Climate change and health in India – impacts and co-benefits

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To my mother,
who could not see this adventure.

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Abstract

Due to its large and growing population and economy, India is pivotal for climate change mitigation globally. However, like other low- and middle-income countries (LMICs), India is also facing many other pressing development challenges. Country-level studies are needed to assess both the scale of India´s vulnerability to climate change as well as the extent to which mitigation actions can be reconciled with its development objectives. Given the complexity of projecting the interplay of human and environmental systems, studies with strong interdisciplinary foundations are required.

The first study in this PhD thesis systematically reviewed and quantitatively assessed the evidence on the association between ambient temperatures and heat waves, and all-cause mortality in South Asia. The results indicated that both high and low ambient temperatures and heatwaves are risk factors for all-cause mortality, with mortality risk increasing more steeply at higher temperatures. The second study used a demographic projection linked to an integrated assessment model (IAM) to forecast the future localised health co-benefits from reduced ambient fine particulate matter ($PM_{2.5}$) in India under global climate change mitigation scenarios and national scenarios for maximum feasible air quality control. Findings suggested that the reduction of ambient $PM_{2.5}$ under the Paris Agreement targets can lengthen life expectancy (LE) at birth and substantially reduce premature mortality from $PM_{2.5}$ in India by 2050 compared to the business-as-usual. Complementing mitigation measures with end-of-pipe air quality control can maximise these co-benefits, especially for regions with lower socio-economic development. The third study employed a static microsimulation model with a link to an IAM and a demographic projection to assess the future localised net benefits for child linear growth from changes in ambient $PM_{2.5}$ and household air pollution (HAP) under a combination of scenarios for climate change mitigation, ambient $PM_{2.5}$ control, and clean cooking access. The results suggested that the increase in child stunting from higher HAP due to higher fuel costs under the 2°C mitigation target can outweigh the reduction in the burden from ambient $PM_{2.5}$ by 2050. However, benefits for child linear growth, especially among the most disadvantaged, can still be realised if mitigation efforts are complemented either with additional ambient $PM_{2.5}$ controls or policies to support access to clean cooking.

Resumen

Debido a su gran y creciente población y economía, la India es fundamental para la mitigación del cambio climático a nivel mundial. Sin embargo, al igual que otros países de renta baja y media, la India se enfrenta a otros muchos y acuciantes retos de desarrollo. Se necesitan estudios a nivel de país para evaluar tanto la magnitud de la vulnerabilidad de la India al cambio climático como la medida en que las acciones de mitigación pueden conciliarse con sus objetivos de desarrollo. Dada la complejidad de la interacción de los sistemas humanos y ambientales, se requieren estudios con una sólida base interdisciplinaria.

El primer estudio de esta tesis doctoral revisó sistemáticamente y evaluó cuantitativamente las evidencias sobre la asociación entre las temperaturas ambientales y las olas de calor, y la mortalidad por todas las causas en el sur de Asia. Los resultados indicaron que tanto las temperaturas ambientales altas como las bajas y las olas de calor son factores de riesgo de mortalidad por todas las causas, y que el riesgo de mortalidad aumenta de forma pronunciada a temperaturas más altas. El segundo estudio utilizó una proyección demográfica vinculada a un modelo de evaluación integrado para pronosticar los futuros beneficios colaterales para la salud de la reducción de las partículas finas ($PM_{2.5}$) en el aire de la India, según los escenarios de mitigación del cambio climático global y los escenarios nacionales de control máximo de la calidad del aire. Los resultados sugieren que la reducción de las $PM_{2.5}$ ambientales, según los objetivos del Acuerdo de París, puede alargar la esperanza de vida al nacer y reducir sustancialmente la mortalidad prematura por $PM_{2.5}$ en la India para 2050, en comparación con el statu quo. Complementar las medidas de mitigación con el control de la calidad del aire al final de la cadena puede maximizar estos beneficios colaterales, especialmente en las regiones con menor desarrollo socioeconómico. El tercer estudio empleó un modelo de microsimulación estático con un enlace a un IAM y una proyección demográfica para evaluar los futuros beneficios netos localizados para el crecimiento lineal de los niños a partir de los cambios en las $PM_{2.5}$ ambientales y la contaminación del aire en los hogares (HAP) bajo una combinación de escenarios para la mitigación del cambio climático, el control de las $PM_{2.5}$ ambientales y el acceso a la cocina limpia. Los resultados sugieren que el aumento del retraso en el crecimiento de los niños debido a un mayor coste del combustible en el marco del objetivo de mitigación de 2°C puede superar la reducción de la carga de las $PM_{2.5}$ ambientales para 2050. Sin embargo, los beneficios para el crecimiento

lineal de los niños, especialmente entre los más desfavorecidos, todavía pueden ser realizados si los esfuerzos de mitigación se complementan con controles adicionales de $PM_{2.5}$ en el ambiente o con políticas para apoyar el acceso a la cocina limpia.

Preface

The present thesis was developed at the Barcelona Institute for Global Health (ISGlobal) between April 2018 and September 2021 under the supervision of Dr. Cathryn Tonne. Part of the analysis on Research Article II was completed by the author during the Young Scientists Summer Program (YSSP) at the International Institute for Applied Systems Analysis (IIASA) under the guidance of Dr. Guillaume Marois and Dr. Gregor Kiesewetter.

The present PhD thesis consists of a compilation of three research articles related to the health impacts of climate change and co-benefits of climate change mitigation policies in India. This thesis advances knowledge in this field by adopting a planetary health perspective and investigating the current and future health dimensions of two of the most important environmental stressors in the country – ambient temperatures and air pollution. It also demonstrates the application of two modelling frameworks for projecting future climate-related health impacts that comprehensively integrate population-environment dynamics – a macro- and a static microsimulation with a link to an IAM. Two of the research articles have been published in peer-reviewed journals and, by the time of writing this thesis, the third one has been submitted for a review in an academic journal. The first research article is complemented with two unpublished analyses with importance to the research topic and methodology.

The PhD candidate is the first author in all of the research articles and, as such, she took a leading role in designing the studies and independently collected the data, performed the analyses, interpreted the results, and wrote and submitted the articles for publication. Apart from the three research articles included in this thesis, the PhD candidate co-authored four further publications related to health implications of air pollution, ambient temperature, and urban environments in high- and low-income settings (see Annex). Moreover, the candidate completed a three months research stay (June-August 2019) at IIASA, Vienna, Austria as part of the YSSP. Within this program, the candidate was based at the demographic and air pollution units of the institute and was supervised by Dr. Guillaume Marois and Dr. Gregor Kiesewetter. The PhD candidate received a scholarship to participate in the United Nations University (UNU) Summer Academy on World Risk and Adaptation Futures, focused on the role of demographic change in shaping future climate risks and adaptation options, which took place in October 2019 in Accra, Ghana. The candidate was also responsible for the organisation of the Air Pollution and Urban Environment research seminars at ISGlobal for the period 2018-2020. In addition, the PhD candidate reviewed four research articles for academic journals, presented findings of this doctoral thesis at various international conferences on environmental health and demographic change, and completed academic courses on epidemiology, modelling of climate change impacts, causal inference, and machine learning (See Annex).

Abbreviations

AAP	Ambient Air Pollution
ABS	Agent-Based Simulation
AEC	Advanced Emission Control
ALRIs	Acute Lower Respiratory Infections
AQG	Air Quality Guideline
CAS	Clean Air Scenario
CCA	Clean Cooking Access
CI	Confidence Interval
CO	Carbon Monoxide
CO_2	Carbon Dioxide
COP	Conference of the Parties
COPD	Chronic Obstructive Pulmonary Disease
CRA	Comparative Risk Assessment
DALYs	Disability-Adjusted Life-Years
ERF	Exposure-Response Function
GAINS	Greenhouse-Gas Air Pollution Interaction and Synergies
GBD	Global Burden of Disease
GDP	Gross Domestic Product
GEMM	Global Exposure Mortality Model
GHG	Greenhouse Gas
HAP	Household Air Pollution
HAZ	Height-for-Age Z-score
HIA	Health Impact Assessment
HLE	Healthy Life Expectancy
IAM	Integrated Assessment Model
IEA	International Energy Agency
IER	Integrated Exposure-Response
IHD	Ischemic Heart Disease
INDC	Intended Nationally Determined Contributions
IPCC	Intergovernmental Panel on Climate Change
IVC	India Vision Case

LC	Lung Cancer
LE	Life Expectancy
LLE	Loss in Life Expectancy
LMICs	Low- and Middle-Income Countries
LPG	Liquified Petroleum Gas
LRIs	Lower Respiratory Infections
MFR	Maximum Feasible Reduction
MSLT	Multi-state Life Table
NAAQS	National Ambient Air Quality Standards
NCDs	Non-Communicable Diseases
NDCs	Nationally Determined Contributions
NFHS	National Family Health Survey
NH_3	Ammonia
NMVOCs	Non-methane Volatile Organic Compounds
NOx	Nitrogen Oxides
NO_2	Nitrogen Dioxide
NPi	National Policy implementation
NPIC	National Programme on Improved Chulha
NPS	New Policy Scenario
O_3	Ozone
OR	Odds Ratio
PAF	Population Attributable Fraction
PAHAL	Pratyaksh Hanstantrit Labh (scheme)
PIF	Potential Impact Fraction
PM	Particulate Matter
PM_2	Fine Particulate Matter
PMUY	Pradhan Mantri Ujjwala Yojana (scheme)
PPP	Purchasing Power Parity
RCP	Representative Concentration Pathway
SDS	Sustainable Development Scenario
SO_2	Sulfur Dioxide
SSPs	Shared Socioeconomic Pathways
STEPS	Stated Policies Scenario
TMREL	Theoretical Minimum Risk Exposure Level

UHI	Urban Heat Island
UI	Uncertainty Interval
UNEP	United Nations Environment Programme
UNFCCC	United Nations Framework Convention on Climate Change
YLL	Years of Life Lost

