Opinion: how will advances in aerosol science inform our understanding of the health impacts of outdoor particulate pollution?

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Abstract. Air pollution, with high levels of particulate matter (PM), poses the greatest environmental threat to human health, causing an estimated seven million deaths annually and incurring 5% of the global GDP. While PM health impacts are influenced by the toxicity of its individual chemical constituents, the PM mortality burden is solely based on its total mass concentration. This is because of a lack of large-scale, high-resolution PM chemical composition data needed for epidemiological assessments. Identifying which PM constituents are harmful for health has been the 'Holy Grail' of atmospheric science, since the seminal six US cities study that first linked PM to mortality in 1993. Ever since, atmospheric scientists have focused on understanding aerosol composition, emission sources and formation pathways, while longitudinal epidemiological studies needed individual level exposure data, using land use regression models for the prediction of exposures at fine resolutions. In this opinion article, we argue that the time has now come to shift focus towards considering PM chemical composition in epidemiological health assessments, laying the foundation for the development of new regulatory metrics. This shift will enable targeted guidelines and subsequent regulations, prioritizing mitigation efforts against the most harmful anthropogenic emissions. Central to this shift is the availability of global long-term, high resolution PM chemical composition data obtained through field observations and modelling outputs. In the article, we underscore key milestones within aerosol science integral for advancing this foundational shift. Specifically, we examine emerging modelling tools for estimating exposure to individual PM components, present the type of ambient observations needed for model developments, identify key gaps in our fundamental understanding of emissions and their atmospheric transformation and propose a forward cross-disciplinary collaboration between aerosol scientists and epidemiologists to understand the health impacts of individual PM components. We contend that aerosol science has now reached a pivotal moment in elucidating the differential health impacts of PM components, as a first step toward their incorporation into air quality guidelines.

1. Preamble

1.1 A brief chronology of air pollution

A tale of global air pollution has already been narrated by Fowler et al., and only a brief chronology will follow, presenting the main milestones reached by the atmospheric science community since the earliest recorded accounts of air pollution (Fowler et al., 2020). The threat of air pollution to human health has been recognized since the time of Hippocrates, around 400 BCE (Jones et al., 1923). Successive written accounts of air pollution occur throughout the following two millennia until

measurements from the eighteenth century onwards demonstrated the growing scale of poor air quality in urban centres. One of the most emblematic early historical documents on air pollution was published in 1661 under the title *Fumifugium* by Evelyn (Evelyn, 1772). Evelyn documented air pollution in London and proposed solutions for reducing the scale of the problem by moving industries to the countryside. Graunt, a contemporary of Evelyn, observed a correlation between rates of mortality and pollution, especially during fog episodes, albeit in the absence of any chemical data or numerical values to quantify the pollutants present (Graunt, 1939). Later, in 1775, Sir Percival Pott was one of the first to document the effects of specific pollutants on health. Pott observed a high incidence of scrotal cancer among chimneysweepers and concluded that exposure to soot was a risk factor for the cancer (Brown and Thornton, 1957).

The industrial revolution accelerated the growth and geographical spread of emissions, as highly polluted cities became the defining problem that culminated with the great smog of London in 1952. This pollution episode of a few days duration caused an estimated 10,000 deaths and injury to more than 100,000 persons (Stone, 2002; Bell et al., 2004). The London smog is believed to be the worst air pollution event in the history of the United Kingdom and the most notorious for its effects on environmental research, government regulation, and public awareness of the relationship between air quality and health. It was instrumental for establishing an unambiguous link between short-term exposure to peak levels of pollution and acute health effects. It also led to the introduction of the Clean Air Act of 1956 that aimed to reduce emissions and mitigate future pollution events. Until the latter decades of the twentieth century, Europe and North America dominated global emissions and suffered the majority of adverse health and environmental effects. By that time, the transboundary issues of acid rain (Egnér and Eriksson, 1955) and ground-level ozone (Volz and Kley, 1988; Fowler et al., 2008) were the focal environmental and political air quality problems (Vasseur, 1973). As emission controls took effect in the Western world, Asia rapidly industrialized, emerging as the primary contributor to global emissions by the early twenty-first century.

Towards the end of the 20th century, the health effects of air pollution resurfaced as a top priority, as new epidemiological evidence highlighted this time the breadth of chronic health problems resulting from long-term pollution exposures (Brunekreef and Holgate, 2002). For this, the emergence of extensive networks of surface measurements, satellite remote sensing, and numerical models was indispensable for providing global air quality data with which epidemiologists could estimate the adverse health effects of air pollution. Since then, numerous studies have documented the chronic and acute health effects of air pollution and burden of disease, many with a global perspective (Burnett et al., 2018; Cohen et al., 2017; Mcduffie et al., 2021; Richard T. Burnett, 2014; Lelieveld et al., 2015; Lelieveld et al., 2019; Chen et al., 2018b; Chen and Hoek, 2020; De Bont et al., 2022; Holtjer et al., 2023; Nyadanu et al., 2022). Today, air pollution remains a major public health concern, and efforts continue to reduce emissions and improve air quality.

1.2 Particulate air pollution

The polluted air we breathe can contain high levels of particulate matter, PM, commonly termed aerosols. PM is a complex mixture of tiny solid or liquid particles suspended in the air, with a size ranging from a few nanometers to a few micrometers (John H. Seinfeld, 2016). These particles can be directly emitted from primary sources, or be formed in the atmosphere by gas-to-particle conversion of secondary oxidation products, e.g. sulfate from SO_2 oxidation, nitrate from NO_X oxidation or secondary organic aerosol (SOA) from the oxidation of volatile organic vapours. Primary PM sources can be either natural or human-made. Natural sources include desert dust, sea-spray, wildfires and biogenic SOA

from the oxidation of plant volatiles, while anthropogenic sources include emissions from residential heating or car exhaust and their secondary oxidation products. As a result, PM has an immensely complex chemical composition with different levels of toxicity depending on the emission sources and/or formation processes (Hallquist et al., 2009; Jimenez et al., 2009). Smaller particles are more likely to enter our bloodstream and travel deep into our lungs, causing damage. Short-term exposure to peak levels of PM can cause acute health effects (Dockery et al., 1993; Liu et al., 2023; Nhung et al., 2017). By contrast, long-term exposure can lead to chronic diseases, such as cardiovascular, cerebrovascular (De Bont et al., 2022) and respiratory diseases (Holtjer et al., 2023), which are responsible for a large share of the air-pollution-related mortality (Burnett et al., 2018; Cohen et al., 2017; Chen and Hoek, 2020). Current epidemiological evidence reveals that no level of air pollution can be deemed safe, and even low levels of PM may carry significant risks (Strak et al., 2021; Pinault et al., 2016; Cohen et al., 2017; Dominici et al., 2022; Brunekreef, 2021; Brauer et al., 2019). Today, according to the Global Burden of Disease project, PM pollution is responsible for an estimated seven million deaths every year (Burnett et al., 2018). This positions PM among the five leading causes of deaths worldwide, alongside high blood pressure, smoking, diabetes and obesity (Cohen et al., 2017).

1.3 PM mitigation: a global challenge of the 21st century

Although particles are compositionally heterogeneous with notable temporal and spatial variations, most studies investigating their adverse health effects used total PM mass concentration, treating them as a uniform entity. This is because total PM mass concentration was routinely measured, primarily as $PM_{2.5}$ in the USA and PM_{10} in Europe[1], and used as the basis of exposure assessment – either directly or modelled – in epidemiological studies. As a result, and based on the accumulated evidence, PM mass serves today as the primary metric for particulate pollution regulation.

In 2021, the World Health Organization, WHO, updated its air quality guidelines to propose a much more stringent limit value for $PM_{2.5}$ of 5 µg m^{-3} (Who). These new guidelines provide a basis to justify aggressive regulation of anthropogenic emissions to improve global air quality. However, such low $PM_{2.5}$ concentrations are currently only found in few remote environments, and over 95% of the world population lives in places where the new guidelines are not met. Several western countries have made significant progress over the past 20 years to meet the former WHO limit for $PM_{2.5}$ of 10 µg m^{-3} last updated in 2005 (Southerland et al., 2022; Hammer et al., 2020). In contrast, $PM_{2.5}$ levels exceeding 50 µg m^{-3} are typical in low- to middle-income countries, e.g. in Eastern-Europe, China or India, where 90% of attributable deaths occur (Lelieveld et al., 2015). This translates to a loss of several years of life expectancy in Asia due to pollution, compared to several months in the West (Lelieveld et al., 2019).

Reducing fossil fuel dependence and residential emissions will undoubtedly significantly improve air quality, especially in polluted environments (Pai et al., 2022; Mcduffie et al., 2021). However, natural sources including desert dust, wildfires and biogenic emissions alone will impede many regions from complying with the new WHO guidelines. This, however, is not a reason to dismiss the evidence-based limit values set by the WHO in 2021 that are set to protect health, but to improve on them. A recent landmark modelling analysis suggests that over 50% of the global population will still be living in places with $PM_{2.5}$ concentrations greater than 5 µg m^{-3}, even if all anthropogenic emissions would be eliminated (Pai et al., 2022). Moreover, natural emissions are likely to increase in the near future due to climate change, further complicating efforts to meet the 2021 WHO guidelines in certain regions (Gomez et al., 2023). Meeting these guidelines will be particularly challenging for many

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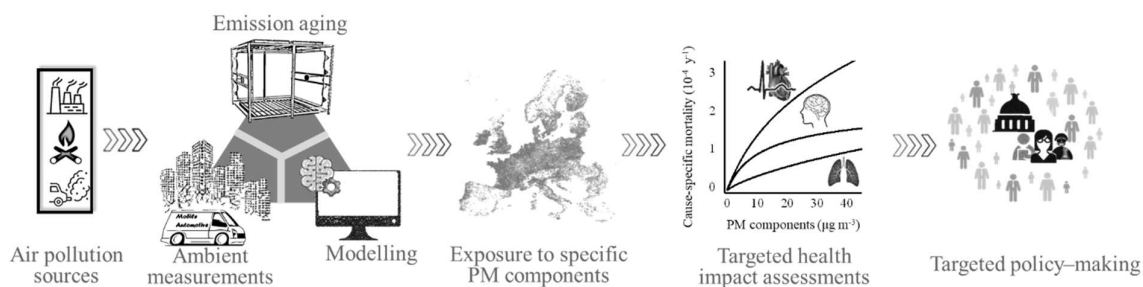
[1] $PM_{2.5}$ and PM_{10}: Particulate matter with a size lower than 2.5 and 10 µm, respectively.

127 regions worldwide, and globally applicable solutions to manage and improve air quality will become
128 no longer evident. This entails a complete rethink of how we should be mitigating air pollution and
129 underlines a need for a new generation of air quality metrics that focus on specific anthropogenic PM
130 components in addition to total PM mass.

