The future health impacts of long-term exposure to air pollution in India under climate change, demographic change and urbanisation

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ABSTRACT: Rapid socio-economic development in India has been accompanied by gains in life expectancy and improvements in a range of health outcomes. However, it is uncertain how the fast pace of urbanisation, the aging of the population and climate change will alter this trend in the future. This study estimates the health co-benefits from projected changes in exposure to ambient fine particulates ($PM_{2.5}$) in India up to 2050 and under alternative climate change mitigation and air quality abatement scenarios, considering future demographic change and urbanisation trends. A multi-dimensional cohort-component projection model is employed to explore dynamically over time the range of potential health impacts across urban and rural areas in all states of India. We show that pursuit of aspirational climate change mitigation targets can bring clear co-benefits from cleaner air by averting up to 10 million deaths and increasing life expectancy at birth by up to one year by mid-century compared to business-as-usual. Combining these targets with policy measures that target air pollution explicitly can double these benefits to human health. The spatial distribution of the health burden from air pollution shows rural areas to be disproportionately affected despite lower concentrations and indicates substantial differences between states, driven by population size, baseline exposure and life expectancy as well as their progression over time.

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1. Introduction

Rapid socio-economic development in India has been accompanied by gains in life expectancy and improvements in a range of health outcomes (KC, Wurzer, Speringer, & Lutz, 2018). Urbanisation has facilitated these trends by providing better opportunities for education and employment and improved access to infrastructure and services for the growing population of the country. However, when poorly planned and inadequately managed rapid urban growth can occur at the cost of growing public health challenges and environmental degradation. Aggravation of air pollution, road injuries, overcrowding and formation of informal settlements, land use change, associated with the urban heat island effect, are some of the most well-known public health risks encountered in the cities of many low and middle income countries (LMIC).

India is not only one of the most rapidly urbanising countries in the world ([1]), but it also hosts 13 of the world´s 20 cities with most polluted air (Purohit et al., 2019). In 2017, the Institute for Health Metrics and Evaluation ranked air pollution as the second most important contributor to mortality and morbidity in India, after malnutrition and dietary risks ([2]). Currently, 99.9 % of the population in India is estimated to live in areas, exceeding the World Health Organisation (WHO) Air Quality Guideline for fine particulate matter ($PM_{2.5}$) of 10 µg/m_3 (GBD MAPS Working Group, 2018). Annual average exposure to $PM_{2.5}$ in India has been increasing over the last decades (IHE, 2018; Dey & Girolamo, 2011). Considering that the country is still in the early stages of its economic development and is expected to experience strong population and economic growth, further industrialisation and urbanisation, accompanied by increased energy and fuel consumption, air quality is likely to remain an important policy concern in the future. This risk is even more pronounced given India´s current energy mix, which is largely dominated by coal (44 % of total energy demand), biomass (24 %) and oil (23 %) as opposed to natural gas (6 %), renewable (2 %) and nuclear energy (2 %) (International Energy Agency, 2016).

The growing population and rapid urbanisation in India are expected to fuel future demand for energy and resources. Considering that the country is currently the third largest emitter of greenhouse gases (GHGs), after China and the US[3], efforts for decoupling economic growth from increases in emissions in India will be pivotal for climate change mitigation globally. Furthermore, such efforts will have the more immediate benefits of improved air quality since many anthropogenic sources of air pollutants also emit CO_2 and other GHGs. Climate change is also projected to alter ambient $PM_{2.5}$ concentrations in India through changes in local and regional temperature, precipitation, humidity and circulation (UNEP, 2019; Pommier et al., 2018b). However, these impacts are expected to be relatively smaller compared to the potential increases in anthropogenic emissions (Fang, Mauzerall, Liu, Fiore, & Horowitz, 2013; Kumar et al., 2018; Pommier et al., 2018a). Due to the close interlinkages between air quality and climate, investigating health impacts associated with both climate change mitigation and air quality controls can help identify important cost-effective measures for tackling these twin challenges.

A realistic assessment of future climate change related impacts, including air pollution, requires not only advanced modeling and projections of environmental risks, but also consideration of

[1] According to UN projections the urban population in India is expected to grow by 404 million people between 2014 and 2050, compared to 292 million in China and 212 million in Nigeria. Overall, these three countries are projected to account for 37 % of the nearly 2.5 billion increase in the world urban population by 2050 (UNDESA, 2014).

[2] http://www.healthdata.org/india (accessed September 13, 2019).

[3] https://www.carbonbrief.org/the-carbon-brief-profile-india (accessed September 30, 2019).

future demographic and human capital transitions as well as their potential interactions with environmental hazards. This is particularly the case for LMIC such as India, which are not only recognised as highly vulnerable to climate risks (Watts, Adger, & Agnolucci, 2015), but also expected to experience dramatic socio-economic and demographic transformations in the next decades. The population in the India is projected to grow from 1.2 billion in 2011 to almost 1.7 billion in 2050 (KC et al., 2018), while the share of the urban population is expected to reach 52.8 % by 2050 from 31.3 % in 2011[4]. While these trends will have paramount implications for economic growth, energy use and GHG emissions, they will also directly alter environmental health risks by increasing baseline population exposed to outdoor air pollution, especially to the extremely high levels found in many urban centers in India. The rising levels of cardio-metabolic diseases and the ageing of the population, associated with the undergoing demographic and epidemiological transition in India, are likely to further amplify the adverse health impacts of air pollution and other climate-related risks by increasing the share of those most vulnerable (Dandona et al., 2017). Thus, understanding the potential interplay of population dynamics and environmental health hazards such as air pollution is crucial for reducing a major source of uncertainty in future climate change vulnerability assessments (Madaniyazi, Guo, Yu, & Tong, 2015). Projections which explore these interactions at sub-national level are particularly needed to help determine regional or local priorities for improving public health through air pollution control, urban development and adaptation measures.

Although most projections on future health burden under different emissions and/or climate change scenarios have focused on countries in Northern America, Europe or the globe as a whole (Madaniyazi et al., 2015), in recent years there have been an increasing number of studies on LMIC, including India. Scenario analysis in relation to air pollution for India has focused either on the country level (Chowdhury, et al., 2019; Chowdhury, et al., 2018; Conibear, et al., 2018b; International Energy Agency, 2016; Pommier et al., 2018; Venkataraman et al., 2017) or on specific cities (Dholakia, Purohit, Rao, & Garg, 2013). Conibear et. al. (2018) used a high-resolution online-coupled model to investigate the impact of different air pollution control pathways on ambient $PM_{2.5}$ concentrations and human health in India. Although the study found substantial health benefits of stricter air quality control, it showed that even under an aspirational scenario with reduction in concentrations, premature mortality from $PM_{2.5}$ exposure is set to increase due to population growth and aging. Chowdhury (2018) projected the mortality burden in India associated with future ambient $PM_{2.5}$ exposure under different climate change and socio-economic and demographic scenarios at national level. However, both studies did not consider sub-national variations in air pollution levels (Dey et al., 2012) and baseline rates of cardio-metabolic disease in the country (Dandona et al., 2017). Chowdhury et al (2019) modeled seven different scenarios of mitigating household $PM_{2.5}$ sources — biomass for cooking, space — and water-heating, and kerosene for lighting – and demonstrated that the Indian National Ambient Air Quality (NAAQ) standard is achievable though a cleaner energy transition of households and could translate to ~13% reduction in premature mortality from ambient $PM_{2.5}$. Another recent study funded by the Health Effects Institute provides a comprehensive assessment of the current and future burden of disease attributable air pollution from major source sectors, including at regional level, considering future mortality projections and three future emission scenarios (GBD MAPS Working Group, 2018). Without further action to curb emissions the study projects deaths attributable to ambient $PM_{2.5}$ to reach 3.6 million in 2050 compared to nearly 1.1 million deaths in 2015, while aggressive action is estimated to avert 1.2 million deaths. The study also suggests increases in

[4] United Nations. World Urbanisation Prospects 2018. Country profiles – India. https://population.un.org/wup/Country-Profiles/ (accessed September 13, 2019).

mortality attributable to air pollution even with reductions of air pollution as a result of population growth and aging.

Most of the aforementioned studies consider projected changes in the size and the structure of the population. However, future mortality rates and population estimates in the models they use are exogenous and based solely on assumptions of future demographics, i.e. they presume the same future mortality rate and total number of deaths under alternative emission scenarios and attribute a certain population fraction of these deaths to air pollution. This approach is somewhat justifiable when the hazard risks from air pollution are very low and health impacts are assessed in the near future. However, it can be misleading for settings with high air pollution and associated hazard risks and for long term predictions since changes in mortality and survival population induced by changes in exposure are not considered (Miller & Hurley, 2003). Sanderson et. al (2013) addressed this limitation by incorporating the "feedback effect" of changes in air pollution on future mortality rates. However, the study reported health impacts for the whole of India and did not consider urban and rural differentials. Recognising this gap, we linked the MESSAGEix-GLOBIOM integrated assessment model (IAM) framework, the GAINS air quality model and the five-dimensional cohort component projection for India (KC et al., 2018) to analyse dynamically over time the health co-benefits from air pollution reduction under alternative climate change mitigation and air pollution abatement scenarios at sub-national level and for urban and rural residence.

