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Post SARS-CoV-2 Urban India: Computing Air Quality Health Indicators (AQHI) for Gurugram City to Assess Imminent Threats to Public Health

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ABSTRACT

We aim to make the authorities aware about re-emergence of health risks for Gurugram City, keyed to renewal of air pollution inthe post-COVID 19 times. We compute multiple Air Quality Health Indicators (AQHI)forPre-Lockdown (denoted as PreLD; pre-COVID normal life; March 5-25, 2020), COVID-19 Lockdown (LD; March 25 - May 31), Un-Lockdown (UNLD; June 1 – August 31) and Post-Lockdown (PostLD life-as-usual conditions; September 1, 2020 – January 31, 2021) using 24-hour,time-weighted average ambient $PM_{2.5}$ and PM_{10} concentrations, obtained from the Central Pollution Control Board. Results indicated that beyond initial reductions in ambient $PM_{2.5}$ and PM_{10} levels in the LD period, they (i) persisted above international/national regulatory thresholds all along the study period; and (ii) rapidly spiked in the PostLD period, indicating reemergence of pollution-induced health concerns. We computed a suit of AQHIs including all-cause mortality for children and infant (5-yr age); respiratory mortality for all age groups;and cardiopulmonary and cancer mortality. Relative risk factor (RR) for all the above have grown in the PostLD periods, with children and infants appearing more vulnerable than other age groups.We highlight to the authorities of short (YLL,YLD, DALY) and long-term benefits of undertaking air quality-health research. We alsoreflect onpotential sources of uncertainties, and underscored main areas for future researchto establish statistically meaningful relationships between air quality and health.

Key words : *Post-COVID urban air quality, Lockdown, Particulate matter, Meteorological factors, Air quality health indicator (AQHI), Environmental health burden, Cardiopulmonary and cancer mortality*

Introduction

Through the later half on 2020, a vast body of environmental literatureemerged, demonstrating the 'healing touch' of the SARS-CoV-2 (COVID-19) Lockdown (*stay-at-home*), to mitigate urban air pollution around the world Venter *et al.*, 2020). Similar observations echoed across India as well, marked by significant reductions in concentrations of various air pollutant species and improvement in ambient air quality (Kundu and Kundu, 2021; Bera *et al.*, 2020; Mahato *et al.*, 2020; Mahato and Ghosh, 2020;

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Sharma *et al.,* 2020).More recently set of literature have begun to emerge that point at renewal of urban air pollution, at the cessation of Lockdown and resumption life-as-usual conditions (Anjum, 2020; Kumar and Chaudhuri, 2021; Kumar *et al.,* 2020; Zowalty *et al.,* 2020).

In view of the above, we aim to offer the urban air quality regulatory and health authorities in India, a bird's eye view of revival of urban air pollution in the post-COVID times, and related health hazards. Here, we take Gurugram City, a rapidly developing industrial hub located in the National Capital Region (NCR), as representative scenario for urban habitats in India. The National Clean Air Program (NCAP) in India listed Gurugram among the 102 'non-attainment' cities in the country that fail to comply with the National Ambient Air Quality Standards (NAAQS), and called for strategic and urgent interventions to improve ambient air quality (MoEFCC, 2019). ** Elevated levels of particulate matter in ambient air, and associated public health threats, is already been reported from the National Capital Region (NCR), where the city of Gurugram is located (Chaudhuri, 2018; Chaudhuri and Roy, 2017a-c).

Worldwide, poor air quality is a prime cause of premature death and disease, and is reckoned among the largest environmental health threats (Cohen *et al.,* 2017; Lelieveld *et al.,* 2015). The UN's Sustainable Development Goals (SDGs) call for urgent reduction of the burden of deaths and diseases from air pollution. Air pollution induced health crises is surging in India as well. Recent studies have attributed elevated level of $PM_{2.5}$ to 'pre-mature' mortality in India (David *et al.,* 2018). A recent nationwide assessment maintained that, "*the high burden of death and disease due to air pollution and its associated substantial adverse economic impact from loss of output could impede India's aspiration to be a $5 trillion economy by 2024* (India State-Level Disease Burden Initiative Air Pollution Collaborators, 2020).

