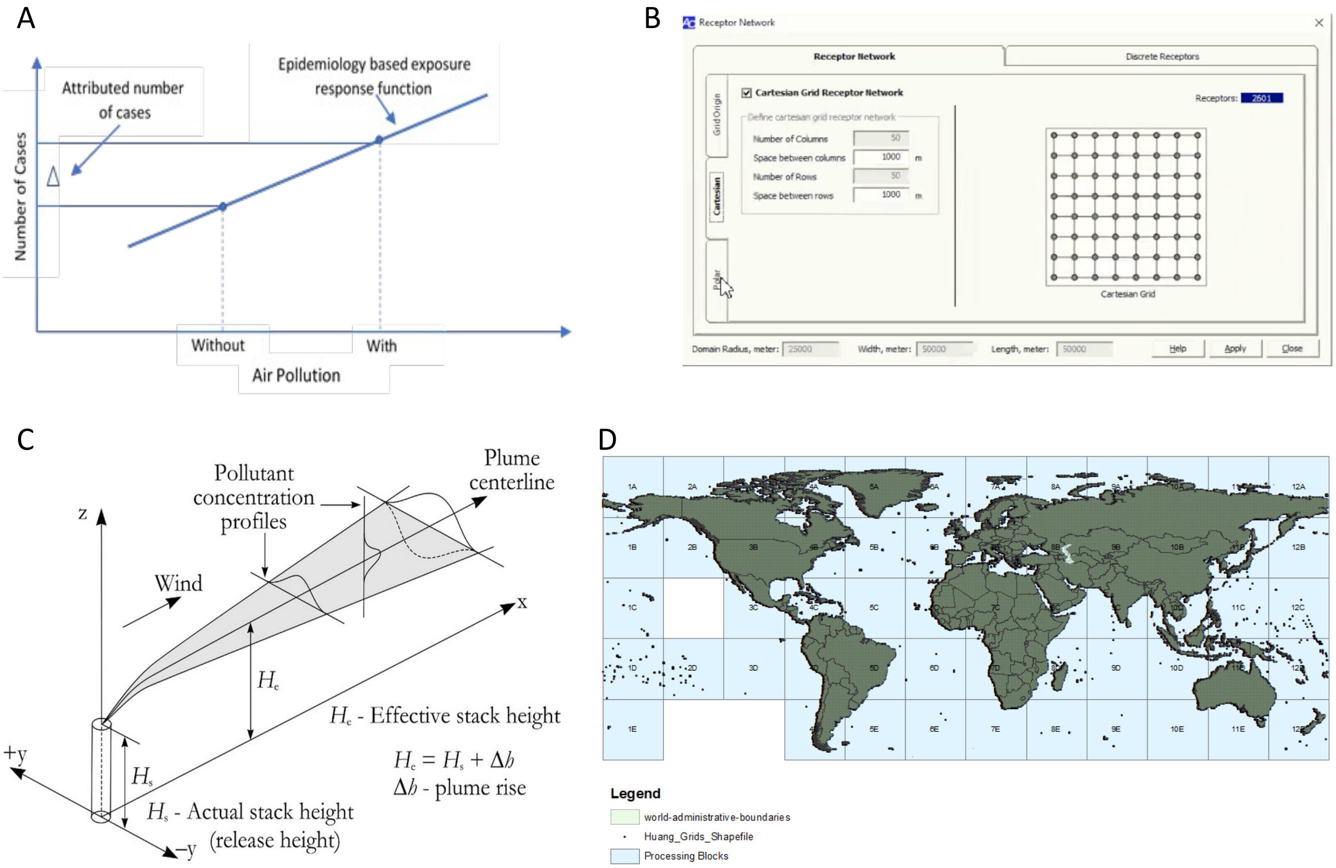

Figure 3: A) Relation between air pollution exposure and cases of disease (Adapted from [43]). B) Arrangement of receptor network for each source. C) Schematic figure of a Gaussian plume. The effective stack height H and the crosswind and vertical deviation of the profile are the key parameters of the model. D) Blocks for global processing. The last row (F) from -90° to -60° is omitted because there were no grid boxes representing land. Similarly, there are no grid boxes in blocks 2C, 2E and 3E, and hence are omitted.

2.2 Step 3: Dispersion of Pollutants

2.2.1 The AERMOD model

An AERMOD atmospheric dispersion modeling system [44], is used to predict the downwind concentration of air pollutants emitted from emission sources based on a steady-state dispersion model (Gaussian plume model Eq. 1), schematized in Fig. 3B. The global pollutant dispersion model is a step by step process itself. The following data-sets are used as inputs to the AERMOD atmospheric dispersion modeling system:

- Source characteristics: details of sources like stack height, length, area, and geographical location are input to the dispersion model. Based on Table 1 and 2 sources are considered in the report. These sources are located at the centre of each of the 67,420 grid boxes.

- Wind speed and direction obtained from CCMP (Cross–Calibrated Multi-Platform) Wind Vector Analysis Dataset [45].

- Atmospheric and climate variables such as temperature, pressure, humidity, sensible heat flux, cloud cover, surface roughness, and latent heat flux are obtained from ERA5 Reanalysis Database [46]. These variables are explained in detail in the appendix, Section 5.

- Receptor grid characteristics: the receptor network corresponding to each source consists of 2601 receptors in a Cartesian coordinate system for each grid box of $0.5° \times 0.5°$. Each receptor is at 1 km distance, as shown in Fig. 3B.

$$C(x,y,z) = \frac{Q}{2\pi U \sigma_y \sigma_z} \times e^{-\frac{y}{2\sigma_y^2}} \times \left(e^{-\frac{(z-h)^2}{2\sigma_z^2}} + e^{-\frac{(z+h)^2}{2\sigma_z^2}} \right) \tag{1}$$

Where,

- $C(x,y,z)$ is the concentration of pollutant (in µg/m^3) at receptor location (x, y,z), i.e., x meters downwind of the source, y meters laterally from the centre line of the plume, and z meters above the ground.

- Q is pollutant emission rate (mass per unit time)

- U is the mean wind speed at release height (in meters per second)

- h is the effective height of the source above ground level (in meters)

- σ_y and σ_z are the standard deviations of a statistically normal plume in the lateral and vertical dimensions, respectively. They are given by

- $\sigma_y = x\frac{\alpha}{\sqrt{1+0.001x}}$, where α parameterises the stability conditions

- $\sigma_z = f(x)$, where $f(x)$ takes various forms depending on stability conditions

- Stability conditions classifications – very unstable, moderately unstable, slightly unstable, neutral, somewhat stable, and stable.