2. Methods

2.1 Ambient $PM_{2.5}$ concentrations

Gridded annual ambient fine particulate matter ($PM_{2.5}$) concentrations (2010-2050) on a five-year interval for the period 2010-2050 are derived from the Greenhouse-Gas Air Pollution Interaction and Synergies (GAINS) model. GAINS is an established model for exploring synergies and trade-offs between air pollution control and global greenhouse gas emissions mitigation (Amann et al., 2011; Li et al., 2019; Rafaj, Kolp, Rao, Klimont, & Schopp, 2010; Rafaj, Schöpp, Russ, Heyes, & Amann, 2013; Shindell et al., 2012). It represents one module in the International Institute for Applied Systems Analysis´s (IIASA) Integrated Assessment Model (IAM) framework, also referred to as MESSAGE-GLOBIOM. The future air pollution trajectories analysed herein are estimated in GAINS on the basis of exogenous projections of anthropogenic emissions and economic activities (e.g. energy consumption, industrial production, transport, and agriculture projections) developed under the energy, land use, economy and climate modules in the IIASA IAM framework[5]. The activity and emissions data from the IAM are combined with source-specific emission factors and source-receptor relationships of aerosol precursors to arrive at estimates of $PM_{2.5}$ concentrations. Our analysis is based on India-specific version of the GAINS model, where the national energy and emission projections are disaggregated across 23 main sub-regions of the country. The approach of modelling PM concentrations follows the methodology described by Purohit et al. (2019). GAINS uses linear transfer coefficients, describing the spatial response of an air quality indicator to changes in precursor emission at each source throughout the model domain, which have been derived from the European Monitoring and Evaluation Programme (EMEP) chemistry transport model (Simpson et. al, 2012) . The model estimates ambient $PM_{2.5}$ concentrations from the following

[5] International Institute for Applied Systems Analysis. MESSAGE-GLOBIOM. https://data.ene.iiasa.ac.at/message-globiom/ (accessed September 13, 2019).

sources: (i) primary ambient particulate matter emitted directly to the atmosphere from anthropogenic sources, (ii) secondary particulate matter formed in the atmosphere through chemical reactions of precursors gasses such as SO_2, NO_x and NH_3, (iii) particulate matter originating from natural sources such as solid dust, sea salt and biogenic sources. PM and its precursor emissions are estimated at a 0.50×0.50 longitude–latitude resolution (Klimont et al., 2017), based on relevant proxy variables.

To determine concentrations for urban and rural areas, the gridded $PM_{2.5}$ concentrations were intersected with urban polygon shapes from Global Rural-Urban Mapping Project[6] (GRUMP), 250m gridded population data from the Joint Research Centre (JRC) and 100x100m gridded population data from the WorldPop project[7] by researchers in the Air Pollution group in IIASA. Urban regions were defined as towns and cities with >100,000 inhabitants and densities >1000 people/km^2 and the rest were classified as rural. The urban-rural distribution from the gridded data resulted in 2 % higher rural population compared to the 2001 population distribution from the India census. To ensure consistency, 2 % of the rural areas were reclassified as urban.

It should be noted that the urban-rural designation used for the exposure differs from the official India census classification, applied in the population projection. In the latter, administrative units are defined as urban when they have (i) minimum 5,000 inhabitants; (ii) at least 75% of the male working population employed in non-agricultural work; and (iii) population density of at least 400 people per square kilometre[8].

Population-weighted exposure for a given year and emission scenario was calculated separately for urban and rural areas within each state as follows:

$$PWE_j = \frac{\sum_{i=1}^{n} P_{i,j} C_{i,j}}{\sum_{i=1}^{n} P_{i,j}}$$

where PWE_j denotes the domain of interest (all urban/rural areas within each state), $P_{i,j}$ is the population and $C_{i,j}$ the $PM_{2.5}$ the concentration in each grid cell within this domain. Smaller states have been grouped together when estimating population-weighted exposure. The population-weighted $PM_{2.5}$ exposure for all years was based on the 2000 population, therefore population growth over time was not considered. As pointed out by Stedman, King, Holland, & Walton (2002) the population-weighted mean would not change by increases in the absolute size of the population (numerator and denominator will both increase by a constant factor), but will be affected by the changes in the distribution of the population relative to the distribution of particles (e.g. internal migration).

2.2 Scenarios

The energy pathways analysed in this paper are developed within the Linking Climate and Development Policies – Leveraging International Networks and Knowledge Sharing (CD-LINKS) project[9]. The population and GDP projections driving the emissions across all the CD-LINKS scenarios are based on SSP2, which is in line with the population projections used in our

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[6] NASA. Global Urban Mapping Project (GRUMP) versión 1. https://sedac.ciesin.columbia.edu/data/collection/grump-v1 (accessed September 13, 2019).

[7] Worldpop. https://www.worldpop.org/ (accessed September 13, 2019).

[8] Inda census 2011 http://www.censusindia.gov.in/2011census/HLO/Metadata_Census_2011.pdf

[9] International Institute for Applied Systems Analysis. CD-LINKS Scenario Database (version 1.0). https://db1.ene.iiasa.ac.at/CDLINKSDB/dsd?Action=htmlpage&page=about (accessed September 13, 2019).

analysis. The scenarios analysed are summarised in the table below. NPi is a our reference scenario, which models the implementation of currently announced targets for climate, energy and development policies up to 2030 and equivalent effort to no climate policy beyond 2030. The INDC scenario assumes that policy commitments specified in countries´ Nationally Determined Contributions (NDCs) are duly implemented by 2030, but no further intensification of emission reduction commitments beyond this

Table 1. Scenario definitions

Scenario	Description
NPi	National Policies until 2030, no climate policy after 2030
INDC	National Policies until 2020, after which implementation of Nationally Determined Contributions (NDCs) until 2025/2030
2° C	National Policies until 2020, after which mitigation measures in line with a >66% chance of staying below 2°C throughout 21st century
1.5° C	National Policies until 2020, after which mitigation measures in line with a >66% chance of staying below 1.5°C in 2100
INDC – MFR	Same as above, but combined with the implementation of measures for maximum feasible reduction of air pollution
2° C – MFR	
1.5° C - MFR	

point is undertaken. The more aspirational scenarios of 2° and 1.5° are based on the NPi scenario. They stipulate implementation of national policies until 2020 and radical policy action for transitioning to global CO_2 budgets consistent with limiting global long-term temperature increases to 2°C and 1.5° C thereafter (cumulated 2011-2100 global CO_2 budget of 1,000 $GtCO_2$ and 400 $GtCO_2$ for the 2° and 1.5° targets, respectively). The IIASA IAM allows determining a portfolio with the most cost-effective mitigation measures to stay within the respective carbon budgets. More detailed information about the CD-LINKS scenarios and their modelling can be found in McCollum et al. (2018). We analyse three additional air pollution scenarios for India, simulated in the GAINS model. These correspond to the CO_2 emission mitigation pathways described above, but on top of them they simulate the implementation of explicit air pollutant control measures (GAINS simulates over 1000 technical control measures, including structural measures and end-of-pipe solutions such as improved cooking stoves, flue-gas desulfurization, ban on open burning of agricultural residues, improved emission standards for vehicles, etc.). Based on these set of available emission control options GAINS estimates the maximum feasible reduction (MFR) of air pollutants, taking into account commercially available technology- and country-specific circumstances.

2.3 Population projections

To estimate how changes in air pollution will affect future life expectancy, mortality as well as the structure and size of the population we use the five-dimensional population projection for India developed by KC, Wurzer, Speringer, & Lutz (2018) at the Wittgenstein Centre for Demography and Global Human Capital (IIASA,VID/ÖAW, WU). Their cohort-component model projects India´s population by state, rural/urban place of residence, age, sex and level of education, with differential fertility and mortality rates applied. The authors have shown that explicitly incorporating these sources of population heterogeneity in the projection model for India produces different total population size forecasts than the conventional approach of only considering the age and sex structure of the population at national level. For instance, including a breakdown by level of education tends to lead to lower projected population size because of the stark improvement of educational attainment, especially for women, in India over time and the well-established negative association between women´s education and fertility rate (KC et al., 2018). On the other hand, failing to account for regional heterogeneities, especially in a country with such strong regional differences in fertility rates such as India, might skew population projections downwards.