Need for process-level research on the air quality-health nexus has become never more dire as in the present times, by potential feedback cycles between SARS-CoV-2 virus attack and air pollution (Figure 1). Poor air quality degrades human respiratory environmenton multiple levels, making cardiac and pulmonary systems ever more vulnerable, thus accentuating COVID-19 disease spread.In the present narrative, we track down ambient particulate matter ($PM_{2.5}$ and PM_{10}) trends in Gurugram, through COVID-19 Pre-Lockdown (PreLD), Lockdown (LD), Un-lockdown (UNLD) and post Un-Lockdown (PostLD). We take the latter (PostLD) as representative of post-COVID *life-as-usual* conditions (normal/near-normal) when most COVID-19 Lockdown restrictions on economic activities and human mobilities were lifted. Several recent Indian studies have shown that short-term and long-term exposure to elevated PM levels are most likely to trigger respiratory disorders among children (Siddique *et al.,* 2011), elevated blood pressure and hypertension (Prabhakaran *et al.,* 2020), and daily mortality (Maji *et al.,* 2011). To that end, we present to the air quality regulatory and health authorities, a suit of Air Quality Health Indicators (AQHI), to demonstrate short-term PM_{10} and $PM_{2.5}$ exposure on children, infants and other age groups. Wereflect oncurrent challenges and future opportunities of conducting air quality-health research, which is yet underdeveloped in India.

Methods

We obtainedambient concentrations of particulate matter ($PM_{2.5}$ and PM_{10}), and trace gases including nitrogen dioxide (NO_2), and carbon monoxide (CO), from the Central Pollution Control Board'sarchive (CPCB), as 24-hour time-weighted average(9:00 am – 9:00 am) for two monitoring stations namely, Gwal Pahariand Vikas Sadanfor following time periods in 2020:

March 5, 2020 – 24, 2020 : Pre-Lockdown *(PreLD)*

March 25, 2020 – May 31, 2020 : Lockdown*(LD)*

June 1, 2020 – August 31, 2020 : Un-lockdown *(UNLD)*

September 1, 2020 – January 31, 2021 : Life-as-usual*(PostLD)*

Assessment of Air Quality Health Indicators (AQHI) estimation involved computation of Relative Risks (RR), which represents the probability of health effects (for PM_{10}, all-cause mortality and lung cancer mortality; for $PM_{2.5}$, cardiopulmonary mortality and cancer mortality) occurring in a population exposed to a level of air pollution higher than that considered as background without any anthropogenic pollution. The analysis was carried out individually for PM_{10} and $PM_{2.5}$.

The RR for short-term exposure PM_{10} (Chalvatzaki *et al.,* 2019) was estimated using the following equation:

RR_{PM10} = exp [β(X_{obs} – X_o)]
(Eq. 1)
where RR_{PM10} = Relative Risk due to short-term PM_{10} exposure
X_{obs} = Observed concentration of PM_{10} (ground-level data)
X_o = Background concentration
β = Empirical coefficient (obtained from literature)
The $RR_{PM10}$is computedfor two cases (Ostro, 2004)

- All-cause mortality for children and infant (<5 years of age)
  - o β taken as 0.00166
- Respiratory mortality for all age groups
  - o μ taken as 0.0008

However, a major challenge faced during the computation was lack of *background* values (X_o) for PM_{10} and $PM_{2.5}$. In absence of such, we took the WHO regulatory threshold ($PM_{2.5}$ = 24 μg.m^{-3}; PM_{10} = 10 μg.m^{-3}) for background concentrations. The idea was, there is higher health risk of population exposed to PM levels above this regulatory threshold.