131   Targeting particulate pollution across individual chemical components allows for the
132 consideration of their varying degrees of toxicity, a concept known as the "differential toxicity of PM
133 components" (Masselot et al., 2022). PM health effects are mediated by their size, solubility, and
134 chemical composition, and hence their sources and formation processes. In our recent work, we have
135 identified the organic and metal fractions to be of particular concern for oxidative stress (Daellenbach
136 et al., 2020) and inflammation (Leni et al., 2020), in contrast to secondary inorganic particles that
137 dominate PM mass. Given that oxidative stress and inflammation are one of the pathway to chronic
138 disease development (Mudway et al., 2020), this necessitates a closer inspection of which sources of
139 PM should be mitigated. It is therefore vitally important for aerosol scientists to provide global PM
140 chemical composition data, enabling epidemiologists to pinpoint the most detrimental components and
141 empowering policymakers to implement targeted, cost-effective measures to reduce specific health-
142 relevant anthropogenic PM sources across different regions.

143 **1.4 Introductory overview**

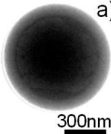
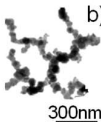
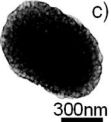
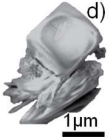
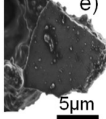
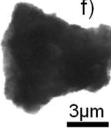
144   In this account, we discuss how the broader atmospheric science community can inform policies
145 and interventions to mitigate sources of PM components that pose risks to human health (Figure 1). We
146 advocate for a foundational shift towards considering PM deferential toxicity in epidemiological health
147 assessments, made possible through improved air quality modelling suitable for exposure assessment,
148 and present the key milestones within aerosol science that, in our view, are necessary for this shift.
149 Section 2 introduces the concept of PM differential toxicity and its potential as an exposure metric.
150 Section 3 critically examines recent advances in modelling tools for estimating fine-scale exposures to
151 specific PM components. In section 4, we identify the type of ambient observations we think are
152 essential for developing and validating exposure models. In section 5, we highlight remaining gaps in
153 our understanding of PM component emissions, their atmospheric transformation and associated health
154 effects and identify research opportunities. Section 6 delves into the need for strong collaboration
155 between research communities to elucidate biological mechanisms underlying the health impacts of
156 specific PM components.

157
158 **Figure 1:** The multidisciplinary framework needed to target PM differential toxicity in policies.

159   **2. Integrating PM chemical composition in health studies**

160 **2.1 PM differential toxicity as targeted air quality metric: more than just PM mass**

161   To quantify the health impacts of PM, we currently rely on dose-response relationships, ideally
162 derived from individual-level data from large cohort studies, that link morbidity and mortality to the

163   concentration of total PM mass. Whilst these relationships are from a broad evidence base, there is
164   significant heterogeneity in the estimated effect size. This variation can be partially attributed to
165   imperfect models approximating exposures or random differences among study populations. Yet,
166   perhaps a large source of error lies in relying solely on PM mass concentration, ignoring the biological
167   activity of different particle constituents. Although some studies have attempted to examine the adverse
168   health outcomes of individual PM components, particularly highlighting associations with combustion
169   and road traffic emissions, such investigations remain relatively infrequent due to the paucity of
170   exposure data. As a result, PM chemical composition has not yet been included into any regulatory
171   framework.

172   With the advent of vast amounts of atmospheric data, the time has now come to redirect our
173   focus towards elucidating dose-response relationships for individual PM constituents. In practical
174   terms, these constituents must be quantifiable, easily accessible, and readily available at the high spatio-
175   temporal resolutions needed for exposure assessment, and across large spatial scales. Our proposal
176   includes considering the following constituents: organic aerosol, elemental carbon, sulfate, nitrate,
177   ammonium, sea-salt, brake-wear, and dust (Table 1). While brake-wear and dust concentrations cannot
178   be directly measured, they can be traced using specific markers, such as Cu for brake-wear and Al for
179   dust. The organic fraction should be ideally subdivided based on a source sectors, including primary
180   and secondary aerosols from car exhaust, residential burning, wildfires, and biogenic emissions.
181   Organic aerosol classes also cannot be directly measured, though might be retrieved through receptor
182   modelling based on spectrometric measurements or chemical transport modelling, as discussed below.
183   The classification of aerosols based on their chemical composition will also establish a direct link to
184   aerosol sources (Table 1), offering policy makers effective and operational strategies for selectively
185   mitigating the most important PM sources for health.

186   Beyond PM chemical composition, various other properties have been proposed to mediate
187   aerosol health effects, including aerosol size, number, solubility, and oxidative potential (Table 1). For
188   example, toxic metals primarily induce oxidative damage in their soluble form (Fang et al., 2017; Wong
189   et al., 2020), whereas insoluble particles like asbestos or elemental carbon are biopersistent in the body,
190   leading to chronic inflammation. Likewise, small particles can penetrate deep into the lungs, traverse
191   the bloodstream and breach the blood-brain barrier, playing a role in respiratory, cardiovascular and
192   neurological diseases (Requia et al., 2017; Maher et al., 2016), while a notable portion of large particles
193   may be ingested leading to an imbalance in our gut microbiome (Fouladi et al., 2020; Alderete et al.,
194   2018; Bailey et al., 2020). Parameters for emerging metrics intended to be used in future
195   epidemiological studies should be standardized and widely available, which is currently unachievable
196   for some of these parameters. PM chemical composition, which is now widely available, is intertwined
197   with these alternative metrics (Table 1) and can constitute an effective mean to address PM health
198   effects.

199   **2.2 Necessity of PM chemical composition data at fine resolutions**

200   More than 70% of the world population is projected to live in urban areas by 2050, with these
201   densely populated agglomerations already being the most polluted environments (Mcduffie et al.,
202   2021). The composition and concentrations of PM in these areas exhibit significant spatial heterogeneity
203   from street to citywide scales. In some cases, intra-city variability exceeds the variability between
204   different cities (De Hoogh et al., 2016; Eeftens et al., 2016; Tsai et al., 2015; De Hoogh et al., 2013;
205   Eeftens et al., 2012a; Zhang et al., 2015; Jedynska et al., 2015). Such spatial heterogeneity is driven by
206   traffic patterns (Simon et al., 2017; Li et al., 2016a; Gu et al., 2018; Elser et al., 2018; Elser et al., 2016),

207 restaurant emissions (Gu et al., 2018), domestic heating emissions (Elser et al., 2018; Elser et al., 2016;
208 Jedynska et al., 2015; Mohr et al., 2011), industrial point sources (Shairsingh et al., 2018) and local
209 geography (Mohr et al., 2011). Atmospheric aging of urban emissions and long-range transport of
210 polluted air masses adds to this complexity, affecting PM background levels and composition on
211 regional scales.

Table 1: PM chemical components, reflecting differential toxicity, suggested to be monitored and modelled to support health research. Components' physical properties that are important determinant of health effects are shown, including size, morphology, and solubility. Components' major sources are also shown. a), b), and c) Transmission electron microscopic images of organic aerosol, elemental carbon aggregates and sulfate adapted from (Li et al., 2011). d) Scanning electron microscopic image of a fresh sea-salt particle adapted from (Li et al., 2016b). e) Scanning electron microscopic image of a coarse brake ware particle adapted from (Kukutschová and Filip, 2018). f) Transmission electron microscopic image of a mineral dust particle adapted from (Xu et al., 2021).

Component	Size	Morphology	Solubility	Source
Organic aerosol	Fine	a) 300nm	Moderately soluble for POA Soluble for SOA	Natural and anthropogenic, primary and secondary
Elemental carbon	Fine	b) 300nm	Insoluble	Biomass and fossil fuel combustion
Sulfate	Fine	c) 300nm	Soluble	Aqueous (65%) and gas phase OH (35%) oxidation of SO_2 from natural marine emissions (15%) and anthropogenic emissions from electricity generation and industries (85%) (John H. Seinfeld, 2016)
Nitrate	Fine		Soluble	Oxidation of NO_X emissions mainly from traffic exhaust
Ammonium	Fine		Soluble	Condensation of gas-phase ammonia mainly from agriculture emissions producing ammonium sulfate and nitrate
Sea salt	Coarse	d) 1µm	Soluble	Natural marine emissions through bursting bubbles at the air-sea interface
Brake wear (Cu)	Coarse	e) 5µm	Depending on the element	Brake pads
Mineral dust (Al, Si, Ti, Fe)	Coarse	f) 3µm	Depending on the element and atmospheric age	Natural wind-blown desert dust on a global scale, in addition, to resuspended dust on an urban scales

212 Urban microenvironments strongly affect long-term exposures to specific PM components
213 (Figure 2A). For example, studies have shown a link between road proximity, exposure to ultrafine

particles, and respiratory, cardiovascular, and neurodegenerative diseases (Alexeeff et al., 2018; Bayer-Oglesby et al., 2006; Yuchi et al., 2020; Boogaard et al., 2022). It has also been shown that exposures to high particle concentrations around train stations during typical daily commutes of less than one hour can contribute up to 21% of total daily PM exposure and more than 50% of daily exposure to key toxic metals such as Cu (Van Ryswyk et al., 2017). Given the substantial spatiotemporal variability in both PM concentrations and composition, it is imperative to determine PM chemical composition at fine spatial and temporal scales relevant to daily human activities. This understanding is vital for evaluating exposures to specific PM components and ultimately their health effects.

