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Quantifying population harm from indoor air contaminants in dwellings

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Abstract

Airborne contaminants cause significant harm to populations of people. People spend most of their time in their own homes and so their greatest exposure is likely to occur there. Existing standards that govern *Acceptable* Indoor Air Quality (IAQ) in residential buildings only consider a few contaminants. Exposure to them is limited using threshold mean concentrations over some period of time, but they do consider the harm they cause to populations of people.

The aim of this work was to evaluate the population harm from exposure to non-pathogen airborne contaminants in dwellings. Four stages of research were completed.

The first stage considered the uncertainty in the concentrations of 45 airborne contaminants in dwellings. Ethanol is the most common contaminant by mass (around 30%) and $PM_{2.5}$ was the fourth most common (around 10%), but presence does not indicate harm.

Harm was evaluated using the disability adjusted life year (DALY) metric, a measure of time where a value of unity is one year of healthy life lost to some disease or injury, or death. DALYs are calculated as the sum of years of life lost to premature mortality and morbidity in a population for some health effect, this is the Burden of Disease (BoD). In the case of IAQ, the

BoD is a measurement of the difference between the current health status of a population of building occupants and an ideal situation where they all live into old age, free of disease and disability associated to exposure to airborne contaminants.

The second stage required the development of a new metric, called a Harm Intensity, with units of DALYs per concentration per year. It links chronic harm (DALY/person/year) to the concentrations of airborne contaminants to which people are exposed to. Its values were determined using epidemiological and/or toxicological models, depending on the availability of information. The metric's values varied by five orders of magnitude depending on the contaminant. It has utility beyond dwellings and can be used wherever people are exposed to airborne contaminants.

The third stage combined the concentrations and harm intensities to identify the harm caused by each of the 45 contaminants in residential dwellings. $PM_{2.5}$ (67% median of all harm), $PM_{10-2.5}$ (17%), formaldehyde (6%), nitrogen dioxide (6%), radon (2%), and ozone (1%) were found to be the most harmful contaminants by around an order of magnitude. From these, ASHRAE 62.2 has chosen 3 contaminants of concern that account for 83% of all harm: $PM_{2.5}$, formaldehyde, and nitrogen dioxide, to add a DALY-based path into Standard 62.2 on residential ventilation and IAQ.

The fourth and final stage used the harm intensities to determine a relative weight of each contaminant that can be used to create a harm budget, where a harm limit is set and then any combination of contaminant concentrations that keeps the contaminant harm below that limit is allowed. Reference concentrations, taken from a reference scenario of dwellings meeting a current IAQ ventilation requirement (ANSI/ASHRAE Standard 62.2-2022) for $PM_{2.5}$, formaldehyde, nitrogen dioxide are set at 8, 20, and 6 $\mu g/m^3$,

respectively. Additionally, the discussion encompasses sensitivity analyses employing diverse exposure limit values to quantify harm, highlights emerging topics, and offers insights into the ventilation rate procedure.

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Chapter 1

Introduction

1.1 Air quality

Air is a mixture of chemicals with varying toxicity. Unexpected substances are contaminants. Harmful contaminants are pollutants (Spengler et al., 2000). Nearly 99% of air comprises nitrogen and oxygen. The rest includes thousands of gases, particulate matter, pathogens and bioaerosols. Inhalation is the common route of pollutant exposure, as discussed by Huijbregts et al. (2005). Air quality depends on pollutant concentrations, determining health and wellbeing.

The Global Burden of Disease estimates quantify the harm to from inhalation of pollutants in air using the disability-adjusted life year (DALY), a metric that accounts for disease, infirmity and premature death from inhaled pollutants (Harikrishnan et al., 2018; HEI, 2020; James et al., 2018; Murray et al., 2020; WHO, 2021). In 2015, fine particulate matter ($PM_{2.5}$) caused 4.2 million deaths and 103 million DALYs (Cohen et al., 2017). In 2016, $PM_{2.5}$ accounted for 7 million deaths, over half from house-

hold sources (WHO, 2018a,b). By 2017, long-term $PM_{2.5}$ exposure contributed 83 million DALYs, 59 million from homes, largely through heart and lung diseases (Cohen et al., 2017; HEI, 2020; Murray et al., 2020). Several studies have linked exposure to $PM_{2.5}$ with major disease burdens (IHME, 2022; Kyu et al., 2018; Vos et al., 2020).

National bodies, environmental agencies and global health organizations around the world attempt to influence air quality by setting short and long-term contaminant thresholds for sundry contaminants, that should not be exceeded over time (Hess-Kosa, 2018; WHO, 2021). Exceeding thresholds help to identify priority contaminants but do not adequately rank importance (Logue et al., 2011a). Different organizations' limit values sometimes differ substantially for identical periods (Abdul-Wahab et al., 2015; Morantes et al., 2016; Salis et al., 2017). Limits reflect policy motivations, policymaker judgments, and differences in contaminant information, not uniform hazard levels. This makes interventions to mitigate against harm inefficient. Alternative metrics also have limitations (Jones, 2017). It makes more sense to prioritize contaminants based on the dual conditions of being harmful and commonly present in the air. This approach would inform more effective mitigation strategies for air quality.

1.2 Indoor Air Quality

The *quality* of indoor air can be defined by its effects on people (Fanger, 2006). Building items, occupants, and combustion introduce pollutants to the indoor environment, influencing its quality (Jones, 2017). As people spend most of their time inside, mainly in homes, the greatest contaminant exposure occurs there (Agency, 1989; Brasche and Bischof, 2005; Commis-

sion, 2003; Jantunen et al., 2011; Klepeis et al., 2001; Lader et al., 2006; Zeghnoun et al., 2010).

Indoor Air Quality (IAQ) has been historically characterized using proxy indicators, like humidity and carbon dioxide (CO_2) levels (Borsboom et al., 2016). CO_2 reflects occupancy instead of direct health impacts (Fisk et al., 2019). Under 1000 ppm CO_2 and 60% humidity represent "good" IAQ, but these are arbitrary cut-offs that work under the implication that external air is relatively uncontaminated, high levels of CO_2 indoors could signal inadequate ventilation (Walker et al., 2022). CO_2 also relates to bio-effluent perception. Occupants often judge IAQ by odor, influenced by volatile organic compounds (VOCs) (Spengler et al., 2000; Zhang et al., 2022). Smell may drive responses, with receptors detecting VOCs first, signaling irritants as odors (the olfactory paradigm). Though not the sole perception influence, this aids understanding reactions (Carrer et al., 2018; Persily, 2006, 2015).

Guidance documents classify IAQ and provide ventilation recommendations for specific building types using CO_2 and odor judgments (Bonino, 2016; Persily, 1997; Zhang et al., 2017). ANSI/ASHRAE standards address healthcare, commercial buildings, and homes in the USA, while German, UK, and international standards cover workplaces, natural ventilation, and general systems (Saffell and Nehr, 2023). This dependence on proxi indicators overlooks diverse contaminants and risks. Standards should instead prioritize health outcomes and occupant well-being (Carrer et al., 2018; Guyot et al., 2019; Persily, 2006, 2015).

ANSI/ASHRAE Standard 62.2 considers acceptable home air quality by lack of dissatisfaction and harmful pollutants (ASHRAE, 2022c). This criterion is binary and is either passed or failed. These criteria can be

influenced over time as a better understanding of population health is developed, notably, the Air Infiltration and Ventilation Centre advocates developing health-focused IAQ metrics beyond existing perception and CO_2 proxies to directly evaluate harm (Borsboom et al., 2016). Proposed metrics should integrate current standards while positively impacting health (Jones, 2017).

1.3 Understanding harm

Indoor air comprises a mixture of contaminants that people are exposed to. The exposure to a given contaminant is a function of its concentration and the duration of exposure, which leads to a dose through various mechanisms. Inhalation is the exposure route of interest for air contaminants. Doses accrued over time are characterized as either acute or chronic. A dose of a contaminant can be quantitatively related to negative health impacts using established dose-response relationships. These health impacts can be measured using metrics like the disability-adjusted life year (DALY).

DALYs account for both shortened life from early mortality and time lived with disability from disease or functional impairment (Fryback, 1998; Homedes, 1996; Murray, 1994). Specifically, DALYs integrate two components: years of life lost from premature death and years lived with disability from non-fatal health outcomes. In essence, DALYs evaluate the cumulative disease burden resulting from exposure to harmful contaminants (Lee et al., 2020; Murray, 1994; Murray et al., 2020; Wang et al., 2017). DALYs also facilitate comparisons and prioritization of exposures (Sherman et al., 2012), providing context to target mitigation efforts.

Health Impact Assessment (HIA) methods aim to quantify harm from expo-

sure to air contaminants. HIAs include hazard assessment, impact analysis, risk attribution, and cost-benefit analysis (Rausand, 2013; von Stackelberg and Williams, 2021). Together, these shape evidence-based IAQ decisions. Global health initiatives and air quality assessments use DALYs as the metric of harm (Hassan Bhat et al., 2021; Hauschild and Huijbregts, 2015; Hauschild et al., 2018; Sacks et al., 2018; WHO, 2011).

Air Pollution Health Risk Assessment (AP-HRA) relate observed disease incidence changes to harm (Lee et al., 2020; Liu et al., 2022; Morawska et al., 2013; Murray et al., 2020), where as, Life Cycle Impact Assessments (LCIAs) do so using contaminant mass (Huijbregts et al., 2005; Rosenbaum et al., 2015; Wu and Apul, 2015). Assessments use either toxicology or epidemiology data. In 2012, Logue et al. proposed combining epidemiology and toxicology to estimate U.S. home contaminant harm. This pioneering health-centric assessment enabled prioritizing contaminants and ventilation to minimize disease burden (Borsboom et al., 2016; Walker et al., 2022).

There is currently no recognized process for selecting priority indoor air quality contaminants that are most harmful and widespread in homes (Guyot et al., 2019; Parthasarathy et al., 2011; Sherman et al., 2022, 2012; Stanley and Bayer, 2009; Walker et al., 2022). A need exists to identify these key contaminants for emphasis and control. Meeting this need requires understanding chronic contaminant exposures, concentration variations, and uncertainties within homes. It also requires a specialized metric linking harm to exposure levels and exposed populations over time (Gronlund et al., 2015; Guyot et al., 2019; Oberschelp et al., 2020; Sherman et al., 2012; Walker et al., 2022). With such a health-impact metric, calculating contaminant harm would be possible when long-term exposures are known. This would make it possible to identify and synthesize priority contaminants to target for health-protective strategies.

Various daily life risks pose some acceptable harm to populations (Murray et al., 2020). The World Health Organization uses DALYs to set allowable harm benchmarks for drinking water (WHO, 2011). Similarly, DALYs could define a maximum allowable harm limit from indoor air pollutants, allowing any concentration combination keeping harm below it (Sherman et al., 2012; Walker et al., 2022). ANSI/ASHRAE Standard 62.2 (ASHRAE, 2022c) proposes a definition for *acceptable* IAQ (AIAQ) in dwellings, but there is still a need for a quantitative definition of AIAQ. The allowable harm limit addresses this need.

1.4 Aims and objectives

The scope of this research is focused on residential environments. Concentrating on homes allows for a detailed examination with direct policy implications for these settings. The emphasis is on long-term exposures and their associated chronic health effects, primarily relying on post-2010 data to ensure relevance. Mixtures and interactions between contaminants are beyond the scope of this study; assessments are conducted for individual contaminants. Only DALYs are used as a health metric in this context; parallel metrics such as Quality-Adjusted Life Years (QALYs) are not considered. Harm is assessed at the population level.

The aim of this thesis is to advance IAQ assessment by developing novel health-based metrics using the Disability-Adjusted Life Year (DALY). This will enable evaluation of harm from residential indoor air contaminants, improve population health, set objective metrics and remove subjectivity when prioritizing contaminants. In pursuit of the aim of this thesis, the following objectives were followed:

First Objective: To synthesize uncertainties in the concentration of air contaminants in dwellings by conducting a systematic review and meta-analyses of existing sampling campaigns, with the goal of generating estimated probability density functions for use in harm assessments.

Second Objective: To develop a novel IAQ harm metric that relates disability-adjusted life years (DALYs) to chronic exposure concentrations of air contaminants, utilizing available epidemiology and toxicology research, with the goal of performing harm assessments.

Third Objective: To evaluate and assess the harm resulting from typical exposures to indoor air contaminants in dwellings, through the integration of the harm metric and concentrations for each contaminant. This synthesis will define the harm assessment framework for this research.

Forth Objective: To identify and synthesize the most harmful airborne contaminants in dwellings, prioritizing them for removal and establishing a harm budget. The outcomes have the potential to inform the development of health policies, building codes and regulations, and influence the design and operation of buildings.

1.5 Thesis outline

This thesis is structured as follows:

Introduction: Provides background and motivations, states research aims and objectives.

Chapter 2 Literature Review: Critically reviews current knowledge on air pollution, health impacts, risk assessment, indoor contaminants, and

harm quantification.

Chapter 3 Quantifying Harm: Describes the modeling approach, data processing, equations, assumptions, coding, and programs used to develop the harm metric.

Chapter 4 Parameters for Determining Harm Intensities: Analyzes required parameters from epidemiology, toxicology, exposure science, discussing interpretations, uncertainties, and literature sources.

Chapter 5 The Harm Intensity: Presents the developed methodology and defines the novel Harm Intensity (HI) metric for air contaminants.

Chapter 6 Airborne Contaminants in Dwellings: Presents the process and results of quantifying representative concentrations of airborne contaminants in dwellings.

Chapter 7 Contaminants Harm in Dwellings: Applies HI to assess harm from indoor contaminants in homes based on representative concentrations.

Chapter 8 Discussion: Synthesizes key findings, including ranking and prioritization of contaminants, proposing a harm budget, comparing to guidelines, assessing limitations, and highlighting applications.

Conclusions: Summarizes the research outcomes, significance, and final remarks.

Chapter 2

Literature Review

Some work from this chapter has previously been published as a book chapter in:

Molina, C., Jones, B., & Morantes, G. (2023). Air Quality in Latin American Buildings. In *Removing Barriers to Environmental Comfort in the Global South* (pp. 195-215). Cham: Springer International Publishing. eBook ISBN: 978-3-031-24208-3

2.1 Air pollution

Humans have the right to breathe clean air. Poor air quality has implications for a wide range of human rights, including the rights to life, health, water, food, housing and an adequate standard of living. States have obligations to protect people on the foreseeable adverse effects of poor air quality and exposure to (toxic) air pollution (Knox, 2019).

Pollution is defined as the introduction into the environment of substances in concentrations that reduce its quality and can be considered harmful to humans (or other living organisms) (Manisalidis et al., 2020). Air pollution refers to the presence in the atmosphere of one or more pollutants (or their combinations) in concentrations and permanence such that they represent a threat to human health, that of animals, plants or that cause adverse effects on infrastructures (Seinfeld and Pandis, 2016). The most convincing

evidence that air pollution is a global environmental problem lies in the growing number of cities that each day increase their concentrations of air pollution caused by different sources and different air pollutants and, the consequent increase in negative effects on health and the environment (Prüss-Üstün et al., 2016). Air pollution can be broadly separated into two distinct categories: Outdoor pollution (or ambient air pollution) and indoor pollution, generated by household combustion of fuels, and high concentrations of pollutants in buildings. The air's quality is evaluated through the concentration of pollutants that are present in it. Air quality (in both environments) is an essential determinant of healthy living and people's well-being. Moreover, air quality is a determinant of the state of the (global/local) physical and social environment, proposed in frameworks for health equity surveillance, for which indicators need to be developed (Marmot et al., 2008).

In the 1960's, investigations on the impacts of air pollution began to be carried out and, as a result, the enactment of environmental legislation, such as the National Environmental Policy Act (NEPA) was initiated and promulgated by the Congress of the United States of America. The starting point for the emergence of programs dedicated to air pollution was the occurrence of critical episodes of air pollution in several locations arround the globe, in Belgium, (Firket, 1936); in London, (Scott, 1953); in U.S.A. (Jacobs et al., 2018). The term *outdoor or ambient air* refers to atmospheric air; its pollution consists of a highly variable and complex mixture of different substances (in gas, liquid or solid phase) that are potentially harmful to human health and the environment (WHO, 2006). The following are ambient air pollutants and considered contributors of disease in humans: particulate matter (PM, particles of variable aerodynamic diameter*), ground level ozone, nitrogen oxide, sulphur dioxide, volatile organic compounds (VOCs), dioxins and, polycyclic aromatic hydrocarbons (PAHs) (Manisalidis et al., 2020; Seinfeld and Pandis, 2016; WHO, 2006).

The term *indoor air* usually applies to non-industrial indoor environments: office buildings, public buildings (schools, hospitals, theatres, restaurants) and private homes. Indoor air is a complex blend of substances originating from both indoor and outdoor sources. Indoor air pollutant levels can mirror outdoor levels (Guardino et al., 1994), yet specific pollutants indoors

*The aerodynamic diameter of a dust particle is the diameter of a sphere-shaped particle that shows the same behaviour in the atmosphere as a dust particle (that does not necessarily have a spherical shape)

can spike up to 100 times higher, as noted by the EPA (Seguel et al., 2017), owing to factors like limited dilution, low wind speed, and concentrated sources including biological pollutants (Siddique et al., 2023).

In the case of industrial environments, pollutant concentrations might be higher compared to that of non-industrial environments, which is why standards and regulations are applied in order to assess indoor air quality (ASHRAE, 2014; Government, 2010; IWBI, 2014; MTA/MA–014/A11, 2012).

Indoor air quality (IAQ) refers to the control of the quality of air inside enclosed spaces (buildings, tunnels, etc.) in order to ensure healthy and clean conditions for the public in general (Heinsohn and Cimbala, 2003). Indoor air quality began to be considered a problem in the late 1960s, although the first studies were not conducted until the 1970s, in scenarios where workers developed negative health effects, mostly of the respiratory type, leading to the study of possible air-suspended pollutants indoor (Jones, 1999; Samet et al., 1987; Spengler et al., 2000).

Indoor air quality is directly affected by pollutant emission sources typical of the space, as well as by the habits of the staff who frequent it. It may also be influenced by outside air characteristics. Overall, indoor air pollution can originate from both outdoor and indoor sources. It is likely that indoor air pollution contribute more to population exposure than the outdoor environment because people spend longer time indoors (WHO, 2006).

The major sources of indoor air pollution worldwide include combustion of solid fuels indoors, tobacco smoking, outdoor air pollutants, emissions from construction materials and furnishings, the inhabitants themselves, improper maintenance of ventilation and air conditioning systems and/or excessive use of cleaning products. The main indoor air pollutants related to health problems and poor quality of life include: carbon monoxide (CO), nitrogen and sulphur oxides, ozone, radon, volatile and semi-volatile organic compounds, fine and biological particles (fungi and mites) (Guardino et al., 1994; Samet et al., 1987; WHO, 2006).

In the IAQ research community, carbon dioxide (CO_2) serves as a key indicator of poor air quality and ventilation effectiveness (Walker et al., 2022), perhaps even impacting cognitive function directly (Satish et al., 2012). However, evidence regarding its direct effects on health, well-being, learning

outcomes, and work performance at typical indoor concentrations remains inconclusive (ASHRAE, 2022a; Fisk et al., 2019). This research views CO_2 as a contaminant gas rather than a pollutant because it is undesirable at high concentrations indoors, but the causal link to health outcomes remains inconclusive.

On average, people in the USA, Europe, and the UK spend 90 % of their time indoors (Agency, 1989; Commission, 2003; Lader et al., 2006). Homes, offices, schools, day care centers, public buildings, health centers or other private and public buildings are examples of indoor environments where people spend their time. Hazardous substances (pollutants), moisture, mold and biological particles found in these spaces lead to a wide range of health-related problems (Guardino et al., 1994; Heseltine and Rosen, 2009; Spengler et al., 2000; Wanner et al., 1993; WHO, 2010).

2.1.1 Air contaminants

This work preferentially uses "contaminant" rather than "pollutant" for indoor chemicals. Contaminant broadly means any unwanted, unnatural material, regardless of toxicity. Pollutant implies confirmed toxicity. Contaminant enables precise, neutral representation without presuming hazards. Contaminant also fits the indoor context better by highlighting foreign alteration of natural conditions. Given these nuances, contaminant is preferred terminology for the wide range of indoor chemicals, only some demonstrably toxic (Spengler et al., 2000).

Thousands of air contaminants exist. Substances repeatedly highlighted across air pollution literature were selected as representative troves for discussion, centered on two classifications: *criteria pollutants* and *other air pollutants* (Manisalidis et al., 2020; Tran et al., 2020; WHO, 2006).

2.1.1.1 Criteria Pollutants

Criteria pollutants are defined as those that have a direct effect on human health, which are commonly found in the atmosphere and are released in large quantities from a variety of emission sources. The criteria pollutants are: particulate matter in its various sizes (PM), sulphur dioxide (SO_2), nitrogen dioxide (NO_2) and, ozone (O_3); furthermore, USEPA in-

cludes carbon monoxide (CO), resulting in five so-called *criteria pollutants* (EPA, 2016; WHO, 2006). There is an extensive scientific knowledge of these pollutants that allows the proposition of relationships between their presence and, their harmful effects on human health or on the environment (SO_2 and NO_2 are related to rain acidification, PMs are associated with haze episodes, and O_3 can cause metal corrosion and lower the rate of photosynthesis in plants).

Particulate Matter (PM) , also referred to as aerosols, is any substance, except pure water, that exists as a liquid or solid in the atmosphere under normal conditions and have microscopic or submicroscopic sizes (Figure 2.1). PM is a heterogeneous mixture of solid and liquid particles including chemical and biological fractions. PM is classified according to its aerodynamic diameter (Dp) in PM_{10} (Dp $\leq$10 µm), $PM_{2.5}$ (Dp $\leq$ 2.5 µm) (fine fraction), $PM_{10-2.5}$ (2.5 $<$ Dp $<$ 10 µm) (coarse fraction), and ultrafine particles (0.1 µm $\sim$100 nm) (Seinfeld and Pandis, 2016). The components of PM_{10} and $PM_{2.5}$ can be organic (polycyclic aromatic hydrocarbons, dioxins, benzene, 1-3 butadiene) or inorganic (carbon, chlorides, nitrates, sulfates, metals) in nature (Manisalidis et al., 2020; Seinfeld and Pandis, 2016; Spengler et al., 2000). Moreover, a substantial component of PMs in indoor and outdoor environments are bioaerosols: solid or liquid particles carrying living organisms from biological sources, including fungi, bacteria, viruses and, pollens (Ariya, 2004; Morakinyo et al., 2016).

Figure 2.1: Relative size of particulate matter. (Ang, 2020)

Ambient or outdoor PM may have a natural or anthropogenic origin. Particles of natural origin come from soil erosion, re-suspended soil dust, sea salt transport, forest fires, volcanic eruptions and emissions of fractionated biological material. Particles of anthropogenic origin are generated as a result of human activity: vehicular traffic (mainly from vehicles with diesel engines), combustion and industrial processes, mining-metallurgical activity and biomass burning (Piña, 2011; Prüss-Üstün et al., 2016; Seinfeld and Pandis, 2016; US-EPA, 2020b).

Sources of particles in the indoor environment include second-hand smoke from tobacco, combustion (candles, incense, wood-or-coal for cooking, wood-or-coal for heating, smoking), cooking, consumer products, building materials, dust, particulate resuspension from human activity, such as the use of vacuum cleaners and foot traffic, infiltration of foreign particles (particles of outdoor origin that migrate indoors) and secondary organic aerosols; furthermore, indoor PM can also be of biological origin: microorganisms (bacteria, viruses, fungi, mold and, bacterial spores) allergens, and pollen (National Academies of Sciences, 2016; WHO, 2014).

Sulphur Dioxide (SO_2) is a colorless gas with an irritating odor, soluble in water. It is usually the product of burning sulphur compounds found in fossil fuels. The oxidation of sulphur dioxide leads to the formation of sulphurous acid (H_2SO_3) and sulphuric acid (H_2SO_4): both responsible for acidifying rainwater (Manisalidis et al., 2020; Seinfeld and Pandis, 2016; WHO, 2006). SO_2 is one of the pollutants that is emitted along with particles during the burning of fossil fuels, it constitutes the largest fraction by mass of fine particles, which makes it an indicator of pollution by particles (Pope et al., 1995).

The main source of SO_2 is the combustion of fuels containing varying amounts of sulphur, according to their source (most notably coal and oil). On combustion, any sulphur in the fuel is converted to sulphur dioxide. Other major source is the sintering process used in metal smelting, which involves roasting metal sulfide ores in a stream of air (WHO, 2006). The SO_2 present in indoor air normally comes from outside, both from natural and anthropogenic sources. It enters a building through ventilation or infiltration. In addition, SO_2 can be absorbed by building materials, furniture, and carpets, for the long-term with negligible re-emission (Tran et al., 2020; Walsh et al., 1977), which can reduce the concentration indoors

relative to that existing outside, particularly when sulphur dioxide concentrations outside are elevated (Guardino et al., 1994). Kerosene-fueled space heaters can also be a source of indoor SO_2 (Samet et al., 1987; Spengler et al., 2000; US-EPA, 2017).

Nitrogen Dioxide (NO_2) is a highly reactive gas formed as a by-product of high-temperature combustion process. Most of the atmospheric NO_2 is emitted in the form of nitric oxide (NO). With sunlight, (NO) combines with atmospheric oxygen to form nitrogen dioxide. NO_2 is also one of the precursors of tropospheric ozone and nitrate aerosols, which make up a significant fraction of the mass of $PM_{2.5}$ (Seinfeld and Pandis, 2016; WHO, 2006, 2010). In ambient air, NO_2 is mostly emitted from automobile motor engines (US-EPA, 2016). On the other hand, indoor sources include tobacco smoke, gas, wood, oil, kerosene, and coal burning appliances, such as stoves, ovens, space and water heaters, and fireplaces. Outdoor NO_2 also influences indoor concentrations (via infiltration), in fact, outdoor air is the main source of nitrogen dioxide in buildings without non-ventilated fuel appliances (Guardino et al., 1994; Manisalidis et al., 2020; Samet et al., 1987; Spengler et al., 2000; WHO, 2010, 2014).

Ozone (O_3) is found in both the troposphere and the stratosphere. It is harmful to the environment (human health and nature) when it is at ground level (*tropospheric ozone*) and beneficial to the energy balance of the planet when it is at the level of the stratosphere (Seinfeld and Pandis, 2016). Ozone in the troposphere (ground-level ozone) is the product of the photochemical reaction of oxygen in the lower layers of the atmosphere with precursor gases, such as NOx, CO and volatile organic compounds in presence of sunlight (US-EPA, 2020a; Villányi et al., 2010). It can be found in indoor environments in special situations where it is generated continuously from sources such as copy machines, electrostatic air cleaners, electrical arcing or, smog. As it degrades rapidly, indoor concentrations are significantly lower that outside (Guardino et al., 1994; OSHA, 1999; Spengler et al., 2000). Ozone degrading means that it undergoes chemical reactions that break it down into other compounds.

NO_2 and O_3 can be further classified as natural reactive oxygen species (ROS). ROS comprise a wide range of oxygen-centered and related free radicals. In the atmosphere, ROS and reactive nitrogen species (RNS)

are generated via photochemistry and gas-phase, heterogeneous and multiphase reactions involving atmospheric oxidants and aerosol particles. ROS include O_3, hydroperoxyl (HO_2), organic oxy and peroxyradicals; RNS include NO, NO_2, NO_2^-, $ONOO^-$, HONO and HNO_3. In the atmospheric sciences, ROS and RNS are usually mentioned as (photo)oxidants and radicals (Poschl and Shiraiwa, 2015). Nitric oxide and certain radicals like HO_2 and organic oxyradicals, can contribute to the generation of O_3 through complex chemical reactions in the atmosphere.

2.1.1.2 Other air pollutants

This section presents a number of pollutants not previously discussed, from which there is evidence that certain exposure concentrations can cause health concerns, with particular emphasis in pollutants found in indoor (non-industrial) environments.

Volatile Organic Compounds (VOCs) are a group of chemical and biological compounds characterized by their ability to pass into the gas phase at room temperature. VOCs are organic compounds that elute between and, including, n-hexane and n-hexadecane on a gas chromatographic column[†] (ISO, 2011). In outdoor air, primary VOC sources include those from incomplete combustion, whereas indoor sources of VOC are construction and building products (paints, varnishes, waxes and solvents), household consumer products (detergents, cleaning products, air fresheners and personal care products) and the use of ink-based electronic devices (photocopiers and printers) (Shrubsole et al., 2019). ISO (2011) present a list of VOCs detected in indoor air emitted from building products. The following are common VOCs:

Benzene is a colorless liquid with a sweet odor. Is a genotoxic carcinogen in humans. Benzene evaporates into the air quickly. Benzene is present in both outdoor and indoor air. People living near hazardous waste sites, oil refineries, petrochemical industries, or gas stations may be exposed to higher concentrations of benzene. The petrochemical industry, oil refineries, the manufacture of coal and coke products, the manufacture of tires, the storage and transportation of benzene and petroleum products con-

[†]Gas chromatography is an analytical method for the separation and identification of components that are gaseous or vaporized without decomposition.

taining benzene, are the main benzene emitters. Benzene concentrations in indoor air are generally higher than outdoors, where tobacco smoke is the main source. Additional indoor emissions sources of benzene include consumer products and construction-remodelling- decorating products (glues, paints, furniture polish). Heating and cooking systems and detergents are also sources. In indoor environments where there are no sources of benzene, concentrations are determined by the concentration of the outside air (Spengler et al., 2000; US-EPA, 2003a; WHO, 2010, 2014).

Formaldehyde is a colourless gas released into the environment from biomass combustion and industrial combustion processes. Formaldehyde is considered primarily an indoor pollutant because, in ambient air, it is quickly photo-oxidized to carbon dioxide and water (WHO, 2010). Emissions from building materials (paints, wallpapers, glues, adhesives, varnishes and lacquers), furniture, construction wooden products, consumer home and office chemicals (detergents, disinfectants, softeners), smoking, burning of fuels (for heating, cooking), or candle or incense burning are indoor sources of formaldehyde (Samet et al., 1988; Spengler et al., 2000; WHO, 2010, 2014).

Naphthalene is a solid white substance that evaporates easily. Its main use in homes is in moth/insect repellants (mothballs) representing the main source of this pollutant indoors. Mothballs are also known as *white tar* and *white camphor*. Naphthalene evaporates from its solid state or from the compounds that contain it. Consumer products, such as multipurpose solvents, lubricants, herbicides, charcoal lighters and hair sprays, unvented kerosene heaters, tobacco smoke and, rubber materials, are also sources (Shrubsole et al., 2019; WHO, 2010).

Xylenes appear as a colorless liquid with a sweet odor that ignites easily. It is found naturally in oil and tar. Chemical industries produce xylene from oil. In indoor air, it is produced by the evaporation of household products that contain it (varnish, dilute liquids) and by the combustion of fossil fuels and tobacco smoke (Spengler et al., 2000). Usually, xylenes are treated as a mixture of its three different isomers: meta-, ortho- and, para-xylene[‡] (Shrubsole et al., 2019).

Trichloroethylene (TCE) is a volatile, colourless liquid with a sweet ethereal (chloroform-like) smell that is widely used as an industrial solvent.

[‡]Xylene exists in three isomeric forms. The isomers can be distinguished by the designations ortho- (o-), meta- (m-) and para- (p-), which specify to which carbon atoms (of the benzene ring) the two methyl groups are attached.

Sources of TCE are wood stains, varnishes, finishes, lubricants, adhesives, typewriter correction fluid, paint removers and, certain cleaners (Spengler et al., 2000; WHO, 2010).

Tetrachloroethylene (PCE) is a readily volatile, colourless liquid with an ether-like smell. Caulks and sealants, miscellaneous materials, paint removers, cleaners, glues and suede protectors are indoor sources (Shrubsole et al., 2019; WHO, 2010).

Polycyclic aromatic hydrocarbons (PAHs) are a class of chemicals present naturally in coal, crude oil, and gasoline. Benzopyrene, acenaphthylene, anthracene and, fluoranthene are common PAHs (Manisalidis et al., 2020). They are emitted from combustion processes of carbonaceous materials at high temperature (traffic, waste incinerators, power generation plants). Indoor air is contaminated by PAHs from smoking, cooking (burning of fossil fuels and biofuel), domestic heating (fuel stoves and open fireplaces) as well as from incense and candle emissions (Spengler et al., 2000; WHO, 2010, 2014).

Radon (Rn) is an inert noble gas that does not interact chemically with other elements. All of the isotopes of radon are radioactive and evaluation of the adverse health effects due to exposure to radon requires consideration. The isotopes of radon encountered in nature (^{219} Rn, ^{220}Rn, and ^{222}Rn) are part of long decay chains starting with isotopes of uranium (U) or thorium (Th) and decay very rapidly into polonium (a particle that bonds with the soil) (Keith et al., 2012). Radon is a pollutant of concern for the indoor environment. As a gas that occurs naturally in soils and rocks, radon has been detected in indoor air as early as the 1950s per sampling campaigns. Radon concentrations indoors depend on the amount of radon-producing uranium in the underlying rocks and soils. Cracks, holes in the ground, small pores, sinks and, drains are ways of entry, as a consequence, radon concentrations are usually higher in basements, warehouses and, other structural areas in contact with the ground (WHO, 2010). Penetration of radon-contaminated soil gas is the principal source of the radon found in homes (Samet et al., 1988; Spengler et al., 2000). The health hazard from radon does not come primarily from radon itself, but rather from its radioactive progeny (Keith et al., 2012).

Biological agents, also bioaerosols, may contaminate the air within indoor environments. These bioaerosols comprise viruses, bacteria, actinomycetes, fungal spores, algae, amoebae, arthropod fragments and, animal or human dander. Most bacteria in indoor air originate from humans, whereas most fungi in indoor air originate from spores from outdoor sources (Heseltine and Rosen, 2009; Samet et al., 1988). A summary of air pollutants, its main categories (Indoor / Outdoor) and possible sources is given in Table 2.1.

Table 2.1: Indoor / Outdoor air contaminants, and known sources. [+]

	Contaminant	Main categories		Related sources	
		I	*O*	*Indoor*	*Outdoor*
Criteria pollutant	Particulate matter ($PM_{2.5}$)	✓	✓	Smoking, cooking, heating, consumer products, building materials, soil (resuspension), infiltration of foreign particles.	Soil (erosion, resuspension), sea salt, combustion (biomass, industrial, fuel).
	sulphur Dioxide (SO_2)		✓	Infiltration of foreign particles.	Combustion (biomass, industrial, fuel).
	Nitrogen Dioxide (NO_2)		✓	Smoking, burning appliances (for cooking/heating), infiltration.	Combustion (industrial, fuel).
	Ozone (O_3)		✓	Reaction with precursors (NOx, CO and VOCs)	
	Carbon monoxide	✓	✓	Combustion (biomass, fuel) for cooking/heating, smoking.	Combustion (biomass, industrial, fuel).
Volatile Organic Compounds	Benzene	✓		Smoking.	Petrochemical activities.
	HCHO	✓		Building materials (paints, glues, varnishes, lacquers, wooden products), cleaning (detergents, disinfectants, softeners), smoking, heating, cooking, candle/incense burning.	
	TCE	✓		Construction products (varnishes, paint removers).	
	PCE	✓			
	Naphthalene	✓		Consumer products with mothballs.	
	Xylenes	✓		Smoking.	Petrochemical activities.
Other air pollutants	Polycyclic aromatic hydrocarbons[*]	✓		Combustion (biomass, fuel) for cooking/heating, smoking.	Combustion (industrial, fuel).
	Radon	✓		Underlying rocks and soils.	–
	Biological Agents	✓	✓	Bacteria, viruses, fungi, mold and, bacterial spores.	Spores, pollen, animal/human dander.

[*] benz[*a*]anthracene, benzo[*a*]pyrene, benzo[*b*]fluoranthene, benzo[*k*]fluoranthene, chrysene, dibenzo[*a,h*]anthracene, benzo[*ghi*]perylene and indeno 1,2,3 [*cd*] pyrene.

[+] Compendium from (Heseltine and Rosen, 2009; ISO, 2011; National Academies of Sciences, 2016; Prüss-Üstün et al., 2016; Samet et al., 1987, 1988; Seinfeld and Pandis, 2016; Shrubsole et al., 2019; Spengler et al., 2000; US-EPA, 2003a, 2010b, 2011, 2017, 2020a,b; Villányi et al., 2010; WHO, 2006, 2010, 2014)

2.1.2 Overview of contaminants in dwellings

Indoor residential exposures constitute 60-95% of lifetime air contaminant contact indoors, as homes are where people spend most time (Section 2.1). Understanding exposure levels and patterns is crucial given the predominance of time spent indoors. Hundreds of chemicals have been measured indoors, reflecting a research shift from outdoor to indoor environments.

Systematic reviews have compiled residential contaminant summary statistics for the indoor air contaminants presented in this research so far, to identify those with the highest central tendency and peak concentrations, often weighted by number of homes measured (Fazli and Stephens, 2018; Halios et al., 2022; Ilacqua et al., 2022; Liu et al., 2023b; Logue et al., 2011a; Morawska et al., 2013, 2017; Nishihama et al., 2021; Vardoulakis et al., 2020; Ye et al., 2017). Figure 2.2 shows central tendencies and variability of measured indoor contaminants categorized this way.

Logue et al. (2011a) showed weighted median and upper bound concentrations for non-biological contaminants from 77 studies in industrialized nations. Fazli and Stephens (2018) review USA studies to describe residential concentrations for selected contaminants. Vardoulakis et al. (2020) presented minimum and maximum concentrations from 141 worldwide studies. Morawska et al. (2013, 2017) reported weighted means and maximums for particulate matter from developed country studies. Ilacqua et al. (2022) gave median and peak PM levels across 538 global studies. Nishihama et al. (2021) focused on Japanese homes, while Ye et al. (2017) and Liu et al. (2023b) covered minimum/maximum and medians, respectively, in China and Halios et al. (2022) examined European dwellings.

According to Borsboom et al. (2016), the most prevalent volatile organic compounds (VOCs) that are measured indoors, grouped and ordered by number of studies, are: toluene; benzene; ethylbenzene, m,p-xylenes, and formaldehyde. The most common semi-volatile organic compounds (SVOCs) are naphthalene and pentabromodiphenyl ethers (PBDEs).

Inconsistencies introduce difficulties in precisely contrasting results across the literature, a challenge largely attributed to the absence of a standardized framework of reference for conducting and reporting results. While enhanced standardization would benefit comparisons, these works collectively furnish valuable perspectives on central benchmarks and concentra-

tion distributions. In the interim, judiciously synthesizing results across metric types provides a useful, albeit constrained, basis for grasping indoor contaminant patterns.

This current snapshot of contaminant sampling campaigns in homes has an extensive global scope. PM has been the focus of more systematic reviews compared to other contaminants. Reported concentrations vary by several orders of magnitude. This variability is due to fluctuations within the same indoor environment, as contaminant levels are ultimately dependent on emissions and control measures. Continued compilation of residential exposure data is crucial for characterizing risks and prioritizing mitigation worldwide.

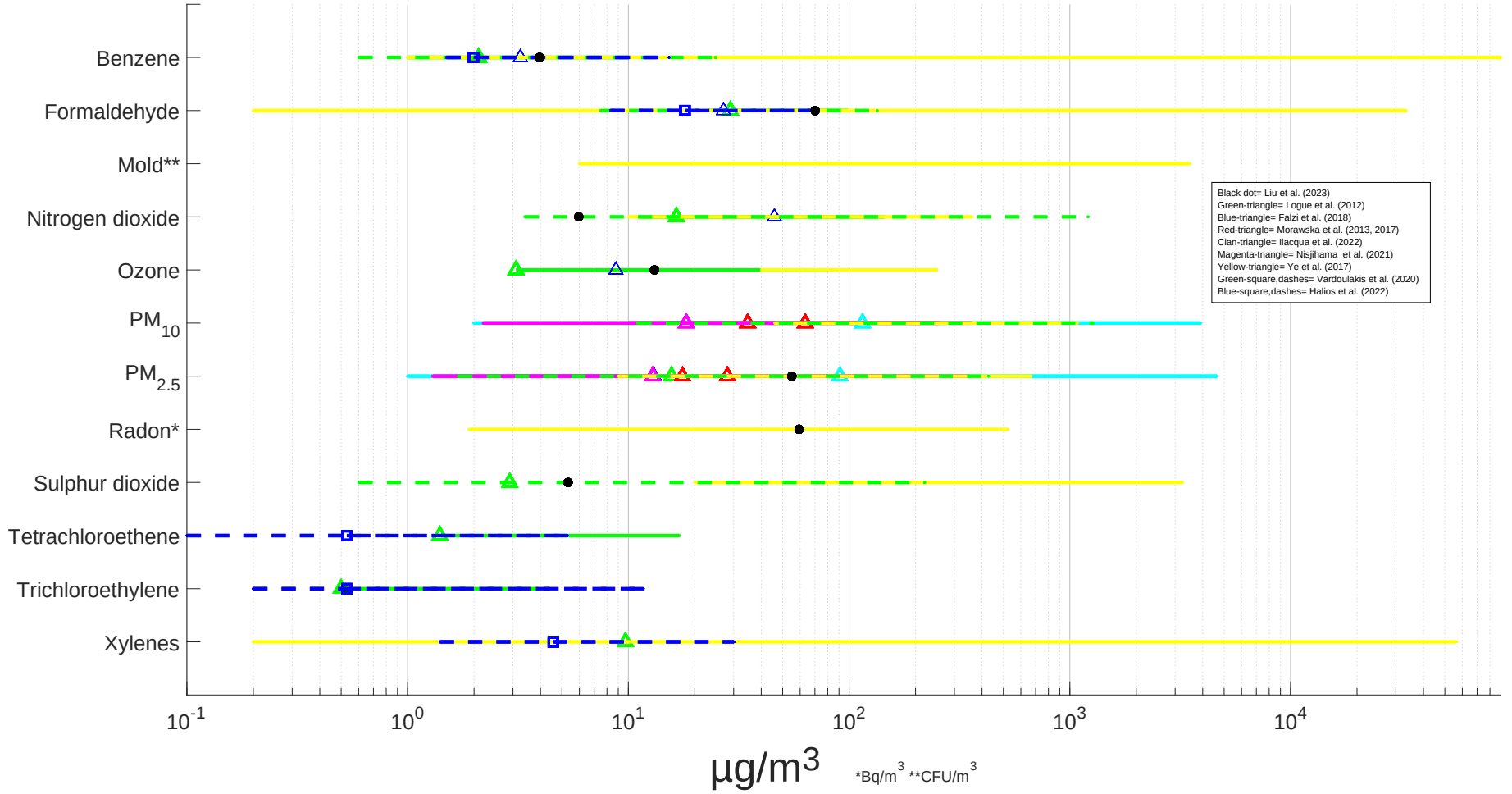


Figure 2.2: Selected indoor contaminants measured in homes. See the key on the plot for meaning of squares, triangles, colours, solid lines and dashed lines.

2.2 Exposure to air contaminants and health impact

While numerous contaminants exist in indoor environments, health impact data are lacking for many compounds beyond those quantified here, as comprehensive dose-response information remains absent across the broad spectrum of potential risks. Two major ways that health impacts associated with exposure have been assessed are via epidemiology and toxicological based studies (Borsboom et al., 2016). Epidemiology and toxicology studies differ significantly in how they define and measure exposure, as summarized in Table 2.2 (Ritter and Arbuckle, 2007). Both fields provide important but complementary insights into contaminant health impacts.

Epidemiology examines the distribution and determinants of health conditions in populations (Bhopal, 2016; Miettinen, 2011). Mortality and morbidity quantify death and illness occurrences. Mortality frequently indicates community health. Epidemiology links real-world exposures statistically to disease incidences, providing population-level evidence on risk factors.

In contrast, toxicology focuses on biological mechanisms of contaminant harm using controlled experiments (Eaton and Gilbert, 2008; Hayes and Kobets, 2023). Animal and cell models determine dose-response relationships. Toxicology elucidates specific toxicological properties and damage mechanisms. Cancer and non-cancer risks dominate toxicology's health concerns.

Both fields inform air contaminants health impacts for mitigation strategies. Epidemiology offers real-world disease insights, while toxicology reveals mechanistic biological effects. Bringing epidemiology and toxicology together serves to better understand cause and effect relationships and causal inference (Adami et al., 2011; Weed, 2002)

Exposure duration is another key aspect, categorized as acute or chronic. Chronic exposure persists more than 24 hours, while acute exposure lasts 24 hours or less (such as 8 hour averages or 1 hour averages). Both appear in air pollution regulations and guidelines regarding public health impacts. Impacts are also classed as chronic or acute effects. Chronic effects concern long-term illnesses like cancer or COPD from persistent exposures. Acute

Table 2.2: Characteristics of the Exposure Assessment in Toxicological and Epidemiological Studies.

Characteristic	**Toxicology**	**Epidemiology**
Design	Experimental	Observational
Study agents	Known and controlled source, vehicle, route	Can be multiple sources, routes and vehicles, not within control of investigator
Timing and duration of exposure	Known, constant and controlled; less likelihood of measurement error	Not controlled, may be of longer duration and even multigenerational and variable over observation period; higher likelihood of measurement error
Magnitude of exposure	Dose often exceeds range relevant to humans	Reflect actual range of human exposure
Exposure categorization	Dose is selected a priori, fixed, limited number of doses administered to groups of animals by investigator; usually one compound at a time	Estimated, commonly based on a one-time environmental (ad libitum exposure to contaminated air, drinking water, food) or biological (blood, urine) sampling; may or may not be categorized; evaluates mixtures to which people are exposed (although exact nature of mixture may not be well characterized)
Study groups	Homogenous (genetic, nutritional, environmental factors) both within dosing groups and between groups, except for the exposure under study	Efforts made to make the groups as homogenous as possible (within and between groups) using selection and restriction criteria for study population and/or data analysis
Relevance to humans	Species and strain selected may have metabolic pathways not representative of humans	Directly relevant if no selection biases present
Statistical analysis	Straightforward; a few select and fixed ordinal doses with a set number of animals exposed to each dose; if doses selected appropriately lends itself well to dose-response curves and threshold determinations (if applicable)	Complicated; concentrations are continuous variables, therefore can be issues such as: (1) data are not normally distributed; (2) may have high proportions of nondetectable concentrations; (3) choice of cut points to categorize data; difficult to identify sufficient numbers of truly nonexposed; choice of statistical model for dose-response curves

effects arise abruptly over hours or days, triggering events like strokes. Health impacts of exposures to air contaminants have traditionally been viewed through this duration lens (Borsboom et al., 2016).

Integrating parameters from epidemiology and toxicology is important for comprehensive quantitative health risk assessment. Epidemiology provides observational data on the relationship between exposures and health outcomes in human populations. Toxicology offers experimental data on dose-response and mechanisms from animal and in vitro studies. These exposures and doses can be both chronic or acute. While derived in different

contexts, certain parameters may be mathematically equivalent across disciplines. For example, the "relative risk" estimated from epidemiology studies represents the ratio of risk between exposed and unexposed groups. This can be quantitatively similar to the dose-response slope estimated from toxicology dose-response curves. As the metrics estimate the same relationship on a per unit exposure basis, they carry the same units and can be combined.

Meta-analysis and weight of evidence approaches are valuable techniques to integrate data across toxicology and epidemiology. By evaluating the consistency of outcomes across studies, predictive models can be developed incorporating multiple sources of evidence. This leverages the strengths of both experimental and observational data for a more robust understanding of potential harm (Adami et al., 2011; Bhopal, 2016; Boyes et al., 2007; Hayes and Kobets, 2023; Hernández and Tsatsakis, 2017; Jaffery et al., 2002).

2.2.1 Health effects

Air pollution has numerous health effects (mostly associated with respiratory and cardiovascular disorders) and is linked to increased mortality and morbidity, particularly for susceptible and sensitive individuals (children, the elderly, pregnant women, smokers and asthmatics) (US-EPA, 2011). In 2018, during the first WHO Global Conference on Air Pollution and Health, the WHO's General Director, Dr. Tedros Adhanom Ghebreyesus, called air pollution a "silent public health emergency" and "the new tobacco" (WHO, 2018d). Both long-term and short-term exposure to air contaminants can be associated to several respiratory health impacts. Short-term effects are temporary and range from discomfort (irritation of the eyes, nose, skin, throat, wheezing, coughing and chest tightness and, breathing difficulties) to more serious states (asthma, pneumonia, bronchitis and, lung and heart problems). Long-term effects are chronic, lasting for years or the whole life and can even lead to death (Manisalidis et al., 2020; US-EPA, 2011; WHO, 2006, 2021). Other non-respiratory health effects associated to air pollution include psychological complications, autism, retinopathy, fetal growth, low birth weight and diabetes (Eze et al., 2014; WHO, 2006, 2021), although epidemiological evidence suggests that air quality in indoor spaces is primarily linked to the respiratory health of its occupants (Bonjour et al., 2007; Samet et al., 1987; Spengler et al., 2000). The majority of epidemio-

logical studies for health effects of air pollution have been conducted using ambient air pollution data. One reason why indoor air pollution studies are scarce, could be that indoor air contaminants have not been as extensively monitored as outdoor air contaminants, even in developed countries: the evidence base for contributions to health effects needs to be strengthened (WHO, 2006, 2021).

Exposures of the same contaminant, from different sources, can be considered as additive because, there is currently little epidemiological evidence to firmly differentiate between health outcomes and the specific source of air pollution (from ambient air pollution, household air pollution (HAP) and/or secondhand tobacco smoke) for the same contaminant (Ebelt et al., 2005; Hime et al., 2018; Prüss-Üstün et al., 2016; WHO, 2006, 2021). The WHO estimated the global burden of disease (BoD)[§] from the joint effects of household and ambient air pollution for 2016 and, accounted for 7 million deaths, categorized in 5 health outcomes related to the respiratory and cardiovascular systems: acute lower respiratory disease (ALRI), chronic obstructive pulmonary disease (COPD), ischaemic heart disease (IHD), lung cancer and stroke (WHO, 2018c). Furthermore, an estimate of BoD focused for indoor air pollution in 2000, indicated that Indoor Air Pollution (IAP) was responsible for more than 1.5 million deaths from ALRI, COPD and lung cancer; although, these results represent the use of biomass fuels and coal for cooking, by women (and their children) in households in developing countries (in many low and middle-income countries women cook indoors with poor, if any, ventilation) because $PM_{2.5}$ from solid fuels is used to represent HAP in the BoD studies (Bonjour et al., 2007).

Particulate matter, benzene and, ozone have been highlighted, as they cause serious damage to the respiratory system: a prediction based on a scenario for raising concentrations of $PM_{2.5}$ and O_3 indicates that, these two contaminants solely, could account to 6-9 million premature deaths (a death that occurs before the average life expectancy for a given population) annually by 2060 (Guardino et al., 1994; Manisalidis et al., 2020; OECD, 2016). Furthermore, some authors have found some small (however, not fully consistent) evidence that the specific components of particulate matter have negative effects on human health (Lavigne et al., 2020). Figure 2.3 shows selected indoor contaminants, their penetration in the human respiratory track and their affected areas.

[§]Death and loss of health due to diseases, injuries and risk factors for all regions of the world

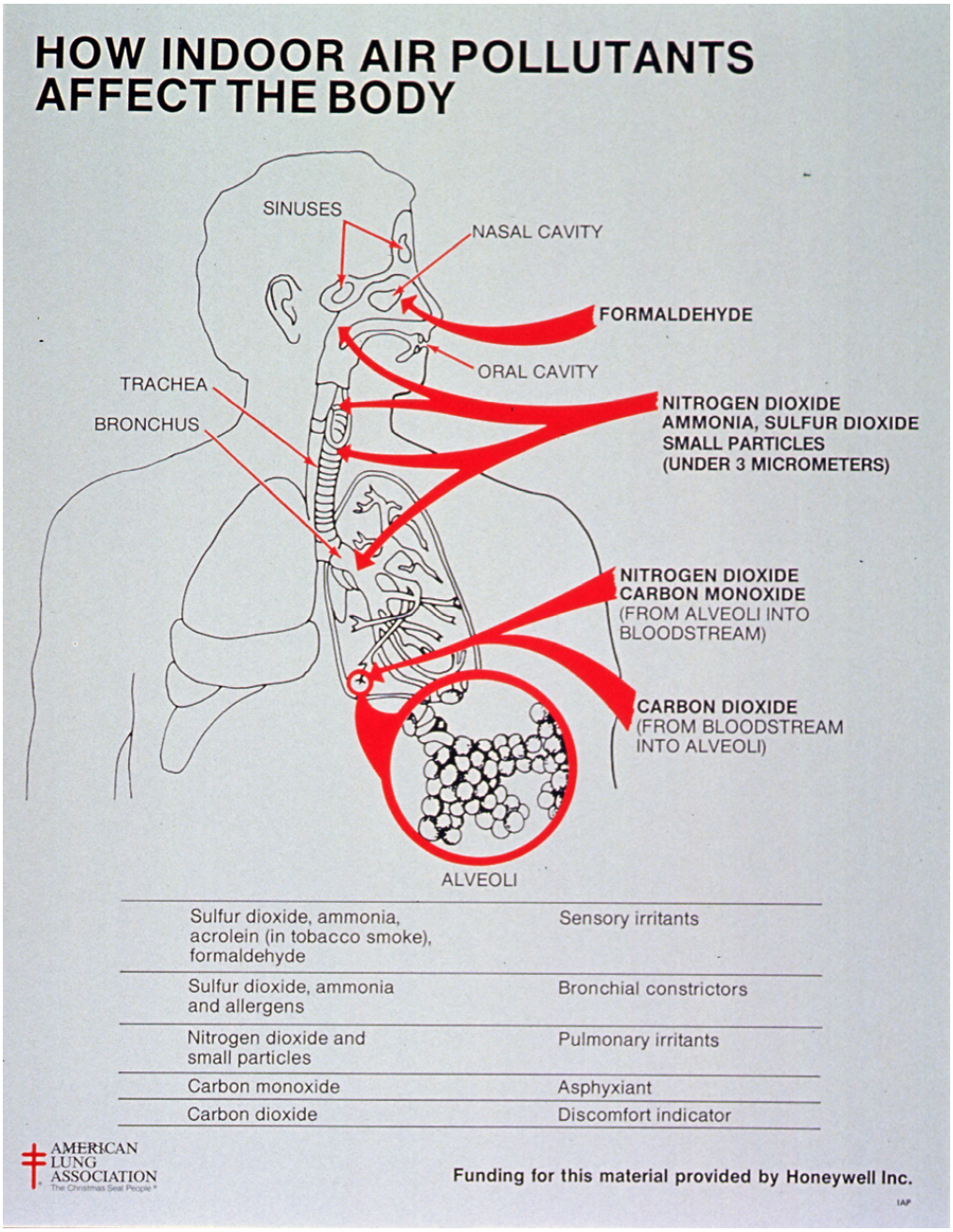


Figure 2.3: How Indoor Air contaminants Affect the Body. (A.L.A., 1987)

2.2.1.1 The criteria pollutants

Particulate Matter (PM). The smallest fractions of the PM have the highest health risks due to their ability to penetrate deeper in the respiratory system reaching into the cardiovascular system (see Fig. 2.4). Epidemiological and clinical studies have linked PM to a range of health outcomes, for short-term (acute) and long-term (chronic) PM exposure. Adverse effects associated to PM exposures include: mortality and hospital

admission in COPD patients, asthma exacerbation, mortality and morbidity for cardiovascular diseases (ischaemic events, arrythmia, cardiovascular events, heart rate variability), diabetes, myocardial infarction, lung/systemic inflammation and respiratory cancer (WHO, 2006, 2021). Short-term (daily time series studies) exposure to PM ($PM_{2.5}$, PM_{10}, $PM_{10-2.5}$) have shown positive associations with risk for total and cause-specific mortality (respiratory, cardiovascular). Long-term exposure to $PM_{2.5}$ has also been found to be related to morbidity (hospital admissions, asthma, cardiovascular outcomes, nonfatal heart attacks - myocardial infarction) and, all-cause and specific mortalities (cardiopulmonary, cardiovascular, lung cancer, COPD, stroke, IHD, ALRI) (Manisalidis et al., 2020; Prüss-Üstün et al., 2016; US-EPA, 2011, 2012, 2020b; WHO, 2006, 2021).

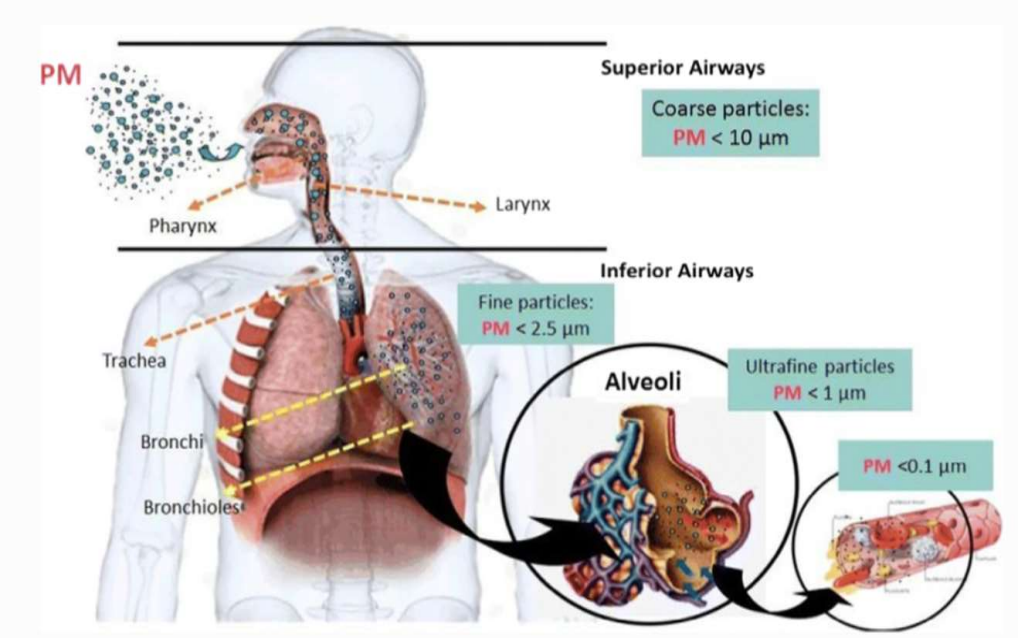


Figure 2.4: Particle size and penetration in the human respiratory system. (CH et al., 2017)

The aerodynamic size of particles is strongly associated with respiratory system diseases, with $PM_{2.5}$ penetrating into the lungs. Emerging evidence indicates health effects may vary by PM chemical composition and physical traits (Manisalidis et al., 2020; National Academies of Sciences, 2016; US-EPA, 2020b). Yet, epidemiology still finds particle size the most consistent, robust predictor of incidence under long-term exposure (Burnett

et al., 2018; Xu et al., 2022). This reflects the equi-toxicity principle - equal estimated toxicity per inhaled unit mass across PM types. More research on composition/source-specific PM health impacts is needed to enable differentiated exposure-response quantification (Xu et al., 2022).

Sulphur Dioxide (SO_2) exposure is associated with health problems such as respiratory irritation, reductions in mean lung function, bronchitis, mucus production, bronchoconstriction and bronchospasm. Moreover, it can influence the autonomic nervous system. Skin redness, damage to the eyes (lacrimation andcorneal opacity) and mucous membranes and, worsening pre-existing cardiovascular disease have also been observed. Asthmatics are particularly vulnerable (Chen et al., 2007; US-EPA, 2010a; WHO, 2006, 2021). Both chronic (years) and acute (hours) exposures have been associated to increased total non-accidental, lung cancer, cardiovascular and respiratory mortality. As for morbidity; hospital admissions for asthma, COPD and respiratory symptoms have been related to SO_2 exposures (Katsouyanni et al., 1997; OSHA, 1999; Prüss-Üstün et al., 2016; US-EPA, 2010a; WHO, 2006, 2021).

Nitrogen Dioxide (NO_2) is toxic, even for short periods of exposure, and its adverse effects are exacerbated by the presence of other contaminants ($PM_{2.5}$, SO_2). Thus it becomes difficult to differentiate the effects of nitrogen dioxide from those of other contaminants in epidemiological studies (WHO, 2006, 2021). Extensive reviews have concluded that respiratory health is associated with nitrogen dioxide exposure, independently of these other exposures (US-EPA, 2016). As an irritant of the respiratory system, it penetrates deep in the lung, inducing changes in pulmonary function, respiratory diseases, cough, wheezing, dyspnea, bronchospasm, airway inflammation, asthma exacerbation; when inhaled at high concentrations is associated with pulmonary edema. Furthermore, it can cause eye, throat and, nose irritation (Chen et al., 2007; Manisalidis et al., 2020; WHO, 2006, 2021). Chronic exposure to high concentrations of NO_2 can be responsible for chronic lung disease and can impair the sense of smell (Chen et al., 2007). Examination of the effects of nitrogen dioxide has focused on people with pre-existing conditions like lung disease, asthma, COPD or chronic bronchitis (WHO, 2006, 2021). Daily mortality (all cause -cardiovascular- respiratory), daily hospital admissions for respiratory disorders and cardiovascular diseases, asthma admissions, asthma in children,

congestive heart failure and ischemic heart disease have been associated to acute (hourly) exposure to NO_2 in epidemiological and time series studies (WHO, 2006, 2021). Cohort studies of long-term health effects have assessed the association between NO_2 and morbidity (cancer, lung cancer, bronchitic symptoms, recurrent wheeze, asthma, respiratory symptoms, preterm birth) and mortality (all-cause, lung cancer, sudden infant death) in children and adults. Epidemiological (cross-sectional and cohort) studies on health effects of indoor nitrogen dioxide exposure have found relationships with prevalence of respiratory illness, (dry) cough, wheeze, asthma, shortness of breath, allergic reactions (US-EPA, 2016; WHO, 2010). Studies have been particularly for children exposed to NO_2 from gas cookers the in home.

Ozone (O_3) even in small amounts, is linked to causing biochemical, morphologic, functional and immunological disorders, including respiratory and cardiovascular conditions. Short-term exposure increases daily mortality (total - nonaccidental, respiratory, cardiovascular) (Manisalidis et al., 2020; US-EPA, 2020a; WHO, 2006, 2021). Acute responses include effects on the pulmonary system (pulmonary function and inflammatory mediators) and the cardiovascular system (reduced heart rate variability, heart failure, impaired heart function, IHD, stroke, cardiac arrhythmia/arrest) (US-EPA, 2020a). Chronic effects include reduced lung function, development of atherosclerosis, asthma/asthma exacerbation and reduction in life expectancy. There is evidence that ozone acutely increases morbidity for respiratory conditions, hospital admissions for asthma, respiratory tract infections and exacerbation of chronic airway diseases (WHO, 2006, 2021). Short-Term ozone exposure is linked to metabolic effects (diabetes) (US-EPA, 2020a).

O_3 and NO_2 are Reactive Oxygen Species - Reactive Nitrogen Species (ROS-NRS). Excess ROS can cause oxidative stress, damaging respiratory cells and tissues. This oxidative damage can accelerate aging, spur cell death, and ultimately contribute to disease (Lakey et al., 2016; Poschl and Shiraiwa, 2015).

2.2.1.2 Other air pollutants

Volatile Organic Compounds (VOCs) contain carbon and evaporate under normal conditions. The 1990 Clean Air Act identified 187 VOCs as hazardous air contaminants, or air toxics (Borsboom et al., 2016). VOC health risks depend on the specific compound, exposure level, and time spent indoors (Shrubsole et al., 2019). Not all VOCs are harmful (Spengler et al., 2000). However, some like benzene, toluene, and formaldehyde associate with cancer in humans (Manisalidis et al., 2020; Spengler et al., 2000). Most data on VOC and air toxic impacts come from toxicology or occupational/accidental exposure studies. The World Health Organization provides health effects information for numerous VOCs detected indoors. While risks vary by compound, chronic VOC and air toxic exposures may have neurological, carcinogenic, and other adverse effects at elevated concentrations. Further research on exposure scenarios is needed.

Benzene causes acute non-cancer (dizziness, nausea) and chronic non-cancer effects (immunological) from high exposures, along with leukaemia and lung cancer from long-term lower exposures (Manisalidis et al., 2020; US-EPA, 2003a; WHO, 2010). *Formaldehyde* leads to odors, irritation, lung impacts, and eczema from indoor exposures. It also causes nasopharyngeal cancer and leukaemia (Samet et al., 1988; US-EPA, 1990a; WHO, 2010). *Naphthalene* risks include respiratory carcinogenicity and haemolytic anaemia, but dose-response data are limited (WHO, 2010). *Xylenes* associate with decreased weight, mortality, and coordination (US-EPA, 2003b). *Trichloroethylene (TCE)* causes neurotoxicity, kidney/liver cancer, autoimmunity, and developmental effects. It is genotoxic (Shrubsole et al., 2019; WHO, 2010). *Tetrachloroethylene (PCE)* causes cancer (oesophageal, cervical, lymphoma) and mucous membrane irritation (WHO, 2010).

Polycyclic aromatic hydrocarbons (PAHs) pose mutagenic and carcinogenic risks via DNA adduct formation. Non-cancer effects include birth defects, bronchitis, and asthma. Cancer effects include lung and bladder cancer (Manisalidis et al., 2020; Spengler et al., 2000; US-EPA, 1990b; WHO, 2010).

Radon primarily causes lung cancer. Leukemia and other cancers also associate with radon (Keith et al., 2012; Samet et al., 1988; Spengler et al.,

2000; WHO, 2010).

Biological agents like mold link to asthma, respiratory infections, Legionnaires' disease, wheezing, coughs, and allergies. Even dead mold emits mycotoxins (Borsboom et al., 2016; Heseltine and Rosen, 2009; Samet et al., 1988).

A descriptive resume of air contaminants and their plausible health outcomes is shown in Table 2.3.

Table 2.3: Air contaminants and plausible health outcomes. [+]

	Contaminant	Plausible health outcomes											
		Mortality								*Morbidity*			
		All cause	Cardiovascular (general)	Respiratory (general)	Lung cancer	COPD	ALRI	IHD	Stroke	Cancer [*]	Asthma	Respiratory	Cardiovascular
criteria pollutant	Particulate matter ($PM_{2.5}$)	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
	Sulfur Dioxide (SO_2)	✓	✓	✓	✓						✓	✓	
	Nitrogen Dioxide (NO_2)	✓	✓	✓	✓						✓	✓	
	Ozone (O_3)	✓	✓	✓								✓	✓
	Carbon monoxide[£]	✓	✓	✓							✓	✓	✓
VOC[**]	Benzene				✓					✓			
	Formaldehyde									✓	✓	✓	✓
	TCE									✓			
	PCE									✓			
	Naphthalene									✓		✓	
	Xylenes									✓			
Other air contaminants	Polycyclic aromatic hydrocarbons[***]				✓					✓			
	Radon				✓								
	Mold										✓	✓	✓

[*] It refers to different cancer.
[**] Volatile Organic Compounds.
[***] benz[*a*]anthracene, benzo[*a*]pyrene, benzo[*b*]fluoranthene, benzo[*k*]fluoranthene, chrysene, dibenzo[*a,h*]anthracene, benzo[*ghi*]perylene and indeno 1,2,3 [*cd*] pyrene.
[£] The evidence found and reported for CO exposure express acute exposures, and even deaths by suicide.
[+] Several sources (Heseltine and Rosen, 2009; Hime et al., 2018; National Academies of Sciences, 2016; Prüss-Üstün et al., 2016; Samet et al., 1987, 1988; Spengler et al., 2000; US-EPA, 1990a, 2003a,b, 2010a,b, 2011, 2012, 2016, 2017, 2020a,b; WHO, 2006, 2021)

2.2.2 Additive, synergistic and multi-contaminant effects

Chemical pollution is characterized by the simultaneous and sequential exposure to unintentionally complex mixtures. This complexity arises from

the presence of mixtures of gases, vapors, and particles that people encounter with every breath taken (Spengler et al., 2000). For air pollution in particular, most toxicological and epidemiological evidence does not focus on multi contaminant mixtures, bar known risks like smoking (Borsboom et al., 2016; WHO, 2021). But combined effects may matter in some circumstances. Joint impacts could match the sum of solitary effects (additivity). Or surpass it, synergistically. Or fall short, antagonistically. One chemical may curb another's influence (inhibition). Or boost it, despite its own nugatory effect (potentiation). Or opposites may cancel each other out (masking effect).

Current proposals for potential mixture risks assume *Concentration Addition*, whereby components behave additively (Section 2.2.1) (Backhaus, 2023; Martin et al., 2021; Martin, 2023). Limited data often necessitates assuming additivity for human toxicity in life cycle assessments of environmental mixtures of air pollutants (Hauschild and Huijbregts, 2015; Hauschild et al., 2018).

If synergies manifest, they likely occur at high concentrations above individual components' points of departure. Several reviews support this, finding limited synergies at typical exposures (Committee et al., 2019; Kortenkamp et al., 2009; Rudén et al., 2019; Socianu et al., 2022). Carbon monoxide is an exception showing synergistic effects at low concentrations (Norris et al., 1986; Ramsden, 2021) (more discussion on CO in Section 8.7). Aside from photo oxidant NOx, knowledge of synergistic or antagonistic air contaminant emissions in life cycle impact assessments remains scarce (Hauschild and Huijbregts, 2015).

Assessing chemical mixture toxicity requires considering potential additive, synergistic, antagonistic, and other non-additive interactions between components. The occurrence of additive, synergistic, or antagonistic effects varies with mixture composition. Equi-toxicity models consider single substances, assuming their toxicity combines additively in generic cases. However, simply summing single chemical effects may miss real-world low-dose exposures. Mixtures exhibit complex interactions deviating from dose additivity models. Exposure timing and sequence also influence outcomes not captured in simplified single chemical studies. Accounting for these nuances is key to advancing mixture risk assessment capabilities (Hauschild and Huijbregts, 2015; Hauschild et al., 2018; Hernandez et al., 2019).

2.3 Health-based metrics

Different metrics to measure disease exits (Miettinen, 2011). Mortality rates show the effect of household and outdoor air pollution on environmental health (WHO, 2018c). Indicators and metrics are used interchangeably in environmental contexts. Indicators tend to be broad, with quantitative data and qualitative descriptions. Concentrations of $PM_{2.5}$, NO_2, O_3, and SO_2 indicate sustainability (ISO, 2016), though urban air contaminant levels also count as metrics (Tanzil and Beloff, 2006). Metrics mostly mean quantitative or semi-quantitative measures (Martenies et al., 2015). Perceived air quality serves as a metric, especially for indoor air. Carbon dioxide indicates poor indoor air (Jones, 2017). Here metrics and indicators mean the same in air pollution research.

Current guidelines and standards for indoor and outdoor air pollution aim to minimise exposures and protect health (Jones, 2017; Sherman et al., 2018). Metrics like mortality, morbidity, life years lost and disability-adjusted life years stem from public health data. But perceived air quality and CO_2 levels do not. Both feature in assessments of indoor and outdoor air quality. Yet what is needed are health-centred indoor air quality metrics based on known health effects (Jones et al., 2018). Moreover, air quality benchmarks should flag hazardous indoor air using human health and comfort as the yardsticks, even if impacts are not immediate (Jones, 2017; Jones et al., 2018; Sherman et al., 2018).

2.3.1 Threshold values

In air pollution, thresholds are concentration limits set as maximum exposures over time to gauge health impacts. “Standards” and “guidelines” refer loosely to ambient and indoor air quality rules. But standards are enforced (EPA, 2016); guidelines are not (WHO, 2010, 2021). For workplaces, exposure limit values (ELVs) and threshold limit values (TLVs) are the norm (Abdul-Wahab et al., 2015).

Cognizant authorities, such as, national bodies, environmental agencies and global health organizations issue air quality standards and guidelines for sundry contaminants. The WHO and America’s EPA publish figures for common contaminants. Oddly, for the criteria pollutants, the EPA’s rules

are looser than the WHO's, the toughest benchmarks for these pollutants. For other contaminants like formaldehyde, cognizant authorities propose a wide range of recommended limits varying by one order of magnitude even (Table 2.4). Such values largely describe air pollution and look to safeguard public health (EPA, 2016; WHO, 2021). Similarly, workplace exposure limits aim to prevent or lessen health risks (Jones, 2017; Salis et al., 2017). Prevention is guided by the "as low as reasonably achievable" (ALARA) principle, aim to minimize exposures while considering technical, economic, and social factors (Andresz et al., 2022).

Bodies proposing indoor, occupational or ambient thresholds have a responsibility to establish thorough values. Countries lacking resources often adopt standards/guidelines published by the USEPA NAAQS or WHO AQG (Morantes et al., 2016). Abdul-Wahab et al. (2015) reviewed international bodies' indoor air quality standards/guidelines, concluding adherence depends on potential health effects. For certain contaminants such as acrolein, meeting standards also hinges on the capability to accurately measure their concentrations.

Importantly, different organizations' limit values sometimes differ substantially for identical exposure periods (Abdul-Wahab et al., 2015; Morantes et al., 2016; Salis et al., 2017). Limit values reflect policy motivations, policymaker judgments, and differences in contaminant information, not uniform hazard levels. Guidelines and standards differ in derivation: some from practical experience, others from comprehensive reviews and consensus of experts on contaminants' health effects. Most come from toxicological/epidemiological health impact assessments (Borsboom et al., 2016).

Thresholds serve as air quality metrics. Concentration/threshold ratios over one signal trouble (Jones et al., 2018; Salis et al., 2017; Sherman et al., 2018). Measured values are compared to guidelines for each contaminant. Exceeding a threshold signals danger; falling short suggests safety. But breaching a limit by 1 % or 10 % counts the same, although not equivalent for health. The extent matters: a threshold cannot measure health burden when various contaminants breach thresholds.

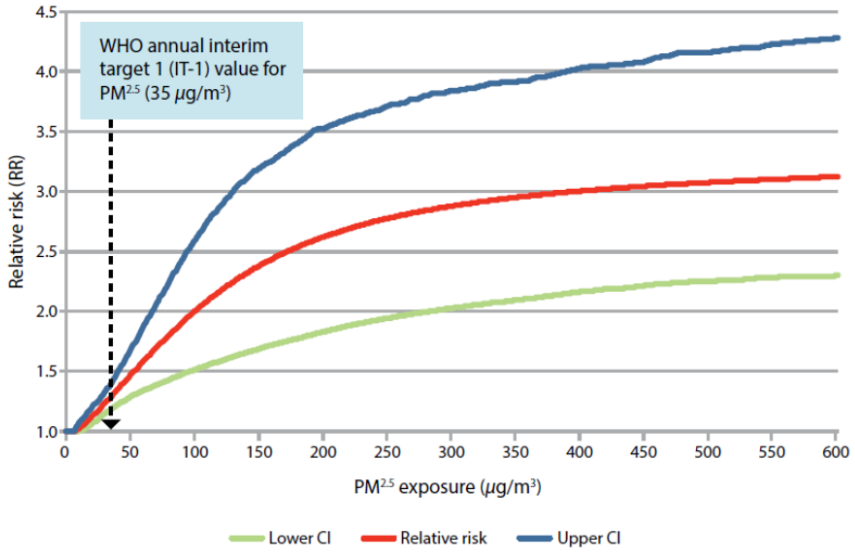
Table 2.4 summarizes major indoor/outdoor air contaminant thresholds from the WHO and the USEPA. Comparing proposed concentrations to year-long exposure thresholds shows, for example, the $PM_{2.5}$ value exceeds both organizations' limits. However, this does not determine the health burden of exceeding a threshold.

Table 2.4: Threshold values for main indoor and outdoor air pollutants.[+]

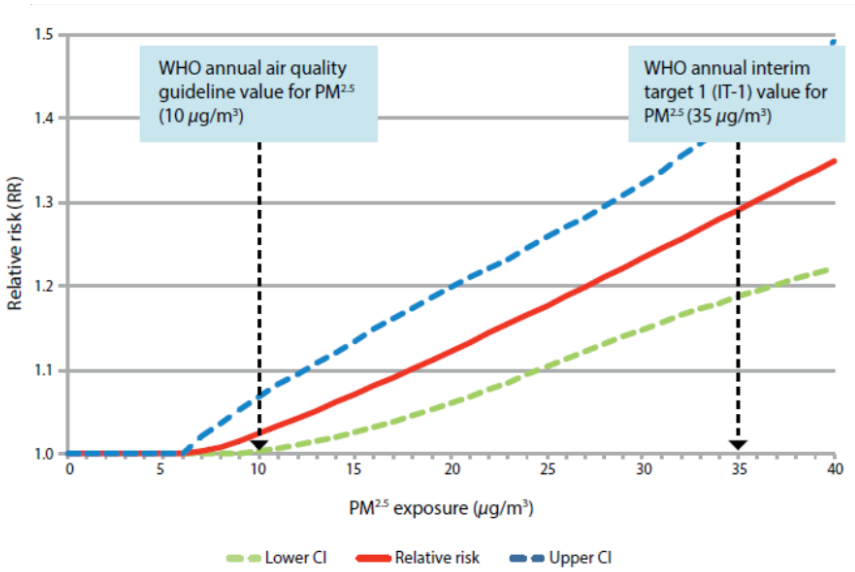
	Contaminant	Indoor/occupational		Outdoor/ambient				In homes[i]
		$\mu g/m^3$	Time	$\mu g/m^3$	Time	Type[j]	By[j]	$\mu g/m^3$
Criteria pollutant	**Particulate matter ($PM_{2.5}$)**	Use ambient values		5	1 year	Guideline	WHO	15.9
				15	24-h	Guideline	WHO	
		9	1 year	9	1 year	Standard	US EPA	
		35	24-h	35	24-h	Standard	US EPA	
		65	24-h	-	1-h	Standard	ASHRAE	
	Sulfure Dioxide (SO_2)	0.012 [a]	1 year	40	24 -h	Guideline	WHO	2.9
		80 (0.03[a])	1 year	75	1 -h	Standard	US EPA	
	Nitrogen Dioxide (NO_2)	ambient values		10	1 year	Guideline	WHO	13.1
				25	24 -h	Guideline	WHO	
		100 (0.05[a])	1 year	53[b]	1 year	Standard	US EPA	
		1800 (1[a])	15-min	100 [a]	1 -h	Standard	NIOSH/US EPA	
	Ozone (O_3)	200 (0.1[a])	8-h	0.07 [a]	3 year	ELV / Standard	OSHA/US EPA	17.2
		120 (0.064[a])	8-h	60	peak season	Guideline	WHO	
	Carbon monoxide	7 [c]	24-h	4[c]	24-h	Guideline	WHO	810
		10[c]	8-h			Guideline	WHO	
		55[c](50[a])	8-h	9 [a]	8-h	PEL / Standard	OSHA/US EPA	
		35 [a]	8-H	35 [c]	1-h	REL / Standard	NIOSH/US EPA	
VOC[d]	**Benzene**	No safe level of exposure can be recommended						2.5
	Formaldehyde	0.1 [c]	30min	–		Guideline	WHO	69
		20	10-h			ELV	NIOSH	
		9	chronic			REL	CA OEHHA	
		10	chronic			ELV	France	
		10	1 year			ELV	UK	
		0.1 [c]	30min			Standard	ASHRAE	
	Trichloroethylene	2	Whole life	–		ELV	VGAI	0.16
		2.3	Whole life			Guideline[e]	WHO	
	Tetrachloroethylene	250	1 year	–		Guideline	WHO	1.7
	Naphthalene	10	1 year	–		Guideline	WHO	1.2
		9	1 year			REL	OEHHA	
	Xylenes	22000	1-h			REL	OEHHA	7.4
OAC[h]	**Polycyclic aromatic hydrocarbons** [f]	No safe level of exposure can be recommended						
	Radon	100[g1]	1 year	–		Guideline	WHO	
	Mold	200[g2]	1 year			ELV	EU	

[a] ppm
[b] ppb
[c] mg/m^3
[d] Volatile Organic Compounds
[e] excess lifetime cancer risk of 1:1,000,000
[f] *a*]anthracene, benzo[*a*]pyrene, benzo[*b*]fluoranthene, benzo[*k*]fluoranthene, chrysene, dibenzo[*a,h*]anthracene, benzo[*ghi*]perylene and indeno 1,2,3 [*cd*] pyrene
[g1] Bq/m^3 (Becquerel)
[g2] CFU/m^3 (Colony Forming Units)
[h] Other Air Contaminants
[i] (Logue et al., 2011a)
[j] REL, Recommended exposure limit; PEL, Personal exposure limit; ELV, exposure limit value WHO, World Health Organization; USEPA,United States Environmental Protection Agency; VGAI, Valeurs Guides de qualité d'Air Intérieur, France; OEHHA, Office of Environmental Health Hazard Assessment, USA; NIOSH, National Institute for Occupational Safety and Health, USA.
[+] From (Abdul-Wahab et al., 2015; EPA, 2016; Morantes et al., 2016; Salis et al., 2017; WHO, 2006, 2010, 2021)

Figure 2.5 links the former WHO $PM_{2.5}$ guideline from 2005 to child ALRI risks. While these guidelines for $PM_{2.5}$ have been updated since 2005 (to 5 µg/m^3), this figure is included to illustrate how a threshold can be linked to a specific exposure-response function. Relating concentrations to a health risk function provides a nuanced understanding of the impact across various exposure levels, surpassing simple threshold comparisons.



(a)



(b)

Figure 2.5: The relationship between level of $PM_{2.5}$ exposure (µg/m^3) and relative risk (95 % CI) of child ALRI, based on the integrated exposure-response (IER) function, for (a) exposure over the range 0–600 µg/m^3, and (b) over the range 0–40 µg/m^3 which spans the WHO annual AQG for $PM_{2.5}$ and the interim target (IT-1). (WHO, 2014)

2.3.2 Disability-Adjusted Life Years (DALYs)

Health-adjusted life years (HALYs) permit simultaneous description of morbidity and mortality within a single population health measure, useful for comparisons across illnesses, interventions and populations (Gold et al., 2002). HALYs include quality-adjusted life years (QALYs) and disability-adjusted life years (DALYs) (Fryback, 1998). DALYs summarize health impacts while QALYs capture both the quantity and quality of remaining life years based on functional outcomes and well-being. Table 2.5 shows descriptors, similarities and differences.

Table 2.5: Descriptives for HALY metrics: QALYs and DALYs.