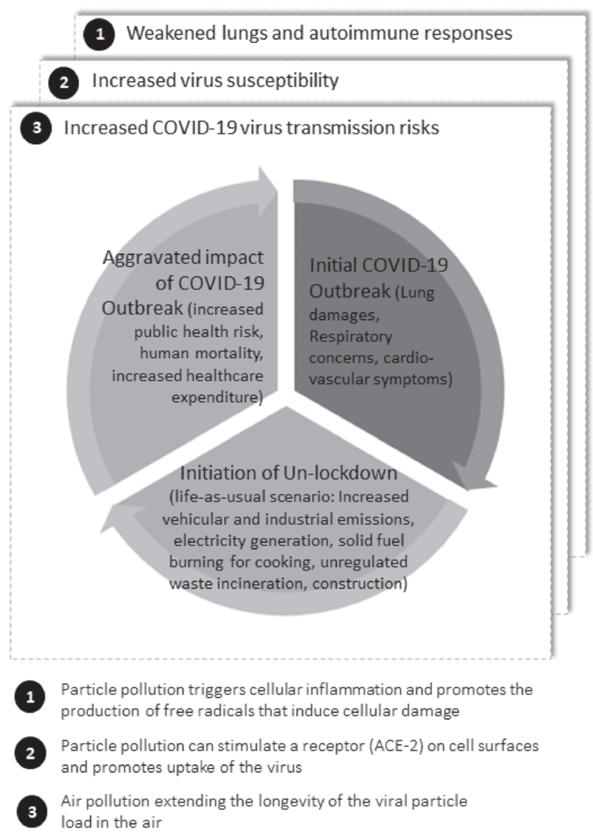

Fig. 1. Potential cyclic feedback loop between initial COVID-19 outbreak, Lockdown/Un-lockdown and renewed urban air pollution, and aggravated COVID-19 disease spread

We take this opportunity to urge the concerned authorities to estimate appropriate background concentrations for each station (Vikas Sadan and Gwal Pahari) for better use in health risk assessment purposes.

For $PM_{2.5}$, the RR was estimated using the following equation:

$$RR_{PM2.5} = \left[\frac{X_{obs} - 1}{X_{bench} + 1}\right]^{\beta} \quad \text{.. (Eq. 2)}$$

Eq. (2) was used to estimate types of mortality risks due to long-term exposure to $PM_{2.5}$, for adults (>30 years) (Pope *et al.*, 2012):

- Cardiopulmonary Mortality: β taken as 0.1551
- Cancer Mortality: β taken as 0.23218

Based on the RR(Eq. 1 and 2), we extended our assessment of potential health outcomes by computing Attributable Function (AF) = (RR - 1)/RR. The AF estimates the proportion of deaths from a disease (e.g., lung cancer), which could be avoided if ambient PM levels were reduced to background concentrations (the WHO regulatory limit in the present context).

Results and Discussion

Temporal Patterns in Air Pollutants

For both monitoring stations, PM levels experienceda drop in the UNLDs, from that of the PreLD, followed by steep jumps in the PostLD period (life-as-usual condition)(Figure 2). At Vikas Sadan and Gwal Pahari monitoring stations, the median $PM_{2.5}$ concentrations increased by about 22% and 104%, respectively in the PostLD, from that of the PreLD period. Median PM_{10} concentration at Gwal Pahari was about 24.5% higher in PostLD period than that of PreLD. Median CO concentrations increased by about 10.5% and 43% in the PostLD, respectively at Vikas Sadan and Gwal Pahari. Median NO_2 concentration at Gwal Pahari was about 43% higher in PostLD than that of PreLD. The above indicates re-emergence of air pollutants, as soon as restrictions were lifted and urban life was allowed to return to life-as-usual conditions. A major point of owe for the air quality regulatory authorities and urban residents, is that: ambient PM levels exceeded (i) the WHO regulatory thresholds (24 and 10 μg.m^{-3} for $PM_{2.5}$ and PM_{10} respectively) all along the study period; and (ii) and NAAQS thresholds for most part of the study period (60 and 100 μg.m^{-3} for $PM_{2.5}$

and PM_{10} respectively), revealing re-emergence of air pollution and public health concerns due to growing particulate matter loadings in ambient air. This was in corroboration with Dey *et al.* (2012) who found that nearly 51% of the subcontinent's 1.4 billion people are exposed to $PM_{2.5}$-related air pollution that exceed the World Health Organization's annual air quality threshold.