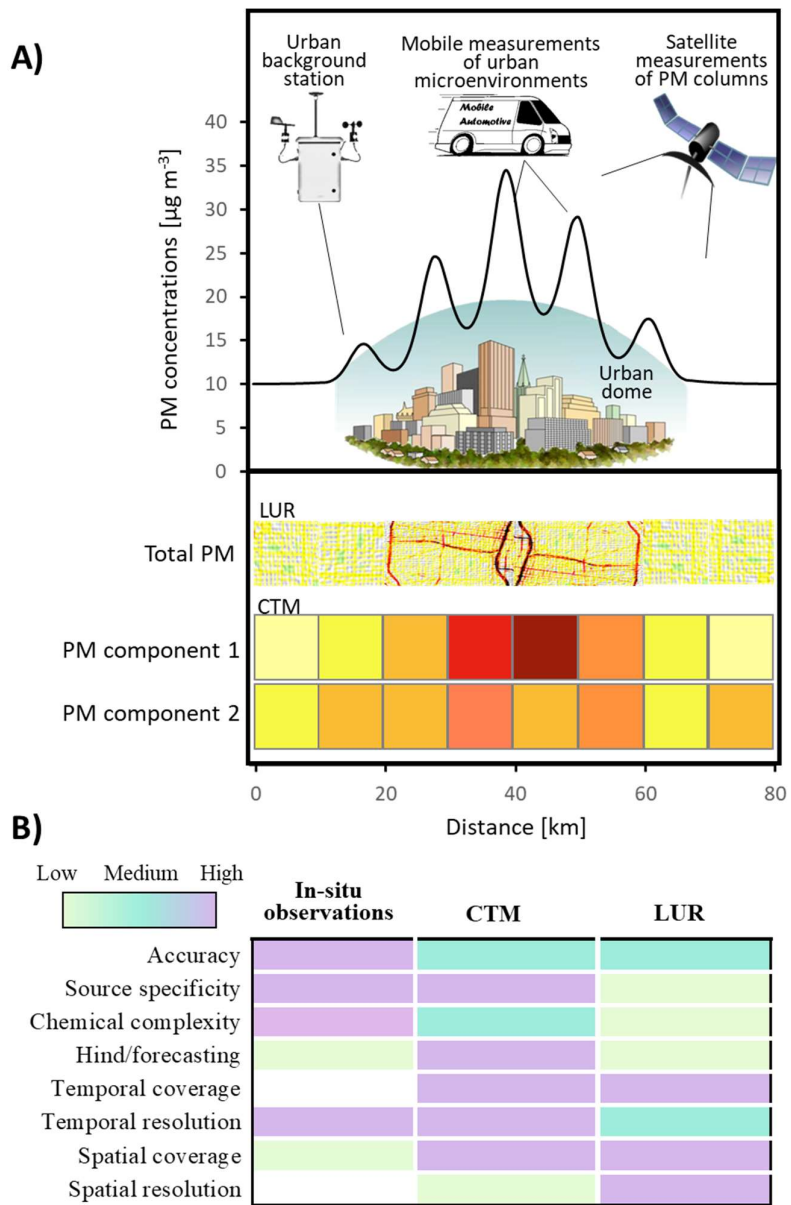
In epidemiological analyses, outdoor PM concentrations at residences are commonly used as proxies for exposure. While there is evidence supporting this approach, its applicability across different settings requires further investigation (Wei et al., 2023). As we spend most of our time indoors and new buildings are increasingly airtight for energy saving, outdoor concentrations may not reflect indoor levels (Schweizer et al., 2007). While indoor emissions, primarily from cooking (Klein et al., 2019) and smoking (Hyland et al., 2008), may influence health, they represent a separate risk factor distinct from outdoor air pollution, akin to contaminated water. This is because (1) different regulatory frameworks are needed to address emissions from indoor and outdoor sources, (2) these sources are often distinct, and (3) they require different control measures. Unlike outdoor air pollution, which often requires collective and regulatory abatement strategies to control emissions, indoor air pollution can be more effectively managed at the individual or household level, by improving ventilation and eliminating or reducing indoor sources. In the absence of indoor emissions, indoor concentrations are 30 to 70% lower than outdoors (Chen and Zhao, 2011) due to variability in infiltration rates. Moreover, exposures can also be influenced by outdoor pollution in other settings, such as workplaces and during commuting, where we spend a large fraction of our time. Health data from citizen cohorts often include questionnaires that offer valuable insights into indoor infiltration rates, workplace conditions and individual's mobility. While we consider outdoor concentrations at residence to be a reasonable proxy of exposure to outdoor pollution, integrating such information can help refining exposure estimations. First, however, the issue of downscaling air quality models to finer resolutions must be tackled.

3. Modelling exposures to individual PM components

The investigation of acute health effects requires the time-series analysis of daily exposures to specific components, typically obtained at an urban background site through long-term measurements (> 3 years) or modelling outputs. By contrast, longitudinal epidemiological studies of chronic diseases require long-term exposures determined at high spatial resolution – ideally at address level. Because high resolution PM composition data are scarce, existing epidemiological analyses considering PM chemical composition have mainly focused on acute effects, while health effects resulting from chronic exposure to individual PM components have rarely been assessed. In this section, we define the state-of-the-art in modelling PM exposure and discuss how recent advances in modelling PM chemical composition can help informing our understanding of PM differential toxicity.

3.1 Existing modelling approaches

Figure 2B compares three traditional classes of approaches used for estimating PM exposures. We put forward eight criteria for comparing these approaches including accuracy, spatial and temporal resolution, spatial and temporal coverage, capability of hindcasting and forecasting required to estimate past and future exposures and finally, source-specificity and chemical complexity, i.e. capability to quantify specific PM components.

257   Early cohort studies used averaged (Pope Iii et al., 2002) or interpolated (Jerrett et al., 2005)
258 PM concentrations measured at routine monitoring stations to characterize the exposure of individual
259 participants in different cities. However, stationary PM measurements are spatially sparse and do not
260 account for the heterogeneity in pollutant concentrations within cities, especially for primary
261 combustion emissions (Eeftens et al., 2012b; Elser et al., 2016; Elser et al., 2018). Therefore, several
262 geo-statistical and process-based chemical transport models (CTMs) have been proposed to fill spatial
263 gaps.

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265 **Figure 2: A)** Representation of urban PM pollution, highlighting the urban increments in PM concentrations
266 over background levels and the presence of microenvironments. State-of-the-art measurement and modelling
267 strategies of PM concentrations at different scales are presented and compared in **B)** in terms of their
268 advantages and limitations. Three different approaches are compared including field observations, chemical
269 transport modelling (CTM) and land-use regression models LUR). The temporal coverage and spatial
270 resolution of in-situ observations are determined by the method employed to obtain them, with white cells
271 being assigned accordingly. Comparison of the performance of CTM vs. LUR is illustrated in **A)**, showing
272 the source specificity of CTM and the high resolution of the LUR.

273   Land-use regression (LUR) models combine in situ observations with GIS based data, e.g. land
274   use, traffic, or population density, as emission indicators to predict ground level PM concentrations on
275   fine grids using regression techniques (Cattani et al., 2017; De Hoogh et al., 2016; De Hoogh et al.,
276   2013; Eeftens et al., 2016; Hoek et al., 2011; Kim et al., 2016; Wolf et al., 2017). These techniques are
277   covered in a review by (Hoek, 2017). LUR techniques are especially pertinent for modelling primary
278   PM components, e.g. metals (Kim et al., 2016; Chen et al., 2020b) or combustion products (Jedynska
279   et al., 2014; Jedynska et al., 2015) in addition to PM mass (Eeftens et al., 2012a). Typically, these LUR
280   models predict annual means, suitable for longitudinal cohort studies on chronic health effects. Their
281   accuracy is moderate, influenced by the number of monitoring sites (Wang et al., 2013) and the
282   inclusion of source-specific predictor variables.

283   With advances in satellite remote sensing, aerosol optical depth, AOD, measurements of entire
284   atmospheric columns have been introduced for assessing exposure to ground level total PM mass with
285   much higher accuracy and relatively high time-resolution. Because AOD-PM relationships are non-
286   linear, interactive, and spatiotemporally variable, AOD measurements are typically combined with
287   other predictors including land-use data and meteorological variables. Machine-learning-based models
288   using geo-statistical and AOD data have been successfully applied at different scales, including city,
289   regional, national and continental scales as well as in different areas around the world, including EU,
290   US, and China (Brokamp et al., 2017; Suleiman et al., 2016; Huang et al., 2018; De Hoogh et al., 2018;
291   Di et al., 2016; Hu et al., 2017; Paciorek et al., 2008; Strawa et al., 2013; Zhan et al., 2017; Di et al.,
292   2019; Xue et al., 2019; Chen et al., 2018b). However, because they are based on past AOD
293   measurements, these models cannot forecast future PM concentrations, e.g., as a response to specific
294   mitigation strategies (Figure 2B). More importantly, they are typically not capable of discriminating
295   between specific PM components, because AOD measurements of PM columns are not yet chemically
296   resolved, although future satellite-based sensors will partially deliver this capability (David et al., 2018).

297   Unlike the other methods, CTMs possess the ability to generate spatial and temporal
298   distributions of chemically resolved PM components and forecast their future evolutions over large
299   spatial scales. CTMs are bottom-up, process-based, numerical models, which simulate PM primary
300   emissions and secondary formation, along with their losses and atmospheric transport in large 3-D
301   Eulerian gridded domains. Despite their spatial coverage, source-specificity, and capability to leverage
302   complex atmospheric oxidation processes, most CTMs are not sufficiently spatially resolved to be
303   suitable for exposure assessments (Figure 2B). Due to computational constraints, highly resolved CTMs
304   are currently limited to city scales. As a result, until very recently, CTM outputs have rarely been
305   exploited for epidemiological analysis, except as an input variables for optimizing the retrieval of total
306   PM mass concentrations in hybrid LUR models (Di et al., 2019; Xue et al., 2019; De Hoogh et al., 2016;
307   Shen et al., 2022).

308   The two fields of air quality modelling, specifically using LUR and CTMs, have evolved along
309   separate trajectories over the past three decades. This separation can be attributed to the modest
310   accuracy of CTMs decades ago and their coarse spatial resolution, struggling to represent the substantial
311   contribution of local pollution. Epidemiologists have then applied LUR techniques taking advantage of
312   their high spatial resolution, reliance on locally measured air pollution data, ease of application, minimal
313   input data requirements and moderate-to-good performance (Hoek, 2017). At that time, CTM
314   developments have primarily focused on implementing representative emission and chemical schemes,
315   aiming to enhance their accuracy. However, with the advancement in CTMs and the increasing regional
316   nature of PM pollution, it is now the time for these two fields to converge to achieve accurate estimation

of exposure to individual PM components at high temporal and spatial resolution and coverage, fulfilling all eight criteria described in Figure 2B.

3.2 How recent advances in modelling PM chemical composition can help informing our understanding of PM differential toxicity?

More recent modelling developments have allowed the production of fine-resolution maps of PM chemical constituents on continental and global scales (Van Donkelaar et al., 2019; Chen et al., 2020b; Mcduffie et al., 2021; Weagle et al., 2018), including the concentrations of secondary inorganic aerosols, black carbon, organic aerosols, and dust. These maps were created using a combination of AOD data and in-situ PM chemical composition measurements to constrain and downscale coarse CTM outputs, via LUR techniques, to spatial scales commensurate with population density distributions. The resulting maps offered the possibility to assess the contributions of different anthropogenic emission sectors to regional and global health burden (Mcduffie et al., 2021; Chen et al., 2021b; Shi et al., 2023).

These recent developments are a fundamental first step for comprehending the differential health effects of PM components. However, models are still directly reliant on AOD and in-situ measurements and as such they cannot forecast future PM concentrations and composition and are limited in identifying the sources of the organic fraction. To address this limitation, the atmospheric science community should develop hybrid models that incorporate land-use data with CTM outputs, enabling the retention of CTMs' source-specificity and forecasting capabilities, while simultaneously benefiting from the fine-resolution information provided by land-use data. In these models, in-situ measurements should be utilized for model training, rather than as model inputs. CTM-based models have the added benefit of being able to quantify the sources of different constituents, which is especially valuable for the organic fraction. Overall, the development of hybrid models that leverage the complementary strengths of CTMs and land-use information will be key in providing exposure data suitable to determining the adverse health effects of individual PM components.