2.2.2 Blocks for global pollutant dispersion modelling

For the simulation of dispersion all over the globe, the globe is divided into 12 columns and 6 rows of size $30°\times30°$. Each block has 60×60 grid boxes. So, each degree has 4 grid boxes since each grid is box $0.5°\times 0.5°$. Longitudes vary from geographical coordinates (WGS) -180° (E) to +180° (W). There are 12 columns along the longitude, presented by numbers 1 to 12. Latitudes vary from -90° (S) to +90° (N). There are 6 columns across the latitudes, presented by alphabets A to F. Additionally, the blocks that do not contain any grid boxes are removed. The final world map showing the blocks is shown in Fig. 3D.

The mapping between the geographical coordinate system and meteorological grids is describe in what follows:

1. **Spatio-temporal interpolation of the u-wind and v-wind** The CCMP (Cross-Calibrated Multi-Platform) wind data, available at a resolution of 0.25 degrees, is not aligned with the grid boxes. Therefore, in order to obtain wind data at the Huang grid centroids, we interpolate the data to the centroid of each grid. Furthermore, as the CCMP wind data is only available every 6 hours, temporal interpolation is also carried out to generate hourly u-wind and v-wind data at each grid centroid.

2. **Calculation of wind speed and wind-direction.** The u-wind and v-wind data from CCMP cannot be used directly as input but converted to wind speed and wind direction data-sets. This step does the conversion of u-wind and v-wind data to wind speed and direction, and then it is combined to get a single wind file.

3. **Spatio-temporal interpolation of 11 ERA-5 outputs** ERA-5 is a state-of-the-art meteorological data-set produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). It provides a comprehensive view of the Earth's atmosphere at high spatial and temporal resolutions, covering the period from 1979 to the present day. The hourly ERA-5 meteorological data is at 0.25 degrees and is aligned differently than the grid boxes. This step is, thus, to obtain the meteorological data at Huang grid centroids. This is done by spatial interpolation of ERA-5 data at the grid centroids.

4. **Blockwise extraction and processing of meteorological data-sets**. The 13 meteorological parameters (ERA-5 and CCMP) are extracted for each processing block using Python. The next step is the block-wise arrangement of extracted meteorological data for ease of processing. After this step the meteorological files are processed for each block to generate block-wise surface and profile files. For each block of size $30° \times 30°$ has 3600 (60×60) grid boxes, each grid box of size $0.5° \times 0.5°$. Each block thus generates 3600 profile files and surface files.

5. **AERMOD Processing.** Finally, the input files are generated for each surface and profile file and the AERMOD is processed at each of the 57 blocks. The AERMOD outputs in terms of the average, range and standard deviation of maximum pollutant concentration is extracted.

2.3 Step 4: Exposure Estimation

The health impacts from the exposures are variable within a population because of differences in individual vulnerabilities or competing risks. Dose-response assessment studies define quantitative relationships between pollutant exposure and health effects [43,47]. An example of the dose-response function, which represents the relation between exposure to air pollution and the frequency of health outcomes, is shown in Fig. 3A. Air pollution affects people locally around the pollution site, therefore it is essential to estimate the regional population density accurately. We use $0.1° \times 0.1°$ grid population densities from the Version 4 database from SEDAC (Socioeconomic Data and Applications Center) NASA Gridded Population of the World [48]. Then we overlap the population densities with the respective average pollutant concentrations for each grid box to provide the number of human subjects exposed to a net increased concentration of pollutants.

2.4 Step 5: Quantification of Health Impacts of Pollutants

To estimate the health impacts of air pollution we rely on Relative Risk (RR) measures. Relative risks (RR) are used to calculate the health impacts of the increased concentration of pollutants in an area. Total mortality and morbidity are calculated for SO_x, NO_x and PM_{10} based on their impact on increased incidences of diseases. The Relative Risk (RR) is the ratio of the probability of a disease occurring in the exposed group versus the probability of the disease occurring in the non-exposed group. RR is defined in Eq. 2 [49]:

$$\text{Relative Risk} = \frac{\frac{a}{a+b}}{\frac{c}{c+d}} \tag{2}$$

Where the parameters a represents the fraction of exposed people who got the disease, b the number of exposed people who did not get the disease, c the number of people developed the disease despite not being exposed, and finally, d is the number of healthy non-exposed people. The numerator of Eq. 5 is the fraction of those exposed who have the disease, and the denominator is the fraction of those not exposed who have the disease. If those two ratios are the same, the odds of having the disease would not depend on whether an individual is exposed to the risk factor, and the relative risk would be 1.0. Above 1.0, the higher the relative risk, and the more the data suggests an association between exposure and risk. For each of the included health endpoints, a relative risk estimate (RR) is determined by pooling the estimates from the available studies, as discussed above. The relative risk is the increase in the probability of a given health effect associated with a given increase in exposure (usually 10µg/m^3 in epidemiological studies). The attributable proportion A of health effects from air pollution for the entire population is calculated in Eq. 3 [15].

$$A = \frac{RR - 1}{RR} \tag{3}$$

Eq. 4 calculates the number of cases attributable to air pollution (E), [24].

$$E = A \times B \times C \times P \tag{4}$$

Where,

- A = Attributable proportion of health effects
- B = Population baseline rate of the given health effect
- C = Relevant change in air pollution
- P = Relevant exposed population for health effect

The RR number is divided by 10 to obtain the risk per unit. B is obtained from available health statistics from GBD 2019 [34], C is obtained from Step 3 of dispersion modelling as the marginal increase of concentration of air-pollutant, and P is obtained as a part of exposure assessment at Step 4.

In agreement with previous literature, we express health impacts using a physical indicator called Disability-Adjusted Life Years or DALY. The DALY indicator for a disease or health condition is defined as the sum of the Years of Lost Life (YLL) due to premature mortality in the population and the Years Lost due to Disability (YLD) for people living with the deteriorated health condition [50].

$$DALY = YLL + YLD \tag{5}$$

2.5 Step 6: Monetary Valuation of Mortality and Morbidity

We choose an Hybrid Human Capital Approach (HCA) for valuing health impacts based on two components: Cost of Illness (COI), which considers the treatment and the medical cost, and the DALY (Disability Adjusted Life Years) introduced above. We use per capita income to value the lost DALYs. GDP per capita values are obtained from the world bank for 2020. COI studies typically address direct medical costs associated with physician services, medication, and hospital stays [51]. This data is collected from scientific and medical community literature and represented in terms of the same year and currency using inflation and exchange rate values from world bank literature [7]. Some of the other impact aspects, such as mental discomfort or loss of income of associated family members, are difficult to estimate and, at times, put a monetary value; therefore, they are not a part of economic valuation.