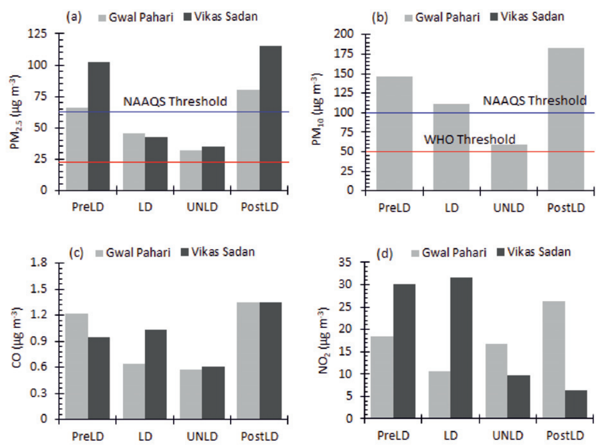

Fig. 2. Comparative summary of median concentrations of different air pollutant species at Gwal Pahari and Vikas Sadan in 2020. PM10 data was not available for Vikas Sadan station for 2020. Red and Blue solid lines in panel (a) and (b) represent the threshold concentrations of World Health Organization and Indian National Ambient Air Quality Standard*(Data Source: Central Pollution Control Board, India)*

AQHI: $PM_{2.5}$ Exposure

Figure 3 indicates that RR forcardiopulmonary and cancer mortality among the adults (>30 years) have been on the rise in the Post LD periods, as $PM_{2.5}$ levels spiked through the PostLD periods. The RR function (Eq. 2) represents proportional increase in health outcomes in response to certain increase in pollutant levels. For example, how much the Cancer Mortality risk would increase if $PM_{2.5}$ levels go up by, say, about 15 µg.m^{-3}. Results indicated consistently higher risks at Vikas Sadan than Gwal Pahari. Transitioning from UNLD to PostLD, the RR (relative risk) levels for cardiopulmonary mortality at Vikas Sadan and Gwal Pahari spiked by 73% and 71.5% on average, respectively, indicating growing risks of health hazards. $PM_{2.5}$is a known health hazard in Indian cities (Chen *et al.,* 2020), reducing visibility (Wang and Chen, 2019; Khare *et al.,* 2018), and increasing disease prevalence (Stafoggia *et al.,* 2019; Gao *et al.,* 2015; Pope *et al.,* 2009), and premature deaths (Gao *et al.,* 2018).

The RR factor, when coupled with Attributable Function (AF), presentsan estimate of by how much of human life expectancy could be increased (if $PM_{2.5}$ exposure is curtailed). The AF values computed in the present context indicate that regulation of ambient $PM_{2.5}$ levels may increase life expectancy in cases of cardiopulmonary mortality, by about 25% and 23% (PostLD3) at Vikas Sadan and Gwal Pahari, respectively (Figure 3a). Similarly, life expectancy in cases cancer mortality, could be raised by about 35% and 34% at Vikas Sadan and Gwal Pahari, respectively (Figure 3b). However, it should be noted that the RR and AF computed this way estimates indicates risks in a defined population as a whole, and not on individual level (Australian De-

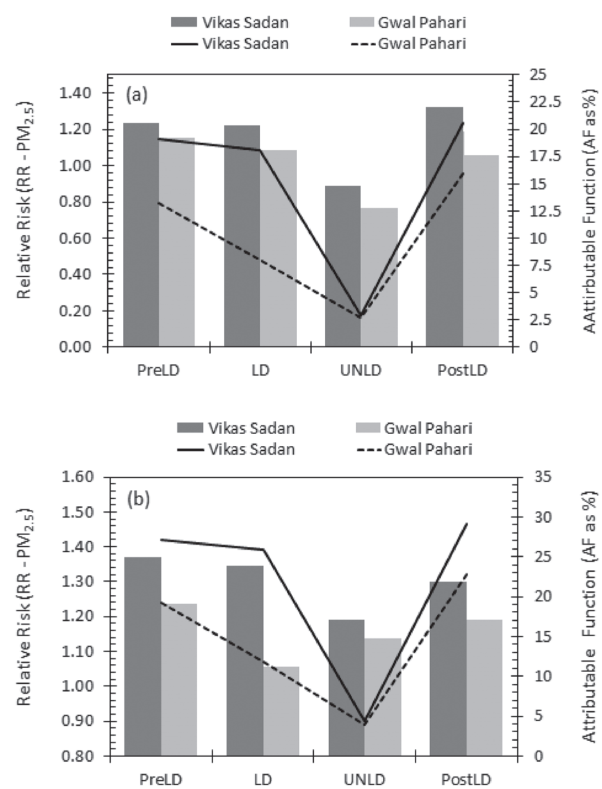

Fig. 3. Median values of Relative Risk (RR) and Attributable Function (AF, expressed as %) through different times periods in 2020among adults (>30 years) for (a) cardiopulmonary and (b) cancer mortality due to long-term exposure elevated concentrations of $PM_{2.5}$ at Vikas Sadan and Gwal Pahari monitoring stations

partment of Health, 2012; McAuley andHrudey, 2006). For the latter, there is need for case-by-case study with more intensive monitoring and information.