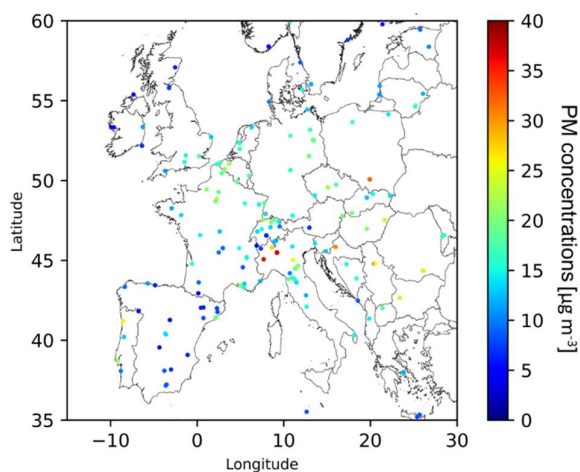
4. Field observations required to understand PM differential toxicity

In this section, we present the type of field observations required in our opinion to best capture the spatial and temporal variation of PM components, enabling validation of exposure models.

4.1 Established monitoring networks of detailed PM chemical composition

Monitoring networks play a vital role in providing essential data for understanding the spatial distribution and long-term trends of air pollution, identifying emission sources, constraining human exposure models, and evaluating the effectiveness of emission reduction measures. International

348 monitoring programs such as SPARTAN[2], EMEP[3], IMPROVE[4], ACTRIS[5] and ASCENT[6] have been
349 critical in establishing and maintaining the operation of these networks. Besides the continuous
350 provision of detailed PM measurements for policymaking, these monitoring programs offer access to
351 outstanding facilities and openly available databases for scientists from academia and the private sector,
352 promoting cutting-edge science and international collaborations.

353   Another advantage of these programs is the standardization of analytical approaches and data
354 formats, ensuring data quality and comparability and facilitating data sharing and use. Data generated
355 from these programs may include particle number-size distributions and the concentrations of elemental
356 and organic carbon, major ions, and metal components. Figure 3 illustrates the distribution of stations
357 across Europe where we have gathered detailed PM chemical properties generated from different
358 national and pan-European programs. For some PM constituents, more than 50,000 daily concentrations
359 at more than 200 sites are available, which is rare, if not unique. This is only possible thanks to such
360 research infrastructures. Datasets of at least this scale are required to form a complete picture of the PM
361 chemical and physical properties and sources, with which our atmospheric modelling community can
362 optimize exposure maps to understand the differential health effects of PM constituents.

363
364 **Figure 3:** European map with site locations where long-term detailed chemical composition data is
365 available. Sites are both urban and rural. Markers are colour-coded with total annual PM concentrations
366 in 2013, to reflect differences in emissions between sites.

367   The composition, emission sources and formation pathways of the organic fraction remain a
368 scientific challenge. Routine measurements (e.g., of organic carbon) are not sufficiently chemically

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[2]SPARTAN: Surface Particulate Matter Network (SPARTAN) provides publicly available data on PM mass,
chemical composition, and optical characteristics for connection with satellite remote sensing and for air quality
management.
[3]EMEP: European Monitoring and Evaluation Programme aims to monitor and model the long-range transport of
air pollutants across Europe.
[4]IMPROVE: Interagency Monitoring of Protected Visual Environments is a long-term monitoring program
designed to assess the visibility and air quality in national parks and wilderness areas in the United States. The
primary goal of the IMPROVE network is to measure PM mass and chemical composition, at over 170 monitoring
sites across the United States.
[5]ACTRIS: Aerosol, Clouds, and Trace gases Research InfraStructure is a pan-European research infrastructure of
several measurement stations across Europe that provides long-term observational data on aerosols, clouds, and
trace gases.
[6]ASCENT: The Atmospheric Science and Chemistry mEasurement NeTwork is a new comprehensive, high-time-
resolution, long-term measurement network in the U.S. for the characterization of aerosol chemical composition
and physical properties.

resolved for the retrieval of the contributing sources. For this, two approaches are currently exploited for long-term monitoring: the aerosol chemical speciation monitor, ACSM (Ng et al., 2011; Fröhlich et al., 2013), which measures the bulk composition of the non-refractory fraction of fine PM and infrared spectroscopy, IR (Weakley et al., 2016), which measures the functional group composition of the organic fraction. We have utilized ACSM data to determine the contribution of residential emissions, vehicular emissions and secondary processes to the organic aerosol fraction across Europe (Chen et al., 2022) and to validate CTM outputs (Ciarelli et al., 2017; Jiang et al., 2019). ACSM measurements are part of ACTRIS and ASCENT, whereas the IMPROVE network has adopted IR measurements. The complex composition of the organic aerosol, especially of the oxygenated secondary fraction, means that no technique is complete. The spectra acquired with both ACSM and IR techniques retain information on the source origins and the formation pathways of the organic fraction. These two techniques are complementary and their combination, although currently only exploited in the laboratory (Yazdani et al., 2021, 2022), can be very powerful to further characterize the organic aerosol fraction in dense networks over long-terms, enabling a better understanding of the relationship between its composition and health effects.

Overall, it is essential that the scientific community continues to leverage chemically-speciated PM data from monitoring networks and generates additional datasets for validating exposure models required to understand PM differential toxicity. These networks should include both urban and rural locations, which is key for accurately characterizing PM concentrations and chemical composition in the different types of areas people reside. It is also vitally important that governments continue investing in monitoring programs to ensure the continuous acquisition of detailed air quality data.

4.2 Why detailed atmospheric chemistry matters: a comparison of severe PM pollution in Northern China and Northern India
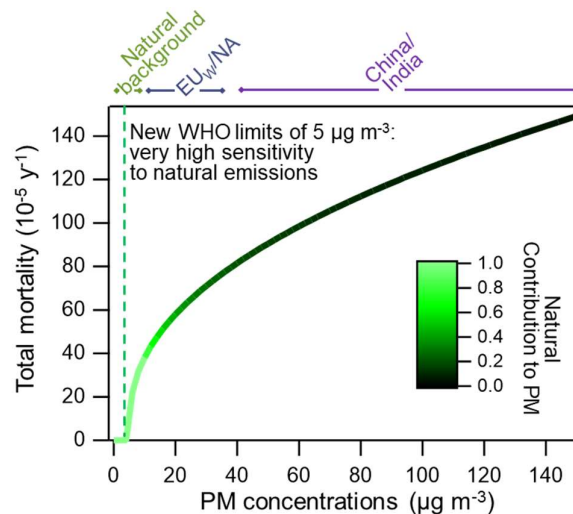
Figure 4: Dose-response relationship between PM concentrations and total attributable mortality, highlighting the sensitivity of mortality to reductions in anthropogenic emissions at low and high pollution levels and potentially to contributions from natural emissions. Reproduction adapted from (Apte et al., 2015). Vertical axes indicate per-capita mortality rates attributable to PM2.5 for a hypothetical global population uniformly exposed to a given level of PM2.5. The dose-response relationship is coloured by the contribution of natural emissions to PM mass. For illustration, we have chosen a natural background concentration of 5 μg m⁻³, representing the level to which 50% of the global population would be exposed if all anthropogenic emissions were eliminated (Pai et al., 2022).

401 The horizontal bars at the top of the figure represent typical PM concentrations in Western Europe/north
402 America (EU$_W$/NA) and China/India, as well as natural background PM concentrations.

403 Modest improvements in PM pollution in relatively clean regions in Western Europe and North
404 America, where most of the current monitoring programs operate, would result in large avoided
405 mortality, owing to the nonlinear concentration-response relationships (Apte et al., 2015). By contrast,
406 major improvements in air quality would be required to substantially reduce mortality in more polluted
407 regions, such as China and India (Figure 4), although such improvements are at least possible as high
408 concentrations result from more controllable anthropogenic emissions. In China and India, 5 million
409 deaths every year are related to air pollution (Lelieveld et al., 2015), with approximately 20% of the
410 total deaths attributable to PM (Figure 5A). Projected demographic shifts in these regions indicate that
411 in order to maintain current PM-attributable mortality rates, average PM levels must decrease by
412 approximately 30% within the next 15 years to counterbalance the rise in PM-related deaths resulting
413 from aging populations (Apte et al., 2015). Therefore, an effective program to deliver clean air to
414 polluted regions is urgently needed to avoid several million deaths every year.

415 In response, China and India launched their country-level clean air plans in 2013 and 2019,
416 respectively. Despite greatly improved national air quality levels compared to ten years ago (Figure
417 5B), China is now finding further air pollution reduction challenging due to the trade-off between
418 controlling PM and ozone pollution (Li et al., 2019). The situation in India is more alarming, with the
419 country's air quality continuing to worsen despite the implementation of its clean air program. A
420 growing number of cities experience severe pollution (Ghildiyal, 2022), resulting in a rise of the
421 mortality attributable to PM (Figure 5B). The mechanism of haze formation in the two regions is also
422 very different. While pollution in China happens on regional scales, local pollution in India plays a
423 prevailing role. The comparison between severe PM pollution in Northern China and Northern India
424 serves as a perfect example for why a detailed understanding of the complex atmospheric chemistry
425 involved is required to comprehend PM differential toxicity in those regions.

426 In China, secondary aerosol production was identified as the main cause behind winter haze
427 events in a study conducted by Huang et al. (2014), the first of its kind to make this discovery a decade
428 ago (Huang et al., 2014). Later studies have confirmed that in Chinese megacities, particle formation,
429 often observed at the onset of haze, is driven by the photochemical production of secondary organic
430 and inorganic species, which happens on a regional scale during the day (Yao et al., 2018; Kulmala et
431 al., 2021). Multiphase chemistry plays another essential role in aerosol formation during haze in China.
432 The high concentrations of anthropogenic sulfate and nitrate, coupled with high relative humidity,
433 provide a reactive medium for heterogeneous aerosol production (Tong et al., 2021). Under haze
434 conditions, gaseous NO$_2$ may also act as an oxidant in the concentrated aqueous aerosol media
435 producing additional secondary PM (Su et al., 2020; Wang et al., 2020). Compared with gas phase
436 photochemical reactions, which are self-buffered against heavy pollution, multiphase chemistry
437 exhibits a positive feedback, which means that higher PM levels accelerate multiphase production,
438 further increasing PM concentrations (Le et al., 2020). Furthermore, because of the nonlinear chemistry
439 of ozone production and titration in winter, the recent reductions in nitrogen oxides result in ozone
440 enhancement in urban areas (Li et al., 2019), further increasing the atmospheric oxidation capacity and
441 facilitating secondary aerosol formation (Le et al., 2020). Substantial oxidation in China's atmosphere
442 is at play even during the night. New findings reveal that between 2014 and 2019, the decrease in
443 pollution has led to an increase in the production rates of nitrate radicals across China, suggesting the
444 growing role of nighttime chemistry to China's air pollution (Wang et al., 2023a). Further mitigating
445 air pollution and its health effects in China will require a detailed mechanistic understanding of the

446 complex multiphase and oxidation chemistry involved, as well as the identification of the major sources
447 of secondary aerosol precursors.