The population projection we use has been built on tabulations from the two most recent Indian censuses (2001 and 2011) and vital rates from the India Sample Vital Registration System (1999-2013). The definition of urban inhabitants used in the projection is in accordance with the 2011 Census definition as outlined above. Assumptions of future trajectories of fertility, mortality, education and urban-rural migrations are based on observations of past trends as well several rounds of consultations with population experts (Kc & Lutz, 2017). Regarding sub-national differences of mortality, the projection model assumes convergence in the rate of change of sex-specific life expectancy to the national predicted average until 2030 and constant rate of change in the future. A detailed explanation of the method and the data sources used in the population projection can be found in the Appendix of KC et al. (2018).

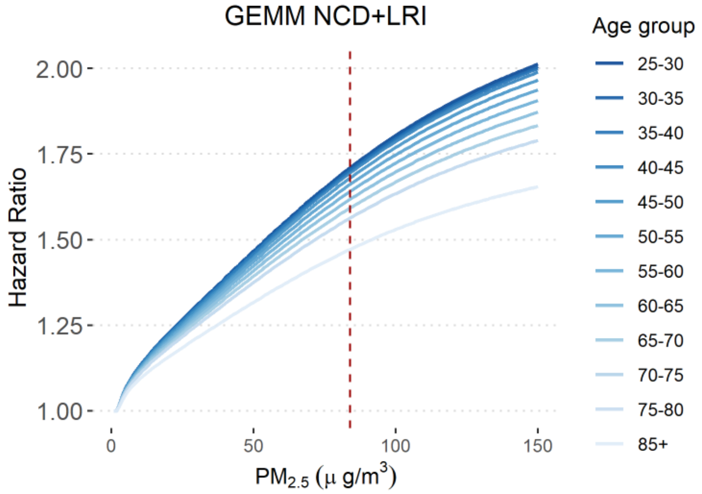
2.4 Exposure response function

To quantify the health impacts of exposure to outdoor fine particulate matter ($PM_{2.5}$) we apply the recently developed Global Exposure Mortality Model (GEMM) (Burnett et al, 2018):

$$HR(z) = \exp\left\{\frac{\theta \log\left(\frac{z}{\alpha}+1\right)}{1+\exp\left\{-\frac{(z-\mu)}{v}\right\}}\right\},$$

where HR denotes the mortality hazard ratio (relative risk of mortality at any concentration compared to the counterfactual concentration of $2.4\mu g/m^3$) for a specific annual exposure to $PM_{2.5}$, z is population-weighted $PM_{2.5}$ exposure ($z = \max(0, PM_{2.5} - 2.4\mu g/m^3$) and θ, z, α, μ are age-specific and disease-specific parameters. Below the counterfactual, which is selected as the lowest observed concentration in any of the 41 cohorts included, GEMM assumes no change in the hazard ratio. Compared to former assessments, which are based on hazard ratio models that draw risk information from multiple $PM_{2.5}$ sources (outdoor and indoor air pollution from use of solid fuels and second-hand and active smoking) and, therefore, require strong assumptions about equivalent exposure and toxicity, GEMM is based solely on studies of outdoor air pollution and incorporates direct evidence from a much larger range in exposure than any other study (15–84 $\mu g/m^3$). This function represents considerable deviation from the integrated exposure response function (IER) currently used by the Global Burden of Disease (GBD) also because of its near-linear shape at higher concentrations. Since the observed effects are reported only for concentrations up to 84 mg/m^3, similarly to Burnett et al (2018), we have extrapolated the GEMM curve to account for the higher $PM_{2.5}$ concentrations found in urban areas in India. As shown in Figure 1, beyond the observed exposure range (84 $\mu g/m^3$) the hazard ratio shows a diminishing increase with increases in concentrations. The shape of the exposure-response function beyond the observed range is a major source of uncertainty and gap in the literature, which calls for more epidemiological studies in high exposure settings. The age-specific GEMMs were used to adjust future adult (>25 y) mortality rates in the population projection to the projected changes in air pollution under each scenario. Cardiovascular risk factors, including $PM_{2.5}$ are shown to decline with age, hence the declining age gradient in magnitude of the hazard ratio on Figure 1 (Burnett et al., 2018; Singh et al., 2013). Due to the lack risk estimates for age groups <25 years, we could not account for the health impacts on younger cohorts. This is an important limitation, considering that up to 6 % of childhood mortality (5-15 years of age) has been attributed to lower respiratory infections from air pollution[10].

Figure 1. Global Exposure Mortality Model Non-Communicable Diseases Plus Lower Respiratory Infections (GEMM NCD+LRI) predictions over observed concentration range by age group (2.4µg/m^3 to 84 µg/m^3) (values until dashed red line). Exstrapolation beyond range of exposure (84 µg/m^3 to 150µg/m^3) (values beyond dashed red line).



It should be noted that the GEMM function refers to deaths from non-communicable diseases and lower respiratory infections. Although these accounted for most non-accidental deaths (>99%) in the 41 cohorts included in the GEMM and for about 94 % in all high income countries[11], their share in LMIC such as India is lower. Estimates differ, but according to IHME these two cause categories accounted for 61 % of all deaths in India in 2011 and 67 % in 2016[12]. Due to the large health and socio-economic inequalities between states, the burden from LRI+NCD is also very unevenly distributed across the country, ranging from 59 % of all deaths in the north-eastern states of Bihar and Odisha to 85 % in the southern state of Kerala[13]. There also likely to be differences between urban and rural areas – for instance, according to the 2011 India census NCD accounted for 57 % of all deaths in urban areas, but only 47 % in urban areas[14]. Therefore, we recognise that our calculations might overestimate the total number of attributable deaths, especially in rural areas and sub-national states with lower socio-economic conditions, where the proportion of communicable diseases is higher. Consideration of disease patterns would be important, but might add further uncertainty — data on cause-specific mortality in India is highly unreliable (Mikkelsen et al., 2015), with the majority of deaths taking place at home without a medically certified cause, and future projections of changes in disease pattern highly uncertain.

[10] https://vizhub.healthdata.org/gbd-compare/ (accessed September 28, 2019).
[11] https://gbd2016.healthdata.org/gbd-search/ (accessed September 28, 2019).
[12] https://gbd2016.healthdata.org/gbd-search/ (accessed September 28, 2019).
[13] https://vizhub.healthdata.org/gbd-compare/india (accessed September 28, 2019).
[14] http://www.censusindia.gov.in/vital_statistics/causesofdeath.html (accessed September 28, 2019).

2.5 Estimation procedure

We linked all the diverse set of models described above in an integrated framework (see Figure 2). The assessment of the health impacts proceeded in several steps. First, we considered the demographic projection for India developed by as our baseline. This approach follows a similar methodology to the one described by Miller & Hurley (2003) and applied by Stedman, King, Holland, & Walton (2002) and Sanderson et al. (2013), with the difference that we use a non-linear exposure response function and a multi-state demographic projection. We made the important assumption that future trends in mortality rates in the baseline did not consider how air pollution might evolve, but were based solely on most likely changes of demographic factors. Since the observed mortality rates in the base year 2010 account implicitly for the impacts of air pollution on mortality, our assumption entails air pollution constant to 2010 level in the baseline projection. The limitation of this assumption is that future trajectories of mortality rates in the baseline might implicitly account for air pollution effects to the extent to which the former are based on past trends. In the next step we re-ran the population projection six times for each emission scenario, adjusting age-specific mortality rates for each state and urban/rural residence to the changes in hazard risk from 2010, associated with the projected changes in $PM_{2.5}$ concentrations over time. The scaling of mortality rates was performed every five-year period as follows:

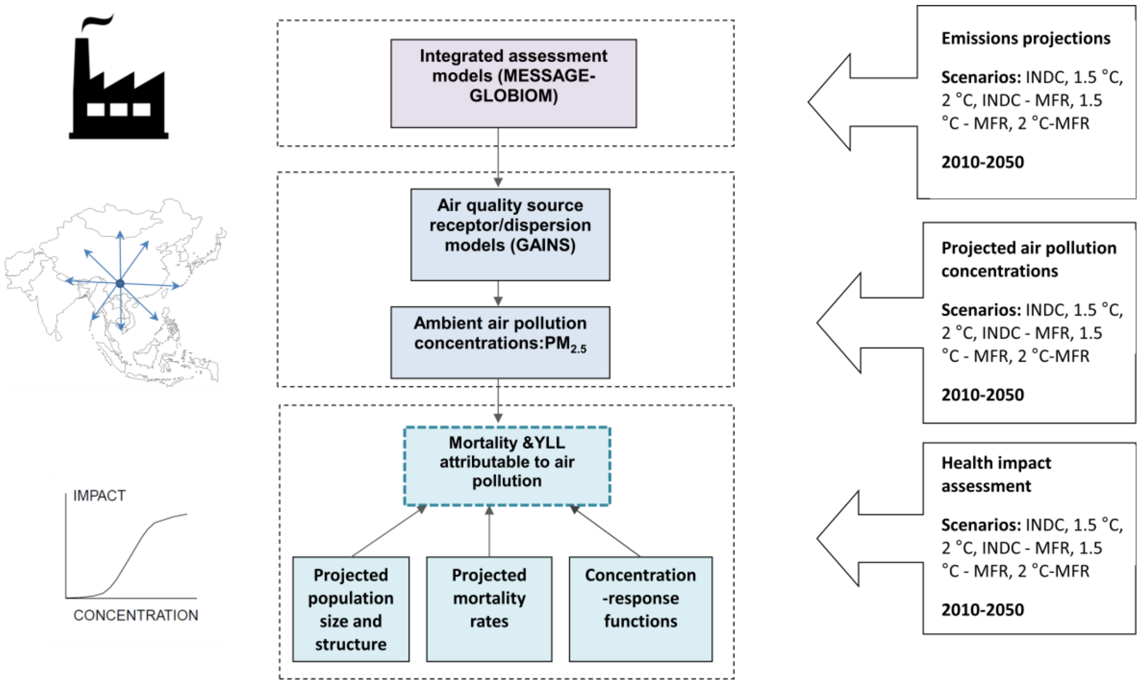
$$m_{age,residence,state}^{scen}(t) = m_{age,residence,state}^{base}(t) \frac{HR_{age,residence,state}(t)}{HR_{age,residence,state}(2010)}$$

where $m_{age,residence,state}^{scen}$ indicates the age-, urban/rural residence- and state-specific mortality rate in the respective emission scenario and $m_{age,residence,state}^{base}$ in the baseline scenario, accordingly. $HR_{age,residence,state}$ denotes the age-specific hazard ratio associated with the $PM_{2.5}$ exposure in each domain (urban/rural residence and state). The population projections under each scenario were implemented in R using version 0.0.4.1 of the MSDem (**M**ulti-**S**tate **D**emography) package[15].

The rescaling of the mortality rate assumptions for each emission scenarios entails changes in survival population over time and hence distinct population size, structure and life expectancies. We used the projected all-cause number of deaths and population size broken down by age, sex, level of education, residence and state from the MSDem outputs and a standard life table method to estimate changes in sex-specific life expectancy at birth *e*0 for the urban and rural areas in each sub-national state and for each future scenario over time. The population projections in each emission scenario were based on the same assumptions of future demographic components such as mortality, fertility, migration and education. Hence, any differences in life expectancy at birth, in the size and structure of the population as well as the number of deaths between scenarios were only due to the changes hazard risk associated with the respective changes in annual average population-weighted $PM_{2.5}$ exposure.

[15] Marcus Wurzer, Samir KC, Markus Speringer. Multi-state Demongraphy (version 0.0.4.1). https://r-forge.r-project.org/R/?group_id=2281 (accessed June 07, 2019).

Figure 2. Proposed integrated modeling framework



We were interested in comparing the results of the dynamic estimation of the health burden with the static health impact assessment approach that most of the existing projection studies are using. In the conventional approach mortality due to air pollution is quantified as a fraction of total mortality that can be attributed to the exposure to $PM_{2.5}$:

$$M_{attr}(t) = Pop(t)m(t)\frac{HR(t) - 1}{HR(t)}$$

where Pop is the population size and m is the baseline mortality rate for a specific year. In this approach, future mortality rates and population estimates are based on assumptions of future demographics only and do not change across emission scenarios, only the proportion of deaths that can be attributable to air pollution changes. This method can be misleading for long term predictions since it does not consider changes in mortality and survival population induced by changes in exposure. The reference point of this static estimation is a counterfactual where air pollution is at its theoretical minimum, below which no health effects are assumed.

To compare this method with the dynamic approach, we also ran the population projection and estimated changes in life expectancy under a counterfactual scenario of theoretical minimum risk exposure level to $PM_{2.5}$ (<2.4 μg/m3), beyond which no health effects are assumed[16]. In other words, this is a hypothetical scenario where ambient air pollution is eliminated as a health risk factor and the risk-deleted mortality rate reflects the rate that would be observed if $PM_{2.5}$ exposure levels were brought to their theoretical minimum. For each future year the mortality rate was calculated as follows:

$$m^{scen}_{age,residence,state}(t) = \frac{m^{base}_{age,residence,state}(t)}{HR_{age,residence,state}(2010)}$$

[16] Based on the GEMM model described above.

While comparison of the baseline scenario with the emission scenarios provides estimates of health impacts due to changes in $PM_{2.5}$ after 2010, the comparison with the counterfactual scenario shows total health impacts attributable to $PM_{2.5}$. The two approaches are conceptually different – the former method quantifies health outcomes that can be reached with changes in current policy and the latter quantifies the total burden of $PM_{2.5}$, even though completely eliminating $PM_{2.5}$ particles is not realistic. The advantage of the counterfactual approach is that it allows more easy comparison with other studies, which have, for the most part, estimated the health burden from $PM_{2.5}$ with reference to the counterfactual.

3. Results

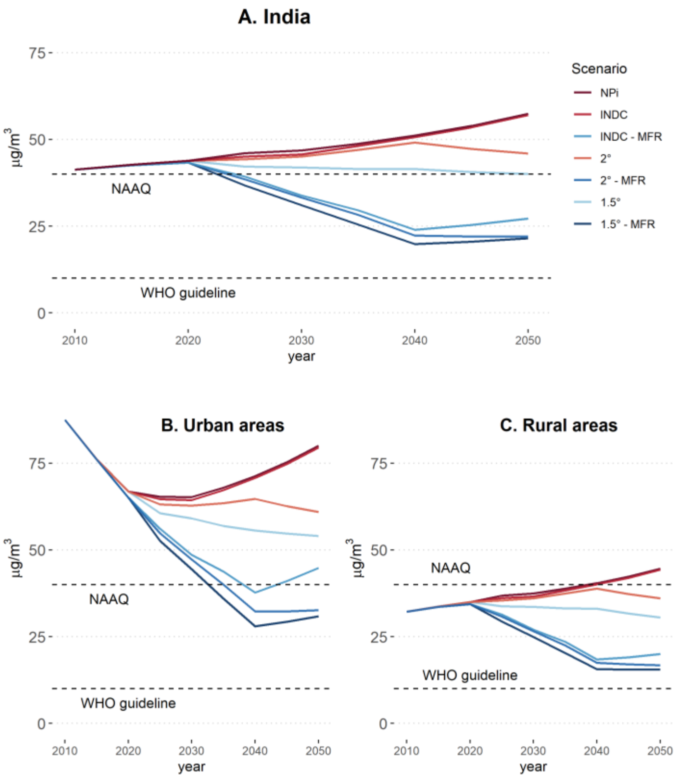
3.1 $PM_{2.5}$ concentrations pathways

Figure 3 below depicts the estimated average annual-population weighted $PM_{2.5}$ exposure over time under each emission scenario for India as a whole and separately for all urban and rural areas. The differences in $PM_{2.5}$ concentration pathways across scenarios seem broadly in line for all three levels of aggregation. With only implementation of current legislation (NPi scenario) $PM_{2.5}$ concentrations are projected to increase steadily over time and more rapidly for urban areas (after their reduction up to 2020 in urban areas). Implementation of Nationally Determined Contributions (NDC) does not bring any further reduction in concentrations than the NPi scenario.

Under global mitigation efforts in line with the 2° target $PM_{2.5}$ concentrations in India are projected to increase, but at a slower rate, up to 2040 and to start falling afterwards. In contrast, CO_2 reductions in accordance with the 1.5° target imply steady reductions in $PM_{2.5}$ concentrations in India over time. The largest reductions in concentrations over time, however, are achieved in the scenarios combining climate change mitigation efforts with maximum feasible controls for air pollutants (MFR scenarios). As seen from Figure 3, $PM_{2.5}$ concentrations in all the MFR scenarios either start to decrease at a slower rate (2° - MFR and 1.5° - MFR) or slightly increase (INDC-MFR) beyond the year 2040. This might be due to depletion of air pollution controls, particularly the diminishing impacts of controls on industry plants, and the eventual rebound of air pollution emissions due to the increase in economic activities and population growth.