Table of contents

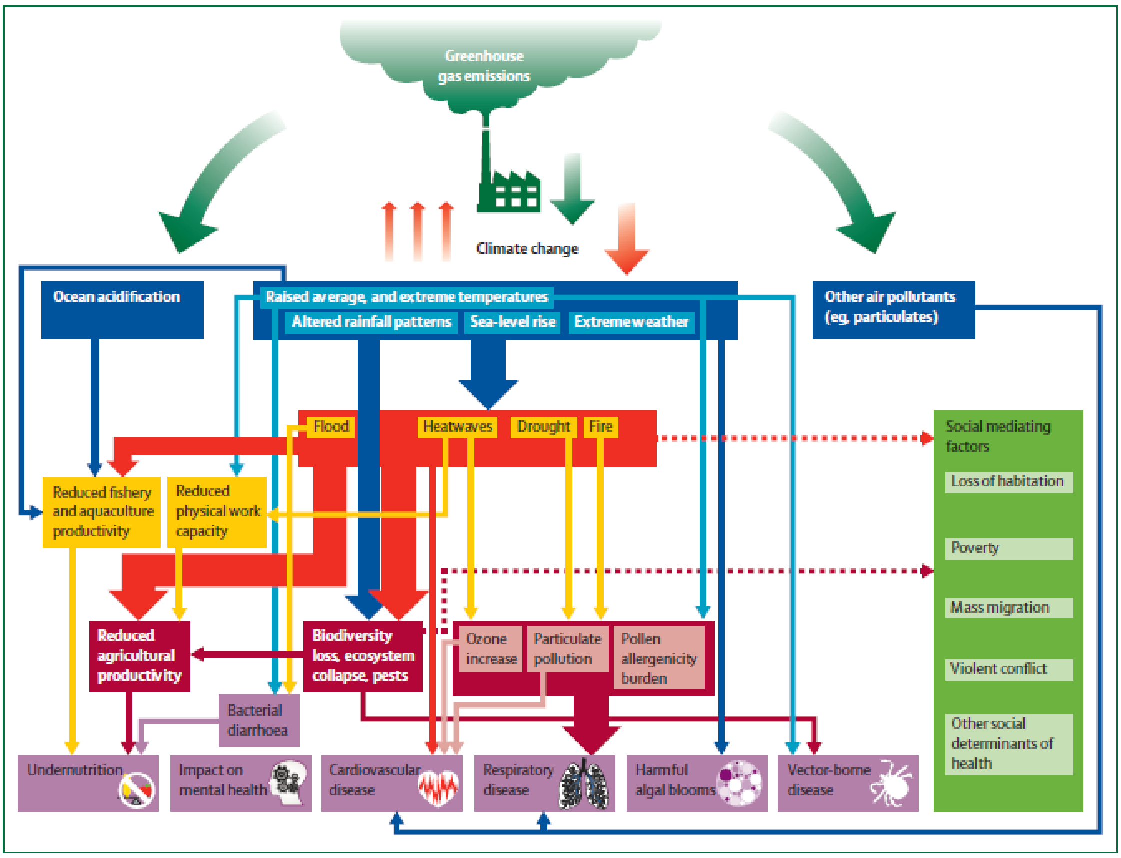
Chapter 1: RESEARCH IN CONTEXT

1.1 Climate change and health

Climate change has been widely recognised as one of the single most important threats for humanity today. The last decade (2011-2020) has been the hottest on record, with mean global near-surface temperatures reaching 0.95–1.20°C above pre-industrial levels (IPCC, 2021). The steep rise in greenhouse gases (GHGs) from human activity since the mid-20th century, mainly carbon dioxide (CO_2), has been the dominant cause of the observed climate warming and of the associated increase of extreme weather events (IPCC, 2021). Without a substantial transformation of our societies and reduction in emissions, continued global warming is projected to increase climate-related risks to health, livelihoods, food security, water supply, human security, and economic development, affecting the low income and marginalised populations the most (IPCC, 2014a).

In recent years the climate change emergency, along with other interferences in the Earth´s system, including biodiversity loss, land and water degradation, and chemicals accumulation, have been increasingly framed as a central public health issue, whereas disruptions to the Earth´s natural system might reverse historically recent progress in health and endanger our own wellbeing and survival as species (Horton et al., 2014; Whitmee et al., 2015). The multitude of potential impacts of climate change on human health has been extensively documented (Ebi et al., 2018; Watts et al., 2019, 2018, 2017, 2016, 2015; WHO, 2018a). Such impacts can occur through various pathways and are modulated both by ecological and socio-economic factors (Figure 1.1). Changes in surface temperatures and precipitation as well as the frequency, intensity, and duration of heat waves, floods, storms, wildfires, and other extreme weather events have direct and immediate effects on mortality and morbidity. Variations in temperatures and rainfall may increase the incidence of vector-borne and water-borne diseases by affecting the distribution of disease vectors such as malaria or dengue. The increase in GHG emissions and associated warming can aggravate air quality both directly – through the increased emissions of air pollutants – and indirectly – by altering atmospheric ventilation and dilution, precipitation, and other removal processes (Fiore et al., 2015). Acute air pollution episodes as a result of wildfires or prolonged heat waves can also affect population health (Smith et al., 2015). Furthermore, by affecting biodiversity and ecosystems, climate change can endanger the goods and services that human health depends on, thus threatening livelihoods, food security, and driving population displacement and conflicts. The overall health burden of climate change could be substantial. According to a 2018 World Health Organisation (WHO) assessment based on a conservative subset of climate-sensitive health risks (malnutrition, malaria, diarrhoea, and heat stress), unchecked climate change could lead to 250,000 excess deaths per year between 2030 and 2050 (WHO, 2018b).

Figure 1.1: Major health risks associated with climate change



Source: Watts et al. (2015)

The potential burden of climate-related health impacts is unevenly distributed across communities and depends strongly on the interaction between exposure to extreme and non-extreme weather and climate events and to underlying socioeconomic conditions and processes. In this respect, the social cost from climate change will be borne most heavily by LMICs both due to their geo-climatic characteristics and low adaptive capacities (Costello et al., 2009).

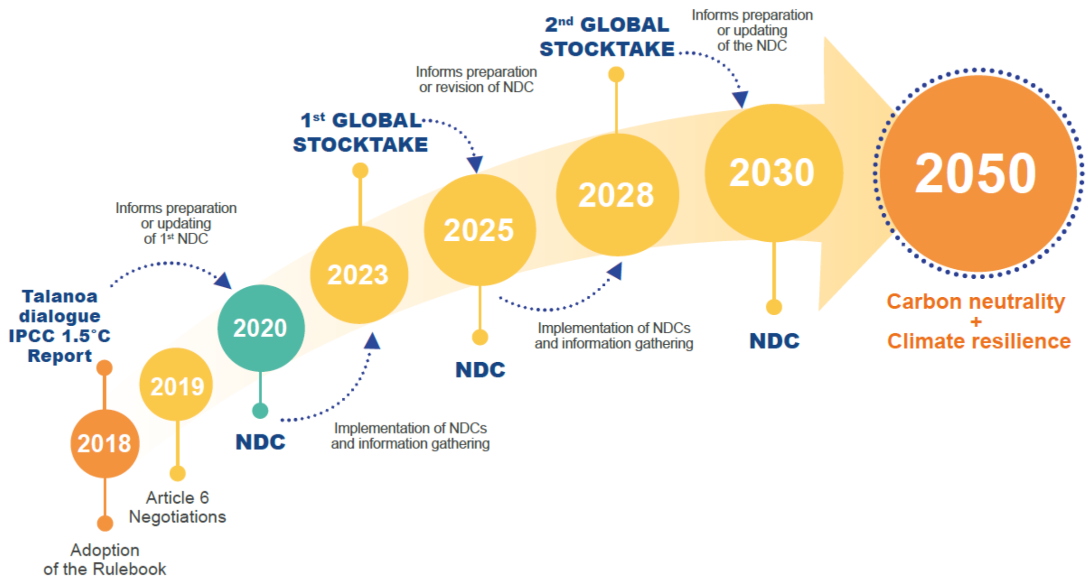
Current research on the impacts of climate change on health focuses on three main areas - current and historical associations between climate-related exposures and disease, attribution of anthropogenic climate change on health, and projections of future impacts of climate change on health. This thesis will mainly focus on the first and last topics.

1.2 Reversing the threat – The Paris Agreement

The collective global response to climate change is likely to shape the health of populations across diverse geographies and generations. The international community has committed to substantially reduce climate-warming GHG emissions, stabilize temperature increase to below 2°C relative to pre-industrial levels and seek to further limit the increase to 1.5°C. These objectives were enshrined in the Paris Agreement adopted by 196 countries at the United Nations Framework Convention on Climate Change (UNFCCC) 21st Conference of the Parties (COP) in 2015 (UNFCCC, 2016). To deliver on these ambitious goals the Agreement foresees reaching peak emissions as soon as possible and achieving climate neutrality by 2050 (Figure 1.2). The main instrument for achieving the Paris Agreement is the Nationally Determined Contributions (NDCs), in which countries´ have to determine, plan and regularly report the actions they will take to mitigate their CO_2 emissions. The NDCs should be communicated every five years and, although there is no mechanism forcing countries to set specific emission targets, ambitions set in the NDCs should be "progressive" and increase over time. The Agreement essentially represents a "bottom-up" approach to climate mitigation, where the ability of countries to increase their ambitions and deliver on their commitments jointly will determine whether the goals could be met. The Paris Agreement retains the principle of "common but differentiated responsibility" enshrined in Article 3(1) of the 1992 UNFCCC. However, it departs from the rigid distinction between "developed" and "developing" countries set in the Kyoto Protocol by requiring all parties to submit plans for emission reductions and to increase their ambition over time (Pauw et al., 2019).

The Paris Agreement is seen as a milestone in international climate negotiations, as it brings, for the first time, all nations under a binding agreement for climate change mitigation. However, current assessments show that collective commitments under the NDCs are very low and insufficient for delivering on the Paris Agreement goals (Roelfsema et al., 2020; Rogelj et al., 2016; Vrontisi et al., 2018). Even if NDCs are fully implemented, the global average temperature is still set to increase to at least to 3.2°C (range: 3.0–3.5°C) by the end of the century (with 66 per cent probability) (United Nations Environment Programme, 2020). Furthermore, there is also inconsistency between the emission levels implied by current policies and those projected under current NDCs by 2030. Therefore, a significant acceleration of efforts is needed if the long-term temperature goals of the Paris Agreement are to be achieved. United Nations Environment Programme´s (UNEP) latest Emissions

Figure 1.2: The cycle of ambition of the Paris Agreement



Source: https://www.expertisefrance.fr/en/actualite?id=806462

Gap Report estimates that staying on track with the 2°C goal and the 1.5°C climate mitigation goals would require countries to collectively increase their NDCs ambitions threefold and fivefold, respectively (United Nations Environment Programme, 2020). Neither of the two targets marks a threshold below which climate change will have no harmful effects. As extensively documented in the 1.5°C report from the Intergovernmental Panel on Climate Change (IPCC), even limiting global warming to 1.5°C will have substantial consequences for the environment and human health (IPCC, 2018), and will therefore still require adaptation measures. In fact, even if anthropogenic emissions are suddenly eliminated, changes in the climate are still expected to continue for hundreds of years due to the inherent inertia in the climate system (IPCC, 2007; Matthews and Caldeira, 2008).