QALY	**DALY**
Measures the quality of life in *health gain*	Measures *health loss* in the quality of life
Patient-centric perspective	Population-level perspective
1 = perfect health	1 = death
0 = death	0 = perfect health
Accounts for healthy years	Accounts for loss of healthy years
QA quality of life	**DA** morbidity
LY quantity of life	**LY** mortality
Quantify health	Quantify burden
Since the 1960's	Since the 1990's
Measure not for specific health outcomes	Measure for specific health outcomes
Usually used in developed or high-income countries (UK)	Usually used in developing or low-income countries; WHO and World Bank
Use life tables	
Can account for discount rates (discount for time preference)	
Can account for age-adjustment	
Do not consider comorbidity (individual experiencing multiple illnesses)	

In 1993, the World Bank and WHO sought to quantify the global burden of premature death, disease and injury: Disability-Adjusted Life Years (DALYs) were the metric developed (Murray, 1994). DALYs indicate time lived with disability and time lost to premature mortality for specific health outcomes (Homedes, 1996). The DALY framework uses *disability* for any illness reducing short- or long-term physical/mental health (Chen et al., 2015). DALYs have been criticized (Anand and Hanson, 1997; Parks, 2014; Williams, 1999) but remain under revision since proposed; however, the underlying model is unchanged (Chen et al., 2015).

DALYs are used in disease burden studies (Kyu et al., 2018). The number of DALYs for a disease equals the Years of Life Lost (YLL) from premature mortality plus Years Lost due to Disability (YLD) (Equation 2.1) (Chen et al., 2015; Homedes, 1996; Mathers et al., 2001):

$$DALY = YLL + YLD \tag{2.1}$$

$$YLL = N \cdot L_1 \tag{2.2}$$

$$YLD = I \cdot DW \cdot L_2 \tag{2.3}$$

where:

DALY is disability-adjusted life year,

YLL is years of life lost,

YLD is years lived with disability,

N is number of deaths,

$\mathbf{L_1}$ is standard life expectancy minus age of death,

I is number of incident cases in reference period,

DW is disability weight,

$\mathbf{L_2}$ is average duration of condition

N, **I** & $\mathbf{L_2}$ are obtained from health organizations data bases, such as the national statistical bureaux or the United Nations Statistics Division. $\mathbf{L_1}$ is a life-expectancy at birth of 82.5 years for women and 80 years for men, the highest average observed globally (Gold et al., 2002; Murray, 1994). In parallel, life expectancy of populations can be obtained using life tables, such as those created by WHO (Murray et al., 2000). The statistical theory for life tables can be seen in Cox (1972). Four different measures that could be used to estimate life expectancy for DALYs are presented in Adam and Murray (2003). **DW** represents the magnitude of health loss associated with an specific outcome, on a scale from 0 to 1, with 0 implying a state that is equivalent to full health and 1 a state equivalent to death. Disability weights for 235 unique health states in the Global Burden of Disease studies (GBD) 2013-2016 are presented in Salomon et al. (2015).

DALYs can account for age weighting and discounting for time preferences (Murray, 1994). The former values young adulthood years more, assuming reliance on middle-aged groups (Barendregt et al., 1996; Gold et al., 2002; Homedes, 1996). The latter discounts future benefits (usually 3% rate) (Gold et al., 2002; Murray, 1994). Current estimates of DALYs in GBD studies omit both (Chen et al., 2015; Kyu et al., 2018).

Equation 2.1 shows that DALYs depend heavily on epidemiological data, which is scarce in developing nations. Most DALY estimates use intricate models covering demographics, birth and death rates, and socioeconomics. Drawbacks include tangled computation (Harikrishnan et al., 2018; James et al., 2018) and data scarcity (population age, life expectancy, incidence, prevalence) (Chen et al., 2015). Collecting such data present significant challenges. Assumptions (like discounting and age-weighting rates) and guesses (onset and death ages) (Rushby and Hanson, 2001) also complicate DALYs. Table 2.6 and Figure 2.6 show DALYs variation for alcohol use disorder from different assumptions, demonstrating estimate sensitivity (Devleesschauwer et al., 2014).

Table 2.6: Years lived with disability (YLDs), years of life lost (YLLs) and disability-adjusted life years (DALYs) for the alcohol use disorder example under different social value choices, (Devleesschauwer et al., 2014).

Scenario $[K;r]$	**Age weighting,** K	**Discount rate,** r **(%)**	YLD	YLL	DALY
DALY[0;0]	No	0	11.0	25.0	36.0
DALY[1;0]	Yes	0	12.3	16.7	29.1
DALY[0;0.03]	No	3	8.3	9.7	17.9
DALY[1;0.03]	Yes	3	9.5	6.7	16.2

DALYs feature prominently in models of environmental risk and in studies of the global burden of disease. DALYs have gained wide acceptance among scientists as health metrics, despite some flaws. They help assess the danger of environmental hazards in particular. Myriad studies quantify air pollution's hidden health tolls using DALYs (Harikrishnan et al., 2018; James et al., 2018; Murray, 1994; Prüss-Üstün et al., 2016). The latest GBD study estimate the DALY burdens of 359 diseases across 195 countries from 1990-2017. Air pollution's impacts were associated to highest disease burden (Kyu et al., 2018). Assumptions for estimating DALYs evolve across studies, reflecting a dynamic field aimed at enabling consistent quantification and comparison of disease burdens across populations and illnesses, fostering continual learning from each model.

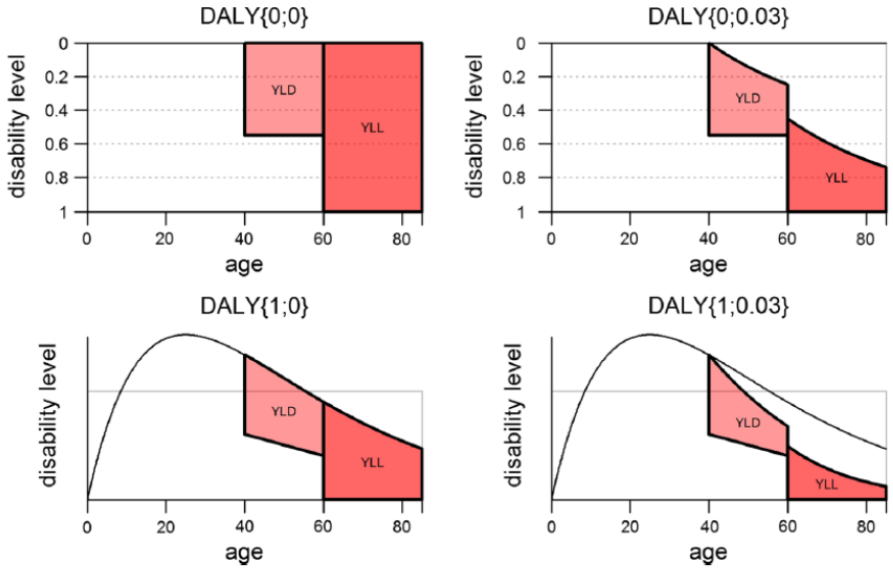


Figure 2.6: 1 Years lived with disability (YLDs) and years of life lost (YLLs) for the alcohol use disorder example under different social weighting scenarios. The top left plot is the basic disability-adjusted life year (DALY) calculation (the "0,0" indicates no age weighting and zero discount rate, see Table 2.6). The bottom left plot includes age weighting; the curved black line is the age-dependent zero disability level, while the straight grey line compares the situation without age weighting. The top right plot includes a 3 % time discount rate; the burden is assigned to the year of disease onset (the age of 40). The bottom right plot, finally, combines age weighting and a 3 % time discount rate (Devleesschauwer et al., 2014).

2.4 Health risk and impact assessment

There are several prominent methods for assessing and prioritizing health impacts of air pollutants (Rausand, 2013; von Stackelberg and Williams, 2021). Hazard assessments compare human exposures to a contaminant's health-based safety level, threshold, or guideline. When exposed to multiple contaminants, summing their individual hazards (the ratio of the dose to the reference) is a common approach (aggregating across risks assumes that there are no interactions or synergies between different contaminants). This assessment identifies exposures of potential concern without ranking risks.

Impact assessments apply toxicological and epidemiological evidence to estimate and rank pollutants by attributable health damage.

Cumulative risk assessment attributes total disease burdens across outcomes to indoor sources, also enabling source prioritization (Sexton, 2012).

Cost-benefit analysis monetizes health benefits of exposure reductions, weighing them against intervention costs (Pearce et al., 2006). Each approach offers insights into indoor pollutants' hidden tolls.

Health risk assessment (HRA) quantifies the likelihood of adverse effects by characterizing pollutant emissions, exposures, and dose-response relationships. HRA models estimate risks to guide guidelines and risk management (Council, 2009).

Comparative risk assessment involves systematic evaluation of changes in population health that would result from modifying the population distribution of exposure to a risk factor or a group of risk factors, using consistent and comparable methods (Ezzati, 2008)

Health impact assessment (HIA) evaluates policies and interventions through a health lens, forecasting potential benefits or validating post-implementation impacts (WHO, 2001).

Among these techniques, cumulative risk assessment holds particular promise for elucidating indoor air pollution's health footprints. By aggregating multiple pollutants' contributions across outcomes, it captures interactive and overlapping effects missed in single-pollutant assessments. Attributed disease burdens encapsulate prevalence and severity, overcoming limitations of incidence-only impact measures. Nevertheless, cumulative assessments require extensive data and modeling, along with uncertain assumptions. Continued research on indoor pollutants' toxicity and population exposure-response relationships will strengthen knowledge bases for cumulative risk efforts.

No single approach provides a complete picture; combinations of techniques offer the most robust insights to guide indoor air quality management. Ultimately, the shared goal remains elucidating pollutants' health burdens to protect the public through evidence-based decision-making.

2.4.1 Health Risk Assessment

Air Pollution Health Risk Assessment (AP-HRA) is a comprehensive methodology aimed at quantifying harm associated with air pollution by using the Disability-Adjusted Life Year (DALY) as the outcome metric. AP-HRA provides an epidemiology-based framework for comparative risk analysis,

cost-benefit evaluation of interventions, accountability assessments of air quality management programs, and setting exposure guidelines and standards (Bhat et al., 2021). Ensuring robust and rigorous AP-HRA is crucial for evidence-based air quality policy and decision-making.

Concentration-response (C-R) functions form the core of AP-HRA. They establish the relationship between changes in incidence or prevalence of adverse health outcomes and changes in air pollutant exposures (Bhat et al., 2021). These C-R coefficients are derived from epidemiological observational studies that investigate the association between air quality indicators (like $PM_{2.5}$ concentrations) and health endpoints (asthma exacerbations, cardiovascular mortality). The C-R function for the incidence rate, for a health outcome k and a contaminant i, $I_{(k,i)}$, is most often described by a no lower threshold (also known as Theoretical Minimum Risk Exposure Level -TMREL, point of zero impact, baseline background concentration, or counterfactual level) saturation expression, using a non-linear relationship (Sacks et al., 2018).

$$I_{(k,i)} = \gamma_{0_k} \left(1 - e^{-(\beta_{(k,i)} \cdot C_i)}\right) \tag{2.4}$$

C_i is the representative or reference concentration where the health effects are calculated. The effect of a lower threshold can be introduced replacing C_i by $C_i - C_0$, with C_0 as a concentration below which effects are not considered.

γ_{0_k} is the baseline incidence rate, $\beta_{(k,i)}$ is an empirical parameter that describes the change in the risk estimate per unit of change in the contaminant concentration (ΔC_i, in $\mu g/m^3$, or an equivalent concentration unit),

$$\beta_{k,i} = \frac{ln(RR_{(k,i)})}{\Delta C_i} \tag{2.5}$$

where RR is a relative risk (Sacks et al., 2018). An all-cause effect of health impact k can be achieved by applying an all-cause disease estimate or, by the sum of the contributions across health endpoints, caused by the contaminant i.

The relative risk ($RR_{(k,i)}$) is determined by $\beta_{(k,i)}$ and C_i. The most commonly used C-R model is a log-linear relative risk (RR) model that relates concentration (C) to RR (Burnett and Cohen, 2020; Nasari et al., 2016):

$$RR_{(k,i)} = e^{(\beta_{(k,i)} \cdot C_i)} \tag{2.6}$$

Here, $\beta_{(k,i)}$ represents the log-linear regression coefficient for health outcome k and pollutant i. This model approximates the observed shapes of air pollutant C-R curves reasonably well. Nonlinearities emerge at high concentrations because the probability of catching a disease cannot exceed 100 %, and the curve flattens at high exposure levels. Epidemiological, biological, and/or chemical mechanisms that may explain the attenuation of a C-R function for airborne contaminants at high concentrations are: (i) The saturation effect (biochemical and cellular processes becoming saturated); (ii) The depletion of susceptible people (the population at risk at high exposure levels contains relatively few susceptible people); (iii) High background rates of disease (competing risks); (iv) A decreased inhalation at high concentrations; (v) For particles, a reduction in the fraction of toxic matter at higher doses (dilution hypothesis) (Nirel et al., 2021; Stayner et al., 2003).

Although alternative nonlinear forms, such as log-log and power law models, also accurately capture C-R behavior across the full concentration range (Burnett and Cohen, 2020; Burnett et al., 2014; Nasari et al., 2016), the log-linear model remains the most widely applied in AP-HRA analyses (Bhat et al., 2021).

Within the field of air pollution epidemiology, researchers make frequent use of a metric known as the population attributable fraction (PAF). This valuable parameter enables quantification of the proportional increase in incidence (cases) via the baseline disease incidence, or harm (DALYs) via the Burden of Disease (BoD), the death and loss of health due to diseases, injuries and risk factors, the last being in this case air pollution:

$$I_{(k,i)} = PAF_{(k,i)} \cdot \gamma_{0_k} \tag{2.7}$$

and,

$$\text{Harm}_{(k,i)} = \text{PAF}_{(k,i)} \cdot \text{BoD}_k \tag{2.8}$$

Despite its conceptual simplicity, in practice the PAF is represented by a range of mathematical definitions and terminologies. Numerous synonymous versions exist, including attributable fraction, attributable risk fraction, and attributable burden. Additionally, several equivalent equations

can be utilized to calculate the PAF, including the fraction of exposed individuals, the ratio of the relative risk minus 1 to the relative risk, and 1 minus the inverse relative risk. Common definitions of PAF include (Sacks et al., 2018):

$$\mathrm{PAF}_{(k,i)} = \frac{\mathrm{RR}_{(k,i)} - 1}{\mathrm{RR}_{(k,i)}} \tag{2.9}$$

$$\mathrm{PAF}_{(k,i)} = \frac{f \cdot \mathrm{RR}_{(k,i)} - 1}{f \cdot (\mathrm{RR}_{(k,i)} - 1) + 1} \tag{2.10}$$

The choice among these interchangeable PAF versions appears somewhat arbitrary, likely driven by historical precedents within a discipline or the personal preferences of a researcher. While this flexibility allows the PAF to be adaptable across diverse study contexts, it also permits inconsistency and hinders comparisons. Nevertheless, regardless of the final equation or terminology used, the PAF meaningfully condenses epidemiological data into a proportion reflecting the disease burden attributable to air pollution exposure. Further research is warranted on standardizing PAF use and terminology in AP-HRA.

AP-HRA converts air quality data into quantifiable health impacts, providing a scientific basis for air pollution policy assessment, accountability, and development. These epidemiology-based definitions align with the environmental health perspective of assessing incremental effects above background risk levels.

While conceptually straightforward, in practice AP-HRA requires extensive data inputs, modeling choices, and uncertainty propagation steps. Evaluating AP-HRA methods to improve accuracy and policy relevance remains an active research area (Bhat et al., 2021). Challenges include:

- Obtaining consistent air pollution and health data across geographic scales for C-R derivation and health impact assessment.
- Selecting appropriate baseline rates, especially for mortality outcomes.
- Extrapolating C-R relationships beyond observed data ranges during application.
- Choosing suitable health impact functions and exposure lags.

- Quantifying and propagating uncertainties from epidemiological data through health impact calculations.
- Enabling analysis of demographic subgroups.
- Incorporating non-health co-benefits and costs.

Despite these complexities, AP-HRA provides a crucial quantitative link between air quality indicators and public health outcomes. Key recent examples of AP-HRA tools and implementations include:

- The Environmental Benefits Mapping and Analysis Program (BenMAP), developed by the U.S. EPA (Sacks et al., 2018).
- Global tool for health risk assessment of air pollution, AIRQ+ 2.1 (WHO, 2020).
- Integrated dispersion and exposure model for air contaminants in Europe, Ecosense (Schmid et al., 2019).
- Household Air Pollution Intervention Tool (HAPIT) (Pillarisetti et al., 2016).
- Greenhouse gas—Air pollution Interactions and Synergies (GAINS) model (Amann, 2008).

These and related tools synthesize available air quality and epidemiological data into integrated web or desktop based platforms for quantitative health impact assessment. They enable comparative risk analysis across pollutants and scenarios, evaluation of air quality regulations and interventions, and accountability assessments of control programs. They often use pooling techniques to synthesize coefficients across studies, resulting in more precise C-R estimates with uncertainty quantification (Sacks et al., 2018). Although data and methodology limitations remain, AP-HRA provides the fundamental scientific basis for evidence-based air quality policy and management.

AP-HRA applies epidemiological C-R evidence within a quantitative framework linking air quality to attributable health burdens. This supports accountable, scientifically guided decision-making regarding air pollution control. While research continues refining AP-HRA methods, existing tools

already provide valuable insights for strengthening air quality policy development, planning, and assessment. Improving AP-HRA models and data will further enhance our understanding of air pollution impacts and empower policymakers to make well-informed choices that effectively protect public health.

In the context of AP-HRA, Cumulative Risk Assessment (CRA) is a specialized approach applied to indoor air pollution. CRA studies have predominantly focused on the impacts of household solid fuel use in low-income countries, with some exceptions in Europe. The EnVIE Study and the World Health Organization (WHO) have conducted CRA analyses to assess the impacts of inadequate housing and indoor air pollution in Europe (Braubach et al., 2011; Fernandes et al., 2009; Jantunen et al., 2011). These studies follow the attributable burden approach. They aggregate the impacts of diseases impacted by indoor air pollution, identify the dominant pollutant exposures causing the diseases, and apportion the diseases to indoor air impacts based on relative indoor/outdoor exposure contributions.

By linking exposure to specific contaminants with health outcomes through C-R functions, researchers can estimate the disease burden and identify the most significant sources of pollution. The use of epidemiological evidence within a quantitative framework strengthens the scientific basis for evidence-based air quality policy and management, supporting informed decision-making to protect public health. Continual improvement of AP-HRA methodologies and tools will further enhance our understanding of air pollution impacts and help develop effective policies to mitigate the adverse effects of air pollution.

Attributable burden techniques estimate the proportional harm reduction if exposures were lowered to hypothetical minimum risk levels. The 2010 GBD developed relative risks from Integrated Exposure-Response (IER) models synthesizing epidemiological evidence across four pollution sources into continuous exposure-response curves linking $PM_{2.5}$ and specific mortalities (ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), lung cancer (LC) and, acute lower respiratory infection (ALRI)) (Burnett et al., 2014):

$$RR_{IER}(z) = 1 + \alpha(1 - e^{-\gamma(z-z_{cf})^{\delta}}) \quad \forall\, z \geq z_{cf} \tag{2.11}$$

where:

$\mathbf{z}$ is the exposure to $PM_{2.5}$ in $\mu g/m^3$,

$\mathbf{z_{cf}}$ is the TMREL (Theoretical minimum risk exposure level) or counterfactual concentration below, there is no additional risk. A TMERL was chosen from the premise that exposure cannot be reduced to zero in practice (Krewski et al., 2009; Prüss-Üstün et al., 2016).

$\boldsymbol{\alpha, \gamma, \delta}$ are unknown model parameters estimated by nonlinear regression methods by Burnett et al. (2014); and released by IHME (2013).

These supra-linear models exhibit attenuation at high concentrations, and represent an alternative to the log-linear function, are congruent with epidemiological and toxicological tenets, and enable health impact estimation across diverse exposure levels (Burnett et al., 2014; Cohen et al., 2017). The IERs for ALRI, stroke, IHD are highly non-linear; they flatten substantially at exposure concentrations greater than approximately 375 $\mu g/m^3$ for ALRI and 125 $\mu g/m^3$ for stroke/IHD. Only reduction to exposure concentrations below such values, will result in lower RRs. As for COPD and LC, the IERs for are more linear, indicating that even incremental exposure reductions will result in differences in RRs. Figure 2.7 show the IERs developed by Cohen et al. (2017).

The IER function is applied to get the PAF (Equation 2.9). The PAF is then multiplied by the BoD, to obtain the attributable burden as a measure of harm, with Equation 2.8.

Based on IER risk relationships, GBD studies attributed 4.2 million deaths and 103 million DALYs to ambient $PM_{2.5}$ in 2015 (Cohen et al., 2017). Similar approaches applied to household air pollution estimate substantial disease burdens from solid fuel use (Smith et al., 2014; WHO, 2018a,e).

Beyond classic and attributable burden methods, multimedia tools facilitate DALY computation (Devleesschauwer et al., 2014). The World Health Organization proffers a simple DALY template for quick estimates (Mathers et al., 2001). More sophisticated tools like the Household Air Pollution Intervention Tool (HAPIT) enable uncertainty propagation using Monte Carlo techniques (Pillarisetti et al., 2016). Users input pre- and post-intervention $PM_{2.5}$ sampling and disease burden data to estimate averted harm (and premature deaths) from interventions. The HAPIT tool applies IER functions, see Fig. 2.8.

The HAPIT tool has great potential for users interested in obtaining harm

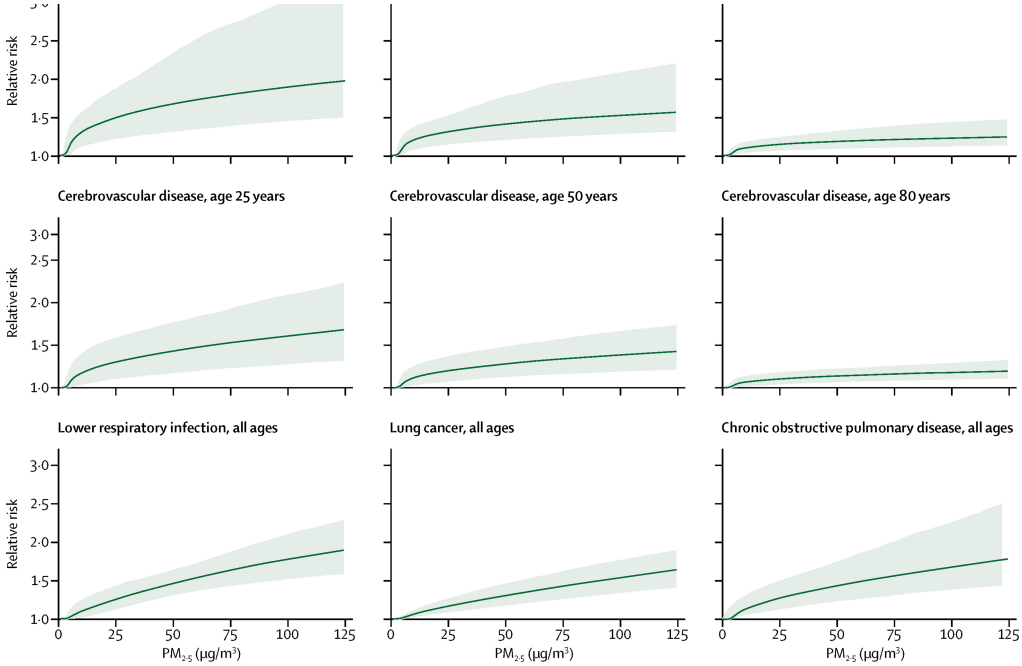


Figure 2.7: **Integrated exposure–response functions**. Curves show the central estimate of the integrated exposure–response (solid lines) and their 95 % uncertainty intervals (shaded areas). The relative risk equals 1 for $PM_{2.5}$ concentrations of 0 – 2.4 µg/m^3 (the lower bound of the theoretical minimum risk exposure level uncertainty distribution) (Cohen et al., 2017).

related to indoor $PM_{2.5}$ based on the best available health effects information.

Diverse harm modelling approaches illuminate air pollution's health tolls. Classic methods underlie foundational global estimates, while attributable and integrated exposure-response models discern risks across exposure levels and contexts. Dedicated multimedia tools empower analysis, from simple point estimates to complex uncertainty characterization. Together, these DALY-based techniques provide vital insights guiding efforts to ameliorate air pollution's public health impacts.

2.4.2 The characterization framework in life cycle assesment

Life cycle assessment (LCA) originated in the late 1960s and early 1970s as a quantitative methodology for modeling potential human health and environmental impacts across the full life cycle of a product or process (Hunt et al., 1996). For human health, LCA aims to characterize the relationship between chemical emissions and resulting population-level disease burdens,

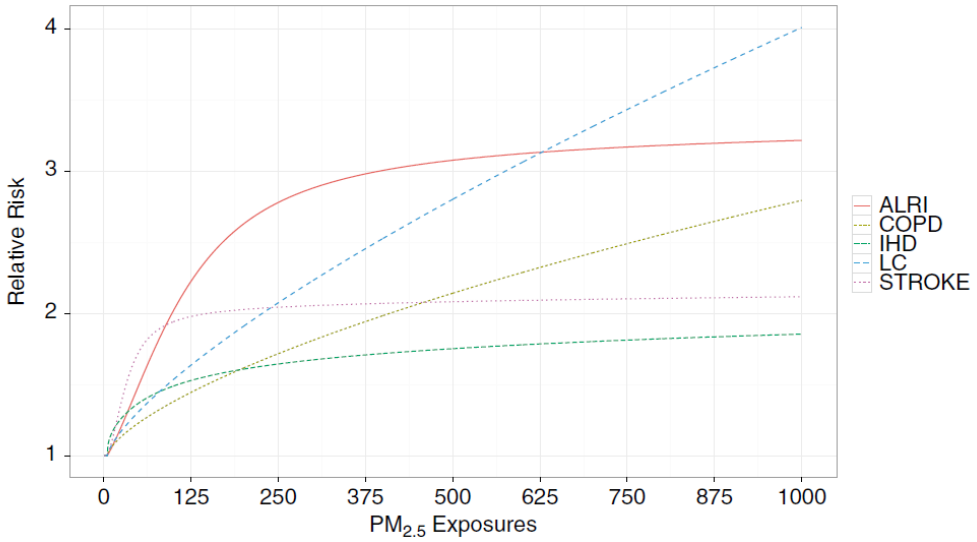


Figure 2.8: Integrated Exposure Response (IER) curves relating Exposure to $PM_{2.5}$ to health endpoints associated with exposure to air pollution, including ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD) and, lung cancer (LC) in adults and acute lower respiratory infection (ALRI) in children (Pillarisetti et al., 2016).

providing an overarching framework for comparative risk assessment and informed decision making (Hauschild and Huijbregts, 2015; Hauschild et al., 2018).

Within LCA, the Life-Cycle Impact Assessment (LCIA) aims to evaluate the impacts of the different inputs and outputs identified in the relevant stages of the LCA. The environmental fate and human exposure model is termed the characterization framework. This translates emitted contaminants into human intake via various exposure pathways. For air contaminants, inhalation of indoor and outdoor air represents the predominant route of exposure (Hellweg et al., 2009; Meijer et al., 2005a,c). The characterization framework thereby establishes a quantitative chain from emission to intake for any compound released into air (Hauschild et al., 2002).

To extend beyond intake and quantify resultant health damages, LCIA provides characterization factors (CFs) that link emission quantities of contaminant i to harm (as disability-adjusted life years, DALYs), a composite metric representing years of life lost and years lived with disability (Murray, 1994). CFs are calculated as the product of an intake fraction (iF) and an effect factor (EF) (Fantke et al., 2021a; Hauschild et al., 2002; Jolliet et al., 2018; Rosenbaum et al., 2007):

$$\mathrm{CF}_i = \mathrm{iF}_i \cdot \mathrm{EF}_i \tag{2.12}$$

The iF encapsulates the environmental fate and exposure model, representing the fraction of an emission taken in by the exposed population (Bennett et al., 2002). It is specific to the emission source, contaminant fate, exposure scenario, and intake mode (inhalation, ingestion etc.). The EF translates mass intake into health impacts, expressed as DALYs per kilogram intake (or any equivalent mass unit). It is dependent on the contaminant and health outcome under consideration but independent of the emission source and exposure context (Rosenbaum et al., 2007).

By combining the iF and EF, the CF provides a scalar linking emission quantity to potential population health damage. It distills multimedia modeling, exposure assessment, C-R relationships and severity weights into a single factor converting emission to burden (Hauschild and Huijbregts, 2015). CFs thereby enable straightforward ranking and comparison of air contaminants based on their damage potential, highlighting chemicals, sources and life cycle stages of greatest health concern (Hauschild et al., 2002).

The effect factor (EF) represents the most complex component of the CF, requiring synthesis of toxicological and epidemiological evidence on exposure impacts (Rosenbaum et al., 2007). The EF sums the contributions across health outcomes k caused by the contaminant i:

$$\mathrm{EF}_i = \sum_k \mathrm{EF}_{(k,i)} \tag{2.13}$$

The disease specific effect factors are a product of a dose-response factor (DRF) and a damage factor (DF),

$$\mathrm{EF}_{(k,i)} = \mathrm{DRF}_{(k,i)} \cdot \mathrm{DF}_k \tag{2.14}$$

The dose-response factor (DRF) encapsulates the toxic potency of the chemical-outcome pair (Huijbregts et al., 2005). A widely used statistical approach for estimating the response of a population to a toxic exposure is the *effective dose* (ED). Generally, the midpoint, or the 50 % response level, is reported and is known as effective median dose, ED50 (Eaton and Gilbert, 2008; Gupta, 2020). The ED50 is a measure of the

human-equivalent daily dose (kg) received by a person over their lifetime that produces a specific effect in 50% of a population. They are derived from toxicological studies in animals or humans.

Ideally, human data is used to derive DRF, with benchmark response levels like ED10 or ED50 serving as points of departure. The current approach of the LCIA characterization framework is to use the ED50 (Crettaz et al., 2002; Fantke et al., 2017a; Huijbregts et al., 2005; Jolliet et al., 2006; McKone et al., 2006; Pennington et al., 2006; Rosenbaum et al., 2008). A linear relationship can then be assumed from the benchmark dose to lower response levels, avoiding reliance on arbitrary safety factors (Crettaz et al., 2002; Huijbregts et al., 2005; Jolliet et al., 2006; McKone et al., 2006; Pennington et al., 2002, 2006; Rosenbaum et al., 2008).

For non-carcinogens lacking ED10 or ED50 data, no-observed adverse effect levels (NOAEL) and lowest observed adverse effect levels (LOAEL) provide alternative points of departure (Huijbregts et al., 2005).

DRFs are proportional to 0.5 over ED50. The default value of 0.5 is a linear, low-dose, extrapolation slope factor that relates the inverse of the ED50 to a potential probability of developing a disease (getting cancer). A default multiplier for human carcinogenic effect of 0.5 assumes a linear effect with a 50% additional chance to get cancer while inhaling a quantity of the contaminant equal to the ED50 over lifetime (Crettaz et al., 2002; Fantke et al., 2017a; Huijbregts et al., 2005; Jolliet et al., 2006; McKone et al., 2006; Pennington et al., 2006; Rosenbaum et al., 2008).

By leveraging human health data and benchmark dose levels where available, the DRF aims to encapsulate chemical potency with minimal uncertainty from cross-species extrapolation or safety factors (Huijbregts et al., 2005; Rosenbaum et al., 2008). The DRF is presented with a superscript to indicate the nature that its associated to toxicology research:

$$\mathrm{DRF}_{(k,i)}^{\mathrm{toxicity}} = \frac{0.5}{\mathrm{ED50}_{(k,i)}} \tag{2.15}$$

For radiological contaminants like radon, the DRF (units as cases of lung cancer.m^3/(yr.Bq)) is obtained from dose coefficients that enable an exposure quantity to be converted into a dose quantity (dose conversion factor, DCF, units of sV.m^3/(yr.Bq)) and fatality coefficients (FC, units of case/sV) that refers to the estimation of the total detriment associated

with lung cancer caused by exposure to radon.

$$\mathrm{DRF}_{(k,i)} = \mathrm{DCF}_{(k,i)} \cdot \mathrm{FC}_{(k,i)} \tag{2.16}$$

Current research shows that DRFs are increasingly based on epidemiological C-R functions combined with human intake rates, avoiding uncertainty from cross-species extrapolation (Fantke et al., 2019; Gronlund et al., 2015; Van Zelm et al., 2016). The DRF is presented with a superscript to indicate the nature that its associated to epidemiological research:

$$\mathrm{DRF}_{(k,i)}^{\mathrm{epidemiology}} = \frac{\mathrm{CRF}_{(k,i)}}{\mathrm{BR}} \tag{2.17}$$

Where CRF is the change in disease rate per concentration increase and BR is the breathing rate.

$$\mathrm{CRF}(k,i) = \frac{\mathrm{PAF}(k,i) \cdot \gamma_{0_k}}{C_i} \tag{2.18}$$

The PAF represents the proportional increase in incidence due to contaminant exposure. It has different, but equivalent definitions:

$$\mathrm{PAF}_{(k,i)} = \frac{\mathrm{RR}_{(k,i)} - 1}{\mathrm{RR}_{(k,i)}} \tag{2.19}$$

$$\mathrm{PAF}_{(k,i)} = \frac{(\mathrm{RR}_{(k,i)} - 1) \cdot C_i}{(\mathrm{RR}_{(k,i)} - 1) \cdot C_i + 1} \tag{2.20}$$

$$\mathrm{PAF}_{(k,i)} = \frac{f \cdot \mathrm{RR}_{(k,i)} - 1}{f \cdot (\mathrm{RR}_{(k,i)} - 1) + 1} \tag{2.21}$$

Where f is the exposed population fraction, and the risk estimate $\mathrm{RR}(k,i)$ represents the risk of disease associated with exposure compared to a baseline risk following a linear, log-linear or IER function, with or without a TMREL (Fantke et al., 2019; Gronlund et al., 2015; Van Zelm et al., 2008, 2016).

So, the CRF can be expressed also as a function of the incidence rate, for a health outcome k and a contaminant i, $I_{(k,i)}$,

$$\mathrm{CRF}(k,i) = \frac{\mathrm{I}(k,i)}{C_i} \tag{2.22}$$

Toxicological and epidemiological DRFs offer complementary ways to gauge chemical toxicity. Effect factors can come just from epidemiological data, like risk estimates or disease rates (Fantke et al., 2019; Gronlund et al., 2015; Oberschelp et al., 2020; Van Zelm et al., 2008, 2016). These count as human epidemiological effect factors. Or they can come from toxicological data, such as the median effective dose, ED50 (Fantke et al., 2017a; Huijbregts et al., 2005). These are human toxicological effect factors.

A damage factor (DF) encapsulates severity, relating mortality/morbidity health outcomes to their corresponding harm. DFs derive from standard DALY estimates by health outcome (k), providing a consistent metric for comparing morbidity and mortality impacts (Hauschild and Huijbregts, 2015).

$$\mathrm{DF}_{(k)} = \frac{\mathrm{BoD}_k}{\gamma_{0_k}} \tag{2.23}$$

When DF_k is needed for the addition of multiple health outcomes (k') for the same contaminant, it is proportional to the baseline incidence as:

$$\mathrm{DF}_k = \frac{\sum_{k'} \mathrm{DF}_{k'} \cdot \gamma_{0_{k'}}}{\sum_{k'} \gamma_{0_{k'}}} \tag{2.24}$$

By combining independently modeled DRF and DF components, the EF offers a flexible toxicological and epidemiological framework for calculating potential air contaminant impacts. Once EFs are available for a given contaminant, the corresponding CF allows rapid conversion of emission estimates into expected harm (Bulle et al., 2019; Fantke et al., 2019; Goel et al., 2019; Gronlund et al., 2015; Kvasnicka et al., 2019; Oberschelp et al., 2020; Petrov et al., 2017; Tang et al., 2018a,b; Van Zelm et al., 2008, 2016):

$$\mathrm{Harm}_i = \mathrm{CF}_i \cdot \mathrm{Emissions}_i \tag{2.25}$$

This LCA-based characterization framework emerged in the 1990s and was formalized into broader LCIA methodologies in the 2000s, with early focus on toxic emissions (Goedkoop et al., 2009; Rosenbaum et al., 2008). It has since expanded to cover a wide range of outdoor air contaminants and health endpoints, with insights from epidemiological studies enhancing accuracy and policy relevance compared to purely toxicological approaches (Huijbregts et al., 2017; Van Zelm et al., 2008, 2016) Application of the characterization framework to indoor air contaminants and exposures fol-

lowed shortly after initial development for outdoor emissions. Foundational studies demonstrated viable approaches for calculating intake fractions and effect factors specifically for indoor contexts (Hellweg et al., 2009; Meijer et al., 2005a,c; Wenger et al., 2012). This paved the way for integrating indoor emissions into multimedia fate and exposure models used in LCA, providing a parallel characterization framework applicable to both indoor and outdoor air pollution health damage (Fantke et al., 2017b; Rosenbaum et al., 2015). Important examples include *ReCiPe* and *USEtox*, which implement indoor and outdoor air exposure models and provide toxicity-based effect factors for characterizing health impacts. An overview of these and other models was done by (Rosenbaum, 2018).

Various LCIA implementations now exist that incorporate both indoor and outdoor air fate and exposure pathways, with some also beginning to integrate epidemiology-based effect factors to supplement or replace toxicity estimates. While differing in modeling details and scope, these LCIA methods use the characterization factor concept as their standard approach for translating air contaminant emissions into potential human health burdens within the LCA framework.

The chronic health effects of indoor air contaminants have been a focus area within the development of LCIA methodology. Human exposures to indoor contaminant emissions and concentrations are increasingly considered when modeling health damage using the DALY metric (Rosenbaum et al., 2015). Early LCA studies on indoor air led to the development of indoor-specific intake fractions, characterization factors, and damage estimates (Hellweg et al., 2009; Meijer et al., 2005a,c; Wenger et al., 2012). Building on this foundation, case studies demonstrated application to indoor environments, and frameworks integrated indoor emissions from building materials and products into LCAs (Collinge et al., 2013; Hellweg et al., 2009; Park et al., 2016; Skaar and Jørgensen, 2013; Wu and Apul, 2015). Recently, the USEtox model, which provides characterization factors for both indoor and outdoor air, has become commonly used, with health impact assessment continuing to rely on foundational DALY estimation work (Huijbregts et al., 2005).

By condensing complex exposure and dose-response relationships into single comparable CFs, the LCA characterization framework enables a straightforward translation of air contaminant emission estimates into estimates of population health burdens. It provides a quantitative basis for ranking

risks, highlighting priority chemicals and sources, and guiding decisions towards improved air quality and public health.

2.5 Assessing harm from indoor air

While many exposure levels and contaminants have been identified indoors, uncertainty remains about which risks drive health impacts. Connecting exposures to health is also critical. Their relationship enables identifying and prioritizing contaminants to reduce based on quantified harm, therefore, identifying hazardous contaminants is essential. Diverse methods have aimed to prioritize indoor contaminants, but quantifying population health burdens supports evidence-based rankings. These aspects are discussed in the following sections.

2.5.1 Exposure impact assessment of indoor air in dwellings

Knowing that indoor air contaminants have diverse health effects, and prioritizing mitigation methods requires a common damage metric, Logue et al. (2012) pioneered an approach to quantify the chronic health impacts of indoor air contaminants using disability-adjusted life years (DALYs). This synthesized available disease incidence data and effect factors with indoor contaminant concentrations to estimate harm attributable to inhalation exposures in dwellings.

Two methods were proposed to calculate harm from estimated exposure concentrations:

1. For the criteria pollutants (Section 2.1.1.1), an intake–incidence–DALY (IND) method using epidemiology-based concentration-response (C-R) functions.
2. For other pollutants (Section 2.2.1.2), an intake–DALY (ID) method, calculating health impacts from intake using human/animal toxicity data.

The IND method combines incidence and damage factors. The ID method associates effect factors with intake. This enabled DALY-based health im-

pact quantification using two distinct approaches. Logue et al. (2012) applied fitted distributions of indoor contaminant concentrations that were representative of the effective exposure concentrations in U.S. homes (Logue et al., 2011a).

2.5.1.1 Intake-Incidence-DALY (IND) method

This follows a health risk assessment approach (see 2.4.1) by using log-linear epidemiology-based C-R functions to quantify disease incidence rates ($I_{(k,i)}$) for health outcome (k) and contaminant (i). The incidence rate is combined with a damage factor ($DF_{(k,i)}$, DALY/case) to estimate harm (DALY/person/year). Addition of outcomes (k) gives all-cause effect.

$$harm_i = \sum_k DF_{(k,i)} \cdot I_{(k,i)} \tag{2.26}$$

Disease incidence ($I_{(k,i)}$) refers to the relationship between concentration (C_i, µg/m^3), risk ($\beta_{(k,i)}$, change/µg/m^3), and baseline incidence ($\gamma_{0_{(k,i)}}$, case/person/year). This relationship is modeled using the log-linear concentration response function:

$$I_{(k,i)} = \gamma_{0_{(k,i)}} \cdot (1 - e^{-(\beta_{(k,i)} \cdot C_i)}) \tag{2.27}$$

The expression of chronic harm is expressed as,

$$Harm_i = \sum_k DF_{(k,i)} \cdot \gamma_{0_{(k,i)}} \cdot (1 - e^{-(\beta_{(k,i)} \cdot C_i)}) \tag{2.28}$$

Quantifying chronic harm requires integrating epidemiologic data across three key parameters, each contributing uncertainty to final damage estimates. These parameters are discussed in the following.

- Baseline incidence rates (γ_0). These show the cases or deaths per person-time for a health outcome. National statistics offices and the WHO offer such data (USEPA, 2018), given cases, population and follow-up. Rates come in cases per person-year, needing information regarding cases of a disease, people affected and time. Baseline incidence rates can be derived from cohort studies, where a group of

individuals is monitored over time to assess health outcomes. Logue et al. (2012) used data available by the EPA (USEPA, 1999).

- Risk estimates from epidemiological C-R models (β). These show health responses per unit pollution change. Air pollution studies report health impact functions (relative risk, odds ratio, hazard ratio) for a given change, which converts to β (USEPA, 2018). For research, risks often reflect overall deaths from long-term exposure and recent pollution (WHO, 2021). In teh case of absent all-cause data, summing diseases approximates the total effect. Logue et al. (2012) used EPA data (USEPA, 1999), adding uncertainty via probability distributions.

- Damage factors (DF). For the IND method, these link harm to incidence for health outcomes tied to a contaminant. Unlike risks, damage factors do not come straight from epidemiology research. They need to be found and extracted from studies stating cases and average DALY losses per contaminant change in similar settings. Logue et al. (2012) used published values from air pollution studies (Lvovsky et al., 2000) and calculated factors from independent works with both harm and incidence (Krewski et al., 2009; Pope et al., 1995). It assumed uncertainty distributions.

2.5.1.2 Intake-DALY (ID) method

This follows the LCIA framework (see 2.4.2) using contaminant-specific effect factors (EF_i, in DALY/kg) and intake (Q_i, the product of concentrations, in µg/m^3, and a breathing rate, in m^3/person/year) to estimate harm. It also considers an age-dependent adjustment factor (ADAF) for cancer exposures

$$\text{Harm}_i = C_i \cdot \text{BR} \cdot ((\text{EF}_{(\text{cancer,i})} \cdot \text{ADAF}) + \text{EF}_{(\text{noncancer,i})}) \tag{2.29}$$

A highlight of the data sources and synthesis used to quantify harm are explained:

- Effect Factor (EF). For carcinogenic and non-carcinogenic effects were derived from dose-response data and disability severity estimates

by Huijbregts et al. (2005). Individual EFs were utilized and uncertainty was incorporated from the same study.

- Breathing rates (BR). A breathing rate of 14.4 m^3/day representing U.S. residential intake per person was used. No uncertainty was assumed.

- Age-dependent adjustment factors ($ADAF$). Were implemented as a factor of 1.6 for cancer risks based on EPA data (EPA, 2005). No uncertainty was included.

These complementary incidence-based model (IND) and effect factor-based model (ID) quantification approaches enabled a generalized DALY-based framework for estimating indoor air pollution health burdens. Figure 2.9 shows a flowchart of the ID and IND methods.

2.5.1.3 Impact assessment

Logue et al. (2012) showed there was promise in using DALYs to gauge the health toll from indoor contaminants in American homes. The study presented harm estimates for 43 contaminants:

Acrolein, Formaldehyde, Ozone, Acetaldehyde, Ammonia, Crotonaldehyde, Xylenes, Chromium, 1,4-Dichlorobenzene, 1,1-Dichloroethene, Xylene (o), Acrylonitrile, Styrene, Naphthalene, Manganese, Carbon tetrachloride, Cadmium, Toluene, d-Limonene, Hexane, Chloromethane, Xylene (m/p), 1,2-Dibromoethane, Ethanol, 2-Butoxyethanol, 1,2-Dichloroethane, Methylene chloride, Vinyl chloride, Tetrachloroethene, Carbon disulfide, Methyl methacrylate, Benzene, Hexachlorobutadiene, Benzyl chloride, 1,1,2,2-Tetrachloroethane, 2-Methoxyethanol, 1,1,2-Trichloroethane, 2-Ethylhexanol, Methyl tert-butyl ether, Sulphur dioxide, Nitrogen dioxide, $PM_{2.5}$, and Carbon monoxide.

Three contaminants—$PM_{2.5}$, acrolein and formaldehyde— appear to cause over 80% of the harm from chronic exposure. With fine particulates contributing the most to the estimated DALYs. The central estimate is 1,100 DALY losses per 100,000 people annually (with a wide confidence interval from 400 to an implausible 13,000 -implausible because it exceeded the burden of disease from all diseases and risks combined). By way of comparison, this means the damage attributable to indoor air is somewhere

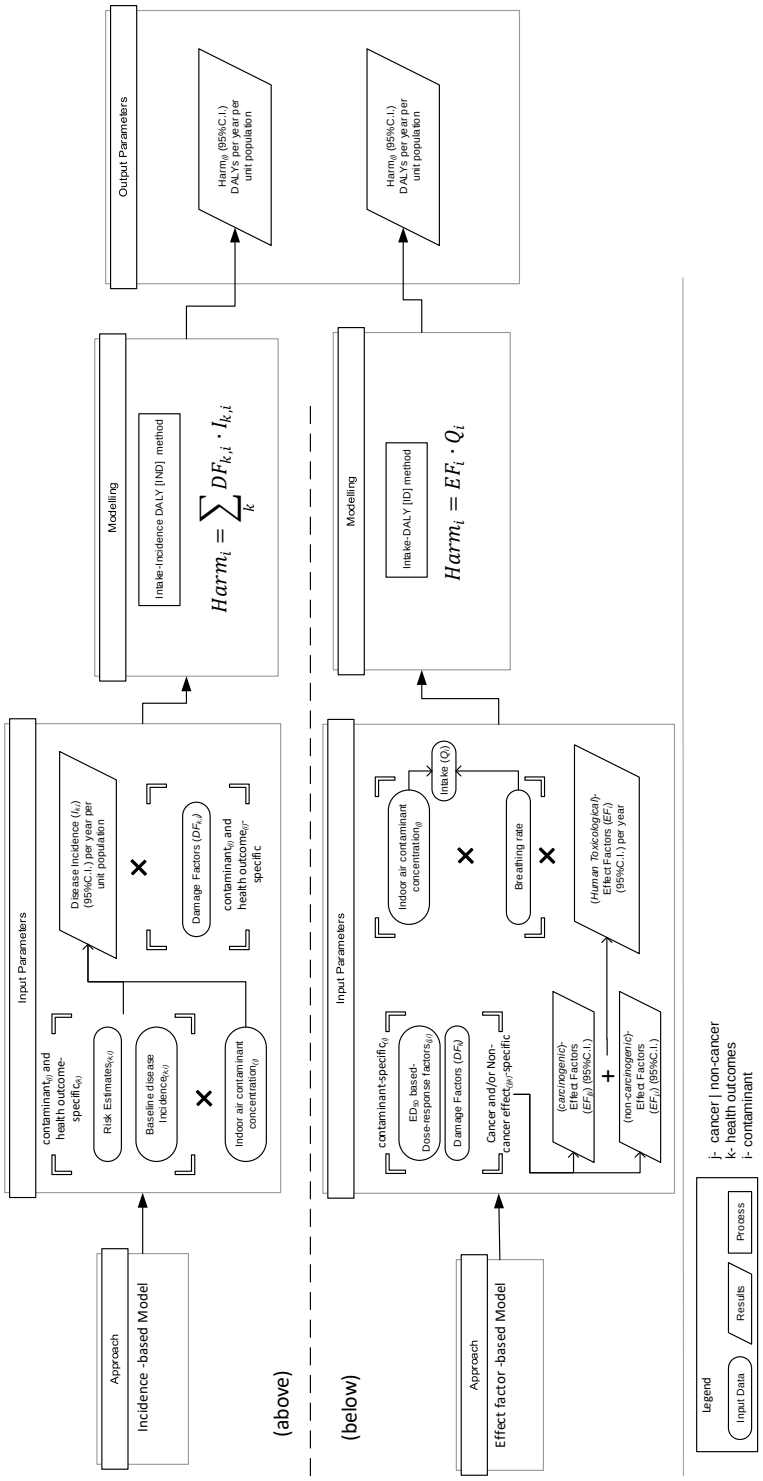


Figure 2.9: **Overview of IND (above in image) and ID (below in image) methods**.

between the health effects of road traffic accidents (400 DALYs/10^5 person/year) and heart disease from all causes (1100 DALYs/10^5 person/year) (Guyot et al., 2019). This trio exacts far more harm than occasional carbon monoxide poisoning. Second-hand smoke and radon could also impose sizeable population-wide harm (see Figure 2.10).

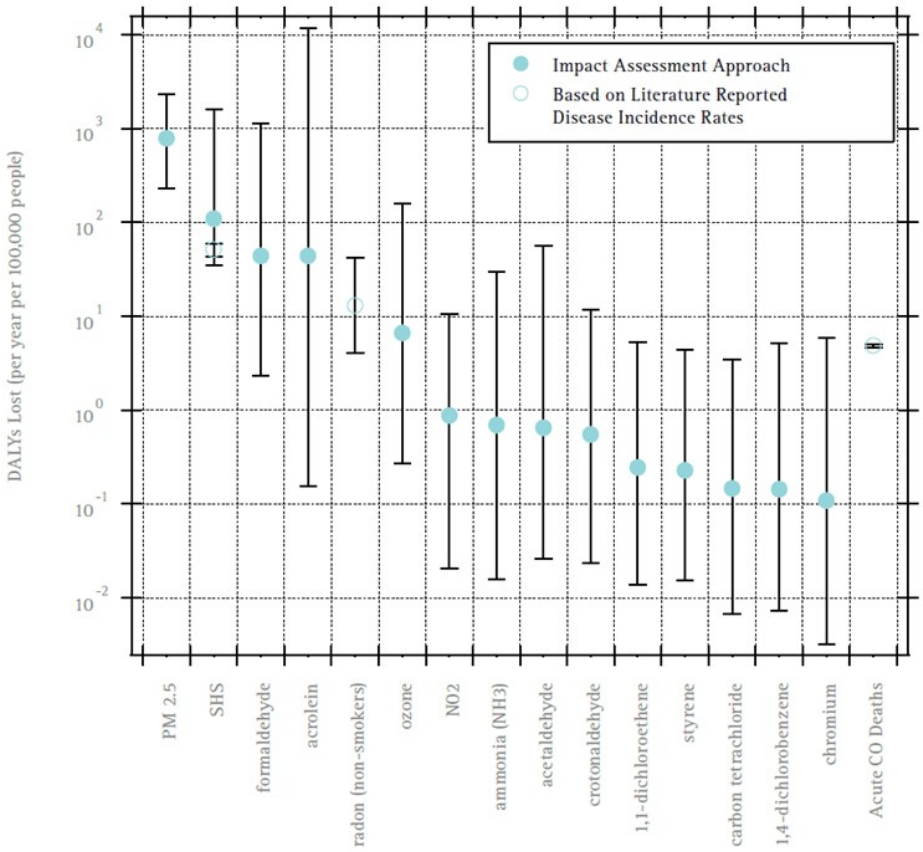


Figure 2.10: Estimated population averaged annual cost, in DALYs, of chronic air pollutant inhalation in U.S. residences; results for the 15 pollutants with highest mean damage estimates. (Borsboom et al., 2016)

Logue et al. (2012) demonstrated the potential of DALY-based models, and upon further examination, insights from their work are now informing the identification of the following limitations:

1. Contaminants scope: bioaerosols such as mold and radiological contaminants like radon, were not subjected to the IND or the ID methods as part of the analysis

2. U.S-only scope: The data on contaminant concentrations, breathing rates, risk estimates, disease incidence, and damage factors were solely for U.S. dwellings. Expanding to global data is needed.

3. Dated data: The epidemiological and toxicological data used was from over a decade ago, prior to 2010. Updated data is needed to reflect latest evidence.

4. Uncertainty: There were large uncertainties and wide confidence intervals in the harm estimates from both the ID and IND methods (The upper estimate exceeds the total burden from all non-infectious diseases). Statistical approaches could help narrow these uncertainties.

5. Damage factors: Assumptions and probability distributions for the damage factors relating incidences to harm were assumed rather than based on data. Improved damage factor estimates could help.

6. Contaminant-specific data: Damage factors and baseline incidence where considered as contaminant-health outcome related variables, however, this parameters are presented in HRA and LCIA as disease specific. More work on this is needed.

7. Unclear origins: The source and reasoning behind some parameter values used was not fully explained in the work. Transparency on data origins would be beneficial.

8. Method complexity: The ID and IND methods for calculating DALYs involve many parameters. Simplified approaches could improve accessibility.

Considering these caveats, Logue et al.'s work served as a start for applying the DALY metric to indoor air, recasting grasped of health impacts from dwelling contaminants. Their framework considering toxicological and epidemiological data has been widely adopted. Fazli and Stephens (2018) used the framework with average contaminant measures to estimate chronic damage from American homes. Turner et al. (2013) used it to quantify impacts of residential ventilation. Patino and Siegel (2018) used it for an specific scenario involving social housing. Ben-David and Waring (2016) assessed simulated office air and energy performance across US cities using Logue et al.'s method. Aldred et al. (2016) quantified the benefits of indoor ozone removal in homes using the framework, and Zaatari et al. (2016) used the approach to study contaminant controls balancing indoor air quality and efficiency in shops.

Harm (as DALYs) from household exposures have also been calculated through independent chronic health impact assessments. Global and European studies have utilized comparative risk assessment approaches based on the population attributable fraction. For example, Morawska et al. (2013) estimated DALYs for total particles, secondhand smoke, and radon. Shan et al. (2022) focused on radon burdens. And the Global Burden of Disease study (Murray et al., 2020) presents DALYs for $PM_{2.5}$ from household solid fuel use, radon, and secondhand smoke.

These complementary works provide additional harm quantifications and comparisons for key residential contaminants using alternative methods beyond the Logue framework. Together, they offer a more comprehensive picture of the disease burden posed by indoor contaminants.

2.5.2 Harm and IAQ strategies

Ventilation has long been utilized to promote healthy indoor spaces by controlling indoor air quality (IAQ). Outdoor air introduction aims to lower exposures by removing or diluting indoor-generated contaminants. However, evidence supporting the ability of ventilation to consistently lower exposures remains of poor quality, with high uncertainty around defining rates that adequately protect against health and comfort issues. While reviews have sought to link minimum ventilation thresholds to risk reduction, these connections rely on limited and variable data (Janssen, 1989). Ventilation likely proves most effective for localized removal of transient bioeffluents in high-emission spaces like kitchens and bathrooms, or whole-house ventilation for ubiquitous gasses like formaldehyde (Logue et al., 2011b). The interplay of factors such as airflow distribution, emission sources, building design, the effectiveness of ventilation strategies, and considerations for both health and comfort contributes to the complexity of ventilation's role in promoting IAQ.

The American Society of Heating, Refrigerating and Air Conditioning Engineer's (ASHRAE) Standard 62.1 and 62.2 leads US indoor and residential ventilation standards, respectively (ASHRAE, 2022b,c). They tackle indoor air quality issues (Logue et al., 2011b).

Ventilation chiefly maintains acceptable indoor air quality by controlling contaminants and minimizing exposures. ASHRAE 62.2 defines acceptable air as lacking odor, irritation or unhealthy concentrations (ASHRAE,

2022c). The standard promotes occupant wellbeing through satisfactory air quality and healthier indoor environments.

To confine ASHRAE standards solely to ventilation oversimplifies their purpose, which is to ensure acceptable indoor air quality (IAQ) by limiting exposure to contaminants. While it is true that ventilation is a common mechanism to achieve IAQ goals, the overarching objective is to attain acceptable IAQ, rather than solely setting ventilation rates.

Ventilation standards largely prescribe rates addressing perceived poor air and irritation, CO_2 concentrations, and odors, as codes note (Carrer et al., 2018). Too little data on indoor sources and health impacts has led standards to rely on engineering guesses, not health or contaminant analyses (Borsboom et al., 2016; Logue et al., 2011b). This gap between standards and health-based limits suggests a need to better focus ventilation guidance (Borsboom et al., 2016). Moving towards a health-based approach raises questions such as whether other gases besides CO_2 would necessitate higher ventilation rates to achieve lower concentrations, particularly in cases where emissions are unknown and therefore removal rates cannot be determined.

ASHRAE 62.1-2022 prescribe ventilation rates using either a ventilation rate procedure or an indoor air quality procedure (ASHRAE, 2022b). The ventilation rate method provides minimum rates based on assumed occupant density and activities, aiming to satisfy 80 % of building occupants in non-smoking environments. The IAQ procedure (IAQP) instead allows deriving customized rates based on design compounds selected during design, comparing their concentrations to design limits from a cognizant authority. This derives a mix exposure sum that should be less than the unity for the design compounds. ASHRAE 62.1-2022 provides a list of 15 contaminants to control to simplify the implementation of the IAQP.

Both approaches partially consider health impacts but also emphasize limiting perceived irritations. Required ventilation systems must supply high-quality outdoor air, including minimum filtration for particles and ozone scrubbing if levels are excessive. However, ventilation only controls other unchecked contaminants if calculations specifically incorporate them into the IAQ procedure's customized rate determination (Carrer et al., 2018).

European health policies have motivated needs for evidence-based ventilation standards that prioritize reducing indoor-attributable disease. The

ENVIE (EU co-ordination action on indoor air quality and health effects) and IAIAQ (promoting actions for healthy indoor air) projects linked indoor contaminants to estimated harm, finding 2 million DALYs annually across 26 European nations (Fernandes et al., 2009; Jantunen et al., 2011). Controlling indoor and outdoor pollution sources alongside moisture could reduce this burden by 0.7 million DALYs per year, while mandated ventilation system inspections and maintenance could prevent another 0.2 million, they projected (Carrer et al., 2018).

Two studies show six long-term indoor contaminants influenced by ventilation (Fernandes et al., 2009; Logue et al., 2012). Environmental tobacco smoke and radon stem chiefly from occupant behaviour and the location of the house, respectively, so ventilation standards should ignore them. The remaining four main causes of chronic risks are $PM_{2.5}$, mold, formaldehyde and acrolein. WHO and ENVIE flagged mold/moisture as an indoor health burden (Braubach et al., 2011; Fernandes et al., 2009; Jantunen et al., 2011). As ventilation affects home moisture, mold joins priority contaminants for ventilation standards, despite occupant and building factors (Borsboom et al., 2016).

Looking ahead, research on dwelling contaminants and health impacts could ultimately shift Standard 62.2's focus to effects of priority contaminants. Ventilation rates would become less important intermediates (Sherman, 2015).

2.5.3 The indoor air quality equivalence

Innovative ventilation management, including variable ventilation, can reduce energy or enhance IAQ and comfort. To ensure innovative ventilation meets standards, methods are needed to determine equivalence in ventilation or IAQ (Sherman, 2004; Sherman et al., 2012).

Equivalent ventilation uses exposure to a generic indoor contaminant to gauge different scenarios' effect on IAQ. With undefined priority contaminants, this may be the best approach for standards. Ideally, equivalent IAQ would use a health metric. That requires ranking and selecting the indoor contaminants by their potential harm (Sherman et al., 2012).

Walker et al. (2022) found that only one study proposes ventilation and IAQ equivalence based on health metrics (Sherman et al., 2012). It applies the

DALY- harm-based models of Logue et al. (2012) to a ventilation context using *unit damage estimate (UDE)* values for contaminants of interest. UDEs represent harm over concentration, akin to EPA's unit risk estimates (Agency, 2015). UDEs can be used to determine the total harm of an exposure to selected contaminants. This is known as the IAQ equivalence principle:

$$\text{Harm} = \sum_i C_i \cdot \text{UDE}_i \tag{2.30}$$

This principle can be adapted as new priority contaminants and toxicological or epidemiological data emerge. Other tentative steps have been made in LCIA to relate harm to a concentration unit for $PM_{2.5}$ (Oberschelp et al., 2020).

The IAQ equivalence principle proposes using UDE values to set a harm limit. Exposures below this limit have equivalent IAQ despite differing contaminants (Equation 2.31). To apply the principle, a limiting harm value is needed. One approach is to use existing standards, translating them into harm via UDEs (Sherman et al., 2012; Walker et al., 2022).

$$\text{Harm}_{\text{limit}} = \sum_i \text{Standard}_i \cdot \text{UDE}_i \tag{2.31}$$

Table 2.7 lists UDEs for key compounds along with chronic exposure standards from the review of Logue et al. (2011a) - the most health-protective of applicable guidelines and regulations. Sherman et al. (2012) set a limit of 820 DALY/10^5 person/year using these UDEs and standards. Addressing $PM_{2.5}$, radon and ozone via prescriptive measures would reduce the DALY limit drastically because the rest of compounds only sum to 9 DALY/10^5 person/year (Sherman et al., 2012).

The IAQ equivalence approach relies on clearly identified and prioritized indoor contaminants, hereon referred to as the *Contaminants of Concern (CoCs)*. For specific applications, engineers and architects need to define CoCs. To answer the question "How do designers choose the CoC?" (Stanke, 2007), there must be consensus on priority contaminants in the literature. ASHRAE 62.1, in their IAQP proposes 15 contaminants.

Currently, there is no recognized process for selecting contaminants to con-

Table 2.7: Indoor air contaminants – UDE and Standard values to implement IAQ equivalence (1 μDALY = 10^{-6} DALYs). From Sherman et al. (2012)

Contaminant	UDE [μDALYs/µg/m^3/person/year]	Chronic standard see(Logue et al., 2011a)[µg/m^3]	Chronic harm [μDALYs/person/year]
Priority contaminants			
1,3 Butadiene	0.02	0.06	0.001
1,4-dichlorobenzene	0.3	0.91	0.024
Acetaldehyde	0.3	3.7	0.96
Acrolein	190	0.02	3.7
Benzene	0.08	0.34	0.025
Formaldehyde	6.8	1.7	11.4
Naphthalene	0.47	0.29	0.14
Nitrogen Dioxide	0.7	40	27
$PM_{2.5}$	500	15	7,500
Other contaminants			
Ammonia	0.23	200	46
Ozone	1.4	147	200
Crotonaldehyde	1.02	N/A	

trol via IAQ standards and regulations in the 62.2 series, that is specific for residential buildings. Several studies have called for a more systematic, health-based approach to identifying priority indoor contaminants in dwellings (Guyot et al., 2019; Parthasarathy et al., 2011; Sherman et al., 2022, 2012; Stanley and Bayer, 2009; Walker et al., 2022). To date, the minimum numbers of CoCs practitioners should consider are the 15 proposed contaminants in the IAQP in 62.1 series. Steps forward into defining a shorter list are being made (Section 8.3.2).

The IAQ equivalence approach lays the groundwork for identifying CoCs through standardized harm-based metrics. In theory, the CoCs would be the contaminants that contribute the most to total harm. This would strengthen the health basis for setting exposure limits, harm thresholds, and ventilation rates. Ongoing toxicology, epidemiology, and exposure research can refine CoC selection and update harm estimates over time.

Two common methods prioritize indoor contaminants using health impacts: (i) determining guideline exceedances and (ii) estimating cancer likelihood. However, these only consider incidences, not overall population harm. Studies ranking dwelling contaminants using these qualitative or

quantitative methods are: Halios et al. (2022) who identified high-priority VOCs based on adverse endpoints and concentration reports. Sarigiannis et al. (2011) who used risk metrics, while Azuma et al. (2016) ranked by margin of exposure. Though identifying exceedances helps pinpoint concerns, it does not enable an equivalence approach.

In contrast, DALY-based studies of indoor exposures like Logue's, EnVIE, IAIAQ, and WHO (Braubach et al., 2011; Fernandes et al., 2009; Jantunen et al., 2011; Logue et al., 2012) allow ranking by harm. This provides a comparable framework for population-level prioritization (Borsboom et al., 2016). Quantifying total harm better informs risk reductions than counting guideline exceedances or cancer probabilities alone. DALYs integrate morbidity and mortality across multiple outcomes, supporting evidence-based contaminant prioritization and risk management.

The ventilation and indoor air quality equivalence principles proposed by Sherman et al. have been partially integrated into ASHRAE Standard 62.2-2016 on residential building ventilation. This is reflected in some U.S. state regulations like California's Title 24 energy performance standards requiring ASHRAE 62.2 compliance. Specifically, ASHRAE 62.2-2019 incorporates methods to calculate minimum constant airflow rates for dwellings based on the equivalence between ventilation and indoor air quality. By adopting key equivalence concepts, the standard represents partial acceptance of the originally proposed performance-based, health-oriented ventilation framework. However, further work is still needed to fully align standards (like the WELL standard) with a contaminant exposure and health effects basis (Guyot et al., 2019).

The WHO Drinking Water Quality Guidelines already apply harm limits using DALYs to define health-based targets (HBTs) (WHO, 2011). The guidelines set a maximum allowable DALY loss of 10^{-6} DALYs/person/year from waterborne pathogens. The *allowable DALY loss* term is equivalent to *tolerable harm* and *acceptable harm* set to describe a limit of DALYs.

The current limit of 10^{-6} DALYs/person/year derives from the U.S. EPA's accepted lifetime cancer risk of 10^{-5} from waterborne exposures. The WHO did this because cancer risk assessment provides a well-established and widely accepted methodology for quantifying the health impacts of exposure to environmental contaminants. It was also a starting point to develop health-based targets. However, this is extremely conservative, being 10,000 times lower than actual U.S. cancer incidence. Mara (2011) sug-

gests increasing the maximum burden by two orders of magnitude. While marginally increasing risks of cancers, diarrheal diseases and ascariasis, this remains a low risk level. But it allows for more cost-effective water and sanitation investments to achieve health gains in low- and middle-income regions. Overall, Mara recommends raising the acceptable disease burden guideline to 10^{-4} DALYs/person/year to balance public health protection with improved access to drinking water and sanitation.

This DALY-based harm limit approach for drinking water resembles Sherman et al.'s proposed IAQ equivalence principle using harm limits. It provides context on applying DALYs for health-relevant limits in indoor air. As with drinking water, feasibility and cost-effectiveness should help determine appropriate IAQ risk targets. Setting HBTs requires value judgements on tolerable risks, analogous to judgements underlying acceptable IAQ. One way to address this complex issue is to consider DALYs that society as a whole already accepts, such as those associated with alcoholism (0.012 DALYs/person/year) or smoking (0.026 DALYs/person/year) (IHME, 2022), or to base acceptability on real-world scenarios of indoor environments that meet established IAQ standards.

2.5.4 Monetizing Harm

Economic considerations in IAQ typically focus on optimizing ventilation costs, including design, installation, and operation. Operating costs, like energy for running and conditioning air, often exceed initial costs. Smart ventilation introduces complexity and value by incorporating benefits like energy savings and exposure reduction, which are harder to monetize. DALYs offer a means to monetize the reduction of contaminant exposure, as economic studies have established the value people place on a DALY (Sherman et al., 2018).

Aldred et al. (2016) conducted a benefit-cost analysis of commercially available activated carbon filters for indoor ozone removal in single-family homes in the USA. The monetary benefit associated with reduced DALYs per 100,000 people was calculated by multiplying the value of one DALY ($ DALYs) by the reduction of harm (in DALYs) achieved when a control is used, compared to no control (see Equation 2.32).

$$Benefit = \$DALYs \cdot \delta Harm \tag{2.32}$$

Harm was calculated using the methods of Logue et al. (2012). A distribution of dollars per avoided DALY ($ DALYs) was estimated using the willingness-to-pay method. The histogram of predicted willingness-to-pay values per avoided DALY was right-skewed, suggesting a log-normal distribution (Aldred, 2015). The dollar value per DALY ($ DALY) was estimated as a median of USD 125,000 [mean 150,000] with a 95% confidence interval of USD 6,940 to 366,020 per avoided DALY.

Furthermore, Jackson (2017) used the dollar value per DALY distribution from Aldred (2015) to obtain the health-based monetary value of reducing HCHO concentrations in a residence to limits equal to specific exposure limit values (Equation 2.33). The value of 150,000 USD per DALY (2014 USD) was used as it was considered reasonable. Such value is approximately equal to three times the per capita gross domestic product in the United States for that year (Aldred et al., 2016). Sherman et al. (2018) deemed a rough value of a DALY in a developed country is on the order of magnitude of 150,000 USD.

$$HB_{a-b} = \$DALYs \cdot (harm_{HCHO_a} - harm_{HCHO_b}) \tag{2.33}$$

where HB is health based monetary value of reducing the annual average concentration of HCHO in a house from a concentration a to b (units of USD); $ DALYs is the value of a DALY; and harm are the DALYs lost for the given HCHO concentrations.

As demonstrated by Aldred (2015); Jackson (2017), the cost of averted DALYs can be used to assign a monetary value to indoor contaminant exposure. Daroudi et al. (2021) calculated the cost per DALY averted in low, middle, and high-income countries, categorized by the Human Development Index (HDI), using evidence from the global burden of disease study (see Table 2.8). The cost per DALY averted was calculated as a function of health expenditure per capita and age-standardized DALY rates (per 100,000 population).

Table 2.8: Cost per DALY averted

Region	Mean $DALYs (range) [2016 USD]
Low HDI	998 (109 - 3507)
Medium HDI	6522 (997 - 36,091)
High HDI	23,782 (4245 - 83,997)
Very high HDI	69,499 (21,509 - 168,720)

The monetary values of harm in USD per DALY, as shown in Table 2.8, can be used to estimate the monetary costs associated with contaminant concentrations once harm estimates for the contaminants are calculated (for discussions on the value of reducing harm from typical exposure levels in dwellings to those proposed by cognizant authorities for selected air contaminants, see Section 8.2).

When estimating the cost of DALYs averted, it's crucial to note that the value extends beyond medical expenses. Disability and premature death also encompass the loss of healthy life, employment, a family provider, and educational opportunities. Additionally, these impacts can be multigenerational, painting a complex picture of costs.

The cost of a DALY for very high HDI countries is approximately half the cost per DALY calculated by Aldred (2015) for the USA, which is $69,499. This amount is roughly equivalent to one GDP per capita in 2016 USD. Although one would expect these monetary values to be similar, the observed difference is difficult to explain due to the methodological differences between the estimates. A deeper understanding of the differences in monetary values of harm derived from a willingness-to-pay approach versus a health expenditure per capita approach is needed.

2.6 Summary

This literature review chapter provided a comprehensive overview of prior research investigating indoor air quality, associated health risks, and quantification methods. Key insights are summarized by section.

Exposure to indoor air contaminants constitutes a major public health concern, as people spend most of their time indoors where contaminant levels can be elevated and risks accentuated (Logue et al., 2011a; Morawska et al., 2013; Ye et al., 2017). Systematic reviews reveal hundreds of chemicals measured across global homes, with concentrations varying widely (Halios et al., 2022; Morawska et al., 2013; Ye et al., 2017). Particulates are the most extensively studied contaminant indoors.

Diverse health effects (including all causes of mortality) are associated with both short and long-term exposure to indoor air pollution, (WHO,

2021). Toxicological and epidemiological research offer complementary insights into biological mechanisms and real-world disease patterns crucial for assessing risks (Adami et al., 2011; Eaton and Gilbert, 2008; Miettinen, 2011; Weed, 2002). Understanding mixture toxicity requires characterizing additivity and non-additive interactions between chemicals like synergism and antagonism. Advancing knowledge in these areas will improve chemical mixture risk assessment capabilities.

There are many health-based metrics, but many focus on mortality and morbidity incidences rather than overall population harm (Jones, 2017). Integrated exposure-response models and cumulative risk assessment enable multi-contaminant health impact estimation (Harikrishnan et al., 2018; Sexton, 2012). Disability-adjusted life years (DALYs) are a versatile metric integrating exposures, risks, and disease severity into a composite population health metric (Harikrishnan et al., 2018; Murray, 1994).

Pioneering studies demonstrate feasible DALY-based models to quantify indoor air pollution health burdens, despite limitations on scope, data currency, and uncertainty (Fernandes et al., 2009; Logue et al., 2012; Shan et al., 2022). Their frameworks synthesize toxicology, epidemiology, exposures, and health data to rank risks and guide mitigation. This means DALYs can be used to assess indoor pollution impacts.

Various health risk and life cycle assessment tools implement DALY calculations, to compare scenarios (Fantke et al., 2017a; Pillarisetti et al., 2016; Sacks et al., 2018). Ongoing methodological development continues to strengthen characterization of contaminants, fate/transport, intake, dose-response relationships, and uncertainties inherent in impact estimation (Hassan Bhat et al., 2021; Hauschild and Huijbregts, 2015; Rosenbaum et al., 2015).

The key insights gleaned from the chapter, are informing the approach to designing health-based ventilation and indoor air quality strategies. It underscores the importance of using the disability-adjusted life year (DALY) metric to guide the establishment of acceptable IAQ standards in dwellings. This approach begins by identifying priority home contaminants that are

both prevalent and highly impactful on health, designating them as Contaminants of Concern (CoCs). Furthermore, a monetary value can be assigned to harm (as DALYs) based on the costs per DALY averted available in the literature.

Chapter 3

Quantifying Harm

3.1 Airborne contaminants of interest

This section describes the iterative process for selecting the airborne contaminants expected in dwellings for which the research aims will be pursued (Section 1.4). The initial scope draws from a list of 43 priority contaminants in dwellings identified by Logue et al. (2012) for their chronic harm in dwellings (Section 2.5.1.3).

Iterative decisions then evaluated additions and exclusions based on:

- Removing contaminants that only have acute health effects, per the chronic focus (Section 1.4). Carbon monoxide (CO) warrants mention. The study of Logue et al. (2012) excluded CO from their harm models while acknowledging that chronic indoor CO exposures, can be up to 810 µg/m^3 in US homes, and that CO can be correlated with increased hospitalization rates for conditions like congestive heart failure. However, an Integrated Science Assessment (ISA) for CO suggests there is not likely to be a causal relationship between relevant long-term CO exposures and mortality. Instead, the evidence indicates a suggestive causal relationship between short-term CO exposures and mortality, highlighting CO's association with acute effects (US-EPA, 2010b) (see Table 2.3). The chronic effects of long-term indoor CO exposures, with specific mortality and morbidity endpoints, remain an emerging topic requiring further exploration. This is discussed in more detail in Section 8.7.
- Inclusion of emerging contaminants, frequently found in dwellings

and associated with health risks as documented in IAQ literature (Section 2.1.2). PM_{10}, 1,3-butadiene, isoprene, and trichloroethylene have been incorporated to align with recent reviews covering prevalent airborne contaminants in residential environments (Gonzalez-Martin et al., 2021). Mold (spores) and radon are included as well. Mold refers to a measured concentration of spores rather than visual mold, which is not use-full when a concentration is needed for harm assessment (Section 3.2).

- Discarding contaminants lacking sufficient health evidence (Sections 3.3 and 3.4). Ammonia, manganese Mn(II), xylene (o), xylene (m/p) are excluded from the list for this reason (Section 4.5.1)

This resulted in 44 contaminants of interest:

Acetaldehyde, Acrolein, Acrylonitrile, Benzene, Benzyl chloride, 1,3-Butadiene, 2-Butoxyethanol, Cadmium Cd(II), Carbon disulfide, Carbon tetrachloride, Chloromethane, Chromium Cr(VI), Crotonaldehyde(trans), 1,2-Dibromoethane, 1,4-Dichlorobenzene, 1,2-Dichloroethane, 1,1-Dichloroethene, Ethanol, 2-Ethylhexanol, Formaldehyde, Hexachlorobutadiene, Hexane, Isoprene, Limonene (d-...), 2-Methoxyethanol, Methyl methacrylate, Methyl tert-butyl ether, Methylene chloride, Mold, Naphthalene, Nitrogen dioxide, Ozone, PM_{10}, $PM_{2.5}$, Radon, Styrene, Sulphur dioxide, 1,1,2,2-Tetrachloroethane, Tetrachloroethene, Toluene, 1,1,2-Trichloroethane, Trichloroethylene, Vinyl chloride, Xylenes.

A 45th - coarse particulate matter ($PM_{10-2.5}$), defined as the difference between PM_{10} and $PM_{2.5}$ - is added given guidelines' focus on particle fractions (Sections 2.3.1, and 3.6). $PM_{10-2.5}$ separates respiratory effects of the coarse fraction from fine particles.

The final list to be considered in here contains 45 contaminants, comprising semi-volatile organic compounds, volatile organic compounds, metals, and the criteria contaminants.

3.2 Quantifying harm

Indoor air quality (IAQ) assessment research uses the disability-adjusted life year (DALY) to quantify health burdens from exposure to indoor contaminants (**Harm**).

$$\text{Harm}_{\text{Indoor air quality}} \propto \text{Harm}_{\text{Indoor air contaminants}} \tag{3.1}$$

This chapter presents the core methodology of the research. It evaluates overall indoor-associated harm per year of exposure, and not the total lifetime. This entails summing the individual harms from contaminants (i) commonly found in residential environments to represent the total population harm.

$$\text{Harm}_{\text{Indoor air contaminants}} \equiv \sum_i \text{Harm}_{\text{i}} \tag{3.2}$$

IAQ assessment is tied to contaminant concentrations (Hess-Kosa, 2018; WHO, 2021), highlighting the essential role of concentrations in evaluating indoor air quality. Achieving the research objectives (Section 1.4) involves developing a harm-based metric that links harm with concentrations. This allows indoor air contaminant concentrations to be used as robust indicators of harm, enhancing comprehension and the proactive control of indoor air quality hazards. For each contaminant, harm can be expressed as:

$$Harm_i \equiv f_i \cdot C_i \tag{3.3}$$

where C_i is the indoor concentration of a contaminant (subscript i) and f_{i} is the concentration-to-harm factor (the harm-based metric). Deriving f for a range of contaminants is an objective of this research.

For well-characterized contaminants, f_{i} can be derived from epidemiological relationships between concentration, disease incidence, and resulting harm (DALYs). When lacking disease data, f_{i} must be approximated using more uncertain statistical approaches. Nevertheless, accurately determining f factors enables the connection of contaminant concentrations to health impacts.

A **Harm Intensity**, **HI** is a metric that relates chronic harm (DALYs/person/year) caused by the inhalation of a specific airborne contaminant (i) to a concentration C_i.

$$Harm_i = HI_i \cdot C_i \tag{3.4}$$

Generally, indoor contaminant concentrations are reported in micrograms per cubic meter ($\mu g/m^3$), but some contaminants have other units, such as Bq/m^3 for radon and CFU/m^3 for mold spores. The harm intensity metric measures the total harm suffered per year and not over a total lifetime. Accordingly, for most airborne contaminants, HI_i has units of $DALY/\mu g/m^3/person/year$.

Indoor air comprises mixtures of gases, vapors, and particles, necessitating exploration of multi-contaminant effects (Section 2.2.2) for the **HI** metric (Spengler et al., 2000). This will enable models to better represent real-world exposure scenarios (Mauderly and Samet, 2009). Research has examined additive versus synergistic effects and statistical assessment methods (Billionnet et al., 2012; Yu et al., 2022). When synergies are identified, they are found to be rare at the concentrations typically found in buildings (Section 2.1.2) (Committee et al., 2019; Kortenkamp et al., 2009; Rudén et al., 2019; Socianu et al., 2022). With some exceptions like for carbon monoxide (Section 2.2.2).

Some combinations of contaminants exhibit clear synergistic effects, like radon and smoking in relation to lung cancer (Lee et al., 1999) and asbestos combined with smoking (Erren et al., 1999). Developing a comprehensive synergistic harm metric necessitates data encompassing chronic effects across all potential combinations, and while some relevant literature exists (Huang et al., 2012; Ku et al., 2017; Liu et al., 2023a; Siddika et al., 2019), evidence for chronic synergies remains limited for most indoor contaminants.

The most accepted approach for multiple chemical exposures is the *Concentration Addition*, whereby components act additively (Backhaus, 2023; Martin et al., 2021; Martin, 2023). It gives very similar or identical predictions to competing concepts or models like the *Effect Addition*. The additive approach is moderately precautionary and more feasible than alternatives requiring full concentration-response data. Overall, research supports dose addition for multiple exposures.

Considering the above, this research follows an additive model for total harm calculation aligning with prevailing risk assessment methods (Li et al., 2023; Mauderly and Samet, 2009; WHO, 2021) (Section 8.8). Furthermore, when evaluating total harm (DALYs) resulting from a mixture of air contaminants, studies typically adopt an additive framework. This approach involves summing the impacts of multiple contaminants across different

concentrations (Guan et al., 2021; Rojas-Rueda et al., 2019; Van Zelm et al., 2008, 2016).

The harm from any number of contaminants can be summed to obtain the *total* harm they cause, where

$$Harm = \sum_{i} Harm_i \tag{3.5}$$

The individual contaminant harms can be compared against the total harm to determine those that contribute the most. This allows the most harmful to be identified and designated *Contaminants of Concern (CoCs)*.

Equation 3.4 is the all-cause harm that aggregates the health impacts from all diseases that exposure to a contaminant might induce. Some data sources may provide all-cause information, but others are disaggregated by disease so that the all-cause harm becomes the sum of the harms for each health outcome, as

$$Harm_i = \sum_{k} Harm_{(k,i)} \tag{3.6}$$

where the subscript k denotes a specific disease. Then, $Harm_{(k,i)}$ can be defined as a function of the harm intensity for each disease, $HI_{(k,i)}$, where

$$Harm_{(k,i)} = HI_{(k,i)} \cdot C_i \tag{3.7}$$

In epidemiology, all-cause mortality often summarizes the effect of major diseases from long-term exposures (represented by k) (WHO, 2021). Summing known diseases approximates the all-cause effect in air pollution impact assessments (Fantke et al., 2019; Gronlund et al., 2015; Van Zelm et al., 2016). However, lacking morbidity data gives only a reasonable lower-bound estimate of total harm. Similarly, in toxicology, health effects are categorized into cancer and non-cancer groups. Their combination should estimate the all-cause effect for a substance. However, given the intricate assumptions about what these categories reflect, this also represents a reasonable lower-bound harm estimate.