3 Sensitivity Analysis and Range of Estimates

3.1 Sensitivity Analysis

Sensitivity analysis (SA) or what-if analysis refers to the study of divergence in the output of a model related to sources of variance in the model input(s) [52]. We apply it to the input variables within the specific boundaries, such as the effect that changes in DALY or Relative Risk (RR) has on the overall air pollution health impact valuation. The literature review shows that various authors considered the selected model sensitive to input parameters such that the model results can be evaluated with an input parameter so that small changes in the input value result in significant changes in the output. We follow the second approach where input parameters sensitivity analysis is done by changing its values and selecting the most important parameter based on its impact on the output valuation numbers. In the case of air pollution, the final impact valuation is primarily a function of DALYs, prevalence[2], GDP per capita, cost of illness (COI), marginal pollution concentration, Total ambient air pollution, grid population density, relative risk (RR) and population attribution fraction (PAF)[3]. Hence, we considered the above mentioned parameters important and included them in the sensitivity analysis. The analysis is carried out by changing (increasing and decreasing) the parameters by -10% to +10%. The results are obtained by changing one parameter at a time from their selected baseline scenario values (Table 2) and keeping the other parameters at their original values. The results of this analysis are shown in Fig. 4.

	Case	DALYs per 10K	Prevalence per 10K	GDP per Capita	COI	Marginal Pollution	Total Ambient Air Pollution	Grid Population	RR	PAF
Baseline Scenario	0	100	100	10000	1000	1	10	100000	1.01	0.01

Table 2: Baseline scenario values of important parameters considered for sensitivity analysis.

The sensitivity analysis results showed that the final output (cost per tonne) is highly sensitive with respect to the relative risk (RR) parameters. As shown in Fig. 4, the RR parameter showed more than a 9000% change in the final output with a 10% change in the input value. The parameters like marginal population concentration, grid population density, DALYs, and GDP per capita were moderately sensitive. Whereas, ambient air pollution concentration (-1%), COI (9%) and prevalence (9%) were the least sensitive parameters.

[2]Prevalence is the proportion of a population who have a specific characteristic in a given time period (National Institute of Mental Health website).

[3]Population attributable fraction (PAF) is a statistical measure used to estimate the proportion of cases of a disease or health outcome in a population that can be attributed to a specific risk factor (WHO).

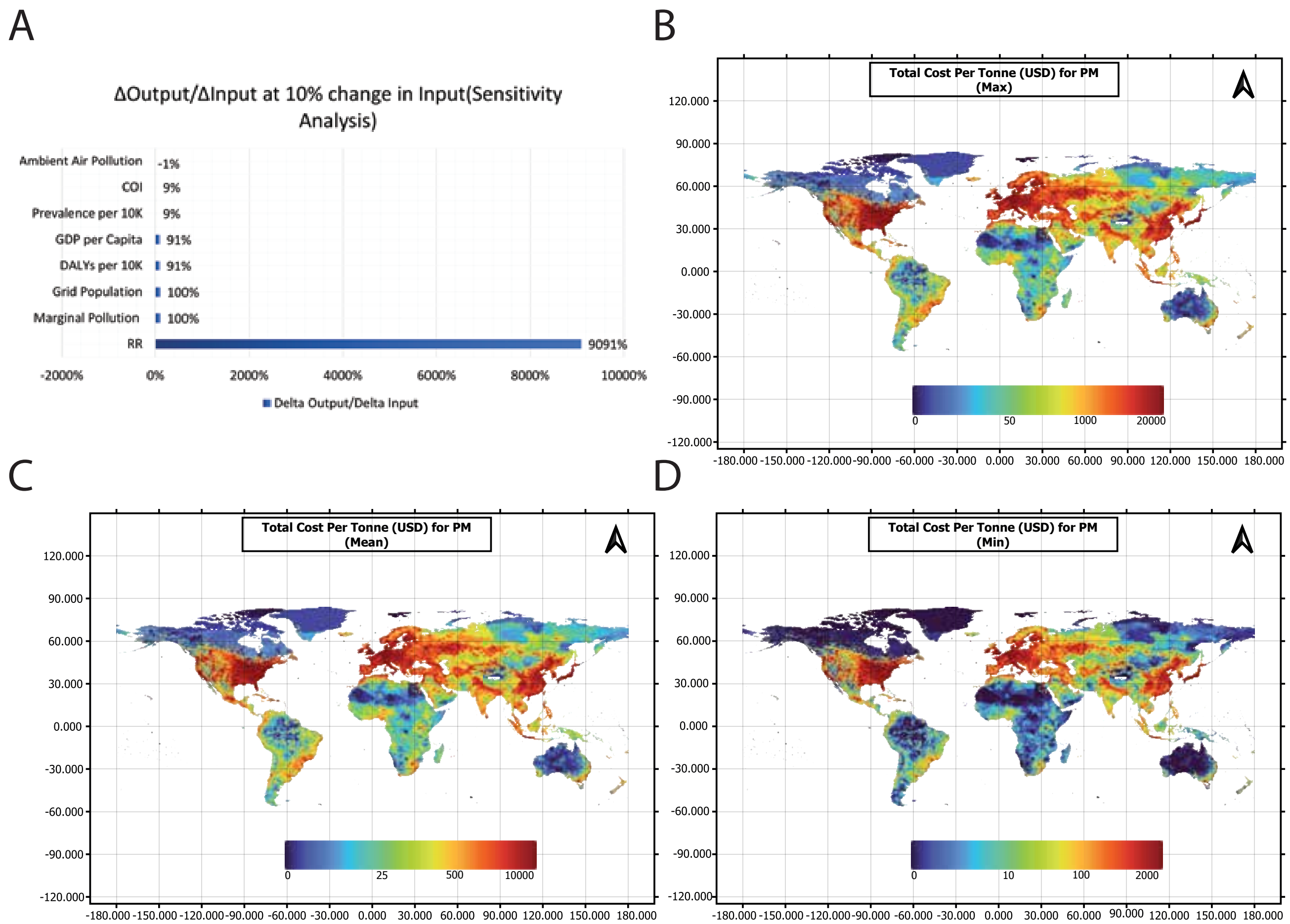

Figure 4: A) Sensitivity analysis results of various parameters in consideration B) Maximum cost of air pollution on human health. C) Mean cost of air pollution on human health. D) Minimum cost of air pollution on human health.