448
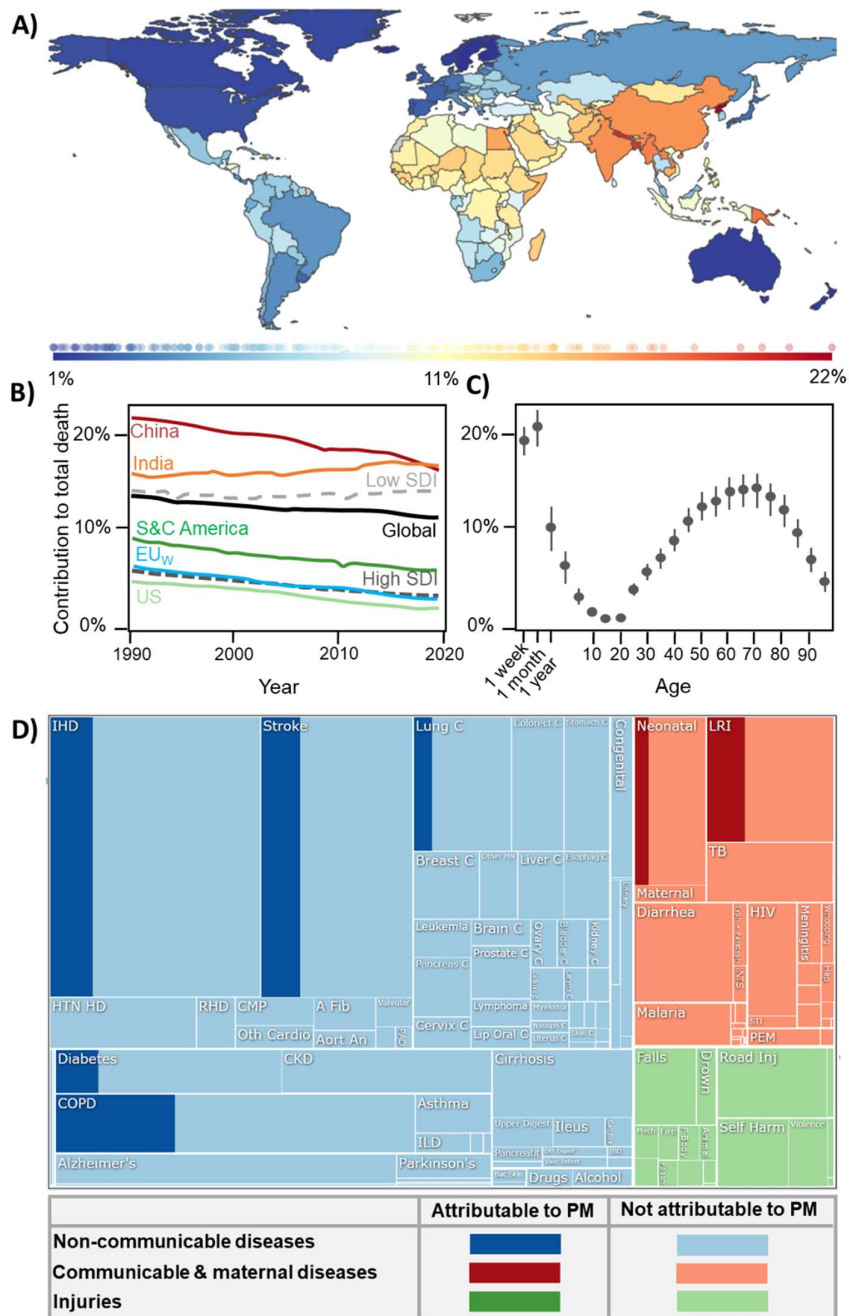
Figure 5: percentage of mortality attributed to particulate pollution. Data are from the Global Burden of Disease Study 2019 Results (Seattle, United States: Institute for Health Metrics and Evaluation, 2020 - available from https://vizhub.healthdata.org/gbd-results/). A) Percentage of PM-related mortality for every country. B) Evolution of the percentage of PM-related mortality from 1990 to 2019 for locations discussed in the text, including China, India, Western Europe (EU_W), US, South and Central America, low SDI (Socio-demographic Index) and high SDI. C) Percentage of PM-related mortality globally as a function of age. D) Percentage of deaths attributable to PM pollution related to non-communicable diseases, communicable & maternal diseases and injuries. The main causes of attributable death to which PM exposure contribute include ischemic heart diseases (IHD), stroke, diabetes, chronic obstructive pulmonary diseases (COPD), neonatal infections, and lower respiratory infections (LRI).

459   In Delhi-India, however, the rapid growth of particles into sizes relevant for haze formation
460 occurs during nights without any photochemistry. We have recently shown that the growth of sub-100
461 nm particles is predominantly driven by primary supersaturated organic vapors from local biomass
462 combustion emissions, whose condensation is promoted by the rapid decrease in air temperature and
463 the increase in emissions during nighttime (Mishra et al., 2023). The formation of ammonium chloride
464 enhances aerosol water uptake through co-condensation at high nighttime relative humidity, which
465 sustains particle growth at higher sizes (Mishra et al., 2023) and leads to fog formation and a 50%
466 reduction in visibility (Gunthe et al., 2021). This process, apparently unique to India's capital, does not
467 involve photochemistry but is instead driven by high emissions of hydrochloric acid, possibly from
468 local industries (Rai et al., 2020). During daylight hours, with the dispersion of NO_X emissions and the
469 increase in the atmospheric oxidation capacity, local combustion of fossil fuels and biomass become an
470 important source for SOA production (Kumar et al., 2022). Toxic heavy metal pollution levels in Delhi
471 are another cause for alarm, with concentrations several hundred times higher than those found in
472 Europe, also due to local industries (Rai et al., 2021). Solving air pollution in India will require
473 international collaboration with local researchers to better understand the local sources of different
474 pollutants, e.g. through mobile measurements (Section 4.3), as well as the effects of local
475 meteorological conditions on air quality. Given the significance of local pollution sources, it will also
476 necessitate the involvement of social scientists and local communities to induce social changes and raise
477 public awareness.

478   The atmospheric science community has already made significant strides in understanding the
479 sources of air pollution in China and India, but knowledge gaps still exist. It is imperative to further
480 understand the non-linear effects of emissions on the atmospheric oxidation capacity, particularly in
481 light of India's potential to face the same problems as China in the near future when primary pollution
482 reduction will lead to an increase in the photochemical production of ozone and secondary aerosols. It
483 is also crucial to identify on a molecular level the specific ingredients contributing to aerosol formation
484 and growth and relate these ingredients to the emission sources of their precursors. We also need to gain
485 a mechanistic understanding of the interplay between the soluble inorganic fraction and water and their
486 effects on the enhanced partitioning and heterogeneous chemistry of organic and inorganic vapors (e.g.
487 N_2O_5, HCl, HNO_3, and oxidized organics). Without this knowledge, we cannot accurately predict the
488 fate of these vapors with future reductions in the anthropogenic emissions of inorganic precursors (SO_2
489 and NO_X). Detailed knowledge of atmospheric chemistry is key for understanding PM chemical
490 composition and differential toxicity in these polluted regions.

491   Finally, it is essential to establish national monitoring networks in both countries that probe the
492 spatial distribution and long-term trends of air pollution and allow us to evaluate the effectiveness of
493 emission reduction measures. The data resulting from these monitoring programs serve as a cornerstone
494 for understanding the health effects of the PM components specific to China and India, enabling us to
495 devise regionally specific solutions aimed at effectively limiting air pollution in these regions. More
496 generally, the inequity of air pollution is flagrant, with locations having a low socio-demographic index
497 (SDI) suffering three times the burden of PM-related mortality compared to locations with high SDI
498 (Figure 5B). This disparity underscores the urgent need for comprehensive monitoring programs in low
499 SDI countries.

500 **4.3 Urban mapping of PM chemical composition**

501   Monitoring networks have limited spatial coverage, which can make it difficult to capture
502 localized pollution hotspots, especially from primary combustion emissions (Eeftens et al., 2012b; Elser

et al., 2016; Elser et al., 2018; Jedynska et al., 2015; Jedynska et al., 2014). Therefore, several approaches have been proposed to enhance the spatial coverage of urban pollution measurements (Figure 2). Both ground-based sensor networks, e.g. for CO_2, black carbon, NO_2, or total PM (Popoola et al., 2018; Caubel et al., 2019; Oney et al., 2015), and satellite retrievals (Di et al., 2016; Griffin et al., 2019) can map the concentrations of individual pollutants at sub-km-scale resolutions, however, these approaches lack the chemical resolution needed for the measurements of PM composition. Aircraft measurements are suited for studying pollution plumes at regional scales (Fry et al., 2018; Decker et al., 2019), but cannot access fine scale variations at the ground level. Ground-based mobile laboratories can house online instrumentations that provide high chemical resolution, while operating with sufficiently high time resolution (i.e., few minutes) for measurements at street levels (Shairsingh et al., 2018; Gu et al., 2018). This makes them ideally suited for spatial mapping of PM composition in urban environments (Hankey and Marshall, 2015; Alexeeff et al., 2018; Apte et al., 2017; Gu et al., 2018).

A large number of studies have measured black carbon, NO_2, total PM mass and number concentrations aboard of mobile platforms (Alexeeff et al., 2018; Apte et al., 2017; Hankey and Marshall, 2015; Shairsingh et al., 2018; Simon et al., 2017; Miller et al., 2020). The Aerodyne aerosol mass spectrometer (AMS) has also been used for the mobile measurements of non-refractory PM components, including secondary inorganic species and organic aerosol (Elser et al., 2016; Elser et al., 2018; Gu et al., 2018; Mohr et al., 2011; Shah et al., 2018). The application of factorization techniques to the measured organic mass spectra has enabled its apportionment to primary traffic, cooking and biomass burning emissions as well as the quantification of a total secondary fraction (Gu et al., 2018; Elser et al., 2016; Elser et al., 2018). From measurements in the EU and the US, it was found that the secondary organic and inorganic fractions are homogeneously distributed across cities, while primary emissions are enhanced by several $\mu g\ m^{-3}$ compared to background levels (Elser et al., 2016; Elser et al., 2018) in correlation with land-use variables (Gu et al., 2018).

Until recently, there has been no robust technology for highly time resolved measurements of airborne particulate metals. Therefore, studies had previously relied on integrated offline samples collected over days-to-weeks at few sampling stations in order to assess the spatial distribution of yearly particulate metals across cities (Li et al., 2016a; Van Ryswyk et al., 2017; Zhang et al., 2015) and countries (Chen et al., 2020b). With such measurements, intra-urban variability in metal concentrations can still be discerned. Recently, the Xact 625 ambient metals monitor, an online XRF spectrometer, has been developed and successfully deployed in the field for the real time measurements of particulate elements (~25) with time resolutions down to 30 minutes (Furger et al., 2017). Due to its high temporal resolution, sensitivity and robustness in the field, the Xact is capable of delivering several month long datasets of 1000s of data points – 10-100 times more than offline techniques (Manousakas et al., 2022), which allow the retrieval of daily concentration patterns. However, further developments are needed to achieve particulate elemental analysis on timescales of minutes suitable for mobile measurements. The availability of such measurements will be transformative, enabling access to PM elemental composition at unparalleled resolutions, and the development of more robust exposure models for metal components.