This follows the characterization framework of Life-Cycle Impact Assess-

ment (LCIA) approach for quantifying harm (Hauschild and Huijbregts, 2015), which is rooted in toxicological and epidemiological research, and has been widely applied in studies of outdoor (Bulle et al., 2019; Fantke et al., 2019; Goel et al., 2019; Gronlund et al., 2015; Kvasnicka et al., 2019; Oberschelp et al., 2020; Petrov et al., 2017; Tang et al., 2018a,b; Van Zelm et al., 2008, 2016) and indoor air pollution, particularly inside or near dwellings (Hellweg et al., 2009; Maury-Micolier et al., 2023; Meijer et al., 2005b,d).

LCIA considers many parameters, but the one that is most similar to the harm intensity is the Effect Factor (EF), relating harm to mass intake ($DALY/kg - intake$). The harm intensity can be related to the effect factor using a Breathing Rate (BR).

$$HI_{(k,i)} = EF_{(k,i)} \cdot BR \tag{3.8}$$

BR is a standardized breathing rate (m^3/person/year) (Section 4.4).

The interest lies in determining the harm, and hence $\mathrm{HI}_{(k,i)}$ for every contaminant (i) and health outcome (k), and so by summing all of the health outcomes associated with each contaminant, the harm intensity can be written for all causes as,

$$\mathrm{HI}_i = BR \cdot \sum_k \mathrm{EF}_{(k,i)} \tag{3.9}$$

Quantifying **Harm** and **Harm Intensity** for each disease and contaminant requires the conversion of existing health data from the forms they are typically reported in, which vary depending on the discipline they originate from. The data from toxicological and epidemiological studies are now examined in turn.

3.3 Toxicological analysis: The Tox-harm approach

Toxicological studies aim to determine the harmful effects of various contaminants on living organisms. Organisms (commonly rodents, mammals and non-human primates) are exposed to doses of contaminants to deter-

mine the quantal dose–response relationship that characterizes the distribution of responses to different doses in a population of individual organisms (Eaton and Gilbert, 2008). The harm from a contaminant can be derived from effect factors (DALY/mass) and their intake (mass) as,

$$\text{Harm}_{(k,i)} = \text{EF}_{(k,i)} \cdot C_i \cdot \text{BR} \tag{3.10}$$

Individual effect factors for each health outcome (k) associated to a contaminant (i) are developed from Dose-Response Factors (DRF, case/kg), indicating the change in morbidity and/or mortality per unit mass intake of the contaminant (i) and the damage factors (DF, DALY/case), explaining the severity of disability (Huijbregts et al., 2005; Logue et al., 2012).

$$EF_{(k,i)} = DRF_{(\text{k,i})} \cdot DF_k \tag{3.11}$$

In toxicology, the specific effective dose for a given disease represents cancerous or non-cancerous effects for each relevant contaminant,

$$EF_{(k,i)} = DRF_{(\text{cancer}|\text{non-cancer},i)} \cdot DF_k \tag{3.12}$$

The dose-response factor is the quotient of a constant and the median effective dose (ED50) that explains a carcinogenic or non-carcinogenic effect, for each contaminant,

$$DRF_{(\text{cancer}|\text{non-cancer},i)} = \frac{0.5}{ED50_{(k,i)}} \tag{3.13}$$

Considering Equations 3.11, 3.12, 3.13, the form of the toxicology-based harm intensities (HI, DALY/µg/m^3/person/year) is

$$HI_{(k,i)} = \frac{1}{2} \cdot \frac{DF_k \cdot BR}{ED50_{(k,i)}} \tag{3.14}$$

Substituting 0.5 for 1/2 in Equation 3.14 is a minor adjustment aimed at enhancing the readability of the expression. This change in representation will be maintained for consistency throughout this work.

These harm intensities can be disaggregated into two categories: for cancer

and non-cancer toxicity. In LCA, toxicology-based chemical impacts are disaggregated into these categories due to the way in which how the related LCA impact scores are interpreted, and used when applying the assessment (Hauschild et al., 2018).

$$\mathrm{HI}_{(\mathrm{cancer},i)} = DRF_{(\mathrm{cancer},i)} \cdot DF_k \cdot BR \tag{3.15}$$

$$\mathrm{HI}_{(\text{non-cancer},i)} = DRF_{(\text{non-cancer},i)} \cdot DF_k \cdot BR \tag{3.16}$$

The sum over specific cancer and non-cancer categories derives the all-cause effect harm intensity (DALY/µg/m^3/person/year) as

$$HI_i = [(DRF_{\mathrm{cancer},i} \cdot DF_k \cdot ADAF) + (DRF_{non-cancer,i} \cdot DF_k)] \cdot BR \tag{3.17}$$

The Age Adjustment Dependent Factor (ADAF) is used to adjust the carcinogenicity effect.

The all-cause effect factor (EF_i, DALY/kg) is,

$$EF_i = (DRF_{\mathrm{cancer},i} \cdot DF_k \cdot ADAF) + (DRF_{non-cancer,i} \cdot DF_k) \tag{3.18}$$

The all-cause Dose-Response Factor (DRF_i, cases/kg) is,

$$DRF_i = (DRF_{\mathrm{cancer},i} \cdot ADAF) + (DRF_{non-cancer,i}) \tag{3.19}$$

Overall, in the Tox-harm approach, the determinants of the effect factor and of the harm intensity are: dose-response metrics ($\mathrm{DRF}_{cancer|non-cancer,i}$, ED50), the breathing rate, and the severity of the disease (DF_k). Background concentrations are not required.

3.4 Epidemiological analysis: The Epi-harm approach

Epidemiology focuses on the patterns of disease and ill-health in a population. (Bhopal, 2016) Epidemiological studies statistically link disease incidences to real-world exposures. They require substantive evidence and so provide less data on contaminants than toxicological studies.

The Air Pollution Health Risk Assessment (AP-HRA) framework focuses on evaluating the health risks associated with air pollution exposure. These risks are typically quantified using Concentration-Response (C-R) functions. These functions, incorporated into AP-HRA tools, reflect the epidemiological evidence linked to particular health outcomes and can take the form of linear or non-linear models (Hassan Bhat et al., 2021; WHO, 2016). This approach is similar to the IND approach of Logue et al. (2012).

The incidence rate is the prime estimate of risk in epidemiology (Bhopal, 2016) and so, health risk assessments use Health Impact Functions (HIF) to estimate changes in outcome incidence. HIF methods require information that includes the size of the exposed population, baseline incidence rates for diseases associated with pollutants, baseline and exposure concentrations, and C-R estimates for each contaminant-disease pair. (Martenies et al., 2015)

The attributable harm caused by a health outcome (k) from exposure to a contaminant (i) ($\text{Harm}_{(k,i)}$, DALYs/person/year) is a function of the baseline disease incidence (γ_{0_k}, cases/person/year), the damage factor (DF_k, DALY/case), a risk-related empirical parameter beta ($\beta_{(k,i)}$, change/µg/m^3), and the contaminant exposure concentration (C_i, µg/m^3), associated through a non-linear relationship that considers saturation at high exposures as

$$\text{Harm}_{(k,i)} = \text{DF}_k \cdot \gamma_{0_k} \cdot (1 - e^{-\beta_{(k,i)} \cdot C_i}) \tag{3.20}$$

Important outlines from this expression are:

- In general, this analysis follows the Comparative Risk Assessment (CRA) conceptual framework (Murray, 1994).
- This expression is equivalent to that used in the Global Burden of Disease (GBD) studies to quantify the environmental burden of dis-

ease attributable to a wide variety of risk factors (Hassan Bhat et al., 2021; Hauschild et al., 2018; Logue et al., 2012; Murray et al., 2020).

- Damage factors express the relationship between the cases of mortality or morbidity attributed to a contaminant and the corresponding harm. These factors are expressed in terms of DALY/case (Fantke et al., 2019; Gronlund et al., 2015; Van Zelm et al., 2008, 2016).
- The term in parenthesis is known as the population attributable fraction in LCIA (Fantke et al., 2019; Gronlund et al., 2015).
- The environmental burden of disease for health outcomes presented in the GBD (DALYs/person/year) is the product of the damage factor and the baseline disease incidence.
- This log-linear model is the most widely used function for health impact assessment (Burnett and Cohen, 2020; Nasari et al., 2016).
- The approach assumes there is no threshold concentration (TMREL) below which effects aren't seen.

Dividing by the concentration derives the harm intensity as,

$$HI_{(k,i)} = \frac{DF_k \cdot \gamma_{0_k}}{C_i} \cdot (1 - e^{-\beta_{(k,i)} \cdot C_i}) \tag{3.21}$$

HI has units of DALY/µg/m^3/person/year. The term in parenthesis models the non-linear, no lower threshold, saturation. The shape of the curve is a function of the exponent (the curve that is generated by the expression is a sigmoid curve, which has a steep linear initial slope that then flattens out as values increase). When the equation is evaluated at the low concentrations normally expected in dwellings (Logue et al., 2011a; Vardoulakis et al., 2020), a linear concentration-response association is often assumed appropriate (Gronlund et al., 2015; Huijbregts et al., 2017; Van Zelm et al., 2016).

$$1 - e^{-\beta_{(k,i)} \cdot C_i} \approx \beta_{(k,i)} \cdot C_i \tag{3.22}$$

The simplification is justified because:

- The range of chronic exposures to contaminants in buildings is expected to be in the low to mid regimes (Halios et al., 2022; Ilacqua

et al., 2022; Logue et al., 2011a; Ma et al., 2022; Sarigiannis et al., 2011; Vardoulakis et al., 2020),

- the incidence rate per person is low,
- it is consistent with statements of a near-linear C-R association for low to moderate concentrations of airborne contaminants (Burnett and Cohen, 2020; Nasari et al., 2016), and
- it is mathematically equivalent to current practice applied by LCIAs of air pollution (Gronlund et al., 2015; Huijbregts et al., 2017; Van Zelm et al., 2016).

The individual intermediate expression of harm (DALYs/person/year) can therefore be described as,

$$\text{Harm}_{(k,i)} = \text{DF}_k \cdot \gamma_{0_k} \cdot \beta_{(k,i)} \cdot C_i \tag{3.23}$$

And the individual intermediate harm intensity (DALY/µg/m^3/person/year) as,

$$\text{HI}_{k.i} = \text{DF}_k \cdot \gamma_{0_k} \cdot \beta_{(k,i)} \tag{3.24}$$

In epidemiological studies, k represents all major diseases and considers both morbidity and mortality. It can be represented by all-cause mortality risk estimates that encompass all causes of death, from long-term exposure-related chronic diseases to deaths hastened by recent exposure to air pollution (WHO, 2021). When this information is not available, different diseases can be summed to approximate the all-cause effect.

When the risk estimate is given for specific causes:

$$\text{HI}_i = \sum_k \text{DF}_k \cdot \gamma_{0_k} \cdot \beta_{(k,i)} \tag{3.25}$$

When the risk estimate is given for all-cause mortality:

$$\text{HI}_i = \sum_k \text{DF}_k \cdot \gamma_{0_k} \cdot \beta_i \tag{3.26}$$

The *all-cause* harm intensity (DALY/µg/m^3/person/year) can now be defined as,

$$\text{HI}_i = \sum_k \text{DF}_k \cdot \gamma_{0_k} \cdot \beta_{(k,i)} \tag{3.27}$$

Analogously, the linear form for the epidemiological effect factor (EF_i, $\mathrm{DALY/kg}_{intake}$) as,

$$\mathrm{EF}_i = \frac{\sum_k \mathrm{DF}_k \cdot \gamma_{0_k} \cdot \beta_{(k,i)}}{BR} \tag{3.28}$$

The Dose-Response Factor (DRF_i, cases/kg) as,

$$\mathrm{DRF}_i = \frac{\sum_k \gamma_{0_k} \cdot \beta_{(k,i)}}{\mathrm{BR}} \tag{3.29}$$

And the Concentration-Response Factor (CRF_k, cases/µg/m^3/person/year) as,

$$\mathrm{CRF}_i = \sum_k \gamma_{0_k} \cdot \beta_{(k,i)} \tag{3.30}$$

Overall, in the **Epi-harm approach**, the determinants of the effect factor and of the harm intensity are: disease incidence metrics (γ_{0_k} and $\beta_{(k,i)}$) and the severity of the disease (DF_k). Background concentrations are not required.

3.5 Connecting Toxicology and Epidemiology

Ideally, the toxicological and epidemiological approaches would yield equivalent harm estimates for a given contaminant (i):

$$\mathrm{Harm}_{(i)}^{\mathrm{toxicity}} \equiv \mathrm{Harm}_{(i)}^{\mathrm{epidemiology}} \tag{3.31}$$

The dose-response factor (DRF) is a shared parameter:

$$\mathrm{DRF}_{(k,i)}^{\mathrm{toxicity}} = \frac{0.5}{\mathrm{ED50}_{(k,i)}} \tag{3.32}$$

$$\mathrm{DRF}_{(k,i)}^{\mathrm{epidemiology}} = \frac{\gamma_{0_k} \cdot \beta_{(k,i)}}{\mathrm{BR}} \tag{3.33}$$

If toxicity reflects a contaminant's cancer (or non-cancer) effects, epidemiology should provide evidence on the associated cancer type (or disease) in populations.

For all-cause Dose-Response factors, DRF_i:

$$\left(\frac{0.5}{\mathrm{ED50}_{(k',i)}} \cdot \mathrm{ADAF}\right)_{\text{cancer}} + \left(\frac{0.5}{\mathrm{ED50}_{(k'',i)}}\right)_{\text{non-cancer}} \equiv \frac{\gamma_{0_{k'''}} \cdot \beta_{(k''',i)}}{\mathrm{BR}} \quad (3.34)$$

Likewise, effect factors (EF_i) should align because damage factors simply translate incidence to harm, unchanged by approach:

$$\begin{aligned} &\left(\frac{0.5}{\mathrm{ED50}_{(k',i)}} \cdot \mathrm{ADAF} \cdot \mathrm{DF}_{(k'\circ)}\right)_{\text{cancer}} \\ &+ \left(\frac{0.5}{\mathrm{ED50}_{(k'',i)}} \cdot \mathrm{DF}_{(k''\circ)}\right)_{\text{non-cancer}} \equiv \frac{\gamma_{0_{k'''}} \cdot \beta_{(k''',i)}}{\mathrm{BR}} \end{aligned} \quad (3.35)$$

And, finally the same is presented for the harm intensity, HI_i:

$$\begin{aligned} &\left(\left(\frac{0.5}{\mathrm{ED50}_{(k',i)}} \cdot \mathrm{ADAF} \cdot \mathrm{DF}_{(k'\circ)}\right)_{\text{cancer}}\right. \\ &\left. + \left(\frac{0.5}{\mathrm{ED50}_{(k'',i)}} \cdot \mathrm{DF}_{(k''\circ)}\right)_{\text{non-cancer}}\right) \cdot \mathrm{BR} \\ &\equiv \mathrm{DF}_{k'''} \cdot \gamma_{0_{k'''}} \cdot \beta_{(k''',i)} \end{aligned} \quad (3.36)$$

The subtle differences in health outcome identifiers are shown using symbol notation. The prime symbol $'$ denotes a general cancer effect category. The circled prime $^\circ$ indicates a specific cancer type identified as associated with the broader cancer effect represented by $'$. Varying numbers of primes visually distinguishes where different, but equivalent, health outcomes are accounted for. For example, k' and k''' could both refer to cancer effects, with k' representing the cancer category and k''' representing leukaemia, in the integrated factor. This symbolic notation shows the nuanced distinctions between related endpoints derived from the toxicity and epidemiology approaches.

With accurate disease rates, health outcome identifiers, and constant equivalences, both approaches could theoretically estimate identical harm. Further research is needed to achieve this equivalence. Meta-analysis can merge toxicity and epidemiology information, supporting progress toward equiv-

alence.

3.6 Harm from the coarse fraction of particulate matter

The coarse fraction of PM_{10} (referred to as thoracic coarse particles or $PM_{10-2.5}$) are, in regulatory terms, particles with an upper 50% cut-point of 10 µm aerodynamic diameter and a lower 50% cut-point of 2.5 µm aerodynamic diameter.

When tallying up air pollution's health impacts, not all particulate matter is equally harmful. Researchers aim to separate the burden attributable to fine particles from their coarser counterparts. Mathematically, the total disease burden (measured in disability-adjusted life years or DALYs) is the sum of the harm from each PM size fraction. This arithmetic summation or subtraction assumes that the harm is being calculated using the means of the PM size fractions' parameters. For non-normal distributions, such as right-skewed data, medians or other robust measures should be considered, noting that the arithmetic operations on medians may not be appropriate (see Section 3.8 for further discussion). The relative contributions depend on the particles' respective harm intensities, which convert exposure to harm.

Ideally, epidemiologists would measure each fraction's unique harm determinants directly from health data. But real-world constraints mean the $PM_{2.5}$ factor is best known, while the coarse one remains elusive. However, since the fine fraction of PM_{10} is reasonably well-established, the coarse factor can be bounded in terms of the other two.

To establish an initial mathematical foundation independent of contextual assumptions, particulate matter (PM) represents particle mass and is therefore a purely additive quantity (for $PM_{2.5}$ greater than zero):

$$PM_{10} = PM_{2.5} + PM_{10-2.5} \tag{3.37}$$

$$PM_{2.5} + PM_{10-2.5} > PM_{2.5} > 0 \tag{3.38}$$

where $PM_{10-2.5}$ represent particles between 2.5 microns and 10 microns. Since there will be some mass in the coarse fraction, PM_{10} will always be greater than $PM_{2.5}$, and thus the inequality is true. The same additive property applies to the harm per person that results from that exposure:

$$\text{Harm}_{PM_{10}} = \text{Harm}_{PM_{2.5}} + \text{Harm}_{PM_{10-2.5}} \tag{3.39}$$

$$\text{Harm}_{PM_{2.5}} + \text{Harm}_{PM_{10-2.5}} > \text{Harm}_{PM_{2.5}} > 0 \tag{3.40}$$

For every contaminant, there is a harm intensity that converts the exposure into the harm. Formally applying that:

$$\text{Harm}_{\text{PM}_{10}} = \text{HI}_{\text{PM}_{10}} \cdot \text{PM}_{10} \tag{3.41}$$

$$\text{Harm}_{\text{PM}_{10}} = \text{HI}_{\text{PM}_{2.5}} \cdot \text{PM}_{2.5} + \text{HI}_{\text{PM}_{10-2.5}} \cdot \text{PM}_{\text{PM}_{10-2.5}} \tag{3.42}$$

$$\begin{aligned} \text{HI}_{\text{PM}_{2.5}} \cdot \text{PM}_{2.5} + \text{HI}_{\text{PM}_{10-2.5}} \cdot \text{PM}_{\text{PM}_{10-2.5}} > \\ \text{HI}_{\text{PM}_{2.5}} \cdot \text{PM}_{2.5} > 0 \end{aligned} \tag{3.43}$$

Understanding the coarse fraction effect becomes important, yet the independent measurement of all three factors might not always be feasible. Nevertheless, relationships between these factors can be established:

$$\text{HI}_{\text{PM}_{2.5}} > \text{HI}_{\text{PM}_{10-2.5}} \tag{3.44}$$

$$\text{HI}_{\text{PM}_{10-2.5}} = \frac{\text{HI}_{\text{PM}_{10}} - f_{2.5} \cdot \text{HI}_{\text{PM}_{2.5}}}{1 - f_{2.5}} \tag{3.45}$$

$$\frac{\text{HI}_{\text{PM}_{10}} - f_{2.5} \cdot \text{HI}_{\text{PM}_{2.5}}}{1 - f_{2.5}} > 0 \tag{3.46}$$

Here the inequalities are known physical limits, that define the fraction of

$PM_{2.5}$ particles as:

$$f_{2.5} \equiv \frac{PM_{2.5}}{PM_{10}} \tag{3.47}$$

$PM_{2.5}$ has more health impact per unit mass than PM_{10}, and $PM_{2.5}$ is measured the most. What is wanted, is an effective harm intensity that includes the harm from the coarse fraction as well as from the measured $PM_{2.5}$:

$$HI_{PM} \equiv \frac{harm_{PM_{10}}}{PM_{2.5}} \tag{3.48}$$

$$\frac{harm_{PM_{10}}}{PM_{2.5}} = \frac{HI_{PM_{10}}}{f_{2.5}} \tag{3.49}$$

$$\frac{HI_{PM_{10}}}{f_{2.5}} > HI_{PM_{2.5}} > HI_{PM_{10}} \tag{3.50}$$

The approach for the coarse fraction can now be defined. The all-cause harm attributable to the coarse fraction of particulate matter ($PM_{10-2.5}$) is estimated by calculating the difference between the harm due to PM_{10} and $PM_{2.5}$ as

$$Harm_{PM_{10-2.5}} = Harm_{PM_{10}} - Harm_{PM_{2.5}} \tag{3.51}$$

The harm intensity for the coarse fraction can be estimated once the harm from each fraction is quantified and once the concentrations of the other PM fractions are known, as

$$HI_{PM_{10\text{-}2.5}} = \frac{Harm_{PM_{10-2.5}}}{C_{PM_{10-2.5}}} \tag{3.52}$$

3.7 Harm Budget

The harm attributable to chronic exposures is calculated using Equation 3.7. The values of harm can be used to rank the contaminants and identify contaminants of concern (CoC). These CoCs can then be used to regulate IAQ in dwellings. One way of doing this is to set a *harm budget*, the distribution of harm that is expected in an acceptable reference scenario. A *reference scenario* is a specific set of dwellings that all comply with a recognized

indoor air quality (IAQ) standard (Chan et al., 2019; Martin et al., 2020; Singer et al., 2020; Zhao et al., 2021) and so the IAQ in those dwellings might be logically assumed to be *acceptable*.

$$Harm\ Budget = \sum_{i=1}^{N_{CoC}} HI_i \cdot \overline{C}_i \tag{3.53}$$

Here N_{CoC} is the number of CoCs and $\overline{C}$ is the concentration representative for a reference scenario. The equation expresses the harm budget in units of DALYs.

For a harm budget with a value of unity, the weight of each contaminant is determined by a partial weight for contaminant i, determined as the product of its harm intensity (HI_i) and the concentration in the reference scenario ($\overline{C}_i$), divided by the harm budget.

$$\text{Partial Weight}_i = \frac{\mathrm{HI}_i \cdot \overline{C}_i}{\text{Harm Budget}} \tag{3.54}$$

Each partial weight is then adjusted to a unitless target value like 1, 10, or 100, for easier interpretation. To do this, the partial weight is multiplied by that unitless value, and the result is a new weighting factor called here Adjusted Partial Weight$'_i$

$$\text{Adjusted Partial Weight}'_i = \text{Partial Weight}_i \cdot \text{Unitless Target} \tag{3.55}$$

A common scaling factor for contaminant i is determined as the ratio of the harm associated with that contaminant to its adjusted partial weight.

$$\text{Common Scaling Factor}_i = \frac{\mathrm{Harm}_i}{\text{Adjusted Partial Weight}'_i} \tag{3.56}$$

A weight (Weight_i) for contaminant i is determined as the ratio of its harm intensity (HI_i) to the common scaling factor. The weight has units of inverse concentration.

$$\mathrm{Weight}_i = \frac{\mathrm{HI}_i}{\text{Common Scaling Factor}_i} \tag{3.57}$$

These equations are used to calculate the partial weights, adjusted partial weights, common scaling factors, and weights associated with each contaminant in the context of the normilized unitless harm budget (More on this in Section 8.3.1).

3.7.1 Regulated Harm Budget (RHB)

Merging the Indoor Air Quality (IAQ) equivalence principle proposed by Sherman et al. (2012) with the concept of the *Harm Budget*, introduces a parallel notion defined here as the *Regulated Harm Budget (RHB)*. This involves utilizing existing contaminant Exposure Limit Values (ELVs) for chronic exposures presented in guidelines or standards, in the context of the Contaminants of Concern (CoCs) and their corresponding harm intensities to quantify the potential harm that represents the total allowed harm from regulated contaminants implicitly set by a regulatory body.

$$\text{Regulated Harm Budget (RHB)} = \sum_{i=1}^{N_{CoC}} HI_i \cdot \hat{C}_i \tag{3.58}$$

Here, N_{CoC} still represents the total number of Contaminants of Concern, and $\hat{C}_i$ denotes the long-term concentration threshold recommended in a relevant standard or guideline The application of this is resolved in Section 8.2.1.1.

3.8 Parameter distributions

3.8.1 Uncertainty Representation

A lognormal Probability Density Function (PDF) is plausible for all parameters that are positive and cannot physically have negative values. This type of distribution is widely used and accepted to adequately adjust for right-skewed data (Blackwood, 1992; Crow and Shimizu, 1987; Jia et al., 2008; Ott, 1990). This approach is consistent with established methodologies (Huijbregts et al., 2005; Imbeault-Tétreault et al., 2013; Shaked et al., 2015a; Slob, 1994). This is usually the default procedure because the parameter values often vary over several orders of magnitude, and it automatically excludes negative values that describe impossible scenarios

(like a negative Harm), which are meaningless and could lead to erroneous uncertainty estimates. The central limit theorem also indicates lognormality for products of multiple independent random variables (Huijbregts et al., 2005; Shaked et al., 2015b; Slob, 1994).

Medians represent the central value due to their robustness against outliers. For non-normal data, medians better depict the typical result than means (Huijbregts et al., 2005).

To characterize dispersion, the geometric standard deviation (GSD) is used. As a multiplicative factor, the GSD indicates the relative spread around the geometric mean rather than absolute variance (Ciroth et al., 2016; Slob, 1994). Being a linear multiplier aligned with lognormal distributions, it quantifies uncertainty without specifying precise bounds. This prevents potential scaling effects that can occur when combining variance-based uncertainty measures. GSD suitably represents uncertainty because real-world data often does not perfectly fit assumed distributions, especially in the tails where true bounds are uncertain, and the analyses do not rely on the extreme 2.5th or 97.5th percentiles.

When lognormality and 95% confidence intervals (CIs) are known, the GSD^2 approximates uncertainty (Slob, 1994):

$$GSD^2 = \sqrt{\frac{97.5 \text{ percentile}}{2.5 \text{ percentile}}} \tag{3.59}$$

The GSD^2 can be used to approximate the 97.5th and 2.5th percentiles of a distribution based on the median, assuming a lognormal distribution:

$$97.5percentile \approx GSD^2 \cdot median \tag{3.60}$$

$$2.5percentile \approx \frac{median}{GSD^2} \tag{3.61}$$

For combined variables, output (y) variance depends on uncorrelated input (x) variance (Hauschild et al., 2018; MacLeod et al., 2002; Morgan et al., 1990):

$$GSD_y^2 = e^{\left(\sqrt{\sum_{i=1}^{n}\left[\ln\left(GSD_{x_i}^2\right)\right]^2}\right)} \tag{3.62}$$

When information is limited, expert judgement and uncertainty factors guide uncertainty assignment for human health impact characterizations. This allows approximating data variability when direct measures like confidence intervals are unavailable (Rosenbaum et al., 2004).

3.8.2 Data Synthesis

The parameters involved in the Tox-harm and Epi-harm approaches can have more than one available estimate of central tendency, and so they need to be combined, or pooled, to produce a single value. Standard meta-analysis statistical approaches were utilized to pool lognormal distributions (Daly and Soobiah, 2022; DerSimonian and Laird, 1986a; Fisher, 2015; Harris et al., 2008; Schmid et al., 2020; StataCorp, 2017, 2019). Meta-analyses combine estimates for parameters with more than one central tendency value available (Schmid et al., 2020). Meta-analyses employ the *random-effects* DerSimonian and Laird estimators in STATA 18.0 (Daly and Soobiah, 2022; Fisher, 2015; Harris et al., 2008). Random-effects models follow maximum likelihood methodology, assuming studies represent random samples accounting for heterogeneity (DerSimonian and Laird, 1986b). For lognormal data, the median and geometric mean are equivalent; the geometric mean closely matches meta-analysis results (StataCorp, 2019). The recommended synthesis approach is pooling independent data points for epidemiology and toxicology harm parameters (Cooper et al., 2019).

3.8.3 Monte Carlo Approach

A Monte Carlo approach (Metropolis and Ulam, 1949; Shaked et al., 2015a) modeled input and output parameter distributions. The approach populates a parameter database via bootstrapping. Combining the database with probability distribution functions generates random input samples to compute outputs (including: Harm, harm intensity, effect factor, dose-response factor, concentration-response factor).

The Monte Carlo simulations ran for a minimum of 100,000 iterations, with

additional iterations as needed to meet a convergence criterion. The convergence criterion was for the mean of the output parameter to become approximately normally distributed. Requiring the output mean to stabilize into a normal distribution indicates that additional iterations are unlikely to shift the central tendency or range substantially. Without convergence, repeated simulations can yield slightly different statistic descriptors due to inherent randomness.

Descriptive statistics were obtained, including means, medians, standard deviations, geometric standard deviations, and confidence intervals. MATLAB is used to code the model and run the sumulations.

Output vectors enable straightforward 95% confidence interval calculation as quantiles. Vector bootstrapping also derives 95% confidence intervals for medians using R's MedianCI function (Signorell et al., 2021). The high iteration count produced narrow median confidence intervals.

3.9 Summary

An iterative, evidence-based process established a list of 45 chronic contaminants in dwellings.

Acute compounds were excluded per the chronic scope. Toxicology and epidemiology guided evaluating each option's inclusion.

Adding $PM_{10-2.5}$ distinguishes the coarse fraction's impacts from fine PM.

The core approach centers on determining contaminant-specific harm intensities. These factors convert exposure concentrations into estimated population harm (DALYs).

Toxicology provides dose-response factors describing contaminant toxicity. Epidemiology offers concentration-response functions from human health studies. Integrating evidence from both domains enables impact estimation while balancing limitations.

Guidelines from life cycle assessment, widely applied in air pollution research, inform the methodology.

By determining harm intensities, ranking contaminant contributions, and setting harm-based benchmarks, indoor air quality is quantitatively linked

to contaminant concentrations and resulting harm.

This methodology demonstrates policy and design value by enabling the development of health-based exposure guidance.

Lognormal probability distribution functions represent uncertainty using median central tendencies and GSD-based dispersion. This aligns with data characteristics while avoiding issues with means, negative values, and scaling effects.

Meta-analysis consolidates multiple estimates into single representative values using established techniques suited for lognormal data.

Monte Carlo simulation modeled parameters and quantified uncertainty, with iterative convergence enabling output confidence intervals.

Chapter 4

Parameters for Determining Harm Intensities

The parameters needed to quantify a toxicology-based and epidemiology-based **Harm Intensity**, **HI** are: (i) Risk estimates from epidemiological studies, linking health effects to contaminant exposures, (ii) Baseline disease/mortality rates, (iii) Damage factors, relating harm to incidence (Equation 3.24), (iv) Breathing rates (Equation 3.8), (v) Dose-response factors, relating incidence to mass intake, (vi) Age-dependent adjustment factors (ADAF) for cancer (Equation 3.19), and (vii) Effect factors (Equation 3.8), relating harm to mass intake.

This study draws on established literature in life cycle impact assessment (LCIA) (Hauschild and Huijbregts, 2015; Hauschild et al., 2018) and health/-comparative risk assessments (Murray et al., 2020; Richmond-Bryant, 2020; WHO, 2021) to identify reliable data sources. Analyzing references in these domains offers insights into trusted sources. To ensure up-to-date data, search strategies use keywords from reputable studies to identify appropriate sources for each parameter.

The following sections detail the search and data-synthesis strategies used to obtain values and distributions for these key exposure, health risk, and harm parameters, for the 44 contaminants of interest (Section 3.1). Characterization of each input forms the basis of the integrated harm estimation methodology developed herein.

4.1 Risk estimates for parameter beta ($\beta_{(k,i)}$)

The parameter $\beta_{(k,i)}$ is an empirical factor that captures the change in a risk estimate associated with a one-unit change in contaminant concentration for a particular health outcome (k) and contaminant (i) (Equation 3.20). It serves as the quantitative link between contaminant long-term exposure and chronic health effects. Chronic statistics comprise deaths from long-term exposure-related chronic diseases as well as those whose passing was hastened by recent exposure to air pollution (WHO, 2021). These risk estimates, represented as relative risks (RRs), odds ratios (ORs), percentage excess alterations, or hazard ratios (HRs), gauge the influence of altering contaminant concentrations on specific health outcomes (Stare and Maucort-Boulch, 2016; Symons and Moore, 2002).

The literature reflects varying viewpoints on the interchangeability of these metrics for pooling in meta-analyses. Some researchers transformed ORs into RRs (or vice versa) (Farhadi et al., 2020; Grant, 2014; Lamichhane et al., 2015; Prasad et al., 2008; Shrier and Steele, 2006; van Rhee and Suurmond, 2015; Wang, 2013); this conversion is only possible given a complete access to raw original data (Grant, 2014; Wang, 2013). Others endorse the equivalence of ORs and RRs (Braithwaite et al., 2019; Kihal-Talantikite et al., 2020; Orellano et al., 2020; Shah et al., 2015; Simoncic et al., 2020; Yuan et al., 2019), based on the "rare disease assumption" (Greenland and Thomas, 1982; Knol et al., 2008; Pace and Multani, 2018). Moreover, other studies correlate RRs with HRs (Chen and Hoek, 2020; Hayes et al., 2020; Kihal-Talantikite et al., 2020; Scheers et al., 2015; Wang et al., 2014; Yuan et al., 2019). There is a "rule of thumb" followed by different authors: Prasad et al. (2008) mention that if $0.67 < \text{OR} < 1.3$ then it is acceptable to assume RRs as equivalent to ORs. Similarly, Stare and Maucort-Boulch (2016) and Symons and Moore (2002) reported that when HR <2.5 it is acceptable to assume HRs are equivalent to RRs.

This study assumes the equivalence of ORs, RRs, and HRs. Standardizing risk estimates for incremental changes in contaminant concentration is done using a linear exposure-outcome relationship (Braithwaite et al., 2019; Chen and Hoek, 2020; Orellano et al., 2020; Shah et al., 2015; Wang et al., 2014; Yuan et al., 2019).

Deriving the beta parameter values involves an exhaustive systematic review of risk estimate articles published after 2010 across databases. The

selected date range aligns with the exposure impact assessment of indoor air in dwellings by Logue et al. (2012) (Section 2.5.1), which relied on risk estimate data from epidemiological studies available up to 2010.

The search strategy incorporates pertinent keywords related to health impacts and contaminants (See Appendix 1) for additional details on the systematic review). This process is complemented by targeted reviews of documents aggregating air pollution-related health data (USEPA, 2018; WHO, 2021), the USEPA Integrated Science Assessments (ISAs) (US-EPA, 2010a,b, 2011, 2016, 2020a,b), and global burden of disease studies (Cohen et al., 2017). Acute data (hourly or daily death rates attributable to recent exposure to air pollution) was not considered because the aim of this work is on chronic effects from long-term exposure to airborne contaminants (Section 1.4). The review was performed for the list of 44 contaminants of interest (the 45th contaminant, $PM_{10-2.5}$, results from subtracting the PM fractions, therefore it is not relevant for the review, Section 3.1). Mortality data was chosen over morbidity data to represent health outcomes where possible because mortality has a higher toll on the global burden of disease than morbidity (Cohen et al., 2017).

For each of the 44 contaminants, there where risk estimates for ten of them: acrolein (C_3H_4O), benzene (C_6H_6), mold spores, formaldehyde (HCHO), nitrogen dioxide (NO_2), ozone (O_3), respirable particulate matter (PM_{10}), fine particulate matter ($PM_{2.5}$), radon (Rn), and sulphur dioxide (SO_2).

The health effects associated to the contaminants where reported as all-cause mortality or morbidity, or as individual outcomes (that can be summed to obtain an all-cause estimate, Section 3). The estimate, or estimates, best capturing the contaminant's total disease burden or attributable mortality is the *best estimate of all-causes*.

All-cause mortality was found to describe best the effect of all-causes for five of the ten contaminants: PM_{10}, $PM_{2.5}$, O_3, SO_2 and, NO_2. They are the commonly known criteria pollutants and have been scrutinized by health assessments (Richmond-Bryant, 2020; WHO, 2021). For C_3H_4O and mold spores, the best estimate of all-causes is represented by asthma morbidity. Long-term mortality from carcinogenic effects was associated with C_6H_6, represented by leukaemia mortality, and by lung cancer for Rn. For HCHO, three health outcomes, leukaemia and lung cancer mortality and asthma morbidity, are added together to obtain the best estimate of all-causes. The health impacts chosen to represent each contaminant are the most

reported, either for mortality or morbidity endpoints.

Table 4.1 shows these contaminants with incidence related data and the recommended input parameters. Here, the term *all-cause mortality* accounts for chronic data, based on cohort studies for total non-accidental mortality causes (codes A00–R99) following the International Statistical Classification of Diseases and Related Health Problems, 10th edition (ICD-10) (WHO, 1993), therefore all-cause mortality excludes accidental deaths. Chronic statistics comprise deaths from long-term exposure-related chronic diseases as well as those whose death was hastened by recent exposure to air pollution (WHO, 2021). The mortality risk estimates reflect all ages, both sexes, and global location; whereas asthma morbidity is for children (with varying ages depending on the contaminant and reference study).

The risk estimates shaping the health impact function, encompassing the β parameter (Equation 2.5), draw from diverse epidemiological studies, and were pooled. This underscores pervasive positive associations between contaminants and health impacts. Importantly, most associations demonstrate statistical significance (Riley et al., 2011).

$PM_{2.5}$ has the most datasets (25) for all-cause mortality, indicating substantial research on its health risks. Radon has numerous lung cancer datasets, consolidating its status as a key contaminant. NO_2 has 24 total datasets, suggesting significant research attention due to its prevalence and known adverse effects. A global systematic review from the WHO represents the most current, relevant, high impact and cited work providing risk estimates for several contaminants, strengthening reliability (WHO, 2021). A current global burden of diseae review had risk estimates for radon (IHME, 2019). Acrolein, benzene, mold, formaldehyde, and sulphur dioxide estimates come from this work's review, providing needed insights on their lesser-studied impacts. The range of morbidity to mortality outcomes shows the complex contaminant-health interplay. Multiple cancer outcomes highlight investigating priority contaminants' carcinogenic potential.

Other authors have used different risk estimates in contaminant harm assessments for ozone (O_3), nitrogen dioxide (NO_2), particulate matter (PM_{10}, $PM_{2.5}$), and acrolein (C_3H_4O). Logue et al. applied available morbidity estimates for SO_2 and NO_2, and mortality for O_3 and $PM_{2.5}$, from pre-2010 cohort studies in the USA or Canada (Logue et al., 2012). Van Zelm et al. used a 2000 European cohort study for chronic PM_{10} mortality and acute O_3 mortality (Van Zelm et al., 2008). Van Zelm et al. used respi-

Table 4.1: Risk estimates data descriptions.

Contaminant$_i$	Health endpoint	Health outcome$_k$	Risk estimate	Beta parameter[a] ($\beta_{(k,i)}$)	Datasets[b]	Main reference
Acrolein						
(C3H4O)	Morbidity	Asthma	4.086 (95% C.I. 2.268-7.359)	0.141 (95% C.I. 0.0819-0.2)	2	(Annesi-Maesano et al., 2012)
Benzene						
(C6H6)	Mortality	Leukaemia	1.22 (95% C.I. 1.11-1.34)	0.000436 (95% C.I. 0.000229-0.000642)	1	(Vlaanderen et al., 2010)
	Morbidity	Asthma	1.287 (95% C.I. 0.97-1.707)	0.0252 (95% C.I. -0.00305-0.0535)	4	Own review
Formaldehyde (HCHO)	Mortality	Leukaemia	1.223 (95% C.I. 0.852-1.758)	0.0201 (95% C.I. -0.016-0.0564)	2	(Kwon et al., 2018)
	Mortality	Lung Cancer	1.04 (95% C.I. 0.97-1.12)	0.00392 (95% C.I. -0.00305-0.0113)	1	(Kwak et al., 2020)
Mold[c]	Morbidity	Asthma	1.134 (95% C.I. 0.978-1.316)	0.00126 (95% C.I. -0.000222-0.00275)	5	Own review
Nitrogen dioxide						
(NO_2)	Mortality	All Cause	1.02 (95% C.I. 1.01-1.04)	0.00198 (95% C.I. 0.000995-0.00392)	24	(WHO, 2021)
Ozone						
(O_3)	Mortality	All Cause	1.01 (95% C.I. 1.000001-1.02)	0.000995 (95% C.I. 0.0000001-0.00198)	7	(WHO, 2021)
Respirable particle matter						
(PM_{10})	Mortality	All Cause	1.04 (95% C.I. 1.03-1.06)	0.00392 (95% C.I. 0.00296-0.00583)	17	(WHO, 2021)
Fine particle matter						
($PM_{2.5}$)	Mortality	All Cause	1.08 (95% C.I. 1.06-1.09)	0.0077 (95% C.I. 0.00583-0.00862)	25	(WHO, 2021)
Radon						
(Rn)	Mortality	Lung Cancer	1.097 (95% C.I. 1.019-1.174)	0.000926 (95% C.I. 0.000188-0.0016)	25	(IHME, 2019)
Sulphur dioxide						
(SO_2)	Mortality	All Cause	1.079 (95% C.I. 1.045-1.114)	0.0058 (95% C.I. 0.00336-0.00824)	11	Own review

[a] Marginal increment in the contaminant concentration: PM_{10}-$PM_{2.5}$-Formaldehyde-Acrolein-O_3-NO_2= 10µg/m^3; SO_2= 5ppb; Radon= 100Bq/m^3; Benzene=456 µg/m^3; Mold= 100 CFU/m^3.
[a] Values to 3 Sig. Figs.
[b] Datasets; number of data estimates for meta-analysis/pooled value.
[c] Fraction of people exposed to mold in homes ≈ 10% (Braubach et al., 2011).

ratory mortality for O_3 and lung cancer and cardio-pulmonary mortality for $PM_{2.5}$ from USA cohort studies (Van Zelm et al., 2016). Gronlund et al. used $PM_{2.5}$ risk estimates for lung cancer, cardio-pulmonary, and all-cause mortality from a 2002 USA cohort study (Gronlund et al., 2015). Fantke et al. and Oberschelp et al. used the integrated exposure response model for $PM_{2.5}$ from the Global Burden of Disease (GBD) study (Burnett et al., 2014; Fantke et al., 2019; Oberschelp et al., 2020). This models five specific mortality causes (ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), lung cancer in adults and, acute lower respiratory infections (ALRI) in children).

This research differs by using all-cause mortality when available, and risk estimates from systematic reviews rather than single cohort studies. All-cause mortality accounts for chronic data on total non-accidental causes per the ICD-10, excluding accidental deaths (WHO, 1993).

There is an implicit assumption of the equitoxicity of PM by applying the selected risk estimates, where particles are equivalently toxic per unit mass intake. There is evolving evidence to suggest that adverse health effects can vary depending on the source and chemical composition of the PM (Thurston et al., 2021; Xu et al., 2022). Nevertheless, the size of the PM is still the most consistent and robust predictor of incidence in studies of long-term exposure (Burnett et al., 2018; Xu et al., 2022).

Finally, Table 4.2 presents the final beta parameter estimates used in this research. These estimates were obtained after adapting the input data to match the parameter distribution decisions (See Appendix 2 for full descriptive statistics).

4.2 Baseline Incidence (γ_{0_k})

The baseline incidence (γ_{0_k}) represents the average number of mortality or morbidity cases for a given health outcome (k) in a population over a defined time period (Van den Broeck et al., 2013). It is expressed in cases per person-time, typically per year. The baseline incidence quantifies the background disease burden in the absence of the contaminant exposure under consideration. Values can be obtained from epidemiological cohort studies reporting case counts, population, and follow-up time. Baseline incidences are also published in global health statistic databases, like the

Table 4.2: Beta parameter estimates, $\beta_{(k,i)}$, change/µg/m^3.*

Contaminant	**Median**	**GSD**
Acrolein	0.135	1.34
Benzene	0.00041	1.39
Formaldehyde$_{(asthma)}$	0.0197	1.99
Formaldehyde$_{(leukaemia)}$	0.0125	2.74
Formaldehyde$_{(lungCancer)}$	0.00236	2.63
Mold	0.0001	2.08
Nitrogen dioxide	0.00173	1.65
Ozone	0.00081	1.91
PM_{10}	0.00379	1.3
$PM_{2.5}$	0.00763	1.14
Radon	0.00082	1.67
Sulphur dioxide	0.0056	1.35

* Values to 3 Sig. Figs.

Global Burden of Disease study.

The GBD 2019 was mainly used to find the necessary mortality and morbidity central tendencies (medians) and variability (95% CI) for the ten contaminants identified in section 4.1, and their corresponding health outcomes (Table 4.3) (IHME, 2022; Murray et al., 2020), assuming that central tendency estimates represent means when the reference is unclear about what was reported.

Several approaches have been used to obtain baseline incidence rates (γ_{0_k}) for contaminant harm assessments: Van Zelm et al. (2008) consulted 2007 European Union statistics. Van Zelm et al. (2016) used 2005 WHO world health data. Gronlund et al. (2015) obtained U.S. data from the CDC National Center for Health Statistics. Fantke et al. (2019) used the 2016 GBD study. Although these may consult similar databases, differences can arise based on the age, sex, and location chosen. This work similarly uses global health data for incidence of the health outcomes pair to each contaminant using their risk estimate, specifically GBD 2019 statistics for all ages, both sexes, and global location. GBD divides all-causes of disease incidence into communicable/nutritional and non-communicable diseases, which were combined for the all-cause estimate. This provides an appropriate value to represent all-cause mortality, differing from previous studies that use specific mortalities.

Table 4.3: Baseline incidence findings.

Contaminant$_i$	Baseline Incidence (γ_{0_k})$^+$ (cases/10^5 person/year)	Main reference
Acrolein	63 (95% C.I. 6.3-630)[a]	(Annesi-Maesano et al., 2012)
Benzene	4.32 (95% C.I. 3.97-4.66)	(IHME, 2022)
Formaldehyde$_{(asthma)}$	8 (95% C.I. 0.8-80)[b]	(Rojas-Rueda et al., 2019)
Formaldehyde$_{(leukaemia)}$	4.32 (95% C.I. 3.97-4.66)	(IHME, 2022)
Formaldehyde$_{(lungCancer)}$	26.4 (95% C.I. 24.3-28.4)	(IHME, 2022)
Mold	504 (95% C.I. 401-633)[c]	(IHME, 2022)
Nitrogen dioxide	675 (95% C.I. 637-715)	(IHME, 2022)
Ozone	675 (95% C.I. 637-715)	(IHME, 2022)
PM_{10}	675 (95% C.I. 637-715)	(IHME, 2022)
$PM_{2.5}$	675 (95% C.I. 637-715)	(IHME, 2022)
Radon	26.4 (95% C.I. 24.3-28.4)	(IHME, 2022)
Sulphur dioxide	675 (95% C.I. 637-715)	(IHME, 2022)

See Table 4.1 for health outcomes (k).
[a] The baseline for asthma and acrolein derives from the corresponding risk estimate study. Chose an uncertainty factor of 10 to reflect the variability of the extracted central estimate.
[b] The baseline for asthma and formaldehyde uses data from Rojas-Rueda et al. and the GBD. Applied an uncertainty factor of 10 to account for variability in the selected central estimate.
[c] The baseline for asthma and mold reflects the age-standardised global burden of disease for asthma, deemed the best match for meta-analyses of risk estimate studies of the mould Cladisporium genome. Those analyses examined varied populations, age groups and sexes.
[+] Figures are rounded to 3 significant figures.

For asthma, the baseline incidence varies highly depending on age and sex (Rojas-Rueda et al., 2019). Asthma risk estimate and burden of disease studies were reviewed to select the best population match, and uncertainty estimates where assigned to reflect the span of values seen in the literature (Annesi-Maesano et al., 2012; Braubach et al., 2011; Rojas-Rueda et al., 2019). This addresses discrepancies from studying different ages, sexes and locations. Logue et al. (2012) used various baseline prevalence sources, mostly extracting untreated incidence from each study without uncertainty.

The baseline disease incidence parameter estimates after applying the parameter distributions utilized in this study (Section 3.8) are presented in Table 4.4 (See Appendix 3 for full descriptive statistics).

4.3 Damage Factors (DF_k)

The damage factor (DF_k) quantifies disability-adjusted life years (DALYs) per disease case (Hauschild and Huijbregts, 2015; Hauschild et al., 2018). It serves as a measure of disease burden per incidence for a given health out-

Table 4.4: Baseline disease incidence parameter estimates, γ_{0_k}, cases/10^5 person/year.*

Contaminant[a]	**Median**	**GSD**
Acrolein	15.5	4.93
Benzene	4.31	1.06
Formaldehyde$_{(asthma)}$	1.92	5.02
Formaldehyde$_{(leukaemia)}$	4.31	1.06
Formaldehyde$_{(lungCancer)}$	26.3	1.06
Mold	497	1.18
Nitrogen dioxide	675	1.04
Ozone	675	1.04
PM_{10}	675	1.04
$PM_{2.5}$	675	1.04
Radon	26.4	1.06
Sulphur dioxide	675	1.04

* Values to 3 Sig. Figs.
[a] See Table 4.1 for health outcomes (k) that relate to each contaminant. Case represent case counts of the disease or deaths

come (k). Studies calculate DFs as the ratio of disease burden to incidence for chosen health outcomes that represent contaminant effects.

In life cycle impact assessment (LCIA), damage factors are traditionally categorized as representing either cancer or non-cancer effects, as originally proposed by Huijbregts et al. (2005). This aligns with the toxicity-based (tox-harm) approach in the present work. However, for the epidemiology-based (epi-harm) method, damage factors are calculated based on the specific diseases identified in the risk estimates for each contaminant. For example, $PM_{2.5}$ should have a damage factor representing all-cause mortality, since its risk estimate derives from a relative risk for all-cause mortality.

Damage factors should use the latest global disease burden data available. A search for current burden of disease and health statistics databases to derive DFs was performed. The Global Burden of Disease Collaborative Network provides 2019 global, both sexes and all ages estimates for disease-specific DALY burdens (IHME, 2022; Murray et al., 2020).

Damage factors are given for both cancer and non-cancer effects, following LCIA conventions useful for the tox-harm approach. Also reported are damage factors for specific diseases relevant to the epi-harm calculations.

Rather than applying broad cancer and non-cancer factors, the epi-harm method utilizes disease-specific damage factors corresponding to the health endpoints in the epidemiological concentration-response data for each contaminant. This represents a key difference between the tox-harm and epi-harm approaches in how damage factors are defined and implemented based on the type of health risk evidence used.

Table 4.5 gives damage factors and uncertainties for cancer or non-cancer effects, for 18 non-communicable disease types representing global health in 2019 (IHME, 2022; Murray et al., 2020) (See Appendix 4 for full descriptive statistics). The disease types align with those presented by Huijbregts et al. (2005) for consistency and comparability. Cancer effects are represented by six specific cancers plus a cancer average. Non-cancer effects include nine disease types and a non-cancer average. One can directly relate contaminants to disease types when toxicological or epidemiological evidence describes their relationship. When evidence is insufficient, the average effect is the representative measure (Huijbregts et al., 2005). The weighted average damage factor for cancers is 10.6 DALYs/case (GSD 1.06) and for non-cancers is 2.05 DALYs/case (GSD 1.06).

In earlier toxicology oriented studies, damage factors came from 1990 GBD data (Huijbregts et al., 2005). An update is provided here by employing the latest global statistics, with representative and consistent damage factors for current health impact assessments.

Several contaminants with epidemiology data report combined all-cause risk estimates representing multiple health outcomes. To define the disease burden (DALYs) and damage factors, specific associated outcomes must be identified (Table 4.6). Using overall all-cause risks requires selecting representative diseases (k) for the total burden. A comprehensive review of cited health studies in Table 4.1 determined outcomes describing all-cause mortality for each contaminant (key sources: WHO, Global Burden of Disease, EPA, toxicology reports) (Braubach et al., 2011; Hauschild and Huijbregts, 2015; Murray et al., 2020; Richmond-Bryant, 2020; WHO, 2021).

Table 4.7 presents damage factors and uncertainties for the disease-specific outcomes identified from epidemiology risk estimates (See Appendix 5 for full descriptive statistics). For contaminants with only one associated health outcome, the damage factor equals that disease's disability weight. However, formaldehyde is represented by the combined effects of multiple risks. All-cause damage factors also differ in magnitude, reflecting differing

Table 4.5: Damage factors, DF_k, DALY/case, by cancer or non-cancer effects based on 2019 GBD data.*

Disease type **Disease**	**Median**	**GSD**
Cancers		
Breast cancer	10.7	1.04
Leukaemia	34.7	1.13
Liver Cancer	24.7	1.05
Lung cancer	21.2	1.04
Mouth and Oropharynx cancer	15.5	1.04
Stomach cancer	19.2	1.05
Cancer Average	10.6	1.06
Non-Cancers		
Cardiovascular diseases	7.07	1.06
Chronic respiratory diseases	1.33	1.1
Asthma[a]	0.576	1.22
Congenital birth defects	6.17	1.18
Diabetes and kidney diseases	2.67	1.09
Digestive diseases	0.2	1.09
Mental disorders	0.327	1.22
Musculoskeletal disorders	0.451	1.22
Neurological disorders	0.113	1.42
Urinary diseases and male infertility	0.0175	1.13
Non-Cancer Average	2.05	1.06

* Values to 3 Sig. Figs.
[a] Asthma is part of chronic respiratory diseases

burdens across contaminants.

Other $PM_{2.5}$ epidemiology-focused research derived their own damage factor estimates by considering the burden of disease from the health outcomes that were most representative of those used for the baseline incidence and risk estimates: Gronlund et al. (2015) used GBD 2010 estimates of Deaths, DALY and YLL for the High-Income North America region for Cardiopulmonary and Lung cancer mortalities. It also quantified a combined DF for both health outcomes, and an all-cause DF that shows the influence of age distribution on the value of the parameter. Gronlund et al. also proves that each author can select the most appropriate descriptors that are more likely to reflect the severity of contaminant-associated disease. Fantke et al. (2019) used the 2016 GBD study to extract burden of disease (BoD) estimates (DALYs) for each specific mortality (IHD, stroke, COPD, lung cancer, and ALRI) associated to $PM_{2.5}$ and divided them by the mor-

Table 4.6: Burden of disease findings

Contaminant	**Health Risk**	**Specific disease (k)** [a]	**Burden of Disease**[b] (BOD_k)	**Relevant sources**
Acrolein	Asthma		8 (95% C.I. 6.15-10.4)[c]	(Annesi-Maesano et al., 2012)
Benzene	Leukaemia		151 (95% C.I. 136-164)	(IHME, 2022; WHO, 2010)
$\text{Formaldehyde}_{(asthma)}$	Asthma		1 (95% C.I. 0.769-1.3)[c]	(Rojas-Rueda et al., 2019; WHO, 2010)
$\text{Formaldehyde}_{(leukaemia)}$	Leukaemia		151 (95% C.I. 136-164)	(IHME, 2022)
$\text{Formaldehyde}_{(lungCancer)}$	Lung cancer		593 (95% C.I. 547-638)	(IHME, 2022)
Mold	Asthma[d]		274 (95% C.I. 217-343)	(Braubach et al., 2011; IHME, 2022; WHO, 2010)
Nitrogen dioxide	All-cause mortality	COPD+LRI+URI+LC	3270 (95% C.I. 2920-3680)	(IHME, 2022; US-EPA, 2016; WHO, 2021)
Ozone	All-cause mortality	COPD+LC	1550 (95% C.I. 1430-1670)	(Cohen et al., 2017; IHME, 2022; US-EPA, 2020a; WHO, 2021)
PM_{10}	All-cause mortality	IHD+DM+Str+COPD+LRI+LC	7930 (95% C.I. 7220-8700)	(IHME, 2022; US-EPA, 2020b; WHO, 2021)
$PM_{2.5}$	All-cause mortality	IHD+DM+Str+COPD+LRI+LC	7930 (95% C.I. 7220-8700)	(Cohen et al., 2017; IHME, 2022; US-EPA, 2020b; WHO, 2021)
Radon	Lung cancer		593 (95% C.I. 547-638)	(IHME, 2019, 2022; WHO, 2010)
Sulphur dioxide	All-cause mortality	COPD	962 (95% C.I. 96.2-9620)[e]	(IHME, 2022; US-EPA, 2017; WHO, 2021)

[a] Abbreviations. LC: Lung Cancer; COPD: Chronic Obstructive Pulmonary Disease; LRI: Lower Respiratory Infections; URI: Upper Respiratory Infections; IHD: Ischaemic Heart Disease; DM: Diabetes Mellitus; Str: Stroke.
[b] Values to 3 Sig. Figs.; . DALYs/10^5 person/year
[c] With uncertainty unavailable for the central estimates, the Global Burden of Disease asthma burden geometric standard deviation squared (GSD^2 1.3) was utilized to approximate variability.
[d] Age-standardised global burden of disease for asthma.
[e] Chose an uncertainty factor of 10 to reflect the uncertainty in the attributed all-cause health outcome.

Table 4.7: Damage factors, DF_k, DALY/case, from epidemiology research*

Contaminant and health outcome	Median	GSD
Acrolein_{asthma}	0.575	1.23
$\text{Benzene}_{leukaemia}$	34.7	1.14
$\text{Formaldehyde}_{Added\ effects}$	21.5	1.21
Mold_{asthma}	0.574	1.23
$\text{Nitrogen dioxide}_{All-cause\ mortality}$	4.82	1.14
$\text{Ozone}_{All-cause\ mortality}$	2.3	1.1
$\text{PM}_{10\,All-cause\ mortality}$	11.7	1.12
$\text{PM}_{2.5\,All-cause\ mortality}$	11.7	1.12
$\text{Radon}_{lung\ cancer}$	21.2	1.04
$\text{Sulphur dioxide}_{All-cause\ mortality}$	0.5	4.23

* Values to 3 Sig. Figs.

tality (deaths) reported for the same health outcomes. Uncertainty was not considered by any of these references.

Compared to previous air pollution burden of disease studies that included $PM_{2.5}$, PM_{10}, and O_3 (Fantke et al., 2019; Gronlund et al., 2015; Rojas-Rueda et al., 2019; Van Zelm et al., 2008, 2016), the DF proposed here align well, although differences arise from varying the health outcomes, summary metrics, demographics, and populations used.

This approaches differ from Logue et al. (2012), who considered harm and incidence estimates from previous air pollution studies rather than a health database. The updated damage factors will benefit researchers using older indoor air contaminant harm estimates (Chan et al., 2016; Fazli and Stephens, 2018; Logue et al., 2012; Zaatari et al., 2016).

4.4 Breathing Rates (BR)

Breathing rates represent the volume of air breathed (in m^3/person/year). An average human intake of 13 m^3/person/day is common in LCIA studies (Fantke et al., 2017b; Gronlund et al., 2015; Hauschild and Huijbregts, 2015; Van Zelm et al., 2016), based on 11.3 m^3 for women and 15.2 m^3 for men aged 19-65+ years (USEPA, 1997).

Accounting for updated data, a change is made for 14.8 m^3/person/day for adults aged 16-81+ years (95% CI 13.5-16.2), pooling long-term inhalation rates (Phillips and Moya, 2013; US-EPA, 2011). The median value is 5400 m^3/person/year (GSD 1.07), and aligns with current epidemiology-based studies (Fantke et al., 2017b; Gronlund et al., 2015; Hauschild and Huijbregts, 2015; Van Zelm et al., 2016). While more comprehensive research into understanding breathing exists (Del Negro et al., 2018; Layton, 1993), and activity-specific breathing rates exist (Paek and McCOOL, 1992), a population average value suffices here, as examining sensitivity to activity levels exceeds the scope of this harm-based analysis.

4.5 Dose-Response Factors ($DRF_{(k,i)}$)

Dose-response factors (DRFs) relate the contaminant intake quantity to potential health risk. DRFs can be derived through two main approaches:

- **Toxicology**-based DRFs use dose-response data from experimental toxicology studies, primarily on animals. A common toxicology dose-response metric is the ED50 - the effective dose resulting in a 50% response (mortality, morbidity). Animal ED50s are converted to human equivalent doses. The DRF represents the slope of the dose-response curve at low doses.
- **Epidemiology**-based DRFs use risk estimates from human population health studies. Relative risk (RR) estimates from cohort studies are commonly used. The DRF is calculated from the RR, reflecting the exposure-response relationship observed in the study population.

Toxicology DRFs provide controlled dose-response information but have uncertainty in animal-to-human extrapolation. Epidemiology DRFs reflect real-world human exposures but are limited to available health studies. Using both approaches provides complementary evidence on contaminant toxicity for assessing health risks and impacts.

4.5.1 DRF based on effective median dose

The $DRF_{(k,i)}$ represents a substance's toxicity component. It describes disease incidence change per intake unit via inhalation, often expressed

as cancer/non-cancer cases (k) per unit mass inhaled of contaminant (i) (cases/kg). The DRF takes as a point of departure the ED50 benchmark measure. The ED50 (median effective dose) is a metric of the human-equivalent lifetime daily dose per person, related to inhalation (intake) of a substance that produces a specific effect (carcinogenic or non-carcinogenic effects) in 50% of the population that is subject to that dose (Crettaz et al., 2002; Fantke et al., 2021a; Pennington et al., 2002).

For life cycle impact assessments (LCIAs), carcinogenic ED50 are obtained from toxicity databases, like the EPA's IRIS, the International Programme on Chemical Safety (IPCS), and the Carcinogenic Potency Database (CPDB). Non-carcinogenic ED50 are typically estimated by extrapolating from the no-observed adverse effect level (NOAEL) and lowest observed adverse effect level (LOAEL) (Huijbregts et al., 2005).

A review of the literature presented by Hauschild and Huijbregts (2015) and Hauschild et al. (2018) is performed to identify relevant LCIA databases compiling DRFs derived using an ED50. Three LCIA databases with inhalation DRFs for airborne contaminants were identified:

1. UNEP-SETAC consensus model for the evaluation of comparative toxicity "USEtox-2019" (Fantke et al., 2017a).
2. Globally Regionalized Life Cycle Impact Assessment Method "IMPACT WORLD+" (Bulle et al., 2019).
3. Life cycle impact (LCIA)-model "ReCiPe 2016" (Huijbregts et al., 2017).

From these three, USEtox® 2.0 (USEtox-2019 consensus toxicity model) was chosen because it is the most widely used and globally accepted model that is the default for screening contaminant toxicity in LCAs (Fantke et al., 2021a; Jolliet et al., 2018; Shaked et al., 2015a; Westh et al., 2015).

USEtox was screened to identify which of the 43 initial contaminants (prioritized by Logue et al., as discussed in Section 2.5.1.3) are included in it. Ammonia, Xylene (o), Manganese Mn(II), and Xylene (m/p) are absent from USEtox. Rosenbaum et al. (2008) provides a comprehensive explanation for the criteria governing the inclusion of contaminants in this database. It specifies that a contaminant may not be included due to reasons such as (a) lack of a consistent set of data, (b) data quality falling

below a specified minimum, and (c) inability to compute characterization factors for as many chemicals as possible.

The carcinogenicity class according to The International Agency for Research on Cancer (IARC) to the substances shown in USEtox can be found in Huijbregts et al. (2005). Radon information from Lecomte et al. (2014) and Reinoehl-Kompa and Grunst (2018).

Uncertainty factors for the $DRF_{k,i}$ are unavailable in USEtox®. Steps to assign uncertainty are shown in Huijbregts et al. (2005). $DRF_{k,i}$ uncertainty relates to extrapolating animal data to humans, time conversions, cancer/non-cancer effect conversions, and exposure route differences. By reviewing USEtox® and Huijbregts et al. (2005), uncertainty factors reflecting current research were provided for all contaminants as geometric standard deviation squared, since the parameter is log-normal. BAuA (2019) and Martin et al. (2013) were used to define following uncertainties: the interspecies conversion factor has an uncertainty of 1 for human, 4 for rat, 7 for mouse, 1.4 for dog, 2 for monkey, 2.4 for rabbit, and 3 for guinea pig via inhalation. The duration of exposure factor is 1 for chronic, 4 for semi-chronic, and 24 for acute/sub-acute exposures. The cancer effect conversion has an uncertainty of 47. The non-cancer effect conversion (NOAEL/LOAEL to ED50) has uncertainties of 9 (NOAEL) and 18 (LOAEL). A conservative approach was used for inorganic substances to account for additional uncertainty with specific element ions (Huijbregts et al., 2005).

USEtox® has toxicological evidence for 38 of the 44 selected contaminants (Section 3.1). Accounting for radiological pollution via Radon, yields 39 contaminants. Table 4.8 presents medians and their deviation for 32 carcinogens and 27 non-carcinogens (See Appendix 6 and 7 for full descriptive statistics). Contaminants labeled carcinogenic in USEtox via inhalation, were considered human carcinogens although, the endpoint ED50 associated to a cancer effect is usually extrapolated from animal tests.

Typical cancer DRF uncertainty factors were 4 and 7, reflecting inter species conversion uncertainty. Some had up to 47, mainly from cancer effect conversion uncertainty. Non-cancer DRF typical uncertainty factor was 16 and 18, maximum 94, primarily from NOEL/LOEL to ED50 conversion uncertainty.

The literature on human-toxicological effect and damage factors of car-

Table 4.8: Dose-response Factors, $DRF_{(k,i)}$, DALY/kg, for cancer and non-cancer effects, via inhalation.[+]

CAS RN	Contaminant$_i$	DRF$_{(cancer,i)}$		DRF$_{(non-cancer,i)}$	
		Median	GSD	Median	GSD
75-07-0	Acetaldehyde	0.0043	3	0.0039	6.9
107-02-8	Acrolein			4.3	7.6
107-13-1	Acrylonitrile	0.13	1	0.033	9.3
71-43-2	Benzene	0.015	1	0.0021	3
100-44-7	Benzyl chloride	0.0096	5.2		
106-99-0	1,3-Butadiene	0.056	1	0.009	8.8
111-76-2	2-Butoxyethanol	0.00042	4.1	0.0027	4.5
22537-48-0	Cadmium Cd(II)	0.17	7.8	1.4	6.4
75-15-0	Carbon disulfide			0.26	1
56-23-5	Carbon tetrachloride	0.037	4.1	0.035	7
78-87-3	Chloromethane			0.00024	16
18540-29-9	Chromium Cr(VI)	1.1	10	0.7	9.5
123-73-9	Crotonaldehyde(trans)	0.13	3.4		
106-93-4	1,2-Dibromoethane	0.41	2.8	0.00063	7.6
106-46-7	1,4-Dichlorobenzene	0.0025	4.1	0.00033	5.7
107-06-2	1,2-Dichloroethane	0.0079	2.9		
75-35-4	1,1-Dichloroethene	0.02	4.2	0.0014	7.5
64-17-5	Ethanol	0.00006	3.4		
104-76-7	2-Ethylhexanol	0.00036	4.8		
50-00-0	Formaldehyde	0.61	2.9	0.0011	6.2
87-68-3	Hexachlorobutadiene	0.0081	3.5		
110-54-3	Hexane	0.00002	4.3	0.0012	6.9
78-79-5	Isoprene	0.0026	4.1		
5989-27-5	Limonene (d-...)	0.0027	3.3		
109-86-4	2-Methoxyethanol			0.0026	6.4
80-62-6	Methyl methacrylate			0.046	3
1634-04-4	Methyl tert-butyl ether	0.0022	2.9	0.0001	6.3
75-09-2	Methylene chloride	0.00064	4.3	0.0028	6.3
91-20-3	Naphthalene	0.042	2.8	0.005	7.3
10028-15-6	Ozone	0.37	4.3		
10043-92-2	Radon[*]	0.052	1.1		
100-42-5	Styrene	0.028	2.9	0.0015	7.1
79-34-5	1,1,2,2-Tetrachloroethane	0.015	4.9		
127-18-4	Tetrachloroethene	0.0028	4.4	0.0023	8.8
100-88-33	Toluene			0.00079	5.1
79-00-5	1,1,2-Trichloroethane	0.011	4.6	0.0083	9.1
79-01-6	Trichloroethylene	0.00098	2.9		
75-01-4	Vinyl chloride	0.11	2.8	0.0098	6.3
1330-20-7	Xylenes	0.00018	3.3	0.0009	7.1

[+] Values to 2 Sig. Figs.
[*] case/10^{-9}Bq; Bq, Becquerels

cinogenic and non-carcinogenic chemicals for life cycle impact assessment indicates that Huijbregts et al. (2005) remains the most relevant study, influencing the developing of USEtox® 2.0 model. Here, advances are done for that study, by assigning new uncertainty factors for the selected contaminants.

4.5.2 DRF based on risk estimates

The dose response factor ($DRF_{(k,i)}$) describes cases per intake mass, and from an epidemiology approach, equals a concentration response factor (CRF) divided by breathing rate (BR) (Equations 3.29 and 3.30). The $CRF_{(k,i)}$ quantifies incidence rate (k) per concentration of contaminant (i). The CRF is a function of the beta parameter (the risk estimate), baseline incidence rate, and concentration. For expected indoor air concentrations, the CRF is approximately linear. Consequently, CRFs and DRFs are estimated for the 10 contaminants with epidemiology research identified in Section 4.1 and their corresponding best estimate of all-cause (Table 4.9 and Table 4.10) (Also, see Appendix 8 and 9 for full descriptive statistics).

Table 4.9: Description for Concentration-Response Factors, CRF_i, case/µg/m^3/10^5 person/year.$^+$

Acronym	**Contaminant$_i$**	**CAS RN**	**All cause health outcome**	**Median**	**GSD**
C_3H_4O	Acrolein	107-02-8	Asthma morbidity	2	5.1
C_6H_6	Benzene	71-43-2	Leukaemia mortality	0.0018	1.4
HCHO	Formaldehyde	50-00-0	Asthma morbidity plus Leukaemia mortality and Lung cancer mortality	0.23	4.2
	Mold		Asthma morbidity	0.048*	2.1
NO_2	Nitrogen dioxide	10102-44-0	All-cause mortality	1.2	1.7
O_3	Ozone	10028-15-6	All-cause mortality	0.54	1.9
	PM_{10}	*NA*	All-cause mortality	2.6	1.3
	$PM_{2.5}$	*NA*	All-cause mortality	5.1	1.2
Rn	Radon	10043-92-2	Lung cancer mortality	0.021**	1.7
SO_2	Sulphur dioxide	10043-92-2	All-cause mortality	3.8	1.3

$^+$ Values to 2 Sig. Figs.
* case/CFU/m^3/10^5 person/year; CFU, Colony-Forming Units
** case/Bq/m^3/10^5 person/year; Bq, Becquerels

$PM_{2.5}$ has the highest median and disease incidences per unit of exposure concentration or mass intake. This represents the $PM_{2.5}$ - associated annual mortality rate per µg/m^3 or kg inhaled for all-cause mortality, all ages, both sexes, and global location. Uncertainty reflects input uncertainties modeled via the Monte Carlo simulation. Acrolein and formaldehyde have the largest uncertainties, reflecting the influence of age distribution when selecting appropriate asthma incidence descriptors in children. CRF and

Table 4.10: Description for Dose-Response Factors, DRF_i, case/kg.$^{+}$

Contaminant$_i$	**Median**	**GSD**
Acrolein	3.8	5.3
Benzene	0.0033	1.4
Formaldehyde	0.43	4.1
Mold	0.088*	2.1
Nitrogen dioxide	2.2	1.7
Ozone	1	1.9
PM_{10}	4.7	1.3
$PM_{2.5}$	9.5	1.2
Radon	0.04**	1.7
Sulphur dioxide	7	1.4

$^{+}$ Values to 2 Sig. Figs. See Table 4.9 for acronyms, CAS and health outcomes
* case/10^{-9}CFU; CFU, Colony-Forming Units
** case/10^{-9}Bq; Bq, Becquerels

DRF uncertainty factors were similar since breathing rate uncertainty was negligible compared to other inputs.

Two relevant aspects are the interpretation of a linear low-dose relationship yielding concentration-independent parameters, unlike previous analyses, and the novel use of all-cause estimates, whereas previous work dealt with specific mortalities (Fantke et al., 2019; Gronlund et al., 2015; Logue et al., 2012; Van Zelm et al., 2008, 2016).

4.6 Age-Dependent Adjustment Factors (ADAF)

Application of age-dependent adjustment factors (ADAFs) to dose response factors is recommended when estimating cancer risks based on age at exposure (U.S. Environmental Protection Agency (EPA), 2023). Higher ADAF values are used for early life exposures to reflect increased lifetime cancer risks (OEHHA, 2009). USEPA suggests the use of ADAF as: (i) 10-fold for exposures before 2 years of age (ii) 3-fold for exposures between 2 and <16 years (iii) 1 for exposures after age 16. These recommendations from EPA

(2005) remain widely applied, including in recent epidemiology-based effect factors (OEHHA, 2009). The recommended ADAF estimate is 1.6 (95% CI 1-10). After using parameter distribution, the ADAF has a median 0.63 (GSD 3.7).

4.7 Effect Factors ($EF_{(k,i)}$)

An effect factor combines a dose-response factor and a damage factor, describing harm (k) change per contaminant (i) intake unit, typically as DALY/kg (Equation 3.11). Existing LCIA methodologies have used DALYs to quantify airborne contaminant chronic health impacts (Hauschild et al., 2018). Effect factors are central in LCIA characterization. They can be derived from epidemiological data like risk estimates, termed epidemiology-based effect factors, or from toxicological data such as the median effective dose (ED50), called toxicology-based effect factors. LCIA applies effect factors from either domain.

4.7.1 Toxicology-Based Effect Factors

Toxicology-based effect factors (EFs) combine dose-response factors (DRFs, cancer or non-cancer cases/kg inhaled) from animal studies with damage factors (DFs, DALY/case) representing human disease burdens. EFs represent the cancer and non-cancer effects from inhaling a contaminant. The EF integrates the DRF describing a substance's toxicity and the DF quantifying associated harm, first presented by Rosenbaum et al. (2008), and relevant for LCIAs (Fantke et al., 2021a; Jolliet et al., 2018). Among the 44 contaminants, 33 have carcinogenic effects and 27 have non-carcinogenic effects. Tables 4.11 and 4.12 present the median EFs, distribution uncertainty as geometric standard deviation (GSD), and associated health outcomes for cancer, non-cancer, and combined effects. A specific cancer was assigned to each contaminant's effect factor based on references identifying carcinogenic outcomes (Huijbregts et al., 2005; Tran et al., 2020; Turiel, 2012). Median cancer EFs range from 10^{-4} to 10^{1} DALY/kg (see Table 4.11, and Appendix 10). Most are higher than Huijbregts et al. due to USEtox® DRF's linear constant and ED50 changes (Fantke et al., 2017a). Formaldehyde has the highest median, consistent with previous VOC emission impact studies (Laurent and Hauschild, 2014).

Table 4.11: Estimates for carcinogenic Effect Factors, $EF_{cancer,i}$, DALY/kg.[+]

CAS RN	Contaminant	Median	GSD	Health outcome
75-07-0	Acetaldehyde	0.09	2.9	Lung Cancer
107-13-1	Acrylonitrile	2.7	1	Lung Cancer
71-43-2	Benzene	0.51	1.1	Leukemia
100-44-7	Benzyl chloride	0.19	4.8	Stomach Cancer
106-99-0	1,3-butadiene	0.6	1.1	Cancer Average
111-76-2	2-Butoxyethanol	0.01	4.1	Liver Cancer
22537-48-0	Cadmium Cd(II)	3.5	13	Lung Cancer
56-23-5	Carbon tetrachloride	0.92	4.4	Liver Cancer
18540-29-9	Chromium Cr(VI)	23	7.8	Lung Cancer
123-73-9	Crotonaldehyde(trans)	3.1	3.4	Liver Cancer
106-93-4	1,2-Dibromoethane	10	2.9	Liver Cancer
106-46-7	1,4-Dichlorobenzene	0.028	4.4	Cancer Average
107-06-2	1,2-Dichloroethane	0.15	2.9	Stomach Cancer
75-35-4	1,1-Dichloroethene	0.43	4.2	Lung Cancer
64-17-5	Ethanol	0.0015	3.4	Liver Cancer
104-76-7	2-Ethylhexanol	0.0086	4.3	Liver Cancer
50-00-0	Formaldehyde	21	2.9	Leukemia+Lung Cancer
87-68-3	Hexachlorobutadiene	0.086	3.7	Cancer Average
110-54-3	Hexane	0.00025	4.9	Cancer Average
78-79-5	Isoprene	0.027	4.3	Cancer Average
5989-27-5	Limonene (d-...)	0.028	3.7	Cancer Average
1634-04-4	Methyl tert-butyl ether	0.074	3	Leukemia
75-09-2	Methylene chloride	0.0067	4.3	Breast Cancer
91-20-3	Naphthalene	0.87	2.9	Lung Cancer
10028-15-6	Ozone	7.9	4.5	Lung Cancer
10043-92-2	Radon	1.1[*]	1.1	Lung Cancer
100-42-5	Styrene	0.3	2.9	Breast Cancer
79-34-5	1,1,2,2-Tetrachloroethane	0.39	4.4	Liver Cancer
127-18-4	Tetrachloroethene	0.1	4.1	Leukemia
79-00-5	1,1,2-Trichloroethane	0.26	4.7	Liver Cancer
79-01-6	Trichloroethylene	0.01	2.8	Cancer Average
75-01-4	Vinyl chloride	2.7	2.8	Liver Cancer
1330-20-7	Xylenes	0.0027	3.3	Mouth And Oropharynx Cancer

[+] Values to 2 Sig. Figs.
[*] DALY/10^{-9}Bq; Bq, Becquerels

Median non-carcinogenic EFs range from 10^{-4} to 10^{2} DALY/kg inhaled. Table 4.12 (and Appendix 11) shows the non-carcinogenic EFs, lower than Huijbregts et al. due to lower average non-cancer damage factors. The 2019 GBD study had a cancer DF of 10.6 versus 11.5 in 1990, and a non-cancer DF of 0.6 versus 2.7 in 1990. The lower non-cancer DFs combined with dose-response changes give lower non-cancer EFs, demonstrating DF influence. Acrolein has the highest median, consistent with previous research (Laurent and Hauschild, 2014). Most contaminants use an average non-cancer effect given insufficient evidence to assign a single outcome. Asthma

was identified as the main non-cancer effect for acrolein and formaldehyde based on epidemiology data; see Table 4.1.

Table 4.12: Estimates for Non-carcinogenic Effect Factors, $EF_{non-cancer,i}$, DALY/kg.$^{+}$

CAS RN	Contaminant	Median	GSD	Health outcome
75-07-0	Acetaldehyde	0.0088	6.9	Non-Cancer Average
107-02-8	Acrolein	2.4	7.2	Asthma
107-13-1	Acrylonitrile	0.068	7.6	Non-Cancer Average
71-43-2	Benzene	0.0043	2.8	Non-Cancer Average
106-99-0	1,3-butadiene	0.018	6.6	Non-Cancer Average
111-76-2	2-Butoxyethanol	0.0054	4.4	Non-Cancer Average
22537-48-0	Cadmium Cd(II)	2.8	5.2	Non-Cancer Average
75-15-0	Carbon disulfide	0.54	1.1	Non-Cancer Average
56-23-5	Carbon tetrachloride	0.069	6.6	Non-Cancer Average
78-87-3	Chloromethane	0.00049	10.	Non-Cancer Average
18540-29-9	Chromium Cr(VI)	1.5	10	Non-Cancer Average
106-93-4	1,2-Dibromoethane	0.0012	5.7	Non-Cancer Average
106-46-7	1,4-Dichlorobenzene	0.00068	6.2	Non-Cancer Average
75-35-4	1,1-Dichloroethene	0.0028	6.5	Non-Cancer Average
50-00-0	Formaldehyde	0.00066	7.4	Asthma
110-54-3	Hexane	0.0024	6.9	Non-Cancer Average
109-86-4	2-Methoxyethanol	0.0051	6.5	Non-Cancer Average
80-62-6	Methyl methacrylate	0.095	2.9	Non-Cancer Average
1634-04-4	Methyl tert-butyl ether	0.00021	6.4	Non-Cancer Average
75-09-2	Methylene chloride	0.0059	6.4	Non-Cancer Average
91-20-3	Naphthalene	0.011	7.9	Non-Cancer Average
100-42-5	Styrene	0.0029	6.8	Non-Cancer Average
127-18-4	Tetrachloroethene	0.0047	6.9	Non-Cancer Average
100-88-33	Toluene	0.0016	5.4	Non-Cancer Average
79-00-5	1,1,2-Trichloroethane	0.016	6.9	Non-Cancer Average
75-01-4	Vinyl chloride	0.02	7.7	Non-Cancer Average
1330-20-7	Xylenes	0.0018	7.2	Non-Cancer Average

$^{+}$ Values to 2 Sig. Figs.

Adding the individual EFs ($EF_{k,i}$) gives the all-cause effect factors (EF_i) (Equation 3.18). Table 4.13 presents the combined toxicology-based EFs for 39 total contaminants ordered by magnitude of their median (See Appendix 12 for full descriptive statistics). Chromium (VI) has the highest median, formaldehyde is highest among VOCs, and ozone is also elevated. Uncertainty is lower than Huijbregts et al. (2005).

Typical uncertainty is a factor of 5 for cancer EFs and 15 for non-cancer, stemming from DRF, DF, and age-adjustment (ADAF) uncertainties. DRF uncertainty relates to animal-to-human extrapolation, time/exposure conversions, and effect conversions. DF uncertainty reflects evolving global disease burden knowledge.