3.2 Range of Estimates

To accurately represent the natural variation of the final air pollution health impact valuation estimates, a range of estimates (RoE) in terms of maximum, mean and minimum values is an excellent first step to improving accuracy. The difference in values of RoEs also indicates the uncertainty propagated into the final output numbers. Taking over from the sensitivity analysis as discussed in the section above, the relative risk (RR) parameter is selected as the catalyst for range estimation of the final impact valuation (cost per tonne) on human health due to air pollution. The relative risk (RR) is the ratio of the probability of a disease occurring in the exposed group versus the likelihood of the disease occurring in the non-exposed group. The maximum, mean, and minimum relative risk (RR) values for selected conditions and pollutants are taken from GBD 2019 and used in Equation 5 to get the population attribution fraction (PAF) ranges (PAF_{max}, PAF_{mean}, and PAF_{min}). The global cost of air pollution to human health (cost per tonne) for particulate matter (PM_{10}) is shown in Fig. 4C to Fig. 4D. Assuming all other parameters constant, the combination of high population density and high per capita income leads to an increased demand for energy and resources, which contributes to higher levels of air pollution and a corresponding increase in health costs associated with air pollution and same can be interpreted through Fig. 4.

4 Results

4.1 Case study 1

We carry out the impact evaluation for the major air pollutants (PM, SO_x, NO_x) from an electric utility company based in Bilbao, Spain.

4.1.1 Scope and Boundary

The *scope* of an evaluation defines the institutional (i.e., corporate, business division, etc.), geographical (i.e., sites, locations, factories, etc.) and product line limits of the evaluation and lists each of the impacts being evaluated. The *boundary* of evaluation defines the value-chain limits for (example: cradle-to-grave, gate-to-gate, gate-to-grave, etc.) of the evaluation. The boundary for evaluation is considered as impact due to direct operations in the industry. An overview of the activities considered under the current evaluation are: 1) emissions due to the use of fossil fuels in power generation, 2) emissions from process stacks, 3) emissions due to electricity transmission and distribution, 4) emissions due to heavy machinery operations, 5) other activities.

4.1.2 Data

The emission data due to the above-mentioned activities are obtained for 2020, as shown in Table 3. The information about stack locations in terms of geographical coordinates is also obtained for the plant.

PM10 (Tonnes)	**SO_x (Tonnes)**	**NO_x (Tonnes)**
1270	1352	62517

Table 3: Emissions per year are provided by an example plant located in Spain.

The quantified emissions from the various activities are used along with source parameters to calculate yearly emission rates, which helps in finding the change in the concentration (ΔC) of the pollutant in the atmosphere through the dispersion modelling exercise described below.

4.1.3 Dispersion modelling to quantify the increase in pollutant concentration (Drivers)

For the given electric generation plant, the source details are input to the AERMOD Modelling system along with the meteorological datasets for the given geographical location and year of analysis. Dispersion modelling is simulated at a resolution of $0.5° \times 0.5°$, the results of which are shown in Fig. 5A-B. The wind rose chart (Fig. 5A) shows how wind speed and direction are distributed for the plant location grid of $0.5° \times 0.5°$ over the year. The AERMOD simulation (Fig. 5B) shows the concentration of air pollutants, which is driven by the meteorological conditions for the given location and period of analysis.

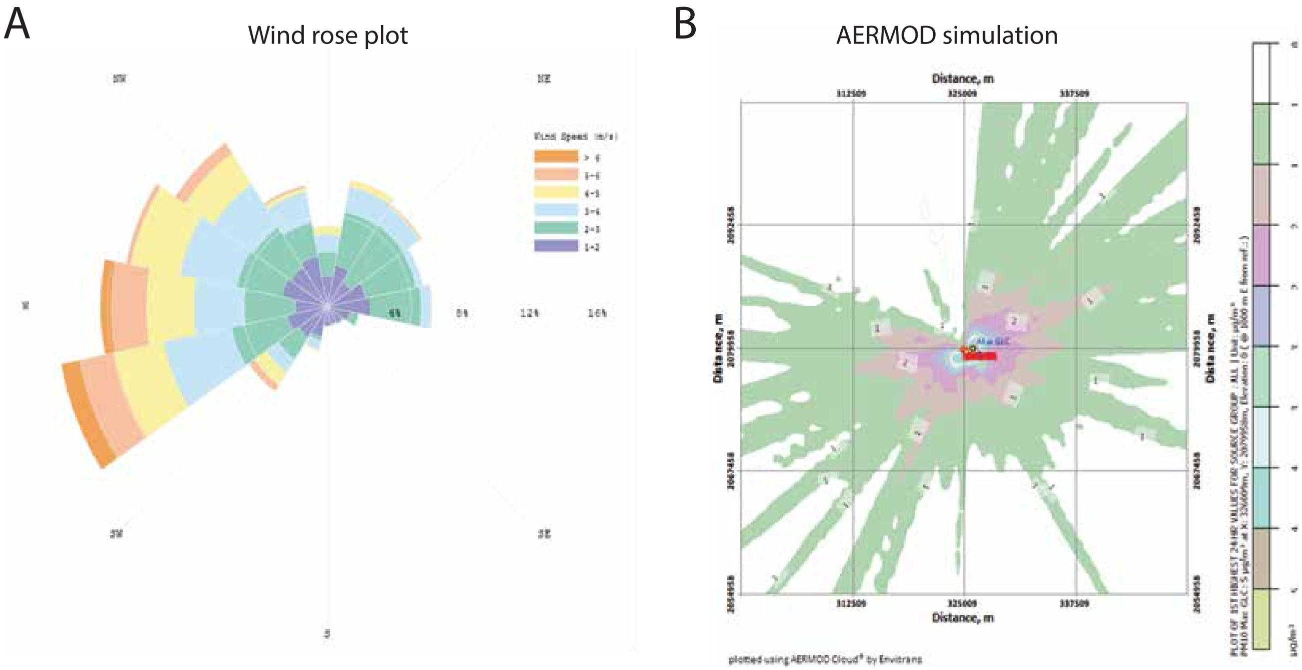

Figure 5: A) The wind rose and B) AERMOD simulation for the location of plant emission sources in a $0.5° \times 0.5°$ region.

4.1.4 Estimating pollutant exposure based on regional population density

For the given location of the plant, the gridded population density for 2020 is obtained from SEDAC for the $0.5° \times 0.5°$ region, which has the maximum direct impact. The simulated pollutant concentrations from the dispersion modelling are overlapped with respective population densities to provide the number of human subjects exposed to a net increased concentration of pollutants. The gridded population was also mapped to their countries (Fig. 6A) for apportioning DALYs and Prevalence rates.