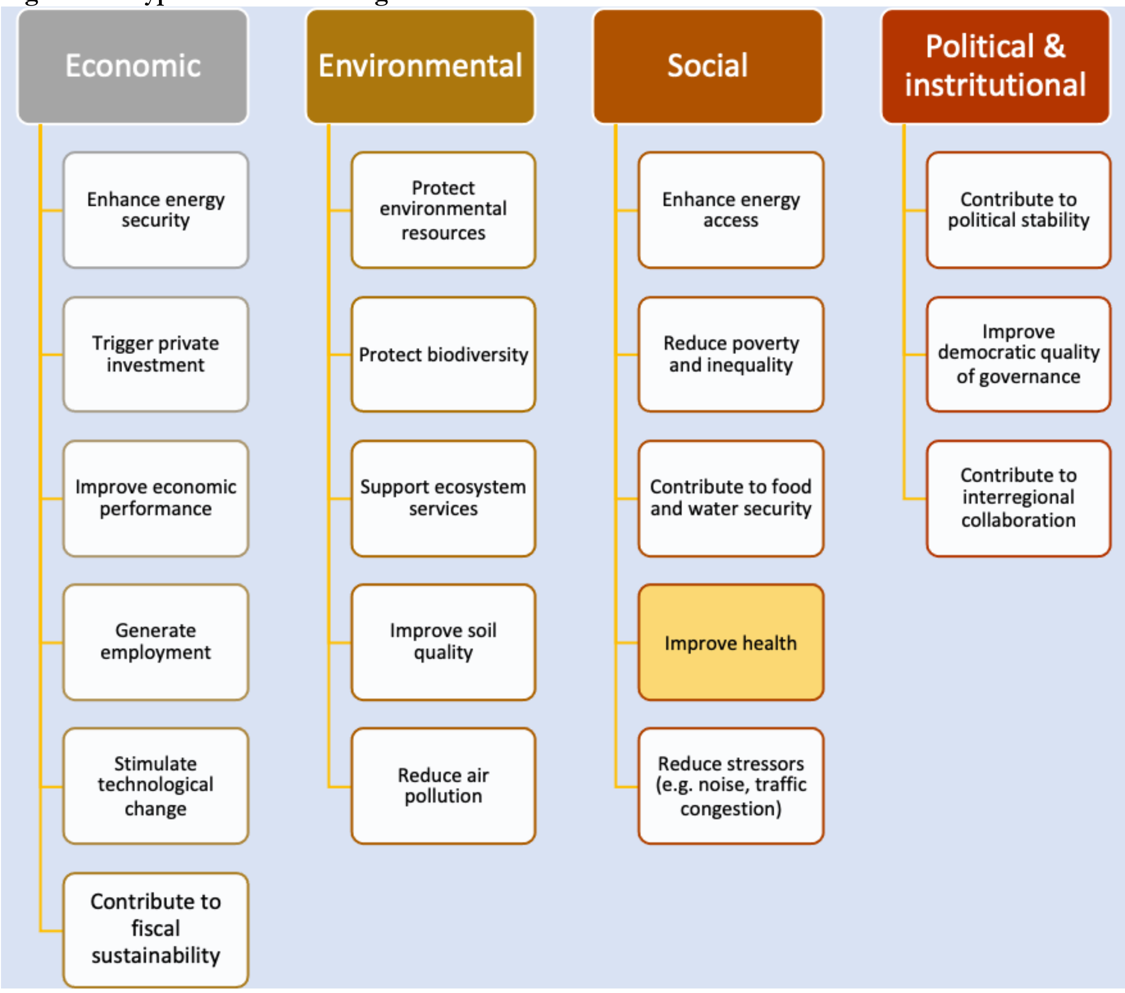
1.3 Health co-benefits of climate change mitigation

Despite the urgent need to curb climate change, progress on climate targets over the last decades has been very slow and uneven. Climate change is often described as a "wicked problem" due to its complexity, deep uncertainty, and the ethical dilemmas that it poses. It is also a collective-action problem, whereas joint action on curbing emissions will benefit all parties, while individual action alone will be insufficient to solve the problem and, despite large costs, will likely not bring direct, discernible, and immediate effects for the individual party. What is more, decarbonisation might be of low political priority in LMICs, in particular, which have low historical responsibility for the problem and more pressing development needs.

Over the past two decades, a new discourse in the scientific community has considerably shifted some of the cost-benefit considerations of climate change mitigation by shedding light on some important non-climate benefits that emission reductions will have in addition to reducing the risk of climate change, so-called co-benefits or ancillary benefits (Bollen et al., 2009; Gao et al., 2018; Karlsson et al., 2020; Mayrhofer and Gupta, 2016; Pittel and Rübbelke, 2008; Rübbelke, 2002). The concept of co-benefits is centrally featured in the IPCC reports, where it has been defined as "the positive effects that a policy or measure aimed at one objective might have on other objectives, irrespective of the net effect on overall social welfare" (IPCC, 2014b, p.14). Beyond this broad definition, three diferent strands of understanding of the concept of co-benefits exist in the acedemic literature (Mayrhofer and Gupta, 2016). By taking a 'development first' approach, some scholars define co-benefits as the impacts that development or sectoral policies could have on global climate change. A second, 'climate first' approach, which is most widely used in the literature and also adopted throughout this thesis, defines co-benefits as the positive local impacts resulting from policies whose primary goal is climate change mitigation (also ancillary benefits). A third strand of research uses the term co-benefits without defining the specific priotarisation of either goal. Irrespective of the exact definition, ancillary benefits of climate policy encompass diverse sectors and can be grouped into four main categories – economic, environmental, social (including health), and political and institutional (Figure 1.3). Due to these positive synergistic effects, the IPCC has concluded that well-designed climate mitigation policies can support and accelerate progress on many dimensions of sustainable development such as poverty alleviation, food security, healthy ecosystems, and equality (Roy et al., 2018).

Some of the most well-studied co-benefits to date are those related to human health (Chang et al., 2017; Gao et al., 2018; Hosking and Campbell-Lendrum, 2012; Smith et al., 2016). In addition to the avoided damages of climate change, positive consequences of climate policies on human health can occur through various pathways (Figure 1.4). For instance, urban

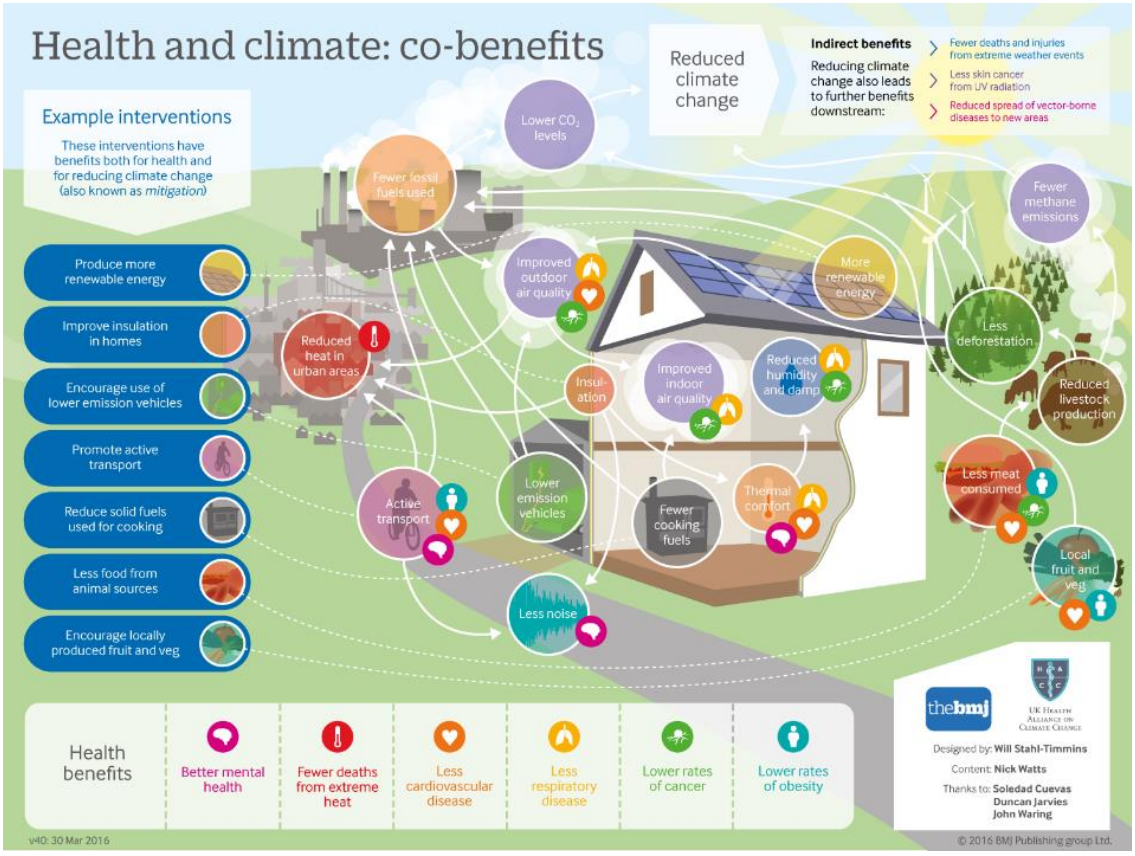
Figure 1.3: Types of climate change co-benefits



Source: Adapted from Mayrhofer and Gupta (2016)

planning programs that encourage "active transport" (walking and cycling) instead of the use of motorised vehicles will reduce climate-altering pollutants, while also directly benefiting population health through increased physical activity, reduced air pollution, and traffic noise. Shifting diets away from high meat and dairy consumption towards healthy plant-based alternatives will help reduce climate-warming methane emissions as well as the large burden of some chronic diseases such as ischemic heart disease (IHD), diabetes, and some types of cancer. Provision of reproductive health services in LMICs, including family planning, will not only help slow down population growth and its associated energy demands but can also reduce the burden of child and maternal mortality through birth spacing. Nearly all climate-altering pollutants, other than CO_2, not only have major implications for climate change but are also damaging to health, either directly or by contributing to the formation of secondary pollutants in the atmosphere. Thus, improvements in energy efficiency and a shift to cleaner energy sources will reduce GHG emissions, but also fine particles and other health-damaging pollutants that are emitted from many of the same sources. Lelieveld et al. (2019), for instance, showed that complete phaseout of fossil-fuel-related emissions can prevent an excess mortality rate of 3.61 (2.96–4.21) million per year related to outdoor air pollution worldwide. According to the latest Global Burden of Disease (GBD) study 2.31 million people die prematurely due to exposure to HAP (Health Effects Institute, 2020). Replacing biomass or coal stoves with cleaner cooking fuels will contribute to climate mitigation by reducing climate-altering pollutants such as CO_2, carbon monoxide (CO), black carbon, while

Figure 1.4: Examples of health co-benefits of climate change mitigation



Source: thebmj (2016)

at the same time reducing the health burden from HAP for poor populations in LMICs, in particular for women and children. Increasing green spaces in urban areas will improve population health by reducing the urban heat island (UHI) effect, reducing noise, and promoting physical activities, but it will also help reduce atmospheric CO_2 via carbon sequestration in plant tissue and soil (Smith et al., 2014). Due to these large health co-benefits, climate change mitigation has been characterised as "the biggest global health opportunity of the 21st century" in the first 2015 report by the Lancet Commission (Watts et al., 2015).

Co-benefits can serve as an important imperative for climate action by helping resolve some of the temporal and spatial discrepancies between climate mitigation costs and climate policy benefits/impacts (Mayrhofer and Gupta, 2016). First, while impacts of climate change occur over long-term horizons and involve large uncertainties, co-benefits can deliver easily predictable and measurable improvements in the short to medium term. Second, while the climate is a common good and emission reductions in one place might bring benefits somewhere else, co-benefits occur within regional and national boundaries and close to the sources of emission reductions (Table 1.1). Lastly, the existence of co-benefits implies large potential reductions in the cost of reducing carbon. Hence, co-benefits can have economic, political, and social appeal by diminishing the social cost of climate change, incentivising stricter GHG control, and legitimising governmental policy action to the wider public (Mayrhofer and Gupta, 2016). That means that by integrating health and other local co-benefits in cost-benefit analysis of climate action countries will have strong incentives to be ambitious, and increasingly so over time, in their efforts to reduce their GHGs, irrespective of what other countries do (Boyd et al., 2015).