Annual $PM_{2.5}$ exposure in India has been increasing in recent years (Dey *et al.*, 2012, Dey and Di Girolamo, 2011). According to WHO (2016), 14 Indian cities are among the world's 20 most polluted in terms of PM2.5 levels. In 2017, this rise in pollution led the Indian Medical Association to declare a public health emergency in the National Capital Region of Delhi (Chowdhury *et al.*, 2019). Cohen *et al.* (2017) demonstrated that annual premature mortality in India attributed to exposure to ambient particulate matter (PM2.5) exceeds 1 million.Conibear et al. (2018a) have already warned that, even in absence of emission growth, the disease burden in India due to ambient $PM_{2.5}$ exposure would rise by 75% in 2050, relative to 2015. In 2017, about 0.67 million deaths were attributed to $PM_{2.5}$, which by 2019 has risen to about 1.7 million, accounting or about 18% of all deaths recorded in India(India State-Level Disease Burden Initiative Air Pollution Collaborators, 2020). In a more recent global appraisal, Lilieveld *et al.* (2020) demonstrated that ambient air pollution, especially exposure to $PM_{2.5}$, is a leading cause of excess mortality and loss of life expectancy (LLE). Globally, the LLE from air pollution surpasses that of HIV/AIDS, parasitic, vector-borne, other infectious diseases, smoking, and even all forms of violence. Overall, we urge the authorities to conduct more in-depth investigation around the health-$PM_{2.5}$ nexus, with more spatially-intensive, real-time monitoring.

AQHI: PM_{10} Exposure

Negative health outcomes due to short-term PM_{10} exposure varied over time (Figure 4). There was a slight drop in the Relative Risk (RR) factor, transitioning from PreLD (normal life) to LD, for both children and infants (<5 years of age). However, it was still high, which owes to one or a combination of three factors: (i) homecoming of the migrant labors from different parts of the country, and (ii) continuation of thermal power plant operations to meet domestic and utility needs. In addition, prolonged homestay and increased domestic activities (cooking, cleaning, heating, gardening, lawn mowing) during the Lockdown periods, can substantially add to outdoor pollutant loads (Gordon *et al.*, 2019). Indoor air pollution is rapidly become a prime source of health concern in India (Chowdhury *et al.*, 2019; Dey *et al.*, 2012). Recent studies have revealed that, residential emissions can also potentially contribute to as high as about 50% of the observed particulate matter concentrations in urban environment, causingsubstantial annual mortalities (Gordon *et al.*, 2019; Conibear *et al.*, 2018b).

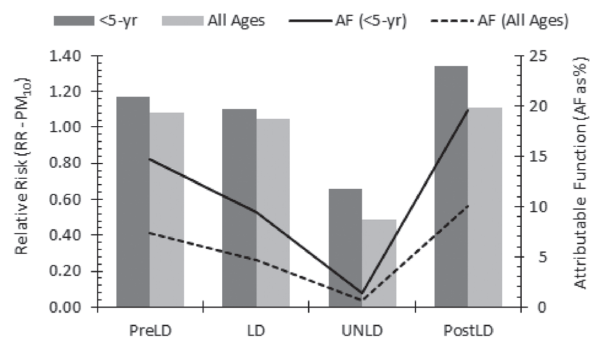

Fig. 4. Median values of Relative Risk (RR) and Attributable Function (AF, expressed as %) children and infants (<5 years of age) and all age groups due to short-term exposure to PM_{10} at Gwal Pahari monitoring station

Our present results further indicated that the RR factor associated with PM_{10} exposure declined substantially in the UNLD before jumping up in the PostLD period. Similar trend was observed for the Attributable Function (AF), with steep rises in the PostLD period, as compared to the UNLD. In the PostLD period, about 25% of life expectancy among children and infants could be increased by regulating short-term PM_{10} exposure. It was interesting to note that all through the study period, health risks for children and infants sailed almost at par with 'all age group'. However, in the PostLD, the children appear more vulnerable to short-term PM_{10} exposure, which calls for intensive monitoring and targeted regulatory interventions.