Table 4.13: All-cause toxicology-based Effect Factors, EF_i, DALY/kg.[+]

Contaminant	**Median**	**GSD**
Chromium Cr(VI)	31	8.8
Formaldehyde	13	5.2
Cadmium Cd(II)	10	12
1,2-Dibromoethane	6.2	6
Ozone	4.8	6.2
Acrolein	2.4	7.2
Acrylonitrile	2.1	4.2
Crotonaldehyde(trans)	2	6.3
Vinyl chloride	1.8	5
Carbon tetrachloride	0.97	6.4
Radon	0.68[*]	3.7
Naphthalene	0.66	5.3
Carbon disulfide	0.54	1.1
1,3-butadiene	0.48	3.6
Benzene	0.32	3.9
1,1-Dichloroethene	0.29	6.7
1,1,2-Trichloroethane	0.28	6
1,1,2,2-Tetrachloroethane	0.24	6.2
Styrene	0.21	5.7
Benzyl chloride	0.12	6.6
Tetrachloroethene	0.1	5.2
Acetaldehyde	0.097	4.6
1,2-Dichloroethane	0.096	5.9
Methyl methacrylate	0.095	2.9
Hexachlorobutadiene	0.054	7.4
Methyl tert-butyl ether	0.048	5.7
1,4-Dichlorobenzene	0.022	7.6
2-Butoxyethanol	0.019	4.8
Methylene chloride	0.019	5.2
Limonene (d-...)	0.018	5.9
Isoprene	0.017	6.9
Xylenes	0.0066	6
Trichloroethylene	0.0064	5.4
2-Ethylhexanol	0.0053	6.8
2-Methoxyethanol	0.0051	6.5
Hexane	0.0034	6.6
Toluene	0.0016	5.4
Ethanol	0.00091	6.1
Chloromethane	0.00049	10

[+] Values to 2 Sig. Figs.
[*] DALY/10^{-9}Bq; Bq, Becquerels

When ranked by median values, contaminants with the highest carcinogenic and non-carcinogenic effects largely match those identified by Huijbregts et al. (2005). A similar consistency emerges when comparing all-cause effect factors, which account for age-adjustment, with estimates from Logue et al. (2012). Uncertainties around carcinogenic, non-carcinogenic and combined effect factors prove narrower here than in the study of Huijbregts et al., and therefore that of Logue et al. too. This is due to lower uncertainties in dose-response and damage factors, both gleaned from data published in the past decade. These updated figures for toxicology-based cancer and non-cancer effects enhance earlier work on life-cycle impact assessments, by Fantke et al. (2019) and Huijbregts et al. (2005). The analysis shows the benefit of using current dose-response and disease-burden data to reduce uncertainties. Compared with the Logue et al. values from 2012, estimates of the median all-cause effect factors are higher for 27 contaminants by an order of magnitude, yet lower for eight. This is because of new GBD data, a revised 0.5 value for ED50 toxicity, updated ED50s in databases, and newly proposed cancer/non-cancer effects for some contaminants. Overall, Logue et al.'s results underestimate effects when compared with the newer data given here. The age-adjustment factor also strongly sways combined estimates. Logue et al.'s mean ADAF of 1.6 contrasts with the log-normal distribution applied here, with the same mean but a lower median of 0.6. This depresses median carcinogenic effects.

Some contaminants now account for both cancer and non-cancer effects, whereas previously only one was known. This, too, can increase median outputs. These effect factors take median effective doses (ED50) from toxicology studies as their starting point, which allows their application for indoor or outdoor exposures. USEtox assumes a linear low-dose response for contaminant-specific lifetime doses of up to a 0.5 lifetime disease probability, which is standard for life-cycle impact assessments. The toxicological approach assumes linearity for inhalation doses of airborne contaminants that remain below the contaminant-specific lifetime dose, as reported in the USETox database. Carcinogenic and non-carcinogenic effects are presented separately for use in LCA. Though toxicology databases feature in LCA analyses, their DALY outputs relied on 1990s data and the methodology of Huijbregts et al. (2005), which has been changed. This update represents an improvement. Limitations of the toxicology-based harm approach followed stem from toxicity database reliance, critical effect choices, ED50 availability, publication bias, animal-to-human uncertainty, dose-response assumptions, and updates proposed by the LCIA bibliography. Further

work should examine multiple toxicity data sources, evaluate alternative critical effects, and explore non-linear dose-response.

4.7.2 Epidemiology-Based EFs

Epidemiology-based effect factors ($EF_{k,i}$) utilize concentration-response functions from risk estimates from human health studies, for a particular health outcome (k) from a specific contaminant (i). This allows epidemiology EFs to be derived using real-world human exposure-response data. However, the lack of availability of cohort studies limits contaminants with epidemiology EFs.

Table 4.14 shows the median epidemiology EFs ranked by their magnitude (with mold and radon moved to the end given their different dimensions) (see Appendix 13 for full descriptive statistics). $PM_{2.5}$ has the highest EF, an order above other contaminants, indicating the greatest potential health impact per kg inhaled. Formaldehyde has the highest EF for VOCs, with NO_2 third highest overall.

Table 4.14: All-cause epidemiology-based Effect Factors, EF_i, DALY/kg.[+]

Contaminant	**Median**	**GSD**
$PM_{2.5}$	110	1.2
PM_{10}	55	1.3
Nitrogen dioxide	10	1.7
Formaldehyde	7.3	2.2
Sulphur dioxide	3.5	4.3
Ozone	2.3	1.9
Acrolein	2.1	5
Benzene	0.11	1.4
Mold	0.051[*]	2.2
Radon	0.84[**]	1.7

[+] Values to 2 Sig. Figs.
[*] DALY/10^{-9}CFU; CFU, Colony-Forming Units
[**] DALY/10^{-9}Bq; Bq, Becquerels

The approach of Logue et al. implicitly used epidemiology-based EFs. By comprehending the interconnections among the equations and parameter properties detailed in Section 3, it becomes possible to reverse-engineer the statistical descriptors for the parameters not explicitly shown by other works. At this juncture, the focus is on the effect factors, enabling a comparison with the epidemiology-based harm approach adopted here.

For $PM_{2.5}$, the median EFs broadly agree with Logue et al., likely due to similar all-cause mortality representations. For O_3, EFs are higher here because the damage factor for ozone applied is one order of magnitude higher. Logue et al.'s NO_2 and SO_2 estimates used available acute data treated as chronic, giving at least a two order of magnitude difference. Overall, two factors influence differences between the IND method and epi-harm approach: first, underlying epidemiology has evolved, suggesting contaminants are more harmful; second, data manipulation differs. The latter refers to parameter probability distribution functions - log-normal here versus Logue et al.'s fitted normal, log-normal, and Weibull. It also involves truncating distributions, and convergence criteria use. The present decisions are justified based on current best knowledge and practice.

LCIAs of O_3, PM_{10}, and $PM_{2.5}$ have been performed (Fantke et al., 2019; Gronlund et al., 2015; Oberschelp et al., 2020; Van Zelm et al., 2008, 2016). Some of these studies presented mean/median EFs explicitly, with and without uncertainty, for all-cause or cause-specific mortality. When parameter descriptors where not shown, they were quantified from the results given in each study. All these references have one thing in common: the approach towards the effect factor is dependent on a background concentration, which could represent a weakness because EFs are sensitive toward fixed contaminant background concentrations (Fantke et al., 2019; Oberschelp et al., 2020). Conversely, background concentrations are not required here.

General overlap is observed between this and previous works, but inconsistencies exist. Ideally, harm related effects for a contaminant should align across studies. However, differences arise due to varied analytical choices influencing uncertainty, including: C-R function, health outcomes, central tendency metrics, spatial/population resolution, breathing rates, background concentrations, and methodological frameworks.

Epidemiology-based effect factors provide unique human evidence on contaminant impacts. Effect factors were derived per current life cycle impact assessment practice, reporting dose-response and disability-adjusted life year factors. However, limitations exist. A linear concentration-response function was assumed given the expected low-moderate exposure levels. Only epidemiology on the specific contaminant was used, avoiding cross-contaminant toxicity assumptions. Pooling risk and health estimates across demographics was done, although stratification can influence results. Re-

liance on cohort studies restricts anaysis to contaminants with available data. Use of all-cause mortality may underestimate chronic effects. Outdoor air studies are relied upon pending more indoor epidemiology.

Particulate matter assumes equitoxicity despite different compositional factors. Additional epidemiological research would reduce uncertainties, especially on particulate matter toxicity mechanisms and demographically-stratified analyses to capture exposure differences. Long-term studies showing chronic effects accounting for PM composition are also needed. While limited by the available data, these initial epidemiology-based factors offer complementary evidence and insights into human health impacts.

4.8 SWOT Analysis

A comparative SWOT (strengths, weaknesses, opportunities, and threats) analysis is performed for each parameter to assess the updated methodology's validity and relevance for quantifying indoor air contaminants harm (Ghazinoory et al., 2011). This evaluation examines interrelations between the approach's internal and external factors. Table 4.15 summarizes the analysis.

The epidemiology-based approach relies heavily on available concentration-response data to derive effect factors, a key limitation. However, the use of pooled results accounts for variability. While curated data is ideal for accuracy, limited availability for certain pollutants or outcomes may cause inaccuracies. The toxicology-based approach utilizes regularly updated expert-reviewed databases, providing current dose-response information. However, lack of standardized procedures to combine cancer and non-cancer effects introduces uncertainty.

A shared strength among the parameters is updated literature-based parameter data, enhancing outputs for policymakers. Reduced uncertainty compared to previous methods is advantageous. Uncertainty representation also aids interpretation of central tendencies and distributions. As databases evolve, parameter updates are enabled. The subjectivity of assumptions is a core weakness. Transparency in documenting assumptions improves reproducibility. Overall, the methodology can produce the necessary parameters to quantify indoor contaminant harm. The SWOT analysis will guide improvements in future work.

Table 4.15: SWOT analysis of updated methodology and recommended parameters.

Parameter	Strengths	Weaknesses	Opportunities	Threats
Effect factor $EF_{(k,i)}$	Expert-guided methodology	Method variability	Continuous updates To enrich datasets Demographic adaptability	Database discrepancies Subjective distribution assumptions Disease-contaminant misalignment
ADAF	Uncertainty management	Limited population representativeness		Subjective distribution assumptions
Dose response factor $DRF_{(k,i)}$	Expert-guided methodology	Expert recommendation discrepancies		Database discrepancies Subjective distribution assumptions Disease-contaminant misalignments
Breathing rate	Uncertainty management	Limited population representativeness		Subjective distribution assumptions
Damage Factor DF_k and Baseline incidence γ_{0_k}	Robust databases Confident uncertainty	Chosen data time scope		Disease-contaminant misalignments
Beta $\beta_{(k,i)}$	Effective risks pooling Confident uncertainty Significant chronic effects Strong epidemiological linkage	Linear assumption Generalized assessment Context limitations Time scope constraints		Heterogeneity health outcomes Single-Reference Endpoints

4.9 Summary

Epidemiological evidence was found for 10 contaminants: acrolein, benzene, mold, formaldehyde, nitrogen dioxide, ozone, PM_{10}, $PM_{2.5}$, radon, and sulphur dioxide. A representative health outcome was identified for each, chosen as the most reported endpoint. This enabled developing epidemiology-based effect factors relating harm to intake mass (DALY/kg) using risk estimates, baseline rates, and damage data. A linear exposure-response function modeled the low-concentration regime. $PM_{2.5}$ had the highest median harm per unit mass.

This work presents carcinogenic and non-carcinogenic toxicology-based effect factors for 39 indoor contaminants. Formaldehyde has the highest median carcinogenic factor. Compared to previous estimates, carcinogenic factors are higher but with reduced uncertainty. Acrolein has the highest non-carcinogenic factor. These are lower than previous estimates but with lower uncertainty.

An integrated methodology has been developed to derive needed parameters for modeling harm, readily applicable in health risk and life cycle assessments. Major strengths include accounting for parameter uncertainties. Key limitations are assumptions required to derive data.

Chapter 5

The Harm Intensity

The contents of Sections 5.4 and 5.5 are part of the publication:

Morantes, G., Jones, B., Sherman, M., & Molina, C. (2023). Harm from residential indoor air contaminants. *Environmental Science & Technology*. Article ASAP DOI: 10.1021/acs.est.3c07374

5.1 Introduction

LCIA use effect factors (EFs) in units of DALY/kg as a step to quantify harm from air contaminants, as the mass emitted is the metric of interest (Section 2.4.2). However, relating total harm to contaminant exposure better evaluates potential population impacts in indoor settings.

Concentration and exposure length influence harm (Hess-Kosa, 2018). Existing IAQ metrics, like limit values, rely on concentrations (Hess-Kosa, 2018; WHO, 2021) but do not directly consider health risks, rather they advise on exceeding limits. To address this, a new harm-based metric called **Harm Intensity** (**HI**) is introduced, linking chronic harm (DALY/person/year) to contaminant concentrations (typically µg/m^3). Therefore, for airborne contaminant (i), HI_i has units of DALY/µg/m^3/person/year. This is equivalent to the EPA's inhalation unit risk relating cancer risk to exposure concentration (Agency, 2015).

Literature on ventilation and IAQ has connected DALYs per concentration unit (Guyot et al., 2019; Sherman et al., 2012) and $PM_{2.5}$ in LCAs (Gronlund et al., 2015; Oberschelp et al., 2020). However, the HI concept has

not been explicitly defined before. HI relates contaminant exposure to estimated harm, enabling the identification of the most harmful contaminants that can be prioritized for control when chronic concentrations are known.

Two evidence domains guide HI derivation: epidemiology and toxicology research on air contaminant health impacts. The following sections discuss defining HI based on each approach.

5.2 A toxicology-based Harm Intensity, HI_i.

This work reviewed relevant LCIA literature to identify current, data sources for key parameters deriving the harm intensity. Examining prominent bibliographies (Hauschild and Huijbregts, 2015; Hauschild et al., 2018) provided insights into sources widely used by experts. Search terms and criteria from these studies enabled the retrieval of up-to-date information.

For damage factors, the 2019 Global Burden of Disease study offered extensive data on disease statistics (IHME, 2022; Murray et al., 2020). For toxicology-based dose-response factors, the USEtox consensus model served as the leading toxicity evaluation reference (Fantke et al., 2017a). US-EPA (2011) data was fundamental to derive an adult breathing rate of 14.8 m^3/person/day. Age-dependent adjustment factors for cancer risk estimations were used, as recommended by EPA (2005). An outline of the relationship between these parameters to obtain a toxicology-based harm intensity is given in Figure 5.1.

Figure 5.2 is a visual representation of the analytical model employed to estimate the toxicology-based harm intensity. It is a more detailed version of Figure 5.1.

Harm intensities following the tox-harm approach were calculated for 39 contaminants commonly found in dwellings (see Sections 3.3, 4.7.1). Single-point median harm intensities (DALY/µg/m^3/10^5 person/year), uncertainty estimates expressed through the Geometric Standard Deviation (GSD) (Section 3.8.1) and the best estimate for all-cause effect (Section 4.1) are shown in Table 5.3, ordered from highest to lowest median. To be consistent with current practice in LCA (LCA), Tables 5.1 and 5.2 show the single-point estimates and uncertainties for harm intensities dis-aggregated per carcinogenic ($HI_{cancer,i}$) and noncarcinogenic ($HI_{noncancer,i}$) effects, re-

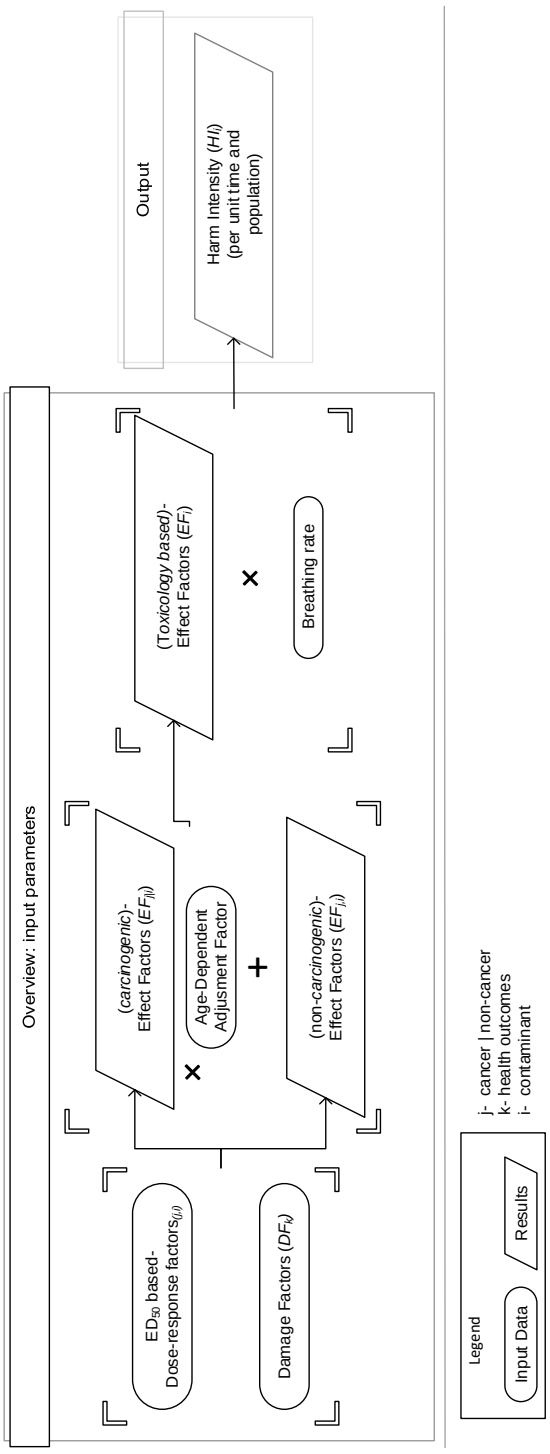


Figure 5.1: Overview of parameters used to determine a toxicology-based harm intensity, HI_i, DALY/µg/m^3/person/year.

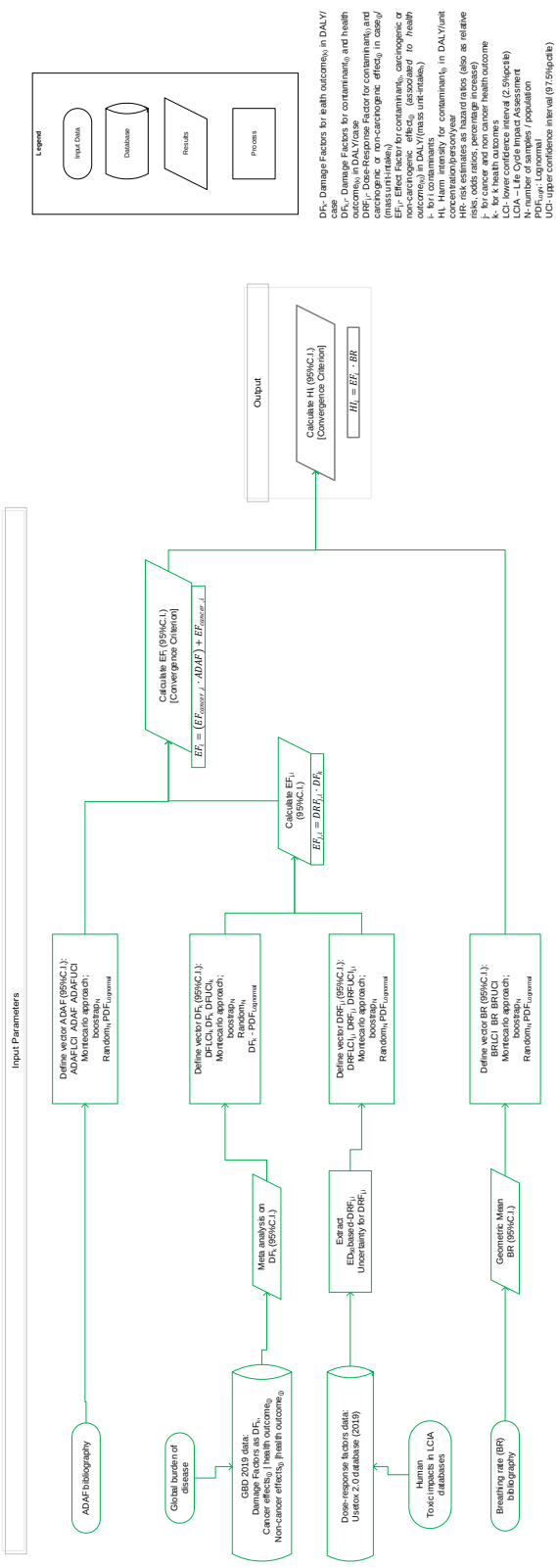


Figure 5.2: Analytical Flow Chart for Toxicology-Based Harm Intensity, HI_i, DALY/µg/m^3/person/year.

spectively (see Appendices 14, 15, 16 for full descriptive statistics).

Table 5.1: Toxicology-based cancer HI_i, DALY/µg/m^3/10^5 person/year.$^+$

CAS RN	Contaminant	Median	GSD	Health outcomeS
75-07-0	Acetaldehyde	0.048	2.9	Lung Cancer
107-13-1	Acrylonitrile	1.5	1.1	Lung Cancer
71-43-2	Benzene	0.27	1.2	Leukemia
100-44-7	Benzyl chloride	0.1	4.5	Stomach Cancer
106-99-0	1,3-butadiene	0.32	1.1	Cancer Average
111-76-2	2-Butoxyethanol	0.0054	4.4	Liver Cancer
22537-48-0	Cadmium Cd(II)	1.9	10	Lung Cancer
56-23-5	Carbon tetrachloride	0.48	4	Liver Cancer
18540-29-9	Chromium Cr(VI)	13	8.5	Lung Cancer
123-73-9	Crotonaldehyde(trans)	1.7	3.3	Liver Cancer
106-93-4	1,2-Dibromoethane	5.3	2.8	Liver Cancer
106-46-7	1,4-Dichlorobenzene	0.015	4.2	Cancer Average
107-06-2	1,2-Dichloroethane	0.084	3	Stomach Cancer
75-35-4	1,1-Dichloroethene	0.23	4.1	Lung Cancer
64-17-5	Ethanol	0.0008	3.2	Liver Cancer
104-76-7	2-Ethylhexanol	0.0046	4.9	Liver Cancer
50-00-0	Formaldehyde	11	2.9	Leukemia+Lung Cancer
87-68-3	Hexachlorobutadiene	0.047	3.7	Cancer Average
110-54-3	Hexane	0.00013	4.8	Cancer Average
78-79-5	Isoprene	0.015	4	Cancer Average
5989-27-5	Limonene (d-...)	0.015	3.4	Cancer Average
1634-04-4	Methyl tert-butyl ether	0.041	2.8	Leukemia
75-09-2	Methylene chloride	0.0036	5.3	Breast Cancer
91-20-3	Naphthalene	0.47	2.9	Lung Cancer
10028-15-6	Ozone	4.2	4.2	Lung Cancer
10043-92-2	Radon*	0.6	1.1	Lung Cancer
100-42-5	Styrene	0.16	2.9	Breast Cancer
79-34-5	1,1,2,2-Tetrachloroethane	0.2	4.7	Liver Cancer
127-18-4	Tetrachloroethene	0.053	3.8	Leukemia
79-00-5	1,1,2-Trichloroethane	0.14	4.7	Liver Cancer
79-01-6	Trichloroethylene	0.0055	2.9	Cancer Average
75-01-4	Vinyl chloride	1.5	3	Liver Cancer
1330-20-7	Xylenes	0.0015	3.4	Mouth And Oropharynx Cancer

$^+$ Values to 2 Sig. Figs.
* DALY/Bq/m^3/10^5 person/year; Bq, Becquerels

Median HI_i have a range of five orders of magnitude from 10^{-4} to 10^1 DALY/µg/m^3/10^5 person/year, implying that some contaminants have 100,000 times the toxic effect of others. The contaminant with the highest median is chromium Cr(VI) ($HI_{Cr(VI)}$ 17; GSD 15), followed by formaldehyde (HI_{HCHO} 7.1; GSD 5.4).

Table 5.3 shows that ozone and acrolein are ranked within the first six most toxic contaminants. High HI_i are obtained for inorganic contaminants, VOCs, and ozone. Although these contaminants have high HI_i, a

Table 5.2: Toxicology-based non-cancer HI_i, DALY/µg/m^3/10^5 person/year.$^+$

CAS RN	Contaminant	Median	GSD	Health outcomeS
75-07-0	Acetaldehyde	0.0045	7	Non-Cancer Average
107-02-8	Acrolein	1.3	7.4	Asthma
107-13-1	Acrylonitrile	0.037	7.6	Non-Cancer Average
71-43-2	Benzene	0.0023	2.9	Non-Cancer Average
106-99-0	1,3-butadiene	0.0097	6.4	Non-Cancer Average
111-76-2	2-Butoxyethanol	0.0029	4.3	Non-Cancer Average
22537-48-0	Cadmium Cd(II)	1.5	5.6	Non-Cancer Average
75-15-0	Carbon disulfide	0.29	1.1	Non-Cancer Average
56-23-5	Carbon tetrachloride	0.038	6.3	Non-Cancer Average
78-87-3	Chloromethane	0.00027	12	Non-Cancer Average
18540-29-9	Chromium Cr(VI)	0.82	9.2	Non-Cancer Average
106-93-4	1,2-Dibromoethane	0.00068	6.2	Non-Cancer Average
106-46-7	1,4-Dichlorobenzene	0.00035	5.6	Non-Cancer Average
75-35-4	1,1-Dichloroethene	0.0016	6.6	Non-Cancer Average
50-00-0	Formaldehyde	0.00036	7.1	Asthma
110-54-3	Hexane	0.0013	7.1	Non-Cancer Average
109-86-4	2-Methoxyethanol	0.0027	7.1	Non-Cancer Average
80-62-6	Methyl methacrylate	0.05	2.8	Non-Cancer Average
1634-04-4	Methyl tert-butyl ether	0.0001	7.4	Non-Cancer Average
75-09-2	Methylene chloride	0.0031	7	Non-Cancer Average
91-20-3	Naphthalene	0.0056	7.4	Non-Cancer Average
100-42-5	Styrene	0.0016	6.9	Non-Cancer Average
127-18-4	Tetrachloroethene	0.0025	8.4	Non-Cancer Average
100-88-33	Toluene	0.00086	5.3	Non-Cancer Average
79-00-5	1,1,2-Trichloroethane	0.0095	8.4	Non-Cancer Average
75-01-4	Vinyl chloride	0.011	6.1	Non-Cancer Average
1330-20-7	Xylenes	0.001	6	Non-Cancer Average

$^+$ Values to 2 Sig. Figs.

representative measure of concentration must be assigned to quantify the magnitude of harm on the population.

Slightly different ranks when compared to the EF_i are observed in the full list, particularly for contaminants with median estimates of similar magnitudes (see section 4.7.1). Differences are attributed to the Monte Carlo (MC) randomization approach. GSDs of harm intensities and effect factors are almost identical, ranging from 1.1 for carbon disulfide to 15 for Chromium Cr(VI), indicating that the influence of the uncertainty from the breathing rate parameter is relatively small, perhaps because BR has the smallest uncertainty factor amongst the parameters in the analysis. The large uncertainties for Cr(VI), acrolein, and chloromethane indicate that a harm intensity estimate can have a wide range of values. The main input parameter driving the GSD of a toxicology-based HI_i is the $DRF_{(non-cancer,i)}$. This is reasonable because the extrapolation from

Table 5.3: Toxicology-based all-cause Harm Intensities, HI_i, DALY/μg/m^3/10^5 person/year.$^+$ (high to low median).

Contaminant	**Median**	**GSD**	**Best estimate of all-cause**
Chromium Cr(VI)	17	15	Lung Cancer & Non-Cancer Average
Formaldehyde	7.1	5.4	Leukaemia & Asthma
Cadmium Cd(II)	5.3	8.9	Lung Cancer & Non-Cancer Average
1,2-Dibromoethane	3.4	5.8	Liver Cancer & Non-Cancer Average
Ozone	2.6	6.2	Lung Cancer
Acrolein	1.3	8.5	Asthma
Acrylonitrile	1.2	4.1	Lung Cancer & Non-Cancer Average
Crotonaldehyde(trans)	1.1	7.2	Liver Cancer
Vinyl chloride	0.98	5.4	Liver Cancer & Non-Cancer Average
Carbon tetrachloride	0.52	7.3	Liver Cancer & Non-Cancer Average
Radon*	0.37	3.7	Lung Cancer
Naphthalene	0.36	5.9	Lung Cancer & Non-Cancer Average
Carbon disulfide	0.29	1.1	Non-Cancer Average
1,3-Butadiene	0.27	3.9	Cancer Average & Non-Cancer Average
Benzene	0.18	4.4	Leukaemia & Non-Cancer Average
1,1,2-Trichloroethane	0.15	5.7	Liver Cancer & Non-Cancer Average
1,1-Dichloroethene	0.15	6.1	Lung Cancer & Non-Cancer Average
1,1,2,2-Tetrachloroethane	0.13	6.2	Liver Cancer
Styrene	0.11	4.7	Breast Cancer & Non-Cancer Average
Benzyl chloride	0.062	11	Stomach Cancer
Acetaldehyde	0.053	4.8	Lung Cancer & Non-Cancer Average
Tetrachloroethene	0.052	6.2	Leukaemia & Non-Cancer Average
1,2-Dichloroethane	0.052	5.4	Stomach Cancer
Methyl methacrylate	0.051	2.8	Non-Cancer Average
Hexachlorobutadiene	0.03	4.8	Cancer Average &
Methyl tert-butyl ether	0.026	4.6	Leukaemia & Non-Cancer Average
1,4-Dichlorobenzene	0.012	6.4	Cancer Average & Non-Cancer Average
Methylene chloride	0.01	5.6	Breast Cancer & Non-Cancer Average
2-Butoxyethanol	0.01	8.7	Liver Cancer & Non-Cancer Average
Limonene (d-...)	0.0093	6.5	Cancer Average
Isoprene	0.0092	7	Cancer Average
Trichloroethylene	0.0035	5.1	Cancer Average
Xylenes	0.0034	6.1	Mouth And Oropharynx Cancer & Non-Cancer Average
2-Ethylhexanol	0.0029	8.4	Liver Cancer
2-Methoxyethanol	0.0028	7.8	Non-Cancer Average
Hexane	0.0018	8.7	Cancer Average & Non-Cancer Average
Toluene	0.00087	5.4	Non-Cancer Average
Ethanol	0.0005	5.8	Liver Cancer
Chloromethane	0.00027	10	Non-Cancer Average

$^+$ Values to 2 Sig. Figs.
* DALY/Bq/m^3/10^5 person/year; Bq, Becquerels

LOAEL or NOAEL to non-carcinogenic effective median doses carries several steps, each adding uncertainty (Section 4.5.1).

5.2.1 Comparison with Previous Work

The concept of *harm intensity* (HI_i) arises from the mathematical combination of dose-response and damage factors (Sections 4.5, 4.3), which leads to the derivation of the effect factor parameter (Section 4.7). In the field of LCIA for air pollution, effect factors are a well-established component.

This research builds upon prior methodologies. Logue et al. (2012) introduced an intake-DALY model to quantify harm caused by indoor airborne contaminants, while Huijbregts et al. (2005) designed a comprehensive set of human damage and effect factors for a wide range of chemical substances. Table 5.4 provides an overview and contrast of the parameters used in deriving HI_i to the ID-DALY approac of Logue et al. and the approach of Huijbregts et al..

Both Logue et al. and Huijbregts et al. provided explicit or implicit estimates of central tendency, with and without uncertainty, for key parameters including damage factors (DF), harm intensities (HI), effect factors (EF), and dose-response factors (DRF). These parameters are associated with various health outcomes, be it all-cause or cause-specific cancer or noncancer effects. The quantification of harm intensity and uncertainty was not explicit in them, so in the current study, these were reverse-engineered from the available data, and using standard assumptions.

Table 5.4: Comparison of determinants for a Tox-approach

Parameter	**Notation**[a]	**Tox-harm approach**	**ID-DALY aproach**	**Huijbregts et al. (2005)**
Age dependent adjustments factors	ADAF	Median with variability	Mean value	N/A
Breathing rate, BR	m^3/person/year	Pooled from relevant sources; Considering variability	Mean value U.S. air intake	Mean human intake; No uncertainty
Dose-response factors $DRF_{(k,i)}$	$\frac{0.5}{ED50_{k,i}}$ case/mass	Disease specific uncertainty; GSD based 95% CI; USEtox and toxicity database sources	N/A	Complex nonlinear
Damage factor DF_k	$\frac{\text{Burden of Disease}_k}{\gamma 0_k}$ DALY/Case	2019 Global burden of disease database	N/A	1990 world representation
(individual) Effect factor $EF_{(k,i)}$	$\text{DRF}_{k,i} \cdot \text{DF}_k$ DALY/mass	Monte Carlo uncertainty	Values and Uncertainty from Huijbregts et al.	$\frac{\partial \text{damage}}{\partial \text{effect}} \cdot \frac{\partial \text{effect}}{\text{intake}}$
(All cause) Effect factor $EF_{(k,i)}$	$(EF_{\text{cancer},i} \cdot ADAF) + EF_{\text{noncancer},i}$ DALY/mass	Monte Carlo uncertainty	Monte Carlo uncertainty	NA

[a] Note: (i) Contaminant, (k) Health outcome - disease - cancer or noncancer effect; $\gamma 0_k$ related baseline disease incidence; ED50: median effective dose.

The most important issue identified by Table 5.4 is that the evidence previously used to determine harm (as Disability-Adjusted Life Years, DALYs) for airborne contaminants is over a decade old, as is the method proposed by Huijbregts et al. to derive an effect factor (later modified by Rosenbaum et al. (2008)) and used by LCIA (Hauschild and Huijbregts, 2015).

Most of the cancer harm intensity ($HI_{\text{cancer,i}}$) estimates in Table 5.1 exceed those derived from Huijbregts et al. (2005) via Toxicology-based Effect Factors, by several orders of magnitude (see Figure 5.3 comparing current and prior work). This divergence stems from differences in the dose-response factor (DRF) derivation. Huijbregts et al. (2005) used a two-part DRF: a disease-specific probability of disease occurrence, and a substance-specific inverse ED50 component. The disease probability was 0.03 for average carcinogenic effects and 0.16 for non-carcinogens. The Fantke et al. (2017a) model updated this DRF derivation via a 0.5 constant multiplyer, yielding higher estimates. Additionally, the toxicity data in USEtox has lower ED50 values for five contaminants, reflecting higher toxicity: Formaldehyde changed from 0.59 to 0.47 mg/kg-day, Crotonaldehyde from 1.85 to 1.83 mg/kg-day, Chromium (VI) from 0.23 to 0.02 mg/kg-day, Acrylonitrile from 7.14 to 3.91 mg/kg-day, d-Limonene from 91 to 89 mg/kg-day, and Vinyl chloride from 8.33 to 2.59 mg/kg-day. Updates to DRF calculation and toxicity data contribute to substantially higher $HI_{\text{cancer,i}}$ estimates in this work versus previous approximations. This implies that previous assessments may have underestimated the cancer-related harm.

A $\text{DF}_{\text{average cancer}}$ of 10.6 (GSD 1.05) was calculated here, whereas the value of Huijbregts et al. was 11.5 (GSD 1.67). These medians are close in magnitude, and so this parameter does not influence the differences in medians found in $\text{HI}_{\text{cancer},i}$.

Median $\text{HI}_{\text{non-cancer},i}$ presented in Table 5.2 are generally lower than the estimates reverse-engineered from Huijbregts et al. That work reported average damage for non-carcinogenic effects of 2.7 (GSD 3.6), whereas here the average was 2.1 (GSD 1.1). The parameter that influences the differences in $\text{HI}_{\text{non-cancer},i}$ is the smaller uncertainty in the DF_k, which effects the median of the lognormally distributed parameter (see Figure 5.4 comparing current and prior work).

Estimates of the median all-cause harm intensities (HI_i) in Table 5.3 exceed those implicit in Logue et al. (2012) for 27 contaminants by one order of magnitude. They are lower for 8 contaminants but within the same order

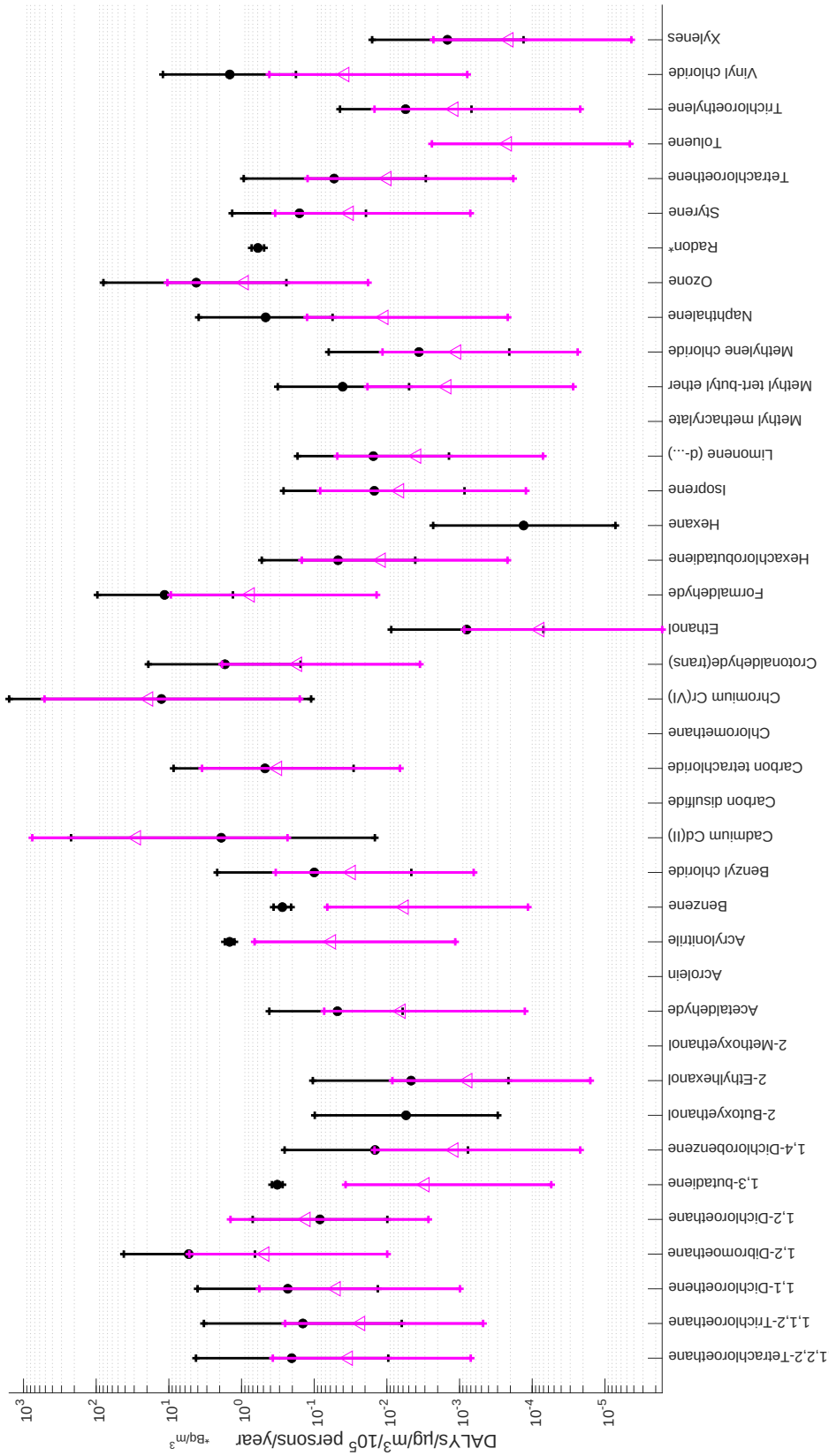


Figure 5.3: Cancer-Harm intensities and previous works. Black: current work, Magenta: Huijbregts et al. (2005). Median and 95% C.I.

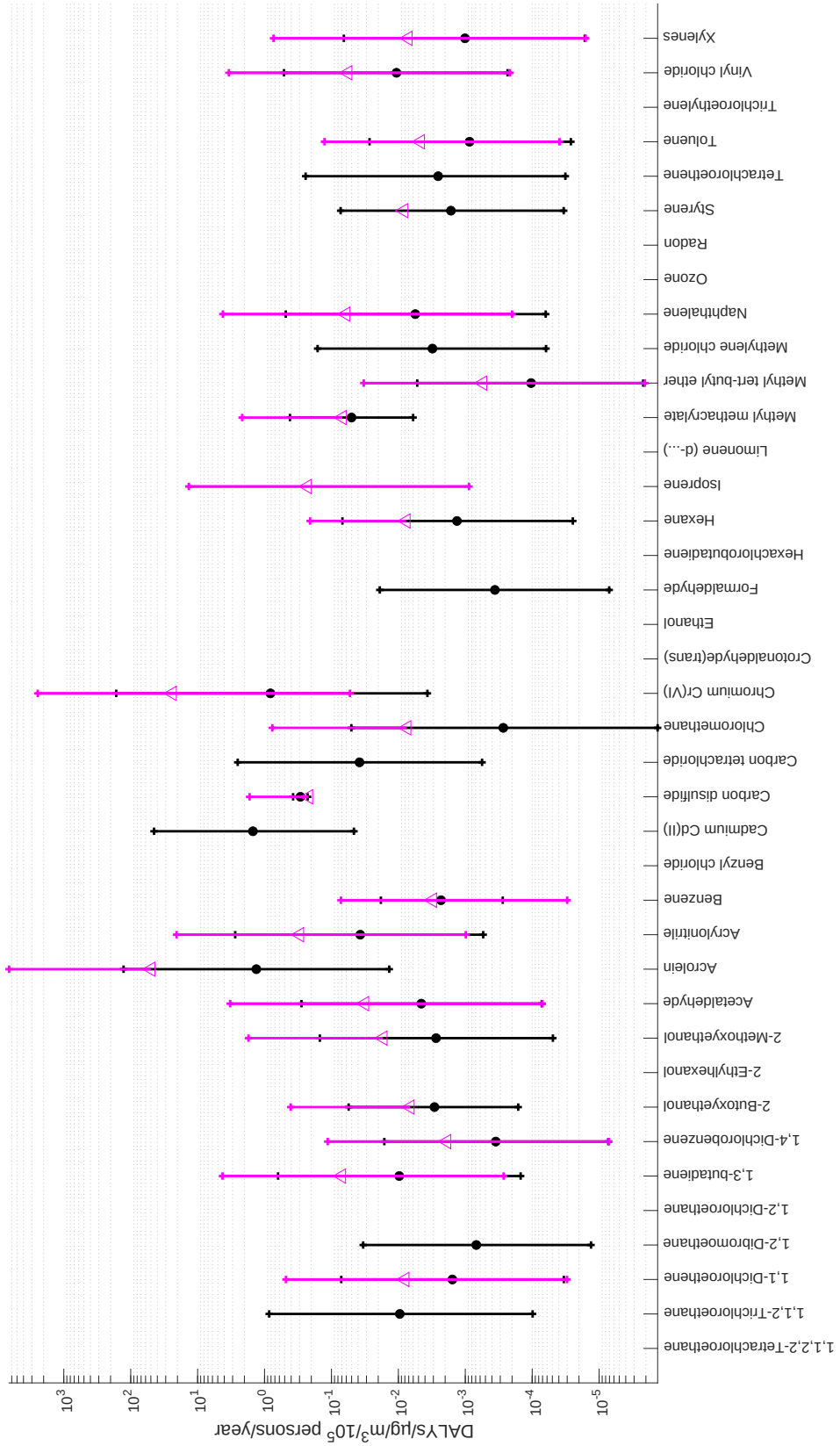


Figure 5.4: Non-cancer-Harm intensities and previous works. Black: current work, Magenta: Huijbregts et al. (2005). Median and 95% C.I.

of magnitude. Overall, Logue et al. (2012) underestimates the effects when contrasted with the results presented here.

The age-dependent adjustment factor (ADAF) influences the combined estimates. Logue et al. (2012) applied a mean ADAF of 1.6, whereas the current work uses a lognormal vector with a median of 0.6. This lowers the median for carcinogenic effects. Additionally, formaldehyde, carbon tetrachloride, cadmium Cd(II), 1,2-dibromoethane, and hexane, in this work have both cancer and non-cancer effects, which increases the output median. Previously, only one effect type was available for these contaminants. Updates to toxicity data and the ADAF parameter contribute to higher HI estimates here versus Logue et al. (2012). Accounting for both effect types also increases median HI for certain contaminants (see Figure 5.5 comparing all cause-Harm intensities in current to prior works).

When ordering harm intensity by their median, contaminants with the highest carcinogenic and non-carcinogenic estimates broadly agree with those of Huijbregts et al.. A similar result was found when comparing the estimate of all-cause effect factors, which account for the ADAF influence, with those of Logue et al. Uncertainties, expressed as a GSD, in carcinogenic, non-carcinogenic, and all-cause HI_i for all contaminants have reduced. For toxicology, Logue et al. relied on uncertainties from Huijbregts et al., where interspecies conversion, effect conversion, and non-cancer damage factors dominated. This work aimed to reduce uncertainties by leveraging improved health data. Some studies report reduced uncertainty factors reflecting increasing certainty in animal-to-human extrapolation, effect conversion, and non-cancer damage quantification (Martin et al., 2013; Xu et al., 2022).

Reverse engineering the harm intensity from available data required incorporating breathing rates. While each study used slightly different values, mainly related to uncertainty handling, the influence on median harm intensity was inconsequential. Logue et al. used 14.4 m^3/person/day, Huijbregts et al. used 13 m^3/person/day, and this work used 14.8 m^3/person/day.

5.2.2 Applications and applicability of Tox-HI_i

The USEtox model assumes a linear low-dose–response for the inhalation of contaminants considered here (Fantke et al., 2017a). In LCIA, this is

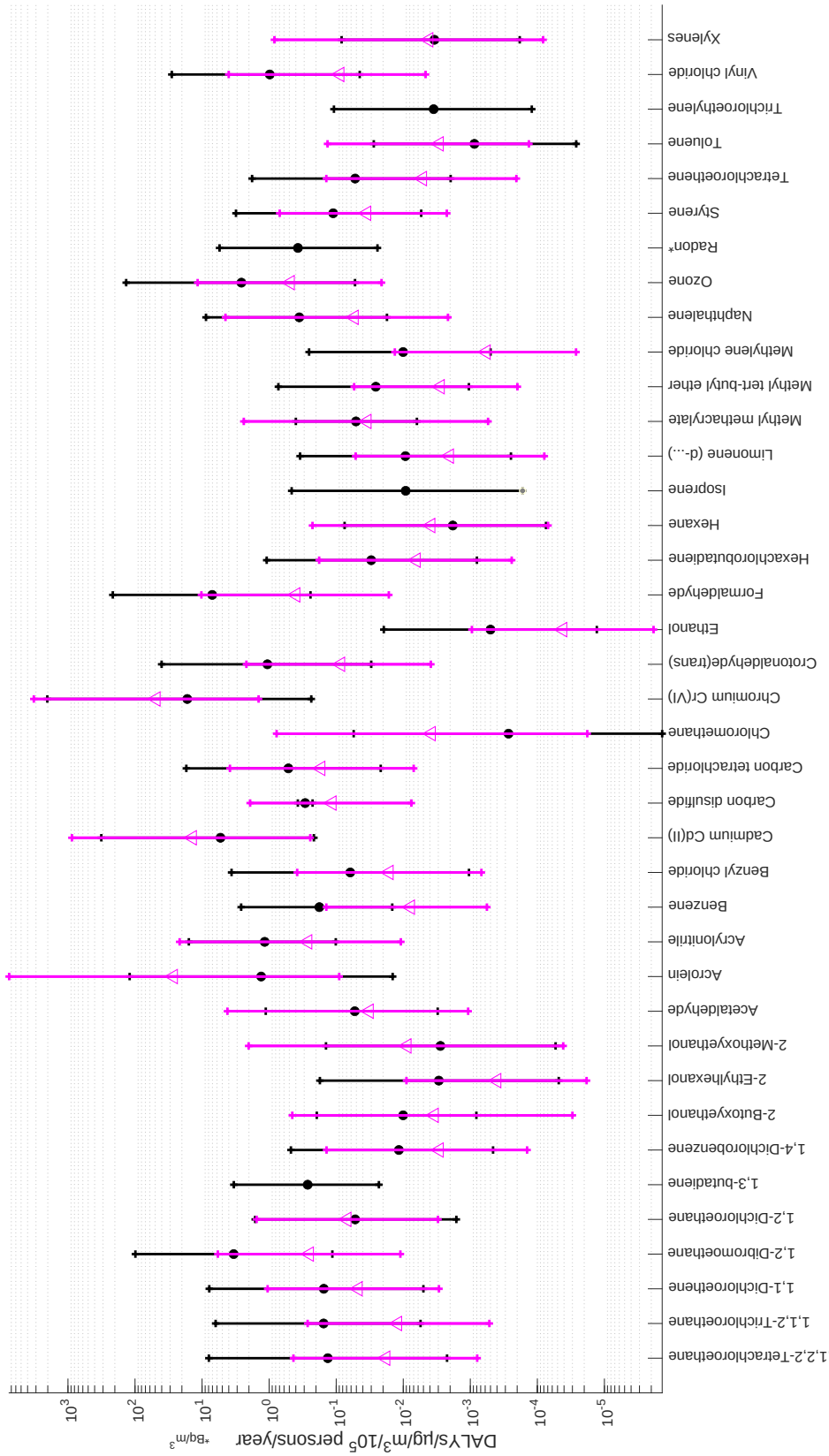


Figure 5.5: All cause-Harm intensities and previous works. Black: current work, Magenta: Logue et al. (2012). Median and 95% C.I.

known as the average approach, and it is applied to derive characterization factors. It states that the distance between the median effective dose, ED50, (known as the current state) and the point of zero impact (known as the state of zero impact) is set to be linear (Hauschild and Huijbregts, 2015; Heijungs, 2021). Thus, proposed harm intensities are valid where intake remains under the contaminant's lifetime dose. These can be compared to indoor concentrations in USEtox. ED50 is derived from toxicology studies independent of indoor or outdoor exposures and so, it can be applied in both contexts.

Carcinogenic and non-carcinogenic harm intensities are presented for LCA use. Although USEtox is widely used, its endpoint DALYs rely on 1990s data. This work updates those values. All-cause effects are also given for IAQ assessments beyond LCA, for works like Fazli and Stephens (2018) and De Jonge and Laverge (2022) aiming to quantify chronic health impacts associated with exposure to indoor contaminants that relied on the ID-method of Logue et al..

In LCA, concentrations and breathing rates are used for estimating the intake fraction (iF, mass intake/mass emitted). The iF translate emissions to intake (Hellweg et al., 2009; Wenger et al., 2012). This is not unlike the harm intensity metric, and LCA could also find the HI_i of use.

A common strength of the harm approach developed here is the consideration of uncertainties throughout. Furthermore, qualitative certainty arises from expert-revised databases. As databases evolve with new estimates, any parameter can be updated.

However, some limitations exist: (i) Severity factors are derived from a global dataset covering all age groups and both genders. Furtheremore, median effective doses are not available by age, sex, or race, or by country or region. (ii) Median effective dose derivation relies on the USEtox database. Other ED50 sources could influence results. (iii) The best estimate of all-causes for toxicology-based harm intensities can impact results. For example, asthma represented acrolein and formaldehyde non-cancer effects here, but other outcomes may be selected.

5.3 An epidemiology-based Harm Intensity, HI_i.

Relevant LCIA, health risk assessment, and comparative risk assessment literature was reviewed (Chapter 4) to identify commonly used data sources for deriving the determinants of the epidemiology-based HI_i: $\beta_{k,i}$, DF_k, and γ_{0_k} (Chapter 4) (Hauschild and Huijbregts, 2015; Hauschild et al., 2018; Murray et al., 2020; Richmond-Bryant, 2020; WHO, 2021). Search terms and criteria from these studies were applied to retrieve current information. Data sources were selected based on their appropriateness for each required parameter.

A literature review of studies published between 2010-2020 and other literature that compiled or reviewed risk estimates to obtain the beta parameter ($\beta_{k,i}$) for risk derivation. The approach is based on individual contaminant risk estimates, considering their availability, while acknowledging the potential of multipollutant regressions in epidemiological exposure assessment studies (Cohen et al., 2017; Sacks et al., 2018; WHO, 2021).

The GBD Collaborative Network was the main database for the estimates of the disease-specific baseline incidence rates (γ_{0_k}) and damage factors (DF_k) for the target health effects (k) identified through the risk estimates ($\beta_{k,i}$). The estimates where extracted for the year 2019, and the global population of all ages and both sexes (IHME, 2022; Murray et al., 2020).

Figure 5.6 and its more detailed counterpart Figure 5.7, offer visual representations of the analytical model utilized for estimating the epidemiology-based harm intensity.

Harm intensities, derived from epidemiological research, were used to relate harm to exposure for the ten indoor airborne contaminants with data on the epidemiological inputs needed (Section 4.7.2). Table 5.5 presents the median harm intensities, along with uncertainty estimates expressed through the Geometric Standard Deviation (GSD), and the best estimate for all-cause effect (see Appendix 17 for full descriptive statistics).

Epidemiology-based HI_i have significant variability, spanning three orders of magnitude (from 10^{-2} to 10^{1} DALY/µg/m^3/10^5 person/year). The contaminant that registers the highest median harm intensity is $PM_{2.5}$ ($HI_{PM_{2.5}}$ 60 DALY/µg/m^3/10^5 person/year, GSD 1.2). These values can later be as-

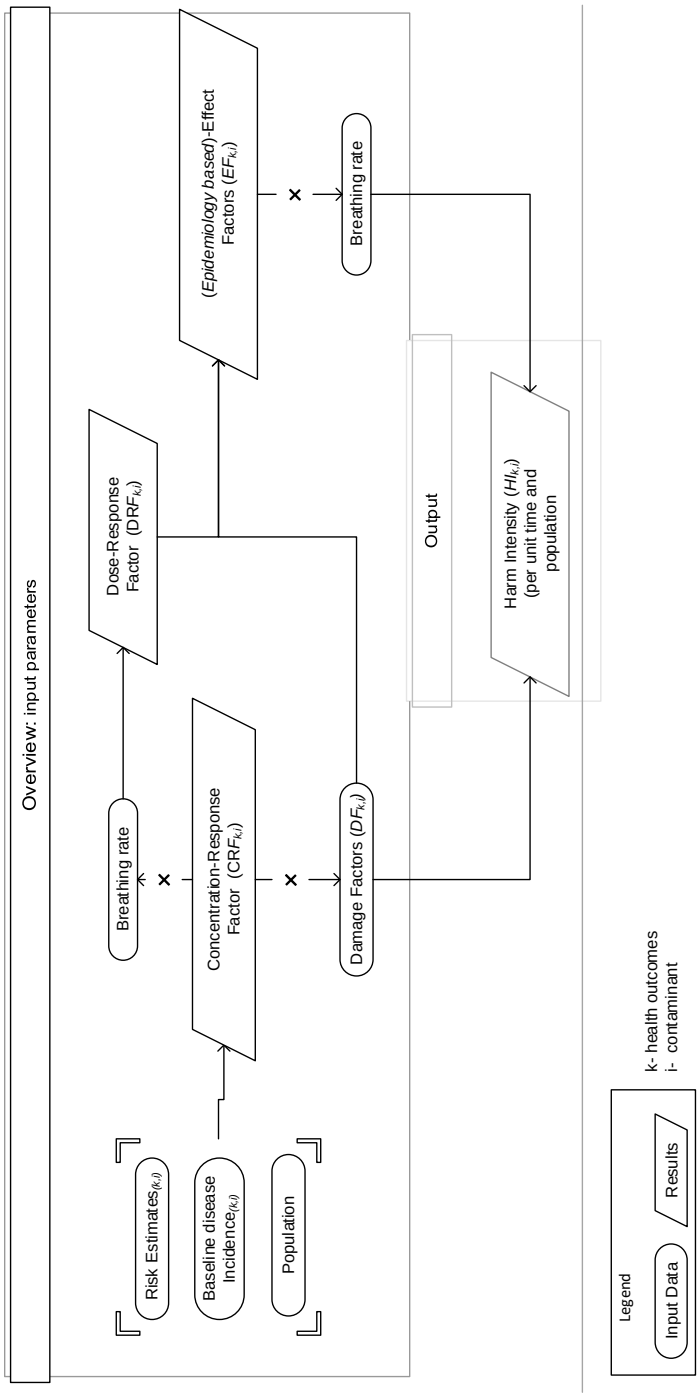


Figure 5.6: Overview of parameters required to determine an epidemiology-based harm intensity, HI_i, DALY/µg/m^3/person/year.

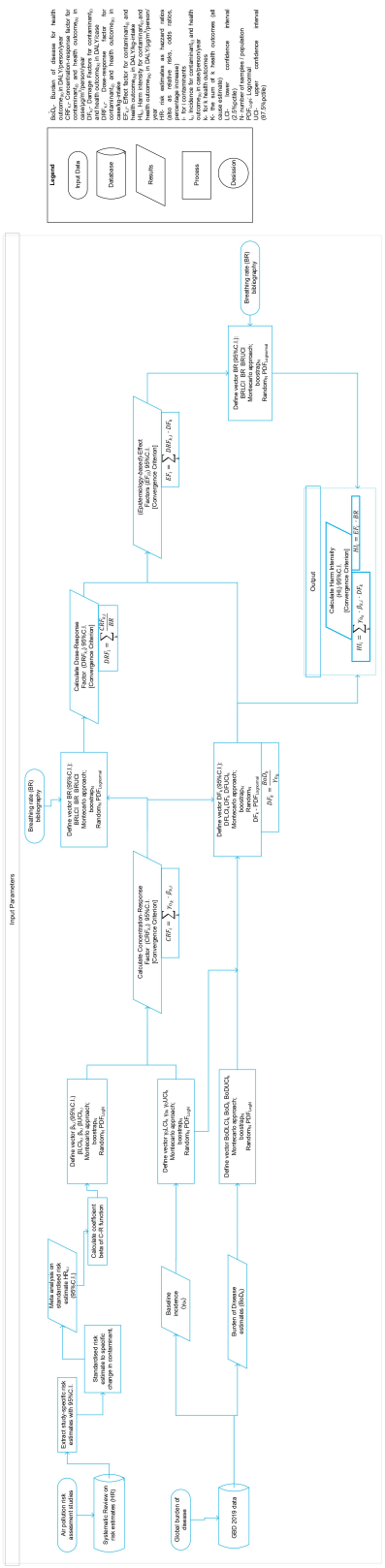


Figure 5.7: Analytical Flow Chart for an Epidemiology-Based Harm Intensity, HI_i, DALY/µg/m^3/person/year.

Table 5.5: Epidemiology-based all-cause Harm Intensities, HI_i, DALY/µg/m^3/10^5 person/year.$^+$ (high to low median)

CAS RN	Contaminant	Median	GSD	Best estimate of all-cause
	$PM_{2.5}$	60	1.2	All-cause mortality (IHD+DM+Str+COPD+LRI+LC)
	PM_{10}	30	1.3	All-cause mortality (IHD+DM+Str+COPD+LRI+LC)
10102-44-0	Nitrogen Dioxide	5.6	1.7	All-cause mortality (COPD+LRI+URI+LC)
50-00-0	Formaldehyde	4	2.2	Asthma morbidity
7446-09-5	Sulphur Dioxide	1.9	4.5	All-cause mortality (COPD)
10028-15-6	Ozone	1.3	1.9	All cause mortality
107-02-8	Acrolein	1.2	5.5	Asthma morbidity
71-43-2	Benzene	0.062	1.4	Leukemia mortality
	Mold	0.027*	2.2	All-cause (LC+Leukaemia+asthma)
10043-92-2	Radon	0.45**	1.7	Lung Cancer mortality

Abbreviations. LC: Lung Cancer; Lk: Leukaemia; COPD: Chronic Obstructive Pulmonary Disease; LRI: Lower Respiratory Infections; URI: Upper Respiratory Infections; IHD: Ischaemic Heart Disease; DM: Diabetes Mellitus; Str: Stroke.

$^+$ Values to 2 Sig. Figs.

* DALY/CFU/m^3/10^5 person/year; CFU, Colony-Forming Units. As mold spores of the genus Cladosporium

** DALY/Bq/m^3/10^5 person/year; Bq, Becquerels

sociated to exposures to quantify harm

A harm intensity has been calculated for radon, the radioactive element found in indoor air that is considered in LCA as well. This harm intensity encompasses mortality attributed to lung cancer resulting from radon exposure. Mold, on the other hand, contributes to harm through exposure to mold spores within households, considering the genome Cladosporium, that represents a significant portion of indoor molds, ranking among the most common fungal genomes in households alongside Penicillium and Aspergillus (Braubach et al., 2011; Garrett et al., 1998). The concentrations of Cladosporium spores were employed as an indicator for mold, as this data is a prerequisite for the epi-harm approach (More on this later in Section 7.1.2).

The ratio of mean harm intensities for $PM_{2.5}$ to PM_{10} is 1.69, indicating that approximately 60 % of the mass in PM_{10} is $PM_{2.5}$. However, the harm intensity of the coarse fraction still requires investigation. Estimating the harm intensity for the coarse fraction involves considering the difference in the harms for PM_{10} and $PM_{2.5}$ separately (this is discussed in chapter 7).

Uncertainties in harm intensities and effect factors exhibit similarities

across the same contaminants, with GSD values ranging from 1.2 for $PM_{2.5}$ to 5.5 for mold. This variation reflects the uncertainty in the baseline incidence, risk estimate and damage factors. The uncertainty associated with breathing rates (BR) is negligible (Section 4.4). Larger uncertainties are observed in mold and SO_2.

5.3.1 Determinants of the epidemiology-based harm intensities

This simplified linear approach for estimating HI_i relies on four essential components: (i) parameters from epidemiology-based exposure-response functions ($\beta_{k,i}$), (ii) mortality or morbidity rates associated with diseases linked to contaminant exposure (γ_{0_k}), (iii) damage factors representing the loss of healthy lifetime (DF_i), and (iv) breathing rates standardized to a chosen time unit (BR).

Based on an analysis of current global data, this research proposes a set of concentration, dose, effect, and harm parameters with applications in LCIA, comparative risk assessment, health impact analysis, and contaminant reduction policy evaluations, from globally-derived epidemiological data lacking geographic specificity.

5.3.2 Evaluation Against Prior Research

5.3.2.1 The Intake-Incidence DALY (IND) Method

Damage factors for NO_2, SO_2, O_3, and $PM_{2.5}$ exceeded prior estimates for U.S. dwellings. Logue et al. (2012) calculated $PM_{2.5}$ and O_3 damage factors using U.S. epidemiological data on mortality and incidence, but details were limited. The approach here suggests their $PM_{2.5}$ and O_3 damage factors likely underestimated impacts, as current results align more closely with the upper confidence intervals. Additionally, Logue et al. significantly underestimated NO_2 and SO_2 severity by assuming identical damage factors across criteria contaminants. Table 5.6 compares the determinants between the IND method and the Epi-harm approach. Logue et al. used mostly U.S. epidemiological data from before 1999 and applied undisclosed assumptions.

Table 5.6: Comparison of determinants for an Epi-approach

Parameter	**Notation**[a]	**Epi-harm approach**	**IND-DALY approach**
Beta $\beta_{(k,i)}$	$\frac{\ln(\text{risk estimate}_{(k,i)})}{\Delta C_i}$	Robust meta analysis methodology	Dated USEPA source; U.S. centric studies; Unexplained PDF (Weibull, Normal) assumptions
	change/concentration		
Baseline incidence rate γ_{0_k}	Case/Person/year	Global burden of disease database	Dated USEPA source; Unexplained values; Mean value
Damage factor DF_k	$\frac{\text{Burden of Disease}_k}{\gamma_{0_k}}$	Global burden of disease database	U.S. $PM_{2.5}$, O_3 study basis; U.S. air pollution study basis; Arbitrary uncertainty factor
	DALY/case		
Breathing rate, BR	m^3/person/year	Pooled from relevant sources; Considering variability	U.S. air intake basis; Point value assumption

[a] Note: (i) Contaminant, (k) Health outcome - disease

Epidemiology-based harm intensities (HI_i) were reverse-engineered for five contaminants from Logue et al. (see Figure 5.8 in the next Section 5.3.2.2). For $PM_{2.5}$, median HI_i broadly agree with Logue et al., likely because both used an estimate to reflect total mortality. For O_3, current values are higher due to the one order of magnitude larger damage factor. Previous NO_2 and SO_2 estimates relied on available specific morbidity data (hospital admissions) treated as chronic, differing by at least two orders of magnitude. In general, uncertainties in this study are lower than those reported in Logue et al. The GSD for $HI_{PM_{2.5}}$ is 1.2 in this study compared to 2.2 in Logue et al.'s work. Similarly, for O_3, this study reports a GSD of 1.9, while Logue's study had a GSD of 3.4. This trend continues with NO_2, where the GSD is 1.7, contrasting with Logue's 4.7.

Two factors influence the differences in medians and GSD between the IND method and the Epi-harm approach: underlying epidemiological data has evolved to indicate greater harm, and data manipulation differs, including probability distribution fitting, confidence interval truncation, and convergence criteria. Nevertheless, current decisions follow best practices and knowledge.

5.3.2.2 LCIAs of Air Pollutants

LCIAs of O_3, PM_{10}, and $PM_{2.5}$ have been proposed (Fantke et al., 2019; Gronlund et al., 2015; Huijbregts et al., 2017; Oberschelp et al., 2020; Van Zelm et al., 2008, 2016). These analyses presented, either explicitly or implicitly, mean/medians with and without uncertainty for DF_i, HI_i, EF_i, DRF_i, and CRF_i, for all-cause or cause-specific mortality risks. For comparison, HI_i medians and GSD were reverse-engineered (see Table 5.7 for further specifications).

This research quantified a median $HI_{PM_{2.5}}$ 60 DALY/µg/m^3/10^5 person-/year to describe the relationship between harm and exposure to $PM_{2.5}$, using a linear concentration-response function. Other estimates include 46 from Van Zelm et al., based on a single study risk estimate; 52 from Gronlund et al., using the risk estimate from the American Cancer Society study and approximating the C-R function linearly; 79 from Huijbregts et al.; Van Zelm et al., by the algebraic summation of specific cardiopulmonary and lung cancer mortalities to represent the all-cause effect and using risk estimates from the re-analysis of the ACS study; 35 from Fantke et al., by algebraic summation of ischemic heart disease, stroke, lower respiratory infections, lung cancer, and chronic obstructive pulmonary disease as specific causes of mortality using a non-linear integrated exposure-response model (that is approximate linear at low concentrations); and 54 from Oberschelp et al., using the same as Fantke et al.. Ozone has been represented by respiratory disease mortality in Huijbregts et al.; Van Zelm et al.. For PM_{10} Van Zelm et al. used chronic mortality.

Figure 5.8 shows there is a general overlap between the estimates of the epi-based HI_i. All these references have one thing in common: the approach towards the harm intensity is dependent on a background concentration, which could represent a weakness because EF_i, and hence HI_i, is extremely sensitive toward fixed contaminant background concentrations (Fantke et al., 2019; Oberschelp et al., 2020). Conversely, background concentrations are not required for the simplified linear Epi-harm approach.

Table 5.7: Further details on current and previous works

	Contaminant$_i$										Parameter				
	Acrolein	Benzene	Mold	Formaldehyde	NO_2	O_3	PM10	$PM_{2.5}$	Radon	SO_2					
Study	Health outcome$_k$										DF_k	$CRF_{k,i}$	$DRF_{k,i}$	$EF_{k,i}$	$HI_{k,i}$
This research	Asthma Morbidity	Leukaemia Mortality	Asthma Morbidity	Added Effects[a]	All-cause Mortality	All-cause Mortality	All-cause Mortality	All-cause Mortality	Lung Cancer Mortality	All-cause Mortality	Median				
Logue et al.					Hospital Admission &/or Respiratory Illness	Mortality		Total Mortality		Hospital Admission	Median[@]	Mean[+]	Median[@]	Median[@]	Median[@]
Gronlund et al.								All-cause Mortality			Mean[@]	Mean[@]	Mean[+]	Mean[+]	Mean[@]
Van Zelm et al.							Chronic Mortality				Mean[@]	Median[@]	Mean[@]	Mean[@]	Mean[@]
Huijbregts et al.; Van Zelm et al.						Respiratory Disease		Lung Cancer & Cardiopulmonary			Median[@]	Median[@]	Median[@]	Median[@]	Median[@]
Fantke et al.								All-cause Mortality[b]			Median[@]	Median[@]	Median[@]	Median[@]	Median[@]
Oberschelp et al.								All-cause Mortality[b]			–	–	–	Mean[@]	Mean[+]

[a] 3 health outcomes: asthma morbidity, and lung cancer and leukaemia mortality.
[b] 5 health outcomes: Ischemic Heart Disease, Stroke , Chronic Obstructive Pulmonary Disease, Lower Respiratory Infection, Lung Cancer.
[+] Value reported by the study.
[@] Value reverse engineered from the study.

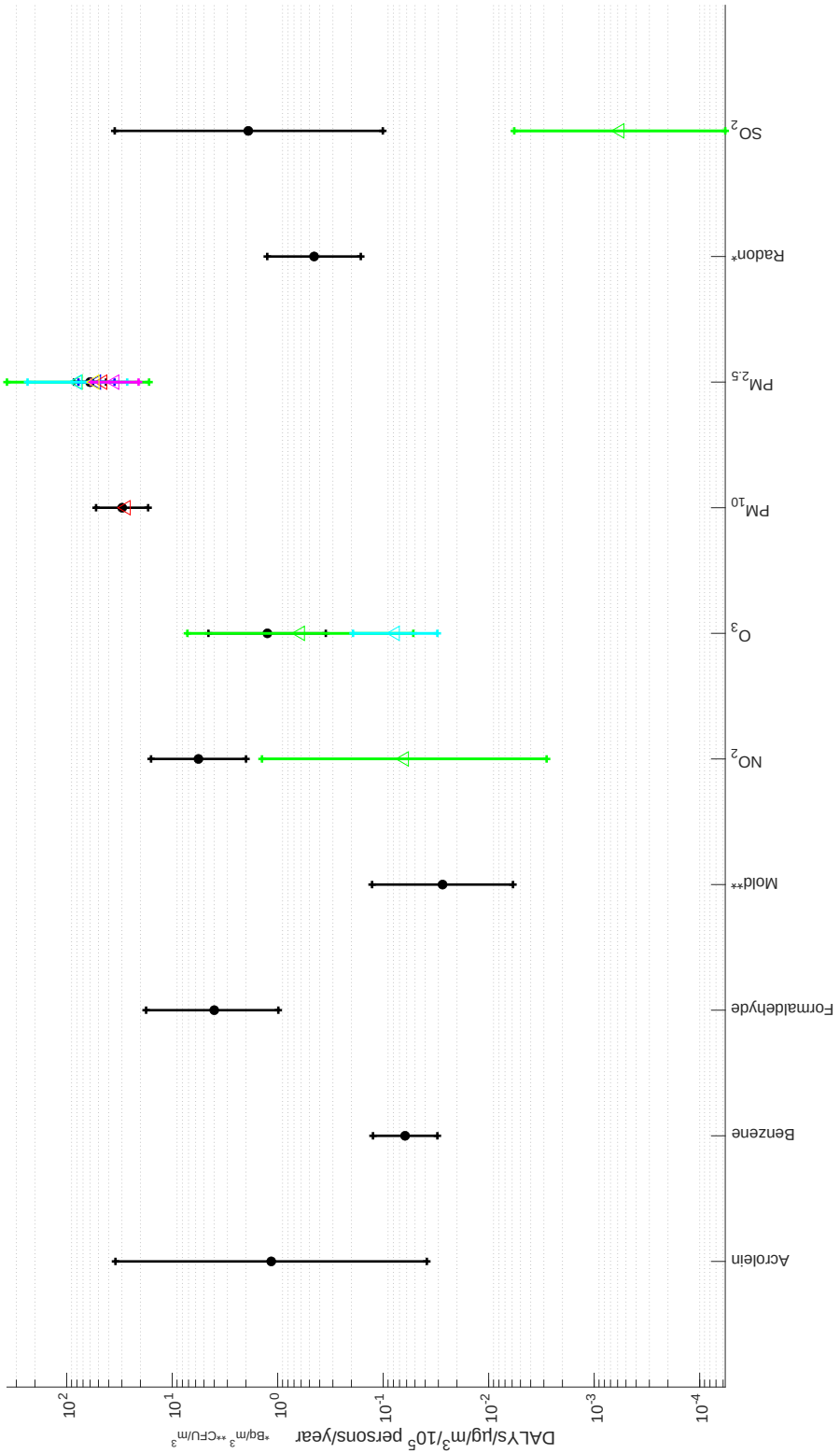


Figure 5.8: Epi harm intensities: Evaluation against prior research. Median and 95%C.I. Black: current work; Green: Logue et al.; Blue: Gronlund et al.; Red: Van Zelm et al.; Cian: Van Zelm et al.; Magenta: Fantke et al.; Yellow: Oberschelp et al.

The GSD for the harm intensity for all-cause mortality from $PM_{2.5}$ of 1.2

here, is lower than 1.7 (Van Zelm et al., 2008), 1.7 (Fantke et al., 2019), and 1.5 (Gronlund et al., 2015). The uncertainty in the distributions and the output metric is a function of the C-R function applied, the use of different health outcomes, the central tendency metric reported, the spatial and population resolution used, the chosen breathing rate, the background concentration, the accounting for variability in all determinants of the harm intensity, and the methodological framework.

5.3.3 Applications and applicability of Epi-HI_i

The epidemiology-based model incorporates both linear (Lin) and log-linear (LogL) no-lower-threshold concentration-response (C-R) functions, which are represented by the following equations:

$$HI_{k,i} = DF_k \cdot \gamma_{0_k} \left(\frac{1 - e^{-(\beta_{k,i} \cdot C_i)}}{C_i} \right) \tag{5.1}$$

The equation for HI_i contains a term in parentheses that signifies a non-linear, no-lower-threshold saturation effect. However, at low concentrations, this equation approximates a linear relationship:

$$HI_{k,i} = DF_k \cdot \gamma_{0_k} \cdot \beta_{k,i} \tag{5.2}$$

The Epi-harm approach employed a linear, no-lower-threshold C-R curve to model HI_i for all contaminants. This choice is due to the adequacy of a linearized curve for low background concentration regimes. It is commonly assumed that linear effects at low exposures are appropriate for LCIA of airborne contaminants (Gronlund et al., 2015; Huijbregts et al., 2017; Van Zelm et al., 2016).

Air pollution risk research has not precisely established quantitative definitions for "low" and "high" concentrations of contaminants. We can draw insights from the integrated exposure-response (IER) model for $PM_{2.5}$(See Figures 2.7 and 2.8). A 30-50 µg/m^3 range potentially constitutes high exposure based on attributable disease burdens (Burnett et al., 2014). No such details can be found for other air contaminants in the literature. Further research and clearer definitions would aid risk analysis.

Figure 5.9 shows median and 95% confidence intervals of HI_i derived from both the linear (Lin) and log-linear (LogL) C-R functions. The linear approach appears as a straight line in the concentration – harm intensity plot because the harm intensity is independent of the concentrations. The log-linear equation has a decreasing exponential shape. At low concentrations, the exponential term approaches 0, resulting in a harm intensity dominated by the quotient of the concentration. As the concentration continues to increase, the exponential term approaches 1, and the harm intensity gradually decreases. Eventually, at high concentrations, the harm intensity flattens as it tends to zero.

The Absolute Percentage Error (APE) and mean absolute percentage error (MAPE), are calculated to assess the agreement between the Lin and LogL approaches. By setting a cutoff point of 10% (approximately one standard deviation), one can identify the concentration range where the MAPE falls below this threshold, taking the log-linear approach as the reference because this C-R function flattens the curve, reflecting a saturation effect of harm at high concentrations. Variability and instability are expected in the MAPE outputs generated by a MATLAB code that creates random harm vectors. Each execution of the code would yield varying MAPE and APE values, introducing challenges in achieving absolute stability in the error metrics. To mitigate this issue, the sample size was increased, convergence criterion were stablished, and average MAPE values across 10,000 sample sets were computed. These strategies were employed to minimize variability and ensure a more consistent evaluation of errors.

Table 5.8 presents the MAPEs for the harm intensities at the concentration distribution of contaminants found in dwellings. These MAPE values represent the discrepancy between applying a linear equation for harm intensity versus the log-linear equation. The MAPE values provide insights into the extent to which the linear output, which remains constant in this case, differs from the log-linear approach. Formaldehyde, PM_{10}, and $PM_{2.5}$ exhibit relatively higher MAPE values of 11%, 9%, and 7%, respectively. The saturation effect becomes prominent at the concentration distribution applied to these contaminants. These MAPE values reassure the appropriateness of interpreting the harm intensity metric as a constant when evaluated at low concentrations.

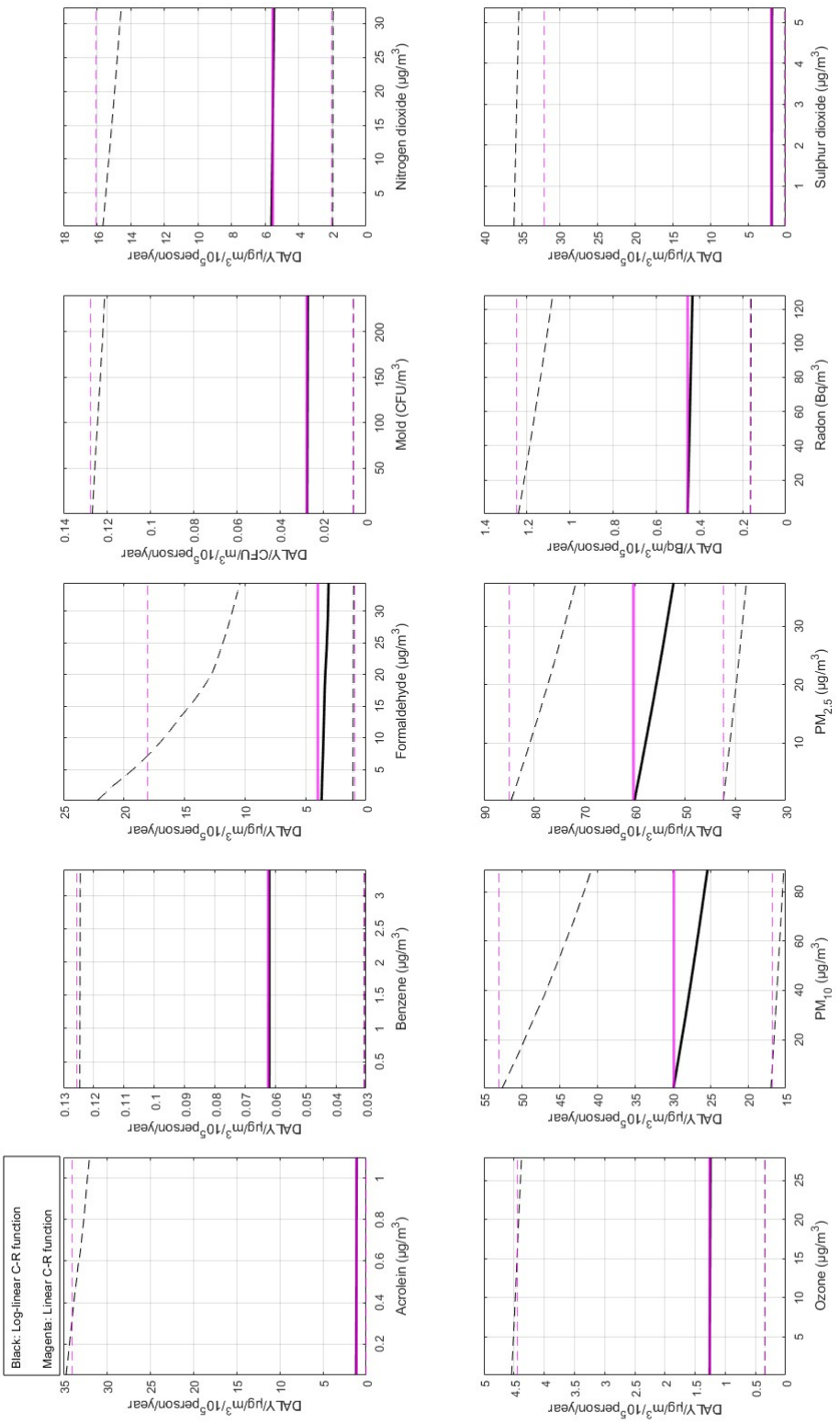


Figure 5.9: Comparison of harm intensities from linear and log-linear C-R functions. Median [solid lines] and 95 %C.I. [dash lines]. The x-axis width represents the low concentration regime for each contaminant, as based on measurements in dwellings (Halios et al., 2022; Ilacqua et al., 2022; Liu et al., 2022; Logue et al., 2011a; Sarigiannis et al., 2011; Vardoulakis et al., 2020)

Table 5.8: Mean Absolute Percentage Error (MAPE) for harm intensities for contaminant concentration distribution expected in dwellings.

Contaminant	Concentration distribution[a,b]	MAPE (%)[b]
Acrolein	(0 - 1.1)	4.4 (95%C.I. 2.9-5.8)
Benzene	(0 - 3.4)	0.4 (95%C.I. 0.056-0.65)
Formaldehyde	(0 - 34)	11 (95%C.I. 9.6-11)
Mold[c]	(0 - 240)	1 (95%C.I. 0.42-2.5)
Nitrogen dioxide	(0 - 32)	1.8 (95%C.I. 1.3-2.1)
Ozone	(0 - 28)	0.86 (95%C.I. 0.28-2.2)
PM_{10}	(0 - 89)	8.8 (95%C.I. 8.1-9.2)
$PM_{2.5}$	(0 - 37)	7.4 (95%C.I. 7-7.9)
Radon[d]	(0 - 130)	2.5 (95%C.I. 1.9-3.4)
Sulphur dioxide	(0 - 5.4)	3.2 (95%C.I. 1.6-5)

[a] µg/m^3; 2 Sig. Figs. (2.5th and 97.5th) percentiles

[b] Averaged over 10,000 interactions

[c] Mold in CFU/m^3 CFU, Colony-Forming Units

[d] Radon in Bq/m^3; ; Bq, Becquerels

Table 5.9 presents the APE between the Lin and LogL approaches for estimating harm intensities (See Equations 3.21, 3.24) at the central tendency estimate of concentrations (from meta-analysis results, See Table 6.2). APEs indicate close agreement between linear and log-linear approaches for most contaminants, ranging from 0.3% to 13%. The contaminants with higher risk estimates and concentrations (the exponential term in the LogL equation) have the highest disagreements to the linear approach, as expected. Particular attention should be given to formaldehyde, having an APE of 21%. Its concentration-response (C-R) function, as depicted in Figure 5.9, illustrates the drastic nature of the saturation effect compared to a linear response. This saturation effect is influenced by the product of the beta parameter (risk estimates) and the concentration. A higher product of these two factors results in a quicker flattening of the curve in a C-R plot (see the upper confidence interval in the sub-plot). Formaldehyde exhibits a relatively high beta value for the health outcomes chosen (asthma and leukemia) compared to the rest of the contaminants, as shown in Table 4.1, and its concentrations span two orders of magnitude. These aspects are the reason of the high APE.