Table 1.1: **Comparison of costs and benefits of climate mitigation and co-benefits.**

	Spatial scale	**Temporal scale**	**Certainty**
Climate change mitigation Benefits	Global	Delayed	More uncertain and harder to quantify
Climate change co-benefits	Local	Immediate	Certain and easier to quantify
Climate change mitigation Costs	Local	Immediate	Certain and easier to quantify

Source: adapted from Mayrhofer and Gupta (2016)

Although there can be some significant variations across countries, studies have shown health co-benefits from air pollution alone to be of the same order of magnitude, or in some cases even larger, as estimated mitigation costs (Karlsson et al., 2020). In this respect, it has been argued that air pollution-related co-benefits, in particular, can provide a strong incentive for climate action among some LMICs with both high air pollution levels and rapidly increasing GHG emissions such as China and India This thesis will address in particular the issue for air pollution-related health co-benefits for LMICs by taking India as a case study. Despite the overwhelming evidence of the potentially large health co-benefits from climate mitigation, these remain largely unaccounted for in economic models of climate change mitigation (Cromar, 2021; Rogelj et al., 2018). Evidence of co-benefits also remains largely overlooked in decision-making, thus distorting the identification of optimal policies (Nemet et al., 2010; Workman et al., 2018). Different explanations for why this may be the case have been put forward, the most prominent being lack of policy integration (i.e. failure to take several objectives into consideration simultaneously when designing a policy) due to fragmented institutional regimes with a number of isolated ministries focusing on specific issues. Limited communication between different academic disciplines and various methodological shortcomings – lack of up-to-date and coherent concepts, methods, and approaches and lack of quantification and monetisation of co-benefits – are another reason for the limited consideration of co-benefits in policy (Karlsson et al., 2020).

1.4 Co-harms of climate change mitigation

There are not only co-benefits, but also potential negative externalities or trade-offs associated with the rapid pace and magnitude of the required mitigation actions. One example is the transformation of natural forests, agricultural areas, and indigenous or privately-owned land into plantations for bioenergy production, which, without careful management, could undermine food and water security, create conflict over land rights and cause biodiversity loss. Negative social externalities could also occur if the energy transition from fossil fuels to cleaner sources is carried out without the necessary planning for the labour force re-training, infrastructure replacement, and shift in investment patterns (Rogelj et al., 2018).

Air pollution reduction can also pose a trade-off between protecting public health and the climate. Apart from their adverse health effects, many air pollutants can also induce changes in the climate by affecting the amount of incoming sunlight that is reflected or absorbed by the atmosphere (aerosol-radiation interactions) or by modifying cloud microphysics and precipitation processes (aerosol-cloud interactions) (Zhao et al., 2019). Reduction in certain air pollutants with warming properties, black carbon being the most prominent, will benefit the climate, while the reduction in others such as sulphates is likely to contribute to increases in global temperatures in the short term. Overall, aerosol emissions have a net cooling effect on the Earth, having counteracted almost a third of the warming from anthropogenic GHGs since the 1950s (Zhao et al., 2019). Lelieveld et al. (2019) showed that complete phase-out of fossil fuels globally, which is necessary to meet the Paris Agreement objectives, could lead to 0.51(±0.03) °C of warming, while removal of all anthropogenic aerosols can induce a 0.73(±0.03) °C warming. In order to accommodate this increase in warming from reduced air pollution, it has been argued that climate mitigation policies need to be designed with a "pollution safety margin", i.e. with additional GHG emission reductions (Arneth et al., 2009).

Another risk related to mitigation policies, which is frequently overlooked in current debates, is the potential increase in energy prices and the resulting energy access and distributive impacts. There is a clear potential of reconciling mitigation actions and energy access through a cost-efficient off-grid provision of electricity through some renewable energy technologies in less densely populated areas. However, climate change mitigation could also increase the price of some "clean" forms of energy in LMICs either as a result of carbon pricing to curb GHG emissions from fossil fuels or because of the uptake of low-carbon but more expensive energy sources such as solar and wind power (Jakob and Steckel, 2014). Liquified Petroleum Gas (LPG) is an example of the former – despite being a fossil fuel (a by-product from the petroleum extractive industry), cooking with LPG causes minimal HAP and health impacts and produces lower emissions than any cooking fuel and technology other than solar and electricity (Norwegian Agency for Development Cooperation, 2020). For these reasons LPG, is often seen as an important transition fuel in LMICs. However, modelling studies have shown that ambitious mitigation policies, which would affect energy prices, could substantially slow down the transition to cleaner cooking fuels such as LPG and electricity in LMICs, with potential negative effects on health and poverty. Nevertheless, it has also been demonstrated that these risks can be successfully managed with redistribution measures to mitigate impacts on the most vulnerable populations (Roy et al., 2018).

Given the large and irreversible impacts of climate inaction, these and other existing trade-offs between climate change mitigation and sustainable development do not present a reason to abstain from more stringent mitigation, but rather for careful planning and design of parallel compensatory policies that protect the most vulnerable. Scenario-based analysis has shown that investment in such complementary policies would be much lower compared to the required mitigation investment (McCollum et al., 2018). Most importantly, after carefully examining existing synergies and trade-offs between climate mitigation and the multiple objectives of the sustainable development agenda, the IPCC report on 1.5 °C of warming concludes that, without the necessary reductions in GHGs to reach the Paris Agreement climate targets, "sustainable development will be exceedingly difficult, if not impossible to achieve" (Roy et al., 2018, p.448).

1.5 The case of India

1.5.1 Health impacts of climate change in India – evidence from the recent past and future projections

With over a billion population, a developing economy, and large levels of poverty and inequality, India stands out as one of the most vulnerable countries to climate change. Given its large territory comprising a wide range of topographies and climatic zones, from humid subtropical and tropical regions to alpine landscapes and semi-arid deserts, the potential climate change impacts in India are diverse. Intense heatwaves, droughts, and floods related to changes in the monsoon, the melting of the Himalayan glaciers, and sea level rise are considered to be the most pressing climate change threats for human health and livelihoods in India (Carabine et al., 2014). Changes in temperature and precipitation patterns are also projected to expand the transmission window and geographical spread of vector-borne diseases in India such as malaria and dengue fever (Dhiman et al., 2010). However, discussion on the impacts of climate change on vector-borne, zoonotic, and infectious diseases in India is outside the scope of this thesis.

Changes in temperature and heat waves

India is already experiencing the consequences of global warming. According to recent government data, average temperatures across India have increased by 0.62°C during the period 1901-2020, with the past decade (2011-2020) being the warmest on record (Government of India, 2021). The rising temperatures have led to more frequent and severe heatwaves across the country. Heat waves are a prolonged period of abnormally high surface temperatures, which are normally characterised both by their intensity and duration. Between 1985 and 2009 western and southern India have experienced a 50 % increase in the number of heatwaves (Picciariello et al., 2021). Both high daily temperatures, as well as heat waves, have severe impacts on human health, manifesting in higher mortality from cardiovascular, cerebrovascular, and respiratory diseases (Gasparrini et al., 2015). Heatwaves in 2013 and 2015 claimed more than 1,500 and 2,000 lives across India (Mazdiyasni et al., 2017), with these numbers likely to be conservative considering the lack of official surveillance and misreporting of heat-related deaths. Heatwaves could also have nonfatal health impacts such as heat stroke, dehydration, and heat exhaustion, which can also affect labour productivity. Urban areas tend to be relatively warmer than surrounding suburban areas, a phenomenon known as the urban heat island effect (UHI). A recent study, analysing 44 major Indian cities, showed that night-time surface UHI intensity (the difference between urban and surrounding rural land surface temperatures) has increased by 0.64°C between 2000 and 2017, largely driven by rapid urbanisation (Raj et al., 2020).

In a world where global carbon emissions continue unabated, it is projected that by 2064 the population in India will be exposed to at least two additional heatwaves per year, which will be on average 12-18 longer in duration (Rohini et al., 2019). The UHI is likely to intensify heat waves, particularly in densely populated urban areas. The difference in heatwave days between Delhi and surrounding rural areas, which is currently 2.9, is projected to increase to more than 13.8 by the end of the century under a high emissions climate scenario (Representative Concentration Pathway (RCP) 8.5[1] (Sharma et al., 2018). In the absence of adaptation responses, even limiting global warming to 2°C could lead to annual heat episodes in Karachi (Pakistan) and Kolkata (India) by 2050 equivalent to their deadly 2015 heat waves (Hoegh-Guldberg, O., D. Jacob et al., 2018). Due to the projected extreme heat and high humidity, which makes body temperature regulation more challenging (Sherwood, 2018), large parts of the country risk becoming uninhabitable by the end of the century without large-scale deployment of cooling technologies (Zhang et al., 2021). A recent study projects that by 2100, without any mitigation measures around 1.5 million more people will die each year in India due to high ambient temperatures, at a rate comparable to the current death rate from all infectious diseases in the country (Carleton et al., 2019). The health risks related to the direct exposure to high temperatures are likely to affect India´s large agricultural

[1] The RCPs represent four future GHG emissions trajectories and span the full range of total anthropogenic radiative forcing found in the scientific literature. The RCPs are named after the possible range in radiative forcing (energy imbalance imposed on the climate system either externally or by human activities) in the year 2100 compared to pre-industrial values, spanning from very low levels of radiative forcing in the mitigation scenario RCP2.6 to medium levels in the two stabilisation scenarios (RCP4.5, RCP6.0), to high levels in the very high emissions scenario RCP8.5.

workforce (43 %) (World Bank, 2019), with the country projected to lose 5.8 % of working hours by 2030 due to increased heat stress (ILO, 2019). The urban poor, often living in overcrowded, poorly ventilated environments, without access to electricity or clean drinking water, as well as the elderly and those with pre-existing health conditions are particularly vulnerable to the projected temperature increases (Mahadevia and Pathak, 2020; Picciariello et al., 2021).

Changes in precipitation patterns

The warming of air and ocean temperatures, which increases atmospheric moisture content and evaporation of water, has contributed to more frequent and severe rainfall events in certain parts of the subcontinent. A threefold increase in extreme rainfall has been recorded over central India during 1950–2015, which has claimed at least 69,000 lives and led to the displacement of millions (Picciariello et al., 2021; Roxy et al., 2015). The rise in the magnitude and frequency of extreme rainfall events has occurred concurrently with a decline in total rainfall in many parts of the country. Average summer monsoon precipitation is estimated to have declined by around 6 % between 1951 and 2015 (Krishnan et al., 2020). This decline has been attributed to a weakening monsoon circulation due to a variety of factors, including warming of the Indian Ocean, increased magnitude and frequency of El Niño events, increased air pollution, and land-use changes (Roxy et al., 2015). The decline in precipitation is putting strains on freshwater supply, with a billion people in the country already facing severe water scarcity for at least one month of the year and 180 million – all year round (Mekonnen and Hoekstra, 2016). With 56 % of the country's total agricultural area being rainfed, it is also threatening agricultural livelihoods and food security (Picciariello et al., 2021). An increase in mental disorders and suicidal tendencies with more severe droughts have also been observed in parts of India (Carleton, 2017; Das, 2018).

With continued warming and the anticipated reduction in anthropogenic aerosols, which weaken the hydrologic cycle, more severe rainfall events concentrated within a shorter period are expected (Krishnan et al., 2020; Picciariello et al., 2021). Parallel to this, mean summer monsoon precipitation is expected to decline in parts of the subcontinent, leading to an increased probability of droughts. The overall reduction in rainfall coupled with the diminishing snowfall and glacier in the Hindu-Kush Himalaya is projected to decrease water flow in the Ganges and Brahmaputra by 17.6 % and 19.6 %, respectively, by 2050 compared to the previous century (Picciariello et al., 2021). These rainfall extremes will increase the risk of both water shortages and flooding, with devastating impacts on human lives, health, infrastructure, and livelihoods. Both deficient and extreme precipitation are expected to affect food production and degrade water quality, thus increasing the already high burden of diarrheal diseases and malnutrition in the country (Dhiman et al., 2010; Dimitrova, 2020).