4.1.5 Quantification of Health Impacts (Outcome)

We use meta-analysis data from epidemiological studies, which estimates the dose-response relationship between pollutant concentration and its health impact. In order to calculate the increase in the number of cases solely associated with increased air pollution, we use country-wise DALYs as per the selected six diseases and the associated population attribution factor (PAF). The attribution factor for a selected disease was calculated using the specific relative risk estimate (RR). The relative risk is the increase in the probability of a given health effect associated with a given increase in exposure (usually $10 \mu g/m^3$ in epidemiological studies. The RR is also converted to risk based on a particular geographic location's baseline or observed concentration. When we are looking into the relationship between the exposure and relative risk (RR) of the population for a particular health impact, the RR factor takes into consideration of all the underlying socio-economic factors such as age, gender, underlying diseases in the population, etc. These human health impact parameters like RR, DALYs, prevalence rates, etc., are taken from the Global Burden of Disease Study, 2019 from IHME. We also conduct a sensitivity analysis of the input

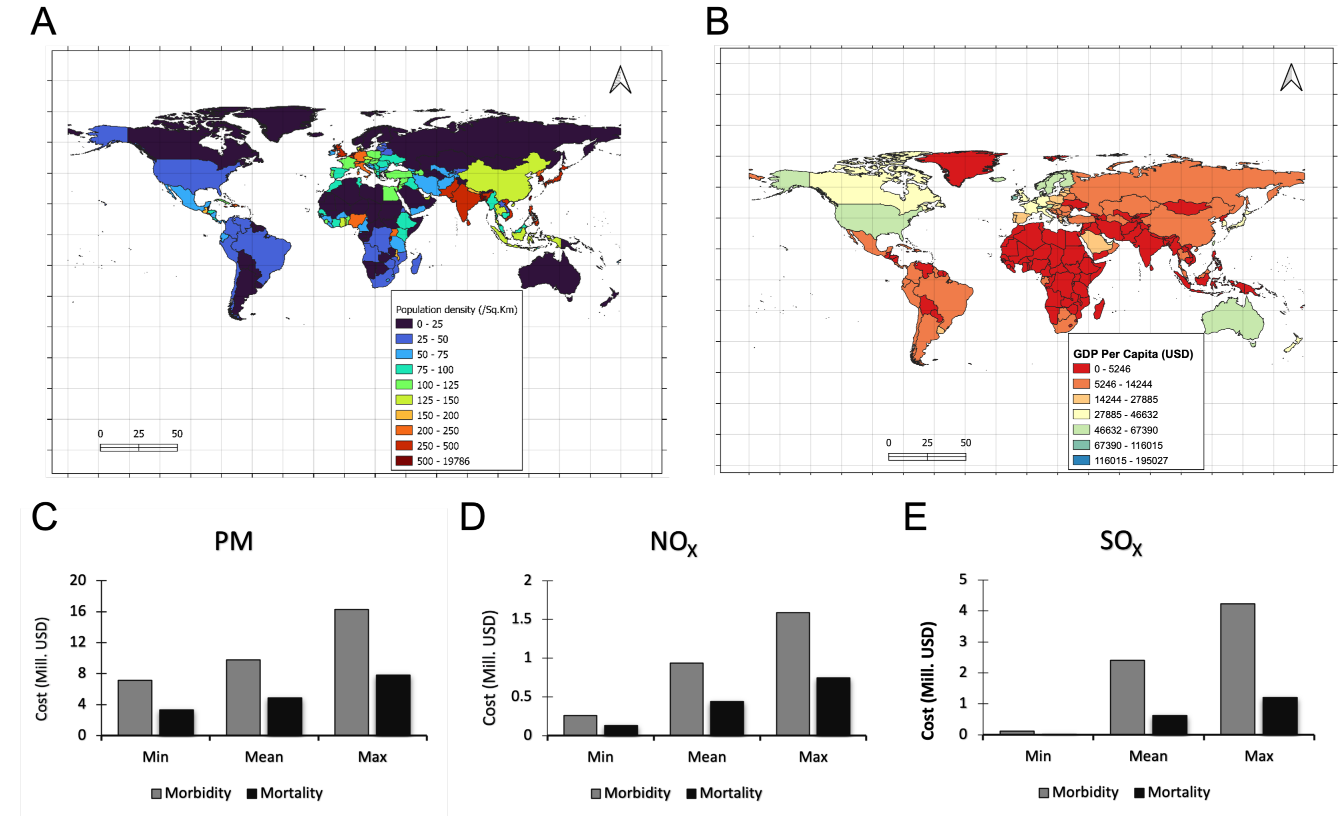

Figure 6: A) Global population density for 2018 [48] B)GDP per Capita (USD) for 2020. (Source: World Bank) C-E) Impact of air pollutant (PM_{10}, NO_x and SO_x) emissions in terms of morbidity and mortality (Reduced life expectancy).

parameters by changing their values and selecting the most important parameter based on its impact on the output valuation numbers. The sensitivity analysis results showed that the final output (cost per tonne) is highly sensitive with respect to the RR, and hence it is selected for the range of estimates (RoE) evaluation.

The attributable proportion (Eq. 3) of health effects from air pollution for the entire population. To calculate the number of cases attributable to air pollution Eq. 4.

For the given geographical location of the plant (Spain), the epidemiological study results in relative risk (min, mean, and max), YLL, YLDs, DALYs, and prevalence rates are collated for PM considering different health outcomes, viz. COPD, respiratory, cardiovascular, stroke, diabetes and lung cancer and is shown in Table 4. Similarly, the relative risk (RR) values differ for NO_x and SO_x, whereas the DALYs (DALYs = YLL + YLDs) and prevalence remain the same for further analysis.

In order to facilitate the comparison between various health effects from various environmental risks, impacts (i.e., No of cases) calculated from the above section are converted to Disability Adjusted Life Years (DALYs), a common comparison metric suggested by World Health Organisation (WHO). Using equation 2 above, the number of DALYs and Prevalence for prevailing health conditions associated with PM, NOX and SOX was calculated for all

Disease	**RR (min)**	**RR(Mean)**	**RR (max)**	**YLL**	**YLD**	**DALY**	**Preva-lence**
Respiratory Disease	1.04	1.09	1.13	155930.42	1846	157776	31526
Lung cancer	1.09	1.16	1.18	516789.31	7497	524287	49700
Cardiovascular diseases	1.16	1.14	1.58	702209.12	40400	742609	1528789
Stroke	1.21	1.29	1.62	426741.33	85639	512380	552068
COPD	1.07	1.12	1.15	348085.65	159618	507703	2905819
Diabetes	1.12	1.28	1.30	116822.81	375256	492079	4478926

Table 4: Relative Risk estimates (RR), YLLs, YLDs, DALYs and Prevalence rates per case for PM and health outcomes in Spain. (Source: IHME (GBD 2019).