Table 5.9: Absolute Percentage Error (APE) for harm intensities from Linear and Loglinear approaches

Contaminant$_i$ [a]	C_i, Central tendency	Approach				APE (%)[c]	Rank	
		Linear		LogLinear				
		median HI$_i$[b]	GSD	median HI$_i$[b]	GSD		Lin	LogL
Acrolein	0.65	1.2	5.1	1.1	5.3	4.6 (95%C.I. 2-6.6)	7	7
Benzene	2.3	0.062	1.4	0.062	1.4	0.34 (95%C.I. 0.19-0.50)	9	9
Formaldehyde	28	4	2.2	3.3	1.8	21 (95%C.I. 20-21)	4	4
Mold	160	0.027	2.2	0.027	2.1	0.88 (95%C.I. 0.19-1.3)	10	10
Nitrogen dioxide	22	5.7	1.7	5.5	1.7	2.2 (95%C.I. 1.8-2.6)	3	3
Ozone	10	1.3	1.9	1.3	1.9	0.37 (95%C.I. 0.19-0.73)	6	6
PM_{10}	64	30	1.3	26	1.3	13 (95%C.I. 12-13)	2	2
$PM_{2.5}$	27	60	1.2	54	1.2	10 (95%C.I. 10-11)	1	1
Radon	83	0.45	1.7	0.44	1.6	3.3 (95%C.I. 2.5-3.8)	8	8
Sulphur dioxide	0.97	1.9	4.5	1.9	4.3	0.73 (95%C.I. 0.26-1.4)	5	5

Values to 2 Sig. Figs.
[a] µg/m^3; Mold in CFU/m^3;Radon in Bq/m^3
[b] DALY/µg/m^3/10^5 person/year(see mold and radon)
[c] Averaged over 10,000 interactions

The APEs support using the linear approach for estimating harm as it yields estimates with minimal deviation from the log-linear approach, being particularly cautions with formaldehyde (for the reasons just mentioned). The relevance of contaminants remains consistent regardless of the approach used.

An extrapolation was conducted to identify the upper limits of the concentration distribution that would yield a MAPE of 10% or below for each contaminant (Table 5.10). The resulting concentration ranges indicate that a MAPE of 10% or below could be achieved within the upper limits typically found in dwellings for all contaminants. For example, when applying the model to PM_{10} concentrations ranging from 0 to 108 µg/m^3, both the linear and log-linear approaches are expected to yield an average MAPE of approximately 10%. The 95% confidence intervals are provided to represent the variability of the error. Similar interpretations can be made for other contaminants.

Table 5.10: Appropriate concentration thresholds for a linear HI_i approach

Contaminant	Concentration distribution[a]	MAPE (%)[b]
Acrolein	(0 - 2.7)	10 (95%C.I. 9-20)
Benzene	(0 - 890)	10 (95%C.I. 8-10)
HCHO	(0 - 33)	10 (95%C.I. 10-10)
Mold	(0 - 3750)	10 (95%C.I. 9-10)
Nitrogen dioxide	(0 - 225)	10 (95%C.I. 10-10)
Ozone	(0 - 495)	10 (95%C.I. 10-10)
PM_{10}	(0 - 108)	10 (95%C.I. 10-10)
$PM_{2.5}$	(0 - 50)	10 (95%C.I. 10-10)
Radon	(0 - 425)	9 (95%C.I. 8-10)
Sulphur dioxide	(0 - 66)	10 (95%C.I. 9-10)

[a] µg/m^3; Mold in CFU/m^3; Radon in Bq/m^3

[b] 1 Sig. Figs.; Averaged over 10,000 interactions

Comparing Table 5.10 with the 97.5th percentile concentrations in dwellings in Table 5.8, one can determine whether reported values fall within a realistic range or appear excessively high. PMs and formaldehyde have upper limit concentrations near the threshold where a 10% MAPE is expected. Users of this metric should exercise caution when applying it to these contaminants to avoid obtaining implausible high estimates of harm. For the remaining contaminants, the linear HI_i metric remains applicable and reasonable, as concentrations required to yield significantly higher APE are improbable in residential environments.

Table 5.11 provides insight into the anticipated concentrations where an APE of approximately 10% is expected for the contaminants. These concentrations represent the point at which the linear approach demonstrates a deviation of around 10% higher compared to the log-linear approach. For particulate matter $PM_{2.5}$, this saturation effect emerges around 25 µg/m^3. The linear HI_i metric is likely to overestimate harm at these median concentrations (compared to the non-linear C-R), although the MAPE for both models remains below the 10% margin of error.

Table 5.11: APE ∼10% (anticipated at)

Contaminant	Median Concentration (SD)[a]
Acrolein	1.5 (1)
Benzene	480 (10)
Formaldehyde	16 (2)
Mold	1900 (50)
Nitrogen dioxide	110 (3)
Ozone	230 (5)
PM_{10}	52 (1)
$PM_{2.5}$	25 (1)
Radon	240 (5)
Sulphur dioxide	36 (3)

[a] 2 Sig. Figs.; µg/m^3; Mold in CFU/m^3; Radon in Bq/m^3

Central estimate concentrations pooled for acrolein, benzene, mold, nitrogen dioxide, sulphur dioxide, ozone, and radon sit well below these thresholds. The linear model should, therefore, reasonably approximate harm for these contaminants, with minimal deviation from the log-linear approach. The linear approach remains effective within the concentrations limits given in Table 5.10.

By contrast, median levels of formaldehyde, PM_{10}, and $PM_{2.5}$ lie closer to these anticipated magnitudes. This signals greater potential for discrepancies between the linear and log-linear models. At higher concentrations than these, the disagreement will keep increasing. With these insights, researchers can make informed decisions about applying the epidemiology-based harm metric. When contaminants approach Table 5.8 thresholds, the log-linear model reflects the flattening of the curve that the literature recommends to reflect the saturation effect. Otherwise, the simple linear model suffices for approximating harm.

The epidemiology-derived harm intensities (HI_i) presented are simple exposure concentration multipliers with quantified uncertainty for assessing chronic indoor contaminant health impacts. However, some limitations exist: Results apply to concentration regimes with approximately linear concentration-response (C-R) functions. Increasing concentrations where the saturation flattens curves will increase disagreement from C-R functions, as the linear is always higher. This work compared only linear and log-linear C-R functions, leaving gaps for future work on other C-R curve fits.

Health data was systematically pooled across geographic regions and demographics without differentiation by country, region, age, sex, or race. The proposed harm metric aims for universal application without singling out specific groups, as is sometimes the case with certain burden of disease harm scenarios targeting only women. Regionalized analysis is especially pertinent in life cycle impact assessment (LCIA) when impacts or environmental conditions exhibit spatial variability. In theory, a regionalized LCIA could yield less uncertain results in life cycle assessments. Likewise, stratified analysis by exposure factors (such as age, gender, occupation, smoking status, and socioeconomic status) becomes necessary depending on the research objective, as seen in studies examining environmental justice disparities.

For particulate matter, equitoxicity was assumed whereby particles are equally toxic per unit of mass intake. Mortality data was preferred to represent harm where possible. However, some contaminant estimates rely on limited outcomes, likely underestimating chronic harm to an unknown degree. Until more indoor epidemiology research emerges, this approach relies on outdoor epidemiology studies to assess indoor impacts.

5.4 Unifying Toxicity and Epidemiology

Toxicology and epidemiology furnish complementary evidence on the health effects of contaminants through a shared parameter: the dose-response factor (DRF). The DRF in toxicology, denoted as $DRF_{(i)}^{tox}$, stems from animal studies. Its epidemiological counterpart, $DRF_{(i)}^{epi}$, relies on human cohort studies. The subscript "i" denotes the nomenclature for a contaminant.

Comparing these DRFs enhances human health assessments. Animal studies provide controlled data but suffer from cross-species uncertainties. In contrast, human studies offer direct evidence but are restricted by the specific cohorts available.

$\text{DRF}_{(i)}^{\text{tox}}$ and $\text{DRF}_{(i)}^{\text{epi}}$ are mathematically equivalent (see equation 3.34). Meta-analysis techniques can unify these independent streams of evidence. This mathematical alignment extends to effect factors (EF_i) and harm intensities (HI_i), which also share units.

Meta-analyses have gained traction for fusing epidemiological and toxicological data in human health risk assessments. They reduce uncertainties and offer a comprehensive view, despite inherent challenges such as heterogeneous study designs and data types (Authority, 2018; Boyes et al., 2007; Hernández and Tsatsakis, 2017; Peters et al., 2005; Verde and Ohmann, 2015).

Five contaminants appeared in both types of studies: acrolein, benzene, formaldehyde, ozone, and radon. Their harm intensities were therefore pooled. Table 5.12 outlines the estimates and uncertainties (See Appendix 18 for full descriptive statistics).

Table 5.12: Pooled Epi and Tox HI_i estimates, DALY/µg/m^3/10^5 person/year.$^+$

Contaminant	**Median**	**GSD**
Acrolein	1.2	4
Benzene	0.067	1.4
Formaldehyde	4.3	2
Ozone	1.3	1.9
Radon*	0.44	1.6

$^+$ Values to 2 Sig. Figs.
* DALY/Bq/m^3/10^5 person/year; Bq, Becquerels

Toxicology often predicts higher harm intensity medians and means than epidemiology, reflecting its greater potency estimates from controlled settings. Yet, it also presents higher uncertainties. Pooled estimates balance these aspects. They keep medians close to epidemiological estimates while raising means, thus integrating high potency evidence from toxicology.

The shared parameters reveal further insights. A mathematical relationship exists between the toxicological effective median dose (ED50) and epi-

demiological risk factors. Equation 5.3 delineates this relationship. This proportional linkage reinforces the complimentary roles of toxicology and epidemiology, highlighting the benefits of integrating both disciplines.

$$\frac{1}{\mathrm{ED50}_{(k',i)}} \propto \gamma_{0_{k'''}} \cdot \beta_{(k''',i)} \tag{5.3}$$

Varying numbers of $'$ visually distinguish where different health outcomes are being accounted for, however considered equivalent (Section 3.5).

In the USEtox model, a 0.5 multiplier is applied to represent assumed linearity in low-dose impacts. This multiplier is mathematically equivalent to key parameters from both disciplines, as shown in Equation 5.4.

$$0.5 \equiv \gamma_0 \cdot \beta \cdot \frac{ED50}{BR} \tag{5.4}$$

When evaluating the 0.5 assumption for specific contaminants based on their parameter inputs, acrolein exhibits a value of 0.004, suggesting appropriateness of the linear low-dose approximation. Benzene and ozone showed reasonable agreement with 0.5. However, radon results in a higher equivalence value of 1.5, indicating potential nonlinearity or threshold effects not captured by this simplifying assumption.

Meta-analyses are underutilized in life cycle and air pollution risk assessments (to pool $\mathrm{EF}^{\mathrm{tox}}_{(i)}$ and $\mathrm{EF}^{\mathrm{epi}}_{(i)}$ for example). This could complement the prevailing 'weight of evidence' approach (Goodman et al., 2021; Richmond-Bryant, 2020), especially when handling complex and varied data streams.

One might think that mean, median, or the central estimate should be identical across both methodologies. However, discrepancies arise due to differences in approach and specificity. Despite these challenges, DRFs, EFs, and harm intensities showed significant alignment for the five contaminants. This underscores the value and validity of this integrated approach, even if perfect parity remains out of reach.

5.5 Harm Intensities, HI_i.

Epidemiological and toxicological research was used, and pooled, to calculate the harm intensity (HI_i) of 44 common indoor air contaminants found

in dwellings (Section 3.1).

Table 5.13 shows the single-point estimates and uncertainties. The HI of the coarse fraction can be calculated once the harm from the other PM fractions is known by subtracting the fine fraction from PM_{10} (this is discussed in chapter 7).

$PM_{2.5}$ shows the greatest harm intensity, but PM_{10} and chromium are also important because they have HI_i that are several times higher than any other of the included contaminants.

The elevated harm intensity observed for PM results from the combined effects of baseline incidence, relative risk, and damage factors, all of which relate to all-cause mortality associated with particle exposure.

Chromium's high magnitude of harm intensity is a function of its toxicological characteristics, specifically the low effective median dose, that induces an effect in the population.

The harm intensities derived from toxicology-based and epidemiology-based approaches are not dependent on specific concentration values.

In the toxicology-based approach, the ED50 (effective dose for 50 % of the population) encompasses the dose, including the exposure itself.

In the epidemiology-based approach, the risk coefficient derived from exposure concentrations implicitly incorporates the exposure. This inherent feature of the harm metric enables its broad application across different environments.

Harm intensities alone do not give a complete understanding of the potential harm a contaminant can cause in a space, and neither do concentrations. Concentrations and harm intensities are required together.

It is important to note that a low concentration of a contaminant with a high harm intensity could pose a higher health risk than a high concentration of a contaminant with a low harm intensity.

Table 5.13: Harm intensities, HI_i, DALY/µg/m^3/10^5 person/year.$^+$

Contaminant	Median	GSD	Approach
Acetaldehyde	0.053	4.8	Toxicology
Acrolein	1.2	4.0	Pooled
Acrylonitrile	1.2	4.1	Toxicology
Benzene	0.067	1.4	Pooled
Benzyl chloride	0.062	11	Toxicology
1,3-Butadiene	0.27	3.9	Toxicology
2-Butoxyethanol	0.010	8.7	Toxicology
Cadmium Cd(II)	5.3	8.9	Toxicology
Carbon disulfide	0.29	1.1	Toxicology
Carbon tetrachloride	0.52	7.3	Toxicology
Chloromethane	0.00027	10	Toxicology
Chromium Cr(VI)	17	15	Toxicology
Crotonaldehyde(trans)	1.1	7.2	Toxicology
1,2-Dibromoethane	3.4	5.8	Toxicology
1,4-Dichlorobenzene	0.012	6.4	Toxicology
1,2-Dichloroethane	0.052	5.4	Toxicology
1,1-Dichloroethene	0.15	6.1	Toxicology
Ethanol	0.0005	5.8	Toxicology
2-Ethylhexanol	0.0029	8.4	Toxicology
Formaldehyde	4.3	2.0	Pooled
Hexachlorobutadiene	0.030	4.8	Toxicology
Hexane	0.0018	8.7	Toxicology
Isoprene	0.0092	7.0	Toxicology
Limonene (d-...)	0.0093	6.5	Toxicology
2-Methoxyethanol	0.0028	7.8	Toxicology
Methyl methacrylate	0.051	2.8	Toxicology
Methyl tert-butyl ether	0.026	4.6	Toxicology
Methylene chloride	0.010	5.6	Toxicology
Mold	0.026*	2.1	Epidemiology
Naphthalene	0.36	5.9	Toxicology
Nitrogen dioxide	5.7	1.7	Epidemiology
Ozone	1.3	1.9	Pooled
PM_{10}	30	1.3	Epidemiology
$PM_{10-2.5}$	3.8	4.3	–
$PM_{2.5}$	60	1.2	Epidemiology
Radon	0.44**	1.6	Pooled
Styrene	0.11	4.7	Toxicology
Sulphur dioxide	1.3	5.3	Epidemiology
1,1,2,2-Tetrachloroethane	0.13	6.2	Toxicology
Tetrachloroethene	0.052	6.2	Toxicology
Toluene	0.00087	5.4	Toxicology
1,1,2-Trichloroethane	0.15	5.7	Toxicology
Trichloroethylene	0.0035	5.1	Toxicology
Vinyl chloride	0.98	5.4	Toxicology
Xylenes	0.0034	6.1	Toxicology

$^+$ Values to 2 Sig. Figs.
* DALY/CFU/m^3/10^5 person/year; CFU, Colony-Forming Units. As mold spores of the genus Cladosporium
** DALY/Bq/m^3/10^5 person/year; Bq, Becquerels

5.6 Summary

This chapter introduced the concept of harm intensity as a metric linking chronic exposure to indoor air contaminants with potential population health impacts. Both toxicology and epidemiology research were leveraged to derive harm intensity values for a range of common indoor pollutants. Key highlights include:

- The harm intensity relates total harm (in DALY/person/year) to annual contaminant exposure, with units of DALY/µg/m^3/person/year. This enables direct estimation of health impacts given exposure concentrations.
- Harm intensities were calculated for 44 contaminants. $PM_{2.5}$ showed the highest median.
- Comparison with previous methods demonstrated reduced uncertainty and updated inputs, yielding revised harm intensity estimates. Toxicology medians exceeded epidemiology, while pooling provided a balance.
- Both linear and non-linear concentration-response epidemiological models were evaluated. The simple linear approximation is reasonable for most contaminants given typical indoor levels. Formaldehyde requires extra caution when used (later on Section 7.1).
- Limitations remain around geographic and demographic specificity, toxicity assumptions, and reliance on outdoor epidemiology evidence. But the metric provides an improved basis for exposure-based risk screening and prioritization.

Chapter 6

Airborne Contaminants in Dwellings

The contents of this chapter are part of the publication:

Morantes, G., Jones, B., Sherman, M., & Molina, C. (2023). Harm from residential indoor air contaminants. *Environmental Science & Technology*. Article ASAP DOI: 10.1021/acs.est.3c07374

6.1 A systematic review to quantify representative concentrations in dwellings (C_i)

This section describes the approach for determining representative indoor air contaminant concentrations (C_i). C_i is defined as the median concentration of an airborne contaminant (i) found in dwellings.

To determine the uncertainty in the concentrations of the 44 contaminants of interest (Section 3.1), a global systematic literature review identified studies reporting measurements of these 44 contaminants in residences, published between 2010-2020. Review was limited towards chronic exposures (periods > 24 hours). Publications in any language were included if an English abstract was available. Modeling, policy, and commentary studies were excluded. The search criteria are listed in Table 6.1 excluding the specific syntax for each database.

Table 6.1: Keywords and Boolean operators when performing systematic reviews on input parameters.

Input parameter	Representative Indoor Air Contaminant Concentration (C_i)
Research question	What are the values of indoor air pollutants in households?
Keywords and Boolean operators [a]	(house* OR domestic OR dwelling*) AND "indoor air" AND ("air pollution" OR "air quality" OR "particulate matter" OR "Nitrogen Dioxide" OR NO2 OR Ozone OR O3 OR "Sulphur Dioxide" OR SO2 OR ("Carbon Monoxide" NOT poison*)) AND (review OR "observational stud*") AND (exposure OR monitor* OR sampl* OR measure*) AND (concentrat*) AND (mean OR median) AND (sample*)
Databases	Scopus, Pubmed, and Web of Science.

[a] All 44 contaminants followed the same logic, with each one as a keyword.

A 45th contaminant, *coarse fraction particulate matter* ($PM_{10-2.5}$), is added by taking the difference between respirable particulate matter (PM_{10}) and fine particulate matter ($PM_{2.5}$). Albeit not included in the review, it is relevant for later analyses.

The search was limited to residential environments including apartments, dormitories, and houses. The 2010-2021 date range was selected based on Logue et al.'s work (Logue et al., 2011a). The search was expanded for contaminants lacking studies in this range. The search was complemented by other indoor exposure reviews (Gonzalez-Martin et al., 2021) and technical reports from international organizations mentioned in these studies. All countries and regions were included. The review considered contaminants regardless of source - emitted indoors, entering from outdoors, or both. Concentrations measured by fixed or portable samplers/monitors and, both optical or gravimetric samplers were included. The results of this process of literature search and publication review are shown in Figure 6.1.

The search strategy concentrated on gathering data from households in common, everyday conditions, aiming to reflect the variety of activities and behaviors typically encountered in such environments (cooking, cleaning, bathing, sleeping, working, and alike). The aim was to create concentration summaries that could be generalized or applied broadly. Highly controlled or constrained scenarios were avoided to prevent outliers: Studies focused

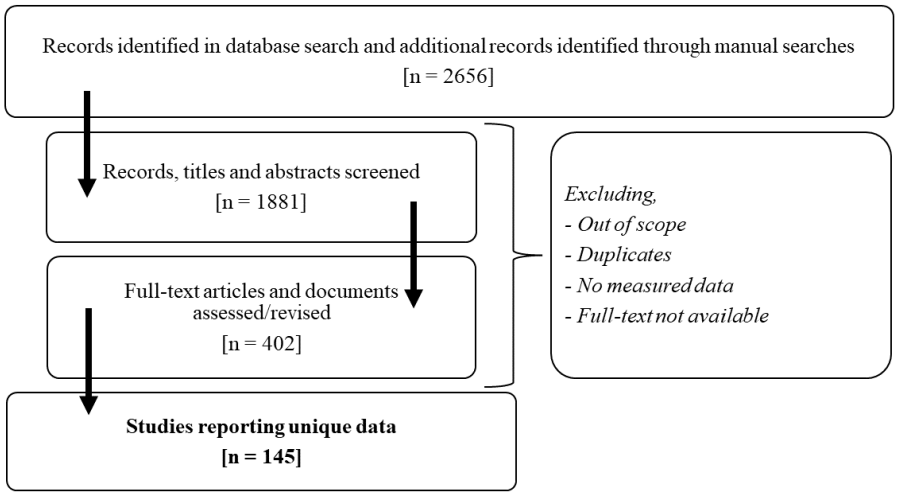


Figure 6.1: Review process diagram.

solely on periodic indoor activities like cooking or cleaning, like O'Leary et al. (2019) for $PM_{2.5}$ emissions from cooking were not considered. Atypical dwellings like passive houses were excluded. The review conducted by Moreno-Rangel et al. (2020) on IAQ parameters in Passivhaus dwellings highlighted a wide variation in $PM_{2.5}$, ranging from 16 to 90 µg/m^3. However, the limited availability of databases impedes drawing definitive conclusions. Moreover, the majority of studies primarily evaluate air quality based on CO_2 levels or perceived stuffiness.

The reviews' aim is to provide evidence of uncertainty in the median contaminant concentrations for dwellings from a non-spatially-restrictive perspective.

The primary data extracted from the studies included concentration statistics and country/region. Concentration measurements' central tendency estimates were reported using various metrics, including means, medians, and geometric means. Statistics used to reflect the spread of the data include standard deviations, confidence intervals, and extreme values (such as the minimum and maximum). To ensure consistency, medians and 95% confidence intervals were extracted from the papers. The assumption is that concentrations follow a right-skewed and log-normal distribution, supported by studies such as Ott (1990) and referenced by Blackwood (1992); Crow and Shimizu (1987); Jia et al. (2008). This remains widely accepted in the field, as indicated by Halios et al. (2022); Logue et al. (2011a); Spengler et al. (2000).

A database was created, including the study, the contaminant, and the median and the 95% confidence intervals (CIs) for each sampling campaign reported in the study (this constitutes a dataset). Descriptive statistics, including mean, standard deviation (SD), minimum, maximum, geometric mean (GM), geometric standard deviation (GSD), and median, are calculated from the list of medians of the database. These are presented in Table 6.2. Next, medians and confidence intervals from the database were pooled using meta-analysis. Meta-analysis combines results accounting for uncertainty. The outputs given from a meta-analysis are a central tendency estimate, called *outcome effect measure* and a 95% CI interval that is affected by the 95% CIs of each input, so that inputs with wide spread of values weight less and have less influence on the results, as well as assumptions regarding normality of distributions (DerSimonian and Laird, 1986b; StataCorp, 2019). Other techniques based on weighted means (Logue et al., 2011a) and geometric means (Halios et al., 2022) have also been used in the literature: medians are often weighted by sample size, and the weighted median is reported as the primary result of the analysis, as shown in Table 6.3. Here, the results from each meta-analysis were taken and modeled by applying parameter distributions (Section 3.8). This process is illustrated in the creation of Table 6.4.

Table 6.2 details a full list of the extracted information with summary statistics of the studies included, and the results of the meta-analyses performed for the datasets of each contaminant (the latter were the inputs for the Monte Carlo approach).

The review included 145 references with 827 indoor air contaminant measurement datasets. The United States, China, Canada, and United Kingdom were most represented. Just these four locations account for 55% of the studies. When considering classification of countries into "the global North" (Lees, 2021) this increases to 82%. The categorization of countries into terms like "the global North" or "developed nations" lacks straightforwardness and is contingent on the context. Certain influential nations defy clear placement within the dichotomy of the global North and South. China, in particular, stands out as a significant example (Lees, 2021). Africa, Latin America, and the Middle East were sparsely studied, potentially leading to lifestyle-based concentration discrepancies. The United States was the most intensely studied country, with 37 publications and 166 of the datasets; followed by China, with 20 publications and 104 of the datasets; and Canada, with 12 publications and 95 of the datasets.

Table 6.2: Systematic review and meta-analysis on indoor air contaminant concentration in dwellings.

Descriptive statistics from the systematic review										**Meta-analysis results**		
CAS	Contaminant	Mean	Std dev	Min	Max	Geom mean	Geom Std dev	Median	Data Sets	Outcome effect measure	2.5ptile	97.5ptile
75-07-0	Acetaldehyde	22	29	6.8	140	15	2.5	17	36	15	7.3	30
107-02-8	Acrolein	2.5	3.5	0.1	15	1	4.7	1.2	20	0.65	0.37	1.1
107-13-1	Acrylonitrile	0.39	0.2	0.27	0.74	0.35	1.7	0.27	4	0.72	0.58	0.89
71-43-2	Benzene	3.3	2.7	0.85	12	2.2	2.3	2.1	65	2.3	1.6	3.4
100-44-7	Benzyl chloride	0.5	0	0.5	0.5	0.5	1	0.5	2	0.5	0.098	2.5
106-99-0	1,3-butadiene	0.88	1	0.05	3.1	0.45	1.4	0.46	11	0.46	0.27	0.79
111-76-2	2-Butoxyethanol	2.9	0.82	2.1	4.5	2.5	1.3	2.8	8	3	1.7	5.1
22537-48-0	Cadmium Cd(II)	0.024	0.024	0.0026	0.07	0.014	3.4	0.018	5	0.015	0.005	0.042
75-15-0	Carbon disulfide	0.34	0	0.34	0.34	0.34	1	0.34	2	0.34	0.19	0.63
56-23-5	Carbon tetrachloride	0.55	0.53	0.077	2.2	0.35	2.7	0.41	18	0.52	0.37	0.72
78-87-3	Chloromethane	1.7	0.1	1.6	1.8	1.7	1.1	1.7	2	1.6	1.5	1.8
18540-29-9	Chromium Cr(VI)	0.0064	0.0042	0.0022	0.011	0.0048	3	0.0064	2	0.006	0.002	0.027
123-73-9	Crotonaldehyde(trans)	1.9	1.9	0.09	5.6	0.85	4.3	1.1	13	0.8	0.34	1.9
106-93-4	1,2-Dibromoethane	0.38	0.43	0.006	0.98	0.094	13	0.14	3	0.096	0.008	1.2
106-46-7	1,4-Dichlorobenzene	15	26	0.05	120	5.3	10	2.8	30	2.2	1.1	4.6
107-06-2	1,2-Dichloroethane	0.73	0.89	0.0032	2.7	0.29	5	0.25	21	0.53	0.38	0.73
75-35-4	1,1-Dichloroethene	0.34	0.24	0.018	0.6	0.16	6.8	0.4	3	0.51	0.3	0.86
64-17-5	Ethanol	350	290	56	860	230	2.8	290	7	130	67	250
104-76-7	2-Ethylhexanol	2.1	0.9	1	3.7	1.9	1.6	1.7	6	2	0.97	3.9
50-00-0	Formaldehyde	32	22	6.6	110	26	1.9	24	67	28	23	34
87-68-3	Hexachlorobutadiene	1.7	0	1.7	1.7	1.7	1	1.7	2	1.7	0.62	4.7
110-54-3	Hexane	3	2.7	0.1	11	1.8	3.4	1.8	19	1.7	0.83	3.3
78-79-5	Isoprene	5.3	4.5	1.6	16	4	2.2	3.6	8	6.5	3.9	11
5989-27-5	Limonene (d-...)	34	87	0.27	410	14	3.3	18	39	15	6.5	33
109-86-4	2-Methoxyethanol	43	61	0.12	130	1.2	56	0.13	4	1.3	0.009	170
80-62-6	Methyl methacrylate	0.27	0	0.27	0.27	0.27	1	0.27	2	0.27	0.034	2.1
1634-04-4	Methyl tert-butyl ether	7.2	5	0.1	16	4.1	5	4.6	8	4.4	1.7	12

continue on the next page.....

Table 6.2 – Continue

Descriptive statistics from the systematic review									**Meta-analysis results**		
CAS	Contaminant	Mean	Std dev	Min	Max	Geom mean	Geom Std dev	Median	Data Sets	Outcome effect measure	2.5ptile	97.5ptile
75-09-2	Methylene chloride	2.2	2.8	0.1	8.2	0.82	5.1	0.98	6	0.91	0.32	2.5
–	Mold	200	140	44	510	160	2.1	180	9	160	110	240
91-20-3	Naphthalene	33	120	0.18	500	1.6	7.4	0.85	19	1.5	0.54	4.4
10102-44-0	Nitrogen dioxide	38	52	2.8	240	23	4.6	23	48	22	16	32
10028-15-6	Ozone	15	16	1.3	59	9.5	5500	9	10	10	4	28
–	PM_{10}	82	76	17	350	60	2.1	53	35	64	46	89
–	$PM_{10-2.5}$[a]	29	–							37	27	52
–	$PM_{2.5}$	52	67	0.022	430	25	4	28	110	27	19	37
10043-92-2	Radon	130	110	32	360	92	2.3	60	10	83	53	130
100-42-5	Styrene	2.2	2.5	0.11	13	1.4	2.7	1.4	34	1.6	1.1	2.4
7446-09-5	Sulphur dioxide	5.9	9	0.09	26	1.4	19	1.4	8	0.97	0.18	5.4
79-34-5	1,1,2,2-Tetrachloroethane	0.24	0.18	0.005	0.42	0.099	8.1	0.27	4	0.088	0.017	0.45
127-18-4	Tetrachloroethene	0.92	0.8		2.9	0.65	2.8	0.58	21	0.84	0.7	1
100-88-33	Toluene	15	15	0.69	95	11	2.2	12	67	13	11	16
79-00-5	1,1,2-Trichloroethane	0.34	0.18	0.1	0.6	0.28	2	0.45	9	0.3	0.18	0.5
79-01-6	Trichloroethylene	0.44	0.54	0.015	1.8	0.23	3.3	0.24	20	0.46	0.39	0.54
75-01-4	Vinyl chloride	0.16	0.0025	0.16	0.16	0.16	1	0.16	2	0.16	0.031	0.8
1330-20-7	Xylenes	7.7	2.9	1.4	13	6.9	1.7	7.7	13	7	4.8	10

Units in $\mu g/m^3$; Radon in Bq/m^3; Mold in CFU/m^3.
[a] $PM_{2.5}$ subtracted from PM_{10} to estimate $PM_{10-2.5}$. Uncertainty calculated per PM fractions. Approach adds uncertainty but is common practice (Sacks et al., 2022). Coarse PM fraction of 0.36 based on mean of table data.

Though a non-spatially-restrictive perspective was pursued, some regions were not well accounted for, likely due to search strategy limitations excluding non-English studies (sampling campaigns published in Spanish, French, Chinese language journals for example) rather than lack of data. Four pre-2010 references were included for cadmium, chromium, mold, and acrolein, which lacked sufficient 2010-2020 studies (Canada, 2020; Finley et al., 1996; Matheson et al., 2005; National Research Council (US) Subcommittee on Zinc Cadmium Sulfide, 1997; Stark et al., 2005).

Sampling of the $PM_{10-2.5}$ size fraction in dwellings is still under-reported in the literature, and it is common practice to derive this contaminant by subtracting $PM_{2.5}$ from PM_{10} (Sacks et al., 2022; US-EPA, 2020b). An uncertainty factor was assigned to the central tendency of $PM_{10-2.5}$ using the GSD for the other PM fractions. The fraction of PM_{10} attributed to $PM_{10-2.5}$ is 0.36 (see mean column Table 6.2).

While substantial, the data may not accurately reflect all countries' contaminant concentrations due to uneven representation. Caution is advised when generalizing results to specific locations. Further work is needed to reduce uncertainty for the 12 contaminants with fewer than 5 data sources. Detailed analysis accounting for country/region, climate, and building differences affecting exposure would improve accuracy for local populations and may reveal other important local contaminants.

Review articles have been conducted on airborne contaminants present in indoor residential environments (Fazli and Stephens, 2018; Halios et al., 2022; Ilacqua et al., 2022; Logue et al., 2011a; Morawska et al., 2013, 2017; Nishihama et al., 2021; Vardoulakis et al., 2020; Ye et al., 2017). However, these studies vary in their objectives, geographical scope, types of contaminants, underlying methodology decisions, and time periods considered. The central tendency and statistics reported in each study varies (mean, median, Weighted Average Geometric Mean- WAGM). Additionally, some review articles employ a narrative approach, without pooling data in a quantitative manner. Table 6.3 summarizes details on existing literature reviews of indoor contaminants in dwellings.

Adopting a non-spatially-restricted perspective has both advantages and limitations. To provide insights on data variability, PM_{10} and $PM_{2.5}$ are examined for the most studied regions: the USA, China, Canada, and the UK. For $PM_{2.5}$, these countries provided: USA 24%, China 22%, Canada 6%, UK 5% of studies. Meta-analysis by country gives concentrations

Table 6.3: Summary of existing literature reviews of indoor air contaminant concentrations in dwellings

Work	Contaminants surveyed	Statistics extracted	Spatial scope	Method of pooling	Time frame	# of Refs	Indoor
	44 (see Section 3.1)						
	PM						
This work	Criteria pollutants [S,V]VOCs	Mean, median, SD, 95%C.I.	Global	Meta-analysis	2010-2020	145	Any residential
	Biological						
	Radiological						
	267 chemical pollutants: PM						
Logue et al. (2011a)	Criteria pollutants [S,V]VOCs	Median, 25thpctile, 95thpctile.	USA and similar countries	Study measurement quantity weighting	1995–2010	77	Residences
	24 selected pollutants:						
Vardoulakis et al. (2020)	PM	Minimum, maximum	No limitations	None	2000-2017	141	Households
	Criteria pollutants [S,V]VOCs						
	10 pollutants:						
Fazli and Stephens (2018)	PM	Median	USA	None	–	72	Houses
	Criteria pollutants VOCs						
Morawska et al. (2013)		Median, minumum, maximum	Developed countries	None	01/1989 to 10/2012	44	Residences (and others)
Morawska et al. (2017)	PM fractions only	Weighted mean, minimum, maximum	No limitations	Study location quantity weighting	1990–2017	12	Homes (and others)
Ilacqua et al. (2022)		Median, minimum, maximum	Worldwide	Mean weighted by study size	1990-2019	538	Residential
Nishihama et al. (2021)		Median, minumum, maximum	Japan	None	2011-2016	–	Households
	23 pollutants						
	PM						
Ye et al. (2017)	Criteria pollutants [S,V]VOCs	Minimum, maximum	China (rural and urban)	None	Assuming 2006-2016	11	Residential
	Biological						
	Radiological						
Halios et al. (2022)	65 individual VOCs	WAGM, minimum, maximum	Europe	WAGM	2000-2020	39	Residences

(95%CI) of: USA 14 (11-18) µg/m^3; China 73 (52-103) µg/m^3; Canada 3 (2-5) µg/m^3; UK 25 (14-45) µg/m^3. The studies included for China reflect the use of solid fuels (wood and coal) in homes, influencing a relatively higher central estimate. The USA estimate aligns well with reported values for that country. The USA and China hold 25% and 23% weight in the $PM_{2.5}$ pooled concentration. Table 6.2 shows the $PM_{2.5}$ pooled concentrations. For PM_{10}: USA 3%, China 17%, UK 9% of studies. By country: USA 20 (5-79) µg/m^3; China 171 (112-261) µg/m^3; UK 42 (25-71) µg/m^3. China has 21% PM_{10} pooled concentration weight. Table 6.2 shows the PM_{10} pooled concentrations.

Source attributions, including appliances, fuel types, and personal activities, were reported by the revised papers during the sampling periods. Recent works provide additional insights on source attribution and their influence on indoor concentrations (Halios et al., 2022; Morawska et al., 2017; Vardoulakis et al., 2020). To investigate findings, $PM_{2.5}$ influencing sources were extracted from included studies. Seven prominent sources were identified and the frequency each one was linked to $PM_{2.5}$: Combustion [candles, incense, cooking, heating/cooling, smoking] - 52%; Cleaning - 9%; Occupant activities - 9%; Outdoor - 9%; Personal care products - 8%; Pets - 3%; Interior modifications - 11%. As expected, everyday combustion activities within homes were the primary $PM_{2.5}$ source.

All sampler types were included, excluding modeled concentrations. Gravimetric equivalency was not addressed (for more see (Okello et al., 2018; Soneja et al., 2014; Zhang et al., 2018)). This represents an opportunity for further discussion, as previous PM reviews do not address this issue. For $PM_{2.5}$ studies in the datasets for the four most studied regions, 3/5 used gravimetric and 2/5 used optical samplers. Pooled values by sampler were: -Optical: 22 µg/m^3 (95% CI 14 - 34); -Gravimetric: 29 µg/m^3 (95% CI 19 - 45). Although differences in these central tendencies exist, statistical significance was not explored, as examining sampler influence on harm differences was outside the current scope.

While indoor contaminant concentrations certainly vary across diverse factors like country, source, and season, the depth of concentration analysis provided sufficiently achieves this research's aim of developing a health-based metrics and its applicability to select contaminants of concern for dwellings. The pooled meta-analyses incorporating available non-spatially-restrictive data are appropriate given this focus. This section prioritized

conveying the fundamental principles of the concentration systematic review to ensure a clear understanding of the approach.

6.1.1 Representative indoor contaminant concentrations (C_i)

Table 6.4 presents the medians, uncertainty in the representative concentrations (after modeling their distributions), and the number of datasets reviewed for each contaminant (See Appendix 19 for full descriptive statistics). Contaminant concentrations are reported in µg/m^3, except for radon (Bq/m^3) and mold spores (CFU/m^3). The five most abundant contaminants by mass are ethanol, PM_{10}, formaldehyde, $PM_{2.5}$, and nitrogen dioxide (NO_2). $PM_{10-2.5}$ is within this group but not mentioned because it was inferred from the other PM fractions. Median representative concentrations for ethanol, PM_{10}, and formaldehyde are 110 µg/m^3 (7 datasets), 62 µg/m^3 (48 datasets), and 28 µg/m^3 (67 datasets), respectively. 28 contaminants have a median concentration of < 2.0 µg/m^3.

The contaminant concentration distributions in Table 6.4 reflect exposures caused by common activities expected to occur in homes, which might include cooking, candle use, smoking, the combustion of solid fuels (wood and coal), and incense burning. There is still significant uncertainty in the concentrations of some contaminants.

The concentration statistics of the 45 contaminants are broadly similar to those reported in other literature reviews (Fazli and Stephens, 2018; Halios et al., 2022; Ilacqua et al., 2022; Logue et al., 2011a; Morawska et al., 2013, 2017; Nishihama et al., 2021; Vardoulakis et al., 2020; Ye et al., 2017). Figure 6.2 illustrates their trends over the past three decades. There are some noticeable differences in the medians, and in the overlaps of the GSD, but generally, there is good agreement between these results (in black) and other studies. Differences may be attributed to the inherent variations in the individual studies (see Table 6.3). The similarities in concentrations may be attributed to the fact that this review, and the previous studies, primarily rely on data from a limited number of countries, including the USA, China, Canada, and the UK; predominantly high-income industrialized nations that are often referred to as Global North countries (these are regions with reasonable data homogeneity and representation).

Table 6.4: Representative concentrations, C_i, µg/m^3.$^+$

Contaminant	Median	GSD	Datasets
Acetaldehyde	13	1.7	36
Acrolein	0.60	1.5	20
Acrylonitrile	0.71	1.2	4
Benzene	2.2	1.3	65
Benzyl chloride	0.22	3.4	2
1,3-Butadiene	0.43	1.5	11
2-Butoxyethanol	2.7	1.5	8
Cadmium Cd(II)	0.011	2.2	5
Carbon disulfide	0.31	1.6	2
Carbon tetrachloride	0.50	1.3	18
Chloromethane	1.6	1.1	2
Chromium Cr(VI)	0.0031	3.2	2
Crotonaldehyde(trans)	0.65	1.9	13
1,2-Dibromoethane	0.018	6.0	3
1,4-Dichlorobenzene	1.90	1.7	30
1,2-Dichloroethane	0.52	1.3	21
1,1-Dichloroethene	0.48	1.5	3
Ethanol	110	1.6	7
2-Ethylhexanol	1.7	1.7	6
Formaldehyde	28	1.2	67
Hexachlorobutadiene	1.3	2.2	2
Hexane	1.4	1.7	19
Isoprene	6.0	1.5	8
Limonene (d-...)	12	1.9	39
2-Methoxyethanol	0.021	12	4
Methyl methacrylate	0.082	4.3	2
Methyl tert-butyl ether	3.3	2.1	8
Methylene chloride	0.67	2.1	6
Mold	160*	1.3	9
Naphthalene	1.1	2.2	19
Nitrogen dioxide	22	1.3	48
Ozone	7.3	2.2	10
PM_{10}	62	1.3	35
$PM_{10-2.5}$	35	1.4	–
$PM_{2.5}$	26	1.3	107
Radon	78**	1.4	10
Styrene	1.6	1.3	34
Sulphur dioxide	0.41	4.0	8
1,1,2,2-Tetrachloroethane	0.040	3.4	4
Tetrachloroethene	0.83	1.1	21
Toluene	13	1.1	67
1,1,2-Trichloroethane	0.28	1.4	9
Trichloroethylene	0.45	1.1	20
Vinyl chloride	0.072	3.3	2
Xylenes	6.8	1.3	13

$^+$ Values to 2 Sig. Figs.
* CFU/m^3; CFU, Colony-Forming Units
** Bq/m^3; Bq, Becquerels

The estimation of $PM_{10-2.5}$ concentrations, determined by subtracting $PM_{2.5}$ from PM_{10}, introduces some uncertainty in interpreting the coarse

fraction. However, the central tendency aligns well with the findings of Ilacqua et al. (2022) who compiled measurements of $PM_{10-2.5}$ from various studies (Figure 6.2). The fraction of PM_{10} attributed to $PM_{10-2.5}$ is 0.36, which is comparable to *in-situ* measurements in dwellings of 0.56 reported by Morawska et al. (2017), 0.46 by Ilacqua et al. (2022), 0.26 by Nishihama et al. (2021) and 0.19 by Morawska et al. (2013).

6.2 Summary

A global systematic review compiled indoor contaminant concentration data to determine representative exposure levels and uncertainties for 44 contaminants of interest, in dwellings. Measurements from 145 studies and 31 countries provided over 800 datasets spanning 2000-2020. Meta-analysis derived central tendencies. While substantial, uneven global representation warrants caution generalizing to all regions. Figure 6.2 provides a visual representation of the distribution uncertainty of air contaminants commonly found in dwellings over the past two decades. This snapshot offers insights into the variability and trends of these contaminants. The concentration data predominantly originate from countries with extensive research, notably the USA, Canada, and the UK—representative of the Global North, and China.

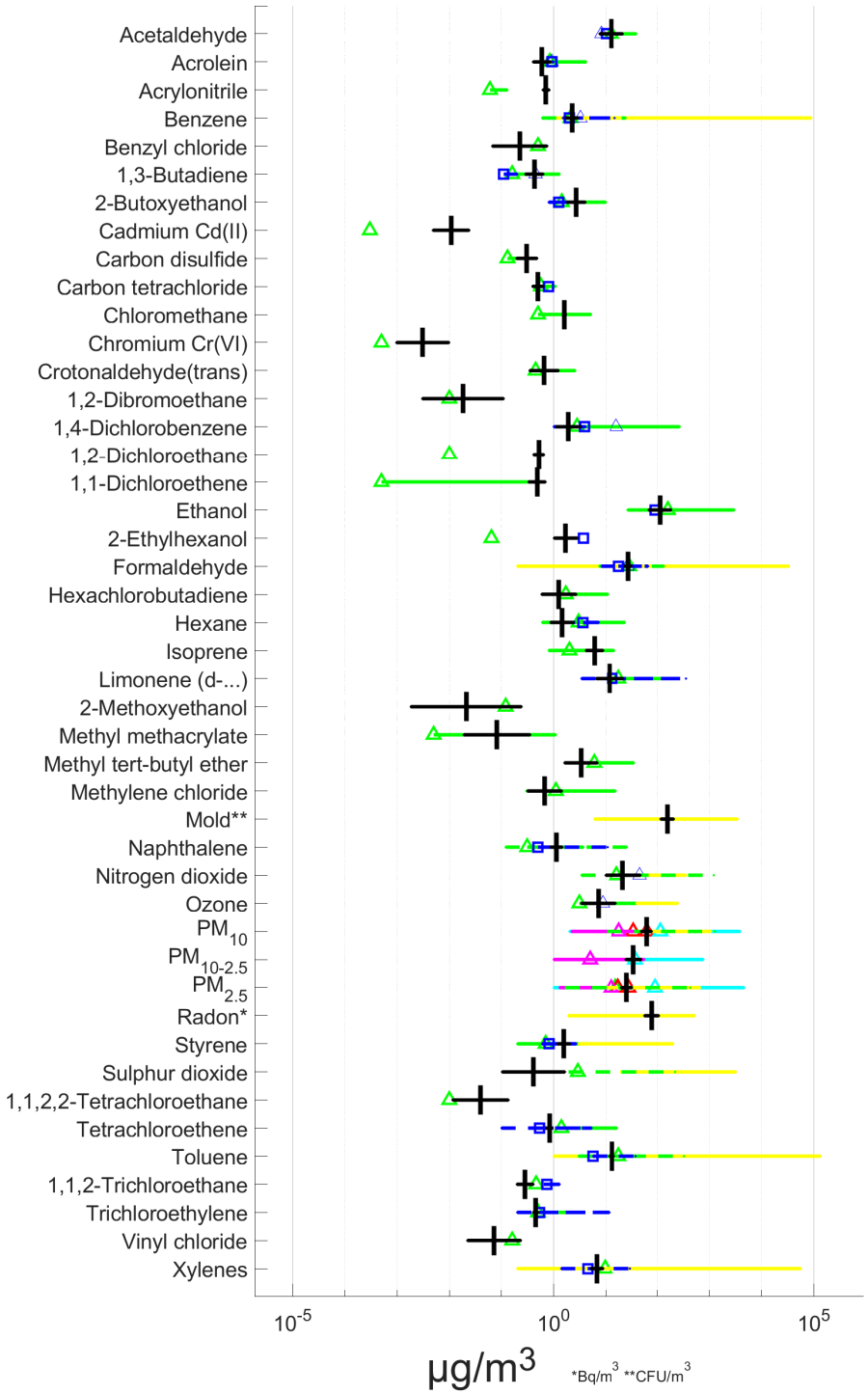


Figure 6.2: Representative airborne contaminant concentrations. Evaluation against prior research. Median & GSD. Black, current work; Green-triangle= Logue et al., Blue-triangle= Fazli and Stephens, Red-triangle= Morawska et al.; Morawska et al.,Cian-triangle= Ilacqua et al., Magenta-triangle= Nishihama et al., Yellow-triangle= Ye et al., Green-square,dashes= Vardoulakis et al., Blue-square,dashes= Halios et al.

Chapter 7

Contaminants Harm in Dwellings

The contents of this chapter are part of the publication:

Morantes, G., Jones, B., Sherman, M., & Molina, C. (2023). Harm from residential indoor air contaminants. *Environmental Science & Technology*. Article ASAP DOI: 10.1021/acs.est.3c07374

In addition, preliminary results from this chapter were previously presented as a long presentation, and paper at the AIVC conference 2022, and as a journal publication:

Morantes, G., Jones, B., Sherman, M., & Molina, C. (2022). Health impacts of indoor air contaminants determined using the DALY metric. In *42nd AIVC - 10th TightVent - 8th venticool Conference* - Rotterdam, Netherlands. 10 pp. ISBN: 2-930471-63-1

Morantes, G., Jones, B., Sherman, M., & Molina, C. (2023). A preliminary assessment of the health impacts of indoor air contaminants determined using the DALY metric. *International Journal of Ventilation*, 1-10. ISSN: 2044-4044

7.1 Harm from air contaminants in dwellings

A preliminary assessment revisited the models proposed by Logue et al., enhancing them with more recent and comprehensive data. Appendix A4.1 provides the complete discussion of the preliminary assessment. However, it did not address the adoption of the proposed unified harm metric - **Harm Intensity** (**HI**)- that is intended to replace both the IND and ID approaches.

The preliminary assessment did not cover several important aspects, including consolidating data on damage factors and incidence from a global burden of disease review into a single database. Additionally, it did not address the linearization of the IND method, or the simplification and separation of the IND and ID methods.

This section aims to identify the most harmful airborne contaminants commonly found in today's dwellings. It involves the combination of harm intensities and contaminant concentrations to assess the harm resulting from representative exposures.

The harm intensity metric, as explained in Chapter 5, is derived from both toxicological and epidemiological health research, specifically for chronic impacts at a population scale. This metric is normalized by a concentration. Importantly, it can be employed to evaluate the harm associated with inhaling airborne contaminants in scenarios where the assumption of a linear concentration-response function holds. Consequently, it is well-suited for application in most types of buildings, where concentrations are expected to be low. While the quality of health data may improve in the future, it is expected that the harm intensity will remain relatively consistent, unaffected by factors such as activity, region, or building type. The assertion is that populations will universally react similarly to exposures. However, this assumption hinges on factors such as biochemical individuality (genetic makeup), detox pathways, nutrition, and health status. If the population under consideration is sufficiently large, this assertion is likely to hold true. This universality makes it a robust and intervention-independent metric. In contrast, contaminant concentrations are subject to variation based on these factors, and interventions can influence them.

Table 7.1 gives the estimated chronic harm (DALYs/10^5 person/year) from exposure to 45 contaminants, in descending order (See Appendix 20 for full descriptive statistics). The all-cause harm attributable to the coarse fraction of particulate matter ($PM_{10-2.5}$) was estimated by calculating the difference between the harm due to PM_{10} and $PM_{2.5}$. Particulate matter shows the greatest harm, with $PM_{2.5}$ and PM_{10} contributing median losses of 1,600 (GSD 1.3) and 1,900 (GSD 1.4) DALYs per 100,000 persons annually. This substantial harm reflects the elevated harm intensities for particles combined with ubiquitous exposure.

After the PM fractions, nitrogen dioxide and formaldehyde also lead to considerable harm exceeding 100 DALYs per 100,000 people annually. Radon and ozone follows with more than 10 DALYs/10^5 person/year. The remaining contaminants show harm below 10 DALYs/10^5 person/year, although many still contribute non-negligible impacts. These central estimates provide an initial basis for comparing and prioritizing contaminants.

These results reinforce particulate matter, nitrogen dioxide, formaldehyde, radon, and ozone as the most concerning chronic contaminant exposures on a population basis. The contaminants identified to pose the highest harm, PM_{10}, $PM_{2.5}$, formaldehyde, and nitrogen dioxide, are extensively studied; see Table 6.4. Ethanol is the most abundant species in dwellings, but its contribution to harm is negligible.

Uncertainty spans several orders of magnitude for most contaminants, highlighting the need for improved exposure and toxicology data to constrain harm estimates. The lowest uncertainty is for PM and other contaminants with extensive dose-response research (carbon disulfide and benzene). Wide uncertainties reflect data gaps limiting more precise quantification currently (Chromium Cr(VI), 2-Methoxyethanol).

Figure 7.1 compares the estimates from this research to Logue et al.'s IND and ID approaches (Section 2.5.1). There are several differences. Three additional contaminants ($PM_{10-2.5}$, radon, and mold) are analyzed in this research, and the IND approach has been expanded to include four contaminants (acrolein, benzene, formaldehyde, and radon) due to the growing number of epidemiology-based studies focusing on their health impacts in recent years.

The similarities in Figure 7.1 suggest that the studies are converging toward the same conclusion, which is perhaps reassuring given the assumption

Table 7.1: Contaminant harm, $harm_i$, DALYs/10^5 person/year+

Contaminant	**Median**	**GSD**
PM_{10}	1900	1.4
$PM_{2.5}$	1600	1.3
$PM_{10-2.5}$	130*	4.5
Nitrogen dioxide	120	1.8
Formaldehyde	120	2.0
Radon	34	1.8
Ozone	10	2.7
Mold	4.0	2.3
Acrolein	0.73	4.1
Acrylonitrile	0.73	4.3
Acetaldehyde	0.68	5.1
Crotonaldehyde(trans)	0.59	8.0
Sulphur dioxide	0.56	8.1
Naphthalene	0.33	6.4
Styrene	0.21	4.8
Carbon tetrachloride	0.19	6.5
Benzene	0.15	1.6
Methyl tert-butyl ether	0.11	5.6
Limonene (d-...)	0.11	7.5
1,3-Butadiene	0.10	4.0
1,1-Dichloroethene	0.10	5.7
Carbon disulfide	0.089	1.6
Vinyl chloride	0.070	7.6
Ethanol	0.068	6.2
1,2-Dibromoethane	0.062	10
Isoprene	0.061	7.1
Cadmium Cd(II)	0.058	9.1
1,1,2-Trichloroethane	0.056	5.9
Hexachlorobutadiene	0.054	5.6
Chromium Cr(VI)	0.045	11
Tetrachloroethene	0.044	5.7
1,2-Dichloroethane	0.030	5.2
1,4-Dichlorobenzene	0.024	6.2
Xylenes	0.018	6.2
Toluene	0.013	5.2
2-Butoxyethanol	0.0098	7.2
1,1,2,2-Tetrachloroethane	0.0083	8.8
Benzyl chloride	0.0075	11
Methylene chloride	0.0061	6.2
2-Ethylhexanol	0.0048	7.9
Methyl methacrylate	0.0042	6.5
Trichloroethylene	0.0018	5.1
Hexane	0.0017	9.8
Chloromethane	0.0010	9.2
2-Methoxyethanol	0.000060	21

+ Values to 2 Sig. Figs.

* Note that these values are medians and DALYs are log-normally distributed. Therefore, subtracting the median $PM_{2.5}$ to the PM_{10} median does not equal the median of $PM_{10-2.5}$ (Section 3.6). Means add up with a minor deviation (See Appendix Table 20)

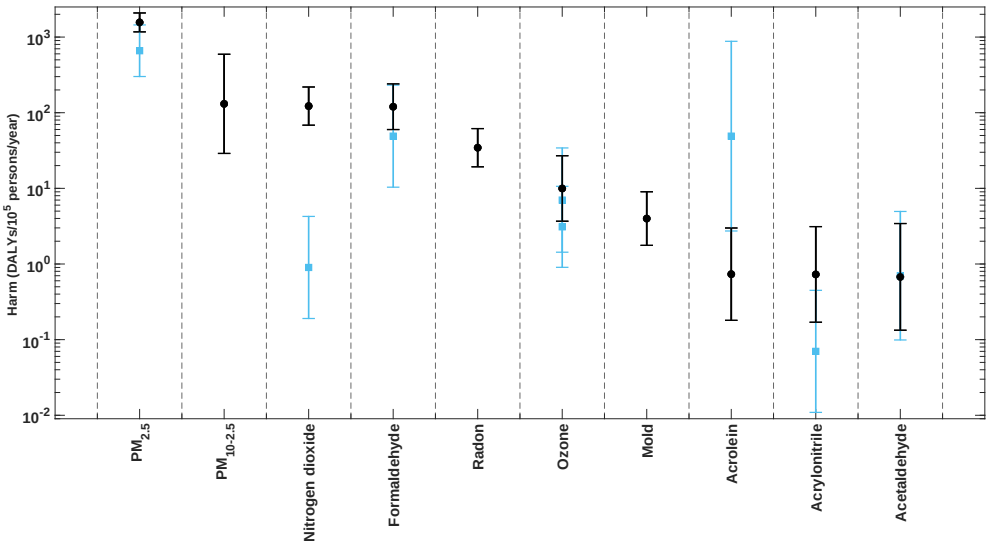


Figure 7.1: Comparing chronic harm for the 10 most harmful contaminants against Logue et al. (2012). Median & GSD. Black, current work; Blue, Logue et al.

of a linear concentration-response relationship at low concentrations used here. However, it is also evident that while the harm estimates for some contaminants remain relatively consistent, there are noticeable changes in the harm estimate for others, such as acrolein. The harm estimates in this research have reduced uncertainty by using the most up-to-date health data, including current GBD damage factors (IHME, 2022) and dedicated uncertainties studies (Martin et al., 2013).

The harm estimate from $PM_{2.5}$ in this research is three times higher than that of Logue et al. and one order of magnitude higher than that of Fazli and Stephens, a work directly linked to Logue's. This is explained by:

- The representative concentrations of this research being higher.
- Using U.S. residential indoor $PM_{2.5}$ concentrations from Logue et al., with a 70 % time-weighting factor, which reduces the estimated harm by 59 %,
- Incorporating concentration data from Fazli and Stephens which further decreases harm by 71 %, highlighting the impact of lower $PM_{2.5}$ exposure levels coupled with time-weighting factors applied in earlier works, and
- The use of a higher risk estimate. Using the risk estimates of these works yields a 30 % reduction in harm, reflecting a smaller yet signif-

icant effect, which indicates that $PM_{2.5}$ is more harmful than previously thought.

However, given identical inputs to the linear or log-linear approaches, one expects that the linear approach estimates greater harm beacuse of the linearity assumption of the harm-concentration function (more later on Section 8.5).

The estimated harm from nitrogen dioxide is higher than that of Logue et al. (2012) and Fazli and Stephens (2018) because they used lower risk and damage estimates solely linked to hospital admissions, whereas this work use the broader measure of all-cause mortality (two to three orders of magnitude above).

Formaldehyde harm was estimated using toxicology evidence. This harm estimate is higher than Logue's because of the 0.5 constant multiplier used for the toxicology-based dose-response factor, and because this research accounts for the effects of three health outcomes, while Huijbregts et al. (2005) only considered carcinogenic effects.

Logue et al. used disease incidence estimates from the literature for radon harm, individually for smokers and non-smokers. The harm estimate in this research falls within the estimates for smokers and non-smokers, indicating that the determinants of the incidence (risk estimate, baseline disease incidence, and median radon concentrations in homes) average out to a similar central tendency at the population scale.

Harm from indoor ozone inhalation was previously estimated using the ID and IND approaches by Logue et al.. Similarly, the present work estimated ozone harm via independent epidemiology and toxicology models. In both cases, the current harm estimates exceeded those of Logue's despite relying on similar risk estimates and concentrations. The higher epidemiology-based damage factor here reflects updated evidence on ozone's all-cause mortality impacts. Logue's toxicology approach was lower due to the 0.5 cases constant multiplier now applied for dose-response factors. Ultimately, pooling the epidemiology and toxicology-based harm led to estimates marginally higher than Logue's and Fazli's.

The estimated harm from acrolein is lower in the present work versus Logue's. The lower severity for non-cancer effects like asthma reduced damage factors. The dose-response factor declined due to the three-fold

lower uncertainty shifting the median downwards. Additionally, the representative acrolein concentration identified in the review was below levels used previously. In contrast, acrylonitrile harm increased due to higher DRFs and concentrations found. For acetaldehyde, harm remained largely unchanged over the past decade, suggesting no change despite new concentration and dose studies.

Mold harm was not included in Logue's analysis. The present work provides initial concentration spores DALY-based harm estimates for this pervasive indoor contaminant. Additionally, estimated harm caused by coarse particulate matter represents a novel contribution, as no previous DALY-based quantifications of $PM_{10-2.5}$ impacts were identified.

Contaminants varied in the range of GSDs covered. The variability (GSD) in the harm estimates in this research is narrower than in Logue et al.. They reported large uncertainties in harm estimates due to assumptions made in quantifying uncertainty. For epidemiology-based damage factors, an uncertainty of 10 was assumed for $PM_{2.5}$ and ozone mortality to broadly span literature values, being coherent with expert judgement guides for assigning uncertainty factors (Rosenbaum et al., 2004). For toxicology, they relied on uncertainties from Huijbregts et al. (2005), where interspecies conversion, effect conversion, and non-cancer damage factors dominated. This research aimed to reduce uncertainties by leveraging improved health data. Damage factors were drawn directly from the 2019 Global Burden of Disease study rather than arbitrarily wide literature ranges (IHME, 2022). For toxicology, dedicated studies were consulted that report reduced uncertainty factors reflecting increasing certainty in animal-to-human extrapolation, effect conversion, and non-cancer damage quantification. Furthermore, health effects data, as exemplified by $PM_{2.5}$, has improved in both robustness and precision over time. Regarding robustness, EPA Integrated Science Assessments between 2009-2019 increasingly classified $PM_{2.5}$ exposure as having a "causal relationship" with mortality/morbidity, reflecting growing strength of evidence (US-EPA, 2020b). For precision, the $PM_{2.5}$ mortality risk estimate used by Logue et al. from earlier epidemiology had an uncertainty factor of 1.027, while the WHO estimate used here has a reduced uncertainty factor of 1.014, demonstrating increased precision.

To assess the validity and context of harm estimates, the literature on harm estimates caused by indoor air contaminants (IACs) in dwellings was reviewed, focusing on Disability-Adjusted Life-Years (DALYs). Logue et al.

seminal work served as the basis for two other US studies (Aldred et al., 2016; Fazli and Stephens, 2018). Three global/European studies (Braubach et al., 2011; Morawska et al., 2013; Shan et al., 2022) followed a comparative risk assessment approach using the population attributable fraction, which is widely employed in Global Burden of Disease (GBD) studies (see Table 7.2 and Figure 7.2).

The analysis revealed similar central tendency estimates for most contaminants, with overlapping variability across the results. Compared to the studies in Table 7.2, the median estimates of harm are higher for 19 contaminants (PM_{10}, $PM_{2.5}$, formaldehyde, nitrogen dioxide, radon, ozone, sulphur dioxide, acrylonitrile, naphthalene, benzene, limonene (*d*-...), 1, 3-butadiene, carbon disulfide, vinyl chloride, methyl tert-butyl ether, hexachlorobutadiene, 1, 1, 2-trichloroethane, 2-butoxyethanol, and 2-ethylhexanol). The median estimate of harm is lower for 12 contaminants (acrolein, 1, 1-dichloroethene, chromium Cr(VI), xylenes, toluene, methylene chloride, methyl methacrylate, hexane, chloromethane, 2-methoxyethanol, and mold). The median estimate of harm is similar for 11 contaminants (crotonaldehyde(trans), acetaldehyde, carbon tetrachloride, styrene, 1, 2-dibromoethane, ethanol, cadmium Cd(II), 1, 2-dichloroethane, tetrachloroethene, benzyl chloride, and 1, 1, 2, 2-TCE) and 1, 4-dichlorobenzene is bound by existing values.

Several factors contribute to variability when comparing harm estimates across different studies, including: (i) Choice of concentration-response function, (ii) Health outcomes used, (iii) Central tendency metrics reported, (iv) Spatial and population resolution, (v) Geographic scope covered, (vi) Concentration estimates, (vii) Methodological frameworks followed. While the disability-adjusted life year facilitates comparison, underlying differences in assumptions, data, and methods across studies lead to uncertainty. Each author's approach regarding the factors above affects results.

The findings of all studies considered are in Figure 7.2. This analysis found that the total harm caused by all the contaminants considered was not implausibly high, despite the possibility of 100 % of the population being affected. Other studies have attempted to address this issue by adjusting the beta parameter or adding a lower percentage of exposure based on the time people spend indoors or at home. However, there is no consensus in the literature on this matter. Despite current GSDs being narrow, are not

Table 7.2: Studies on Harm in Dwellings Using DALYs

Work	**Statistics extracted**	**Spatial scope**	**Method**[a]	**Contaminants**	**Concentrations from:**	**Indoor type**
Logue et al. (2012)	Median and GSD	USA	$Harm_{k,i} = \gamma_{0_{k,i}} \cdot (1 - e^{-\beta_{k,i} \cdot C_i}) \cdot DF_{k,i}$	Same 44 contaminants as our work	Systematic review	Dwellings
Fazli and Stephens (2018)				$PM_{2.5}$, NO_2, HCHO, O_3, acrolein, acetaldehyde, benzene, 1,3-butadiene, 1,4-dichlorobenzene	Modelling	Residences
Aldred et al. (2016)			$Harm_{k,i} = \text{mass}_i \cdot ((EF_{\text{cancer},i} \cdot ADAF) + EF_{\text{non-cancer},i})$	O_3		Homes
Shan et al. (2022)	Age-standardized disability-adjusted life rate and GSD	Global/Europe	$Harm_{k,i} = PAF_{k,i} \cdot BoD_k$	Radon	GBD database	Residential
Morawska et al. (2013)	Minimum and maximum			Total particles, second-hand smoke, radon	No info	Indoor
Braubach et al. (2011)	Central estimate and GSD			Mold	Do not apply	Homes
IHME (2022)				$PM_{2.5}$-household air pollution (from solid fuels), radon, second-hand smoke	Modelling	Household

[a] BoD, Burden of Disease (the sum of DALYs across a population). health outcomes (k); contaminant (i).

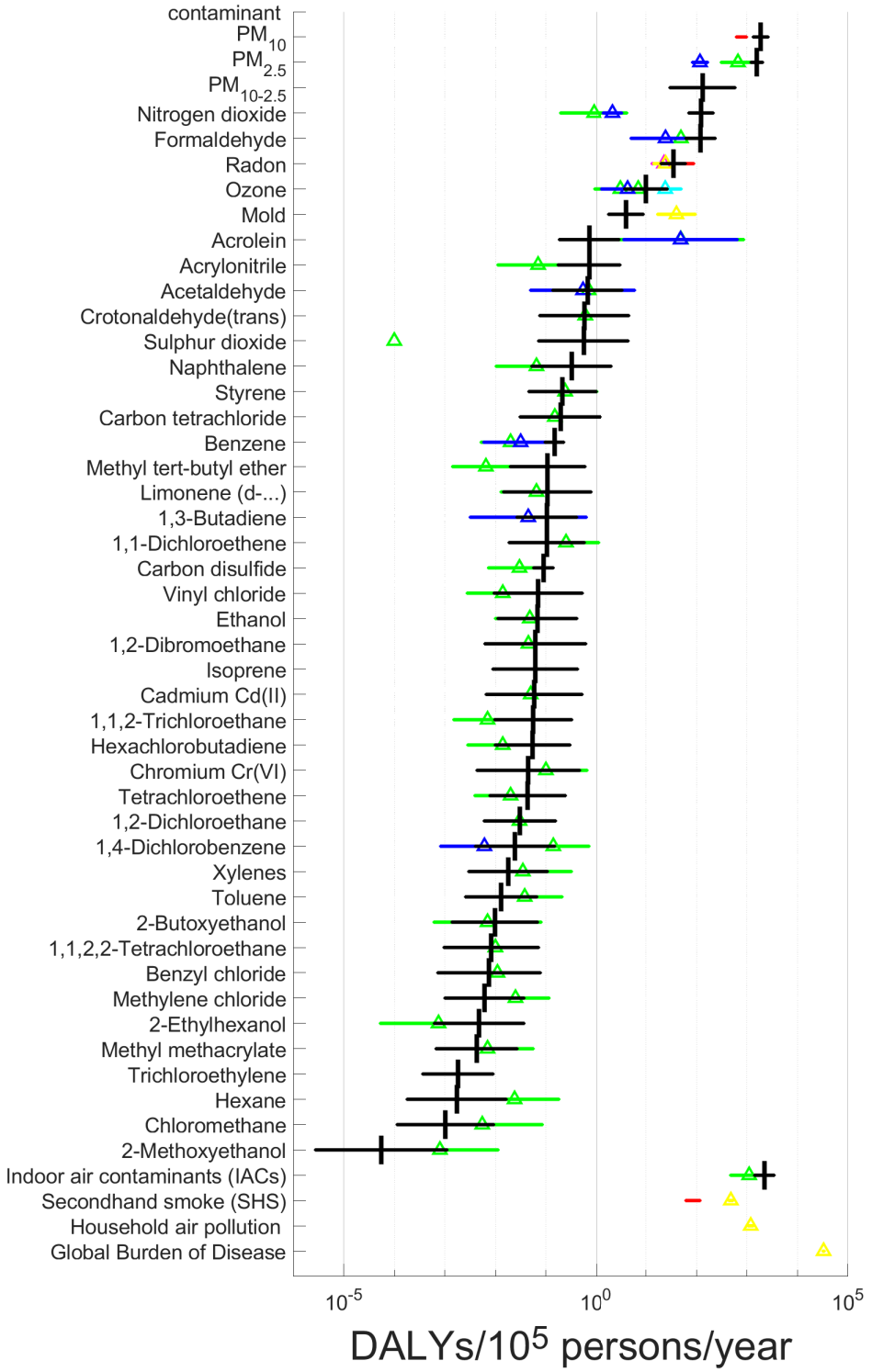


Figure 7.2: Studies on harm of air contaminants in dwellings using DALYs. Median & GSD. Black, current work; Green-triangle= Logue et al., Blue-triangle= Fazli and Stephens, Red-triangle= Morawska et al., Cian-triangle= Aldred et al., Magenta-triangle= Shan et al., Yellow-triangle= Braubach et al.; IHME.

implausible, as current GBD results indicate an even narrower ranges.

7.1.1 Harm from radon exposure

The estimated harm from radon is 34 DALYs/10^5 person/year, derived from the pooling of available epidemiological and toxicological data. This estimate falls within the same order of magnitude as previous global harm assessments that encompass all age groups and both sexes.

Residential radon exposure contributed to 24 DALYs/10^5 person/year of lung cancer cases globally in 2019. This estimation is based on the average daily exposure to indoor air radon gas levels in homes, primarily associated with a relative risk of 1.1 (95% CI: 1.0–1.2) per 100 Bq/m^3 increase in exposure (IHME, 2019, 2022).

A global burden assessment for lung cancer attributed to residential radon exposure during 1990–2019 resulted in a central tendency estimate of 23 DALYs/10^5 person/year, as reported by Shan et al. (2022) using the Global Burden of Disease Study health statistics. The similarities between these estimates arise from the usage of comparable risk estimates and exposure concentrations, with the primary distinction lying in the methodological approaches employed to quantify and report harm estimates.

Morawska et al. (2013) indicated that the European BoD associated with household radon exposure ranged from 60 to 90 DALYs/10^5 person/year in 2011. Over the period from 1990 to 2019, the global lung cancer burden attributable to residential radon exposure has exhibited a decline due to the implementation of effective interventions aimed at reducing residential radon levels (Shan et al., 2022).

7.1.2 Harm from mold exposure

For the contaminants discussed in the previous section, all but one had harm estimates allowing for a harm intensity to be reversed-engineered, except **mold** because, unlike previous analyses that relied on visual mold presence (Braubach et al., 2011) this assessment of mold burden incorporates the measured concentration of Cladosporium mold spores. Mold

emerges adding 0.2 % to the overall harm, and its significance is underscored by its widespread presence in thousands of dwellings.

Exposure to mold contaminants has been shown to have a substantial impact on health, as highlighted by the WHO Europe Asthma burden study, which measured DALYs and deaths in 45 European countries for children (age 0-14) affected by indoor mold and dampness-related asthma (Braubach et al., 2011). The burden from damp and moldy housing was estimated at 40 DALYs/10^5 person/year (GSD 2.4). The median harm estimated for mold in the present research considering Cladosporium mold spores was 4 DALYs/10^5 person/year (GSD 2.3). Remarkably, the estimated harm from damp and moldy housing indicates that mold can be a higher priority in homes than radon (34 DALYs/10^5 person/year) and ozone (10 DALYs/10^5 person/year), becoming the fifth most harmful contaminant in dwellings, ranking after formaldehyde (See Contaminants of Concern in Section 8.1).

It is essential to address the differences between present harm estimate and the WHO estimate, and explore the reasons behind such a one-order-of-magnitude discrepancy. Braubach et al.'s reported burden being the higher of the two (Figure 7.2).

The primary divergence lies in the methodology used to define exposure to mold in dwellings. While the WHO relies on non-destructive (primarily visual) observation of mold as an indicator of microbial growth based on visible mold and/or mold odor, the present work uses actual concentrations of mold using colony-forming units (CFU) specifically for mold spores of the genus Cladosporium. This approach may lead to an underestimation of mold harm due to the consideration of a single genome of mold in the environment. Furthermore, damp and moldy housing conditions likely involve multiple exposures to different spore genomes and its influenced by the humidity effect that may contribute to the development of asthma, potentially resulting in an overestimation of asthma-related health effects.

This discussion is necessary to better understand the relationship between qualitative and quantitative indicators of mold exposure and the corresponding quantification of harm. The current approach is not meant to represent an improved approach to evaluate mold in homes, rather exploring these aspects will provide insights into the accurate assessment of mold-related health risks and help bridge the gap between qualitative observations and quantitative measurements in mold exposure assessment.

7.1.3 The harm intensity from coarse PM

The harm intensity for the coarse fraction was estimated once the harm from each fraction was quantified, and the concentrations of the other PM fractions were known. Median harm intensities per 100,000 population, uncertainty estimates expressed through the GSD, and the best estimate for all-cause effects are shown in Table 7.3 (see Appendix 21 for full descriptive statistics).

In the present analysis, the harm from $PM_{10-2.5}$ that is not covered by $PM_{2.5}$ is explained by the coarse fraction, suggesting an effect on all-cause mortality from chronic exposure to this fraction. While there are still limitations and uncertainties in the health evidence base for long-term $PM_{10-2.5}$ exposure and all-cause or cause-specific mortality, epidemiologic studies reporting positive associations suggest there is a relationship between long-term exposure to this fraction and all-cause mortality (specifically cardiovascular and respiratory morbidity and metabolic disease) (Sacks et al., 2022).

Table 7.3: Epidemiology-based pseudo all-cause Harm Intensity for the coarse fraction, $HI_{PM_{10-2.5}}$, DALY/µg/m^3/10^5 person/year.$^+$

Contaminant	**Median***	**GSD**	**Best estimate of all-cause**
$PM_{10-2.5}$	3.8	4.3	Pseudo All-cause mortality (IHD+DM+Str+COPD+LRI+LC)

Abbreviations. LC: Lung Cancer; COPD: Chronic Obstructive Pulmonary Disease; LRI: Lower Respiratory Infections; IHD: Ischaemic Heart Disease; DM: Diabetes Mellitus; Str: Stroke.

$^+$ Values to 2 Sig. Figs.

Guidelines are still proposed based on $PM_{10-2.5}$ exposures to continue to provide protection against effects associated with chronic exposure to thoracic coarse particles (PM_{10}). Considering the harm attributable to the coarse fraction helps to highlight that $PM_{2.5}$ is the main driver of the health burden from particulate matter (Cohen et al., 2017; WHO, 2021).

A lack of specific test methods or epidemiology for $PM_{10-2.5}$ exists. $PM_{10-2.5}$ comprises $PM_{2.5}$ plus $PM_{10-2.5}$. This work calculated $PM_{2.5}$ and $PM_{10-2.5}$ harm intensities based on specific evidence per PM size. $PM_{10-2.5}$ HI gets determined by assuming additive harm extends across sizes. This relies on additive harm across fractions and no nonlinear interactions, which is reasonable but requires verification. A caveat is, while *causal* all-cause mortality $PM_{10-2.5}$ epidemiology does not exist currently, estimation is pos-

sible.

7.2 Plausibility and Implications

Some contaminants pose a higher or lower level of harm than previously estimated. This change is not solely attributed to the methodology, because it is similar to those followed in previous studies of harm in dwellings (Aldred et al., 2016; Fazli and Stephens, 2018; Logue et al., 2012; Morawska et al., 2013; Murray et al., 2020; Shan et al., 2022).

Acrolein, benzene, formaldehyde, radon, and ozone have data from both epidemiology and toxicology studies. However, the most harmfull contaminants $PM_{2.5}$, $PM_{10-2.5}$, and nitrogen dioxide are only characterized by epidemiological data. This highlights a key need for additional toxicological research into these pollutants to improve the understanding of their health effects and provide a more comprehensive and robust estimate of the harm they cause.

The analysis of harm caused by the coarse fraction suggests that chronic exposure to it has a considerable impact on health (Sacks et al., 2022; US-EPA, 2020b). Nevertheless, the analysis also shows that $PM_{2.5}$ contributes more to the health burden.

The total harm for all 44 independent indoor airborne contaminants has a median value of 2,200 DALYs/10^5 person/year (GSD 1.6). This is roughly 5 times higher than the Global Burden of Disease (GBD) from secondhand smoke in dwellings of 480 DALYs/10^5 person/year, double the GBD from $PM_{2.5}$ Household Air Pollution (HAP) and alcoholism of 1,200 DALYs/10^5 person/year, and a bit lower than the global burden from smoking 2,600 DALYs/10^5 person/year (Murray et al., 2020).

The burden from the 44 contaminants, estimated at 2,200 DALYs/10^5 person/year, represents approximately 7% of the total GBD, which is estimated at 33,000 DALYs/10^5 person/year (GSD 1.1) (Murray et al., 2020). Direct validation of this figure is lacking in existing studies. To address this gap, an approximation is made based on several factors: 1) the reported burden of HAP is 1,200 DALYs/10^5 person/year according to the GBD, with $PM_{2.5}$ emitted from solid fuels for cooking being the contributor, 2) analysis of Table 7.1 suggests that $PM_{2.5}$ accounts for 65% of the total

household burden, and 3) applying this relationship to the overall HAP burden suggests that the combined burden from all contaminants may be around 1,850 DALYs/10^5 person/year, constituting 5.5% of the total GBD (1,850 DALYs/10^5 person/year out of 33,000 DALYs/10^5 person/year) This is approximately similar to the value of 7% and provides some reassurance of its plausibility.

7.3 Summary

This chapter presented a health-centered approach to quantify chronic harm caused by indoor air contaminants using the Disability-Adjusted Life-Year (DALY). Chronic harm is estimated from the harm intensities (Section 5) and representative concentrations in dwellings of 45 contaminants (Section 6). The most harmful contaminants in dwellings are $PM_{2.5}$, $PM_{10-2.5}$, NO_2, formaldehyde, radon, and O_3, accounting for over 99 % of total median harm of 2,200 DALYs/10^5 person/year. The chronic harm caused by all airborne contaminants in dwellings accounts for 7 % of the total global burden from all diseases (See Table 8.10 in next chapter for an expanded comparision).

Chapter 8

Discussion

Findings in Section 8.3, are part of:

Morantes, G., Jones, B., Molina, C., & Sherman, M. (2023). A Harm Budget Approach to Indoor Air Quality Acceptability. In *CIBSE ASHRAE Technical Symposium 2023 Delivering Sustainable, Safe and Healthy Buildings for a net zero future* - Glasgow, Scotland. 16 pp.

Findings in Section 8.6.1, are part of:

Morantes, G., Jones, B., Molina, C., & Sherman, M. (2022). Quantifying Harm from Exposure to Fine Particles ($PM_{2.5}$) Emitted by Cooking. In *PLEA 2022 SANTIAGO Will Cities Survive?* - Santiago, Chile. 581-585 pp. ISBN: 978-956-14-3068-6

Sections 8.1, 8.3, 8.4, are part of:

Morantes, G., Jones, B., Sherman, M., & Molina, C. (2023). Harm from residential indoor air contaminants. *Environmental Science & Technology.* Article ASAP DOI: 10.1021/acs.est.3c07374

8.1 Contaminants of concern in dwellings

To implement the IAQ Procedure effectively, designers must know the Contaminants of Concern (CoCs). This section addresses the critical issue of determining the CoCs that practitioners should consider. The harm attributable to chronic exposures was calculated using the representative indoor concentrations (Table 6.4) and the harm intensities (Table 5.13). The results are used to rank the contaminants by harm and identify CoCs. This rank can then be used to regulate air quality in dwellings.

Table 7.1 showed the estimated chronic harm (DALYs/10^5 person/year) from exposure to the 45 contaminants, in descending order. $PM_{2.5}$, $PM_{10-2.5}$, nitrogen dioxide, formaldehyde, radon, and ozone are ranked first with estimated median of 1600 (GSD 1.3), 130 (GSD 4.5), 120 (GSD 1.8), 120 (GSD 2.0), 34 (GSD 1.8) and 10 (GSD 2.7) DALYs/10^5 person/year respectively; higher than the remaining contaminants by at least one order of magnitude (see Figure 8.1).

The total harm for all 44 contaminants at their representative concentrations gives a total median harm of 2,200 DALYs/10^5 person/year (GSD 1.6). $PM_{2.5}$, $PM_{10-2.5}$, nitrogen dioxide, formaldehyde, radon, and ozone account for 99 % of the total harm caused by typical indoor air contaminants. Therefore, they should be considered *Contaminants of Concern, CoC* for dwellings (Section 2.5.3).

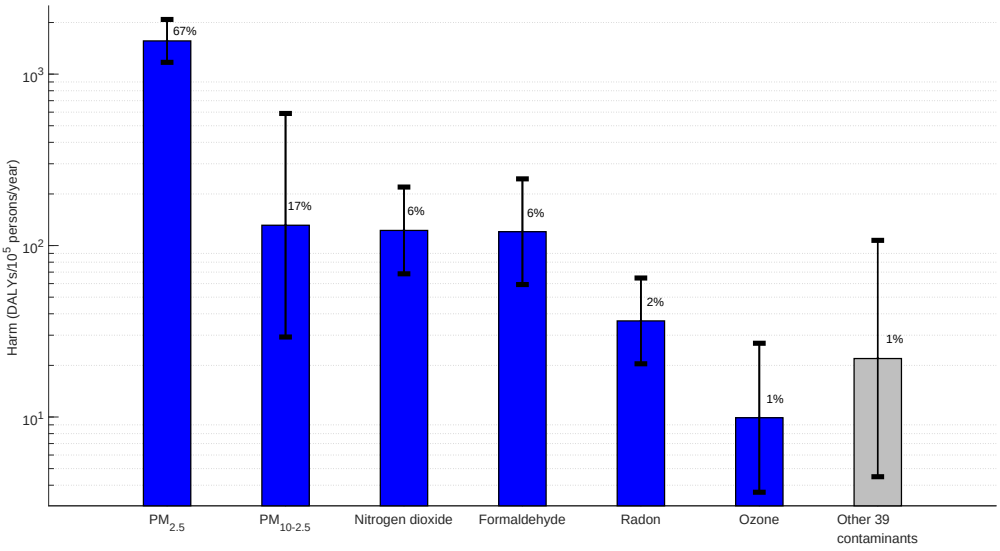


Figure 8.1: Harm caused by contaminants of concern. Median (bar) & GSD (error bar). Percentage contribution for total harm.