Melting of glaciers

As an area, the Hindu-Kush Himalaya contains approximately half of all the glaciers outside the polar regions, with the population in the region being highly dependent on their run-off for meeting their freshwater demands. However, evidence from the last four decades indicates that those glaciers have retreated with an average rate of 18 meters a year, with implications for the freshwater supply, livelihoods, and economy of densely populated downstream regions (Singh et al., 2016). The Hindu Kush Himalayan region is extremely susceptible to global temperature increases, projected to experience the highest average temperature increases in the region (Carabine et al., 2014).

With climate change unchecked, the IPCC concludes that the glacier retreat in the Hindu-Kush Himalaya will continue, with the risk that by the end of the century the region loses 60 % of its glaciers (Hock et al., 2019). While the increase in river flows due to the rapid melting of glaciers will pose a risk for human health through more frequent floods and landslides in the medium-term (2050-60), the declining water levels and droughts in the long term will threaten the availability of water for domestic use, agriculture and hydroelectricity for the 2 billion population in the region currently relying on it (Wester et al., 2019).

Coastal flooding

Sea level rise is another major threat, with a third of the Indian population estimated to live along the coast (Krishnan et al., 2020). The north Indian Ocean has risen by 3.3 mm per year on average in the recent decades (1993-2012), both due to ocean thermal expansion and the melting of ice sheets (Krishnan et al., 2020). As seasonal cycles of sea-level rise coincide with monsoon rains, the rising sea levels pose a risk of prolonged inundation, while also causing higher storm surges and more intense cyclones. By interacting with other climatic, geological, and human-induced factors, sea level rise also causes seawater intrusion, making coastal groundwater and soil unusable for agricultural and other uses (Prusty and Farooq, 2020).

Climate models project that under a mid-range emission scenario (RCP4.5) and excluding ice melt contributions, sea levels along the Indian coast are likely to increase by 20–30 cm by the end of the century relative to 1986–2005 levels (Krishnan et al., 2020). This will have devastating implications for human health and security, assets, and agricultural land, especially so for the low-lying and densely populated coastal cities such as Mumbai, Chennai, and Kolkata.

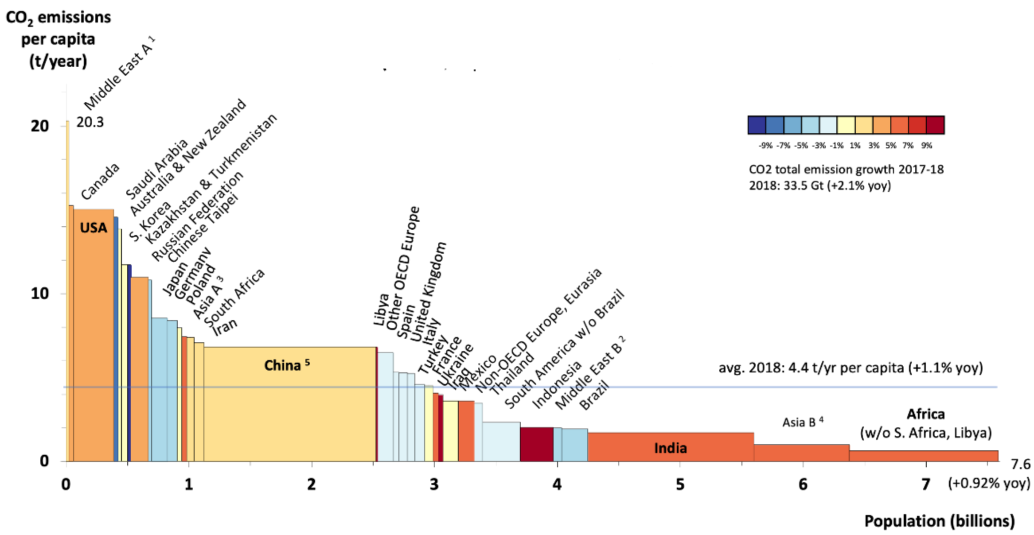
1.5.2 India´s stance in global climate negotiations – reconciling mitigation and development

Despite its high vulnerability to climate change, India´s historical and per capita emissions are low. The country hosts 17.8 % of the world's population, but accounts for only 3.2 % of cumulative emissions and has GHG per capita emissions seven times lower than the United States of America (USA) and less than half of the world average (Figure 1.5)(Picciariello et al., 2021; Global Change Data Lab, 2021; CarbonBrief, 2019). Thus, by the principle of "common but differentiated responsibility" established in the global climate accord, the country has less of an obligation for mitigating climate change. Furthermore, as a developing economy with large poverty and inequality, India faces many other pressing priorities such as the provision of clean energy, decent housing, access to improved water and sanitation, and expansion of healthcare and welfare access. However, there is another side of the coin. With over a billion population, India´s total annual CO_2 emissions are the third largest[2] and, although still being a long way behind China and the USA, they have been increasing rapidly (Figure 1.6). India´s energy use has doubled since 2000 and 80 % of its demand is still being met by coal, oil, and solid biomass (Figure 1.7; IEA, 2021a). Growth in demand for electricity, vehicles, housing, domestic appliances, and air conditioners is set to expand, with India soon expected to surpass China as the most populous country (K. C. et al., 2018). The growing population and urbanisation and the rapidly expanding and still industrialising economy mean that India´s future development trajectory (and hence emissions) will be crucial for global mitigation goals. This places the country in an intriguing dual position in climate

[2] Fourth largest if EU-28 are considered altogether.

negotiations, whereas the equity frame entails a more modest contribution to climate mitigation efforts, but its increasing emissions call for a more proactive role (Dubash, 2013).

Figure 1.5: CO_2 emissions per capita in 2018, by region

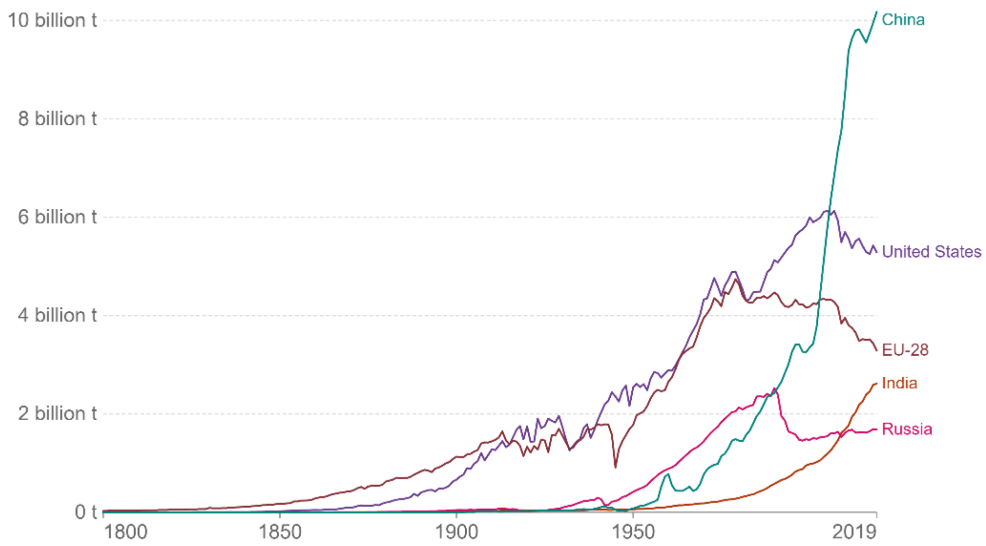


Source: Thomas Shulz, 25-Oct-2020, AQAL Capital GmbH. Based on IEA data from (IEA, 2020).

[1]Middle East A: Bahrain, Oman, Kuwait, Katar, United Arab Emirates
[2]Middle East B: Israel, Jordan, Lebanon, Syrian Arab Republic, Yemen
[3]Asia A: Brunei Darussalam, Malaysia, Mongolia, Singapore
[4]Asia B: Asia without Asia A, China, India, Thailand, Chinese Taipei, Indonesia, S. Korea, Japan
[5]China: People´s Rep. of China, Hong Kong
Notes: Energy-related CO_2 emissions only; no other GHG or natural sources; aviation and marine bunkers not shown as territory, but included I average and totals

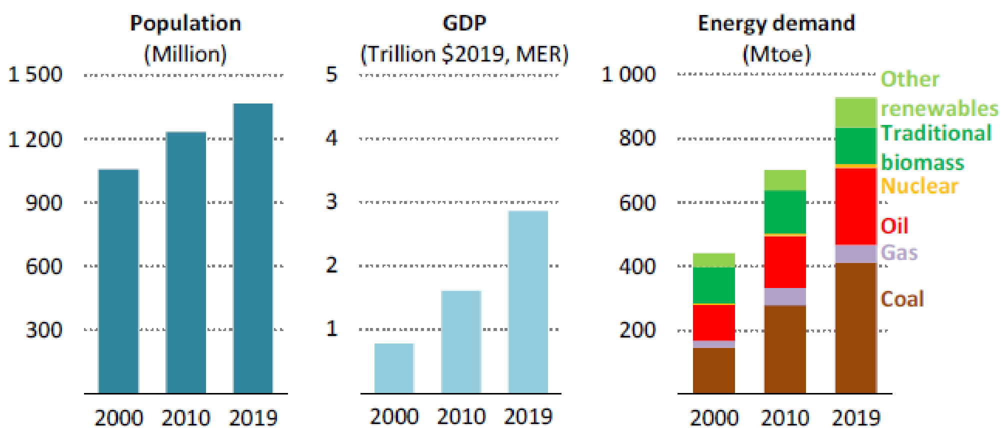
The recent emergence of the concept of 'co-benefits' from actions that can deliver both development and climate gains has recently offered an opportunity to reconcile these two opposing perspectives. Low carbon development pathways hold the promise of yielding a range of benefits for the country such as cleaner air, job creation, and greater energy, food, and water security (Picciariello et al., 2021; Dubash, 2013). Parallel to this, there has been a growing recognition that minimising the effects of climate change will crucially determine the country´s prospects of meeting many of its development objectives, including those related to public health as discussed above, but also poverty and inequality (Muthukumara et al., 2018). These are two compelling reasons for India to boost its commitments and they have already influenced ongoing discussions of the adoption of a net-zero 2050 target, much ahead of China (Chaudhary, A., Rathi, A. and Singh, 2021). Co-benefits, understood as development actions that also bring climate gains[3], are also explicitly recognised as the main policy driver within India's National Action Plan on Climate Change (Atteridge et al., 2012; Dubash, 2013; Ürge-Vorsatz et al., 2014).

Figure 1.6: Annual CO_2 emissions from the burning of fossil fuels for energy and cement production, by country/region



Source: Our World in Data, data based on Global Carbon Project, Carbon Dioxide Information Analysis Centre.
Note: CO_2 emissions are measured on a production basis, meaning they do not correct for emissions embedded in traded goods. Emissions from land use change are not included.