Street-level PM composition data can enhance, challenge, or confirm various air quality datasets used to retrieve PM differential toxicity, such as CTM outputs, land-use regression predictions, and remotely sensed observations. This refinement can also aid addressing the effect of human mobility in epidemiological studies (Zeger et al., 2000).

5. Gaps in understanding emissions

Human activities have profoundly altered the earth's environment, impacting emissions, atmospheric composition, global temperatures, and land cover. In Figure 6, we categorize the complex anthropogenic effects on PM composition into four broad classes:

- **Direct emissions:** encompassing anthropogenic PM and PM precursors directly released into the atmosphere.
- **Land-use changes:** including changes in urban infrastructure, green initiatives, deforestation/forest management, and agricultural practices, affecting emissions and their accumulation patterns.
- **Direct effects of anthropogenic emissions on the chemistry of natural PM:** whereby pollutants from human activities react with biogenic emissions leading to PM formation.
- **Indirect perturbation of natural PM:** through anthropogenic emissions that impact natural ecosystems, such as global warming, increased CO_2 concentrations, shifts in vegetation patterns, or desertification.
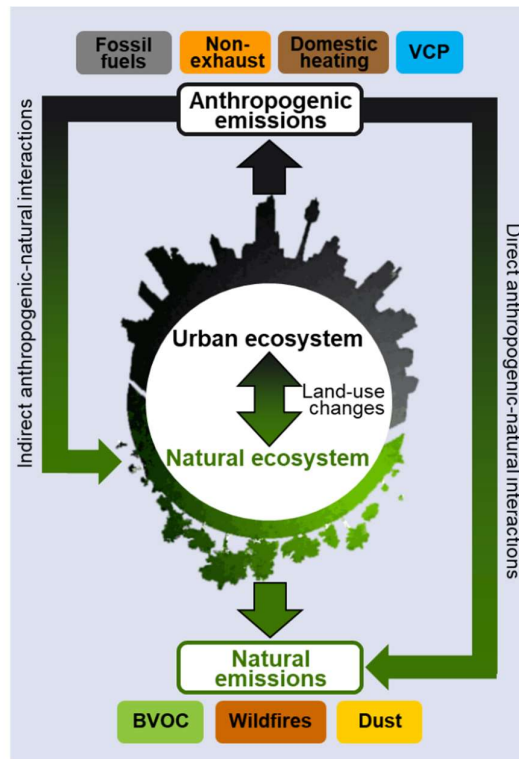
Figure 6: Anthropogenic effects on PM through (1) direct emissions, (2) land-use changes, (3) direct and (4) indirect perturbation of natural PM. (3) comprises the direct effects of anthropogenic emissions on the chemistry of natural aerosols, while (4) describes the influence of anthropogenic emissions on natural ecosystems, e.g. through global warming, or increase in CO_2 concentrations. Natural emissions from terrestrial systems include biogenic volatile organic compounds (BVOCs), wildfire emissions and dust. Anthropogenic emissions include NO_X and SO_2 from fossil fuel combustion, non-exhaust emissions, solid fuel combustion for domestic heating, and volatile chemical products (VCPs).

This section addresses existing gaps in understanding anthropogenic emissions, their atmospheric transformation, and their direct and indirect influence on natural PM. It is crucial for the atmospheric science community to approach these gaps from a mechanistic standpoint and incorporate them into models to accurately quantify the anthropogenic impacts on PM composition and thereby health effects. In section 5.1, we discuss anthropogenic PM sources that hold relevance for public health,

573 while in section 5.2, we examine the future trajectory of the natural PM background and its interactions
574 with anthropogenic activities.

5.1 Legacy and emerging anthropogenic PM emissions

576 Anthropogenic emissions remain a predominant source of primary and secondary PM, posing
577 a critical scientific and policy challenge in identifying the most harmful components to human health.
578 Existing reviews have compiled epidemiological and toxicological evidence linking specific emissions
579 to health endpoints (Wyzga and Rohr, 2015; Adams et al., 2015; Rohr and Wyzga, 2012; Yang et al.,
580 2019; Morton Lippmann Lung, 2023). While ample literature covers short-term effects, especially
581 through measurements at few stations, longitudinal epidemiological studies investigating the effect of
582 PM chemical composition on chronic health outcomes are relatively scarce. Despite inconsistencies
583 across studies, elemental carbon, organic aerosols, sulfate and metals have been consistently associated
584 with increasing risks of cardiovascular and respiratory mortality and hospitalization (Chen et al., 2018a;
585 Yang et al., 2019; Masselot et al., 2022; Wang et al., 2022; Wyzga and Rohr, 2015; Adams et al., 2015;
586 Rohr and Wyzga, 2012; Badaloni et al., 2017; Wang et al., 2017).

587 We believe that the principal challenge in establishing robust epidemiological associations with
588 specific PM components lies in their correlation with other pollutants, such as other PM components,
589 O_3 and NO_X. Therefore, we call for improved high-resolution large scale chemically detailed exposure
590 models that will offer the necessary variability for overcoming limitations related to correlations.
591 Moreover, we advocate for the continual development of epidemiological multi-component methods
592 that estimates the joint health impacts of PM components, instead of isolating the effect of individual
593 ones. In this section, we will focus on major anthropogenic emissions, including fossil fuel emissions,
594 non-exhaust on-road emissions, volatile chemical products (VCPs), and residential biomass burning
595 (Table 2).

596 Fossil fuel combustion is an important source of sulfate, nitrate, and elemental carbon.
597 Numerous accounts reported the higher differential toxicity of primary elemental carbon emissions,
598 especially leading to cardiovascular morbidity and mortality (Chen et al., 2020a). Consequently, in
599 2021, the WHO has listed the elemental (or black) carbon (EC or BC) as one of the pollutants of
600 emerging concern, calling for more evidence on their chronic health effects that can be used for future
601 guidelines and regulations. For this, it is vital to provide high resolution, national and continental BC
602 maps suited for large scale epidemiological studies (Section 3), ideally distinguishing between biomass
603 and fossil fuel burning BC emissions (Table 2).

604 Sulfate and nitrate are not toxic in isolation, and their high fraction in PM and extended spatial
605 variation complicates the determination of their health effects. Yet, the toxicity of these secondary
606 components is perhaps indirect, through a complex multiphase interplay with other components.
607 Sulfate, from energy production emissions of SO_2, provides an acidic medium for organic reactions,
608 and may increase the solubility and hence the bioavailability of metal particles, potentially increasing
609 their toxicity. Mobile emissions of NO_X have profound effects on atmospheric oxidation (Section 5.2),
610 but also lead to enhanced partitioning (Lv et al., 2023) and subsequent multiphase reactions of soluble
611 organic molecules, through nitrate formation. Traditionally, nitrate was considered the chemical end
612 point of the reactive nitrogen life cycle in the atmosphere prior to wet or dry deposition. However, there
613 has been growing evidence for particulate nitrate photochemical renoxification in the presence of light
614 and organic molecules (Jiang et al., 2023; Bao et al., 2020). While this process is mainly examined for
615 its potential to produce oxidant precursors (NO_X and HONO), how it alters the composition of the
616 organic fraction is currently not understood. The mechanistic understanding of these multiphase

processes involving the interactions of secondary inorganic particles with organic and metal components is indispensable for constraining their impact on PM chemical composition and differential toxicity (Table 2). There is a need for fundamental mechanistic investigations of these processes in the laboratory and the field, especially in polluted areas, like China, where multiphase chemistry plays a key role for haze formation (Section 4.2).

As traffic exhaust emissions of NO$_X$, PM and hydrocarbons are increasingly regulated, car engines underwent a technological revolution, improving combustion efficiency and after-treatment technologies. In contrast, non-exhaust emissions, such as brake and tire wear, have increased with the growing number of vehicles and currently exceed exhaust emissions (Timmers and Achten, 2016). These emissions include toxic metals such as copper, which enhance PM oxidative potential (Daellenbach et al., 2020). Even with the electrification of the fleet, non-exhaust emissions will remain an issue, potentially worsened by the heavier weight of electric cars (Timmers and Achten, 2016). While public transportation, including trams and trains, may also be an important source of metal particles, their contribution is not yet well quantified. Multi-site long-term measurements (Section 4.1) and mobile measurements to map trace element concentrations (Section 4.3) may offer new opportunities to represent the distribution of on-road non-exhaust emissions in exposure models (Table 2).

Table 2: Future changes in anthropogenic emissions, key observations needed for coupling with health data, high priority model developments for understanding the health effects of anthropogenic emissions and their future evolution.

Source	Future changes	Key observations	Model developments
Fossil fuel combustion	Decrease by several % per year of SO$_2$, NO$_X$ and BC in the West and China.	Long-term, multi-site measurements of BC, ammonium sulfate and nitrate for model improvements. Mobile measurements of BC in urban and rural locations. Apportionment of BC between fossil and non-fossil emissions. Fundamental studies and field observations of the multiphase interactions between ammonium sulfate and nitrate with the organic and metal components.	Fine resolution modelling of BC concentrations, ideally from different combustion sectors. Implementing the effects of nitrate and sulfate on the organic and metal components and estimating future changes with decreasing fossil fuel emissions.
Non-exhaust emissions	Increase of the total burden by several % per year with the increase and electrification of the vehicular.	Long-term, multi-site measurements of elements, with a focus on copper. Mobile measurements of trace elements in urban and rural locations.	Fine resolution modelling of PM elemental composition, with a focus on copper. Utilization of long-term trends for separating between the effects of exhaust and non-exhaust emissions. .
Volatile chemical products (VCPs)	Increase of the total burden by several % per year with the increase and westernization of the global population.	Identification and multi-site measurements of VCPs and VCP SOA markers. Determination of SOA formation potential of individual and real-world mixtures of VCPs.	Modelling of SOA and ozone formation from VCPs on continental levels for exposure assessment.
Biomass burning for residential heating	Area dependent.	Long-term, multi-site measurements of biomass burning primary and aged emissions. Mobile measurements of primary and aged biomass burning emissions in urban and rural areas. Fundamental studies of biomass smoke aging.	Fine resolution modelling of biomass burning emissions. Implementing biomass burning aging mechanisms in models. .

With the drastic reduction of on-road transportation emissions, VCPs, which are partly from indoor emissions, have emerged as one of the largest sources of outdoor urban organic emissions in US and European cities, modulating urban chemistry (Coggon et al., 2021; Gkatzelis et al., 2021; Mcdonald et al., 2018). These ubiquitous emissions encompass pesticides, coatings, printing inks, adhesives, cleaning agents, and personal care products. Human exposure to fossil carbonaceous aerosols may be transitioning from transportation-related sources to VCPs. These emissions have comparable, if not greater, SOA potentials compared to vehicular emissions, which may influence human health. Variations in SOA potentials and chemistry among VCPs, as revealed by laboratory experiments, highlight the need for further characterization of these unconventional emissions (Shah et al., 2020). Furthermore, it is now possible to include these emissions into exposure models (Pennington et al., 2021). Existing regulations on VCPs emphasize reducing ozone and air toxics, but currently exempt numerous chemicals that contribute to SOA formation. Efforts to refocus mitigation strategies require atmospheric scientists to provide data quantifying the contribution of VCP emissions to SOA, and the global burden of disease (Table 2).