	Attributable Fraction			**Attributed DALYs**			**Attributed Prevalence**		
Disease	AF_Min	AF_Mean	AF_Max	Min	Mean	Max	Min	Mean	Max
Respiratory Disease	0.04	0.08	0.11	12.93	25.66	35.91	2.58	5.12	7.18
Lung Cancer	0.08	0.13	0.15	82.65	140.26	158.76	7.83	13.29	15.05
Cardiovascular Disease	0.14	0.12	0.36	207.52	278.45	545.69	427.23	467.09	1123.42
Stroke	0.17	0.22	0.37	176.76	231.43	391.59	190.46	249.36	421.93
COPD	0.07	0.10	0.13	69.62	104.30	134.30	398.44	596.98	768.68
Diabetes	0.50	0.70	0.72	105.81	217.49	228.14	963.11	1979.63	2076.60

Table 5: Attributed DALYs and Prevalence calculation due to particulate matter emission.

selected six diseases. For the given data in Table 1 (RR, DALYs and prevalence) and gridded population density, a sample calculation of attributable fraction, DALYs, and prevalence for PM is shown in Table 5. The selection of health conditions is based on [25].

4.1.6 Economic Valuation of Health impacts (Impact)

A Hybrid Human Capital Approach (HCA) is used for valuing health impacts which has two components: the first component is the Cost of Illness (COI) which considers the treatment and the medical cost, and the second component values the lost DALYs (Disability Adjusted Life Years), which is equivalent to the number of productive days lost due to illness (this also includes reduced life expectancy). We use per capita income to value the lost DALYs. GDP per capita values are obtained from the world bank for 2020 (Fig. 6B). COI studies typically address direct medical costs associated with physician services, medication, and hospital stays Robinson (2008). This data is collected from scientific and medical community literature and represented in terms of the same year and currency using inflation and exchange rate values from world bank literature [7].

4.1.7 Results

The impacts from the release of air pollutants were calculated based on the health effects from morbidity (illness from disease) and mortality (reduced life expectancy). The range of impacts of air pollutants, including oxides of sulphur, nitrogen and particulate matter for all six diseases mentioned above, is evaluated and shown in Fig. 6C-E. The sample calculation for PM using the our air pollution impact valuation model discussed above is shown in

PM	Att. Prevalence (Mean)	Att. DALY (Mean)	GDP Per capita in USD (2020)	COI per patient (USD)	Treatment Cost	DALY Cost
Respiratory Disease	5.12	26	27063	974	25000	694441
Lung Cancer	13.29	140		27985	3925208	3795883
Cardiovascular Disease	467.09	278		8108	3787049	7535745
Stroke	249.36	231		3527	879560	6263234
COPD	596.98	104		974.27	101616	2822691
Diabetes	1979.63	217		3683	7291017	5885973
					Total Cost (USD)	43007418
					Cost per tonne (USD)	13638

Table 6: Mean air pollution impact valuation in USD/tonne for PM using the HCA approach.

Table 6. The GDP per capita for Spain was taken as USD 27063 for 2020. The mean total air pollution impacts were estimated at around 28.72 million USD. The major cost of air pollution is associated with PM emissions (56% of total cost) and SO_x emissions (35% of total cost), as shown in Fig. 6C-E.

4.2 Case Study 2: Aggregated Air Pollution Impact Assessment of 1000 Companies

In the Methods section, we explain how to derive the coefficients to convert a company's reported drivers into impacts. We follow a three steps process: **1) Data extraction and Validation.** The process of extracting or data crawling is done from the company's annual public disclosures (annual reports, sustainability reports, ESG reports etc.) downloaded or sourced from their websites to our database using the "validator" tool. The relevant data in the report is tagged for the respective KPIs (GHG emissions, Sales, Revenue, employee numbers etc.) in the internal portal called "validator", which is then analysed by our data delivery team. The precondition of crawling data using our validator tool is that the disclosed company document should be available as a PDF or URL and be publicly accessible without any limitations. After the consolidated raw company data (in this case, the PM, SO_x and NO_x emissions and other relevant KPI data) is extracted, processed and pushed into the database, the next step is raw data apportioning.

2) Apportioning. In the next step, the extracted air pollutant emission data is apportioned and multiplied with the respective coefficients to generate impacts with a sense of granularity. Over the years, we have observed that, generally, most companies provide information about the geographical breakdown of scope 1 and scope 2 emissions, revenue, sales, and the number of employees. For geographical apportionment, we prioritise the apportioning data tagging as in Table 7. The rationale behind the above priority list is that scope 1 emissions generally happen at the region of the company's operations, and so it gives us a more accurate apportionment of corresponding impact values, i.e., the number of emissions from operations is directly proportional to impacts on the region and population. In the absence of scope 1 emissions, the next priority is given to scope 2 emissions as it captures the amount of electricity/heat/steam consumed; this can provide us with an idea of the extent of operations in a

Priority	Apportioning Data Point	Apportioning Groups
1st	Disclosure of scope one emission	1
2nd	Disclosure of scope two emission	2
3rd	Number of employees	3
4th	Sales	4
5th	Revenue	5

Table 7: Priority in apportioning data points.

region (presence of offices/manufacturing locations). If both are not disclosed, the next priority is the number of employees, followed by sales and revenue. The revenue/sales and the number of employees data can easily be found in any company's sustainability or annual reports, which can be used in the absence of scope 1 and 2 disclosure.

3) Impact Valuation. Finally, the overall impact due to air pollution for the selected companies is calculated by: i) distributing the specific pollutant (PM, SO_x and NO_x) based on the apportioning logic discussed above and ii) multiplying the impact multiples (USD/Tonne) with the emissions quantity (Tonnes) to get the air pollution impact in USD.

We present the impact estimation for the major air pollutants (PM, SO_x, NO_x) for 1000 selected companies from 2016 to 2018 belonging to pollution-intensive sectors, along with their sectoral impact intensity based on revenue. The details of selected sectors and the numbers of companies belonging to each sector are shown in Table 8.

Sl. No.	Sector Name	Sector code	No. of companies
1.	Conglomerates	CONG	91
2.	Performance and Industrial Chemical Manufacturing	PERF	161
3.	Utilities - Generation and Distribution	GENE	84
4.	Cement Manufacturing	CEME	42
5.	Building Construction	BLDG	35
6.	Oil and Gas	OGES	223
7.	Coal Mining	COAL	21
8.	Transportation Equipment Manufacturing	TRAN	141
9.	Metal Ore Mining	MOMI	101
10.	Alumina and Aluminium Production	AAMA	14
11.	Agriculture	AGSA	11
12.	Utilities - Distribution and Transmission	DIST	20
13.	Other Metal Manufacturing	OMMA	23
14.	Iron and Steel Manufacturing	IRON	31
15.	Paper and Pulp	PAPM	33
16.	Heavy Civil Construction	INDE	2
17.	Retail (Retail & Wholesale; on-line and shops)	WHRE	1
18.	Pharmaceuticals	PILL	2
		Total	**1036**

Table 8: Sectoral details of the selected companies.