Figure 1.7: India´s population, Gross Domestic Product (GDP) and energy demand, 2000, 2010 and 2019



Source: IEA (2021a)

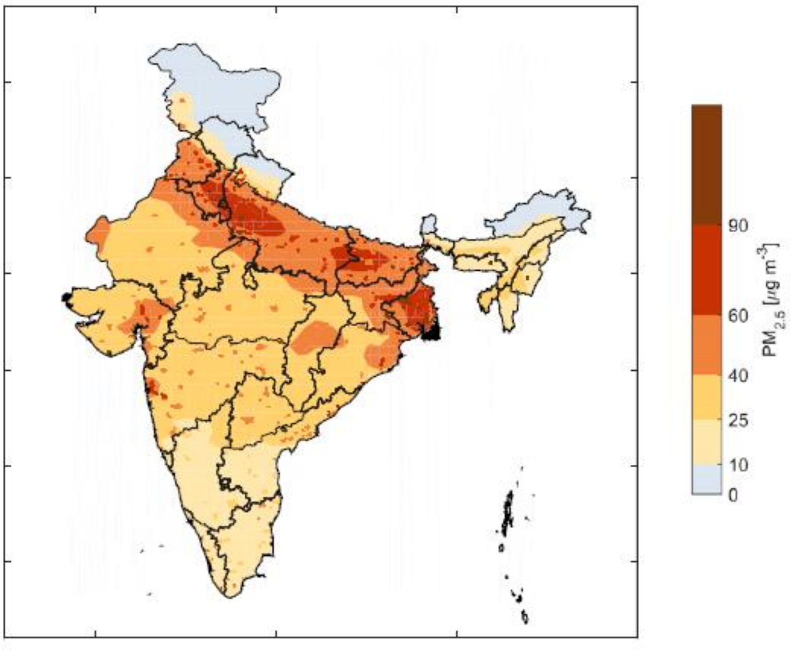
[3] Although similar, the formulation of co-benefits used in India's National Action Plan on Climate Change differs from the definition used throughout this thesis. Namely, co-benefits are understood as the potential impact of development objectives on global climate change and not the other way around.

1.5.3 Ambient air pollution and related health co-benefits in India

Ambient air pollution

One of the most well-studied climate co-benefit actions for India, which can help directly deliver on some of its development objectives, is air pollution reduction. India has some of the highest air pollution levels globally, hosting 13 out of 20 of the most polluted cities in the world (Purohit et al., 2019). Air pollution levels are also relatively high in rural areas, with overall less than 1 % of the population in the country living in areas in compliance with the former WHO's Air Quality Guideline (WHO-AQG) for annual mean concentrations of ambient $PM_{2.5}$[4] of 10 µg/m^3 (GBD MAPS Working Group, 2018). More than 50 % of the population in the country (677 million people) experiences air quality that does not conform to the Indian National Ambient Air Quality Standards (NAAQS) – India´s more conservative $PM_{2.5}$ standard of 40 µg/m^3 (Purohit et al., 2019). Although all parts of the country are affected, northern states have especially high levels of air pollution, with particular acuteness in the winter months (Figure 1.8). Most air quality health impact assessment studies in India to date have focused on particulate matter (PM) or ozone (O_3). The analysis in this thesis and the rest of this chapter focuses on $PM_{2.5}$ and its related health burden (Box 1).

Figure 1.8: Ambient $PM_{2.5}$ concentrations (annual mean concentrations), 2015



Source: IIASA and CEEW (2019)

[4] As of 2021 the WHO guideline for annual average concentrations of $PM_{2.5}$ has been updated to 5 µg/m^3.

Sources of ambient $PM_{2.5}$ in India

Anthropogenic sources are the main contributor to the high ambient $PM_{2.5}$ concentrations in India, estimated to account for 60 % of mean population-weighted exposure (Venkataraman et al., 2018). Leading sectors influencing ambient $PM_{2.5}$ are residential biomass combustion (for cooking, space- and water-heating and lightning) and fossil fuel combustion in power generation, industrial processes, and road transport (Figure 1.9) (Amann et al., 2017; Conibear et al., 2018a; Gordon et al., 2018; IIASA and CEEW, 2019; Venkataraman et al., 2017). Several recent studies have identified residential biomass fuel use as the single largest contributor to ambient $PM_{2.5}$ in India (20-50 % of total concentrations) (Butt et al., 2016; Conibear et al., 2018a; Lelieveld et al., 2015; Venkataraman et al., 2018; Chowdhury et al., 2019; Apte and Pant, 2019; Rao et al., 2021).

Box 1: Ambient air pollution

Ambient air pollution is comprised of many particles and gases, whose composition and sources vary over space and time. Air pollution and the major sources contributing to it are normally measured and detected by a small subset of these gases and particles in the atmosphere. Fine particles with aerodynamic diameters $\leqslant$2.5 μm ($PM_{2.5}$) and tropospheric O_3 are two of the most widely used air quality indicators to quantify exposure to outdoor air pollution.

Ambient $PM_{2.5}$ concentrations are a complex mixture of solid and liquid aerosols, which originate from a variety of sources and can be either directly emitted (primary – e.g. black carbon and organic carbon emitted from biomass burning; sea salt; soil; road dust, etc) or formed in the atmosphere through chemical reactions between gaseous precursor emissions (secondary – e.g. ammonia (NH_3) emitted primary from agricultural sources, sulfur dioxide (SO_2) and nitrogen oxides (NO_x) from fuel combustion, and non-methane volatile organic compounds (NMVOCs)). Secondary particles comprise about one-third of ambient $PM_{2.5}$ (IIASA and CEEW, 2019).

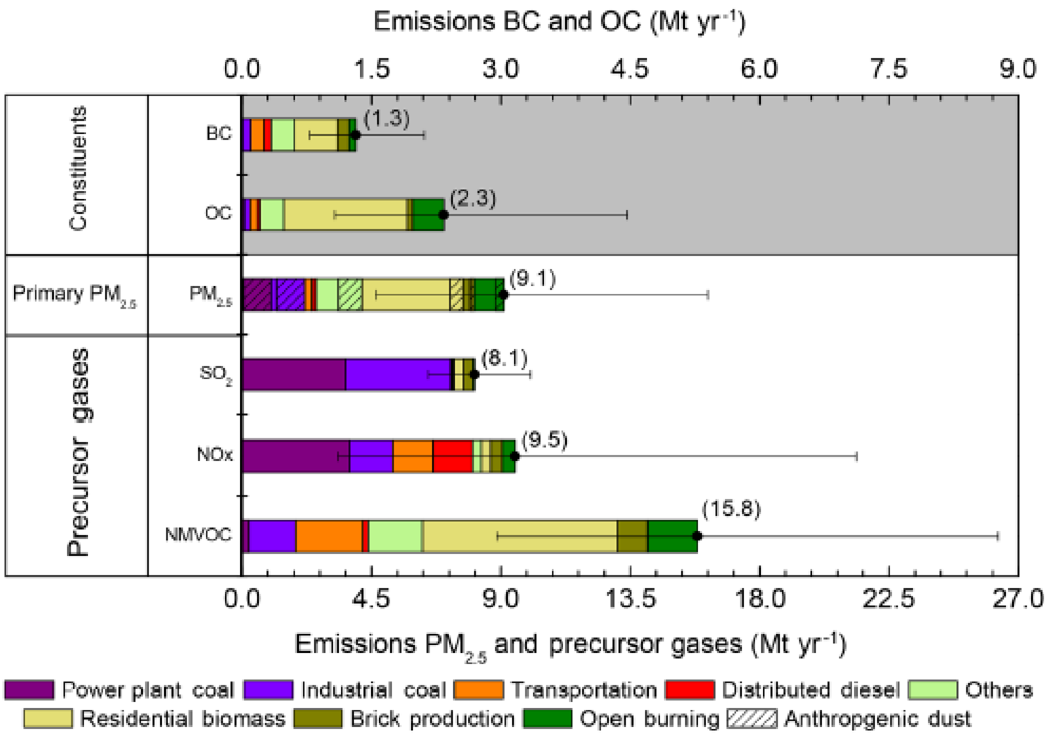
Due to their small size, $PM_{2.5}$ particles penetrate deep into the lungs, where they can cause a wide range of adverse health impacts. Epidemiological studies show consistent and robust associations between long-term exposure to $PM_{2.5}$ and increased risk of mortality from IHD, stroke, Chronic Obstructive Pulmonary Disease (COPD), Lower Respiratory Infections (LRIs), and lung cancer (LC) (Health Effects Institute, 2018). Short-term exposure has been associated with an increased risk of respiratory and cardiovascular morbidity, including aggravation of asthma, respiratory infections, and hypertension (WHO, 2013). A wide range of other chronic health effects of $PM_{2.5}$ exposure have also been documented, affecting reproductive, maternal (short gestation, decreased fetal growth), child (low birth weight, pneumonia, respiratory infections, reduced growth in lung function), and adult (diabetes, neurodegenerative diseases, high blood pressure, pneumonia) health (Thurston et al., 2017). Both for short-term and long-term exposure to $PM_{2.5}$ there has been no evidence of a safe level of exposure, with adverse health impacts occurring even at very low levels (WHO, 2016).

Ozone (O_3), is a gas formed in the atmosphere as a secondary reaction of several precursor pollutants, which have both natural and man-made sources. O_3, which is high up in the atmosphere (in the stratosphere) has a protective role, shielding the Earth from harmful rays and ultraviolet radiation. However, O_3 which is near ground level (in the troposphere) acts as a GHG and a health-damaging air pollutant (Health Effects Institute, 2019). Most ground-level ambient O_3 is produced when precursor pollutants (mainly, volatile organic compounds and NO_x) emitted from human activities (e.g. transport vehicles, power plants, factories, and other sources) react in the presence of sunlight with hydrocarbons emitted from diverse sources (Pandey et al., 2021). O_3 has been associated with increases in morbidity and mortality from respiratory causes (Jerrett et al., 2009), specifically chronic obstructive pulmonary disease, and also with a reduction in crop productivity (Emberson et al., 2018). As O_3 concentrations are highly seasonal, peaking in the summer in mid-latitudes, exposure measurements in epidemiological studies normally focus on the warm season rather than annual averages.

Hence, high ambient air pollution (AAP) is highly interrelated with the problem of energy poverty and the high indoor air pollution in India, which already contributes significantly to the disease burden in the country (see section 1.5.4). The majority of electricity in the country is produced by coal (57 %), with thermal power plants characterised by low adherence to existing regulations, lack of flue-gas desulphurisation, and low energy efficiencies (Conibear, 2018). Informal activities such as open waste and agricultural burning, fired-brick production that is based predominantly on traditional technologies, and unregulated use of personal diesel generator sets, are other important sources of particulate pollution (Gordon et al., 2018; Venkataraman et al., 2017). In some areas, such as construction sites and places characterised by little green cover and resuspension of road dust, ambient PM levels are also aggravated by dust sources (Gordon et al., 2018).

Transboundary emissions, especially dust originating from West Africa and the Middle East, have also been identified as an important source of $PM_{2.5}$ in the Indian sub-continent (Liu et al., 2009). Because of their small size and thermodynamic properties, $PM_{2.5}$ particles remain in the atmosphere for several days, and during this period they can be transported over several hundreds of kilometers (Purohit et al., 2019). As a result, a large share of the particles found in a specific location at a certain point in time originates from distant sources. Transboundary pollution is especially high in north-western regions in India, where it contributes 15-30 % of total ambient $PM_{2.5}$ (Venkataraman et al., 2017). According to Zhang et al. (2017), in 2007, $PM_{2.5}$ generated within India contributed to 75 thousand premature

Figure 1.9: National emissions of $PM_{2.5}$ and precursor gases for 2015 (Mt yr^{-1}).



Source: Venkataraman et al. (2017)

deaths outside of the country, while $PM_{2.5}$ generated outside of India contributed to 67 thousand premature deaths inside the country. A recent analysis by Purohit et al. (2019)

demonstrated that also within many of the administrative states in India dominant contributor sources to ambient $PM_{2.5}$ are emissions originating outside of their immediate jurisdictions. The transboundary nature of ambient $PM_{2.5}$ underscores the need for strong regional cooperation for the successful improvement in local air quality.