AQHI: Short- and Long-term Benefits

The above estimates demonstrate the burgeoning severity of air quality related health disorders, which are on the rise since resumption of life-as-usual conditions (PostLD). Short-term benefits of such research may include, estimation of number of the attributable deaths or cases of disease due to air pollution; years of life lost (YLL), disability-adjusted life years (DALYs); and change in life expectancy attributable to total exposure to air pollution or a change in exposure, to name a few (Table 1).

Table 1. Short-term benefits of conducting air pollution-health research.

Health Function	Salient Features
Number of attributable deaths or cases of disease to air pollution	Determined as the difference in number of deaths or cases of diseases between the incidence/rate at the exposure measured over a specific period and that at baseline exposure, e.g. difference between current disease incidence and historical incidence or projected future incidence, or total health risk (in relation to zero exposure or to some assumed threshold value)
Years of life lost (YLL)	A measure of the years of life lost as a result of premature death. In simplified terms, the calculated number of deaths attributable to changes in exposure to air pollution is multiplied by the standard life expectancy at the age at which death occurs.
Years lost due to disability (YLD)	Estimated by multiplying the number of incident cases of a particular health outcome in a particular period by the average duration of the case until remission or death (years) and a disability weight factor that reflects the severity of the disease on a scale from 0 (perfect health) to 1 (dead).
Disability-adjusted life years (DALY)	One DALY is one lost year of healthy life. The sum of DALYs across a population– the burden of disease – can be thought of as a measurement of the gap between actual health status and an ideal situation in which the entire population lives to an advanced age, free of disease and disability. Total DALYs for a particular disease or health condition in a population are calculated as the sum of YLL and YLD

As long-term benefits, the AQHIs can address policy questions such as (WHO Regional Office for Europe, 2014):

i. What is the public health burden associated with current levels of air pollution?
ii. What are the human health benefits associated with changing an air quality policy or applying a more stringent air quality standard?
iii. What are the human health impacts of emissions from specific sources or selected economic sectors, and what are the benefits of policies related to them?
iv. What are the human health impacts of current policy or implemented action?
v. What are the policy implications of the uncertainties of the assessment?

Responses from the above, could be used in economic evaluation of health benefits resulting from policy change (implementing more stringent regulatory measures).

Aqhi: Future Research Directions

A prime impetus to undertake this study was to highlight to the regulatory authorities the environmental health burden due to re-emergence in air pollutants in the PostLD period. This research could serve as a wake-up call to undertake more in-depth process-level research to establish direct causal linkages (statistically significant) between ambient PMconcentrations and environmental health in many Indian cities (Lung Care Foundation, 2019). However, itwill require a self-introspection to related eteriorating air quality in the post-COVID times with health outcomes (observed, as well as predicted) (Fig. 5).

- Who are the people most vulnerable to air pollution (age group, socioeconomic class, gender, people with existing diseases, occupational groups)?
- How best to characterize the mode of exposure?
- What is the spatial extent of exposure?
- What health outcomes are anticipated (long-term vs. short-term, sub-clinical effects, hospital admissions, reduced physical activity, respiratory disorders, impaired lung functions, mortality, incidence rate of a specific disease, work loss)?
- Whichare the priority pollutants?