The contaminants of concern in dwellings, $PM_{2.5}$, $PM_{10-2.5}$, nitrogen dioxide, formaldehyde, ozone, and radon, each contribute 67 %, 17 %, 6 %, 6 %, 2 %, and 1 % to the median total harm, respectively. This shows that it is possible to influence the air quality in a dwelling by addressing only a few contaminants. This finding is important for building professionals and regulatory bodies.

The value of an avoided DALY for very high HDI countries fits a probabilistic distribution with a mean of 2016$ 69,499, ranging from $21,509 to $168,720 (see Table 2.8). This has a median value of approximately $55,000 (2016 US dollars) per avoided DALY (after fitting a log-normal distribution). This monetary value per DALY is used to calculate the costs of harm due to exposure to the contaminants of concern (CoCs) in dwellings. Table 8.1 shows the annual monetary losses in 2016 dollars due to harm from CoCs in dwellings. Additionally, the median value per annual average concentration of the CoC in a home per person per year in 2016 dollars is also calculated ($/µg/m^3).

Table 8.1: $ lost annually due to the CoCs in dwellings per person$^+$

Contaminant	**Concentration**[a]	**Harm**[b]	**$ lost**	**GSD**	**$/µg/m^3**
$PM_{2.5}$	26	1600	850	2.1	33
$PM_{10-2.5}$	35	130	71	5.3	2
Nitrogen dioxide	22	120	67	2.5	3
Formaldehyde	28	120	65	2.6	2.3
Radon	78^{++}	34	19	2.5	0.24^{++}
Ozone	7.3	10	5.5	3.2	0.75

[a] µg/m^3
[b] DALYs/10^5 person/year
$^+$ Values to 2 Sig. Figs.
$^{++}$ Bq/m^3

If the cost of applying control strategies for each contaminant is less than the monetary value per DALY, then these strategies can be explored as potentially cost-effective interventions for homes. This analysis does not yet consider offsets such as additional energy use or societal costs. Evaluating the cost-effectiveness of potential control strategies is the first step in understanding the economic implications of mitigating harm from indoor contaminants.

Interestingly, significant global efforts have been dedicated to reducing radon exposure, with evidence spanning at least two decades of research on this topic. Recent findings have addressed the cost-effectiveness of such ef-

forts (Denman and Phillips, 1998; Gaskin et al., 2019; Khan et al., 2019). However, as shown in Table 8.1, the level of harm associated with radon is substantially lower compared to contaminants such as $PM_{2.5}$, $PM_{10-2.5}$, NO_2, and HCHO. Therefore, one could argue that the resources allocated to mitigate radon exposure may be disproportionate relative to the potential health benefits, especially when contrasted with the more significant burdens imposed by other indoor air contaminants.

When considering ventilation standards to protect public health, certain contaminants require focus based on their widespread presence and harm potential. Past reviews have highlighted fine particulate matter, mold, formaldehyde, acrolein, environmental tobacco smoke, ozone, and radon as key chronic exposure risks in indoor environments (Fernandes et al., 2009; Logue et al., 2012). The hazards of tobacco smoke and radon may be more widely recognized and limited to a fraction of homes. $PM_{2.5}$, nitrogen dioxide, and formaldehyde are prevalent in dwellings and harmful to its occupants yet, there may be less recognition of their impacts.

Much of the literature considers ventilation's contribution to IAQ. While dilution ventilation is an effective strategy, not all CoCs react similarly to ventilation and dilution. HCHO and PM can be efficiently removed or diluted through ventilation due to their primarily area-based emissions, dispersing easily indoors. However, others like radon or certain gases from localized sources, such as combustion appliances, may not respond as readily to ventilation, requiring tailored removal strategies like filtration, ventilation or, chemical filtration (carbon/sorbents) (Table 8.2).

Mechanical filtration is the primary method for removing particles. High efficiency particle arresting (HEPA) filters are used by professionals. Furthermore, ASHRAE 241 (Sherman and Jones, 2023) requires a minimum filtration efficiency of Minimum Efficiency Reporting Values (MERV) 11A or ISO 16890 $ePM_{2.5}$ 50%. ASHRAE 62.2 currently mandates a minimum efficiency of MERV 11. It also gives credit for using higher efficiency filters. HEPA filters are over 95% efficient in removing particles of all sizes (Kelly and Fussell, 2019). Therefore, meeting $PM_{2.5}$ filtration standards should also remove $PM_{10-2.5}$ particles. NO_2 and O_3, which are associated with outdoor air infiltration into dwellings, can be effectively controlled through adsorption using activated carbon (Kelly and Fussell, 2019).

Table 8.2: Contaminants of concern and Control Strategies

Contaminant	**Sources**	**Main Strategy**
$PM_{2.5}$	Formed from combustion (cooking, heating, smoking), outdoor air, reactions with gases.	Ventilation and mechanical filtration efficacious for removal.
$PM_{10-2.5}$	Resuspended dusts, indoor activities like cleaning.	Enhanced filtration and dust control help reduce levels.
NO_2	Primarily of outdoor origin, some gas appliances.	Dilution ventilation effective, gas stove replacements beneficial. Adsorption (activated carbon)
Formaldehyde	Off-gassing from materials/furnishings.	Source control via low-emission materials impacts levels. Ventilation.
Radon	Soil/rock source.	Building shell mitigation and ventilation dilution are primary controls.
Ozone	Primarily of outdoor origin, some electronic devices.	Dilution via ventilation lowers indoor levels. Air cleaning could assist. Adsorption (activated carbon)

8.2 Hazard assessment and monetary costs analysis for the contaminants of concern

This hazard assessment quantifies the harm of the contaminants of concern at recommended Exposure Limit Values, ELVs. This includes computing a *regulated harm* by multiplying suitable ELVs with respective harm intensities, which allows for exploring Regulated Harm Budgets (RHBs). Additionally, assessing a *relative harm*, examining the ratio between a benchmark contaminant's harm and that of each individual contaminant. Lastly, determining an *equivalent harm threshold*, representing the threshold needed to yield the same harm as the benchmark contaminant. Only CoCs accounting for 99% of harm are evaluated in this section. Other contaminants have a negligible impact relative to the CoCs. The goal is to identify and understand the appropriateness of the ELVs. The assessment is divided into two parts, the first focusing on the WHO air quality guidelines, and the second exploring ELVs from other cognizant authorities.

8.2.1 Part 1. WHO Global air quality guidelines

Recommended ELVs vary between regulatory bodies (see Table 2.4 in Chapter 2). Chronic World Health Organization (WHO) thresholds, are used for the Part 1 of this hazard assessment. For formaldehyde, 100 µg/m^3 is the threshold recommended to protect the general population from acute and chronic health effects in occupied buildings (WHO, 2010, 2021).

Fine particulate matter ($PM_{2.5}$) serves as the benchmark contaminant for comparing harm across different contaminants. $PM_{2.5}$ is a major contributor to harm in dwellings among the CoCs. Additionally, it stands out as one of the most extensively studied contaminants in air pollution literature (Sections 2.1.1.1 and 2.2.1.1). While the choice might seem somewhat arbitrary, selecting a specific contaminant is necessary, and $PM_{2.5}$ proves to be a suitable candidate for this purpose.

Harm quantification for the CoCs based on their recommended WHO thresholds is shown in Table 8.3. An annual monetary cost can be attributed to the regulated harm shown in this Table. In this dissertation, a median of 2016$ 55,000/DALY is used. For $PM_{2.5}$ at 5 µg/m^3, the median annual cost is $160/person/year ($16 million/10^5person/year). Furthermore, at the upper bound of the 95% CI the value reaches $510/person/year (Table 2.8).

The World Health Organization thresholds should all lead to the same harm. However, the regulated harm vary substantially across contaminants: (i) $PM_{2.5}$ threshold of 5 µg/m^3 allows up to 300 DALYs/10^5 person/year, establishing a benchmark for comparison. (ii) The PM_{10} threshold of 15 µg/m^3 allows for 450 DALYs/10^5 person/year, encompassing $PM_{2.5}$ harm. This value is seen as protective against $PM_{10-2.5}$ with 150 DALYs/10^5 person/year. Further consideration is warranted. (iii) Nitrogen dioxide threshold caps DALYs at 57 DALYs/10^5 person/year, below the $PM_{2.5}$ benchmark. (iv) Formaldehyde threshold results in 430 DALYs/10^5 person/year, higher than the $PM_{2.5}$ benchmark. The short-term guideline may not adequately protect from chronic exposures. (v) Ozone and radon also remain below the $PM_{2.5}$ benchmark, at 78 DALYs/10^5 person/year and 44 DALYs/10^5 person/year respectively.

While $PM_{2.5}$ is a significant contributor to indoor air pollution and poses substantial health risks, relying solely on it as the benchmark may not fully

Table 8.3: Contaminant thresholds and harm.[+]

Contaminant$_i$	**HI**[b]	**GSD**	**WHO**[c]	**Regulated harm**[d]	**$lost**[h]	**Relative harm**	**Equiv.** [c]
$PM_{2.5}$	60	1.2	5	300	160	1	5
PM_{10}	30	1.3	15	450	250	1.5	10
Nitrogen dioxide	5.7	1.7	10	57	31	0.19	53
Formaldehyde	4.3	2	100	430	240	1.43	70
Ozone	1.3	1	60	78	43	0.26	230
Radon	0.44[e]	1.6	100[f]	44	24	0.15	680[f]
Regulated Harm Budget (RHB)				960[g]	530		

[+] Values to 2 Sig. Figs.
[b] DALY/$\mu g/m^3/10^5$ person/year
[c] $\mu g/m^3$; Equivalent harm threshold
[d] DALYs/10^5 person/year
[e] DALY/$Bq/m^3/10^5$ person/year; Bq, Becquerels
[f] Bq/m^3
[g] Do not include PM_{10}
[h] 2016$ lost/person/year

capture the overall health impacts. Considering a broader range of contaminants and their additive effects provides a more comprehensive assessment of health risks (more on this in Sections 8.2.1.1 and 8.3).

Using $PM_{2.5}$ as a benchmark reveals inconsistencies in the regulated harm calculated from WHO thresholds. Contaminants with higher DALY ratios (relative harm) indicate guidelines permitting disproportionately more harm than fine PM's limit. Conversely, lower DALY ratios suggest overly stringent thresholds. This raises concerns about inadequate protection of public health.

This is not suggesting that thresholds should be based on a regulated harm being the unity ($1\,\text{DALYs}/10^5$ person/year) because, while safeguarding health is critical, excessively low limits may be impractical to implement, unachievable in real-world conditions, or financially burdensome. A relative harm of 1 in Table 8.3 for all contaminants means that they are all regulating the same harm.

Optimizing thresholds by aligning allowed harm could balance health protection and feasibility. This would lead to standards that benefit public well-being and promote compliance. There is a compelling need to re-evaluate guidelines to determine if they strike the right balance between protection and attainability. Adjusting disproportionate ratios could result in more effective indoor air quality standards.

To align with the principle that all DALYs have equal significance, WHO thresholds considered here warrant re-evaluation (see Table 8.3): (i) The PM_{10} limit could be rethought considering that includes the harm from $PM_{2.5}$. (ii) The formaldehyde guideline may need lowering to 70 $\mu g/m^3$ to match the $PM_{2.5}$ benchmark. (iii) Nitrogen dioxide could be raised to 53 $\mu g/m^3$ to permit 300 DALYs. (iv) Ozone and radon limits could also be adjusted to allow equivalent regulatory harm as $PM_{2.5}$.

Optimizing thresholds so that all threshold led to the same regulated harm would promote a more equitable approach to public health protection. Further analyses on the feasibility and health trade-offs of revised limits is still needed. But aligning permitted harm creates a principled starting point for determining appropriate chronic exposure guidelines.

8.2.1.1 Regulated Harm Budget using WHO guidelines

A *Regulated Harm Budget* utilizes existing chronic exposure limit values of the CoCs and their corresponding harm intensities to quantify harm (*regulated harm*). The RHB sums the harm permitted at each guideline value for five CoCs (as per for the harm budget Section 8.3). It can also be conceptualized as an IAQ index.

Proposed in absolute terms, the median of the RHB representing the total allowed harm by the WHO thresholds (WHO-RHB), rounded to one significant figure, is 1000 DALYs/10^5 person/year (GSD 1.5) (Table 8.3). In this context, using one significant figure makes sense because the thresholds are expected to vary. Consequently, it will cause the output to fluctuate, most likely converging around the same order of magnitude.

The median WHO-RHB of 1000 DALYs/10^5 person/year exceeds the harm budget (Section 8.3). The primary driver is the formaldehyde guideline, which is four times higher than the concentration used in the harm budget's reference scenario. This guideline is also the most uncertain input, as it is based on acute rather than chronic effects. Discussions are underway to lower the formaldehyde threshold by an order of magnitude (HCSP's Environmental Health Expert Committee (CSRE), 2019), which would reduce the RHB below the harm budget.

Ideally, exceeding the WHO-RHB would indicate guidelines are not protective enough for typical exposures. However, this conclusion is uncertain due to high variability in thresholds across cognizant authorities. For example, using American or European Union guidelines instead of WHO would alter the standard budget substantially. To shed light on this conundrum, the following section expands to include ELVs proposed by cognizant authorities for the CoCs in a sensitivity analysis of limit values for regulated harm.

8.2.2 Part 2. Sensitivity analysis using ELVs from cognizant authorities

A comprehensive database of ELVs from cognizant authorities worldwide was recently presented by Dimitroulopoulou et al. (2023). This database, hosted by the International Society of Indoor Air Quality and Climate

(ISIAQ) STC34 Indoor Environmental Quality (IEQ), comprises 844 entries. Given the chronic focus of the present research, entries in the database were categorized based on averaging times, denoted as chronic (>24h, annual), acute (<24h), and no data. Entries without exposure periods were retained by assuming applicability across all timeframes. Only ELVs appropriate for residential environments are considered here. The ELVs for the CoCs in dwellings were used to calculate their regulated harm. When multiple values were provided by the same agency, accounting for both 24-hour and annual exposures, each estimate was considered. Hence, some agencies in the tables feature more than one harm estimate. All ELVs specified by cognizant authorities/countries, the corresponding median regulated harm, and the 2016$ lost annually due to such harm are presented in Tables 8.4, 8.5, 8.6, 8.7, and 8.8, for $PM_{2.5}$, NO_2, HCHO, O_3, and radon, respectively. The WHO thresholds are included for reference.

For $PM_{2.5}$, there are 17 entries in the database (after deleting unclear data inputs), resulting in 10 different harm values due to multiple cognizant authorities regulating at the same ELV. The regulated $PM_{2.5}$-attributable harm ranges from 480 to 3000 DALYs/10^5 person/year. Comparing these ELVs to the WHO threshold in Table 8.3, all exceed it, implicitly allowing more harm. The values from Table 8.4 can be used to assess the value of interventions aimed at reducing $PM_{2.5}$ concentrations to the WHO threshold (Table 8.3). Reducing the annual $PM_{2.5}$ ELV from 50 to 5 µg/m^3 results in an annual monetary benefit of approximately $1,900/person/year. At the upper bound of the 95% CI, this value increases to $5,900/person/year. The same approach can be applied to evaluate interventions for other contaminants as presented in the respective tables.

Concerning NO_2, the database contains 10 entries, resulting in 5 distinct harm values due to overlapping ELVs regulated by different authorities. Regulated NO_2-attributable harm ranges from 1100 to 110 DALYs/10^5 person/year. Similarly, all these ELVs exceed the WHO threshold in Table 8.3, indicating a tolerance for higher harm levels.

For HCHO, the database includes 18 entries, that derive into 9 regulated harm values due to regulatory discrepancies. An ELV proposed by the CA OEHHA is added to this list given its relevance. Regulated HCHO-attributable harm ranges from 520 to 39 DALYs/10^5 person/year. Notably, while six countries report the same threshold as WHO (Table 8.3), three countries regulate harm at one order of magnitude lower.

Table 8.4: ELVs (µg/m^3), regulated harm (DALYs/10^5 person/year) and 2016$ lost ($/person/year) for $PM_{2.5}$. Highest to lowest median.$^{+\,!}$

Cognizant authorities/Countries	**ELV**	**Harm**	**$lost**
China	50	3000	1600
Lithuania	40	2400	1300
Singapore	37.5	2300	1300
United States of America	35	2100	1200
Finland, Germany, South Africa, Thailand	25	1500	820
Norway, Spain	20	1200	660
ASHRAE*, Norway, WELL Standards**	15	910	500
Finland, South Africa	10	600	330
United States of America	9	540	300
Norway	8	480	260
WHO	5	300	160

$^{+}$ Values to 2 Sig. Figs.
** see https://standard.wellcertified.com/air/air-quality-standards
* ASHRAE 62.2-2022, Table E-1
$^{!}$ ELVs presented in this section were extracted from the ISIAQ database. However, some database inputs appear unclear or questionable, like ASHRAE's 35 µg/m^3 input for the United States, which is not included due to ambiguity. A thorough review of the database inputs is warranted for future work.

Table 8.5: ELVs (µg/m^3), regulated harm (DALYs/10^5 person/year) and 2016$ lost ($/person/year) for NO_2. Highest to lowest median.$^{+}$

Cognizant authorities/Countries	**ELV**	**Harm**	**$lost**
Spain	200	1100	600
ASHRAE, China	100	570	310
India, Lithuania, Norway, South Africa, United Kingdom	40	230	130
Canada	21	120	66
France	20	110	60
WHO	10	57	31

$^{+}$ Values to 2 Sig. Figs.

Regarding O_3, the database contains 8 entries, resulting in 4 distinct harm values due to varying ELVs set by different authorities. Regulated O_3-attributable harm ranges from 260 to 27 DALYs/10^5 person/year. Most authorities/countries regulate at higher thresholds compared to the WHO (Table 8.3). O_3 presents a unique challenge due to the scarcity of chronic ELVs, with the WHO threshold being relatively new. The database includes 24-hour ELVs for Poland and Thailand, while the rest are as-

Table 8.6: ELVs (µg/m^3), regulated harm (DALYs/10^5 person/year) and 2016$ lost ($/person/year) for HCHO. Highest to lowest median.$^+$

Cognizant authorities/Countries	**ELV**	**Harm**	**$lost**
Italy, Netherlands	120	520	290
Denmark, Germany, Japan, Slovenia, Thailand	100	430	240
Finland, Poland	50	220	120
ASHRAE	33	140	77
WELL Standards	32	140	77
India	30	130	71
Poland	20	87	48
United States of America	19	83	46
Bulgaria, France*, Lithuania, United Kingdom	10	43	24
CA OEHHA	9	39	21
WHO	100	430	240

$^+$ Values to 2 Sig. Figs.
* The database shows France having the 100 µg/m^3 ELV. The table includes the more recent 10 µg/m^3 ELV found in the bibliography, given its relevance.

sumed for chronic exposure. Current Chinese indoor ozone standards of 160 µg/m^3-1h and 112 µg/m^3-8h do not significantly reduce mortalities (Xiang et al., 2019). Much lower indoor ozone guidelines are needed. Xiang et al. (2019) suggests that a 1-h standard of 10 µg/m^3 could reduce premature mortalities by 83%. Applying the harm intensity of ozone to this 1-h ELV results in 13 DALYs/10^5 person/year, this is lower than all other regulated harm shown in Table 8.7. Although using the chronic harm intensity for an acute threshold is not ideal, it provides a preliminary insight and underscores the need to explore acute harm intensities (Section 8.8).

For Rn, there are 18 entries in the database, resulting in 5 unique harm values due to regulatory variations. Regulated Rn-attributable harm ranges from 180 to 44 DALYs/10^5 person/year. Similarly to O_3, most authorities/-countries regulate at higher thresholds compared to the WHO (Table 8.3).

As discussed in Section 7.1.2, mold could be considered a Contaminant of Concern in dwellings, given the harm estimates by Braubach et al. (2011). Therefore, its ELVs are also explored here. Based on the same database, Belgium, Finland, France, Singapore, and Spain have ELVs for mold, measured in CFU/m^3, with some specifically addressing Cladosporium. These ELVs range from 50 to 1000 CFU/m^3, resulting in harm estimates of 1.3

Table 8.7: ELVs (µg/m^3), regulated harm (DALYs/10^5 person/year) and 2016$ lost ($/person/year) for O_3. Highest to lowest median.$^+$

Cognizant authorities/Countries	**ELV**	**Harm**	**$lost**
Spain	196	260	140
ASHRAE, Poland, Slovenia, WELL Standards	100	130	71
Thailand	98	130	71
India	50	67	35
Finland	20	27	15
WHO	60	78	43

$^+$ Values to 2 Sig. Figs.

Table 8.8: ELVs (Bq/m^3), regulated harm (DALYs/10^5 person/year) and 2016$ lost ($/person/year) for radon. Highest to lowest median.$^+$

Cognizant authorities/Countries	**ELV**	**Harm**	**$lost**
Slovenia	400	180	99
Estonia, EU, Finland	300	130	71
Canada, China, Ireland, Latvia, Norway, Spain, Sweden, Finland	200	88	48
Romania	140	62	34
Belgium, Denmark, Russia, South Africa, United Kingdom	100	44	24
WHO	100	44	24

$^+$ Values to 2 Sig. Figs.

to 26 DALYs/10^5 person/year. The median harm of 4 DALYs/10^5 person-/year found in this research is lower than the regulated harm for Belgium but higher than that for the other countries.

The variability in regulated harm among contaminants raises concerns regarding the effectiveness of current IAQ building recommendations in protecting public health. Moreover, significant discrepancies exist between different contaminants. For instance, a residential building in the UK may fully comply with formaldehyde guidelines (preventing 43 DALYs/10^5 person/year, Table 8.6), yet allow NO_2 levels associated with 230 DALYs/10^5 person/year (Table 8.5). The sensitivity analysis clearly highlights doubts regarding the true preservation of occupants' health when meeting ELVs.

The range of values for a disability-adjusted life year typically spans from

$70,000 to $150,000. Table 8.9 presents the monetary savings that could result from reducing the harm caused by the concentrations of contaminants of concern in residences, from the levels found (Table 6.4) to the most conservative exposure limit values discussed in Sections 8.2.1 and 8.2.2. Although this table considers the most stringent ELVs, a critical question remains: What level of harm should ELVs aim to consider acceptable, tolerable, or allowable?.

Table 8.9: Saved $ costs by reducing concentrations in dwellings to most conservative ELVs[+]

Contaminant	**Concentration in dwellings**[a]	**Lowest ELV**[a]	**Averted $lost**[b]
$PM_{2.5}$	26	5	930
NO_2	22	10	52
HCHO	28	9	76

[+] Values to 2 Sig. Figs.
[a] µg/m^3
[b] 2016$/person/year Note that $PM_{10-2.5}$ does not appear in the table because no exposure limit value has been established for this contaminant. Additionally, Rn and O_3 are not included as the concentrations typically found in residences are lower than the most conservative ELVs.

The assessment shown in Sections 8.2.1 and 8.2.2 serve as an initial evaluation of standards rather than a definitive benchmark. Several caveats should be noted in this hazard assessment considering ELVs:

- While the database is relatively recent, ELVs may have been updated for any of the entries since its publication.
- ELVs for certain agencies, such as CA OEHHA (the California Office of Environmental Health Hazard Assessment), do not seem to appear in the database. For example, CA OEHHA proposed a chronic ELV at 9 µg/m^3 for HCHO, which was particularly included for its relevance.
- The ELVs used were specified in the database to apply to residential environments. ELVs for non-residential, commercial, and industrial environments were filtered out and do not appear in the hazard assessment.
- Several entries were considered to apply to chronic exposures, and this needs to be explicitly checked. Due to the exclusion criteria for chronic exposure, some ELVs that are known in the IAQ community were not shown. For instance, HCHO has ELVs from NIOSH (National Institute for Occupational Safety and Health) at 20 µg/m^3 for 8 hours; this is classified as an acute ELV (Chapter 2.2).

- Upper concentration limits were proposed to avoid overestimations of harm (Table 5.10), and some contaminants have ELVs higher than that, so the regulated harm shown might be higher than what is adequate.

- A RHB was calculated for the WHO thresholds. Equivalent calculations can be done exploring the cognizant authorities/countries that have ELVs for all five CoCs and adding the regulated harm. All these aspects can be explored in a focused work.

More research is needed on guideline development and resulting health impacts, as there is considerable uncertainty in this arena. Nonetheless, this approach provides a starting point for assessing the protectiveness of indoor air quality regulations. While addressing the CoCs in dwellings is sufficient from a harm perspective, extending the analysis to contaminants prevalent in dwellings (Table 6.4) would enhance understanding and reveal additional inconsistencies in limit values.

8.2.3 Comparing harm, risks, and monetary costs

Table 8.10 summarizes the harm, and the corresponding annual monetary cost per person for various contaminants found in residential dwellings, as well as several environmental and behavioral risks (IHME, 2022; Vardell, 2020). Among the indoor air contaminants, $PM_{2.5}$ stands out as the most harmful, accounting for 1,600 DALYs/10^5 person-/year and nearly (2016)$ 900 per person annually. While present at lower levels indoors, nitrogen dioxide, formaldehyde, and radon collectively cause over 270 DALYs/10^5 person/year and $150 in costs per person yearly. The table also highlights the substantial global burdens imposed by risks outside of residences, such as road injuries, alcoholism, self-harm, interpersonal violence, unsafe water, and unsafe sex, underscoring the importance of addressing both indoor and outdoor environmental hazards and behavioral risk factors.

8.2.4 Harm intensity ratios relative to $PM_{2.5}$

$PM_{2.5}$ has a median harm intensity of 60 DALY/µg/m^3/10^5 person/year. Ratios are calculated by dividing this by each HI_i for the other CoCs. This

Table 8.10: Contaminant or risk, harm, and costs summary[+]

Contaminant or risks	**Harm**[a]	**$cost**[b]
PM_{10}	1900	1000
$PM_{2.5}$	1600	880
$PM_{10-2.5}$	130[*]	71
Nitrogen dioxide	120	66
Formaldehyde	120	66
Radon	34	19
Ozone	10	6
Other 39 contaminants	22	12
All 44 independent IACs	2200	1200
Harm Budget	580	320
Dampness and mould (WHO)	40	22
Carbon Monoxide (24-h)[c]	180	99
Road Injuries	1300	710
Alcoholism	1200	660
Self harm	630	350
Interpersonal violence	500	270
Unsafe water	930	510
Unsafe sex	600	330

[+] Values to 2 Sig. Figs.
[a] DALYs/10^5 person/year
[b] (2016)$/person/year
[c] See Table 8.21
[*] Note that these values are medians and DALYs are log-normally distributed. Therefore, subtracting the median $PM_{2.5}$ to the PM_{10} median does not equal the median of $PM_{10-2.5}$ (Section 3.6). Means add up with a minor deviation (See Appendix Table 20)

gives: $PM_{2.5}$: 1 Nitrogen Dioxide: ≈ 11 Formaldehyde: ≈ 14 Ozone: ≈ 46 Radon: ≈ 136 (μg/Bq)

These ratios serve as a relative "weight" for comparing harm intensities to the $PM_{2.5}$ benchmark. A value closer to 1 indicates similar harm per unit concentration, assuming equal exposure time. For example, nitrogen dioxide would need to be 11 times more harmful per µg/m^3 to equal $PM_{2.5}$'s impact.

The ratios quantify each contaminant's potency relative to fine particulate matter. This provides perspective on the harm intensities, giving a principled basis for comparing the hazards posed by different pollutants. The ratios contextualize the risks and highlight which contaminants are of greatest concern on a per unit basis.

8.3 Framework for a harm budget and acceptable IAQ

The selected six contaminants of concern (CoCs) in Section 8.1 can also be used to regulate Indoor Air Quality (IAQ) in dwellings. One way of doing this is to set a *harm budget*, this is, the distribution of harm that is expected in an acceptable reference scenario. A *reference scenario* can be a specific set of dwellings that all comply with a recognized indoor air quality standard (Chan et al., 2019; Martin et al., 2020; Singer et al., 2020; Zhao et al., 2021) and so the IAQ in those dwellings might be assumed to be *acceptable*.

To quantitatively define Acceptable IAQ (AIAQ), reference concentrations are required for the CoCs from the reference scenario (this is like the use of archetypes). A reference scenario can be the Healthy Efficient New Gas Home study (HENGH2020), described by Singer et al. (2020), that comprises a cohort of 70 Californian homes that comply with the mechanical ventilation requirements of California's building energy efficiency standards (CalEnergy Code) (ASHRAE, 2022c; Commission, 2018). Thus, the contaminant concentrations in these homes reflect AIAQ defined by the current CalEnergy Code. In this study, it is used as a reference scenario for the concentrations of the CoCs. The harm budget is calculated by multiplying the concentrations in these homes by their individual harm intensities (Section 3.7). This sample may not be as large as is desirable but a cohort with high statistical power where all dwellings comply with an IAQ standard does not exist. This is the best available.

The HENGH2020 study is used as a reference for (median) concentrations of $PM_{2.5}$, formaldehyde, and nitrogen dioxide at 5, 23, and 9 $\mu g/m^3$, respectively (Singer et al., 2020). The logic behind using median concentration for a CoC, rather than a higher percentile, aligns with ANSI/ASHRAE 62.2 defining requirements based on typical buildings without predetermining allowable exceedances. Ozone and radon were not measured in these dwellings and so guideline values of 40 $\mu g/m^3$ and 100 Bq/m^3 are used as reference concentrations, respectively (Niculita-Hirzel, 2022). The $PM_{10-2.5}$ is not considered here because a guideline value does not exist. A $PM_{10-2.5}$ threshold could be inferred, but the goal here is to illustrate the flexibility of the harm budget approach instead and not set new arbitrary thresholds that carry their own uncertainty. Furthermore, these three

contaminants are likely to only contribute a small proportion of the total harm. This is an imperfect compromise.

Homes complying with ASHRAE 62.2 in California exhibit a harm distribution with a median of 600 DALYs/10^5 person/year (GSD 1.2), rounded to one significant figure. In this context, using one significant figure makes sense because the reference concentrations are expected to vary. Consequently, it will cause the output to fluctuate, ultimately leading to convergence around the same order of magnitude. Since these dwellings meet the existing ventilation standard, their central tendency harm logically represents an acceptable indoor air quality benchmark. The median harm in 62.2-compliant homes therefore anchors the proposed budget, aligning new standards with current regulatory frameworks. Contaminants' harm from the typical median concentrations for dwellings given in Table 6.4 exceed this budget by just under 4 times (Appendix A5.2 includes the conference paper that first presented this assessment, which is updated to latest analyses since).

Table 8.11: Dwellings' Harm Budget, DALYs/10^5 person/year.[+]

Contaminant	**Median**	**GSD**
$PM_{2.5}$	300	1.2
Formaldehyde	100	2
Nitrogen dioxide	51	1.7
Radon	44	1.6
Ozone	54	1.9
Budget	580	1.2
Contaminants harm	2200	1.6
Exceeds	380%	

[+] Values to 2 Sig. Figs.

The harm budget assesses households conforming to the 62.2 standard by calculating the resultant harm according to measured contaminant concentrations, yielding a distribution of harm for homes that comply with the current 62.2 standard. The median of this distribution represents the central tendency. Setting the harm budget equal to this median implies equivalency as by definition half of dwellings meeting 62.2 will have a lower harm and half will have higher harm. Anchoring to the median also avoids predetermining an acceptable percentile of dwellings that may exceed the harm benchmark. Ultimately the median provides a reasonable central

harm level reflecting the performance of homes compliant with current ventilation requirements.

Anchoring to the median harm level is expected to shift the distribution of harm in homes towards central tendency compared to using an upper percentile as the benchmark. Since harm follows a lognormal distribution, homes currently above the median will reduce harm to move closer to the 50th percentile under a median-based budget. This contrasts with a less protective outcome from choosing an upper percentile, like the 97.5th, which would allow the distribution to remain more dispersed with more homes exceeding that looser benchmark. Choosing a lower percentile will be "more protective" but a 2.5th percentile will be mostly unrealistic.

A median-anchored benchmark compresses and shifts the lognormal harm distribution leftwards versus an upper percentile target, cutting off the high DALY (harm) half of that distribution and allowing (but not requiring) the low-DALY part to use less ventilation. More homes clustered nearer the median reflects improved health protection across a stock and population.

The harm budget approach used here is a proof-of-concept. It is likely that concentrations, and hence the harm, in another cohort of dwellings compliant with ASHRAE 62.2 could be higher or lower than those given here. It is unknown how representative this cohort is of all other dwellings that also conform to ASHRAE 62.2, but this is a starting point for evaluating harm budgets, rather than a definitive solution. It is expected that the magnitude of the budget will change over time as they are compared to other (non-IAQ) hazards and as more houses are evaluated. The process does show, however, several key factors that should be considered before the harm budget approach can be implemented in standards.

8.3.1 Normalized harm budget

Transforming the harm budget from absolute to relative terms enhances its relevance. This conversion involves expressing the absolute harm budget as a unitless threshold of one ("1"). To achieve this, a weight is calculated for each contaminant as detailed in Section 3.7. The contaminants' harm intensities (Table 5.13) are divided by a common scaling factor. The specific common scaling factor is denoted by Equation 3.56 and equals 580 DALYs/10^5 person/year. Table 8.12 shows the intermediary calcula-

tions involving the normalized harm budget.

Table 8.12: Intermediary steps for calculating a normalized harm budget

CoCs	$\overline{C}_i$ [a]	HI_i [b]	Harm [c]	Partial weight [d]	Adjusted partial weight [d]	Common scaling factor for 1 [c]	Weight [e]
$PM_{2.5}$	5	60	300	0.517	0.517	580	**0.1**
HCHO	23	4.3	100	0.172	0.172	580	**0.0074**
NO_2	9	5.7	51	0.087	0.087	580	**0.0098**
O_3	40	1.3	44	0.075	0.075	580	**0.0022**
Rn	100	0.44	54	0.093	0.093	580	**0.00076**
	Harm Budget		580				

[a] µg/m^3; [b] DALY/µg/m^3/10^5 person/year; [c] DALYs/10^5 person/year; [d] Unitless; [e] m^3/μg

The following equation shows the normalized harm budget (nHB) for the five CoCs considered:

$$\begin{aligned} nHB = {} & W_{\mathrm{PM_{2.5}}} C_{\mathrm{PM_{2.5}}} + W_{\mathrm{HCHO}} C_{\mathrm{HCHO}} \\ & + W_{\mathrm{NO_2}} C_{\mathrm{NO_2}} + W_{\mathrm{O_3}} C_{\mathrm{O_3}} + W_{\mathrm{Rn}} C_{\mathrm{Rn}} \leq 1 \end{aligned} \tag{8.1}$$

Where:

nHB : Normalized harm budget [-]

Acceptable IAQ : Less than or equal to 1

$C_{\mathrm{PM_{2.5}}}$: Median concentration of $PM_{2.5}$ [$\mu g/m^3$]

C_{HCHO} : Median concentration of Formaldehyde [$\mu g/m^3$]

$C_{\mathrm{NO_2}}$: Median concentration of Nitrogen Dioxide [$\mu g/m^3$]

$C_{\mathrm{O_3}}$: Median concentration of Ozone [$\mu g/m^3$]

C_{Rn} : Median concentration of Radon [Bq/m^3]

$W_{\mathrm{PM_{2.5}}}$: $PM_{2.5}$ weighting: 0.1 [m^3/μg]

W_{HCHO} : Formaldehyde weighting: 0.0074 [m^3/μg]

$W_{\mathrm{NO_2}}$: Nitrogen Dioxide weighting: 0.0098 [m^3/μg]

$W_{\mathrm{O_3}}$: Ozone weighting: 0.0022 [m^3/μg]

W_{Rn} : Radon weighting: 0.00076 [m^3/Bq]

8.3.2 A connection to the ANSI/ASHRAE 62.2 standard

Expressing harm in DALYs enables a comparison against other common hazards, better informing risk trade-offs. In November 2022, the ASHRAE Standards Committee proposed adding a DALY-based path into Standard 62.2 on residential ventilation and IAQ. This attempt uses the representative concentrations (Table 6.4) and harm intensities (Table 5.13) from the present work to quantify health effects. If adopted, it would represent a major advancement for evidence-based IAQ management.

ASHRAE 62.2 compliance is required by California's Title 24, from the U.S. state building regulation, affecting over 300 million people. Integrating health impact assessment is overdue for hazardous indoor pollutants, even though it is routine for chemicals in the ambient air. The proposed DALY path aligns indoor air with environmental-health best practice. This is intended to address indoor air quality concerns beyond indoor CO_2 levels and stuffiness.

However, some considerations remain before fully implementing the harm budget into ASHRAE 62.2. Limiting contaminants of concern to the most harmful ($PM_{2.5}$, formaldehyde, NO_2) would simplify source control and enforcement. Radon is more impacted by buildings characteristics (such as the depressurization of subfloors) and ozone is mainly an outdoor pollutant but it can also be controlled by infiltration and ventilation. Different ways of reducing CoCs were presented in Table 8.2. Figure 8.2 illustrates the CoCs with a color scheme that highlights the aforementioned idea. It combines $PM_{2.5}$ and $PM_{10-2.5}$ to show that PM_{10} accounts for 84% of the harm.

The harm budget provides a template to progressively evolve guidelines based on accumulating evidence, using health metrics to link exposures to quantified impacts. While current knowledge has limitations, even crude DALYs offer valuable new information versus arbitrary concentration thresholds alone. Overall, the pioneering adoption of health-based equivalence principles in ventilation standards signifies important movement toward fully performance and risk-driven guidelines.

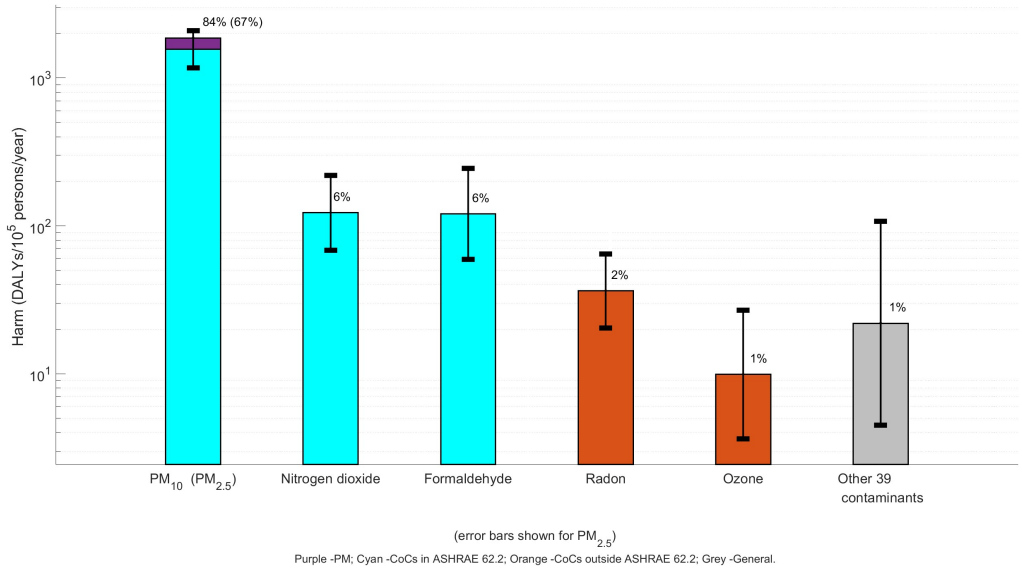


Figure 8.2: Colour scheme: Harm caused by contaminants of concern. Median (bar) & GSD (error bar). Percentage contribution for total harm.

8.4 Contaminant ranking and prioritization

The DALY metric allows contaminants to be ranked by the harm they cause and then prioritized. Other studies that ranked and prioritized airborne contaminants in dwellings used different qualitative or quantitative methods.

Halios et al. (2022) identified a subset of high-priority VOCs based on their adverse-effect endpoints and the number of studies reporting their concentrations. The VOCs they prioritized were: trichloroethylene, tetrachloroethylene, 2-methylbutane, tetrachlorocarbon, benzene, ethylbenzene, m + p-xylene, o-xylene, styrene, toluene, trimethylbenzene, acetone, acetaldehyde, formaldehyde, naphthalene, $\alpha-$pinene, and limonene. Sarigiannis et al. (2011) used a combination of quantitative risk characterization metrics to prioritize ten major organic compounds, and highlight benzene as the indoor contaminant of major concern, followed by formaldehyde, toluene, and xylenes. Azuma et al. (2016) ranked acrolein, nitrogen dioxide, and benzene as the highest risk pollutants (from a list of 49 indoor contaminants), utilizing the ratio of the contaminant threshold to its measured concentration (where a lower value signifies a higher level of health concern).

These studies prioritized contaminants by interpreting risk using predefined thresholds or chosen rules, whereas this research applied the DALY metric.

Furthermore, they all follow a different prioritization method, whereas the DALY provides a quantitative number that allows a direct comparison between contaminants.

There is agreement with the three studies of Azuma et al. (2016); Halios et al. (2022); Sarigiannis et al. (2011) in that formaldehyde and nitrogen dioxide are CoCs. One study highlights that acrolein is important, but this current study uses more up-to-date toxicology and epidemiology data and finds that it is less important than previously thought. The three references agree that benzene is a priority contaminant because it is highly carcinogenic in humans. The harm intensity for benzene considers this too, and when carcinogenic health effects are considered as DALYs, their contribution to the total harm is negligible when compared to the other contaminants (ranked the 17th most harmful contaminant in Table 7.1). This indicates that the presence of benzene in dwellings is trivial at the concentrations identified in this research (See Table 6.4). It may be necessary to regulate the sources of carcinogens (35 of the 45 contaminants are carcinogens) or their concentrations in air via IAQ standards if they are expected to be high, under the premise that they induce harm.

8.5 Linear vs Log-Linear Modeling

The epidemiology-based approach to assessing air contaminants places significant emphasis on the Concentration-Response (C-R) function, one of its most critical yet uncertain parameters (Fantke et al., 2019). Various relative risk models have been proposed to estimate mortality due to $PM_{2.5}$ exposure: the log-linear model, the Global Burden of Disease's Integrated Exposure-Response Model (GBD's IER), and the Global Exposure Mortality Model (GEMM) (Burnett and Cohen, 2020). Different outcomes arise from each model, introducing uncertainty in the true magnitude of $PM_{2.5}$'s impact on mortality. Such extensive analysis remains absent for other airborne contaminants.

In this research, a linear, no-lower-threshold, C-R model is utilized to assess a range of contaminants for which epidemiological data are available. These include acrolein (C_3H_4O), benzene (C_6H_6), mold, formaldehyde ($HCHO$), nitrogen dioxide (NO_2), ozone (O_3), respirable particulate matter (PM_{10}), fine particulate matter ($PM_{2.5}$), radon (Rn), and sulphur dioxide (SO_2). While a non-linear (frequently log-linear) C-R relationship could be applied

across a broader range of ambient exposures, the assumption of linearity is particularly appropriate for low-concentration regimes. This linearity is corroborated by Life Cycle Impact Assessment (LCIA) studies of airborne contaminants (Gronlund et al., 2015; Huijbregts et al., 2017; Van Zelm et al., 2016), and further supported by chronic exposure assessments associated with child asthma and HCHO (Lam et al., 2021), all-cause mortality and NO_2 (Henschel et al., 2013; Huangfu and Atkinson, 2020), mortality and O_3 (with less certainty, (Agency, 2013)), all-cause mortality and $PM_{2.5}$(US-EPA, 2020b), lung cancer mortality and Rn (Gaskin et al., 2018), and respiratory effects and SO_2 (Johns and Linn, 2011).

The existing body of research on airborne contaminants in LCIA primarily uses three effect models to determine the distance between the current exposure state and the point of zero impact: marginal, average, and linear effect models (Hauschild and Huijbregts, 2015; Heijungs, 2021). For the purposes of this study, the theoretical minimal risk exposure level (TMREL) (Section 2.4.1) was set to zero for all studied contaminants. This approach aligns with the linear effect model. TMRELs greater than zero have been proposed in previous research for various health outcomes (Burnett and Cohen, 2020; Henschel et al., 2013; Turner et al., 2016), often based on statistical considerations like the minimum or fifth percentile values in risk assessments. However, no existing studies provide biological mechanisms to explain why a certain level of pollution would have no effect.

The "epi-Harm" model accommodates both linear (Lin) and log-linear (LogL) approaches, as demonstrated in Figure 8.3. Furthermore, Figure 8.4 outlines the C-R curve for $PM_{10-2.5}$, obtained by subtracting values of other PM fractions. The width of the x-axis represents the concentrations regime for the contaminants. The upper limit of each x-axis was set as the 97.5th percentile of the distribution of the concentration (Table 19).

Research on air pollution risk lacks definitive quantitative thresholds to distinguish "low" from "high" concentrations of airborne contaminants. Drawing upon the integrated exposure-response model for $PM_{2.5}$, a range of 30–50 $\mu g/m^3$ is considered to signify high exposure (Burnett et al., 2014). Although, the risk C-R plots of Burnett and Cohen (2020) also show flattening of the curve at 100 or 300 $\mu g/m^3$. This is influenced by each health outcome considered.

A useful strategy for establishing concentration thresholds involves analysing discrepancies between linear and non-linear exposure-response

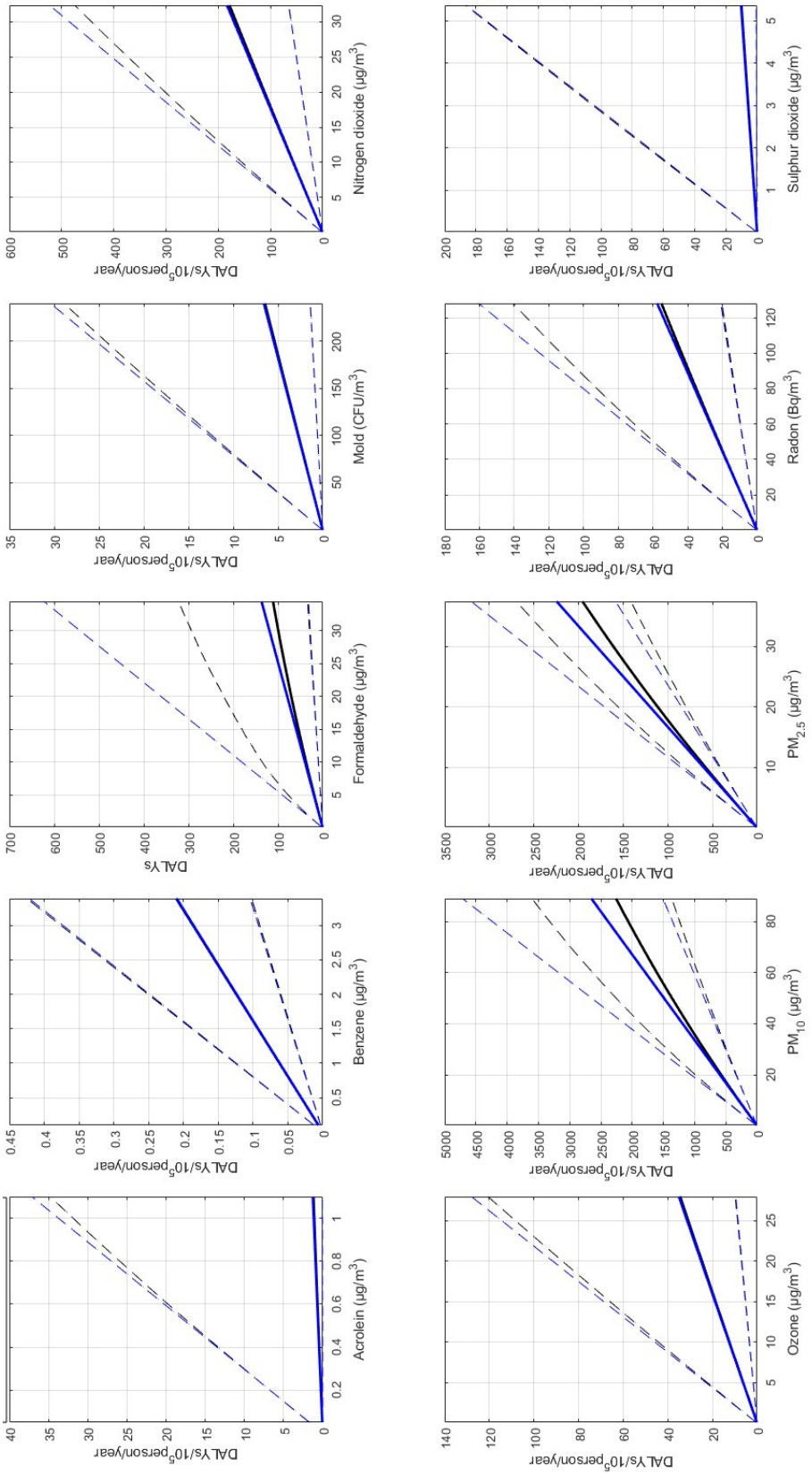


Figure 8.3: Comparison of harm from linear and log-linear C-R functions. Median [solid lines] and 95%C.I. [dash lines]. (Black: Log-linear; Blue: Linear)

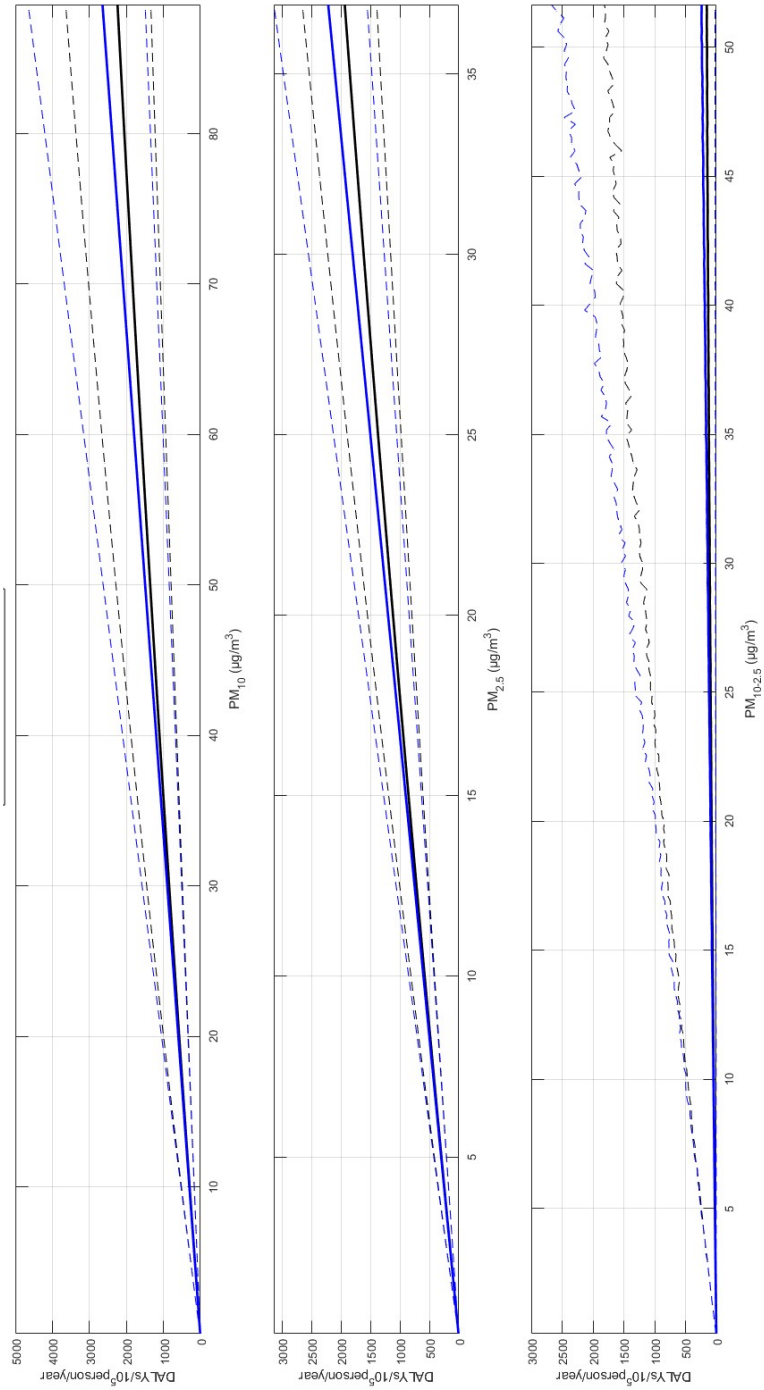


Figure 8.4: Concentration – Harm plots for PM fractions. Median [solid lines] and 95%C.I. [dash lines]. (Black: Log-linear; Blue: Linear).

models in Figure 8.3. Instances where these models agree strongly could denote a regime of low exposure. On the other hand, a divergence exceeding a predetermined error margin could signify a transition to high-exposure regimes where non-linear effects become significant. Therefore, the degree of congruence between the models could serve as a data-driven criterion for establishing thresholds for low and high concentrations. Figures 8.3 and 8.4 offer a qualitative estimation of the agreement between the two concentration-response curves and the extent of the overestimation of harm associated with the linear approach, particularly at higher concentrations.

In the assessment of agreement between Lin and LogL models for C-R relationships, two error metrics are important: the absolute percentage error (APE) and the mean absolute percentage error (MAPE). Transitioning from general assessment to a specific criterion, this study employs a MAPE threshold of 10%—roughly equivalent to one standard deviation—to discern concentration ranges where the models are in better agreement. Here, the log-linear model serves as the reference point because its C-R function has an upper asymptote for high concentrations representing a saturation effect.

Table 8.13 shows the MAPE values corresponding to the concentration distribution of the contaminants in the epi-Harm approach. Formaldehyde and PM_{10} manifest the highest MAPEs, warranting further scrutiny. Disparities between Lin and LogL are most apparent for Formaldehyde and PM_{10}, where the curve flattening in the LogL model causes a notable divergence from the Lin model. These discrepancies suggest that the concentration ranges derived are suitable as thresholds for harm, particularly when comparing the Lin model against the LogL counterpart.

Table 8.14 gives the APE when predicting harm at median contaminant concentrations in residences, using both Lin and LogL models. For a majority of the contaminants, the APE ranges between 0.77% and 12%, showing alignment between the Lin and LogL models arround the 10%. However, formaldehyde is an exception, demonstrating an APE of 21%. The high APE for formaldehyde can be attributed to the large risk estimates associated with its related health outcomes—asthma and leukemia—which diverge significantly from other contaminants. This discrepancy manifests in the β term of the equation, leading to a flattened curve for formaldehyde. Therefore, while the Lin model provides estimates with minimal deviation for most contaminants, caution is advised when applying it to

Table 8.13: Comparison of Contaminant Concentration Ranges and Mean Absolute Percentage Error (MAPE)

Contaminant	Concentration distribution[a,b]	MAPE (%)[b]
Acrolein	(0 - 1.1)	4.5 (95%C.I. 1.8-10)
Benzene	(0 - 3.4)	0.45 (95%C.I. 0.024-1.1)
Formaldehyde	(0 - 34)	10 (95%C.I. 9.6-12)
Mold	(0 - 240)	1 (95%C.I. 0.27-2.9)
Nitrogen dioxide	(0 - 32)	1.7 (95%C.I. 0.73-2.8)
Ozone	(0 - 28)	0.94 (95%C.I. 0.28-2.6)
PM_{10}	(0 - 89)	9.1 (95%C.I. 8.2-9.6)
$PM_{2.5}$	(0 - 37)	7.4 (95%C.I. 7.1-7.9)
Radon	(0 - 130)	2.6 (95%C.I. 1.7-3.5)
Sulphur dioxide	(0 - 5.4)	2 (95%C.I. 0.41-5.7)
$PM_{10-2.5}$	(0 - 52)	25 (95%C.I. 18-35)

Values to 2 Sig. Figs.
[a] µg/m^3; Mold in CFU/m^3; Radon in Bq/m^3
[b] Averaged over 10,000 sample sets

formaldehyde.

Consistent rankings of contaminants by their level of harm are generally found in both Lin and LogL models (Table 8.14). However, some variations arise; for instance, nitrogen dioxide ranks fourth in the Lin model but ascends to third in the LogL model. $PM_{10-2.5}$ is third and then forth, respectively. These discrepancies underline the significance of the chosen modeling approach in determining the perceived harm of contaminants, with a particular sense of ambiguity surrounding $PM_{10-2.5}$. The estimation of harm for this particle size fraction takes into account the variance in PM estimates. Furthermore, assessing its impact on all-cause mortality could offer more definitive insights into its health implications.

Table 8.15 shows concentration thresholds corresponding to the concentration range within which the MAPE is anticipated to fall below 10%.

This research identifies concentration thresholds that ensure an average MAPE of 10% or lower between linear and saturation models. For example, when modelling PM_{10} concentrations in the range of 0 to 108 µg/m^3, both the linear and log-linear models yield a MAPE around 10%. The accompanying 95% confidence intervals reflect the error variability.

Table 8.16 delineates the median concentrations at which the APE is expected for each contaminant of concern. These median concentrations mark points of divergence between the linear and log-linear models, typically with

Table 8.14: Absolute Percentage Error (APE) for Harm (Median) from Linear and Log-Linear Approaches

Contaminant$_i$ [a]	C_i, Central tendency	Approach				APE (%)[c]	Ranking	
		Linear		Log-Linear				
		median HI$_i$[b]	GSD	median HI$_i$[b]	GSD		Linear	Log-Linear
Acrolein	0.6	0.69	5.8	0.66	5.7	4.2 (95%C.I. 0.42-7.5)	10	10
Benzene	2.2	0.14	1.6	0.14	1.6	0.20 (95%C.I. 0.037-0.54)	11	11
Formaldehyde	28	110	2.2	92	1.8	20 (95%C.I. 17-22)	5	5
Mold	160	4.3	2.3	4.2	2.2	0.61 (95%C.I. 0.00037-1.4)	8	8
Nitrogen dioxide	22	120	1.8	120	1.8	1.8 (95%C.I. 1.1-2.7)	4	3
Ozone	7.3	9.3	2.7	9.3	2.7	0.57 (95%C.I. 0.0097-1.6)	7	7
PM_{10}	62	1900	1.5	1600	1.4	12 (95%C.I. 12-13)	1	1
$PM_{2.5}$	26	1600	1.4	1400	1.3	10 (95%C.I. 9.8-11)	2	2
Radon	78	35	1.8	34	1.8	3.2 (95%C.I. 2.2-4.1)	6	6
Sulphur dioxide	0.41	0.78	8.1	0.77	6.8	1.3 (95%C.I. 0.27-3.3)	9	9
$PM_{10-2.5}$	–	130	3.9	100	4.1	33 (95%C.I. 25-44)	3	4

Values to 2 Sig. Figs.
[a] µg/m^3; Mold in CFU/m^3;Radon in Bq/m^3
[b] DALY/µg/m^3/10^5 person/year(see mold and radon)
[c] Averaged over 10,000 sample sets
[d] Coarse fraction of PM from substraction of other PMs

Table 8.15: Appropriate concentration thresholds (µg/m^3) for a linear **harm** approach

Contaminant	Concentration distribution[a]	MAPE (%)[b]
Acrolein	(0 - 2.7)	10 (95%C.I. 6-20)
Benzene	(0 - 890)	10 (95%C.I. 9-10)
HCHO	(0 - 33)	10 (95%C.I. 9-10)
Mold	(0 - 3750)	10 (95%C.I. 8-10)
Nitrogen dioxide	(0 - 225)	10 (95%C.I. 9-10)
Ozone	(0 - 495)	10 (95%C.I. 9-10)
PM_{10}	(0 - 108)	10 (95%C.I. 10-10)
$PM_{2.5}$	(0 - 50)	10 (95%C.I. 9-10)
Radon	(0 - 425)	9 (95%C.I. 8-10)
Sulphur dioxide	(0 - 66)	10 (95%C.I. 6-10)
$PM_{10-2.5}$	(0 - 25)	10 (95%C.I. 5-20)

[a] Mold in CFU/m^3; Radon in Bq/m^3
[b] 1 Sig. Figs.; Averaged over 10,000 sample sets

the linear model overestimating by about 10%. However, these overestimations are within acceptable bounds, as they fall under the predefined MAPE threshold of 10%.

Table 8.16: Median concentrations (µg/m^3) for expected APE of 10%.

Contaminant	Median Concentration (SD)
Acrolein	1.3 (0.3)
Benzene	430 (30)
Formaldehyde	17 (3)
Mold	1900* (200)
Nitrogen dioxide	110 (10)
Ozone	240 (5)
PM_{10}	51 (3)
$PM_{2.5}$	25 (1)
Radon	240** (20)
Sulphur dioxide	34 (5)
$PM_{10-2.5}$	12 (3)

$^+$ 2 Sig. Figs.
* Mold in CFU/m^3
** Radon in Bq/m^3

Table 8.16 indicates that an APE of approximately 10% occurs at a PM_{10} concentration of around 51 µg/m^3 (95% CI: $48 - 54$). This concentration serves as the point of divergence between the linear and log-linear models.

The same analysis applies to the rest of the contaminants.

To evaluate the error for the coarse fraction, the Harm-Ci curves are subtracted, and the MAPE is calculated between the resultant curves. With a concentration ratio of 2.4 between the fractions and equivalent x-axis values, the MAPE for the 0 - 51.66 µg/m^3 range is 24% (95% CI $22 - 28$). The divergence between the linear and log-linear models becomes more pronounced at higher concentration percentiles. For the coarse fraction, the recommended concentration range for the linear model is 0 - 25 µg/m^3, which results in an MAPE of 10% (95% CI $5.0 - 10$). An APE of 10% is anticipated at 12 µg/m^3($\pm$3).

Lastly, the error in harm estimates between PM_{10} and $PM_{2.5}$ concentrations at the median level expected in dwellings is 33% (95% CI $26 - 42$). This error equates to assessing harm at a $PM_{10-2.5}$ concentration of 37 µg/m^3, highlighting the potential overestimation of harm by the linear model compared to the log-linear approach.

This section offers an understanding of harm caused by various contaminants, specifically following the epi-harm approach. $PM_{2.5}$ consistently emerges as the predominant driver of harm. A second tier of contaminants includes the $PM_{10-2.5}$, nitrogen dioxide, and formaldehyde, while a third category comprises radon and ozone. These contaminants make up the Contaminants of Concern (CoC).

For a more comprehensive view, it is crucial to employ the tox-harm approach, particularly for acrolein, formaldehyde, benzene, radon, and ozone. This complementary method enriches the understanding of these contaminants' impacts. Ultimately, minimizing concentration levels is a vital strategy for reducing errors across both the epi-harm approach.

8.6 Application of harm approaches

8.6.1 Harm from exposure to $PM_{2.5}$ from cooking meals

Cooking is a primary contributor to fine particulate matter (particles with a diameter $\leq 2.5\,\mu m$) in households, accounting for up to two-thirds of indoor emissions (Li et al., 2017). An increasing body of research, such as

the study by O'Leary et al. (2019), is focusing on ventilation as a mitigation strategy for $PM_{2.5}$ emitted during cooking from degradation of the food itself.

In England, the statutory Approved Document F (ADF) outlines ventilation guidelines for dwellings (Government, 2010). However, the ADF does not sufficiently address fine particulates generated by cooking. Moreover, the lack of a performance verification mechanism in the ADF puts its actual health benefits into question.

This section quantifies potential health benefits—measured in Disability-Adjusted Life Years (DALYs)—resulting from the implementation of six ventilation strategies prescribed in the ADF.

The analysis expands on prior work that provided a statistically representative sample of English kitchens (O'Leary et al., 2019). This prior study predicted $PM_{2.5}$ concentrations for six different ventilation strategies in existing English homes. Given that most of these strategies exceed recommended concentration thresholds, predicated on a 10% MAPE in linear models, this assessment employs a log-linear epi-Harm approach. Appendix A5.1 includes the conference paper that first presented this assessment. This section updates that work, incorporating the most recent analyses conducted post-conference.

Table 8.17: Ventilation Strategies (O'Leary et al., 2019)

Strategy	**Fan flow rate (L/s)**	**Details**
A	0	Infiltration only
B	13	Constant general extract ventilation at the high rate from ADF
C	60	Intermittent general extract ventilation just during cooking
D	60	Same as C but for an additional 10 minutes after cooking
E	30	Intermittent extract through a cooker hood, CE=50%, just during cooking
F	30	Same as E but for an additional 10 minutes after cooking

In a scenario relying solely on infiltration, the median [mean] DALYs observed is 5,400 DALYs/10^5 person/year [5,300] (GSD 1.5). When a 30 L/s

cooker hood is used for the duration of cooking plus an additional 10 minutes reduces this number to 1,500 DALYs/10^5 person/year [1,700] (GSD 1.8), averting a median of 2,900 DALYs/10^5 person/year [3,500] (GSD 1.8) (See Table 8.18). The transition from the worst to the best ventilation scenario results in a **median reduction of 54%** (mean 66%).

Table 8.18: Averted DALYs for Various Ventilation Strategies, DALYs/10^5 person/year+

Strategy	Median	Mean	GSD
Strategy A	5400	5300	1.5
Strategy B	2700	2800	1.5
Strategy C	2600	2900	1.7
Strategy D	1300	1500	1.7
Strategy E	2200	2600	1.7
Strategy F	1500	1700	1.7
Averted DALYs, A to F	2900	3500	1.8

+ Values to 2 Sig. Figs.

The distribution of $value/DALY for very high HDI countries, with a mean of $69,500/DALY (see Table 2.8), is used to calculate the cost per person per year for installing a kitchen hood that exhausts to the outside. Averting 2,900 DALYs/10^5 person/year provides a median [mean] value of $1,600 [$2,400] per person per year (GSD 2.5). This amount represents the annual health-based monetary value of reducing $PM_{2.5}$ emitted from cooking, from the worst to the best ventilation scenario per person in a dwelling. If the cost per person for installing and maintaining a kitchen hood that exhausts to the outside is less than or comparable to the $2,400/person/year, the intervention would be cost-effective.

The health-based monetary value of reducing $PM_{2.5}$ in a dwelling must be balanced against the additional energy used, the cost of energy, and any societal cost of carbon associated with that energy (Jackson, 2017). These aspects are not included in the current estimation and warrant further investigation in future research.

The study by Rosenthal et al. (2018) explored health benefits from cleaner cooking solutions across 40 countries with varied income levels following the methodology of Pillarisetti et al. (2016). Switching to Liquefied Petroleum Gas (LPG), employing advanced fans, or utilising local cookstoves led to reduced mean exposures from 285 µg/$m^3$to 35, 74, and 182 µg/m^3, respec-

tively. These changes corresponded to averted DALYs/10^5 person/year of $9,000$, $7,000$, and $1,500$.

Despite some methodological differences ($PM_{2.5}$ from combustion vs $PM_{2.5}$ tied to the meals), both their study and the current research underline the importance of mitigating $PM_{2.5}$ exposure through robust strategies, applicable across diverse income settings.

However, this study has limitations. The $PM_{2.5}$ concentrations are model-derived averages across various kitchens, and the study assumes lifetime exposure at these levels. Despite these constraints, the harm-based metrics provide a valuable tool for evaluating the cost-effectiveness of different interventions.

Incorporating such health-focused metrics into guidelines could mark a substantial advancement in indoor air quality research. These quantifiable health metrics should be the focal point of future studies, benefiting stakeholders such as policymakers, researchers, and the general public by providing actionable insights into effective mitigation strategies. The data presented here for harm from cooking reaffirm that using local ventilation, such as hoods, as the typical recommendation for a practical solution/design is very adequate to prevent harm.

8.6.2 Preliminary assessment of harm in office environments

While this research focuses on residential settings, its methodologies and harm intensity metrics are directly transferable to office environments, so long as the concentrations are within the boundaries in Section 5.3.3. The literature offers robust studies on IAQ in offices. Sérafin et al. (2021) identify 71 priority contaminants (out of 342) based on hazard quotient and classifications like carcinogenicity (a subjective compromise). However, a gap exists in quantifying the actual harm—measured in Disability-Adjusted Life Years (DALYs)—caused by these contaminants.

In an attempt to bridge this gap, this section adapts the epi-harm and tox-harm approaches previously employed for residential settings. Chapter 5 already provides harm intensities (HIs) for 17 out of the 71 priority office contaminants. For the remaining 54, the focus turns on those listed in the USETox database (Fantke et al., 2017a). 27 contaminants appear in the

USETox database, for which new HIs are proposed. Table 8.19 presents the median and uncertainty for the derived HI_i, as well as the specific diseases contributing to the all-cause health effect estimate for each contaminant..

Table 8.19: Harm intensities for contaminants not included in Section 5.5 Highest to lowest median.[+]

CAS No	contaminant	median[a]	GSD	approach	disease
53-70-3	Dibenz[a,h]anthracene	150	6.5	Toxicology	Lung cancer
50-32-8	Benzo[a]pyrene	140	6.5	Toxicology	Stomach cancer
193-39-5	Indeno[c,d]pyrene	6.3	7	Toxicology	Cancer average
207-08-9	Benzo[k]fluoranthene	6.2	8	Toxicology	Cancer average
56-55-3	Benzo[a]anthracene	6.1	7.1	Toxicology	Cancer average
205-99-2	Benzo[b]fluoranthene	6.1	7	Toxicology	Cancer average
1024-57-3	Heptachlor epoxide B	4	7.1	Toxicology	Liver cancer; Non-cancer average
542-75-6	1,3 DCP	1.9	3.3	Toxicology	Liver cancer; Non-cancer average
76-44-8	Heptachlor	1.8	6.9	Toxicology	Liver cancer; Non-cancer average
57-74-9	Chlordane	1.7	6.9	Toxicology	Liver cancer; Non-cancer average
218-01-9	Chrysene	0.62	9.5	Toxicology	Cancer average
118-74-1	HCB	0.54	6.4	Toxicology	Liver cancer; Non-cancer average
50-29-3	pp-DDT	0.2	8.3	Toxicology	Liver cancer; Non-cancer average
58-89-9	Lindane	0.17	6.7	Toxicology	Liver cancer
72-55-9	pp-DDE	0.17	7	Toxicology	Liver cancer
78-87-5	DCP	0.057	6.5	Toxicology	Liver cancer; Non-cancer average
127-18-4	Tetrachloroethylene	0.043	6.4	Toxicology	Leukemia; Non-cancer average
115-96-8	TCEP	0.023	5.6	Toxicology	Cancer average
67-66-3	Chloroform	0.018	6.4	Toxicology	Liver cancer; Non-cancer average
117-81-7	DEHP	0.0071	7.2	Toxicology	Liver cancer; Non-cancer average
1163-19-5	BDE 209	0.0056	8.4	Toxicology	Liver cancer; Non-cancer average
75-09-2	Dichloromethane	0.0056	5.5	Toxicology	Breast cancer; Non-cancer average
85-68-7	BBP	0.0042	5.4	Toxicology	Pancreas cancer; Non-cancer average
120-82-1	1,2,4-Trichlorobenzene	0.00035	6.2	Toxicology	Non-cancer average
80-05-7	Bisphenol A	0.00027	7.6	Toxicology	Non-cancer average
110-80-5	2-Ethoxyethanol	0.00019	7.9	Toxicology	Non-cancer average
84-74-2	Dibutyl phthalate	0.00006	6.4	Toxicology	Non-cancer average

[+] Values to 2 Sig. Figs.
[a] DALY/µg/m^3/10^5 person/year

Utilising data from Sérafin et al. (2021), which offers a review of office contaminant concentrations from 2000 to 2020, this study makes necessary adjustments for the time individuals typically spend in office environments. Based on prior research, it is assumed that individuals are present in offices for 6 to 8 hours per day, amounting a quarter of a 24-hour day (Chan et al., 2016; Louis and LAVERGE, 2022; Sun et al., 2023). The analysed

concentrations comply with the 10% MAPE criteria. Given that the ratio of $PM_{2.5}$ to PM_{10} concentrations is 0.87, it is appropriate to use the previously calculated harm intensity for $PM_{10-2.5}$. This approach eliminates the risk of obtaining negative harm values when subtracting PM_{10}, a possibility that, while mathematically feasible, is conceptually illogical.

Table 8.20 gives the estimated chronic harm (DALYs/10^5 person/year) from exposure to the 44 contaminants, in descending order. $PM_{2.5}$, sulphur dioxide, nitrogen dioxide, formaldehyde, $PM_{10-2.5}$, and acrolein are ranked highest with estimated median 250 (GSD 3.6), 34 (GSD 7.6), 30 (GSD 2.0), 15 (GSD 2.1), 1.7 (GSD 7.9), and 0.46 (GSD 3.9) respectively; higher than all other contaminants by at least one order of magnitude. The median for $PM_{2.5}$ and HCHO appear coherent given they are prevalent in offices; however, other less apparent contaminants such as SO_2 and NO_2 that appear here beg the question of what gives rise to their presence in this environment, and warrant further investigation into their sources and potential health impacts.

Summing the harm for the 44 contaminants at their representative concentrations in office gives a total median harm of 470 DALYs/10^5 person/year (GSD 4.4). $PM_{2.5}$, SO_2, NO_2, formaldehyde, and $PM_{10-2.5}$ account for 99.6 % of total harm. Therefore, they can be preemptively considered as priority contaminants in offices. Figure 8.5 visually illustrates the contribution of each contaminant's median to the total, focusing on contributions surpassing 2%. It indicates that the prioritization of office air contaminants can be narrowed down to six main substances causing harm.

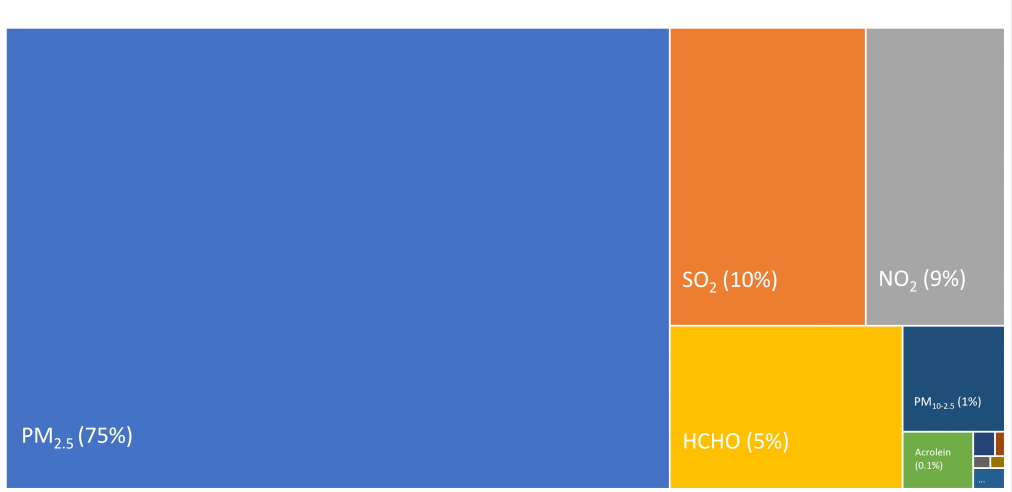


Figure 8.5: Median harm in offices treemap. Percentage contribution for total median harm.

Table 8.20: Contaminant harm in offices, DALYs/10^5 person/year.[+]

Contaminant	Median	GSD
$PM_{2.5}$	250	3.6
Sulphur dioxide	34	7.6
Nitrogen dioxide	30	2
Formaldehyde	15	2.1
$PM_{10-2.5}$	1.7	7.9
Acrolein	0.46	4.1
Acetaldehyde	0.073	5.7
1,3 DCP	0.065	7.8
Carbon tetrachloride	0.045	7.1
Styrene	0.033	5.3
Benzene	0.027	2.6
1,3-Butadiene	0.011	4.1
Benzyl chloride	0.0058	17
Benzo[a]pyrene	0.0052	7.7
Tetrachloroethylene	0.0052	6.7
Ethanol	0.0047	9.7
1,2-Dichloropropane	0.0026	14
1,2-Dichloroethane	0.0024	5.5
Chloroform	0.0012	7.2
1,2,4-Trichlorobenzene	0.0012	7.5
Benzo[k]fluoranthene	0.00082	6.7
Benzo[b]fluoranthene	0.00079	7
Di-2-ethylhexyl phthalate	0.00063	7.7
Isoprene	0.00053	11
Benzo[a]anthracene	0.00043	6.3
Indeno[c,d]pyrene	0.00041	8.4
Trichloroethylene	0.00036	5.3
Benzyl butyl phthalate	0.00032	6.6
2-Methoxyethanol	0.00027	7.7
Methylene chloride	0.00023	9.8
Chrysene	0.00011	8.5
2-Ethoxyethanol	0.00009	7.8
TCEP	0.00003	5.8
Dibutyl phthalate	0.00001	6.5
Chlordane	0.00001	9.7
Heptachlor	0.00001	10
BDE 209	0.000004	7.4
Hexachlorobenzene	0.000004	7.3
Lindane	0.000003	10
Heptachlor epoxide B	0.000001	11
Dibenzo[a,h]anthracene	0.0000004	14
pp-DDT	0.0000001	13
Bisphenol A	0.00000003	6.7
pp-DDE	0.00000002	12

[+] Values to 2 Sig. Figs.
[a] (Trans-1,3-dichloropropene Telone II, technical grade (with 1% pichlorohydrin))
[b] Tris(2-chloroethyl) phosphate
[c] (Decabromodiphenyl oxide), (Decabromophenyl ether)
[d] (c-1,2,3,4,5,6-Hexachlorocyclohexane)(2,2-(4,4'-Dihydroxydiphenyl) propane)
[e] (2,2-(4,4'-Dihydroxydiphenyl) propane)

In the context of assessing harm from IAQ in offices, specific pollutants consistently emerge as significant contributors. According to Chan et al.

(2016) the harm resulting from exposure to $PM_{2.5}$ is an order of magnitude higher than those from Volatile Organic Compounds (VOCs). This observation aligns with a study focused on U.S. offices by Sun et al. (2023) which highlighted $PM_{2.5}$ significantly exceeding that of formaldehyde, ammonia, benzene, toluene, and xylene. Importantly, both studies draw on methodologies developed by Logue et al. (2012).

These studies share a common theme: when $PM_{2.5}$ and formaldehyde are present, they typically act as the principal causes of harm. Moreover, $PM_{2.5}$ tends to dominate, being an order of magnitude more impactful in terms of harm than other pollutants.

This preliminary assessment lays the groundwork for future research opportunities. Subsequent work could aim to derive new Harm Intensities for pollutants not covered by the USETox database. Additionally, expanding the scope of this preliminary assessment beyond the list of priorities outlined by Sérafin et al. (2021) to include the full range of 342 different airborne contaminants. Ozone is present in offices but was absent from the list of contaminants in offices in this preliminary assessment. This is attributed to its exclusion from the priority list of 71 contaminants by Sérafin et al. (2021), as it did not meet the inclusion criteria for the priority designation. A harm-based prioritization might lead to a different result.

It is important to note the caveats highlighted by Sérafin et al. (2021), which indicate that considerations such as the spatial and temporal coverage of the review of measurement campaigns in office buildings, the sampling design, and the prevalence of emissions from office sources, can lead to exclusion of contaminants from the 342 list. A closer look at this limitations could serve to curate the list of substances and identify those that are expected to be found in offices with more certainty, hence deriving the *Contaminants of Concern in Offices*.

The continued relevance of Logue et al.'s models in current studies indicates that the HIs developed here are valuable contributions to knowledge. Specifically, the use of the HI for $PM_{10-2.5}$ in this assessment affirms its wider applicability and validates the decision to include it in this study.

In summary, this section has demonstrated the adaptability of the harm-based methodology to quantifying health impacts in indoor environments beyond residential settings. By replicating the process of deriving harm intensities and harnessing crowd-sourced data to characterize uncertainty in

office contaminant concentrations (leveraging insights from a comprehensive systematic review of sampling methodologies in office environments), estimated harm was calculated for this alternate context. This quantification of harm will help address the present question of whether it is safer to work at home or to spend time in the office. A quick calculation based on the median harm in dwellings of 2,200 DALYs/10^5 person/year (or 550 if 8 hours assumed) and the median harm in offices here of 470 DALYs/10^5 person/year (8 hours at the office) suggests that perhaps it is safer to work in the office.

While assumptions were necessarily made regarding factors like exposure time, the application to offices further evidences the flexibility of the harm approach to provide health-based IAQ insights across locations, conceivably applicable to any indoor space, from trains to space stations.

8.7 Emerging topics and new evidence

This section discusses evidence considered new, as it was published in the very late stages of research for this thesis. These emerging topics and recent findings provide additional context and insights that may impact the understanding and implications of the primary research presented.

Particulate matter is a major driver of harm. Interest in quantifying the health effects of smaller fractions, in relation to total or specific mortality, is growing. Hu et al. (2022) presents health effects of PM_1, and using their results along with the methodology from this research, a chronic harm intensity for PM_1 could be proposed, albeit specifically for asthma. While this may not cover all-cause mortality, it is still a valuable metric. On the other hand, according to Marval and Tronville (2022), the health evidence for ultrafine particles (UFP) is not yet sufficient to quantify a chronic harm intensity. However, as research and interest continue to grow, it is likely that such a harm metric can be quantified for these smaller PM fractions in the near future.

Carbon monoxide (CO) warrants mention. Studies have examined non-acute CO exposures in UK homes, focusing on hourly exposures rather than cooking-related peaks (Croxford and Fairbrother, 2005; Croxford et al., 2006; Croxford and Kynigou, 2005; Milner et al., 2006). Others have study non-acute low-level CO exposure on neuropsychological/neurological

symptoms (Croxford et al., 2008; Volans et al., 2006). Low-levels of CO can go unnoticed and lead to long-term exposures (Holgate et al., 2020). For sub-acute CO exposures, single-day lag studies offer insights into short-term effects (Evangelopoulos et al., 2021; US-EPA, 2010b). Bae and Kwon (2019) reviewed 27 air pollution studies in South Korea, with 8 focusing on single-day lag effects of CO and mortality. Among 12 reported outcomes, CO exhibited higher relative risks compared to $PM_{2.5}$ and other pollutants. These findings corroborate earlier evidence on the health effects of short-term CO exposure and mortality (US-EPA, 2010b). Further investigation into morbidity from non-acute CO exposures, indoors or outdoors, is warranted (Bae and Kwon, 2019). Most studies reviewed by Bae and Kwon (2019) focus on the short-term effects of air pollution, with only three cohort studies examining long-term effects, and just one addressing carbon monoxide. It was a Korean cohort study that found a hazard ratio of 1.72 (95% CI: 1.52 - 1.92) for every 0.25 ppm increase in chronic CO exposure, indicating a 72% rise in all-cause mortality among healthy individuals in Seoul, Korea (Bae and Kwon, 2019; Kim et al., 2017). Identifying the specific diseases linked to CO exposure-related mortality will aid in deriving a chronic harm intensity for CO, a valuable addition to this research.