The small difference in MFR concentrations across scenarios implies that air pollution-specific controls alone have a substantial potential for limiting air pollution. Therefore, better coordination of climate change mitigation policies with air quality controls can bring much greater benefits for air pollution reduction then pursuing these independently as is often the case. It should be noted that even under the most aspirational scenarios, $PM_{2.5}$ concentrations still remain relatively high compared to other countries (Cohen et al., 2017). This might be partly explained by the high starting point of concentrations as well as natural background and transboundary concentrations from other countries, which have been shown to be significant for India and other countries in the region (UNEP, 2019; Purohit et al., 2019;David, et al., 2018)

Figure 3. Average annual population-weighted $PM_{2.5}$ exposureby emission scenario



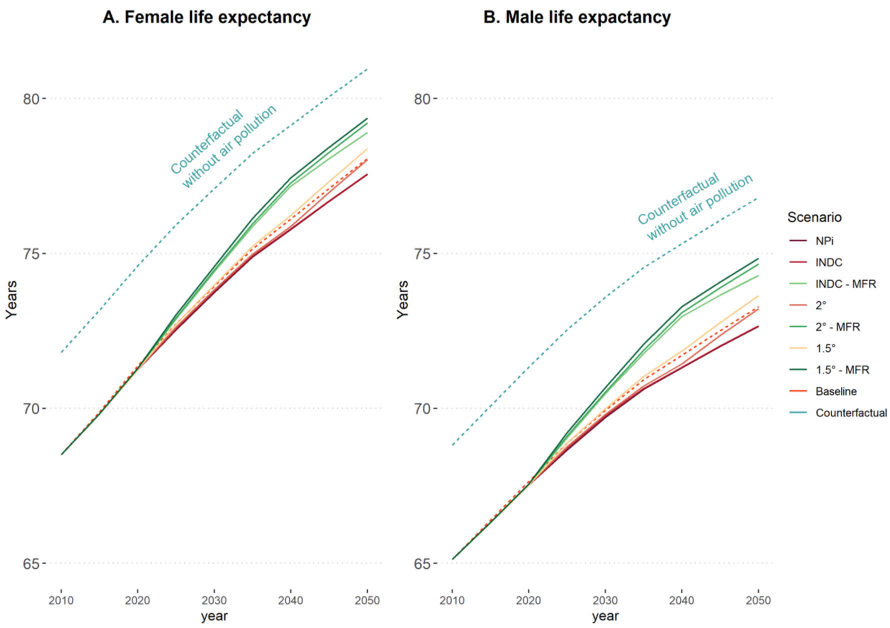
Comparing the concentration pathways in rural vs. urban areas, a stark reduction in $PM_{2.5}$ concentrations can be observed in the 2010-2020 period in urban areas against the steady increase in rural areas. This might be due to current national legislation, the implementation of which is modeled across all scenarios up to the year 2020, affecting $PM_{2.5}$ sources in urban areas the quickest (e.g. industry plants). Overall, larger potential for reduction in concentrations can be seen in urban areas in India. It is notable that under the most inspirational scenarios average $PM_{2.5}$ exposure in urban areas in India in 2050 can reach the levels observable in rural areas today (~30μg/m^3).

3.2 Changes in life expectancy

In the period 2010-2050 average life expectancy at birth for both females and males in India is projected to increase by at least 8 years under all scenarios. This is not surprising considering the future development prospects in the country and the associated catching-up in life expectancy with higher income countries as a consequence of a range of factors, including wider reach of healthcare access, reduced poverty, improved nutrition and drinking water and others. However, there are substantial differences in the projected life expectancy trajectories across emission scenarios as a result of deaths being brought forward or delayed as a result of changes in air pollution exposure. With continuation of current policy and no further efforts for mitigating climate change globally or addressing air pollution locally (NPi scenario), the increase in average life expectancy at birth between 2010 and 2050 is projected to be 9 years for females and 7.5 years for males from the starting 68.5 and 65.1 years, respectively.

In contrast, in the most aspirational scenario (1.5° – MFR) life expectancy for females and males in the same period could increase by 10.9 and 9.7 years, respectively. This implies a potential of increasing the average life expectancy of children born in 2050 by up to 2 additional years compared no further emission control (74.8 vs. 72.6 years for females and 79.4 vs.77.5 years for males). The average lifespan forecasts in the rest of the scenarios fall in between, again without a significant difference between the INDC and NPi scenario, but the potential for increasing life expectancy at birth through air pollution reduction is more limited through mitigation of CO_2 emissions only. Our estimates show that pursuing the 2° and 1.5° targets can still bring increases in life expectancy through improvements of air quality, but in the year 2050 these would be in the magnitude of 1 year or less compared to NPi (0.9 years under 1.5° and 0.5 years under the 2° scenario for females and males combined).

Figure 4. Life expectancy at birth by scenario



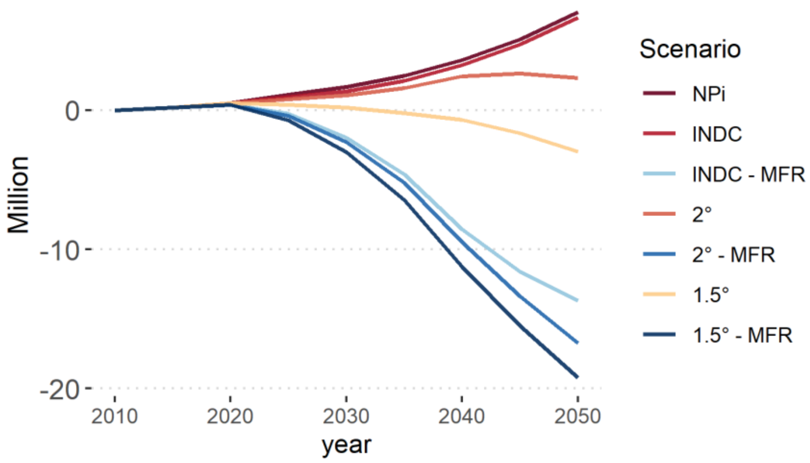
Comparison with the counterfactual scenario shows the total losses in average life expectancy attributable to air pollution. In 2010, exposure to $PM_{2.5}$ reduced average life expectancy by 3.3 years for females and 3.7 years for males. In the most aspirational scenario this gap is projected to fall to 1.6 years for females and 2.0 years for males, while without further efforts it is expected to increase to 3.4 for females and 4.2 years for males.

3.3 Deaths attributable to air pollution

We also show the health co-benefits related to air pollution reduction from climate change mitigation as number of lives that could be saved (Figure 5). The number of avoidable deaths from $PM_{2.5}$ in the period 2010-2050 is estimated as the number of deaths projected to occur in the baseline (demographic) scenario (about 91 million in the whole period) minus those that would take place under a particular climate change mitigation and air quality control scenario. It should be emphasised that here we refer to realistically avoidable deaths on the basis of plausible reductions in CO_2 emissions and $PM_{2.5}$ concentrations from 2010 levels onwards and not to total deaths that could be avoided compared to an unrealistic counterfactual scenario of eliminating anthropogenic emissions almost completely to bring $PM_{2.5}$ concentrations to the level with minimum observable health impacts (~2.4mg/m^3).

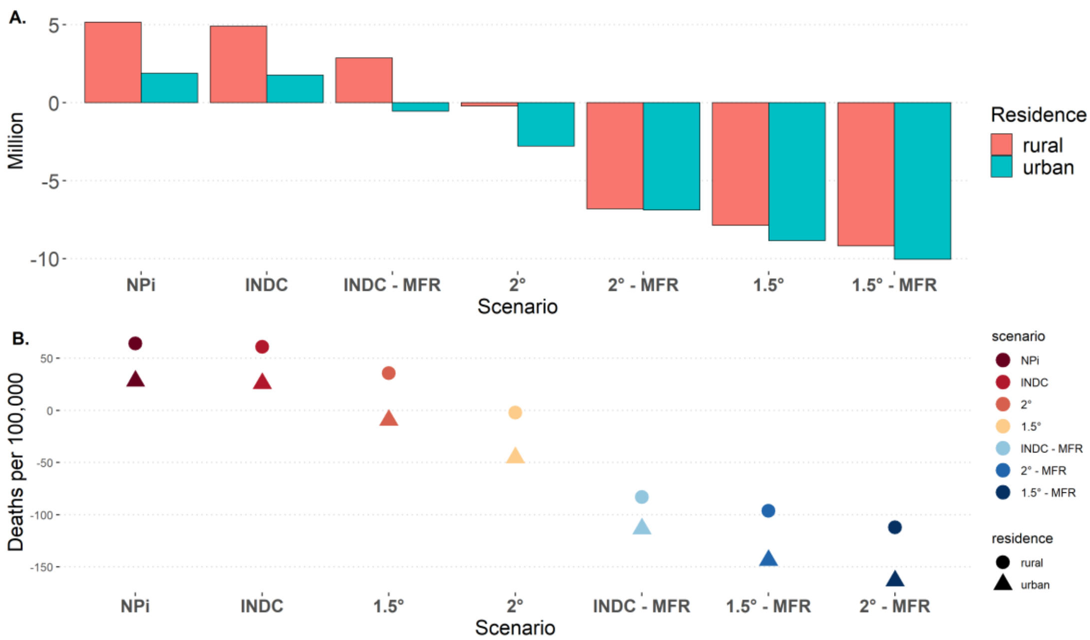
Implementation of measures stipulated in current and planned legislation, as well as commitments specified in the NDCs is not sufficient to reduce number of deaths from $PM_{2.5}$ in India by mid-century. In particular, avoidable deaths from air pollution are projected to increase by 167 and 176 thousand per year on average, for the NPI and INDC scenarios, respectively.