The public health burden from AAP

The public health burden of air pollution in India is significant. Exposure to air pollution (both ambient and household) in India is ranked as the second most important contributor to mortality and morbidity, after malnutrition and dietary risks (IHME, 2019) and it also accounts for 25 % of the global disease burden attributable to air pollution (Conibear, 2018). Ambient air pollution is estimated to cause between 483 thousand and 1.2 million[5] (IIASA and CEEW, 2019; Pandey et al., 2021) premature deaths annually in India, with ambient $PM_{2.5}$ accounting for 10.4 % (8.4-12.3%) and O_3 for 1.8 % (0.9-2.7%) of total deaths in the country, respectively. This burden is mainly attributable to stroke, heart attack, chronic obstructive pulmonary disease (COPD), LC, and respiratory diseases. When additional causes of death than those considered previously are included, this death toll is estimated to be as high as 2.2 million (Burnett et al., 2018). Rural regions in India are shown to experience the majority of deaths from $PM_{2.5}$ and O_3 (Karambelas et al., 2018), which might be due to their larger population size and lower LE compared to urban areas. In terms of morbidity, in 2017 the DALY (disability-adjusted life years) rate attributable to ambient $PM_{2.5}$ in India was 2,239 (1,768–2,699) and for O_3 – 220 (108-347) (Balakrishnan et al., 2019). It has been estimated that within the last decade (1990-2019) the death rate from ambient PM and O_3 pollution in the country has increased by 115 % (95% uncertainty interval (UI): 28–344) and 139 % (97–196), respectively (Pandey et al., 2021). According to different estimates, exposure to ambient $PM_{2.5}$ reduces the LE of the population in India by 0.9-4.3 years on average (Apte et al., 2018; Balakrishnan et al., 2019; Ghude et al., 2016; Greenstone and Fan, 2018; Guo et al., 2018; Lelieveld et al., 2020). These health impacts also cause a significant burden on the economy: in 2019, the total loss of output due to the premature mortality and disease burden in the country was estimated at $37 billion (27–48), which was 1.36 % of GDP (Pandey et al., 2021).

[5] The large differences in estimates are explained by variations in baseline ambient $PM_{2.5}$, health, and population data as well as the epidemiological functions linking $PM_{2.5}$ and mortality and the diseases considered.

Extrapolation of global exposure-response functions to the Indian context

A major source of uncertainty in the estimates of the mortality burden of ambient $PM_{2.5}$ in India reported above is the exposure-response function (ERF), relating ambient air pollutants to mortality risks, used for these quantifications. Due to the lack of India-specific epidemiological studies on the mortality effects from long-term exposure to air pollution, existing disease burden estimates for India have been based on ERFs from other parts of the world, mostly Europe and North America. This is a major limitation since estimates from high-income countries might not be readily transferrable to the Indian context for a variety of reasons, including differences in concentration ranges (observed ambient $PM_{2.5}$ exposures in India being several-folds higher), source mixtures, demographics, activity patterns, underlying health status, and healthcare systems. It has been argued, however, that similarities in risk estimates for effects of short-term exposure on daily mortality in Indian and global studies support the temporary use of such global ERFs for quantifying the disease burden in India (Gordon et al., 2018).

Most estimates of the number of deaths attributable ambient $PM_{2.5}$ in India to date, including those from the GBD, have been based on the Integrated Exposure-Response (IER) model, which combines evidence on exposure and risk of mortality from five causes of death (IHD, LC, stroke, COPD and LRIs) derived from epidemiological studies on AAP and HAP as well as second hand and active smoking (Burnett et al., 2014). This model is based on the strong assumption of equal toxicity of $PM_{2.5}$ per total inhaled dose from these different sources. The non-linear shape of the IER function has major implications for the quantification of the disease burden of $PM_{2.5}$ in highly polluted areas as it generally leads to a decreasing marginal risk of mortality per increment in $PM_{2.5}$ at high concentrations. The Global Exposure Mortality Model (GEMM) has been developed more recently, which is based only on AAP cohort studies and covers much of the global $PM_{2.5}$ exposure range, thus allowing to relax many of the underlying assumptions in the IER model (Burnett et al., 2018). The near-linear shape of the GEMM model at higher concentrations and the inclusion of additional causes of death than those considered by the IER model implies a much larger burden of ambient $PM_{2.5}$ than previous estimates, and especially so for highly polluted regions such as India.

Air pollution epidemiology in India

Epidemiological studies on the adverse health effects of air pollution in India have been growing over the last years (Balakrishnan et al., 2019; Gordon et al., 2018). However, several reviews of the existing evidence on the health effects of air pollution exposure in India have highlighted that the available literature is still inadequate in terms of the number of studies and scope (Khilnani and Tiwari, 2018; Pant et al., 2016; PHFI&CEH, 2017; Rajak and Chattopadhyay, 2020). A vast majority of the existing epidemiological studies were based on data from large urban centres (Delhi, Mumbai, Bangalore, Chennai, Kolkata), and most reported on the prevalence of respiratory symptoms such as cough and wheeze, asthma in children and adults, and diminished lung function (Pant et al., 2016; Gordon et al., 2018). Health effects in smaller cities and towns and rural areas have been less researched (Tirado, 2019). Most of the literature was limited to coarse PM (PM_{10} or PM_5), while little research has been carried out on the exposure to fine and ultrafine PM. Furthermore, only a few cohort studies to date have reported mortality effects related to long-term exposure to air pollution (Rajak and Chattopadhyay, 2020). The main barriers for air pollution epidemiology remain the lack of routinely collected health data as well as the still very limited routine monitoring of air quality, with current monitoring nearly exclusively confined to urban centres. To overcome the barrier in exposure assessment, hybrid models which combine data from chemical transport modelling with satellite retrievals and available monitoring data have been developed (Brauer et al., 2012; Dey et al., 2012; Shaddick et al., 2018; van Donkelaar et al., 2010). New epidemiologic cohort studies on both urban and rural populations have also been launched in an effort to provide estimates of the long-term effect of AAP on different child (birth weight), maternal (acute respiratory infections) and adult health outcomes (chronic respiratory symptoms, lung function, cardiovascular function, mineral density) (Balakrishnan et al., 2015; Ranzani et al., 2020a; Ranzani et al., 2020b; Gordon et al., 2018).

Scenario analysis of air pollution interventions

Previous studies have demonstrated the large potential health benefits from alternative air pollution interventions in India, with all of them focusing either on $PM_{2.5}$ or O_3. Scenario analysis in relation to air pollution in India has focused either on the impacts of targeted air quality controls (Chowdhury et al., 2019; Conibear et al., 2018b; GBD MAPS Working Group, 2018; IEA, 2021a, 2016; Limaye et al., 2019; Purohit et al., 2019; Sanderson et al., 2013; Venkataraman et al., 2017) or on co-benefits from climate change mitigations (Chowdhury et al., 2018; Dholakia et al., 2013; Hamilton et al., 2021; IEA, 2021b; Rafaj et al., 2018, 2013; Sampedro et al., 2020; Silva et al., 2016; Tibrewal and Venkataraman, 2021; Vandyck et al., 2018; West et al., 2013).

- **Health benefits of targeted AAP controls**

The International Energy Agency (IEA) developed a New Policy Scenario (NPS), which considers all relevant existing and planned policies as of 2016, and the Clean Air Scenario (CAS), which represents ambitious policy measures based on proven energy policies and technologies tailored to national circumstances (IEA, 2016). Evaluation of the health implications of these scenarios suggests a +53 % increase in the disease burden from air pollution under the NPS or a -5 % reduction under the CAS scenarios by 2040 compared to 2015.

Conibear et al., (2018b) re-evaluated IEA´s NPS and CAS scenarios using a higher spatial resolution air pollution model and updated baseline mortality data and ERFs. Similarly, the authors demonstrated a large potential for reduction in premature mortality from AAP by 2050 under the CAS scenario compared to NPS (-35 %), but an increase in the total burden relative to 2015 even under this aspirational scenario (+7 %).

More recently, the IEA produced new scenarios for the future of India´s energy sector, considering the potentially far-reaching impacts of the COVID-19 pandemic: Stated Policies Scenario (STEPS), which represents current policy ambitions and effective COVID-19 management in 2021; India Vision Case (IVC), which foresees a more swift recovery from the pandemic, faster economic growth, and more complete realisation of policy objectives and the Sustainable Development Scenario (SDS), which envisions accelerated efforts towards meeting the 2°C climate targets and other sustainable development objectives (IEA, 2021a). Despite the realised air pollution reduction in the STEPS scenario, premature deaths from energy-related AAP are projected to increase by +50 % by 2040 compared to 2019 due to population growth. However, the more substantial reductions in air pollutants under the IVC and SDS can reduce this burden by -17 %.

Purohit et al. (2019) explored two ambitious air pollution reduction pathways in India – implementation of Advanced Emission Control (AEC) technologies as those already widely adopted in industrialised countries and AEC plus the additional implementation of sustainable development policies, including the 2 °C climate target – and compared them to the evolution of air quality under current legislation (2015[6] and 2018 legislation). While an AEC pathway could provide NAAQS-compliant air quality for 60 % of the Indian population by 2050, when complemented with national sustainable development policies this could increase to 85 %, thus reducing current population exposure to above-NAAQS air quality by two-thirds (IIASA and CEEW, 2019).

The GBD MAPS Working Group developed another set of scenarios for India´s air quality throughout 2050, including a business-as-usual reference scenario, an ambitious scenario reflecting stringent emission standards, and an aspirational scenario (GBD MAPS Working Group, 2018). The study projected increases in total annual premature mortality from ambient $PM_{2.5}$ exposure between 2015 and 2050 under all $PM_{2.5}$ pathways (+234 % in the business-as-usual, +194 % in the ambitious, and +125 % in the aspirational scenarios), despite the estimates of a 35 % reduction in population-weighted ambient $PM_{2.5}$ concentrations under the aspirational scenario. The authors attributed these increases largely to the rapid growth and aging of the population.

Chowdhury et al (2019) developed seven different scenarios of mitigating household $PM_{2.5}$ sources — biomass for cooking, space and water heating, and kerosene for lighting. Using these as a counterfactual to the present level of $PM_{2.5}$ exposure and disease burden, they demonstrated that the NAAQS is achievable through a cleaner energy transition of households and could translate to a ~13 % reduction in premature mortality from ambient $PM_{2.5}$.

Overall, all the above-mentioned modelling studies demonstrated that while current legislation would not be sufficient to deliver significant air quality improvements, large potential public health benefits relative to the business-as-usual can be realised through stringent air quality management. Another consistent finding is that the capacity for reduction of $PM_{2.5}$ and its related mortality burden over time will be somewhat limited due to the impacts of rapid economic growth, urbanisation, population growth, and aging. While

[6] The 2015 legislation scenario is in line with IEA´s CAS scenario mentioned above.

the expansion of economic activity is projected to offset some of the impacts of new emission controls, demographic change is expected to compensate even for more ambitious air quality improvements.