In a recent study, Liu et al. (2023b) investigated the disease burden associated with specific indoor air pollutants (IAPs) in Chinese residences from 2000 to 2017. This study evaluated annual exposure levels and assessed risks through systematic reviews. Harm, measured in DALYs, was determined using the population attributable fraction method (Section 2.4, Equation 2.9). Table 8.21 presents a summary of the findings from Liu et al. (2023b), alongside the results of the current research, with contaminants ranked by median harm for comparability (note that using the mean slightly alters the ranking order).

The total harm for the 44 contaminants at their representative concentrations in dwellings, assessed in this research, results in a median harm of 2,200 DALYs/10^5 person/year, representing approximately 7% of the total GBD in 2019. In comparison, the ten IAPs considered for China caused 4,050 DALYs/10^5 person/year, accounting for 15% of the total GBD in China in 2010. A thorough comparison of the similarities and differences between these studies is warranted for future analysis. Notably, carbon monoxide is a contaminant that stands out and is discussed further.

Table 8.21: Comparing results between China and current global approach.

Contaminant	Study						Ranking	
	China (2017)			Current Global (2019)				
	Ci[a]	Harm[b]	%[c]	Ci[a]	Harm[b]	%[c]	China	Current
$PM_{2.5}$	55	3300	84%	26	1600	67%	1	1
CO	1000	180	4.7%	NA			2	NA
Radon	59	88	2.3%	78	36	2%	3	5
NO_2	6	63	1.7%	22	120	6%	4	3
Benzene	4	62	1.8%	2.2	0.15	<0.6%	5	16
SO_2	5.3	58	1.5%	0.41	0.56	<0.6%	6	12
O_3	13	58	1.5%	7.3	10	1%	7	6
HCHO	70	53	1.4%	28	120	6%	8	4
Toluene	5	20	<0.6%	13	0.013	<0.6%	9	34
p-DCB	0.24	8.50	<0.6%	1.9	0.024	<0.6%	10	32

Values to 2 Sig. Figs.
[a] $\mu g/m^3$; Radon in Bq/m^3
[b] in DALYs/10^5 person/year
[c] Percentage contribution to total harm

The harm from carbon monoxide in the study by Liu et al. (2023b) was determined using an exposure-response relationship for cardiovascular diseases mortality, which indicated a hazard ratio of 1.024 (95% CI: 1.011 to 1.038) for each 1 mg/m^3 increase in average carbon monoxide concentrations on the present day and the previous day (lag 0–1). This implies a significant increase in mortality of 2.4%. However, it's crucial to note that these findings are based on short-term exposure to ambient carbon monoxide and its association with cardiovascular disease mortality. The risk estimates are drawn from time-series studies examining same-day effects, focusing on daily cardiovascular mortality in relation to acute exposure. This aligns with previous findings of mortality and short-term exposure to CO (US-EPA, 2010b). It's essential to highlight that the risk estimate used by Liu et al. (2023b) differs from those applied to other contaminants, as it's not derived from long-term exposure-response relationships in cohort studies. Therefore the harm estimated should be interpreted carefully, furthermore deriving a chronic harm intensity for CO from this data is not feasible. Carbon monoxide can have synergistic effects when combined to other substanses in the air, even at low concentrations (Norris et al., 1986; Ramsden, 2021). This aspect is interesting to integrate into the harm assessment in future works.

The annual mean concentration of carbon monoxide reported for residences by Liu et al. (2023b) is lower than China's current air quality standards for carbon monoxide, set at 4 mg/m^3 for a 24-hour period. France has established a chronic 1-year ELV for long-term CO exposures at 30 mg/m^3. As-

suming a linear exposure-response function, this ELV would correspond to a regulated harm of 5,400 DALYs/10^5 person/year for chronic CO exposures. Importantly, this regulated harm far exceeds that of other contaminants with ELVs, as discussed in Section 8.2.

Some contaminants are still not well understood, known as emerging contaminants of concern. Emerging contaminants are defined as chemicals not currently, or only recently, regulated, and about which concerns exist regarding their impact on human or ecological health (Salthammer, 2020). PM_1 and UFP fall into this category. Suggesting a minimum ventilation rate to cover these emerging contaminants impacted by ventilation is currently outside the scope of this research. Inferring a ventilation rate or which cleaning technologies are adequate to use requires a more in-depth investigation (Mata et al., 2022).

8.8 Limitations and Future Developments

This work derives estimates of harm as the product of a harm intensity and representative concentrations of airborne contaminants found in dwellings. While providing valuable insights, the straightforward approach to estimating harm has limitations.

This analysis does not explicitly address how demographics, habits, and regional differences may influence exposure variations. The focus was overall contaminant impacts, so these factors were accounted for implicitly through uncertainties. Furthermore, studies adjusting for sub-populations align with the generalized results. Current standards seldom tailor to specific groups. Nonetheless, further stratified analyses accounting for environmental justice factors like race, ethnicity, gender, socioeconomic status, and vulnerable (immune compromised) populations could be attempted. Examining if air pollution exposure relates to social determinants, and the potential for disproportionate impacts on vulnerable groups, would provide valuable insights. Incorporating environmental justice considerations into future research and policy-making could help develop targeted interventions that reduce exposure disparities. By acknowledging the role of these factors in shaping health outcomes, this study recognizes the need to better understand variability across sub-populations most at risk.

The indoor contaminant concentrations primarily reflect Global North na-

tions. The extensive compilation of 827 datasets may underrepresent some countries. Caution is advised when comparing the results to specific regions, as lifestyle and location discrepancies could lead to inaccuracies. More fieldwork is imperative to reduce uncertainties, especially for scarcely studied contaminants.

This work focused on a limited list of 45 contaminants commonly found in dwellings, selected based on their known harmful effects and availability of data. However, an important limitation is the omission of emerging contaminants like PM_1 and ultrafine particles $PM_{0.1}$, fungicides and pesticides, flame retardants, endocrine disruptors such as phthalates, and the chronic effects of long-term carbon monoxide exposures which have gained increasing attention in research (Hu et al., 2022; Liu et al., 2023b, 2022; Marval and Tronville, 2022; Page et al., 2023). These substances have the potential to significantly contribute to harm in indoor environments. Therefore, future studies should expand the scope to include these emerging contaminants, enabling a more comprehensive assessment of harm. The list contains several semi-VOCs (1,4-Dichlorobenzene, Hexachlorobutadiene, and Naphthalene). It may not be so important to consider semi-VOCs in future work for IAQ standards – not because they are unimportant -– but because they are not always removed by ventilation. Increasing ventilation has only a small impact on their airborne concentration because their net emission generally increases as their airborne concentration decreases (Borsboom et al., 2016; Parthasarathy et al., 2010). This makes estimating exposure to them complicated (Liu et al., 2015) and so the mitigation solution is source control rather than ventilation. Addressing emerging contaminants by specifying a minimum ventilation rate falls beyond the scope of this research (Mata et al., 2022).

The analysis assumes PM equitoxicity, where all particles are equally toxic per unit mass inhaled. Emerging evidence suggests health effects can vary by PM composition (US-EPA, 2020b) but more studies on the health impacts of PM from different sources are needed before it is possible to determine exposure-response relationships (Xu et al., 2022). Accurately assessing the health risks linked to PM exposure in indoor and outdoor environments poses a significant challenge. Existing methods for estimating PM exposure do not offer separate chronic risk estimates for indoor and outdoor settings. Consequently, distinguishing between the health effects of indoor versus outdoor PM exposure solely based on indoor PM concentrations proves difficult. Hence, there's a pressing need for enhanced methods

to evaluate and quantify the health risks associated with indoor and outdoor PM exposure independently.(Sandoval Diez, 2022). For perspective, the indoor $PM_{2.5}$ harm intensity would need to be ≈11 times lower to be equal to that of nitrogen dioxide, and would need to be 2,200 times lower to be equal to that of acrolein, when it would cease to be a contaminant of concern. Overall, PM size remains the most robust predictor of long-term harm (National Academies of Sciences, 2022).

This analysis' harm intensity methodology builds on LCIA models, with dose-response factors from the USETox database anchored to ED50 values (doses inducing 50% effect) (Section 3.13). Examining toxicity benchmarks like EPA's Integrated Risk Information System (IRIS) (U.S. Environmental Protection Agency (EPA), 2023) and OEHHA (OEHHA, 2011) for current research trends shows that cancer unit risks and slope factors now derive from ED10 or LED10 - the 95% lower confidence limits on 10% effect doses (California Environmental Protection Agency (CalEPA), 2009). This aligns with evolving LCIA methodology prepared to transition to ED10 or lower when reporting effecting median doses in toxicology research (Fantke et al., 2021b). Deriving and adapting harm intensities based on dose-response factors from ED10/LED10 might represent a change to the tox-harm approach presented here. However, until LCIA databases are updated to include dose-response factors based on ED10 or LED10, the precise impact of this change on the harm metric remains difficult to define.

This analysis relies on an additive assumption when evaluating the combined effects of indoor air pollutant mixtures (Section 2.2.2). While providing a useful harm estimate, additivity overlooks potential synergistic or antagonistic interactions between contaminants. Assuming simple additivity may underestimate or overestimate the true impact of complex pollutant mixtures. Exploring synergistic and antagonistic mixtures requires sophisticated modeling beyond this study's scope. The additive approach, though limited, is widely employed for its practicality. Further research should investigate pollutant interactions to give a more comprehensive understanding of mixture effects. By acknowledging additivity as a simplification, this study recognizes the need for future work to capture the intricacies of multi-pollutant impacts. Incorporating those dynamics could provide greater accuracy in assessing overall harm from indoor exposures.

While focused on dwellings, harm intensities can be applied broadly to other environments where concentration-response linearity is expected, or

where toxicology research is the only source of C-R data. Linearity is limited to low-moderate exposures. Extrapolations to high levels warrant detailed exploration. Error quantification between linear and non-linear approaches can be used to decide where a linear C-R function is adequate. Gases may exhibit non-linear and non-monotonic concentration-response curves, known as hormetic curves, resembling the shapes of U, V, or J. Such curves suggest that the healthiest dose of endogenous vital gases is never zero, lying between high toxicity and low deficiency ranges (Calabrese and Baldwin, 2002). Further research is required to understand these dynamics, particularly concerning air contaminants.

Future work can expand to include a hazard assessment that compares the harm identified in Chapter 7, Section 7.1 to the harm associated with complying with the Exposure Limit Values (ELVs) given in existing IAQ standards and guidelines, for the full list of contaminants considered in this work. This would show the relative protectiveness these standards provide to the occupants of the buildings they regulate. This analysis would provide valuable insights into whether the harm caused by the inhalation of airborne contaminants in dwellings aligns with the acceptable levels set by regulators and the wider public. A comparison will contribute to a better understanding of the potential health risks and the importance of adhering to standards and guidelines. In short, while ELVs exist within standards, their effectiveness in providing protection from chronic harm remains unclear.

Both the epidemiological and toxicological data that underpin the harm intensities and the concentrations are linked to chronic effects and exposures, and so it is not possible to consider acute health effects with them. For some of the contaminants, like carbon monoxide, or reactive oxidizing species including ozone and nitrogen dioxide, acute impacts from elevated short-term exposures (this being classified as 24-h exposures, same-day, or lag0) may be more important than the chronic harm calculated. For example, a gas leak from a faulty stove can swiftly elevate CO levels in a kitchen, leading to acute poisoning, causing symptoms like dizziness, nausea, and loss of consciousness. One can estimate acute harm intensities using the same methods proposed in this study, by adapting the data to align with equivalent evidence from acute epidemiology and toxicology.

This analysis required assumptions and methodological decisions that inherently introduce limitations. For example, choosing distribution shapes,

statistical measures, and data truncation approaches in MATLAB can impact results. There is no set protocol for making these choices when combining epidemiology, toxicology, life cycle assessment, and health risk research. The interdisciplinary nature of this work meant navigating diverse perspectives to determine suitable assumptions. While aiming to make the best judgments based on current evidence, a degree of subjectivity is unavoidable without an established methodology. By acknowledging these limitations, this research recognizes the need for continued methodological refinements as multidisciplinary indoor air quality assessments evolve. As protocols emerge through collective experience, uncertainties stemming from flexible assumptions can be reduced. Nonetheless, this study represents an initial foray into blended research that highlights the potential of bridging disciplines to enable more holistic harm evaluations.

This analysis relied solely on disability-adjusted life-years (DALYs) as the metric of harm. However, other valid metrics exist, like Quality-Adjusted Life Years (QALYs). While DALYs effectively capture disease burden, QALYs could offer a complementary perspective by incorporating perceived quality of life impairments. Exploring the use of QALYs in future indoor air quality assessments could strengthen the evaluation of health-related quality of life impacts. By acknowledging the study's exclusive use of DALYs, the door remains open for future work to incorporate a multi-metric perspective when quantifying total harm. Both DALYs and QALYs provide a standardized framework for comparing the impact of different health conditions and interventions. Shifting from DALYs to QALYs for IAQ mitigation may not significantly impact policy effectiveness. The choice between the two metrics depends on practical considerations such as ease of application within the healthcare system or country.

DALYs can be converted into a monetary value. This work used the 2016 USD monetary value of averted DALYs for very high HDI countries to estimate the annual cost per person due to exposure to contaminants in homes at different concentrations. However, this does not constitute a complete cost-benefit analysis. It is necessary to explore the costs of interventions and any potential offsets. Quantifying the cost-effectiveness of interventions to reduce contaminant concentrations in dwellings based on thresholds, such as GDPs per capita, should also be considered (Iino et al., 2022).

In considering evidence for harm estimates from different methodologies and recent studies, findings suggest that mold and carbon monoxide could

be deemed contaminants of concern in dwellings due to their significant contribution to overall harm. The evidence regarding carbon monoxide health effects is highly based on short-term exposures. The classification of exposures as acute, sub-chronic, or chronic is subject to interpretation. In health research, 24-hour exposures are typically classified as short-term and therefore acute. However, this thesis focuses on long-term exposures with chronic effects based on cohort studies. Comparing 24-hour exposures to chronic exposures is akin to -comparing apples to oranges- illustrating a comparison between two fundamentally different factors, rendering the comparison inappropriate (See Table 8.10).

This research provides a comprehensive estimate of the total harm from residential indoor air contaminants, using representative indoor concentration data of Global North countries, and globally-derived epidemiological and toxicological data lacking geographic specificity. The results presented here can be used to inform appropriate remediation by showing where the greatest reduction in harm can be achieved. Cost-benefit analyses could be used to show the interventions that give the greatest harm reductions for the least capital outlay. Furthermore, the harm intensities can be used to assess the harm from airborne contaminants measured in field surveys or predicted by models in other non-residential environments.

Chapter 9

Conclusions

A *harm budget* was conceived as a way to quantitatively determine *acceptable* indoor air quality in dwellings, based on exposure to $PM_{2.5}$, nitrogen dioxide, formaldehyde, ozone, and radon, in compliant residences. The current limit is around 600 DALYs/10^5 person/year. This harm budget can guide setting ventilation rates in standards and guidelines to ensure this threshold is not exceeded. Three of these contaminants account for 80% of all harm: $PM_{2.5}$, formaldehyde, and nitrogen dioxide, furthermore, considering that control of $PM_{2.5}$ also controls for $PM_{10-2.5}$ the harm mitigation could be up to 96%. ASHRAE is considering to add $PM_{2.5}$, HCHO and NO_2 into its ANSI/ASHRAE Standard 62.2 for ventilation and acceptable IAQ in residential buildings. Adopting this methodology could influence millions of dwellings.

Integrating harm intensities with typical indoor concentrations reveals that fine and coarse particulate matter ($PM_{2.5}$, $PM_{10-2.5}$), nitrogen dioxide, formaldehyde, ozone, and radon emerge as top priorities based on their harm. These contaminants, termed *Contaminants of Concern, CoCs*, collectively account for over 99.5% of the total harm, DALYs/10^5 person/year, from typical exposures in dwellings. This identification serves multiple purposes: prioritizing them for removal and control, enabling targeted guidelines and strategies; establishing an initial harm budget approach for health-based indoor air quality standards; informing policies, codes, and building practices for contaminant reduction source control over dilution; focusing design, operation, and technology development on contaminants causing the most harm; and raising awareness of these prevalent contaminants in dwellings.

A metric, termed *Harm Intensity*, was developed to relate harm to contaminant exposure (DALY/µg/m^3/person/year). Calculated for 45 indoor air contaminants based on toxicology and/or epidemiology evidence, this metric, where both types of evidence existed, showed reassuringly similar results. Particles ($PM_{2.5}$, PM_{10}), hexavalent chromium, cadmium, nitrogen dioxide, and formaldehyde exhibited the highest harm intensities, implying that even low exposure levels may cause harm. The metric's simplicity and its applicability beyond dwellings make it a versatile tool for assessing both indoor and outdoor air pollution scenarios. The Harm Intensity metric plays a crucial role in proposing a normalized harm budget, which offers a standardized approach to defining acceptable IAQ in dwellings. By prioritizing mitigation efforts based on the severity of potential health risks, resources can be allocated effectively.

Recent literature on residential indoor exposures for 45 common contaminants in dwellings was compiled, analyzed, and summarized. This compilation adds to the knowledge of the prevalence and uncertainty of airborne contaminants in dwellings. Widely measured contaminants, especially volatile organic compounds and known carcinogens, contribute minimally to overall population harm, except for formaldehyde, when they are present in homes at the median exposure values presented here.

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Appendices

A1 For parameters deriving harm intensities

Further information for the beta parameter relevant for epidemiology-based harm intensities and effect factors for exposure to indoor air contaminants.

Table 1: Keywords and Boolean operators when performing systematic reviews on Risk estimates for deriving parameter beta parameters.

Input parameter	**Research question that guided the systematic review**	**keywords and Boolean operators**	**Databases**
Risk estimates (beta parameter)	what (Criteria)-pollutant C-R functions outcomes have been developed. - Human Health Effects of Criteria Pollutants	The following keywords were searched in titles, abstracts, AND keywords: (("Health" or "Effects" OR "concentration-response" OR "risk" OR "relative risk") AND (partic*matter AND air)) OR (o?one OR air OR O3) OR ("Nitrogen dioxide" OR NO2 AND air) OR ("Sulfur dioxide" OR SO2 AND air) OR ("carbon monoxide" OR "C.O." AND air); ("Health" OR "Effects" OR "concentration-response" OR "risk" OR "relative risk").	AMED, ovid ASSIA, CINAHL, Cochrane Library, EMBASE, ovid SCI, Web of Science, Medline, ovid Pubmed, ovid PROSPERO, PSYCINFO, ovid Scopus, and Google Scholar

[a] All 44 contaminants followed the same logic, with each one as a keyword.

Table 2: Full statistic descriptors: Beta parameter estimates.

Contaminant	central input	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Acrolein$_{(asthma)}$	0.1408	0.1346	0.1406	0.0423	0.0756	0.2396	0.2941	1.3419	1.8008
Benzene$_{(leukaemia)}$	0.0004	0.0004	0.0004	0.0001	0.0002	0.0008	0.3311	1.3924	1.9389
Formaldehyde$_{(asthma)}$	0.0252	0.0197	0.0251	0.0195	0.0050	0.0757	0.6891	1.9918	3.9674
Formaldehyde$_{(leukaemia)}$	0.0201	0.0125	0.0201	0.0266	0.0018	0.0857	1.0082	2.7406	7.5106
Formaldehyde$_{(lung\ cancer)}$	0.0039	0.0024	0.0039	0.0048	0.0003	0.0172	0.9678	2.6321	6.9277
Mold$_{(asthma)}$	0.0001	0.0001	0.0001	0.0001	0.0000	0.0004	0.7320	2.0792	4.3230
Nitrogen dioxide$_{(AllCauseMort.)}$	0.0020	0.0017	0.0020	0.0011	0.0006	0.0047	0.5031	1.6539	2.7354
Ozone$_{(AllCauseMort.)}$	0.0010	0.0008	0.0010	0.0007	0.0002	0.0029	0.6477	1.9111	3.6525
PM$_{10(AllCauseMort.)}$	0.0039	0.0038	0.0039	0.0010	0.0023	0.0064	0.2625	1.3002	1.6904
PM$_{2.5(AllCauseMort.)}$	0.0077	0.0076	0.0077	0.0010	0.0059	0.0098	0.1316	1.1407	1.3011
Radon$_{(lung\ cancer)}$	0.0009	0.0008	0.0009	0.0005	0.0003	0.0023	0.5143	1.6725	2.7972
Sulphur dioxide$_{(AllCauseMort.)}$	0.0058	0.0056	0.0058	0.0018	0.0031	0.0101	0.2992	1.3487	1.8190

Units in change/µg/m^3; Radon in change/Bq/m^3; Mold in change/CFU/m^3.
Central input from systematic review. std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 3: Full statistic descriptors: Baseline disease incidence parameter estimates.

Contaminant	central input	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Acrolein	63.000	15.505	62.972	215.932	0.560	427.241	1.596	4.932	24.321
Benzene	4.320	4.312	4.320	0.250	3.854	4.836	0.058	1.059	1.122
Formaldehyde$_{(asthma)}$	8.000	1.925	7.694	27.175	0.074	50.622	1.613	5.017	25.165
Formaldehyde$_{(leukaemia)}$	4.320	4.308	4.319	0.248	3.853	4.818	0.057	1.059	1.122
Formaldehyde$_{(lungCancer)}$	26.400	26.346	26.410	1.421	23.726	29.342	0.054	1.055	1.114
Mold	504.280	496.984	504.055	83.795	359.445	687.029	0.165	1.180	1.391
Nitrogen dioxide	674.990	674.174	674.621	28.113	622.053	731.903	0.042	1.043	1.087
Ozone	674.990	675.029	674.986	28.453	620.525	731.054	0.042	1.043	1.088
PM_{10}	674.990	674.172	674.671	27.731	622.078	731.537	0.041	1.042	1.086
$PM_{2.5}$	674.990	674.448	674.886	28.309	621.299	732.788	0.042	1.043	1.087
Radon	26.400	26.367	26.404	1.448	23.655	29.371	0.055	1.056	1.116
Sulphur dioxide	674.990	674.456	674.897	27.958	620.924	730.721	0.041	1.042	1.086

Units in cases/10^5person/year.
Central input from burden of disease database or related reference. std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 4: Full statistic descriptors: Damage factors parameter estimates.

Disease	central input	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Cancers									
Breast cancer	10.7538	10.7488	10.7548	0.37782	10.0266	11.5182	0.03512	1.0357	1.0728
Leukemia	34.9954	34.6869	34.9371	4.3829	27.251	44.3771	0.12496	1.1331	1.2839
Liver Cancer	24.7071	24.672	24.6942	1.1132	22.5893	26.9835	0.045057	1.0461	1.0943
Lung cancer	21.1772	21.1795	21.1771	0.83435	19.5768	22.8182	0.039383	1.0402	1.082
Mouth and oroph cancer (oral)	15.5312	15.5219	15.5291	0.56447	14.4561	16.6791	0.036337	1.037	1.0754
Stomach cancer	19.2363	19.2154	19.2331	0.9276	17.4516	21.0941	0.048201	1.0494	1.1012
Cancers	10.6	10.581	10.598	0.56825	9.52484	11.7537	0.05358	1.055	1.1131
Non-Cancers									
Cardiovascular diseases	7.0759	7.0745	7.0808	0.40235	6.33	7.9176	0.056776	1.0584	1.1203
Chronic respiratory diseases	1.3344	1.3308	1.3353	0.12432	1.1055	1.5975	0.092905	1.0974	1.2042
Asthma	0.58753	0.57574	0.58705	0.11937	0.38695	0.85562	0.20128	1.223	1.4956
Congenital birth defects	6.2689	6.1735	6.2629	1.0379	4.4983	8.5391	0.1646	1.1789	1.3899
Diabetes and kidney diseases	2.6893	2.6747	2.6904	0.24242	2.2422	3.1912	0.089923	1.0941	1.197
Digestive diseases	0.20113	0.2003	0.201	0.016943	0.17011	0.23651	0.084146	1.0878	1.1833
Mental disorders	0.33475	0.32709	0.33437	0.066691	0.22492	0.48336	0.19751	1.2184	1.4844
Musculoskeletal disorders	0.46057	0.45087	0.45988	0.093696	0.3022	0.66817	0.20167	1.2234	1.4968
Neurological disorders	0.11908	0.11252	0.11972	0.042945	0.057558	0.22216	0.34792	1.4161	2.0054
Urinary diseases and male infertility	0.017624	0.0175	0.017642	0.002113	0.013847	0.022096	0.11937	1.1268	1.2696
Non-Cancer Average	na	2.047	2.0558	0.12782	1.829	2.3273	0.062114	1.0641	1.1323

Units in DALY/case.
Central tendency input; std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 5: Full statistic descriptors: Damage factors for epidemiology related contaminants parameter estimates.

Contaminant	central input	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Benzene	34.995	34.707	35.018	4.458	27.193	44.650	0.127	1.135	1.289
Formaldehyde$_{(Addedeffects)}$	NA	21.526	20.269	3.858	8.584	24.331	0.189	1.208	1.458
Mold	0.588	0.574	0.588	0.121	0.390	0.864	0.204	1.226	1.503
Nitrogen dioxide	4.850	4.818	4.858	0.632	3.747	6.214	0.130	1.138	1.296
Ozone	2.309	2.296	2.308	0.230	1.889	2.789	0.099	1.104	1.220
PM_{10}	11.763	11.700	11.762	1.316	9.384	14.587	0.112	1.118	1.250
$PM_{2.5}$	11.773	11.707	11.773	1.301	9.429	14.499	0.110	1.116	1.246
Radon	21.177	21.176	21.188	0.834	19.594	22.888	0.039	1.040	1.082
Sulphur dioxide	1.453	0.500	1.476	3.899	0.028	8.797	1.441	4.225	17.853

Units in change/µg/m^3; Radon in change/Bq/m^3; Mold in change/CFU/m^3.
Central tendency. std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 6: Full statistic descriptors: Dose-response Factors for cancer, parameter estimates.

DRFc	DRFc U. Factor	Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
7.49E-03	4	Acetaldehyde	0.00426	0.00754	0.01134	0.00053	0.03398	1.08780	2.96769	8.80720
1.28E-01	1	Acrylonitrile	0.12795	0.12795	0.00009	0.12777	0.12814	0.00072	1.00072	1.00144
1.47E-02	1	Benzene	0.01468	0.01468	0.00001	0.01466	0.01470	0.00071	1.00071	1.00143
3.32E-02	8	Benzyl chloride	0.00958	0.03340	0.12707	0.00045	0.20837	1.65500	5.23283	27.38255
5.65E-02	1	1,3-butadiene	0.05645	0.05645	0.00004	0.05637	0.05653	0.00072	1.00072	1.00143
1.19E-03	7	2-Butoxyethanol	0.00042	0.00119	0.00297	0.00002	0.00694	1.40490	4.07518	16.60707
3.39E+00	47	Cadmium Cd(II)	0.16948	3.26186	26.50233	0.00129	24.26408	2.05060	7.77246	60.41116
1.08E-01	7	Carbon tetrachloride	0.03662	0.10429	0.26711	0.00214	0.63744	1.42230	4.14648	17.19327
2.26E+01	47	Chromium Cr(VI)	1.10430	23.58830	357.90100	0.00941	143.61180	2.33310	10.30980	106.29270
2.73E-01	5	Crotonaldehyde(trans)	0.12830	0.27659	0.51826	0.01131	1.47224	1.22740	3.41232	11.64392
7.25E-01	4	1,2-Dibromoethane	0.40706	0.72235	1.00417	0.04822	3.35468	1.03720	2.82140	7.96029
7.53E-03	7	1,4-Dichlorobenzene	0.00253	0.00746	0.01862	0.00014	0.04358	1.40650	4.08177	16.66088
1.42E-02	4	1,2-Dichloroethane	0.00791	0.01396	0.02034	0.00098	0.06335	1.06720	2.90730	8.45237
5.90E-02	7	1,1-Dichloroethene	0.01972	0.05907	0.15280	0.00108	0.36503	1.42840	4.17181	17.40403
1.26E-04	5	Ethanol	0.00006	0.00013	0.00024	0.00001	0.00067	1.21890	3.38331	11.44678
1.21E-03	8	2-Ethylhexanol	0.00036	0.00125	0.00413	0.00002	0.00798	1.57600	4.83576	23.38456
1.06	4	Formaldehyde	0.60531	1.06265	1.51093	0.07510	4.87904	1.05160	2.86215	8.19192
1.74E-02	5	Hexachlorobutadiene	0.00809	0.01734	0.03323	0.00072	0.09306	1.24170	3.46139	11.98119
6.74E-05	7	Hexane	0.00002	0.00007	0.00018	0.00000	0.00041	1.45770	4.29619	18.45722
7.45E-03	7	Isoprene	0.00255	0.00711	0.01800	0.00014	0.04235	1.41480	4.11572	16.93919
5.62E-03	5	Limonene (d-...)	0.00266	0.00565	0.01021	0.00022	0.02979	1.20360	3.33216	11.10329
3.86E-03	4	Methyl tert-butyl ether	0.00222	0.00391	0.00572	0.00028	0.01787	1.06970	2.91450	8.49433
1.86E-03	7	Methylene chloride	0.00064	0.00188	0.00509	0.00004	0.01079	1.45720	4.29385	18.43719
7.30E-02	4	Naphthalene	0.04156	0.07274	0.10021	0.00521	0.32903	1.03160	2.80542	7.87039

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Table 6 – Continue

DRFc	DRFc U. Factor	Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
1.09	7	Ozone	0.37201	1.08060	2.88963	0.02018	6.59873	1.44850	4.25667	18.11928
		Radon	0.05222	0.05234	0.00347	0.04597	0.05937	0.06615	1.06840	1.14150
4.92E-02	4	Styrene	0.02755	0.04915	0.07179	0.00345	0.22062	1.06870	2.91167	8.47784
5.33E-02	8	1,1,2,2-Tetrachloroethane	0.01521	0.05354	0.18105	0.00071	0.33441	1.58770	4.89225	23.93410
8.50E-03	7	Tetrachloroethene	0.00282	0.00852	0.02441	0.00016	0.05230	1.49000	4.43731	19.68975
3.71E-02	8	1,1,2-Trichloroethane	0.01084	0.03734	0.11317	0.00050	0.24487	1.52350	4.58807	21.05038
1.72E-03	4	Trichloroethylene	0.00098	0.00173	0.00256	0.00011	0.00800	1.07620	2.93340	8.60483
1.93E-01	4	Vinyl chloride	0.10802	0.19024	0.26082	0.01296	0.88090	1.02840	2.79670	7.82152
3.69E-04	5	Xylenes	0.00018	0.00036	0.00064	0.00002	0.00186	1.18860	3.28256	10.77521

Units in cases/kg; Radon in case/10^{-9}Bq.
Central tendency. std. dev.: standard deviation; GSD: geometric standard deviation (and squared).
DRFc, Central tendency descriptor in USETox database; DRc U. Factor, Uncertainty factor assigned to the DRFc in this research.
[radon] Dose conversion factor radon 14.1 mSv.m3/MBq.h; Radon DCFR equilibrium factor 0.4; fatality coefficient for lung cancer 0.0057 /Sv.

Table 7: Full statistic descriptors: Dose-response Factors for non-cancer, parameter estimates.

DRFnonc	DRFnonc U. Factor	Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
3.85E-02	22	Acetaldehyde	0.0039323	0.0385927	0.2469739	6.40E-05	0.260965	1.933	6.91034	47.7528
59.7359	33	Acrolein	4.256	55.5008	427.7748	0.046744	390.8631	2.0251	7.57699	57.41073
0.3521	25	Acrylonitrile	0.033488	0.388135	4.60642	0.000491	2.373647	2.2259	9.26212	85.78691
3.72E-03	4	Benzene	0.0021152	0.00378439	0.005833584	0.000261	0.01776	1.1031	3.01338	9.08043
8.45E-02	22	1,3-butadiene	0.009012	0.0864091	0.9069341	0.000141	0.578801	2.1705	8.7625	76.78145
7.92E-03	7	2-Butoxyethanol	0.0026848	0.00799303	0.02309186	0.000143	0.049521	1.495	4.45927	19.88512
6.21E+00	11	Cadmium Cd(II)	1.3652	6.67961	36.34144	0.043138	44.60649	1.8496	6.35728	40.41502
2.64E-01	1	Carbon disulfide	0.26409	0.264093	0.000191061	0.26372	0.264468	0.000723	1.00072	1.001448
3.58E-01	24	Carbon tetrachloride	0.035204	0.33858	2.238382	0.000468	2.384126	1.9494	7.02439	49.34209
8.84E-03	84	Chloromethane	0.0002375	0.0122104	0.5719387	1.26E-06	0.042169	2.7738	16.0193	256.6195
2.89E+01	94	Chromium Cr(VI)	0.69766	24.2852	308.4409	0.003548	139.1844	2.256	9.54477	91.10262
4.71E-03	18	1,2-Dibromoethane	0.00062741	0.0049241	0.0380133	1.30E-05	0.031877	2.0259	7.58285	57.49964
2.23E-03	16	1,4-Dichlorobenzene	0.00033314	0.00217441	0.009566287	7.26E-06	0.015775	1.7359	5.67403	32.19464
9.45E-03	16	1,1-Dichloroethene	0.0014237	0.00968215	0.07361504	3.08E-05	0.062386	2.0185	7.52691	56.65443
0.00847	18	Formaldehyde	0.0010863	0.00826619	0.04267449	2.24E-05	0.057296	1.822	6.18422	38.24463
9.16E-03	18	Hexane	0.0011814	0.00923258	0.05868335	2.32E-05	0.063299	1.9296	6.88663	47.42569
1.97E-02	18	2-Methoxyethanol	0.0025842	0.0191262	0.1045645	5.02E-05	0.142475	1.8521	6.37341	40.62033
8.13E-02	4	Methyl methacrylate	0.046242	0.0812272	0.1228613	0.005331	0.374027	1.091	2.97719	8.863631
6.46E-04	16	Methyl tert-butyl ether	9.63E-05	0.00064885	0.003506652	2.03E-06	0.004477	1.8461	6.33507	40.1331
2.17E-02	18	Methylene chloride	0.0027915	0.0203504	0.1093967	5.59E-05	0.141061	1.8433	6.31739	39.90937
7.19E-02	33	Naphthalene	0.0050103	0.068126	0.490145	5.79E-05	0.473854	1.9914	7.32605	53.671
9.84E-03	16	Styrene	0.0014516	0.0100798	0.06756924	2.97E-05	0.06799	1.9563	7.07336	50.0324
3.23E-02	32	Tetrachloroethene	0.0023023	0.0342284	0.3668873	2.63E-05	0.215346	2.1801	8.84684	78.26662
3.64E-03	11	Toluene	0.00078595	0.00359392	0.01315967	2.63E-05	0.024718	1.6333	5.12089	26.22353

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Table 7 – Continue

DRFnonc	DRFnonc U. Factor	Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
1.16E-01	32	1,1,2-Trichloroethane	0.0082904	0.123509	1.422728	1.02E-04	0.74931	2.2126	9.13933	83.52731
6.69E-02	16	Vinyl chloride	0.009813	0.0646127	0.3456248	0.000226	0.447873	1.8407	6.30105	39.70325
8.58E-03	22	Xylenes	0.00089767	0.00833245	0.05616547	1.50E-05	0.05611	1.9591	7.09292	50.30948

Units in cases/kg.
Central tendency. std. dev.: standard deviation; GSD: geometric standard deviation (and squared).
DRFnonc, Central tendency descriptor in USETox database; DRFnonc U. Factor, Uncertainty factor assigned to the DRFnonc in this research.

Table 8: Full statistic descriptors: Concentration-response factor parameter estimates.

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Acrolein	2.005	8.755	31.514	0.069	59.140	1.624	5.071	25.715
Benzene	0.002	0.002	0.001	0.001	0.003	0.337	1.401	1.963
Formaldehyde	0.230	0.395	1.039	0.054	1.653	1.439	4.218	17.787
Mold	0.048	0.063	0.056	0.011	0.210	0.756	2.129	4.533
Nitrogen dioxide	1.176	1.340	0.735	0.428	3.215	0.513	1.670	2.790
Ozone	0.545	0.671	0.481	0.155	1.921	0.644	1.905	3.629
PM_{10}	2.556	2.649	0.720	1.512	4.313	0.267	1.306	1.705
$PM_{2.5}$	5.141	5.194	0.731	3.906	6.762	0.140	1.150	1.323
Radon	0.021	0.024	0.013	0.008	0.059	0.515	1.674	2.804
Sulphur dioxide	3.752	3.923	1.201	2.080	6.724	0.299	1.349	1.820

Units in case/µg/m^3; Radon in case/Bq/m^3; Mold in case/CFU/m^3.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 9: Full statistic descriptors: Epi-based Dose-response factor parameter estimates.

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Acrolein	3.7631	16.3573	64.4975	0.1290	109.6971	1.6752	5.3398	28.5133
Benzene	0.0033	0.0035	0.0012	0.0017	0.0064	0.3418	1.4075	1.9810
Formaldehyde	0.4299	0.7383	1.8932	0.1033	3.0576	1.4230	4.1495	17.2182
Mold	0.0878	0.1174	0.1034	0.0200	0.3911	0.7576	2.1332	4.5507
Nitrogen dioxide	2.1698	2.4788	1.3763	0.7831	5.9935	0.5184	1.6793	2.8200
Ozone	1.0126	1.2524	0.9106	0.2835	3.6277	0.6515	1.9183	3.6800
PM_{10}	4.7411	4.9231	1.3856	2.7527	8.1524	0.2761	1.3180	1.7371
$PM_{2.5}$	9.5430	9.6539	1.5017	7.0545	12.9064	0.1546	1.1672	1.3624
Radon	0.0396	0.0454	0.0254	0.0142	0.1107	0.5221	1.6855	2.8410
Sulphur dioxide	6.9644	7.2950	2.2926	3.8165	12.7043	0.3069	1.3592	1.8474

Units in cases/kg; Radon in case/10^{-9}Bq.; Mold in case/10^{-9}CFU.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 10: Full statistic descriptors: cancer-Effect factor parameter estimates.

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Acetaldehyde	0.0904	0.1603	0.2350	0.0112	0.7204	1.0710	2.9182	8.5160
Acrylonitrile	2.7070	2.7093	0.1057	2.5081	2.9238	0.0390	1.0398	1.0811
Benzene	0.5101	0.5137	0.0647	0.3975	0.6509	0.1255	1.1337	1.2852
Benzyl chloride	0.1888	0.6346	2.0587	0.0083	3.9580	1.5635	4.7753	22.8034
1,3-butadiene	0.5982	0.5991	0.0329	0.5371	0.6665	0.0549	1.0564	1.1160
2-Butoxyethanol	0.0101	0.0290	0.0715	0.0006	0.1762	1.3997	4.0541	16.4355
Cadmium Cd(II)	3.4554	86.2825	2273.0347	0.0297	414.8180	2.5581	12.9114	166.7041
Carbon tetrachloride	0.9213	2.7616	7.8600	0.0522	17.3735	1.4861	4.4197	19.5333
Chromium Cr(VI)	23.4009	407.0925	3322.9048	0.2010	2661.8407	2.0528	7.7897	60.6797
Crotonaldehyde(trans)	3.1136	6.7721	12.9016	0.2767	35.2537	1.2379	3.4484	11.8917
1,2-Dibromoethane	10.0141	17.8050	26.0673	1.2165	82.0460	1.0702	2.9159	8.5027
1,4-Dichlorobenzene	0.0276	0.0815	0.2299	0.0016	0.4849	1.4809	4.3968	19.3319
1,2-Dichloroethane	0.1533	0.2744	0.3912	0.0183	1.2625	1.0533	2.8670	8.2198
1,1-Dichloroethene	0.4276	1.2736	3.3275	0.0232	7.6757	1.4344	4.1970	17.6150
Ethanol	0.0015	0.0031	0.0057	0.0001	0.0156	1.2240	3.4008	11.5652
2-Ethylhexanol	0.0086	0.0290	0.0778	0.0004	0.1891	1.4508	4.2666	18.2035
Formaldehyde	20.9500	37.1315	54.9863	2.4480	168.1486	1.0775	2.9372	8.6273
Hexachlorobutadiene	0.0861	0.1872	0.4043	0.0077	0.9873	1.3170	3.7321	13.9282
Hexane	0.0002	0.0007	0.0026	0.0000	0.0044	1.5952	4.9295	24.2999
Isoprene	0.0269	0.0796	0.2144	0.0015	0.4900	1.4528	4.2752	18.2772
Limonene (d-...)	0.0283	0.0605	0.1267	0.0025	0.3056	1.2980	3.6619	13.4097

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Table 10 – Continue

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Methyl tert-butyl ether	0.0739	0.1350	0.2064	0.0091	0.6258	1.0979	2.9979	8.9875
Methylene chloride	0.0067	0.0196	0.0542	0.0004	0.1187	1.4674	4.3378	18.8168
Naphthalene	0.8716	1.5521	2.2488	0.1082	6.9933	1.0636	2.8967	8.3906
Ozone	7.8759	24.2668	70.5159	0.4171	155.0903	1.4985	4.4748	20.0238
Radon	1.1044	1.1088	0.0838	0.9528	1.2854	0.0755	1.0784	1.1630
Styrene	0.3004	0.5265	0.7623	0.0376	2.4006	1.0631	2.8954	8.3833
1,1,2,2-Tetrachloroethane	0.3854	1.2853	3.6143	0.0178	8.3019	1.4788	4.3878	19.2530
Tetrachloroethene	0.1030	0.3058	0.7812	0.0056	1.8826	1.4208	4.1403	17.1424
1,1,2-Trichloroethane	0.2568	0.9423	2.9465	0.0117	5.8614	1.5419	4.6736	21.8427
Trichloroethylene	0.0103	0.0180	0.0248	0.0013	0.0814	1.0317	2.8059	7.8729
Vinyl chloride	2.7192	4.7582	6.6920	0.3378	21.9367	1.0446	2.8424	8.0790
Xylenes	0.0027	0.0058	0.0102	0.0002	0.0298	1.1865	3.2757	10.7302

Units in DALY/kg; Radon in DALY/10^{-9}Bq.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 11: Full statistic descriptors: Noncancer-Effect factor parameter estimates.

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Acetaldehyde	0.0088	0.0776	0.4983	0.0001	0.5632	1.9350	6.9240	47.9414
Acrolein	2.4129	31.6291	221.0203	0.0249	211.7958	1.9770	7.2212	52.1461
Acrylonitrile	0.0676	0.7939	6.2338	0.0010	5.1373	2.0341	7.6457	58.4571
Benzene	0.0043	0.0076	0.0106	0.0005	0.0354	1.0402	2.8297	8.0070
1,3-butadiene	0.0178	0.1548	0.9061	0.0003	1.1668	1.8877	6.6041	43.6138
2-Butoxyethanol	0.0054	0.0166	0.0474	0.0003	0.0996	1.4897	4.4357	19.6755
Cadmium Cd(II)	2.7570	12.4412	46.0122	0.0865	84.0645	1.6390	5.1501	26.5232
Carbon disulfide	0.5396	0.5428	0.0597	0.4367	0.6692	0.1096	1.1158	1.2450
Carbon tetrachloride	0.0690	0.7194	4.1605	0.0009	4.8637	1.8813	6.5620	43.0597
Chloromethane	0.0005	0.0202	0.2919	0.0000	0.0979	2.3119	10.0935	101.8783
Chromium Cr(VI)	1.5306	65.1261	1017.1515	0.0072	323.3055	2.3454	10.4376	108.9431
1,2-Dibromoethane	0.0012	0.0094	0.0416	0.0000	0.0661	1.7418	5.7079	32.5795
1,4-Dichlorobenzene	0.0007	0.0047	0.0242	0.0000	0.0328	1.8240	6.1969	38.4015
1,1-Dichloroethene	0.0028	0.0192	0.1074	0.0001	0.1347	1.8650	6.4556	41.6751
Formaldehyde	0.0007	0.0047	0.0347	0.0000	0.0320	2.0079	7.4475	55.4657
Hexane	0.0024	0.0185	0.1167	0.0000	0.1242	1.9243	6.8505	46.9293
2-Methoxyethanol	0.0051	0.0405	0.2302	0.0001	0.2695	1.8725	6.5047	42.3116
Methyl methacrylate	0.0954	0.1675	0.2415	0.0114	0.7774	1.0604	2.8875	8.3376
Methyl tert-butyl ether	0.0002	0.0014	0.0075	0.0000	0.0097	1.8493	6.3554	40.3912
Methylene chloride	0.0059	0.0460	0.2546	0.0001	0.3086	1.8584	6.4135	41.1326
Naphthalene	0.0107	0.1440	1.2072	0.0001	1.0146	2.0656	7.8904	62.2588

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Table 11 – Continue

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Styrene	0.0029	0.0193	0.1201	0.0001	0.1394	1.9196	6.8180	46.4857
Tetrachloroethene	0.0047	0.0643	0.4049	0.0001	0.4270	1.9249	6.8545	46.9838
Toluene	0.0016	0.0078	0.0314	0.0000	0.0533	1.6908	5.4236	29.4158
1,1,2-Trichloroethane	1.60E-02	0.219106	1.3840536	0.000193358	1.538362	1.9264	6.86506	47.12899
Vinyl chloride	0.0204	0.1383	1.0957	0.0005	0.9416	2.0384	7.6780	58.9510
Xylenes	0.0018	0.0179	0.1254	0.0000	0.1231	1.9777	7.2261	52.2161

Units in DALY/kg.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 12: Full statistic descriptors: Toxicology based -Effect factor parameter estimates.

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Chromium Cr(VI)	30.81490	681.49270	7266.25370	0.42247	3815.07890	2.17770	8.82558	77.89088
Formaldehyde	13.09560	59.99489	223.67009	0.42783	402.06424	1.64360	5.17357	26.76587
Cadmium Cd(II)	9.98833	125.68630	2568.63010	0.39010	568.99485	2.45700	11.67030	136.19530
1,2-Dibromoethane	6.17595	27.28766	132.33906	0.19712	162.67306	1.78870	5.98176	35.78149
Ozone	4.80513	37.85280	195.51772	0.08985	272.14289	1.82230	6.18592	38.26561
Acrolein	2.41291	31.62911	221.02030	0.02495	211.79579	1.97700	7.22122	52.14606
Acrylonitrile	2.12838	5.16782	13.39709	0.18683	28.96186	1.42960	4.17722	17.44916
Crotonaldehyde(trans)	1.99295	10.95723	58.78541	0.05393	76.83481	1.84230	6.31082	39.82640
Vinyl chloride	1.79271	7.78073	27.51052	0.08625	51.21929	1.61330	5.01943	25.19467
Carbon tetrachloride	0.96789	5.14770	28.30030	0.03904	32.95752	1.85500	6.39199	40.85754
Radon	0.68204	1.73190	3.65870	0.04759	9.89550	1.30310	3.68060	13.54690
Naphthalene	0.65574	2.63813	10.09834	0.03322	16.89286	1.65850	5.25143	27.57750
Carbon disulfide	0.53960	0.54280	0.05966	0.43666	0.66915	0.10958	1.11580	1.24502
1,3-butadiene	0.48167	1.11076	2.21956	0.04333	6.19380	1.26810	3.55402	12.63108
Benzene	0.32292	0.83312	1.95210	0.02752	4.65462	1.36760	3.92586	15.41234
1,1-Dichloroethene	0.28721	2.06462	12.50872	0.00920	13.71026	1.90520	6.72084	45.16965
1,1,2-Trichloroethane	0.27898	1.71873	8.26057	0.00935	11.78004	1.78390	5.95286	35.43658
1,1,2,2-Tetrachloroethane	0.24437	2.01903	10.58134	0.00413	13.89765	1.82990	6.23357	38.85739
Styrene	0.20685	0.88249	3.96259	0.00998	5.61152	1.74710	5.73772	32.92146
Benzyl chloride	0.11735	0.96877	5.58318	0.00198	6.73532	1.87950	6.55044	42.90825
Tetrachloroethene	0.10080	0.51200	1.90115	0.00397	3.52167	1.64130	5.16178	26.64400

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Table 12 – Continue

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Acetaldehyde	0.09743	0.32593	0.99024	0.00578	2.07508	1.52490	4.59479	21.11208
1,2-Dichloroethane	0.09570	0.44054	2.05361	0.00302	2.86632	1.76740	5.85561	34.28812
Methyl methacrylate	0.09537	0.16750	0.24148	0.01141	0.77741	1.06040	2.88749	8.33761
Hexachlorobutadiene	0.05429	0.30344	2.20582	0.00141	2.04902	1.99650	7.36333	54.21862
Methyl tert-butyl ether	0.04768	0.21821	0.97092	0.00190	1.43479	1.74210	5.70919	32.59487
1,4-Dichlorobenzene	0.02191	0.13322	1.02680	0.00088	0.83272	2.02510	7.57706	57.41181
2-Butoxyethanol	0.01881	0.06134	0.20418	0.00154	0.37009	1.57840	4.84736	23.49689
Methylene chloride	0.01859	0.07526	0.28416	0.00090	0.48993	1.65070	5.21080	27.15248
Limonene (d-...)	0.01780	0.10053	0.47428	0.00048	0.66986	1.77390	5.89375	34.73627
Isoprene	0.01680	0.12391	0.78295	0.00033	0.79300	1.92660	6.86596	47.14143
Xylenes	0.00658	0.02720	0.13133	0.00034	0.16829	1.78640	5.96769	35.61329
Trichloroethylene	0.00640	0.03005	0.11951	0.00021	0.20215	1.68000	5.36535	28.78695
2-Ethylhexanol	0.00532	0.04657	0.28816	0.00008	0.31840	1.91600	6.79347	46.15122
2-Methoxyethanol	0.00513	0.04050	0.23024	0.00009	0.26950	1.87250	6.50474	42.31159
Hexane	0.00336	0.01977	0.11700	0.00013	0.12821	1.89320	6.64029	44.09347
Toluene	0.00162	0.00775	0.03143	0.00005	0.05331	1.69080	5.42363	29.41576
Ethanol	0.00091	0.00470	0.02333	0.00002	0.03195	1.80170	6.06020	36.72601
Chloromethane	0.00049	0.02021	0.29189	0.00000	0.09790	2.31190	10.09350	101.87830

Units in DALY/kg; Radon in DALY/10^{-9}Bq.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 13: Full statistic descriptors: Epidemiology based -Effect factor parameter estimates.

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
$PM_{2.5}$	111.588	113.745	21.832	77.095	162.196	0.190	1.210	1.463
PM_{10}	55.324	57.790	17.619	30.800	98.979	0.298	1.347	1.815
Nitrogen dioxide	10.450	12.063	6.945	3.681	29.825	0.535	1.708	2.916
Formaldehyde	7.341	9.908	9.136	1.774	33.606	0.784	2.191	4.801
Sulphur dioxide	3.495	10.575	29.048	0.191	64.870	1.465	4.326	18.716
Ozone	2.325	2.877	2.110	0.641	8.379	0.656	1.927	3.714
Acrolein	2.148	9.380	33.111	0.072	62.252	1.612	5.015	25.149
Radon	0.841	0.963	0.540	0.300	2.345	0.523	1.687	2.844
Benzene	0.115	0.123	0.046	0.056	0.234	0.364	1.439	2.072
Mold	0.051	0.069	0.064	0.011	0.237	0.788	2.199	4.834

Units in DALY/kg; Radon in DALY/10^{-9}Bq.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

A2 For the Harm Intensity

Table 14: Full statistic descriptors: Toxicology-based cancer harm intensities parameter estimates.

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Acetaldehyde	0.04791	0.08606	0.12564	0.00607	0.41466	1.06840	2.91075	8.47245
Acrylonitrile	1.45827	1.46211	0.11283	1.25133	1.69710	0.07706	1.08010	1.16662
Benzene	0.27457	0.27708	0.03949	0.20806	0.36218	0.14181	1.15235	1.32792
Benzyl chloride	0.09979	0.34510	1.01712	0.00461	2.16262	1.50690	4.51273	20.36477
1,3-butadiene	0.32191	0.32327	0.02768	0.27202	0.38134	0.08547	1.08923	1.18642
2-Butoxyethanol	0.00545	0.01623	0.04587	0.00030	0.09828	1.48180	4.40086	19.36754
Cadmium Cd(II)	1.90159	43.67683	636.47372	0.01464	221.69377	2.31580	10.13310	102.67910
Carbon tetrachloride	0.47518	1.40320	3.33145	0.02871	8.60540	1.37570	3.95796	15.66543
Chromium Cr(VI)	12.66010	256.28800	2508.43890	0.11031	1576.33890	2.13840	8.48557	72.00486
Crotonaldehyde(trans)	1.69201	3.60895	6.48682	0.15407	19.15304	1.20100	3.32340	11.04502
1,2-Dibromoethane	5.32631	9.24707	12.53951	0.65341	41.66581	1.02150	2.77728	7.71331
1,4-Dichlorobenzene	0.01455	0.04240	0.11124	0.00077	0.25556	1.43690	4.20771	17.70486
1,2-Dichloroethane	0.08350	0.15061	0.22665	0.00986	0.70194	1.08770	2.96750	8.80607
1,1-Dichloroethene	0.23098	0.67467	1.69366	0.01332	4.02692	1.41000	4.09599	16.77717
Ethanol	0.00080	0.00166	0.00287	0.00007	0.00871	1.17770	3.24699	10.54295
2-Ethylhexanol	0.00464	0.01643	0.05652	0.00021	0.10452	1.59750	4.94086	24.41208
Formaldehyde	11.46000	20.52467	30.15667	1.31433	96.24940	1.07250	2.92259	8.54156
Hexachlorobutadiene	0.04700	0.10097	0.21568	0.00407	0.52678	1.31000	3.70628	13.73651
Hexane	0.00013	0.00039	0.00128	0.00001	0.00231	1.56600	4.78723	22.91757
Isoprene	0.01491	0.04268	0.10484	0.00086	0.26408	1.39670	4.04199	16.33767
Limonene (d-...)	0.01537	0.03250	0.05954	0.00140	0.16952	1.21320	3.36421	11.31788

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Table 14 – Continue

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Methyl tert-butyl ether	0.04062	0.07091	0.10014	0.00495	0.31745	1.04720	2.84960	8.12020
Methylene chloride	0.00362	0.01104	0.04243	0.00021	0.06317	1.66090	5.26414	27.71113
Naphthalene	0.46633	0.84423	1.23811	0.05591	3.88764	1.07130	2.91913	8.52130
Ozone	4.19960	12.67740	33.75466	0.24147	79.55480	1.44590	4.24556	18.02476
Radon	0.59542	0.59865	0.06059	0.48943	0.72624	0.10095	1.10620	1.22370
Styrene	0.15964	0.28509	0.40698	0.01942	1.34539	1.05410	2.86946	8.23381
1,1,2,2-Tetrachloroethane	0.20398	0.70584	2.23775	0.00957	4.23556	1.55000	4.71152	22.19844
Tetrachloroethene	0.05328	0.15019	0.33208	0.00292	0.93250	1.33160	3.78698	14.34119
1,1,2-Trichloroethane	0.14336	0.51277	1.63086	0.00625	3.29441	1.55190	4.72038	22.28198
Trichloroethylene	0.00553	0.00972	0.01395	0.00069	0.04418	1.05750	2.87902	8.28877
Vinyl chloride	1.45196	2.60877	3.94849	0.17848	12.07642	1.09140	2.97842	8.87098
Xylenes	0.00147	0.00311	0.00574	0.00013	0.01596	1.21850	3.38203	11.43809

Units in DALY/µg/m^3; Radon in DALY/Bq/m^3.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 15: Full statistic descriptors: Toxicology-based Non-cancer harm intensities parameter estimates.

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Acetaldehyde	0.00454	0.04131	0.26820	0.00007	0.28061	1.94020	6.96046	48.44805
Acrolein	1.32570	18.04730	132.34340	0.01368	127.86230	2.00080	7.39502	54.68633
Acrylonitrile	0.03710	0.41146	3.17876	0.00054	2.74411	2.02630	7.58559	57.54125
Benzene	0.00230	0.00408	0.00589	0.00028	0.01826	1.06130	2.89025	8.35356
1,3-butadiene	0.00970	0.08646	0.47932	0.00015	0.62797	1.85940	6.41992	41.21540
2-Butoxyethanol	0.00289	0.00891	0.02419	0.00016	0.05533	1.45780	4.29662	18.46098
Cadmium Cd(II)	1.49070	7.03413	30.22840	0.04615	44.82216	1.72300	5.60134	31.37502
Carbon disulfide	0.29072	0.29315	0.03738	0.22705	0.37410	0.12701	1.13543	1.28920
Carbon tetrachloride	0.03810	0.35306	1.87020	0.00056	2.51596	1.83560	6.26877	39.29744
Chloromethane	0.00027	0.01146	0.27244	0.00000	0.05041	2.51780	12.40180	153.80520
Chromium Cr(VI)	0.81612	28.13390	329.13150	0.00368	164.66530	2.21950	9.20287	84.69278
1,2-Dibromoethane	0.00068	0.00496	0.02570	0.00001	0.03357	1.82430	6.19849	38.42128
1,4-Dichlorobenzene	0.00035	0.00225	0.00969	0.00001	0.01621	1.72420	5.60822	31.45216
1,1-Dichloroethene	0.00156	0.01041	0.06020	0.00003	0.07134	1.88130	6.56195	43.05917
Formaldehyde	0.00036	0.00277	0.01875	0.00001	0.01896	1.96120	7.10752	50.51680
Hexane	0.00133	0.01035	0.06963	0.00002	0.06855	1.95800	7.08480	50.19445
2-Methoxyethanol	0.00274	0.02216	0.15090	0.00005	0.14904	1.96410	7.12849	50.81541
Methyl methacrylate	0.05007	0.08861	0.12051	0.00602	0.41718	1.02330	2.78247	7.74216
Methyl tert-butyl ether	0.00010	0.00076	0.00560	0.00000	0.00523	2.00430	7.42071	55.06692
Methylene chloride	0.00310	0.02421	0.15958	0.00006	0.16101	1.94800	7.01441	49.20197
Naphthalene	0.00559	0.07272	0.53591	0.00006	0.48158	2.00320	7.41301	54.95273

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Table 15 – Continue

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Styrene	0.00164	0.01060	0.06703	0.00003	0.07293	1.92700	6.86884	47.18091
Tetrachloroethene	0.00254	0.03767	0.36535	0.00003	0.24320	2.13410	8.44957	71.39527
Toluene	0.00086	0.00400	0.01549	0.00003	0.02697	1.66500	5.28589	27.94060
1,1,2-Trichloroethane	0.00952	0.12345	1.17650	0.00010	0.85258	2.12600	8.38138	70.24747
Vinyl chloride	0.01067	0.07316	0.37267	0.00023	0.51181	1.81490	6.14057	37.70657
Xylenes	0.00101	0.00855	0.04167	0.00002	0.06524	1.79160	5.99915	35.98980

Units in DALY/µg/m^3.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 16: Full statistic descriptors: Toxicology-based All-cause harm intensities parameter estimates (high to low median).

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Chromium Cr(VI)	16.63140	609.55040	25589.65740	0.23521	2032.42030	2.73400	15.39510	237.00790
Formaldehyde	7.05694	32.61758	131.23938	0.24163	214.40277	1.68650	5.40054	29.16586
Cadmium Cd(II)	5.31568	58.09412	628.67019	0.21512	318.37824	2.18440	8.88528	78.94826
1,2-Dibromoethane	3.37842	15.59755	72.34535	0.11405	98.68934	1.76470	5.83973	34.10239
Ozone	2.58899	19.53409	100.27429	0.05238	135.46198	1.81900	6.16566	38.01535
Acrolein	1.31476	17.39771	171.11318	0.01437	120.26726	2.14060	8.50472	72.33020
Acrylonitrile	1.16436	2.77264	6.97339	0.10141	15.74535	1.41120	4.10071	16.81580
Crotonaldehyde(trans)	1.06063	6.30593	43.60021	0.03003	40.11482	1.97180	7.18332	51.60011
Vinyl chloride	0.97893	4.15008	16.77101	0.04457	28.27544	1.68890	5.41368	29.30790
Carbon tetrachloride	0.51649	2.77542	19.57295	0.02167	17.17216	1.98160	7.25409	52.62177
Radon	0.37192	0.95081	1.99660	0.02423	5.48710	1.29930	3.66670	13.44440
Naphthalene	0.35546	1.41134	6.62482	0.01749	8.74299	1.77110	5.87757	34.54582
Carbon disulfide	0.29024	0.29265	0.03788	0.22485	0.37295	0.12888	1.13756	1.29404
1,3-butadiene	0.26602	0.61644	1.41793	0.02307	3.36221	1.35610	3.88118	15.06353
Benzene	0.17820	0.45689	1.29228	0.01458	2.61336	1.48230	4.40309	19.38724
1,1,2-Trichloroethane	0.15401	0.90947	4.02120	0.00552	6.27680	1.73860	5.68954	32.37081
1,1-Dichloroethene	0.15303	1.10426	5.56660	0.00501	7.80815	1.80940	6.10658	37.29035
1,1,2,2-Tetrachloroethane	0.13339	1.09424	5.69459	0.00222	7.92227	1.82620	6.21054	38.57076
Styrene	0.11090	0.44398	1.38001	0.00540	3.12074	1.53840	4.65706	21.68817
Benzyl chloride	0.06165	0.61493	11.41023	0.00105	3.63392	2.41750	11.21800	125.84450
Acetaldehyde	0.05286	0.17975	0.59236	0.00306	1.12255	1.57260	4.81938	23.22642

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Table 16 – Continue

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Tetrachloroethene	0.05223	0.27792	1.43683	0.00196	1.79536	1.82280	6.18893	38.30280
1,2-Dichloroethane	0.05214	0.24310	0.97640	0.00161	1.61318	1.68550	5.39522	29.10843
Methyl methacrylate	0.05074	0.08828	0.12175	0.00626	0.39950	1.03220	2.80716	7.88012
Hexachlorobutadiene	0.03004	0.14890	0.49046	0.00080	1.08735	1.57240	4.81800	23.21310
Methyl tert-butyl ether	0.02567	0.10485	0.31878	0.00105	0.72778	1.52530	4.59674	21.12998
1,4-Dichlorobenzene	0.01162	0.07107	0.38610	0.00046	0.47316	1.84880	6.35223	40.35083
Methylene chloride	0.01004	0.04016	0.17203	0.00050	0.25347	1.72120	5.59130	31.26258
2-Butoxyethanol	0.01004	0.03706	0.38454	0.00081	0.19480	2.16530	8.71705	75.98704
Limonene (d-...)	0.00929	0.05123	0.29494	0.00025	0.34561	1.87900	6.54723	42.86625
Isoprene	0.00920	0.06832	0.45404	0.00017	0.46116	1.95200	7.04284	49.60160
Trichloroethylene	0.00352	0.01525	0.05615	0.00012	0.10802	1.63650	5.13701	26.38890
Xylenes	0.00343	0.01361	0.06886	0.00018	0.08303	1.81150	6.11945	37.44768
2-Ethylhexanol	0.00295	0.02730	0.26407	0.00005	0.17501	2.13290	8.43936	71.22282
2-Methoxyethanol	0.00279	0.02125	0.17212	0.00005	0.14195	2.04910	7.76065	60.22764
Hexane	0.00182	0.01240	0.12868	0.00007	0.07493	2.16550	8.71856	76.01328
Toluene	0.00087	0.00412	0.01673	0.00003	0.02750	1.69190	5.43000	29.48495
Ethanol	0.00050	0.00281	0.01300	0.00001	0.01949	1.76370	5.83377	34.03291
Chloromethane	0.00027	0.00989	0.15271	0.00000	0.05484	2.34080	10.38940	107.93870

Units in DALY/µg/m^3; Radon in DALY/Bq/m^3.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 17: Full statistic descriptors: Epidemiology-based All-cause harm intensities parameter estimates (high to low median).

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
$PM_{2.5}$	60.181	61.154	11.004	42.382	85.337	0.179	1.195	1.429
PM_{10}	29.800	31.112	9.216	16.906	52.668	0.290	1.336	1.786
NO_2	5.639	6.480	3.689	1.997	15.862	0.530	1.699	2.885
Formaldehyde	3.995	5.314	4.747	0.986	17.677	0.766	2.151	4.627
SO_2	1.900	5.782	17.048	0.101	35.054	1.507	4.514	20.373
O_3	1.253	1.555	1.146	0.350	4.533	0.658	1.932	3.732
Acrolein	1.151	5.226	21.682	0.039	34.489	1.704	5.493	30.177
Benzene	0.062	0.066	0.025	0.031	0.125	0.359	1.432	2.051
Radon	0.452	0.517	0.288	0.163	1.256	0.520	1.682	2.830
Mold	0.027	0.037	0.034	0.006	0.127	0.779	2.179	4.748

Units in DALY/µg/m^3. Moved to end because of units, Radon in DALY/Bq/m^3; Mold in DALY/CFU/m^3.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 18: Full statistic descriptors: Pooled harm intensities parameter estimates.

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Acrolein	1.207	3.173	7.552	0.081	18.557	1.377	3.964	15.711
Benzene	0.067	0.071	0.025	0.034	0.132	0.346	1.413	1.997
Formaldehyde	4.333	5.442	4.141	1.159	16.384	0.676	1.966	3.864
Ozone	1.347	1.635	1.127	0.401	4.558	0.623	1.865	3.479
Radon	0.442	0.496	0.255	0.170	1.145	0.485	1.624	2.637

Units in DALY/µg/m^3. Radon in DALY/Bq/m^3.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

A3 For airborne contaminants in dwellings

Table 19: Full statistic descriptors: Representative concentrations parameter estimates.

Contaminant	central input	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
1,1,2,2-Tetrachloroethane	0.0880	0.0396	0.0888	0.1690	0.0035	0.4811	1.2375	3.4469	11.8811
1,1,2-Trichloroethane	0.3040	0.2832	0.3025	0.1157	0.1356	0.5800	0.3694	1.4469	2.0935
1,1-Dichloroethene	0.5120	0.4800	0.5141	0.2001	0.2295	0.9973	0.3755	1.4558	2.1193
1,2-Dibromoethane	0.0960	0.0183	0.0962	0.4761	0.0006	0.6731	1.7996	6.0470	36.5665
1,2-Dichloroethane	0.5300	0.5172	0.5304	0.1255	0.3229	0.8114	0.2334	1.2629	1.5948
1,3-Butadiene	0.4610	0.4261	0.4617	0.1915	0.1994	0.9368	0.3985	1.4895	2.2187
1,4-Dichlorobenzene	2.2010	1.9120	2.2170	1.3244	0.6506	5.6493	0.5524	1.7375	3.0188
2-Butoxyethanol	2.9540	2.7042	2.9400	1.2533	1.2258	6.0625	0.4086	1.5047	2.2642
2-Ethylhexanol	1.9600	1.6964	1.9444	1.0851	0.6043	4.6564	0.5207	1.6832	2.8332
2-Methoxyethanol	1.2700	0.0210	1.1391	22.6732	0.0001	5.6499	2.4463	11.5456	133.3019
Acetaldehyde	14.8820	12.8534	14.8921	8.5578	4.5810	37.0247	0.5342	1.7061	2.9106
Acrolein	0.6460	0.5962	0.6450	0.2662	0.2726	1.3040	0.3966	1.4867	2.2103
Acrylonitrile	0.7190	0.7120	0.7185	0.1084	0.5295	0.9481	0.1500	1.1618	1.3497
Benzene	2.3010	2.2318	2.3116	0.6640	1.2622	3.8701	0.2816	1.3252	1.7562
Benzyl chloride	0.5000	0.2235	0.4884	0.9000	0.0196	2.6546	1.2168	3.3763	11.3994
Mold	161.6570	155.5503	162.8233	48.6562	88.8014	279.6607	0.2925	1.3397	1.7949
Cadmium Cd(II)	0.0150	0.0108	0.0149	0.0143	0.0023	0.0524	0.8055	2.2378	5.0076
Carbon disulfide	0.3400	0.3062	0.3402	0.1641	0.1257	0.7543	0.4575	1.5802	2.4969
Carbon tetrachloride	0.5150	0.4997	0.5161	0.1294	0.3079	0.8119	0.2470	1.2802	1.6388
Chloromethane	1.6030	1.6004	1.6042	0.1070	1.4032	1.8216	0.0667	1.0689	1.1426
Chromium Cr(VI)	0.0060	0.0031	0.0060	0.0101	0.0003	0.0283	1.1662	3.2099	10.3036

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Table 19 – Continue

Contaminant	central input	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Crotonaldehyde(trans)	0.7990	0.6548	0.8024	0.5716	0.1818	2.2579	0.6407	1.8977	3.6013
Ethanol	129.1630	113.0447	128.2706	67.9501	42.4494	300.4899	0.4973	1.6443	2.7039
Formaldehyde	28.0100	27.7114	28.0133	4.2563	20.7191	37.3662	0.1511	1.1631	1.3528
Hexachlorobutadiene	1.7000	1.2586	1.7080	1.5313	0.2773	5.6921	0.7680	2.1555	4.6463
Hexane	1.6570	1.4495	1.6466	0.9048	0.5283	3.9483	0.5137	1.6714	2.7935
Isoprene	6.4830	6.0498	6.5220	2.5929	2.8794	12.8958	0.3831	1.4668	2.1514
Limonene (d-...)	14.6110	12.0476	14.5980	9.9266	3.5967	40.9755	0.6165	1.8524	3.4315
Methyl methacrylate	0.2700	0.0818	0.2675	0.7362	0.0039	1.6758	1.4658	4.3309	18.7568
Methyl tert-butyl ether	4.3670	3.3276	4.3660	3.6685	0.7782	14.0864	0.7309	2.0769	4.3134
Methylene chloride	0.9080	0.6701	0.8968	0.7960	0.1430	3.0694	0.7622	2.1430	4.5923
Naphthalene	1.5410	21.7545	22.4973	6.0998	12.8204	36.5653	0.7919	2.2076	4.8737
NO_2	22.4434	1.1218	1.5305	1.4294	0.2329	5.2045	0.2663	1.3052	1.7035
O_3	10.0000	7.3307	9.9137	9.0617	1.6067	33.3032	0.7793	2.1800	4.7522
PM_{10}	63.9810	62.1581	63.9823	15.5839	38.6281	98.9778	0.2401	1.2713	1.6163
$PM_{2.5}$	26.6710	25.8732	26.7399	6.6139	16.1542	41.7495	0.2437	1.2759	1.6280
PM_{10-2.5}	37.3100	35.0283	37.2891	13.3476	17.8080	69.7367	0.3472	1.4151	2.0026
Radon	82.5460	78.3758	82.4396	27.2825	41.3810	146.7515	0.3224	1.3804	1.9055
SO_2	0.9694	0.4095	1.0052	2.4508	0.0324	5.4292	1.3921	4.0233	16.1866
Styrene	1.6250	1.5595	1.6248	0.4761	0.8932	2.7287	0.2870	1.3325	1.7755
Tetrachloroethene	0.8350	0.8273	0.8350	0.1125	0.6335	1.0696	0.1341	1.1435	1.3077
Toluene	13.2170	13.1458	13.2198	1.5552	10.4120	16.4652	0.1172	1.1244	1.2642

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Table 19 – Continue

Contaminant	central input	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Trichloroethylene	0.4560	0.4531	0.4560	0.0554	0.3573	0.5737	0.1212	1.1288	1.2742
Vinyl chloride	0.1570	0.0722	0.1575	0.2751	0.0060	0.8563	1.1826	3.2629	10.6462
Xylenes	7.0140	6.7636	7.0189	1.9784	3.8941	11.6460	0.2765	1.3185	1.7384

Units in µg/m^3; Radon in Bq/m^3; Mold in CFU/m^3.
Central input from systematic review. std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

A4 For contaminants Harm in Dwellings

Table 20: Full statistic descriptors: Contaminant harm parameter estimates.

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
PM_{10}	1859.914100	1988.245600	749.759120	913.696400	3805.270700	0.364630	1.439990	2.073559
$PM_{2.5}$	1562.641600	1627.793500	478.235400	890.041020	2742.582200	0.287730	1.333400	1.777963
$PM_{10-2.5}$	130.990470	405.902560	1201.992600	6.909442	2483.530900	1.509700	4.525430	20.479550
Nitrogen dioxide	122.339800	144.949080	91.891819	38.983204	382.261170	0.581230	1.788240	3.197808
Formaldehyde	119.968300	152.310300	119.842660	30.915147	465.507780	0.694170	2.002050	4.008200
Radon	34.479887	40.835117	25.911619	11.018908	108.408030	0.581690	1.789050	3.200711
Ozone	9.964071	16.382066	21.363510	1.404446	70.250853	0.996740	2.709420	7.340974
Mold	3.987512	5.573023	5.419583	0.802471	19.840040	0.815850	2.261110	5.112602
Acrolein	0.733741	2.022111	5.038358	0.043747	12.007083	1.405400	4.077270	16.624100
Acrylonitrile	0.728215	2.002026	5.416812	0.044617	11.859194	1.455600	4.287000	18.378410
Acetaldehyde	0.675697	2.663785	9.593756	0.026518	17.294776	1.623900	5.072750	25.732780
Crotonaldehyde(trans)	0.585434	5.123343	43.848716	0.009940	34.023766	2.075400	7.968020	63.489390
Sulphur dioxide	0.562093	5.290360	46.360979	0.008830	35.041381	2.086600	8.057820	64.928520
Naphthalene	0.326069	2.174751	11.887111	0.007298	15.071894	1.852000	6.372720	40.611620
Styrene	0.213425	0.725620	2.345029	0.009878	4.594561	1.561200	4.764750	22.702860
Carbon tetrachloride	0.193993	1.409802	7.907280	0.003883	9.963069	1.865500	6.458940	41.717960
Benzene	0.147321	0.162858	0.076930	0.061343	0.354410	0.448790	1.566420	2.453681
Methyl tert-butyl ether	0.108496	0.462815	1.999251	0.003867	2.987925	1.725900	5.617370	31.554810
Limonene (d-...)	0.106361	0.773455	5.865916	0.002176	5.227442	2.017300	7.517680	56.515530
1,3-Butadiene	0.103939	0.282420	0.682083	0.006553	1.665103	1.386300	3.999900	15.999230
1,1-Dichloroethene	0.103621	0.569856	2.524787	0.002756	3.917388	1.739800	5.695940	32.443780

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Table 20 – Continue

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Carbon disulfide	0.089169	0.099611	0.049610	0.035397	0.224746	0.470720	1.601140	2.563662
Vinyl chloride	0.070440	0.664721	5.215700	0.001159	4.436908	2.033800	7.642870	58.413450
Ethanol	0.067828	0.363727	1.873128	0.001868	2.444520	1.820700	6.176160	38.144950
1,2-Dibromoethane	0.061727	1.477942	21.923574	0.000444	8.739838	2.323400	10.210700	104.258500
Isoprene	0.061407	0.458402	3.053481	0.001219	3.052252	1.953200	7.051000	49.716570
Cadmium Cd(II)	0.058365	0.865319	9.897955	0.000611	5.491700	2.209400	9.110530	83.001700
1,1,2-Trichloroethane	0.056110	0.278840	1.325148	0.001713	1.846458	1.777800	5.916890	35.009570
Hexachlorobutadiene	0.054466	0.250386	1.082425	0.001773	1.681242	1.726300	5.619700	31.581070
Chromium Cr(VI)	0.044727	3.176749	51.504951	0.000135	14.888064	2.361200	10.604100	112.445900
Tetrachloroethene	0.043511	0.227447	1.015197	0.001225	1.548717	1.743800	5.719010	32.707030
1,2-Dichloroethane	0.030500	0.127100	0.478894	0.001073	0.828335	1.649600	5.204730	27.089250
1,4-Dichlorobenzene	0.024472	0.156173	0.816012	0.000560	1.071895	1.828400	6.223670	38.734050
Xylenes	0.017799	0.096274	0.492159	0.000500	0.647225	1.816800	6.152120	37.848600
Toluene	0.013020	0.054484	0.204585	0.000463	0.363469	1.647600	5.194640	26.984240
2-Butoxyethanol	0.009755	0.108177	0.748632	0.000130	0.743194	1.972200	7.186570	51.646760
1,1,2,2-Tetrachloroethane	0.008294	0.099411	1.061291	0.000106	0.634283	2.178200	8.830660	77.980580
Benzyl chloride	0.007507	0.294307	4.766121	0.000037	1.567481	2.360700	10.598900	112.336400
Methylene chloride	0.006071	0.035516	0.184326	0.000147	0.244792	1.824800	6.201520	38.458860
2-Ethylhexanol	0.004769	0.053727	0.450962	0.000064	0.362096	2.066200	7.894500	62.323080
Methyl methacrylate	0.004243	0.023810	0.135285	0.000111	0.160702	1.872200	6.502430	42.281570
Trichloroethylene	0.001815	0.006959	0.025219	0.000072	0.045352	1.627400	5.090840	25.916680

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Table 20 – Continue

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
Hexane	0.001715	0.020425	0.274215	0.000022	0.133387	2.280300	9.779830	95.645140
Chloromethane	0.001026	0.016136	0.190478	0.000010	0.100615	2.223500	9.240030	85.378110
2-Methoxyethanol	0.000055	0.033267	3.197558	0.000000	0.054728	3.021800	20.528100	421.404700

Units in
DALYs/10^5 person/year[] std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

Table 21: Full statistic descriptors: Harm intensity for the coarse fraction of PM parameter estimates.

Contaminant	median	mean	std. dev.	2.5ptile	97.5ptile	sigma	GSD	GSD2
$PM_{10-2.5}$	3.761	10.813	29.313	0.223	65.14	1.457	4.292	18.421

Units in DALY/kg; Radon in DALY/10^{-9}Bq.
std. dev.: standard deviation; GSD: geometric standard deviation (and squared).

A4.1 A preliminary assessment using DALYs to express chronic harm in dwellings

Logue et al. (2012) proposed methods using disability-adjusted life years (DALYs) to estimate health impacts from indoor contaminants. The Intake-Incidence DALY (IND) method combined concentration-response and disease incidence. The Intake-DALY (ID) method used contaminant effect factors.

However, limitations existed around outdated health data. This work aimed to enhance quantification by: (i) leveraging the past decade's epidemiology and toxicology research, (ii) incorporating current dose-response factors via LCIA frameworks, (iii) meta-analyzing results across models.

Logue et al.'s derivations for damage factors and baseline incidences were maintained, using systematic reviews and epidemiological data. A log-linear concentration-response function related concentration to incidence. Overall, this preliminary assessment still depended on effect factors (DALY/kg intake) as the main metric linking exposure to harm.

Figure 1 summarizes pooled effect factors for 45 contaminants and Figure 2 presents harm results following the preliminary decisions made in the research. The analysis underscores the prominence of $PM_{2.5}$, which exhibits the highest median DALYs per unit intake, signifying its significant potential for harm. $PM_{2.5}$ is closely followed by PM_{10}, formaldehyde, nitrogen dioxide, radon, and ozone, each displaying substantial attributable DALYs. Furthermore, contaminants like acrolein and sulphur dioxide fall within the same order of magnitude range, whereas mold-related bioaerosols retain their significance with over 0.5 DALYs per 100,000 exposed population annually.

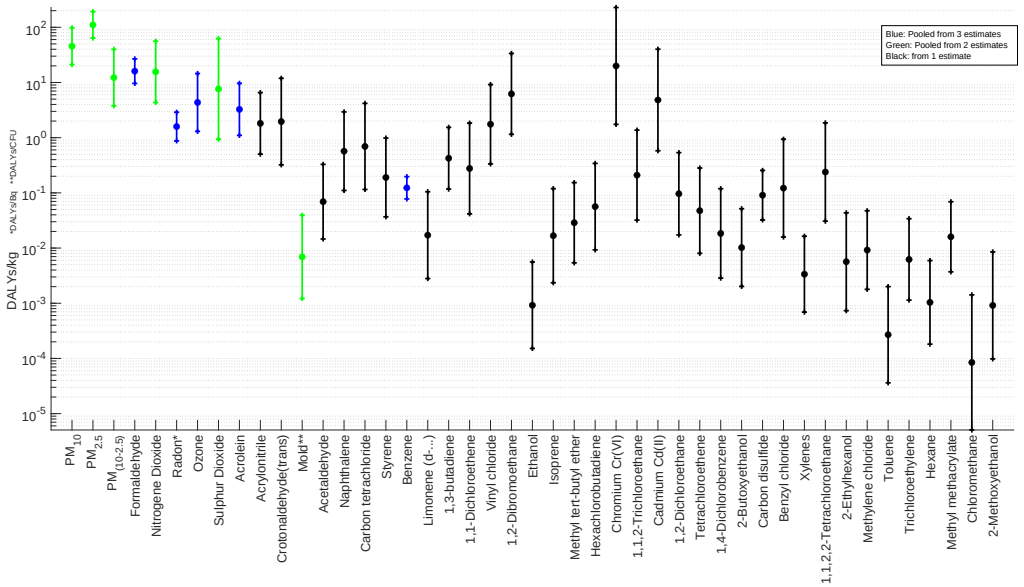

Figure 1: Pooled effect factors. Highest to lowest median harm. Median & GSD.