Figure 5. Cumulative number of avoidable deaths from air pollution 2010-2050 for six scenarios for India



Pursuit of aspirational climate mitigation targets can bring clear health co-benefits: in the 2° scenarios avoidable deaths are projected to increase by only 58 thousand per year on average and in the 1.5° scenario the increasing trend of air-pollution-related deaths can be even reversed, with a projected decrease of 78 thousand per year on average within the same period. This implies that, compared to the NPi scenario, overall 4.7 million and 10 million deaths from air pollution could be reversed in the period 2010-2050 by limiting CO_2 emissions in line with the respective climate change mitigation targets. The latter number is sizeable to the most recent estimates of the total burden of $PM_{2.5}$ globally (~ 8.9 million).

Figure 6. Mortality burden from $PM_{2.5}$ by residence: A. Cumulative number of avoidable deaths from $PM_{2.5}$ 2010-2050 B. Population-weighted annual average number of avoidable deaths from $PM_{2.5}$ 2010-2050



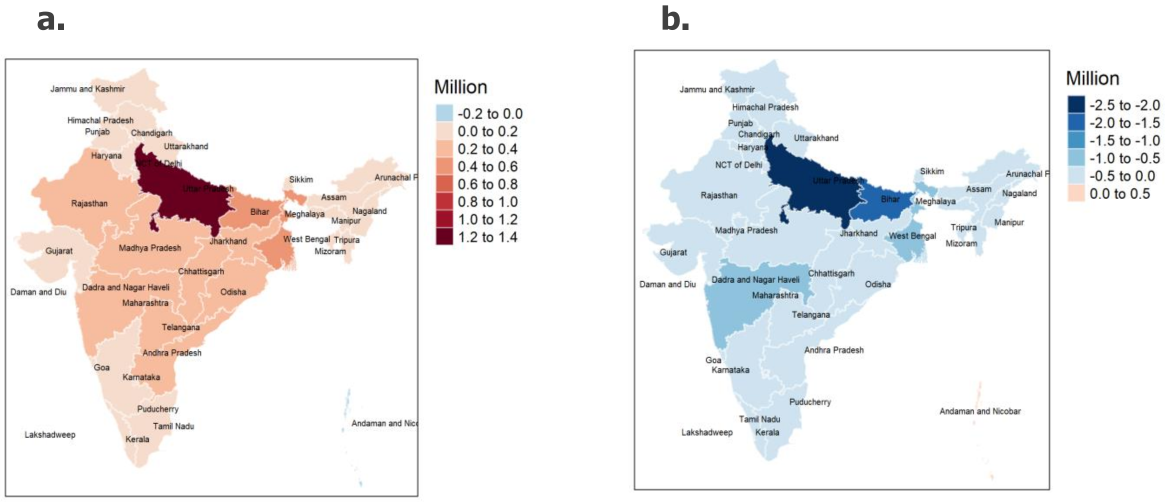
Similarly to life expectancy, we see that combing climate change mitigation efforts with measures targeting air pollution explicitly can yield maximum benefits for human health in the future: with the maximum possible take-up of air quality controls in India avoidable deaths from air pollution can decrease on average from 342 thousand per year in INDC-MFR scenario to around 480 thousand per year in the 1.5° – MFR scenario. Compared to the NPi scenarios, these translate in 20 to 26 million cumulative avoidable deaths over the period 2010-2050.

Even though projected $PM_{2.5}$ concentrations in rural areas are much lower than in urban areas (see Figure 3), without climate change mitigation rural areas are still expected to have about two times larger number of cumulative avoidable deaths from air pollution in 2010-2050 (NPi and INDC scenarios). This might be due to the distribution of the population between urban and rural areas as well as the lower baseline life expectancy in rural India (KC et al., 2018). However, rural areas are disproportionately affected even when accounting for population size (Figure 6B).

3.4 Regional differences

The total mortality from air pollution is expected to be very unevenly distributed not only across urban and rural areas but also across states (Figure 7 and Figure 8). With continuation of current policy and without additional efforts for mitigation of climate change or air pollution control the highest number of avoidable deaths from air pollution in the period 2010-2050 will be concentrated in the rural areas located in the northern regions of Uttar Pradesh (more than 1 million deaths), followed by Bihar and West Bengal (up to 0.5 million).

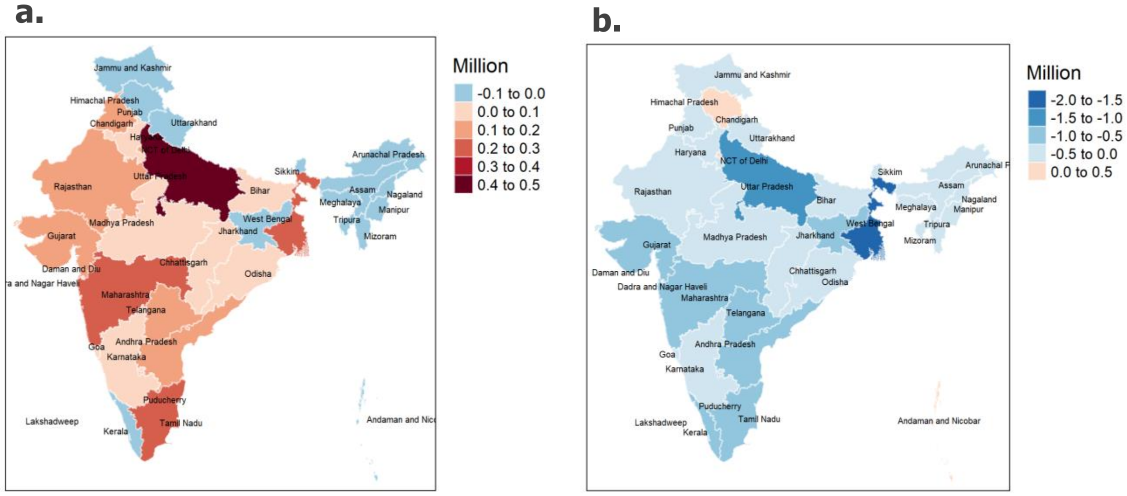
Figure 7. Cumulative number of avoidable deaths from air pollution in rural areas, 2010-2050 for a. scenario NPi and b. scenario 1.5° - MFR



In reverse, these would be the regions with highest potential for reduction of premature mortality from air pollution, with maximum reduction in avoidable deaths ranging from 2.5 up to 1 million in the 1.5° - MFR scenario. In contrast, rural areas in the most affluent southern regions of India, such as Tamil Nadu, Kerala and Karnataka, will experience the lowest increases.

Uttar Pradesh will also be the region with highest expected number of cumulative avoidable deaths in urban areas, followed by urban centres in Maharashtra and Tamil Nadu and West Bengal – between 0.2 and 0.5 million. The underlying drivers of these spatial distributions are related to regional differences in population size, baseline mortality and $PM_{2.5}$ concentrations as well as the evolvement of each of these factors over time.

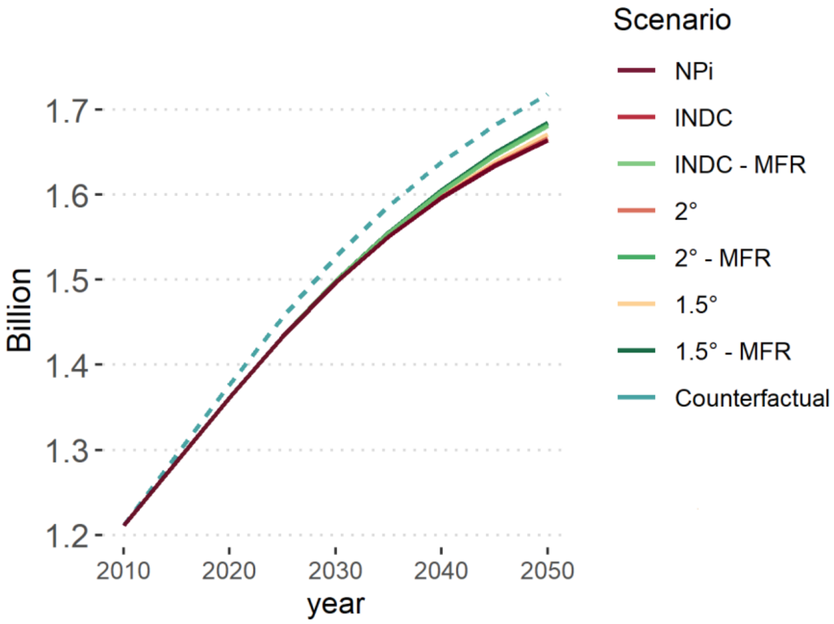
Figure 8. Cumulative number of avoidable deaths from air pollution in urban areas, 2010-2050 for a. scenario NPi and b. scenario 1.5° - MFR



3.5 Implications for population size and structure

Since air pollution exposure affects mortality and population survival in the dynamic approach, different emission scenarios result in different total population size and structure. Although deviations from the baseline demographic projection are not significant given the large population of the country (see Figure 9), they still represent a substantial number. In the most aspirational scenario, the total population in the country is projected to be 20 million larger compared to a business-as-usual scenario (NPi) in the year 2050. In the hypothetical case of completely eliminating anthropogenic sources of $PM_{2.5}$ population size would be even 50 million above the business-as-usual projections.