Achieving net-zero emissions for climate goals does not necessarily guarantee clean emissions for air quality. Biomass combustion, adopted as a carbon neutral energy source for residential heating, is a potent anthropogenic source of pollution during winter. The emitted organic vapours rapidly react in the atmosphere with OH and NO_3 radicals, resulting in substantial SOA production (Kodros et al., 2020; Stefenelli et al., 2019). The SOA formed contains high levels of oxygenated and nitro-aromatic compounds, which likely cause the high oxidative potential of this fraction (Daellenbach et al., 2020). Recent laboratory investigations (Liu-Kang et al., 2022; Wang et al., 2023b) and airborne field measurements (Morgan et al., 2020; Zhou et al., 2017) suggest that primary biomass emissions, which absorb near UV light, can undergo photoreactions in the particle phase, resulting in a doubling of the emissions oxidation state in few hours. The dominant transformation processes of biomass burning emissions and their impact on aerosol toxicity remain unclear. Overall, biomass smoke has not shown a reduction trend in many regions worldwide, underscoring the importance of comprehending the fate of these emissions in the atmosphere and their implications for human health (Table 2).

5.2 Anthropogenic effects on natural PM

With the increasing regulations on anthropogenic emissions, the contribution of natural emissions, including biogenic volatile organic compounds (BVOCs), wildfires and desert dust, will gain prominence (Figure 4). While these emissions stem from natural ecosystems, they are also significantly perturbed by anthropogenic activities, as illustrated in Figure 6. The traditional picture that distinguishes biogenic and anthropogenic sources obscures human impacts on ostensibly natural systems. Anthropogenic effects on natural PM can be either direct, through the alteration of atmospheric reactivity, or indirect, through feedback mechanisms triggered by changes to the biosphere. We need to understand these effects quantitatively to devise best practices to mitigate their impacts. For example, WHO good practice statement on particles originating from sand and dust storms (SDS in the WHO 2021 air quality guideline document) includes measures that can be implemented to mitigate exposure. In this section, we discuss the human influence on natural PM concentrations, chemical composition, and future trends (Table 3).

Biogenic SOA (BSOA) is the most important source of OA in the atmosphere (Jiang et al., 2019), with anthropogenic NO_X playing a vital role in moderating its formation and composition. NO_X effects on BSOA are multifaceted and involve (1) altering the fate of biogenic RO_2 radicals, (2) increasing the atmospheric oxidant concentrations and (3) providing an aqueous medium for additional

677 multiphase reactions (Xu et al., 2015; Pye et al., 2019; Carlton et al., 2018). As NOx emissions decrease,
678 RO$_2$ autoxidation becomes increasingly important, potentially enhancing BSOA formation, while
679 oxidant availability driving RO$_2$ formation rates simultaneously declines, possibly slowing regional
680 BSOA formation. Recent modelling analyses (Carlton et al., 2018), along with in-situ (Xu et al., 2015)
681 and airborne measurements (Pye et al., 2019; Shrivastava et al., 2019) consistently suggest that
682 anthropogenic NO$_X$ leads to a net enhancement in BSOA concentrations by 20-50% depending on the
683 location and season. Like NO$_X$, SO$_2$ emissions from electricity generation, the main source of
684 particulate sulfate, modulate the aqueous formation of isoprene SOA. Models (Carlton et al., 2018) and
685 measurements (Xu et al., 2015) over the US demonstrate that between 40–70% of the BSOA can be
686 controllable by reducing anthropogenic NO$_X$ and SO$_2$. Similar analysis is still lacking at other locations
687 worldwide.

Table 3: Future changes (2050-2100) in natural emissions, key observations needed for coupling with health data, high priority model developments for understanding the health effects of emissions and their future evolution.

Source	Future changes	Key observations	Model developments
Biogenic SOA	Increase in global BSOA burden by 30-150%.	Long-term, multi-site measurements of BSOA precursors, oxidant precursors, chemistry, and burden. Global analysis of response of BSOA chemistry and burden to anthropogenic emissions and climate change. Fundamental studies of anthropogenic-biogenic interactions and their effects on BSOA chemistry and burden.	Improving the understanding of the response of BVOC emitting species to climate change (temperatures, soil nutrients, CO$_2$, nitrogen deposition, droughts, vegetation shifts). Implementing the effects of anthropogenic-biogenic interactions on BSOA chemistry and burden
Wildfires	Increase in wildfires frequency by ~100% and emission burden by ~30%.	Long-term global records of fire occurrence and associated PM emissions. Global analysis of response of wildfire emission occurrence and budget as function of climate change, and fire drivers (temperature, droughts, lightning). Determination of wildfire emission rates for different ecosystems. Fundamental studies of wildfire emission and their atmospheric transformation processes.	Coupling fire and vegetation models. Improving the understanding of the impact of land and fire management on fire emissions.
Dust	Uncertain	Long-term global records of dust emission burden, size and chemical composition. Quantification of the contribution of soil vs. urban dust in major cities. Field and laboratory observations of dust aging and its impact on the bioavailability of key elements.	Improving dust emission schemes. Implementation of dust updated aging schemes.

688   BSOA concentration exhibits a strong temperature dependence, driven by the exponential
689 increase in BVOC emissions and their oxidation rates. Our analysis of multi-field observational datasets
690 from European and North American locations reveals that BSOA contributes [0.9–2.5] µg m^{-3} at 15°C,
691 compared to [2.1–6.3] µg m^{-3} at 25°C (Xu et al., 2015; Daellenbach et al., 2017). Climate models project
692 a global increase in BSOA mass by approximately 30–150% with a temperature rise of 2°C and a few
693 hundred ppb increase in atmospheric CO$_2$ concentrations (Carslaw et al., 2010). When changes in
694 vegetation are accounted for, predictions of BVOC emissions become extremely uncertain, with
695 projected increases ranging from 10s to 100s of percent (Table 3). These uncertainties arise from the
696 unpredictable response of vegetation to future climates, including longer growing seasons, increased
697 leaf area index with the fertilization effect of CO$_2$, changes in water stress and expansion of the boreal

698 and temperate forests. With the rise in BVOC emissions and the denitrification of the atmosphere, it is
699 expected that the oxidation capacity of the atmosphere may decrease leading to slower production of
700 BSOA and a complete change in its composition. Understanding the non-linear interactions among
701 anthropogenic emissions of oxidant precursors, greenhouse gases, atmospheric oxidation conditions,
702 and the biosphere is crucial for understanding BSOA concentration, chemical composition, health effect
703 and future concentration trends in different regions.

704 While reducing NO_X and SO_2 can control a significant portion of BSOA, the rise in BVOC
705 emissions with climate change, albeit highly uncertain, may offset this reduction. Currently, there is
706 very limited understanding of the impact of BSOA on human health, with only one study suggesting a
707 3.5 times higher cardiorespiratory mortality associated with anthropogenically-influenced BSOA
708 compared to $PM_{2.5}$ mass (Pye et al., 2021). Atmospheric scientists should capitalize on emerging multi-
709 year, multi-location observations of detailed PM chemistry to enhance model predictions of BSOA
710 (Table 3).

711 Wildfires have become increasingly frequent in many regions worldwide, making them the
712 second largest contributor to atmospheric organic carbon on a global scale. This source can be directly
713 affected by anthropogenic activities, through deforestation, forest management and fire suppression or
714 indirectly by climate change. Climate models predict that global warming will amplify wildfire
715 emissions by ~30%, owing to longer fire seasons, higher temperatures, increased droughts, and
716 increased convection-induced lightning as an ignition source (Carslaw et al., 2010). Studies have shown
717 short-term health effects of PM from wildfire emissions, including pulmonary complications (Stawovy
718 and Balakrishnan, 2022), respiratory mortality and cardiovascular mortality (Chen et al., 2021a), while
719 understanding the long-term health effects of these emissions remains an ongoing area of research
720 (Grant and Runkle, 2022; Gao et al., 2023). Recent studies investigating Amazonian (Yu et al., 2022)
721 and Canadian Boreal (Korsiak et al., 2022) wildfire emissions have highlighted an elevated risk of
722 various cancers, surpassing the effects of non-wildfire PM emissions for equivalent exposure doses. A
723 crucial first step in improving prediction of wildfire emissions and their health effects is the analysis of
724 global fire occurrence records and associated PM emissions, establishing robust relationships between
725 emissions, ecosystems, climate change, fire management and fire drivers (Table 3).

726 Another naturally occurring PM component, dust, is the most important source of elements in
727 the atmosphere. Wind speed, soil moisture and vegetation cover are the main drivers of dust emission
728 fluxes, size distribution and mineralogical composition (Carslaw et al., 2010). During transport, dust
729 particles react with acids increasing the bioavailability of key elements, including iron. It has been
730 shown that anthropogenic sulfate from fossil fuel combustion modulates soil dust iron solubility and
731 toxicity (Wong et al., 2020). The reactive uptake of gases onto dust particles heavily depends on dust
732 mineralogical composition, with particles rich in carbonates exhibiting strong atmospheric reactivity.
733 Like wildfires, both direct human activities and climate change can influence dust emissions, making
734 future predictions uncertain (Carslaw et al., 2010). Dust outbreaks have frequently been associated with
735 mortality and hospital admissions (Stafoggia et al., 2016; Crooks et al., 2016), albeit with moderate
736 effects and associated high uncertainties (Zhang et al., 2016). This uncertainty may result from the large
737 variability in dust particles morphology, size, solubility, and chemical composition, depending on their
738 origin and transport time in the atmosphere. A particular challenge is the provision of long-term, large-
739 scale datasets, which is crucial because of the strong spatial and temporal variability of dust particles in
740 the atmosphere. Therefore, additional observational data on dust phenomenology is required for model

evaluation, with which we can comprehend the toxicity of dust and the contributing factors. Finally, fundamental research on dust transformation processes is also warranted (Table 3).

While anthropogenic emissions are destined to decrease, natural emissions will most likely increase. Part of this increase can be controllable through reducing anthropogenic emissions and managing land-use. The atmospheric science community is now ready to provide the field measurements, laboratory observations and model outputs needed to quantify the contribution of anthropogenic, and controllable natural emissions globally and predict their evolution with global changes. This data will form the foundation for understanding the toxicity of anthropogenic PM sources and determining the natural PM background in different regions.

6. Supporting epidemiology by enhancing chemically-resolved PM exposure estimation

As aerosol scientists, we must shift our focus from seeking a single, elusive chemical or toxicological metric describing PM health effects to providing chemically resolved atmospheric observations and modeling outputs, with which epidemiological evidence linking PM components to diseases can be established. Epidemiology drives regulatory changes, and working with epidemiologists, atmospheric scientists can now assume a central role in determining PM composition and spatial distribution to unlock a better understanding of the complex epidemiological relationships between PM composition and health outcomes. This section highlights some notable advancements in modern environmental epidemiology that may not yet be fully appreciated within the atmospheric chemistry community.