4.2.1 Data Extraction

The air pollutant (PM, SO_x and NO_x) and other relevant data are extracted and validated from the sustainability reports of all the selected 1036 companies for 2016 to 2018 using a similar approach as discussed above. An example of the sustainability report of one of the selected companies (CLP Holdings) is shown in Figure 1, and the extracted KPI data was converted to the standard unit (tonne), as shown in Table 9.

KPI code	Company	Reporting year	data (tonnes)
AP-1	CLP holdings	2020	7700
AP-2	CLP holdings	2020	47000
AP-3	CLP holdings	2020	44700

Table 9: Raw KPI data (AP-1, AP-2 and AP-3) data extracted and converted.

4.2.2 Apportioning

The geographical apportioning of PM, SO_x, and NO_x data for the selected companies is based on the type of data provided in scope 1 and scope 2 emissions, revenue, sales, and the number of employees. The geographical breakdown of the air pollution emission data in their countries of operations is based on the priority list provided above. An example of apportioning using the scope 1 emissions information for CLP Holdings Limited operating in Australia, China, Hong Kong and India is shown in Table 10.

Country	Scope 1 emissions (MTCO2e)	Ratio	PM (AP-1)	NOX (AP-2)	SOX (AP-3)
Australia	21334000	0.41	3157	19270	18327
China	7023000	0.13	1001	6110	5811
Hong Kong	17496500	0.34	2618	15980	15198
India	6224000	0.12	924	5640	5364
Total	52077500	1.00	7700	47000	44700

Table 10: Apportioning of air pollutants for CLP Holdings from scope 1 emissions

4.2.3 Impact Valuation

Finally, the country-specific impact multiples (USD/tonne) for the selected companies are multiplied by the country-specific apportioned emissions. The impact numbers are added to get a total impact in millions of USD due to air pollution from 2016 to 2018. In addition to the air pollution impact value due to PM, SO_x and NO_x emissions, we also evaluated their sectoral impact intensity based on revenue. The air pollution impact (million USD) for the top 10 companies out of a selected 1036 companies from different sectors for the years 2016 to 2018 is in Fig. 7A. The top 10 companies on this list are predominantly from the energy and materials sectors, which are identified as major contributors to air pollution.

Additionally, the sectoral impact intensity based on revenue for various industry sectors in 2016, 2017, and 2018 was calculated and shown in Fig. 7B. The impact intensity metric provides a way to understand how much impact a particular sector has on the environment or other factors based on the revenue generated by that sector. For example, we can see that the "Cement manufacturing (CEME)" sector had a higher impact intensity than other sectors in the three years, with the highest being in 2016. On the other hand, the "Retail and Wholesale (WHRE)" sector had the lowest impact intensity in each of the three years, with the lowest being in 2018.

These impact intensity numbers can help policymakers and businesses identify the sectors that have the highest impact on the environment or other factors and take steps to reduce their impact. They can also be useful for

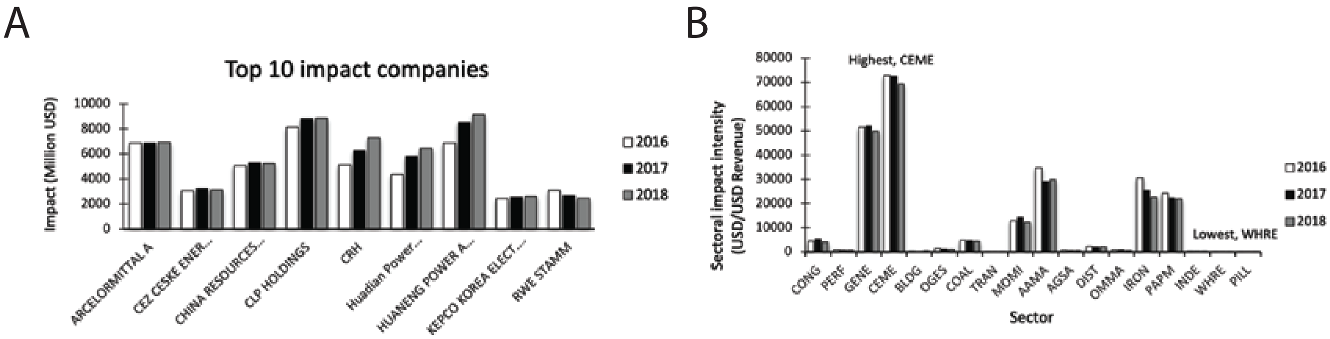

Figure 7: A) Top 10 companies having the highest air pollution impact (million of USD). B) Sectoral air pollution impact intensity based on revenue.

investors interested in socially responsible investing or who want to understand the sustainability performance of companies in different sectors.

5 Conclusions/Discussion

Our air pollution approach uses a combination of the Impact pathway approach (IPA) and hybrid human capital approach (HCA) to comprehensively understand the impacts of air pollution and inform effective mitigation strategies. The report narrows its focus on calculating the cost of reduced life expectancy and morbidity resulting from air pollution. Disease-specific DALYs and RR data from the GBD 2019 study were used to determine the cost in USD/tonne of air pollutants released for each $0.5^{\circ} \times 0.5^{\circ}$ grid across the globe. This method allows us to determine cost factors for larger regional units like cities, states, countries, and regions. If a company's pollutant release data is disclosed at the country level, we use the mean cost factors at the country level to determine the impacts. A company's air pollution impact valuation can be broadly divided into three major steps: 1) data extraction and validation, 2) geographical apportioning and 3) economic impact valuation, which are described in detail in the Method section.

There are several areas where our framework and the Natural Capital Protocol [53] align: i) both frameworks emphasize the importance of understanding the links between human activities and the environment; ii) they both acknowledge that human activities can have negative impacts on natural capital, leading to negative consequences for human well-being and iii) both frameworks recognize the importance of measuring and valuing natural capital in order to make informed decisions about its management.

An advantage of our approach compared to previous approaches within the widely used IPA framework is that it is more adaptable to a large number of applications.

By quantifying the health damage caused by air pollution in monetary terms, the paper aims to assist policymakers and decision-makers in developing countries in making informed decisions about addressing air pollution. This information is essential in determining the priority of policy and intervention programs to control air pollution, given the competing development challenges, budget constraints, and other resource limitations.

Indeed, measuring environmental impact is becoming more and more fundamental to comply with the ongoing regulatory developments in the space of ESG and sustainability. The EU Corporate Sustainability Reporting Directive has clearly highlighted the need for impact or externality evaluation of companies. But there are more projects, such as the transparency project, impact management project, etc., which have highlighted the need for impact measurement or externality evaluation.