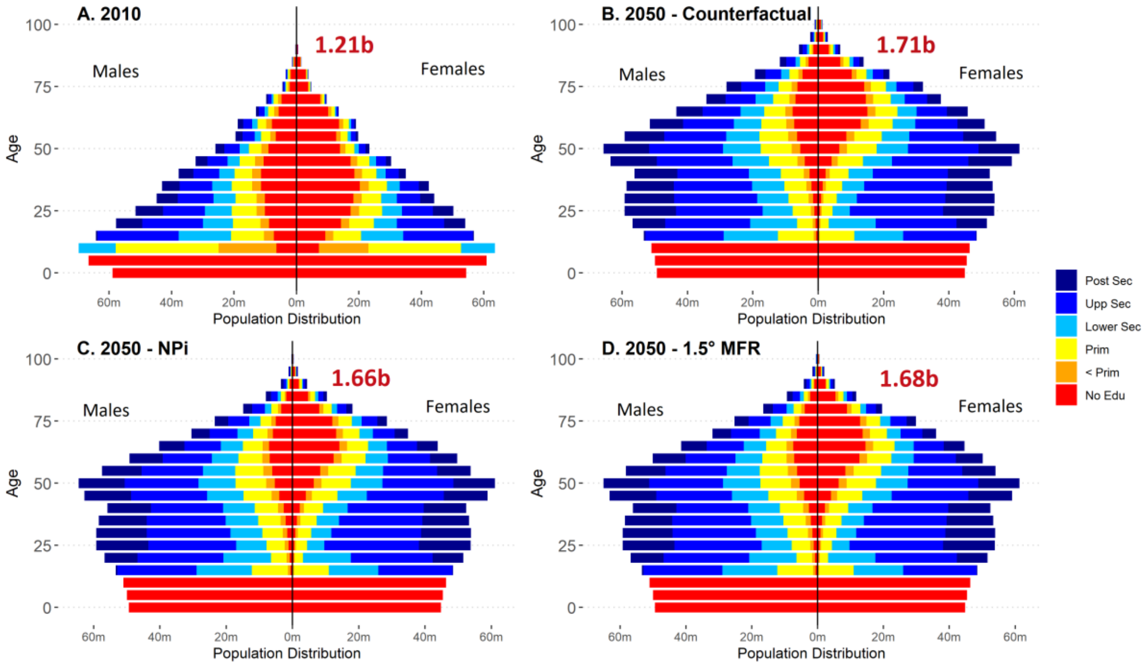
Figure 9. Total population size in India, 2010-2050, by scenario



Due to the demographic transition, the structure of the population will change as it starts to age. Although this is not immediately visible in the population pyramids (Figure 10), slight differences across scenarios can be observed. For instance, the share of the population aged

65+ in India in the year 2050 is projected to reach 15.8 % under the NPi scenario and 16.8 % under the most aspiration scenario from 5.5 % in 2010. In the hypothetical scenario where air pollution is eliminated this share is projected to account for 17.9 % of the whole population in 2050.

Figure 10. Population distribution of India by sex, age and level of education in 2010 and 2050 by scenario



4. Discussion

We investigated the medium term health co-benefits from reduction in air pollution in India under alternative global and national emission scenarios, taking into consideration future demographic change and trends in urbanisation. We find compelling evidence for the health co-benefits related to air quality improvement under the aspirational 2° and 1.5° climate change mitigation targets laid out in the Paris Agreement. In particular, efforts for limiting CO_2 emissions to reduce global mean temperatures to 2° and 1.5° could increase life expectancy at birth in 2050 by one year and half a year on average, respectively, compared to no further climate action than currently announced measures. In terms of mortality burden in the period 2010-2050, this translates to an overall reduction of avoidable deaths from air pollution of 4.7 million and 10 million for each scenario, respectively.

We also demonstrated that maximum benefits for human health can be achieved by combing climate change mitigation measures with policies that explicitly target outdoor air pollution. Such policies could add between one and one and a half years additional gains in average life expectancy at birth in 2050 on top of the gains from global climate change mitigation. It should be acknowledged that these maximum feasible air pollution control scenarios are associated with considerable expenses, which might not make them immediately viable. However, they can be viewed as a potential upper bound of any policy efforts striving for stricter air quality control. Furthermore, previous studies on India have demonstrated that the economic costs of maximum feasible reduction policies would still be extremely low compared to the economic benefits of air pollution reduction associated with higher productivity through reduction in mortality and work absenteeism (Sanderson et al., 2013). Our results also highlight the importance of policy coordination to address the twin challenges of CO_2 emission reductions and air quality improvements.

Our analysis showed that in 2010 $PM_{2.5}$ is associated with average decrement in life expectancy in India of 3.5 years and this could be reduced to 1.8 years by mid-century with the implementation of most ambitions climate change mitigation and air quality abatement measures. Apte et al. (2018) estimate the life expectancy impact of ambient $PM_{2.5}$ to be only 1.53 years for India. In contrast, using the Air Quality Life Index (AQLI) developed by the University of Chicago's Professor in Economics Milton Friedman, Greenstone and Qing Fan (2018) calculate this decrement to be more than 4.3 years and up to 10 years the Delhi. These differences could be attributed to the shape and mortality causes included in the exposure response functions used, the mortality and air pollution data sources as well as the general methodology applied.

We modelled the health impacts of changes in air pollution also across space and demonstrated substantial geographical differences in the health burden and its potential for reduction. Implementation of measures in line with the aspirational climate change mitigation scenarios can bring largest benefits related to air quality improvement over time for the population in rural India. Despite their lower air pollution levels, rural areas are more susceptible to the adverse air pollution impacts due to their larger population and lower baseline life expectancy compared to urban areas. Previous studies have already demonstrated the unequal burden of air pollution in urban and rural areas for some parts of India (GBD MAPS Working Group, 2018; Karambelas et al., 2018). The GBD MAPS Working Group (2018) estimated that as of 2015 the mortality burden in rural areas in India was three times larger than in urban areas and they projected this factor to increase to 5 in 2050 without further action and to 4 with aggressive air quality control. Using the same urban-rural designation as in this paper, Karambelas et al., (2018) find total excess mortality attributable to $PM_{2.5}$ and O_3 to be three to five times larger in the rural regions of northern India, compared to the urban ones. The authors find the rural-urban gap of health impacts to hold for all major $PM_{2.5}$-related diseases (IHD, stroke, COPD and lung cancer), but not when accounting for population size, with somewhat greater rate for urban areas. In contrast, our results show higher health burden of air pollution even after controlling for population size. Part of this difference could be explained by the exposure-response function used (non-linear and flattening at higher exposures vs near-linear) and variation in disease burden (NCD and LRI) between urban and rural areas. We only modelled impacts from changes in outdoor air pollution. However, future studies simulating the improvements in indoor air quality associated with the energy transitions in the climate change mitigation scenarios can demonstrate even greater health co-benefits in rural areas. Our results also confirmed recent evidence of the higher mortality burden from air pollution in the regions along the Indo-Gangetic Plains (Balakrishnan et al., 2019; Chowdhury & Dey, 2016; Conibear, Butt, Knote, Arnold, & Spracklen, 2018a), which could be attributed both to their larger population size and higher $PM_{2.5}$ concentrations. Vast inequalities in health outcomes can be observed across different regions in India, with regional differences in life expectancy in the country ranging by up to 10 years in 2010[17]. The spatial variations in the health burden from air pollution highlight the potential of climate change mitigation and air quality control for reducing some of the urban-rural and regional health inequalities in the country.

[17] Own calculations based on tabulations from Samir KC

We demonstrated that climate change mitigation and air policy control will also have some implications on the future size and structure of the population in the country. Most aspirational policies will contribute to reducing number of deaths and improving life expectancy, which will also have the effect of increasing population size and the share of the elderly. Therefore, while public policy strives to improve population health and prolong life expectancy, it is important that this progress is accompanied by measures for reducing the carbon footprint of individuals and decoupling environmental pressures such as increases in emissions, air pollutants, waste, etc from economic growth. Otherwise, sustaining a growing population with the same patterns of development and consumption might undermine future wellbeing as recognised in the principles of sustainable development and the Sustainable Deveopment Goals.