6.1 Collaboration between atmospheric scientists and epidemiologists

Recently, eight hallmarks of environmental insults have been proposed (Peters et al., 2021). They encompass oxidative stress and inflammation, genomic mutations, epigenetic alterations, mitochondrial dysfunction, endocrine disruption, altered intercellular communication, changes in microbiome communities, and impaired nervous system function. These hallmarks jointly underpin the health effects resulting from lifelong environmental exposures, even to relatively modest concentrations of contaminants.

PM, as one of the most important environmental insults, can infiltrate our body through various barriers, e.g., our lungs or digestive system, affecting individuals through a complex web of biological pathways. Figure 5C illustrates the contribution of PM pollution to total mortality across ages, highlighting its staggering impact on infants and the elderly. Short-term exposure has been linked to sudden infant death as well as increased mortality and morbidity rates due cardiorespiratory and renal complications, particularly affecting children and individuals with chronic conditions (Heft-Neal et al., 2018; Zhang et al., 2023; Liu et al., 2023; Guo et al., 2023). Meanwhile, long-term exposures have been linked to numerous non-communicable diseases that manifest at a later stage of life (Figure 5C), including cardiovascular diseases (Requia et al., 2017; Lelieveld et al., 2019), respiratory symptoms, different types of cancers (Turner et al., 2020), diabetes (Yang et al., 2018), and neurodegenerative diseases (Maher et al., 2016; Shi et al., 2020).

Unlike infectious diseases, non-communicable diseases have multiple causes and involve various factors, which individually may neither be necessary nor sufficient to cause the disease. Early-life exposures may leave enduring marks in the body, leading to manifestations that emerge many

782 decades later. Given the multifactorial nature of the problem, epidemiology is irreplaceable when it
783 comes to investigating PM-related non-communicable diseases and working with citizen cohorts is
784 essential in circumventing the challenges of randomization and cofounding effects. Citizen involvement
785 is simply inevitable in understanding their own health.

786 To bolster the causal interpretation of epidemiological associations derived from observational
787 studies, it is crucial to elucidate how the hallmarks of environmental insults connect exposure and
788 disease development. This requires a robust methodological approach, combining insights from aerosol
789 science into PM chemical composition, sources and spatial distribution, with modern environmental
790 epidemiology techniques, including molecular phenotyping, multiomics, epigenetics, imaging, and
791 personalized and digital medicine.

6.2 Working with citizen cohorts to establish causal links

793 The establishment and maintenance of national biobanks and citizen cohorts is key for
794 investigating the causal links between exposure to PM components and diseases. These cohorts are the
795 gold standard for understanding long-term health effects of environmental factors (Probst-Hensch et al.,
796 2022). They provide evidence where randomized trials are unethical or unfeasible (Peters et al., 2022).
797 Cohorts are critical for approaching a causal understanding of how social, environmental, behavioral,
798 and economic factors promote or hinder health, while also enabling the evaluation of the long-term
799 impacts of public health interventions. They allow studying health trajectories across different ages,
800 providing a life course perspective. As such, they serve as a fundamental pillar for addressing the health
801 effects of PM in the context of other major public health challenges of the 21st century, including
802 population growth, aging societies, urbanization, global warming, digital transformation and increasing
803 social inequalities.

804 As highlighted in (Probst-Hensch et al., 2022), Europe has a longstanding tradition of
805 implementing and maintaining large-scale (>100k participants) and long-term (>20 years) cohorts,
806 including the UK Biobank (Sudlow et al., 2015), Lifelines (Stolk et al., 2008), Constances (Zins et al.,
807 2010), and the German National Cohort (Peters et al., 2022). Innovations in these cohorts include
808 recruitment from birth to old age, implementation of novel eHealth tools, involvements of psychologists
809 and social scientists, and citizen participation during planning and execution to address response rate
810 challenges. Biomaterial collection within these cohorts enables sequencing and in-depth molecular
811 characterization, differentiating between genetic and environmental factors.

812 A noteworthy addition to national cohorts is the global mortality dataset, maintained by the
813 Global Burden of Disease Collaborative Network, within the Institute for Health Metrics and Evaluation
814 (see Figure 5). Although the dataset is limited to cause-specific mortality, this network has shaped
815 modern epidemiology and allowed the quantification of the global burden to PM mortality (Burnett et
816 al., 2018). Another emerging dataset is from the multi-country, multi-city network, which provides
817 daily mortality for several locations around the world, ideal for the assessment of short-term PM
818 exposures (Masselot et al., 2022; Liu et al., 2019). Such datasets synergistically complement the causal
819 investigations into PM health effects based on cohort data, providing a global perspective.

820 Our vision is of a closer collaboration such that detailed knowledge of PM composition and
821 exposure can be integrated into citizen cohorts, including an increasing focus on polluted areas like
822 China and India (section 4.2). Working together will advance understanding of the involvement of
823 specific PM components or combination of components in disease development and the detection of

824 early changes resulting from exposure. It will generate even more compelling evidence for science-to-
825 citizen-to-policy partnerships needed to affect regulatory frameworks.

6.3 Disease prevention through the mitigation of detrimental PM components

827   It is vital to prioritize quality of life and healthy aging over simply extending life expectancy,
828 especially in high SDI regions. This necessitates a shift towards primary prevention and the
829 implementation of drastic changes in health promotion starting at childhood and early adulthood, well
830 before the onset of diseases. In the case of PM, it is essential to identify and mitigate the specific
831 components responsible for different diseases, to alleviate their impacts on our wellbeing. A reduction
832 in detrimental PM components will also result in an extension of life expectancy, especially in low SDI
833 locations.

834   Dementia serves as a perfect illustration of the major challenges facing our aging society.
835 Dementia is a severe decline in cognitive function, which considerably affects the wellbeing of older
836 adults and their families, while imposing substantial costs on public programs. In 2010, approximately
837 135 million adults were living with dementia worldwide (Prince et al., 2013), resulting in estimated
838 economic impacts of \$600 billion (Wimo et al., 2013). Given the sharp rise in dementia incidence
839 beyond the age of 75 and our increasingly ageing society, global dementia cases are forecasted to triple
840 by the year 2050. Recent studies in the US have shown that every 5 μg m^{-3} increase in annual PM
841 concentrations results in a 13% increased risk of first-time hospital admissions for dementia (Shi et al.,
842 2020), with elemental carbon and sulfate particles having the strongest effects (Shi et al., 2023). While
843 more research, including at other locations, is necessary to confirm these associations and understand
844 the underlying biological pathways involved, these studies already shed light on possible interventions
845 to slow the trajectory of cognitive decline and ensure the wellbeing of our aging society. This example
846 reinforces that a collaborative effort – combining the expertise of epidemiologists in understanding
847 disease patterns with the experience of atmospheric scientists in measuring and modelling PM
848 composition – is crucial for mitigating the impact of PM components on the wellbeing of our society.
849 Such collaboration will also enable identifying the PM components contributing to other diseases,
850 potentially operating through distinct biological pathways in their development.

7. Conclusions

852   In the 21st century, we have witnessed a remarkable rise in life expectancy and shifts in global
853 disease patterns, attributable to a combination of public health interventions and advancements in
854 healthcare and healthcare accessibility. Yet, ten million deaths attributable to environmental exposures
855 can still be preventable every year (Neira and Prüss-Ustün, 2016; Landrigan et al., 2018), highlighting
856 the need for proactive measures. Relying solely on high-tech medical interventions for managing
857 disease progression may exacerbate existing social inequalities within healthcare systems and yield
858 diminishing returns. Therefore, we advocate to shift towards enhancing quality of life and promoting
859 healthy aging through early prevention and the creation of healthy environments for all. Our vision for
860 realizing this goal is a close collaboration between atmospheric scientists and epidemiologists, to
861 integrate chemically detailed global air quality data with large-scale personalized medical information
862 from citizen cohorts. The provision of global PM composition maps will require the atmospheric
863 science community to (1) develop spatially and chemically detailed exposure models, (2) provide long-
864 term time-series of PM chemical composition from monitoring networks, (3) map pollution hot-spots
865 through mobile measurements, (4) understand emerging anthropogenic emissions and their chemical

transformation, especially in heavily polluted areas like China and India, and (5) understand the future evolution of natural emissions with climate and land-use changes.

As an aggressive attempt to promote healthy environments, WHO has set new guidelines to limit PM concentrations to below 5 $\mu g \, m^{-3}$. Achieving these limits may be challenging for many regions due to the contribution of natural emissions from wildfires, biogenic species, and desert dust. Concurrently, scientific consensus underscores the critical role of PM chemical composition in influencing associated health effects, necessitating a revaluation of how we should be mitigating PM pollution and the development of new generation of air quality metrics focusing on detrimental PM components. Focusing on the PM differential toxicity offers two key advantages. First, it allows for targeted measures aimed to limit specific health-relevant PM sources. Second, PM chemical composition is intertwined with other properties that may also drive PM's health effects, such as solubility, number size distribution and oxidative potential. Atmospheric science has reached a pivotal moment to provide detailed global air quality maps, at a sufficiently fine resolution, supporting epidemiological studies to determine the differential toxicity of PM components, crucial for integrating PM chemical composition into regulatory frameworks, informing targeted policy-making and operational decisions.

Routine, widespread availability of high-resolution atmospheric data could have transformative implications for air quality research, epidemiology, and environmental management. This valuable data can reveal localized pollution hotspots, offering new opportunities for implementing targeted pollution control measures. When combined with personal GPS data, it enables comprehensive personalized exposure analytics, potentially influencing individual behavior. This parallels the way real-time traffic data currently shape driving patterns at an individual level or how health applications motivate individuals to engage in active exercise.

By providing open access to global high-resolution pollution maps, atmospheric scientists can assume a broader societal role in raising public awareness of air pollution, and its impacts on health and environmental equity. These pollution maps empower citizens, local communities and policy makers with the necessary tools to optimize emission reduction strategies and sustainable urban planning. This can include the application of targeted measures for limiting the most important PM sources for health, or shifts in urban land-use design for better air quality. This wealth of data can be utilized to train models that predict the future evolution of air pollution sources and its health impacts with climate change, land use change, urban planning, mitigation strategies and energy policies. Long-term global air quality data are a key cornerstone for establishing targeted strategies to improve public health and anticipate its future trajectory.

In the process of reevaluating and implementing air quality guidelines, a multidisciplinary collaborative approach involving atmospheric scientists, climate scientists, toxicologists, epidemiologists, public health experts, social scientists, policy-makers, and the public is crucial. Therefore, governments must ensure sustainable funding to foster these collaborations, the returns in terms of lives and costs saved being increasingly evident. By alleviating the burden of air pollution-related diseases, we will prioritize the health and wellbeing of individuals and create sustainable and resilient communities.

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916

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