If ground-level monitoring (as was used in the present study)isto be used to answer the above, it should be a combination of background levels (estimation of baselines), traffic emissions (mobile), and industrial emissions (stationary). For Indian cities, emissions from roadside food stalls couldbe major pollutant sources (stationary) as well, as most of these operate on 'unclean' fuels (diesel, biomass, coke etc.). Once the desired data have been identified (and made available), health impacts associated

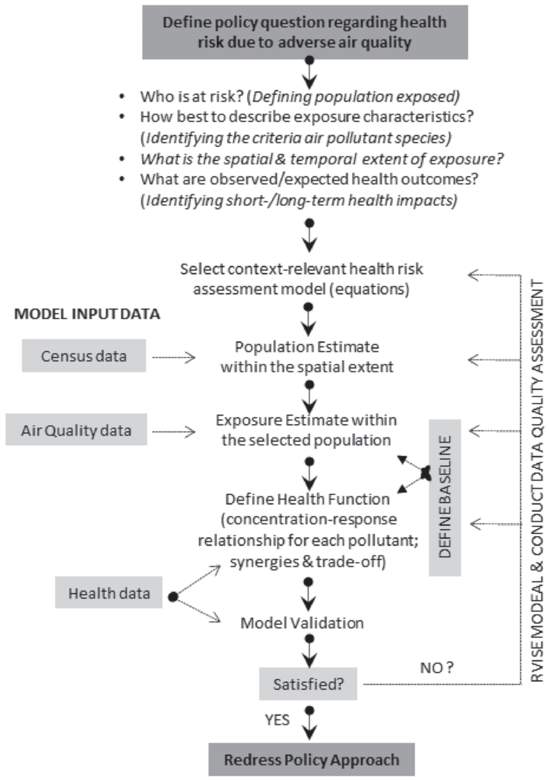

Fig. 5. A potential workflow strategy for data acquisition for computing Air Quality Health Indicators (AQHI) related to ambient particulate matter pollution (Adopted from WHO Regional Office for Europe, 2014; US EPA, 2012)

with exposure are to be estimated following asequential approach

Stage I: Estimation of baseline for (i) pollutant concentrations and (ii) health

Stage II: Estimate the exposure for the assessed population.

Stage III: Use the exposure estimates and baseline health outcome rates as input data for a function describing the concentration–response relationship. This will allow the health risk associated with the estimated exposure to be assessed for the population.

Stage IV: Model validation, using observed health trends to assess the efficiency of the model and suitability for decision-making. Based on the congruency between observed and modeled responses, the model might need to be changed or more data

Studies of acute PM exposure should typically involve daily observations over several months or years (Pope *et al.*, 2009; Ostro, 2004). It should involve multivariate regression analysis, incorporating information from different sectors -health, environment, urban development, economics, social sciences. Long the line, while attempting to establish statistically meaningful correlations between air quality and health, the regulatory authorities should be aware of potential uncertainties in the statistical

Table 2. Potential sources uncertainties associated with air pollution-health research.

Confounding Factors	Salient Features
Air pollutants exist as a complex mixture	Observed health impacts attributed to an individual air pollutant may actually be (partly) attributable to other pollutants in the mixture which are correlated with the assessed pollutant.
Pollution exposure level	As there is yet lack of intensive geographical coverage of ground level air quality monitors (Vikas Sadan station lack PM_{10} monitoring) disease estimation has to rely to some extent on modelling to estimate exposure. Modelling is also needed for estimates of future exposure based on predicted changes in air pollution as a result of new policies or technological improvements. Since air quality models are based on a set of assumptions, it is not possible to be certain that the estimated exposure coincides with the actual ambient concentrations in a given location.
Counterfactual level of air pollution	It is related to confusions regarding the baseline or reference exposure against which the health impacts of air pollution are calculated. This level of air pollution may be ascertained differently, depending on the policy question to be answered. It may, for example, be defend as the national air quality standard, the WHO air quality guideline level, the natural level (i.e. without anthropogenic influence) or the lowest level observed in epidemiological studies. Uncertainty in the counterfactual level may be due to imperfect knowledge about the exact effect of some previous policy change or a theoretical minimum level of pollution.

model **(Table 2)**. The idea would be to unravel causal relationships based on real physical evidence of mortality/cancer.

For regulatory purpose, robust statistical models should be developed to correlate daily counts of mortality or cause-specific hospitalizations with daily PM concentrations, after accounting for co-variates and confounding variables, which may vary over space and time, and across regulatory/management regimes. The co-variates are generally context specific but usually include co-pollutants, and seasonal changes in population growth (meteorological impacts). Such predictive modeling of PM-related health outcomes calls robust time series analysis, with large sample size (8-10 years of daily data) for a range of population demographics.

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