This study compared two different methodologies — dynamic and static — for conducting health impact assessment against a common counterfactual scenario where air pollution is reduced to its theoretical minimum. Although the dynamic method has been already applied in previous studies, to our knowledge the outcomes of the two methods have not been comprehensively compared and the static method of projection of health impacts has been the norms. While the dynamic model considers changes in mortality and population survival induced by changes in exposure, in the static model these dynamics are not reflected. Outputs of the two methods in terms of total number of attributable deaths differed both in the direction and magnitude of the projected impacts. We argue that the two methods offer different tools for assessing two different policy questions. The static method allows assessing total number of deaths in a certain period if air pollution only in this but no previous or subsequent periods is eliminated (thus not changing population structure over time). The dynamic method, on the other hand, allows assessing total premature mortality attributable to $PM_{2.5}$ compared to a counterfactual scenario where air pollution is eliminated in the current and every subsequent period. Thus, the static method is appropriate for assessing impacts of policy interventions at one point in time, while the dynamic method is more appropriate for assessing feedback effects of a policy over time. Summing up avoided deaths from air pollution over time in the static method theoretically leads to overestimation of number of deaths as it does not consider that if deaths from air pollution were avoided in one period they might still have occurred at a later stage due to other unrelated causes, affecting future population size and mortality. However, due to the somewhat counterintuitive results when using the dynamic method to assess attributable number of deaths — decrease in total deaths attributable to air pollution in a scenario with increasing air pollution — we argue that a different indicator of health outcomes might be more appropriate for comparison of the dynamic and static method, e.g. total person-years of life lived, healthy life years, etc.

We have strived to arrive at a realistic assessment of the future health implications of cleaner air in India by linking in a consistent way modelling frameworks from a diverse set of disciplines, ranging from climate, energy systems and atmospheric sciences to demography and epidemiology. By using a comprehensive and advanced population projection model we were able to reduce one of the major sources of uncertainty related to future health impact assessments. The applied methodology allowed us to report the independent impacts of air pollution on mortality (direct impacts as well as indirect impacts due to changes in the structure of the population) in contrast to the conventional approach, which does not disentangle these from the effects of population aging and growth. The dynamic approach used in this paper, which accounts for the impacts of changes in air pollution to survival population, allowed us not only to more realistically represent exposure-outcome interactions, but also to assess gains in life expectancies associated with different emission pathways.

Uncertainty is a major issue when projecting any future impacts of climate change due to the inherent complexity and uncertainty of the modeled processes. They key sources of uncertainty in our modeling study will likely stem from uncertainties related to (1) current emission inventories and future GHG emission trajectories, (2) air pollution modeling, (3) emission downscaling, (4) air pollution exposure response function and (5) population projections. The propagation of each of these uncertainties in our model produces a cascading effect, resulting in considerable uncertainty in the final impact. Due to the large uncertainties inherent in our model, the study results should not be considered as predictions or forecasts, but rather as plausible future outcomes that are most appropriate for relative comparisons between scenarios and for promoting awareness of the range of potential health implications of global and national policy decisions.

We also acknowledge some important limitations, which we were not able to address in our study. The exposure response function that we use models the association between $PM_{2.5}$ exposure and hazard risk from non-communicable (NCD) and lower respiratory infections (LRI). Although these account for the majority of deaths in the cohorts included in the GEMM (>99 %) and in developed economies, this does not necessarily hold true for LMIC like India, with larger share of non-communicable diseases. Furthermore, due to their socio-economic differences, sub-national states in India have been shown to have substantial variation in their current state of the epidemiological transition (Dandona et al., 2017), which will certainly impact susceptibility to air pollution. A multi-decrement population projection, considering the potential evolvement of air pollution-related disease burdens over time and within the country would be necessary in order to account for this source of uncertainty. However, this was beyond the scope of our study due to the lack of reliable data and projections on cause-specific mortality for the urban and rural areas of each sub-national state and for all 5-year age groups in India. Therefore, we argue that our results could be used as an upper bound of potential health impacts associated with air pollution. All things considered, we have used consistent demographic assumptions across emission scenarios, which still allows for comparing plausible futures.

Another limitation related to the use of the GEMM to estimate health impacts in India is that the models is based on cohort studies conducted in mainly in Northern America and Europe, where ambient exposures are much lower compared to those commonly observed in low- and middle-income countries like India. Estimates from high-income countries are not readily transferrable to the Indian context also for other reasons such as differences in air pollution source type (a number of pollution sources are either only present in developing countries or more widespread than in developed ones) and differences in activity (in developed countries people spent most of their time in indoor microenvironments, but this does not necessarily hold true for developing countries) (Pant, Guttikunda, & Peltier, 2016). Differences in the exposure-response function between high- and low- and middle-income countries might also arise because of variations in the chemical composition of pollutants and differences in their baseline health status and healthcare systems (WHO, 2016).

Furthermore, we note that our results might slightly underestimate impacts at highly polluted urban areas due to the logarithmic form of the exposure-response function at concentrations above 84 $\mu g/m^3$ and the fact that we average concentrations across urban grid cells. A more precise estimation would have required quantifying the health impacts at grid level, but this would have involved additional set of assumptions regarding spatial distribution of future population growth.

While the analysed climate change mitigation scenarios assume a transition towards cleaner sources of energy, we did not account for the potential reduction in the health burden associated with household air pollution (HAP) in the future. HAP is significant in India, with 43 % of the population in the country still relying on biomass for cooking and heating (PHFI&CEH, 2017), but it is expected to decrease in the future with urbanisation, reduction in poverty and the uptake of cleaner sources of energy. Therefore, the potential reduction of the air pollution burden in the analysed climate change scenarios might be even greater than estimated, especially for women and children in rural areas who are disproportionately affected by indoor air pollution (HEI, 2019). However, with residential combustion estimated to contribute between 20 %- 55% of the total burden of premature mortality from outdoor air pollution in the country (Apte & Pant, n.d.), our analysis still accounts largely for the substantial benefits from cleaner household energy use.

Although we considered the health co-benefits from climate change mitigation related to reduction in anthropogenic emissions, the impacts of changes in weather systems on $PM_{2.5}$ concentrations was not considered. On the one hand, air pollutants such as ozone and particulate matter can interact with radiation and meteorology (sunlight, wind, clouds) and thus induce changes in the climate (Fiore, Naik, & Leibensperger, 2015). On the other hand, climate change is expected to aggravate air quality in many polluted regions through various mechanisms: by altering atmospheric ventilation and dilution, precipitation and other removal processes and by triggering amplified responses in atmospheric chemistry, anthropogenic and natural sources (Fiore et al., 2015). Ultimately, the net effects of climate change on air quality are likely to vary for different pollutants and from one region to another (IPCC, 2007). An ensemble of climate-chemistry models needs to be applied in order to account comprehensively and assess the health implications of these additional interactive effects (Silva et al., 2016), which was beyond the scope of this study.

We also did not account for the additive and synergistic effects on mortality from the simultaneous exposure to high temperature and air pollution. There is an emerging evidence on the potential interactive effects between temperature and air pollution (Kinney, 2018). Considering that the frequency of simultaneous exposure to high temperature and air pollution is projected to increase with climate change all around the globe and especially in India, this could be an important area for future research.

5. Conclusions

This study revealed important synergies between climate change mitigation policies and air quality control for avoiding further deterioration in air quality and its associated health impacts in India. In particular, global policy commitment in line with the 2° and 1.5° targets of the Paris Agreement can substantially decrease air pollution in India and contribute to improvements in life expectancy and decrease in premature deaths from exposure to $PM_{2.5}$. Although our estimates quantified only one of the multiple health co-benefits from climate change mitigation, these could serve as prominent incentives for climate action.

Results also showed that even larger benefits for human health can be achieved with coordination of climate change mitigation and air quality control policies. This is of particular relevance, considering that policy responses to air pollution and climate change are often formulated independently by different policy departments. While further studies are needed to compare the financial viabilities of such measures and identify a portfolio of most cost-effective controls, implementation of any policies in this direction is likely to bring substantial gains for public health. This study also showed that both climate change mitigation and air quality control policies have the potential to contribute to a reduction in large health inequalities between states and urban and rural areas in India.

While most previous studies assessing the future health impacts of air quality improvement in India have applied a static method, assuming future population structure and mortality rates independent from changes in exposure, we used a methodology which allowed us to relaxed this assumption and assessed the "feedback" effects of air pollution on population size and life expectancy through changes in survival population over time. Thus we have addressed one of the main sources of uncertainty in future health impact assessment, lending more credibility to the study outcomes.

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