Moreover, by aggregating the results from different companies, this analysis can be used to evaluate the air pollution impact of a portfolio, making the use of this methodology suitable for financial institutions that want to better evaluate the risk of investing in a company.

The model presented leaves room for future improvement. First of all, the Gaussian dispersion model does not differentiate between molecules and particles. One of the major assumptions of the AERMOD Gaussian Plume model is that the plume spread results primarily from molecular diffusion, and chemical reactions between pollutants are also not considered. Due to these assumptions, AERMOD is not recommended to be used in model domains larger than $0.5^{\circ} \times 0.5^{\circ}$. Models like the Lagrangian model CALPUFF deal with particle deposition and molecular dispersion. The AERMOD air dispersion model does not assume that the background or ambient intensity is zero nor does it take any difference with observed concentration for its estimation. The model predicts the marginal air concentrations of a compound at specific spatial locations (called receptors) using mathematical equations (Gaussian dispersion equation) that represent the numerous and complex meteorological processes responsible for dispersion. We use the marginal concentration to get the attributed DALY, YLL, YLDs, and prevalence values, which were primarily based on the Ambient air pollution (AAP) or observed concentration.

Supplementary Material

Meteorological Datasets

The following are the spatial data-sources which are used as inputs for modelling Air-pollution dispersion and exposure:

Description of Datasets

Reanalysis Dataset from Copernicus Climate Data Store

This data is available at daily resolution. This dataset is based on ERA-5. Compared to the earlier version ERA-Interim, ERA-5's atmospheric model uses both land data and satellite data.

A full list of input from satellite data and in-situ data is shown in Table 14 and Table 15 of ERA-5 documentation, respectively.

The satellite data includes data from:

- AIRS (Atmospheric Infrared Sounder) Sensor mounted on AQUA satellite from NASA Space agency
- AMSRE (Advanced Microwave Scanning Radiometer for EOS :Earth Observing System) sensor on the AQUA satellite owned by JAXA (Japan Aerospace Exploration agency),
- MODIS (MODerate resolution Imaging Spectroradiometer) sensor on AQUA and TERRA satellites from NASA, etc.
- Other satellite agencies include NOAA (National Oceanic and Atmospheric Administration), US Navy, ESA (European Space Agency), etc.

The atmospheric parameters that we extract from the ERA-5 dataset are defined in the section "Definitions of Meteorological Variables".

This data can be downloaded from the Climate Data Store (CDS) disks website ($https://cds.climate.copernicus.eu/$). For the present analysis, we use "ERA5 hourly data on single levels from 1979 to present" gridded data for the required climate variables were selected and downloaded in the NetCDF format. The ERA5 climate data can be downloaded from the CDS website using the web interface or using the Python-based CDS application programming interface (API).

CCMP Wind dataset

This data is updated 4 times a day, i.e. every 6 hours The Cross-Calibrated Multi-Platform (CCMP) gridded surface vector winds are also reanalysis datasets. The V2 CCMP combines multiple satellite products (e.g. NASA's. QuikScat, ESA's ASCAT, etc.), moored buoy wind data, and ERA-Interim model wind fields using a Variational Analysis Method (VAM) to produce four maps daily of 0.25 degree gridded vector winds. This data can be downloaded from $https://www.remss.com/measurements/ccmp/$ in the NetCDF format. In the present AERMOD modelling, CCMP Version-2.1 analyses data is used. The wind data can be downloaded from both FTP and HTTP servers at the following link: $https://data.remss.com/ccmp/v02.1.NRT/Y2019/$ for any particular period.

Definitions of Meteorological Variables

Boundary layer height: depth of layer of air (in meters) next to ground which has higher inertia to transfer momentum, heat moisture across the surface. The lower is boundary layer height, the higher is the concentration of pollutants (emitted from the Earth's surface). The boundary layer height is calculated with an algorithm based on the bulk Richardson number R_{ib}, initially proposed by [54]:

$$R_{ib} = h_{bl} \frac{2g(S_{vhbl} - S_{vn})}{(S_{vhbl} + S_{vn} - gh_{bl} - g_{zn})|\Delta U^2|} \tag{6}$$

where h_{bl} indicates the boundary layer height, i.e the level where $R_{ib} = 0.25$, index n indicates the lowest model level. S_v is the virtual dry static energy and U the 10-metre u-wind speed.

Forecast surface roughness: surface resistance, or aerodynamic roughness length in metres. It determines the transfer of momentum from air to surface. For given atmospheric conditions, a higher surface roughness causes a slower near-surface wind speed. Over the ocean, surface roughness depends on the waves. Over the land, surface roughness is derived from the vegetation type and snow cover. The roughness length z_o is given by the Charnock's formula; $z_o = \frac{\mu^2_{*a})}{g}$, where, u_{*a} is the friction velocity, g is the acceleration of gravity, and m is the Charnock's constant = 0.0418 -0.0418,

Latent heat flux: energy exchange between the surface and the atmosphere occurs when water is evaporated from or condenses onto the surface. Near IR albedo for direct radiation It is a measure of the reflectivity of the Earth's surface. This parameter is the fraction of direct solar (short-wave) radiation with wavelengths longer than 0.7 (microns, 1 millionth of a metre) reflected by the Earth's surface (for snow-free land surfaces only).

Relative humidity: it transfers heat between the Earth's surface and the atmosphere through the effects of turbulent air motion (but excluding any heat transfer resulting from condensation or evaporation). The magnitude of the sensible heat flux is governed by the difference in temperature between the surface and the overlying atmosphere, wind speed and surface roughness.

Surface sensible heat flux: It parameterises the transfers of heat between the Earth's surface and the atmosphere through the effects of turbulent air motion (but excluding any heat transfer resulting from condensation or evaporation). The magnitude of the sensible heat flux is governed by the difference in temperature between the surface and the overlying atmosphere, wind speed and surface roughness. Mean surface downward short-wave radiation flux (clear sky) It estimates the total short-wave radiation (both direct and diffuse) that reaches the Earth's surface.

Surface Pressure: pressure of the atmosphere on the surface of land, sea and in-land water. It measures the weight of all the air in a column vertically above the area of the Earth's surface represented at a fixed point. The units of this parameter are Pascals (Pa).

Total Cloud Cover: fraction of the sky covered by all the visible clouds. In this context, the total cloud cover is related to the proportion of the grid box (climate data) covered by clouds, and it varies from 0 to 1.

Total Precipitation: accumulated liquid/frozen water that falls to the Earth's surface. It is the sum of large-scale precipitation and convective precipitation. The units of this parameter are depth in metres of water equivalent.

Temperature: atmospheric temperature in kelvin (K).

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