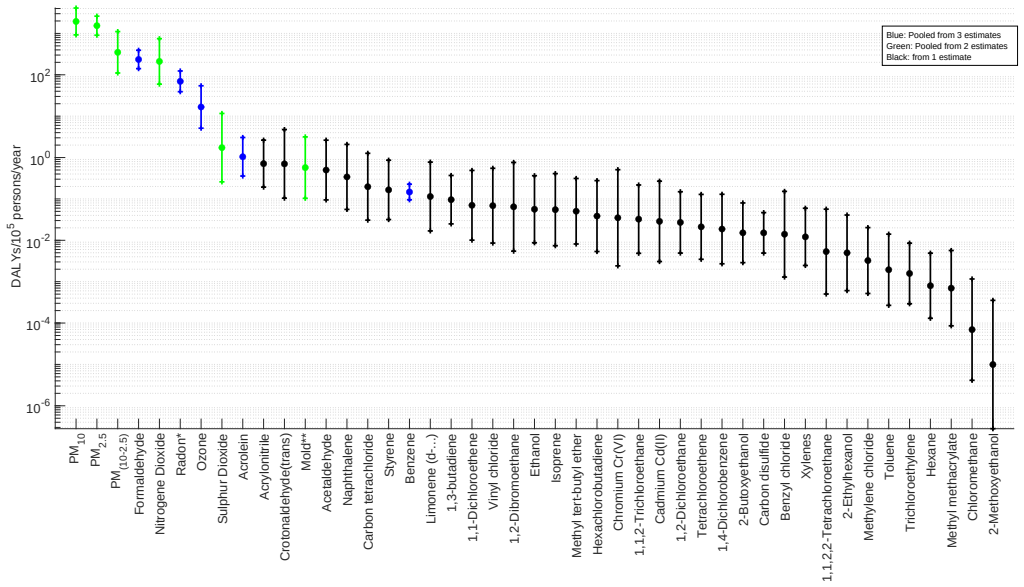

Figure 2: Pooled harm. Highest to lowest median. Median & GSD.

Notably, the so-called criteria pollutants present the highest median DALYs, underscoring their potential for harm. Epidemiological evidence strongly suggests that these contaminants have the capacity to cause adverse health effects, as corroborated by various health-based metrics (WHO, 2021). Additionally, contaminants like formaldehyde, radon, acrolein, and mold also exhibit elevated harm values, making them noteworthy considerations in the context of indoor air.

Following is the conference paper that shows the work presented. This is shown as an Appendix because the findings presented at this stage of the research where superseded by the complete harm assessment of Chapter 7.

Health impacts of indoor air contaminants determined using the DALY metric

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1. ABSTRACT

Common metrics used for assessing air quality are based on guidelines and/or standards for regulating concentrations that should not be exceeded over a period. Exceeding those values would represent problematic situations. A lack of agreement on appropriate norms or standards deem this approach sub-optimal. Moreover, this approach does not relate a proportion of exceedance to specific health outcomes. A need to develop health-centered IAQ metrics that can quantify burden of disease in terms of epidemiological evidence of population morbidity and mortality supported by the best knowledge of health effects, is pressing. This work proposes an approach that harnesses the advantages of using Disability Adjusted Life Years (DALYs) as a valuable metric to quantify and rank the burden of household air pollution, as a global perspective. Two methods were used to compute DALYs, one mainly based on incidence data and another mainly based on effect factors (i.e. DALYs per unit-intake of contaminant of interest). The methods are based on the following parameters: risk estimates, baseline incidence rates, damage factors, indoor air contaminant concentrations, human toxicological & epidemiological effect factors, dose-response factors, cancer-related variables and breathing rates. Systematic searches and reviews of peer-reviewed literature (including systematic reviews and meta analyses) were performed to find information on said input parameters. Meta-analysis was used to pooled and synthesize data from different studies. A Monte Carlo approach was used to model results in disability-adjusted life-years (DALYs) lost. Over 1000 articles were revised and overall ~200 unique sources were used as sources of data.
Ten contaminants were accounted for with specific risk estimates and damage factors data, for which human epidemiological effect factors were derived. Representative concentrations of 45 contaminants were calculated. 39 contaminants were accounted for human toxicological effect factors. Total pooled DALYs were estimated per 100,000 exposed population with corresponding uncertainty intervals. Estimated population-averaged annual cost, in DALYs lost, of chronic air contaminant inhalation in dwellings indicate that the contaminants with highest median DALY loss estimates are PM_{10} and $PM_{2.5}$ (magnitudes of 10^3); PM_{coarse}, formaldehyde, and NO_2 could be found with magnitudes of 10^2; contaminants with magnitudes of 10^1 include radon and ozone, finally SO_2 and acrolein would have magnitudes of 10^0; mould-related bioaerosols could be of interest as well. The updated strategies allowed for the quantification of contaminants and health outcomes that were not accounted for in previous works. Computed DALYs have lower uncertainty intervals than those previously proposed. The updated methodology presented in this study may be used to assess cumulative health impacts of indoor air contaminants.

2. KEYWORDS

DALYs; IAQ; health; dwellings

1 INTRODUCTION

Air pollution is one of the most serious health risks (WHO, 2021), and there now is enough scientific evidence to justify establishing and/or upgrading approaches for quantifying the health burden of (indoor)-air contaminants using current epidemiological and toxicological research. Common metrics used for assessing air quality are based on guidelines and/or standards for regulating concentrations that should not be exceeded over a period. Exceeding them would be problematic but the magnitude of doing so is unclear (Jones, 2017). This is because the approach does not relate a proportion of exceedance to specific health outcomes. Therefore, there is a pressing need to develop health-centered IAQ metrics that can quantify burden of disease in terms of epidemiological evidence of population morbidity and mortality supported by the best knowledge of health effects. Consequently, the Disability Adjusted Life Year (DALY) has been adopted worldwide in air pollution global burden of disease studies (Cohen et al., 2017). It was developed in the 1990s and is the sum of the years of life lost, and the time lived with a disability, attributable to some cause (Homedes, 1996).
A methodology to estimate the population-average health effects attributable to the inhalation of selected air contaminants in U.S. residences was proposed in Logue *et al*. (2012) using disease incidence data and health-related effect factors, and accounting for output uncertainty. It uses the DALY metric by defining an Intake-Incidence DALY (IND) method and an Intake-DALY (ID) method. Although the method proposed by Logue *et al.* (2012) is pioneering because it quantified DALY losses based on two distinct methods, the approach has limitations. Here we provide a way of strengthening the method, harnessing the advantages of using Disability Adjusted Life Years (DALYs) as a valuable metric to quantify and rank the burden of household air pollution, using a global perspective.

2 METHODS

Two methods were used to compute DALYs, one based on incidence data [IND-method], and another based on effect factors that use a DALY value per unit-of-mass-intake of the contaminant of interest [ID-method] (Logue *et al.*, 2012).

2.1. THE IND METHOD

The IND method (Equation 1) uses an epidemiologically-based concentration-response function to quantify disease incidence, which, when combined with a damage factor (DF), yields an expected DALY loss.

$$DALY\ losses = \frac{\partial DALYs}{\partial (incidence) case} \times \partial (incidence) case \quad (1)$$

In the IND model, a damage factor is used to represent the life-years adversely impacted by each disease event, in DALY.(incidence)case^{-1}. The DF_{IND} is expressed for a specific contaminant *h* and disease *k* as

$$\frac{\partial DALYs}{\partial (incidence) case} = DF_{IND\ k,h} = Damage\ factor \quad (2)$$

The second term on the right of Eq 1, the disease incidence, refers to the relationship between contaminant concentration (IAP), risk of disease (β), and baseline incidence (γ_0); see Eq (3). This relationship is modeled using a log-linear concentration response function given by Eq. (3). As mortality is expected to have a greater impact on the global disease burden than morbidity, it is recommended that mortality data be used to represent disease incidence for most air pollution-related diseases (Cohen *et al.*, 2017).

$$\partial(incidence)case = \gamma_{0_{k,h}} \times (1 - e^{-(\beta_{k,h} \times IAP_h)}) \times population \quad (3)$$

where, $\gamma_{0_{k,h}}$ is the baseline incidence of disease *k* of contaminant *h*, and IAP_h is a statistic describing the concentration of contaminant *h*.
Beta $\beta_{k,h}$ is an empirical parameter representing the estimated change in risk for a given change in contaminant concentration, ΔC, for disease *k* and contaminant *h*. This is expressed as

$$\beta_{k,h} = \frac{Ln(Risk\ Estimate)}{\Delta C} \quad (4)$$

A breathing rate (BR, in $m^3.yr^{-1}$) combined with the IAP_h parameter (in unit-intake.m^{-3})[1] is used to obtain an estimate of the human epidemiological effect factor (EF_{IND}, in DALYs per unit-intake of contaminant) via the IND method, as shown in Eq. (5)

$$Effect\ factor\ (EF_{IND\ k,h}) = \frac{DALY\ losses}{intake} = \frac{DALY\ losses}{BR \times IAP_h} \quad (5)$$

2.2. THE ID METHOD

The ID method (Eq. 6) quantifies DALYs as the product of effect factors (EF_{ID}), intakes, a cancer-related parameter (ADAF), and breathing rates (BR), involving Eq. (6) to (9). In this method, the EF_{ID} is the product of a dose–response factor (DRF, in case.kg_{intake}^{-1}) and a damage factor (DF_{ID}, in DALY.(cancer or non-cancer)case)$^{-1}$.

$$DALY\ losses = \frac{\partial DALYs}{\partial intake} \times \partial intake \quad (6)$$

$$\partial intake = IAP_h \times Breating\ Rate \quad (7)$$

$$\frac{\partial DALYs}{\partial intake} = Effect\ factor\ (EF_{ID\ j,h}) = DRF_{j,h} \times DF_{ID(cancer\ or\ non-cancer)j} \quad (8)$$

$$\text{With } DRF_{j,h} = \left(\frac{0.5}{ED_{50\,j,h}}\right) \quad (8a)$$

$$\text{And } \frac{\partial DALYs}{\partial intake} = EF_{ID\ combined\ j} = \left(\frac{\partial DALYs_{cancer}}{\partial intake} \times ADAF\right) + \left(\frac{\partial DALYs_{non-cancer}}{\partial intake}\right) \quad (8b)$$

or

$$\frac{\partial DALYs}{\partial intake} = Effect\ factor\ (EF_{IND\ k,h}) = DRF_{k,h} \times DF_{IND\ k,h} \quad (9)$$

$$\text{With } DRF_{k,h} = \left(\frac{CRF_{k,h}}{Breating\ Rate}\right) \quad (9a)$$

2.3. THE INPUT DATA

Parameters described in Section 2, can have more than one available value or set of data; see Datasets in Table 1. Thus, pooling independent data points is the recommended strategy for data synthesis (Schmid et al., 2020).
For the IND method, values of the parameters beta (β), baseline incidence (γ_0), representative contaminant concentration (IAP_h), and damage factor (DF_{IND}) are obtained by combining systematic reviews with supplementary references. Baseline disease incidences are derived from epidemiological studies.
For the ID method, damage factors, representing overall cancer or non-cancer effects should be based on the latest available data from the World Health Organization (WHO) and/or the Global Burden of Disease studies. The DRF takes as a point of departure either the ED_{50} (median effective dose) benchmark measure (see Eq. 8a) or concentration-response factors (CRF) (see Eq. 9a). The ED_{50} is the human-equivalent lifetime daily dose per person, related to inhalation (intake) of a substance that produces a specific effect (e.g carcinogenic or non-carcinogenic

[1] A *unit-intake* could be kg, Bq, or Colony Forming Units (CFU).

effects) in 50% of the population that takes that dose (Fantke *et al.*, 2021) and CRFs are contaminant-associated mortality or morbidity rates per unit concentration of contaminant inhaled (Gronlund et al., 2015). ED_{50} based- DRF (ED_{50}-DRF) for the contaminants of interest are extracted from Life Cycle Impact Assessment (LCIA) databases. CRF based- DRF (CRF-DRF) are compute using the same epidemiological inputs as the IND method and can be derived following Fantke *et al.* (2019). When EFs are based on the ED_{50}, they are referred to as human toxicological effect factors (Eq. 8) while those based on CRFs are called human epidemiological effect factors (Eq. 9). The ADAF parameter used for the estimation of cancer risks and the breathing rates representing the volume of air breathed indoors each year, are determined from relevant sources following a focused literature review.

2.4. THE MODELLING

Since each method will derive an estimate of DALY and EF (one estimate via IND method and two estimates via ID method, for a total of three theoretically possible independent DALY and EF estimations), we pooled the results from each independent method via meta-analysis to obtain *pooled DALYs* and *pooled Effect Factors*. To account for the uncertainty of the parameters, the Monte Carlo (MC) method is applied. First, a bootstrapping technique is applied to populate a synthetic database for each parameter and described using a probability distribution function (PDF). The PDF is then combined with the bootstrapped results to generate random samples of the inputs, which in turn are used to compute the three outputs: i) disease incidence, ii) effect factors and iii) DALYs. We repeated this process until the means of the results were normally distributed. All outputs are reported by their median and 95% confidence interval of its distribution, representing the range that contains 95% of the population values.

Preliminary analysis of the input data showed that they can be well described by a lognormal distribution around its median. This type of distribution is widely used and accepted to adequately adjust for right-skewed data (Crow and Shimizu 1987). A MATLAB code was used to run the Monte Carlo simulations. All pooled estimates (meta-analysis) were computed with STATA 16.0's "metan" commands, using the DerSimonian and Laird (random effects) estimators (Harris *et al.*, 2008).

3 RESULTS

Systematic searches and reviews of peer-reviewed literature (including systematic reviews and meta-analyses) were performed to extract information on the input parameters. Over 1000 articles were identified and ~200 unique sources were used as sources of data. Tables 1 and 2 provide descriptive statistics and recommended values for each input parameter for IND and ID model, respectively. Ten contaminants were accounted for with specific risk estimates and damage factors data: Acrolein, Benzene, Mould-related bioaerosols, Formaldehyde, NO_2, O_3, PM_{10}, $PM_{2.5}$, Radon and SO_2 (see Table 1). The methodology allowed for the identification, using the literature, of a single representative health outcome for each of the ten contaminants (see Table 1). The health outcome chosen to represent each contaminant is the most reported health impact associated with it, either for mortality or morbidity endpoints.

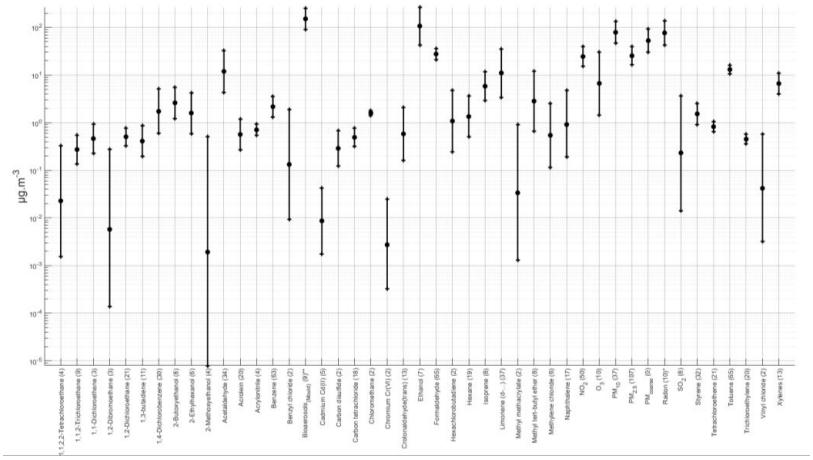
Representative concentrations of 45 contaminants were calculated. They are all included because they have previously been identified as contaminants of interest in dwellings (Logue *et al*., 2011). Fig. 1 shows the representative mid-range concentrations, including a 95% CI and the magnitude of individual values (data sets) used to obtain them. Mid-range indoor concentrations for the contaminants are, in general, within the values reported by others

(Vardoulakis et al., 2020, Logue et al., 2011). With over 50 data sets, $PM_{2.5}$, formaldehyde, Toluene, Benzene, and NO_2 would be the contaminants with the most reported values.

Table 1: Summary descriptive of the IND model inputs and disease incidence output for selected contaminants[+].

Contaminant	Health outcome	Beta parameter (β)	Baseline incidence rate (γ_0)	Damage factor (DF_{IND})	Annual disease incidences, per 10^5 pop.
		Parameter values [Datasets] {Main reference}			
Acrolein	Asthma	0.141 (95%C.I.-0.082-0.200) [2] {Annesi et al. (2012)}	0.001 {Annesi et al. (2012)}	0.588 (95%C.I.0.059-5.875) [1] {GBD (2019)}	8.287 (95%C.I. 3.577-18.729)
HCHO	Added effects*	--*		9.789 (95%C.I.4.249-54.005)	46.478 (95%C.I. 9.607-1015.678)
O_3	ACM	0.001 (95%C.I.0.000-0.002) [7] {WHO (2021)}	0.008 (95%C.I.0.004-0.016) {Crouse et al. (2015)}	15.346 (95%C.I.6.856-34.348) [3] {OS/RD)}	1.305 (95%C.I. 0.031-55.739)
PM_{10}	ACM	0.004 (95%C.I.0.003-0.006) [17] {WHO (2021)}	0.013 (95%C.I.0.007-0.026) {Fischer et al. (2015)}	9.554 (95%C.I.2.528-36.101) [3] {OS/RD)}	349.077 (95%C.I. 190.536-603.739)
$PM_{2.5}$	ACM	0.008 (95%C.I.0.000-0.002) [25] {WHO (2021)}	0.007 (95%C.I.0.003-0.018) {Crouse et al. (2015)}	15.303 (95%C.I.11.798-19.850) [40] {OS/RD)}	102.893 (95%C.I. 24.256-433.625)

ACM: All-Cause Mortality. LCM: Lung Cancer Mortality. HCHO: Formaldehyde. OD/SR: Own data/ systematic review. *added effects of epidemiological data from LCM, leukaemia and asthma. [+]Other contaminants not shown due to spacing issues and are available upon request.



[*]Radon in $Bq.m^{-3}$. [**]Bioaerosols in $CFU.m^{-3}$

Figure 1: Recommended representative concentrations for the 45 contaminants included in the analysis. In alphabetical order. Central estimate and 95% C.I. of distribution in black. Datasets in parenthesis

The annual incidence of disease for the ten indoor contaminants and selected typical health outcomes was calculated using Eq. (3) and data inputs are presented in Table 1. The highest disease incidences are found in PM_{10}, $PM_{2.5}$, and mould, with estimates exceeding magnitudes of 10^2. Because particle contaminants are based on all-cause mortality risk estimations, this is to be expected. Mould-bioaerosols have a high value because asthma morbidity in children accounts for a large portion of the illness burden.

Table 1 presents the damage factors for the contaminants in the IND model and their corresponding number of datasets found. Our method for calculating this parameter yielded novel damage factors for a broader range of contaminants not presented before in related works (Fazli et al., 2018). Results are based on contaminant and health outcome-specific effects, which allows the information gaps on contaminant-related damage factors to be reduced.

To account for updated information and variability of data for standard breathing rates (Phillips and Moya, 2013), we pool recommended values for long-term inhalation rates for adults aged 16-81+ yrs (USEPA, 2011). For the ADAF parameter, the review of pertinent references indicates that the USEPA (2005) recommendations are still in use; see CalEPA (2009). The recommended estimate for the standard breathing rate is 14.80 $m^3.(pop.d)^{-1}$ (95%C.I.13.50-16.20) and for the ADAF parameter is 1.6 (95%C.I.1-10). The USEtox database was used to extract ED_{50}-DRFs (Fantke *et al.*, 2017). The USEtox model is chosen because it is a widely used global scientific consensus model for characterising human toxicological consequences in LCIA. CRF-DRFs were calculated following Fantke *et al.* (2019). Regarding the DF_{ID} parameter, we use the latest results from the 2019 GBD study. Table 2 shows descriptive for ID model.

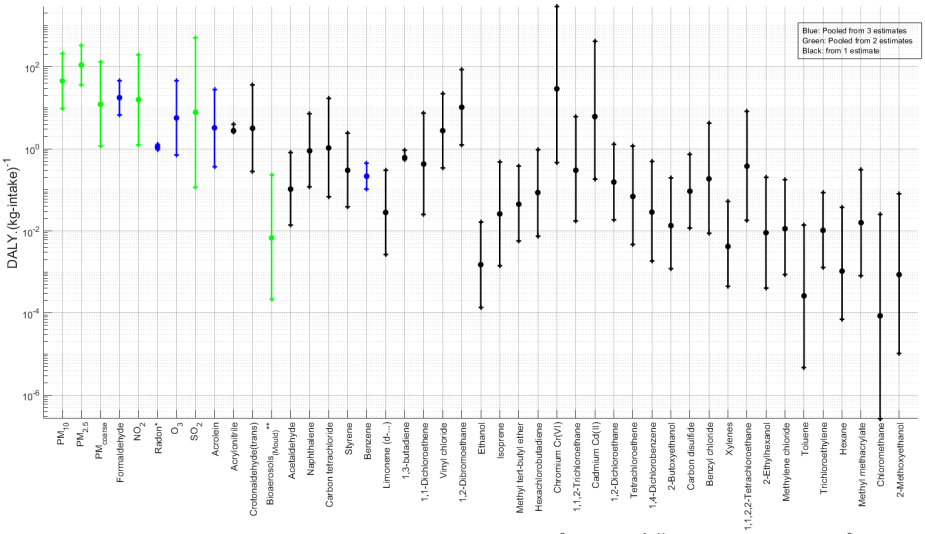
Table 2: Summary descriptive of the ID model inputs, for selected contaminants[+]

Contaminant	**ED_{50}-DRFc**	**ED_{50}-DRFnonc**	**CRF-DRF**	**$DF_{ID}C$**	**DF_{ID}nonc**
	From USEtox Database		Own computation	From GBD (2019)	
Acrolein	NA	59.74 (95%C.I. 1.82-1963.49) {non-carcinogenic effects}	25.15 (95%C.I. 7.34-83.37) {Asthma}	NA	0.59 (95%C.I. 0.44-0.77) {Asthma}
HCHO	1.06 (95%C.I. 0.27-4.25) {carcinogenic effects}	0.01 (95%C.I. 0.00-0.15) {non-carcinogenic effects}	2.92 (95%C.I. 0.52-63.65) {Added effects}	41.77 (95%C.I. 38.60-45.15) {added Leukaemia and lung cancer}	0.59 (95%C.I. 0.44-0.77) {Asthma}
O_3	1.09 (95%C.I. 0.16-7.60) {carcinogenic effects}	NA	0.29 (95%C.I. 0.00-18.70) {ACM}	21.18 (95%C.I. 20.06-22.36) {Lung Cancer}	NA
PM_{10}	NA		7.98 (95%C.I. 3.21-18.91) {ACM}	NA	
$PM_{2.5}$			7.33 (95%C.I. 1.58-33.75) {ACM}		

Note. Curly brackets represent {health outcome}. ACM: All-Cause Mortality. ED_{50}-DRFc = carcinogenic Dose-Response Factor; ED_{50}-DRFnonc = non-carcinogenic Dose-Response Factor; CRF-DRF = concentration-response based Dose-Response Factor; $DF_{ID}C$ = ID model carcinogenic Damage Factor; DF_{ID}nonc = ID model non-carcinogenic Damage Factor. HCHO = Formaldehyde. Added effects from LCM, leukaemia and asthma. OD/SR: Own data/ systematic review. NA= not applicable. GBD (2019):https://ghdx.healthdata.org/gbd-results-tool
[+]Other contaminants not shown due to spacing issues and are available upon request.

Combined carcinogenic and non-carcinogenic (toxicological)-effect factors were computed for 39 contaminants using Eq. (8b) whilst (epidemiological)-effect factors were computed for ten contaminants using Eq. (5) and Eq. (9). The results are pooled, giving 45 contaminants with effect factors. Results are shown in Fig. 2. $PM_{2.5}$ has the highest pooled effect factor [1.1×10^{2} (95%C.I. 3.6×10^{1}-3.3×10^{2})] (an order of magnitude higher than the other contaminants) indicating that this would be the contaminant with the highest chronic health impacts per kg inhaled in the exposed population, in dwellings. Other PMs are among the contaminants with the highest EFs, with chromium, NO_2 and formaldehyde having all $>10^{1}$ effect factors. These results represent an update to the preeminent work on human-toxicological&epidemiological effect and damage factors of carcinogenic and noncarcinogenic chemicals for life cycle impact assessment presented by Fantke *et al.* (2019) and Huijbregts *et al.* (2005). The results given in Fig. 2 have narrower confidence intervals when compared with those of Huijbregts *et al.* (2005).

Total pooled DALYs were estimated per 100,000 population with corresponding uncertainty intervals; see Fig. 3. Estimated population-averaged annual cost, in units of DALYs lost, of chronic air contaminant inhalation in dwellings, indicate that the contaminants with the highest median pooled DALY loss estimates are PM_{10} [1.9×10^{3} (95%C.I. 4.4×10^{2}-8.7×10^{3})] and $PM_{2.5}$ [1.5×10^{3} (95%C.I. 5.3×10^{2}-4.4×10^{3})]. PM_{coarse}, formaldehyde, NO_2, radon and ozone have medians among 10^{2}-10^{1}. Acrolein and SO_2 are within 10^{0}. Mould-related bioaerosols could still be of interest having >0.5 DALYs per 100.000 exposed population. The confidence intervals of the results indicate a lower uncertainty range than those presented by Logue *et al.* (2012).



*Radon in DALY.(10^{-9}Bq-intake)$^{-1}$. **Bioaerosols in DALY.(10^{-9}CFU-intake)$^{-1}$

Figure 2: Pooled effect factors. Highest to lowest DALY median. Central estimate and 95% C.I. of distribution in black.

Contaminant with highest median DALYs include the so called criteria pollutants, which are defined as the indoor contaminants with the highest health impacts based on the DALY metric. There is sufficient epidemiological evidence that indicates PM_{10}, $PM_{2.5}$, NO_2, O_3 and SO_2 have the potential to be associated with harm in humans, using other health based-metrics such as relative risks (WHO, 2021). Other airborne contaminants where health based-evidence exists to indicate that they are contaminants of interest in the indoor environment, having also elevated DALY values, include Formaldehyde (Golden, 2011), Radon (Pawel and Puskin, 2004), Acrolein (Ghilarducci and Tjeerdema, 1995) and mould (Heseltine and Rosen, 2009).

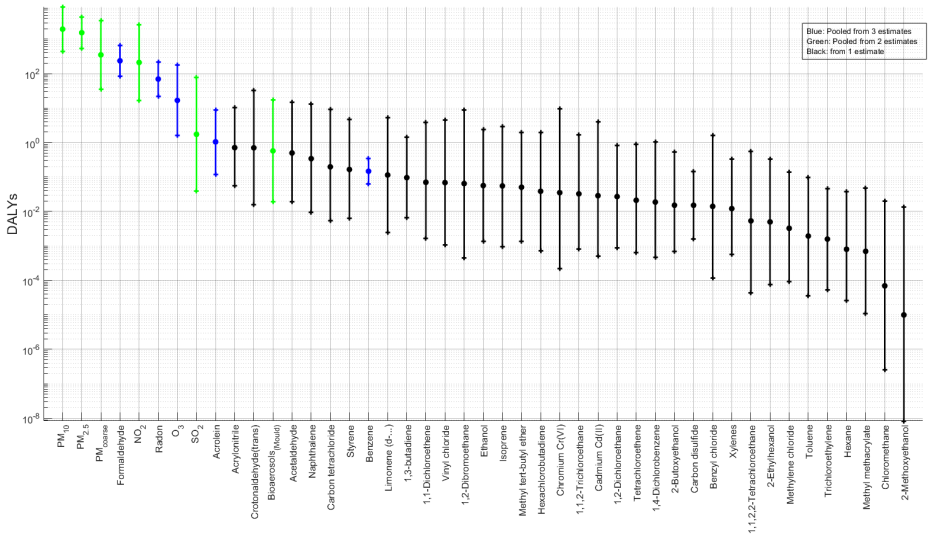


Figure 3: Pooled DALYs. Highest to lowest median. Central estimate and 95% C.I. of distribution in black.

4 CONCLUSIONS

$PM_{2.5}$ have the highest median DALYs per unit intake (1.1×10^{2} (95%C.I. 3.6×10^{1}-3.3×10^{2})), being one order of magnitude above the rest of contaminants included in the analysis, indicating that higher harm is associated with fine PM. The highest absolute DALY medians were found for PM_{10} with 1.8×10^{3} (95%C.I. 4×10^{2} -9×10^{3}) and $PM_{2.5}$ with 1.9×10^{3} (95%C.I. 4.4×10^{2}-8.7×10^{3}). PM_{10} is higher because it includes the burden associated with the $PM_{2.5}$ fraction. Reporting representative indoor concentrations or disease incidence as the sole metrics to assign harm from exposure to contaminants, is rendered suboptimal. Computed DALYs have lower uncertainty intervals than those previously proposed. The updated methodology presented in this study may be used to assess cumulative health impacts of indoor air contaminants and contribute to the development of standards.

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A5 For discussion

A5.1 Conference Paper PLEA

This section includes the conference paper referenced in the main text.

PLEA SANTIAGO 2022
Will Cities Survive?

Quantifying Harm from Exposure to Fine Particles ($PM_{2.5}$) Emitted by Cooking

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ABSTRACT: Emissions from cooking have been estimated to contribute to two-thirds of total fine particulate matter (particles with diameter ≤ 2.5µm, $PM_{2.5}$) pollution in homes, so assessing $PM_{2.5}$ emissions from cooking complete meals is a growing need of research. Furthermore, indoor exposure to $PM_{2.5}$ has been associated with an increased risk of adverse health effects. Quantifying health effects can be performed using metrics based on health. Here, we use averted-Disability Adjusted Life Years, a performance-based health-centred metric, to investigate and quantify the tangible change in the burden of disease for mitigating exposure to $PM_{2.5}$ pollution using ventilation strategies proposed by England's statutory Approved Document F. The median [mean] annual DALYs for the worst ventilation scenario was found to be 6063 [7368] (95%CI: 1108 - 21788), which reduces to 1822 [2437] (95%C.I. 364-8165) when using an exhaust system through a 30L/s cooker hood during cooking time plus 10 minutes (best ventilation scenario). Both estimations assumed exposure to $PM_{2.5}$ from cooking occurs every day and all exposure represent the intake, and as such represent extreme cases. A change from worst to best scenario results in 3187 [5016] (95%C.I. 499-20310) annual averted DALYs per 100,000 of exposed population. The focus should be made towards these health metrics, as wide information and data sources exist for computing them. Expected interested parties in these results include policymakers, scientists, and the public.
KEYWORDS: DALYs, Cooking, Health, $PM_{2.5}$

1. INTRODUCTION

Air pollution is a primary cause of morbidity and premature mortality worldwide. Current standards attempt to minimize exposure by specifying threshold average-concentrations. However, this does not necessarily indicate the impact on human health. To do this, methods can use reference values, risk or damage factors, and health centred metrics, such as DALYs or QALYs [1]. The DALY (disability-adjusted life-years lost) metric was developed in the 1990s, and corresponds to the years of life lost, and the time lived with a disability, attributable to some cause [2]. The DALYs for a disease is defined as the sum of the Years of Life Lost (YLL) due to premature mortality in the population and the Years Lost due to Disability (YLD) [2-4]. DALYs can be computed for any disease or cause of mortality over a lifetime, allowing for a comparison of causes and the prioritization tasks. The harm caused by chronic exposure to airborne contaminants can be quantified using DALYs [5].

Exposure to airborne contaminants primarily occurs indoors. Indoor air pollutants (IAPs) lead to a variety of diseases. Thus, a standard metric of harm is needed to prioritize mitigation methods and to compare IAPs. Logue et al. [6] proposed a method to quantify and compare health impacts (harm) from the inhalation of a subset of IAPs. They used available information on disease incidence and impacts for specific pollutant–disease combinations and data on the uncertainty in IAP concentrations measured in US dwellings. They showed that indoor exposure to fine particles (with diameter ≤2.5µm, $PM_{2.5}$) causes more harm than any other contaminant, by an order of magnitude. For 2016, estimates of the joint effects of household (HAP) and ambient air pollution (AAP) indicated that, globally, 7 million deaths were attributable to exposure to $PM_{2.5}$, 4.2 million to AAP and 3.8 million to HAP [7]. Furthermore, in 2017, long-term exposure to $PM_{2.5}$ contributed to a burden of 83×10^6 disability-adjusted life years (DALYs) globally; specifically, household air pollution contributed to 59×10^6 DALYs (2.4% of total DALYs) from ischemic heart disease, stroke, COPD, lower-respiratory infections, and type 2 diabetes [8].

Cooking is a significant source of $PM_{2.5}$ in dwellings [9] and can be removed from a space using ventilation [10]. England's statutory Approved Document F (ADF) [11] prescribes three ventilation strategies to control the quality of air in a kitchen: (1) an intermittent ventilation rate of 30 l/s through a cooker/range hood; or (2) 60 l/s elsewhere; or (3) a continuous ventilation rate of 13 l/s. The provision of one of these strategies is obligatory in new dwellings, whereas it is only necessary to maintain an existing ventilation system when refurbishing any other dwelling. These ventilation rates were chosen

to remove moisture, with the further expectation that they will dilute NO_2 and CO emitted by gas cooking. $PM_{2.5}$ and other contaminants generated during cooking, were not considered.

A cooker hood captures a proportion of all emitted contaminants and extracts them directly outside [10]. This has been shown to be the most effective kitchen ventilation strategy for minimising mean $PM_{2.5}$ concentrations, especially when the fan is also run for 10 minutes after cooking finishes [10]. However, ADF does not require a performance verification mechanism for cooker hoods. Cooker hood *capture efficiency* (CE) is defined as the fraction of an emitted contaminant that is extracted before it mixes with room air [12]. The CE of a hood is a function of its airflow rate, installation height, hood capture volume, and the fraction of the stovetop covered by the hood [13,14]. An ASTM standard prescribes a steady-state test of CE [15,16]. CEs have not been measured in UK dwellings, but they have been found to vary between 12% [12] and 98% [13] elsewhere. ADF implicitly assumes a CE of 50%.

To test the efficacy of ADF, it is important to investigate whether using a cooker hood makes a tangible difference to the health of the occupants of existing dwellings at a population scale. Therefore, to investigate the reduction in harm to the English population attributable to the installation of a cooker hood in a proportion of all domestic kitchens, this paper uses *averted Disability Adjusted Life Years*, a performance-based health-centred metric, to quantify the change in the burden of disease in a population.

2. THEORY

The US EPA's National Ambient Air Quality Standard (NAAQS) defines six *criteria pollutants*[1] as common contaminants that have an adverse effect on health and wellbeing, and they include particulate matter (PM). In response, an Intake-Incidence DALY method (IND) was defined to estimate chronic health impact for criteria pollutants [6]. The IND-method (eq. 1) uses epidemiology-based Concentration-Response functions to quantify disease incidence rates that, combined with a damage factors (DF), yield the expected DALY losses.

$$DALY\ losses = \frac{\partial DALYs}{\partial(incidence)case} \times \partial(incidence)case \quad (1)$$

A damage factor represents adversely affected life years per disease case, in DALYs.(case)$^{-1}$. The DF for a contaminant *h* and a specific disease *k* is represented by

$$\frac{\partial DALYs}{\partial(incidence)case} = DF_{k,h} = Damage\ factor. \quad (2)$$

[1]https://www.epa.gov/criteria-air-pollutants.

The disease incidence refers to a relationship between a contaminant concentration (IAP in eq. 3), a disease (β), and a baseline incidence rate (γ_0). This relationship is modelled with a log-linear Concentration-Response function determined by eq. (3). It is expected that mortality will have a greater effect on the global burden of disease than morbidity and so, for most air pollution-related diseases [5], mortality data is recommended over morbidity data to represent the incidence of a disease.

$$\partial(incidence)case = \gamma_{0_{k,h}} \times (1 - e^{-(\beta_{k,h} \times IAP_h)}) \times population \quad (3)$$

where, $\gamma_{0_{k,h}}$ is the baseline incidence rate of disease *k* for the contaminant *h,* and IAP_h is a statistic that describes the concentration of contaminant *h.* $\beta_{k,h}$ is an empirical parameter that denotes the change in a risk estimate for a given change in contaminant concentration, ΔC, for the disease *k* and contaminant *h*. It is represented by

$$\beta_{k,h} = \frac{Ln(Risk\ Estimate)}{\Delta C} \quad (4)$$

3. METHOD

We followed the evaluation of ventilation scenarios presented by [10] for a statistically representative sample of English domestic kitchens. They considered a significant, but not extreme, emission profile where three meals were cooked per day: (1) breakfast that involves the toasting of bread; (2) lunch that involves the cooking one of four typical northern European meals using a gas hob/stove/burner; and (3) dinner that involves the cooking of another of the four typical meals. The duration of each cooking event and the emission rates were all uncertain, and so this was accounted for using a Monte Carlo (MC) approach. The varying geometry of kitchens was also accounted for by sampling volumes from the UK Government's English Housing Survey [17], a statistically representative survey of the English Housing stock.

To investigate the efficacy of ADF, we estimate the harm (DALYs) and benefits (averted DALYs) that occur when the six ventilation strategies, given in Table 1, are applied in all English kitchens.

Table 1:
Ventilation strategies

Strategy	Fan flow rate (L/s)	Details
A	0	Infiltration only
B	13	Constant general extract ventilation at the high rate from ADF
C	60	Intermittent general extract ventilation just during cooking
D	60	Same as C but for an additional 10 minutes after cooking
E	30	Intermittent extract through a cooker hood, CE=50%, just during cooking
F	30	Same as E but for an additional 10 minutes after cooking

The concentrations for each of the six ventilation strategies (parameter IAP_h in eq. 3) are predicted and reported as 24-hour mean average concentrations ($\mu g/m^3$) for the existing stock of dwellings in English kitchens [10]. These values are also given probabilistically, so it is possible to sample from their distributions. Methods and outputs that describe the concentration analysis are given in [10].

For the other parameters described in Section 2, there will often be more than one available value or data set; see table 2. Combining or pooling independent data points is the recommended strategy for data synthesization [18] Values for the beta (β), baseline incidence (γ_0), and damage factor (DF) parameters were obtained by combining global systematic reviews with complementary references. To be consistent with the recent literature, we use the WHO's pooled estimate data that describes relative risks associating *All-Cause mortality* (ICD-10 A00-R99) with $PM_{2.5}$ [19]. The baseline incidence rate of diseases was mined from epidemiological studies presented by [19]. The damage factor values are derived from pooled values determined from a systematic review of the environmental burden of disease studies (conducted by the authors) for *All-Cause mortality* and attributed to $PM_{2.5}$.

The number of DALYs associated with the intake of estimated exposure concentrations of $PM_{2.5}$ for the six ventilation strategies were calculated using Equations 1-4. To compare between different ventilation scenarios, *averted DALYs* are calculated as the difference between the best and worst-case scenarios (difference between strategy A and strategy F).

To account for the uncertainty of the parameters, a Monte Carlo (MC) approach was applied as follows. Firstly, a bootstrapping technique is applied to populate a synthetic database for each parameter, which are then described using probability distribution functions (PDFs). Then, the PDFs are combined with the bootstrapped results to generate random samples of inputs that, in turn, are used to calculate the DALYs and averted DALYs. The process is repeated until the results are normally distributed (*convergence criterion*). This technique results in a vector of DALY losses, and so it can be reported using a defined PDF, with its median and 95% confidence interval.

A preliminary analysis of the input data showed that they can be well described by LogNormal distributions around their median. This type of distribution is widely used and accepted to fit right-skewed data adequately [20].

To visually represent the distributions of parameters, we use (violin)plots. The Monte Carlo analyses were carried out using MATLAB. All pooled estimates (meta-analysis) were performed using the "*metan*" commands from statistical software STATA 16.0, which applies the DerSimonian and Laird (random effects) estimator for pooling estimates [22]. Graphs are plotted using MATLAB and *R*.

4. RESULTS

O'Leary [10] predicted median (mean) $PM_{2.5}$ concentrations to be 186 (250) $\mu g/m^3$ (96%CI: 39-867) for the worst scenario (Strategy A: infiltration only) and 31 $\mu g/m^3$ (96%CI:14-81) for best (Strategy D: using extract through a cooker hood). These values represent exceedances of current WHO-recommended thresholds for (indoor)-$PM_{2.5}$-24h of 15 $\mu g/m^3$ [19]. This general exceedance of a recommended threshold was already highlighted by [10] however, the magnitude of the change in health impacts remains. Here, we have extended the analysis to quantify tangible health impacts (harm) associated with their kitchen exposures, assuming that the whole population is exposed.

Table 2 provides descriptive statistics and recommended values for input parameters (See section 2). Table 3 summarises the estimated annual disease incidences and DALYs per 100,000 population for the six strategies on ADF. Estimated mortality due to exposure to $PM_{2.5}$ in the kitchen area is 3.5 times higher for strategy A than for strategy F, therefore, about a threefold reduction in expected mortality cases could be associated with that recommendation on ADF. Here, the chronic exposure-relevant $PM_{2.5}$ concentrations from cooking scenarios was set 100% of the indoor concentration (total intake), assuming exposure occurs every day (all time exposure), therefore, our values must be interpreted as extreme, but possible cases.

Table 2:
Summary descriptives of the model inputs for ALL-Cause.Mortality, $PM_{2.5}$.

	Central estimate (95% C.I.)	Main reference	Datasets
Risk estimate	1.08 (95%C.I. 1.06-1.09)	WHO (2021)	25
Beta[A]	0.008 (95%C.I.0.000-0.002)		
$\gamma 0$[B]	0.007 (95%C.I.0.004-0.015)	Crouse et al. (2015)	1
DF[C]	15.303 (95%C.I.11.798-19.850)	Own data/ syst. review	40

Note: all PDF assumed LogNormal (LogN)
[A] Current global recommended approach [19]; [B] Consistent with [21,23,24]; [C] Consistent with [25].

Table 3: *Summary Annual estimated disease incidences and DALYs, per 100,000 population, and averted DALYs between the best and worst-case scenarios.*

	Disease Incidence Median [mean] (95%C.I.)	DALYs Median [mean] (95%C.I.)
Strategy A	406 [482] (95%C.I. 76-1351)	6063 [7368] (95%C.I. 1108-21788)
Strategy B	214 [264] (95%C.I. 57-778)	3194 [4035] (95%C.I. 814-12456)
Strategy C	209 [270] (95%C.I. 39-866)	3133 [4148] (95%C.I. 563-13774)
Strategy D	107 [140] (95%C.I. 23-458)	1605 [2140] (95%C.I. 331-7160)
Strategy E	178 [236] (95%C.I. 31-784)	2666 [3599] (95%C.I. 444-12302)
Strategy F	121 [159] (95%C.I. 25-511)	1822 [2437] (95%C.I. 364-8165)
Averted $DALYs_{A-F}$	-----	3187 [5016] (95%C.I. 499-20310)

Figure 1 shows the estimates and distributions for annual disease incidences (and corresponding distribution) computed for each ventilation strategy, represented in log-scale on the y-axis. A visual decrease tendency can be noted from scenario A to scenario F, as expected. Figure 2 shows the quantified harm (and corresponding distribution) by different ventilation scenarios. The predicted median for annual DALYs per 100,000 of the exposed population of scenario A (infiltration only) is 6.1×10^3 (95%C.I. 1.1-21.8×10^3). Although the lowest estimates for DALYs are associated with strategy D (60 L/s general extract), strategy F, which represents half that ventilation rate using cooker hoods, yields equivalent DALYs, around 1.8×10^3 (95% C.I. 0.4-8.2×10^3). Regarding the PDFs of the disease incidences and DALYs (see Fig. 1 and 2, bottom), they show similar right-skewed distributions for the different scenarios. Data indicate that the disease incidence and DALYs can be described using log-normal distributions; this detail gains importance when using incidence as an input for the Monte Carlo (MC) approach. Furthermore, it promotes using a median over a mean as the best estimate for a central tendency, for reporting, and discussing these health impact metrics.

We quantified changes in health (as *averted DALYs*) due to interventions designed to lower the exposure to household air $PM_{2.5}$ pollution, defined by the ventilation strategies on ADF (see Tables 1, 3 and blue line in Fig. 2). The results suggest that half of the households (Med) could have approx. median 53% (mean 68%) of reduced harm by implementing a 30 L/s cooker hood with 50% CA, and fan use for the cooking period plus 10 minutes (strategy F), compared to using infiltration only (strategy A) (averted median DALYs as 3.2×10^3, 95% CI:0.5-20.3×10^3 annual DALYs per 100,000 of exposed population).

Similar work by Rosenthal et al. [26] on the health benefits of implementing clean cooking technology for households in a study of 40 low and middle-income countries, following the methodology for averted DALYs proposed by Pillarisetti et al. [27], found that a change from 285 $\mu g/m^3$ to 35, 74, and 182 $\mu g/m^3$ of the mean exposures in the cooking area resulted from three strategies: changing to LPG, using an advanced fan, and implementing locally made cookstoves. These changes were estimated as 9, 7, and 1.5 $\times10^3$ averted DALYs, respectively.

Although both studies quantify the health benefits of applying cooking-related intervention strategies, two main differences are highlighted to fully interpret the comparability of results: (1) Rosenthal et al. [26] focus on $PM_{2.5}$ from combustion sources used for cooking, whilst the present work dwells on $PM_{2.5}$ associated with the meals, and (2) the underlying differences in the methodologies used for the quantification of DALYs. Nevertheless, these harm costs and benefits show the importance of setting intervention strategies and standards that aim to reduce exposure to $PM_{2.5}$, including cooking activities, for high, middle and low-income countries.

Figure 1:
Annual Disease Incidence (in number of cases), per 100,000 population. (Top) Central estimate and 95% C.I. in black; (Bottom) Violin plots for distribution and density of predicted data. The interquartile ranges and mean are shown at the core, while the exterior of the plot shows the data distribution.

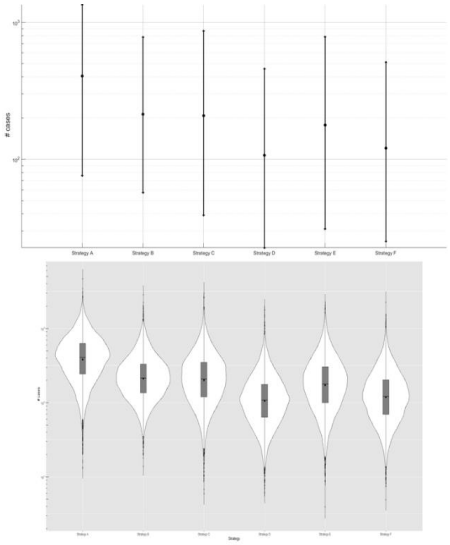
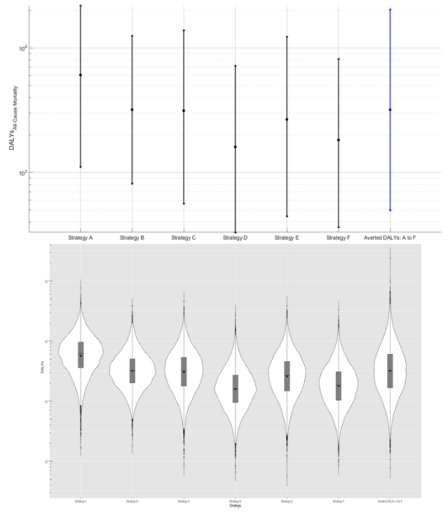


Figure 2:
DALYs by ventilation strategy. (Top) Central estimate and 95% C.I. of DALYs by ventilation strategies in black; Central estimate and 95% C.I. of averted DALYs between strategy A and F in blue. (Bottom) Violin plots for distribution and density of data. Interquartile ranges and means are shown at the core of the plots, while the exterior shows the data distribution.



5. CONCLUSIONS

Averted Disability Adjusted Life Years, related to disease incidence data, were used to compare ventilation strategies on England's statutory Approved Document F for mitigating exposure to $PM_{2.5}$ air pollution from cooking meals, on existing dwellings at a population scale. Our approach yielded a median annual DALYs per 100,000 of an exposed population of Strategy A (infiltration only) of 6.1×10^3 (95%C.I. $1.1\text{-}21.8\times10^3$), whereas instituting a 30 L/s extract through a cooker hood with 50% capture efficiency for the cooking period plus 10 minutes (Strategy F) lowered the harm to 1.8×10^3 (95% C.I. $0.4\text{-}8.2\times10^3$), representing a median decrease by 53% (mean 64%). Health benefits are quantified as 3.2×10^3, 95% CI:0.5-20.3×10^3 averted Disability Adjusted Life Years per 100,000 of exposed population per year by implementing Strategy F over A. Therefore, using a cooker (has the potential to)-make a tangible difference to the health of the occupants. These numbers describe the burden from all-time exposure/intake of $PM_{2.5}$ pollution from the cooking scenarios.

A focus should be made towards health-based metrics, as wide information and data sources exist for computing them. Relying solely on threshold-based approaches might lead to un-accounting the benefits on health burden associated with implementing a pollution reduction strategy, since this change would not be tangible in high (ambient- or indoor)- air pollution scenarios exceeding the chosen threshold. Expected interested parties in these results include policymakers, scientists, and the general public.

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A5.2 Conference Paper CIBSE

This section includes the conference paper referenced in the main text.

A Harm Budget Approach to Indoor Air Quality Acceptability

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Abstract

This paper used the Disability Adjusted Life Year to quantify and rank the harm from exposure to airborne contaminants in dwellings. The main results from this work identified $PM_{2.5}$ as the most harmful contaminant, followed by coarse particulate matter, nitrogen dioxide, ozone, and formaldehyde. For this reason, they are now designated as Contaminants of Concern (CoC). The CoCs were used to formulate a harm budget approach, which sets an acceptable threshold for total harm caused by exposure to all CoCs. Policy makers can use the harm budget approach to determine acceptable harm in indoor environments. The ASHRAE 62.2 standard has proposed adding the harm budget, i.e. a harm-based procedure as an alternative compliance method, marking a significant shift in thinking and the use of evidence.
Keywords Disability Adjusted Life Year (DALY), contaminants of concern, harm, harm intensity, effect factor, harm budget.

1.0 Introduction

Indoor air quality is often assessed on the basis of occupant perception and can be influenced by odours and various contaminants (1, 2). Other metrics include sub-indices, exposure limit values, and rating systems, but they all have disadvantages (3). The ANSI/ASHRAE 62.2 (4) standard provides requirements for ventilation and acceptable indoor air quality for residential buildings. It is used by professionals and organisations involved in the design, construction, and operation of residential buildings and is mandated by programs, building codes, and regulations worldwide. Health and comfort are the main considerations of the standard (5). Policy makers must consider the potential health risks of indoor air contaminants, which is a leading contributor to the global burden of disease (6). Indoor contaminants should be identified and ranked based on the harm they cause and by the likelihood of their presence in indoor air. Health-centered metrics, such as the Disability-Adjusted Life-Year (DALY), can be used to measure and rank the impact of indoor air contaminants on population morbidity and mortality (7).

In the past, Air Pollution Health Risk Assessment (AP-HRA) tools (8) and Life Cycle Impact Assessment (LCIA) methodologies (9) have quantified the chronic health effects of airborne contaminants using the DALY metric. AP-HRAs quantify DALYs by relating observed changes in the disease incidence of a population to local changes in contaminant concentrations, whereas LCIAs apply Effect Factors (EF), which are the number of DALYs per unit of mass uptake of a contaminant. To increase understanding of the potential harm caused by indoor air contaminants, Logue *et al.* (10) proposed a methodology that combines disease incidence data and effect factors, accounting for input/output uncertainty. They introduced the Intake-Incidence DALY (IND) method and the Intake-DALY (ID) method for estimating the population-average health costs caused by the chronic inhalation of several airborne

contaminants frequently found in US dwellings. The IND method is similar to AP-HRA tools, while the ID method is similar to the LCIA methodology.

While the models of Logue *et al.* represented a significant advance, they have limitations. For example, the data used to describe contaminant concentrations, inhalation uptakes (rate of volume of inhaled air), risk estimates (fractional change in disease burden), disease incidence (number of cases of a disease per unit time), and damage factors (DALYs per disease incidence) were all specific to US dwellings. Additionally, the effect factors they used were originally proposed by Huijbregts *et al.*(11), which only accounted for uncertainty in some parameters. However, Logue *et al.* stated that alternative statistical approaches and new data might be used in the future to reduce the large uncertainties in these factors. Therefore, a method was followed to augment the approach of Logue *et al.* using the most up-to-date epidemiology and toxicology research published over the last decade.

Assessing the harm caused by indoor air contaminants requires considering the concentration of the contaminant. Concentration is the primary measure because guidelines and standards often use threshold values based on concentrations (12, 13). Moreover, particular scenarios can use reference concentrations.

A harm budget is a way to determine an acceptable level of harm that a particular environmental factor can cause, such as airborne contaminants in buildings. The harm budget can be expressed and communicated to interested parties using the number of DALYs lost due attributable to exposure to an environmental factor. For example, in the context of indoor air quality and the ventilation in buildings, the adoption of a harm budget can be used to set standards or guidelines for acceptable concentrations of contaminants in indoor air based on their potential to cause harm to human health. The harm budget approach involves establishing a maximum acceptable level of harm, and then setting ventilation standards that are designed to ensure that the actual level of harm does not exceed this limit. By setting a harm budget, policymakers and regulators can help minimize the risk of physical harm from indoor air contaminants, while still allowing people to live indoors.

The definition of acceptable IAQ in 62.2 is constant and has binary outcomes. A building either has acceptable IAQ or it does not. This paper aims to discuss a harm budget approach for defining the acceptability of indoor air quality and explore potential ways in which the ANSI/ASHRAE 62.2 standard can adopt this approach. The results of this study can potentially inform the development of health policies, building codes, and regulations, as well as the design and operation of residential buildings.

2.0 Methods

Two methods were used to compute DALYs, based on the approaches of Logue *et al.* (10), the AP-HRA tools (8), and the LCIA methodology (9). These methods were chosen because of their established reliability and relevance to the research questions being addressed.

2.1 The IND-method

The IND-method closely follows the methodology applied by AP-HRA tools and uses epidemiologically based Concentration-Response functions to quantify disease incidence rates ($I_{k,i}$, case/person/year) for a specific contaminant (i) and health outcome (k) for a population size (N). The incidence rate is then combined with a damage factor ($DF_{k,i}$, DALY/case), which is the quotient of the number of DALYs and the disease incidence rate, to estimate harm (in DALY/person/year). Note that the addition of individual health outcomes (k) would result in an all-cause effect (K).

$$harm_i = \sum_{k=1}^{K} DF_{k,i} \cdot I_{k,i} \quad (1)$$

The second term on the right of equation (1), disease incidence, refers to the relationship between contaminant concentration (C_i, usually in µg/m^3), risk of disease ($\beta_{k,i}$, 1/µg/m^3), and baseline incidence ($\gamma_{0_{k,i}}$, case/person/year). This relationship is modeled using the log-linear concentration response function shown in Equation (2). It is generally recommended to use mortality data to represent disease incidence for most airborne contaminant-related diseases, as mortality is expected to have a greater impact on the global disease burden than morbidity (6). This approach allows the health impacts of indoor air contaminants to be quantified accurately using relevant epidemiological data and measures of the severity of diseases or injuries.

$$I_{k,i} = \gamma_{0_{k,i}} \left(1 - e^{-(\beta_{k,i} \cdot C_i)}\right) N \quad (2)$$

The concentration of a contaminant (i), represented by C_i, can be a dwelling representative or reference concentration. This variable is essential for assessing the harm caused by indoor air contaminants, as it determines the magnitude of exposure and the potential physical health impacts. The choice of concentration metrics depends on the research question and the available data.

$\beta_{k,i}$ is an empirical parameter representing the estimated change in risk for a given change in contaminant concentration, ΔC, for a contaminant (i) and a health outcome (k). This parameter is expressed by

$$\beta_{k,i} = \frac{Ln(R)}{\Delta C_{k,i}} \quad (3)$$

where R is the relative risk, and ΔC_i is the change in contaminant *i* concentration.

The IND method is used to estimate the human epidemiological effect factor ($EF_{k,i}$, DALY/kg). This method involves combining a breathing rate (BR, m^3/person/year) with a concentration where

$$EF_{k,i} = \frac{harm_{k,i}}{BR \times C_i} \quad (4)$$

In this study, the IND-method was improved by following Life Cycle Impact Assessment methodologies. The resulting effect factor allows the calculation of the health impacts of indoor air contaminants based on the breathing rate and the human uptake of them. Furthermore, is important when assessing the acceptability of indoor air quality because it considers the concentration of the contaminants, which is already a metric used by many building codes and regulations.

2.2 The ID-method

The ID-method follows a LCIA methodology and the work of Huijbregts *et al.* (2005) and uses effect factors ($EF_{j,i}$) and the uptake (Q_i) of a specific contaminant (i) to estimate harm in DALYs lost, where

$$harm_i = \sum_{j=1}^{J} E_{j,i} \cdot Q_i \quad (5)$$

The uptake is a function of the breathing rate and the indoor air contaminant concentration.

$$Q_i = C_i \cdot BR \quad (6)$$

The sum of $EF_{j,i}$ (where j indicates carcinogenicity or non-carcinogenicity) is derived as

$$EF_i = \left(EF_{cancer,i} \cdot ADAF\right) + EF_{noncancer,i} \quad (7)$$

where $ADAF$ is a cancer risk age-dependent adjustment factor.

This study evolves the effect factors of Logue et al. by applying principles and insights from current approaches in LCIAs (9, 14). This updated approach allows for more accurate and nuanced assessments of the health impacts of indoor air contaminants a populations of people, as it uses a dose-response factor ($DRF_{j,i}$, case/kg) that indicates the change in morbidity and/or mortality per unit of mass uptake, and a damage factor (DF_k ,DALY/case) that is solely representative of a disease and is unspecific to any particular contaminant

$$EF_{j,i} = DRF_{j,i} \cdot DF_k \quad (8)$$

The dose-response factor is the quotient of a constant and the median effective dose, $ED_{50j,i}$.

$$DRF_{j,i} = \frac{0.5}{ED_{50j,i}} \quad (9)$$

$ED_{50j,i}$ is a measure of the human-equivalent daily dose received by a person over their lifetime that produces a specific effect in 50% of a population (15-17). The constant of 0.5 relates the inverse of the ED50 to the probability of developing a disease. For example, a default multiplier of 0.5 is used for human carcinogenic effects, which assumes a linear relationship between the dose and the probability of cancer. This assumption is currently used in LCIA research (18-22).

2.3 The input data

This study obtained values for the parameters used in the IND and ID methods by combining systematic reviews with supplementary references and pooling independent data points. This approach is recommended for data synthesis (23).

For the IND method, the study gathered values for beta, baseline incidence, and damage factor through a combination of systematic reviews and the literature, compiling and reviewing risk estimates (6, 13, 24) and the USEPA Integrated Science Assessments and Global Burden of Disease studies. The baseline disease incidences are derived from epidemiological studies.

For the ID method, damage factors representing overall cancer or non-cancer effects are based on the latest data from the World Health Organisation (WHO) and/or the Global Burden of Disease studies (25). The dose-response factor data for this study is extracted from the UNEP-SETAC consensus model for the evaluation of comparative toxicity, known as USEtox-2019 (18). The USEtox model is chosen for deriving DRFs because it is a widely used model with global scientific consensus and is the default model for screening for the toxicity of contaminants in Life Cycle Assessments (LCAs). In addition, this model has been validated by a range of studies (26-29). The Age-dependent adjustment factor (ADAF) parameter, used for the estimation of cancer risks, is reported in the literature for the estimation of cancer risks as i) a 10-fold ADAF exposures before 2 years of age, ii) a 3-fold ADAF for

exposures between 2 and <16 years of and iii) ADAF of unity for exposures after after 16 years of age. The breathing rates are determined from relevant sources through a literature review; 14.80 m^3/person/day for adults 16-81+ years is used, accounting for updated information and data variability (30-33).

The concentration parameter C_i in the IND and ID methods depends on the desired output. This study considers two scenarios. In the first scenario, C_i is based on *representative concentrations* of contaminants in dwellings derived from a systematic review of measurements (34-37). The aim of using representative concentrations for this scenario is to obtain the expected total harm in dwellings. This allows to rank contaminants based on their contribution to total harm and to identify which contaminants are of concern. The second scenario involves applying the IND and ID methods to the contaminants of concern identified in the first scenario using *reference concentrations*. In this case, C_i can be based on the expected concentrations of contaminants in dwellings that meet a particular ventilation building standard (38-43) or on air-quality guidance levels (44). In the second scenario, the IND and ID methods use reference concentrations as inputs to estimate an acceptable harm budget; this is the maximum amount of harm considered acceptable based on these reference concentrations.

2.4 The modeling

The Monte Carlo (MC) method was applied to obtain an estimate of harm and effect factors that accounts for the uncertainty of the parameters. A bootstrapping technique was used to populate a synthetic database for each parameter and describe the resulting data using a probability distribution function (PDF). The PDF was then combined with the bootstrapped results to generate random samples of the inputs, which were used to compute the two outputs: i) effect factors (as DALY/kg) and ii) harm (as DALY/person/year). The process is repeated until the mean averages of the results were normally distributed. All outputs are reported by their median and 95% confidence interval (CI) of their distribution, representing the range that contains 95%CI of the population values.

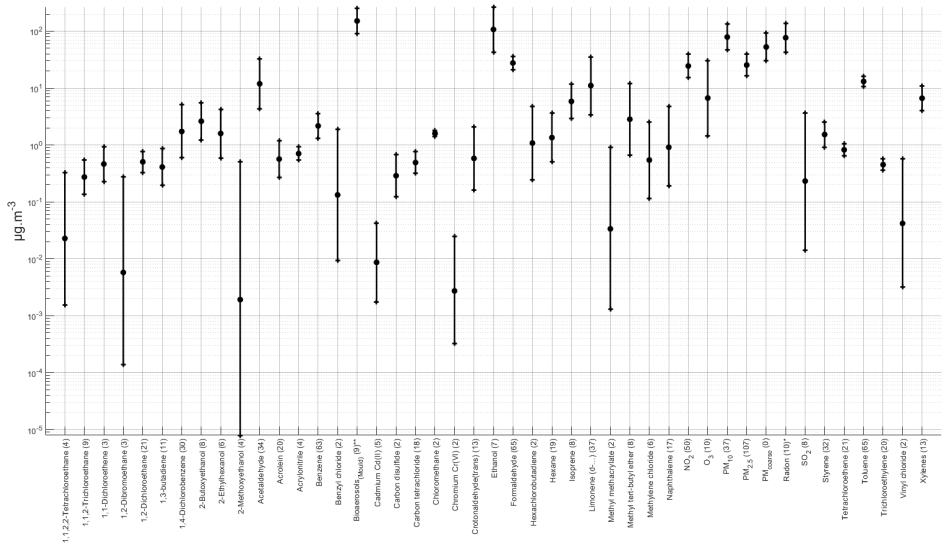
Preliminary analysis of the input data showed that it can be well described by a lognormal distribution around its median. This type of distribution is widely used and accepted for adequately adjusting for right-skewed data (45). A MATLAB code was used to run the Monte Carlo simulations and computed all pooled estimates (meta-analysis) with STATA 17.0's "metan" commands using the DerSimonian and Laird (random effects) estimators (46-48).

Each method derives an estimate of harm and effect factors (one estimate via the IND method and one via the ID method) and so the results are pooled from each independent method via a meta-analysis to obtain a single value that considers both the epidemiological and toxicological research.

3.0 Results and Discussion

3.1 Total harm

The evaluation was limited to 45 contaminants and their representative concentrations because to they were previously identified as contaminants of interest in dwellings (10, 49). Figure 1 shows the representative mid-range concentrations of each contaminant, a 95% confidence interval, and the number of individual values used to compute them. Generally, the mid-range indoor concentrations fall within the values reported by others (34, 35). With over 50 data sets, $PM_{2.5}$, formaldehyde, toluene, benzene, and nitrogen dioxide are the contaminants with the most reported values.



*Radon in Bq.m^{-3}. **Bioaerosols in CFU.m^{-3}

Figure 1 – Representative concentrations of the 45 contaminants analysed, in alphabetical order. Central estimate and 95% CI of distribution in black. The number of datasets in parentheses.

For each of the 45 contaminants, epidemiological evidence was found for the beta parameter and the baseline incidences, and the damage factors for ten of them: acrolein (C_3H_4O), benzene (C_6H_6), bioaerosols$_{mold}$, formaldehyde (HCHO), nitrogen dioxide (NO_2), ozone (O_3), respirable particulate matter (PM_{10}), fine particulate matter ($PM_{2.5}$), Radon (Rn), and sulfur dioxide (SO_2) (see Table 1 for a summary of the epidemiology evidence considered in this paper for selected contaminants). This study's methodology involved identifying a single representative health outcome for each of the ten contaminants. The health outcome chosen to represent each contaminant was the most reported health impact associated with it, either for mortality or morbidity endpoints. This was taken as the best estimate for all-causes.

Table 1 – Summary descriptive of epidemiology-based parameters[+]

Contaminant	Health Outcome	Beta parameter (β)	Baseline incidence rate (γ_0)	Damage factor (DF_{IND})
		Parameter values [Datasets] [Main reference]		
C_3H_4O	Asthma morbidity	0.141 (95%CI 0.082-0.200) [2] [(50)]	0.001 [(50)]	0.588 (95%CI 0.059-5.875) [1] [GBD]
NO_2	All cause mortality	0.002 (95%CI 0.001-0.004) [24] [(13)]	0.013 (95%CI 0.001-0.132) [(51)]	17.034 (95%CI 8.589-29.727) [1] [OS/RD]
O_3		0.001 (95%CI 0.000-0.002) [7] [(13)]	0.008 (95%CI 0.004-0.016) [(52)]	15.346 (95%CI 6.856-34.348) [3] {(53)}
PM_{10}		0.004 (95%CI 0.003-0.006) [17] [(13)]	0.013 (95%CI 0.012-0.015) [(51)]	9.554 (95%CI 6.403-14.255) [3] [OS/RD]
$PM_{2.5}$		0.008 (95%CI 0.000-0.002) [25] [(13)]	0.007 (95%CI 0.003-0.018) [(52)]	14.954 (95%CI 11.627-19.233) [40] [OS/RD]

The column of Health Outcome shows the best estimate for all-cause health outcome. OD/SR: Own data/ Systematic Review. [+]Other contaminants not shown due to spacing issues and are available upon request. GBD :https://ghdx.healthdata.org/gbd-results-tool

Table 1 presents the damage factors for the contaminants in the IND model and the corresponding number of datasets found is in brackets. These damage factors were calculated using a method that yielded damage factors for a broader range of contaminants not previously presented (54). The results are based on contaminant- and health outcome-specific effects, allowing for the reduction in information gaps on contaminant-related damage factors.

Table 2 presents selected toxicology evidence for certain contaminants. The 95% confidence intervals shown for the dose-response factors are novel because the USEtox database does not provide measures of uncertainty for the DRFs. The damage factors represent an update those used by Huijbregts *et al.* (11) and are a new contribution to the field.

Table 2– Summary descriptive of toxicology-based parameters[+]

Contaminant	DRF_{cancer}	$DRF_{non-cancer}$	DF_{cancer}	$DF_{non-cancer}$
	From USEtox Database [health outcome]		From GBD [health outcome]	
C_3H_4O	NA	59.74 (95%CI 1.82-1963.49) [non-carcinogenic effects]	NA	0.59 (95%CI 0.44-0.77) [Asthma]
HCHO	1.06 (95%CI 0.27-4.25) [carcinogenic effects]	0.01 (95%CI 0.00-0.15) [non-carcinogenic effects]	41.77 (95%CI 38.60-45.15) [added Leukaemia and lung cancer]	0.59 (95%CI 0.44-0.77) [Asthma]
O_3	1.09 (95%CI 0.16-7.60) [carcinogenic effects]	NA	21.18 (95%CI 20.06-22.36) [Lung Cancer]	NA
PM_{10}	NA		NA	
$PM_{2.5S}$				

Note. Health outcome in curly brackets is the best estimate of all-cause health outcome c = carcinogenic; nonc = non-carcinogenic. NA= not applicable. GBD: https://ghdx.healthdata.org/gbd-results-tool [+]Other contaminants not shown due to spacing issues and are available upon request.

Both toxicological and epidemiological data were available to derive harm and effect factors for five contaminants: C_3H_4O, C_6H_6, HCHO, O_3, and Rn. Equation (7) was used to calculate the combined toxicological effect factors for carcinogenic and non-carcinogenic contaminants for 39 contaminants, and Equation (4) was used to calculate the epidemiological effect factors for ten contaminants. Finally, results are pooled to give effect factors for all 45 contaminants. Figure 2 shows that $PM_{2.5}$ has the highest effect factor [$1.1 \cdot 102$ (95%CI $3.6 \cdot 10^{1}$-$3.3 \cdot 10^{2}$)], indicating that it has the highest chronic health impacts per kg inhaled, an order of magnitude higher than all other contaminants. Other PMs also have high effect factors, as do chromium, nitrogen dioxide, and formaldehyde, which all have effect factors of $>10^{1}$. These results update the comprehensive work on human-toxicological and epidemiological effect and damage factors of carcinogenic and non-carcinogenic chemicals for life cycle impact assessment. The results have narrower confidence intervals compared to those of Huijbregts *et al.* (11).

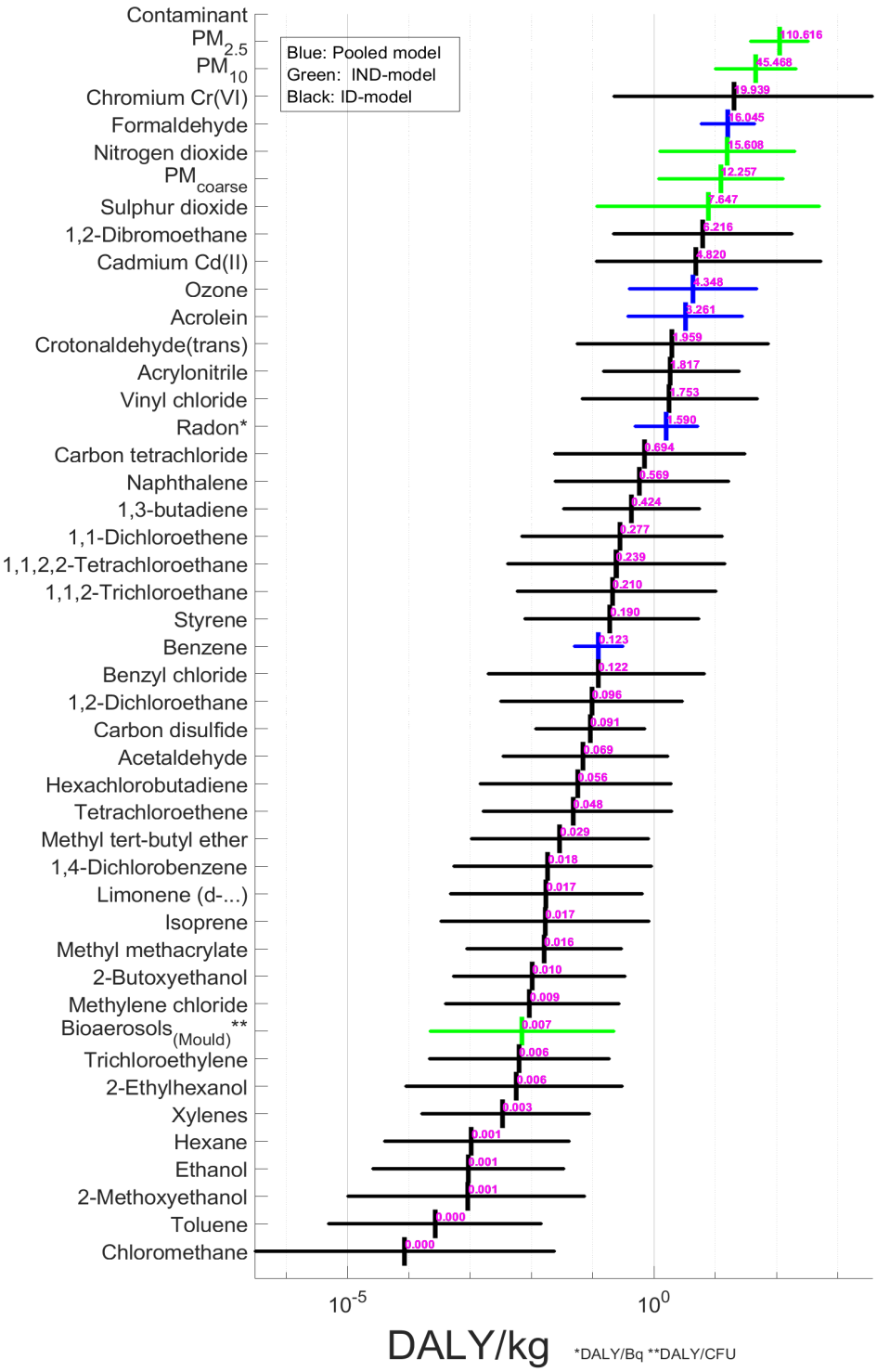


Figure 2 – Effect factors. Highest to lowest magnitudes. Medians and 95%CI.

Figure 3 shows the total harm per 100,000 people, with corresponding 95%CI . The results of this study show that PM_{10} and $PM_{2.5}$ are the contaminants with the highest median pooled DALY loss estimates, with values of $1.9 \cdot 10^3$ and $1.5 \cdot 10^3$, respectively. These values are accompanied by uncertainty intervals of 95%CI $4.4 \cdot 10^2$ - $8.7 \cdot 10^3$ and 95%CI $5.3 \cdot 10^2$ - $4.4 \cdot 10^3$, respectively. Other contaminants with substantial median pooled DALY loss estimates include PM_{coarse}, formaldehyde, nitrogen dioxide, radon, and ozone, with values ranging from 10^1-10^3. Acrolein and sulfur dioxide have lower estimates of 10^1. It is worth noting that the confidence intervals for these results show a lower uncertainty range compared to those presented in previous research (10).

Contaminants with the highest median DALYs include five of the six so-called *criteria pollutants*[1]*:* PM_{10}, $PM_{2.5}$, NO_2, O_3, and SO_2. In addition to these criteria pollutants, other contaminants with elevated DALY values and evidence of health impacts in the indoor environment include formaldehyde (55), radon (56), acrolein (57), and mold (58).

After running the ID and IND models and pooling the results, six major contaminants were identified: $PM_{2.5}$ (particulate matter with a diameter less than 2.5 micrometers), PM_{coarse} (particulate matter with a diameter between 2.5 and 10 micrometers), HCHO (formaldehyde), NO_2 (nitrogen dioxide), Rn (radon), and O_3 (ozone). These six contaminants account for 99% of the total harm, so that they can be defined as *contaminants of concern* in dwellings.

3.2 The harm budget

To determine an acceptable level of harm, reference concentrations are required for the contaminants of concern. A study of 70 Californian homes was applied as a reference for $PM_{2.5}$, HCHO, and NO_2 concentration at 5, 23, and 9 $\mu g/m^3$, respectively (38). All houses were detached and built between 2011 and 2017 and were found to comply with the mechanical ventilation requirements of California's building energy efficiency standards. Therfore, their contaminant concentrations can be used to reflect the total harm caused by air quality considered *acceptable* by the current Californian building energy efficiency standards. Accordingly, it is used to calculate the acceptable harm, or *harm budget*, for all homes so that the harm budget matches current complaince. The acceptability of this harm can be discussed in the future when it is compared against other activities that have a socially and politically acceptable level of harm using a risk analysis approach.

The coarse fraction was assumed to be 40% of the PM_{10} (59). Unfortunately, no references were found for measurements of O_3 and Rn in dwellings that comply with a ventilation standard, so guideline values were used as their reference concentrations at 40 $\mu g/m^3$ and 100 Bq/ m^3, respectively (44). It should be noted that these concentration guidelines are not based on real-life scenarios for buildings that comply with a given ventilation standard, and are sometimes established for statistical, health protection, or policy purposes.

The ID and IND methods were then run again using these reference concentrations to estimate the resulting harm. In absolute terms, the harm budget estimate was calculated to be 1215 DALYs/10^5person/year, considered as the harm acceptable by the current standard. When comparing this budget to the total harm from typical concentrations in dwellings, shown in Figure 3 (~2500 DALYs/10^5person/year), it can

[1] The criteria pollutants is a group of six outdoor air contaminants that are regulated by the United States Environmental Protection Agency (EPA) due to their harmful effects on human health and the environment 13. Organization WH. WHO global air quality guidelines: particulate matter (PM2. 5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide: World Health Organization; 2021.

be deduced that the harm budget limit might be exceeded in these dwellings by ~200%.

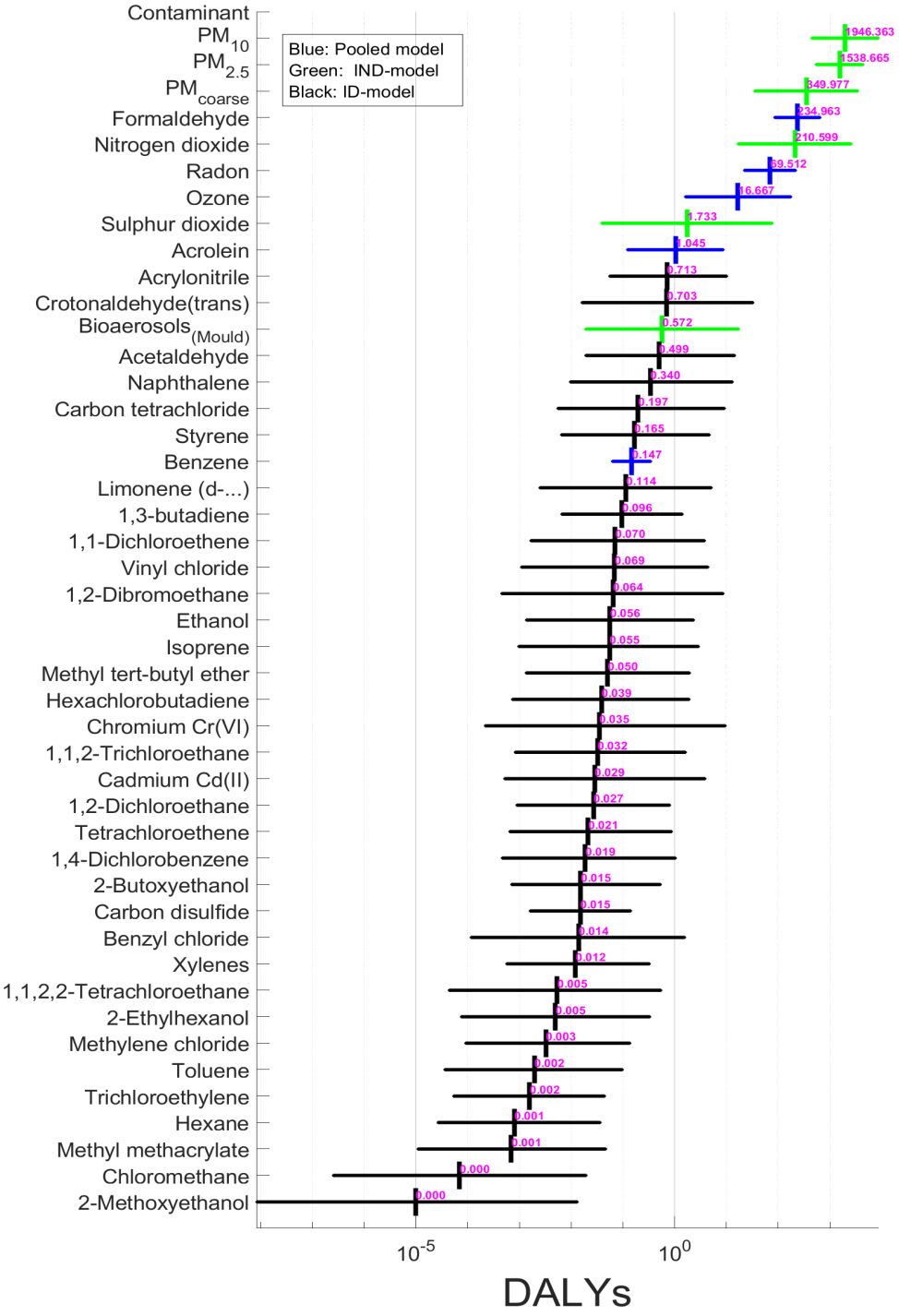


Figure 3 – Total Harm, as DALYs per 100,000 person-year. Highest to lowest magnitudes. Medians and 95%CI.

3.3 Recommendations for future work

The authors used the DALY metric to estimate harm of all 45 contaminants and to identify six contaminants of concern, which are likely to comprise 99% of the total harm. However, to make the most of the harm budget approach and include it in relevant standards, several key aspects should be considered by interested parties:

- The analysis was based on effect factors, which relate harm to uptake using measures of mass. However, in the built environment, concentrations are more relevant (12, 13) because they can be measured and because they are used by existing standards to regulate indoor air quality. Therefore, a new metric is required, termed a *harm intensity*, which represents the increase in DALYs due to chronic exposure to a specific concentration of a contaminant (expressed as DALY/µg/m^3/year/person).
- Limiting the contaminants of concern to two or three of the most harmful would be beneficial to make source control, remediation, and enforcement simpler.
- Instead of using absolute terms, it would be useful to consider the harm budget in relative terms, using a unitless magnitude.

3.4 A connection to the ASHRAE 62.2 standard

In November 2022, the ASHRAE Standards Project Committee, responsible for maintaining ASHRAE Standard 62.2 - Ventilation and Indoor Air Quality for Residential Buildings, voted to release a proposal that adds an optional path based on the health effects of three of the six contaminants of concern identified here. The committee is using the work contained herein on representative concentrations and harm intensities as their fundamental scientific approach, but specific provisions are outside the scope of this paper. This represents the first attempt to use this approach, and to use the DALY metric, to quantify harm in dwellings in a regulatory environment. Other desition makers, such as the Chartered Institute of Building Services (CIBSE) might be interested in these findings when reviewing their ventilation and IAQ standards.

4.0 Conclusions

The study identified six airborne contaminants of concern in dwellings: $PM_{2.5}$, PM_{coarse}, HCHO, NO_2, Rn, and O_3. These contaminants are found to contribute a total of 99% of the total harm from exposure to airborne contaminants in dwellings. The DALY metric was used to estimate the harm caused by these contaminants and determined the acceptable harm budget to be 1215 DALYs/10^5person/year. Typical dwellings exceed the acceptable harm budget by more than 200%. To optimize the harm budget approach and incorporate it into relevant standards, it is proposed to use a metric that directly relates harm to the concentration of indoor airborne contaminants, limiting the contaminants of concern to the most harmful, and using a relative harm budget. The ASHRAE Standards Project Committee has voted to release a proposal that adds an optional path for Ventilation and Indoor Air Quality compliance in Standard 62.2 based on the health effects from three contaminants using this harm approach. Policy makers can also use the harm budget approach to establish acceptable levels of harm in regulatory contexts and health policies.

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