- **Health co-benefits of climate change mitigation**

Health co-benefits related to air pollution reduction from climate change mitigation have also been analysed for India, although mainly as part of large global studies. The potential air pollution-related co-benefits from climate change mitigation for a certain country depend on many factors, including not only the global temperature target and associated GHG emissions reductions, but also on the temporal and spatial allocation of the global carbon budget and the technological pathway for achieving these reductions (Sampedro et al., 2020). In this respect, modelling studies based on the Paris Agreement have demonstrated that India can realise some of the largest air pollution-related health co-benefits with ambitious climate change mitigation by mid-century, irrespective of the global burden-sharing mechanism (Markandya et al., 2009) and the mitigation technologies used (Sampedro et al., 2020). Studies have also shown that when monetised these co-benefits will largely exceed climate change mitigation costs even under most aspirational scenarios (Markandya et al 2018, Sampedro et al 2020). For instance, Sampedro et al. (2020) estimate that with a "least-cost approach of mitigation" and under a range of technological pathways consistent with the 2°C mitigation target, India is expected to account for 33–37 % of the global health co-benefits related to $PM_{2.5}$ and O_3, while bearing only 14 % of the global mitigation costs. Analyses of India´s NDCs[7] show that the country´s currently outlined carbon mitigation plans would be insufficient for achieving notable air quality co-benefits as compared to a business-as-usual scenario (Hamilton et al., 2021; Markandya et al., 2018; Vandyck et al., 2018). Hamilton et al. (2021) compared health co-benefits related to air pollution, active travel, and diet for nine high emission countries, including India. Based on a sustainable development pathway scenario compatible with the 2°C target, it was estimated that in 2040 health co-benefits related to air pollution will be the second most important for India after those from improvements in diet (434 thousand avoided deaths from air pollution improvement compared to 1.7 million from diet and 365 thousand from active travel).

[7] Refers to the 2015 NDCs, the updated 2021 NDCs of India were still not available at the writing of this thesis.

Two studies considered the impact of climate changes on future air quality, using an ensemble of climate-chemistry models and a different set of global scenarios – the RCPs (Silva et al., 2016; Chowdhury et al., 2018). Overall, the effect of climate-driven meteorology on future concentrations of O_3 and $PM_{2.5}$ is shown to be relatively smaller compared to the effect of changes in anthropogenic emissions. However, Chowdhury et al. (2018) estimated that climate-induced meteorology can potentially mitigate about 7 %–17 % of the rise in $PM_{2.5}$ concentrations in the future under the RCP4.5 scenario. Silva et al. (2016) projected that although the premature mortality burden of both O_3 and $PM_{2.5}$ will increase in the medium term (i.e. 2030-2050) in India in most scenarios, stringent climate action (RCP2.6) can still help prevent 102 thousand premature deaths from O_3 and 315 thousand from ambient $PM_{2.5}$ in 2050 compared to a high emissions scenario (RCP8.5). Focusing exclusively on India, Chowdhury et al. (2018) considered not only different climate change scenarios (RCP4.5 and RCP8.5) but also socio-economic and demographic scenarios (Shared Socioeconomic Pathways - SSPs)[8]. Considering all plausible SSPs combinations, the premature mortality burden from $PM_{2.5}$ in India was estimated to be 9.7–17.9 % and 28.5–38.8 % higher under RCP8.5 scenario relative to RCP4.5 scenario in 2050 and 2100, respectively. It should be noted that a major limitation in the RCP scenarios is that they assume a decrease in emissions of air pollutants globally over time due to increasingly stringent air pollution control policies in line with rising income levels (van Vuuren et al., 2011). As such, the RCPs do not span the full range of plausible future air-pollutant pathways found in the literature (Rogelj et al., 2014).

Several studies considered the impact of climate change mitigation along with or in comparison to targeted air pollution control measures (Purohit et al., 2019; IEA, 2021a; Dholakia et al., 2013;). As outlined in the previous section both Purohit et al. (2019) and IEA (2021a) demonstrated that while 2°C-compatible climate action and additional sustainable development policies will help reduce $PM_{2.5}$ exposure and the associated mortality burden in India, the largest benefits in the future occur with the concurrent adoption of advanced emission controls. A 2013 study focused on Delhi showed that climate change mitigation policies will have only a modest impact on reducing $PM_{2.5}$ concentrations and the associated mortality burden in the capital, while city-specific policies related to the transport, waste,

[8] The Shared Socioeconomic Pathways (SSPs) are scenarios of projected socioeconomic global changes up to 2100 in the absence of climate policy. The SSPs provide narrative storylines of alternative socio-economic developments that pose different challenges to adaptation and mitigation of climate change (O'Neill et al., 2014), many elements of which have been quantified.

energy, and other sectors can bring much larger improvements in local air quality, with trans-boundary pollution measures potentially playing a critical role as well (Dholakia et al., 2013). Overall, existing studies have highlighted the importance of complementing GHG mitigation strategies with air pollution control measures in order to achieve more substantial health benefits. At the same time, it has been highlighted that advanced air quality technologies alone will not be sufficient to substantially reduce the $PM_{2.5}$ mortality burden everywhere in the country, especially in regions where major sources are related to poverty and underdevelopment rather than industrial development and more affluent lifestyles (Purohit et al., 2019).

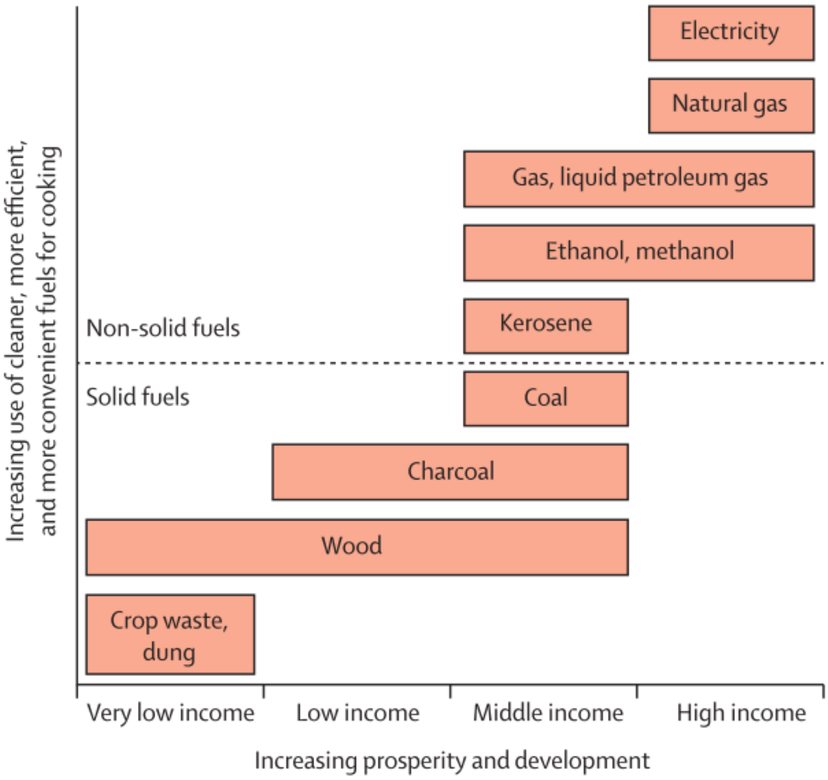
1.5.4 Household air pollution

Context and characteristics

Around 660 million people or half of India´s households are estimated to live without access to modern clean cooking fuels or technologies (IEA, 2021a). Energy poverty is especially a problem for rural areas in the country, where more than 90 % of the population lives without access to clean cooking. Solid fuel use is geographically concentrated in the Indo-Gangetic Plain (IGP), with ten states accounting for 75 % of all solid fuel use in the country (Uttar Pradesh, Bihar, West Bengal, Andhra Pradesh, Madhya Pradesh, Maharashtra, Rajastan, Odisha, Tamil Nadu, Karnataka) (Conibear, 2018). LPG has been prioritised as the main cleaner alternative to solid fuel use in India. However, its widespread adoption is hampered by the high upfront connection and recurring fuel costs, as well as lack of distribution in rural areas (Conibear, 2018; Edwards et al., 2014; Jain et al., 2015; Smith and Sagar, 2014; Smith, 2017). In low-income rural areas, biomass and other traditional fuels are preferred as these are abundantly available at no or minimal monetary cost compared to the much more expensive LPG. It has been documented that as households get wealthier, they tend to switch to cleaner and easier to use fuels, thus ascending a metaphorical "energy ladder" as they get richer (Figure 1.10).

Incomplete combustion from the burning of solid cooking fuels (mostly bushwood, but also charcoal and coal, animal dung, and crop residues) in traditional stoves results in the emission of hundreds of different chemical substances, including health-damaging $PM_{2.5}$, CO, nitrogen dioxide (NO_2), SO_2 and others (Gordon et al., 2018). According to estimates based on an

Figure 1.10: The energy ladder



Source: Rehfuess (2006); Gordon et al. (2014)

India exposure model, $PM_{2.5}$ concentrations in households using solid-fuels could reach up to 337 μg/m^3 (Balakrishnan et al., 2013; Gordon et al., 2018), far exceeding the current WHO-AQG interim target 1[9] of 35 μg/m^3 and the Indian NAQQ standard of 40 μg/m^3. Individual exposure to HAP is shown to depend on a variety of factors including fuel/stove type and fuel quantity, ventilation of kitchen area, and time spent near the cooking area (Gordon et al., 2018; Milà et al., 2018). As women tend to spend longer time at home and cooking, while also taking care of young children and infants, they are disproportionately exposed to high levels of HAP. In addition to the multitude of damaging health impacts, residential biomass use in India also imposes a cost on women's and children's productive time, due to the time and effort involved in the wood collection, and on the environment due to its effects on deforestation and the climate (IEA, 2021a).

[9] The WHO-AQG interim targets are not end targets, but rather serve as incremental steps towards ultimately achieving the stipulated AQG levels.

Household air pollution interventions

Solid fuel interventions aim at helping households "ascend the energy ladder" before they get wealthy. This is accomplished either by *making the available clean*, i.e. promoting the adoption of more efficient biomass cookstoves that lower particulate emissions, or *making the clean available, i.e.* through price support or direct subsidies for cleaner cooking fuels (Smith and Sagar, 2014). About 10 % of solid fuel users in India use improved biomass cookstoves, which can come in many varieties (e.g. with chimneys, fans, combustion chamber insulation) and have different performance characteristics and emissions (Venkata Ramana et al., 2015). Although improved cookstoves are seen as an important short-term strategy to reduce HAP, results from field studies suggest emission reductions of these are substantially lower than observed under controlled conditions in laboratory studies (Edwards et al., 2014; Muralidharan et al., 2015; Patange et al., 2015). Furthermore, evidence on their health benefits is mixed (Conibear, 2018; Gordon et al., 2017; Hanna et al., 2016) and it has been suggested that "improved" cookstoves may not reach sufficiently low emission levels to generate meaningful health benefits (Venkata Ramana et al., 2015). Between 1984 and 2001 the Indian government launched a national campaign on improved cookstoves, introducing 32 million improved cookstoves into rural areas through the National Programme on Improved Chulha (NPIC). The programme, which reached only 27 % of its aim, is widely considered as unsuccessful due to its top-down approach, limited feedback, and poor-quality materials (Conibear, 2018; Gifford, 2010; Venkataraman et al., 2010). Some of the distributed improved cookstoves were even reported to have higher air pollutant emissions and similar efficiencies as the traditional biomass stoves (Conibear, 2018; Smith, 1989).

The Indian government has recently established two subsidy programmes to increase the adoption and regular use of LPG in rural areas: Pradhan Mantri Ujjwala Yojana (PMUY) and Pratyaksh Hanstantrit Labh schemes (PAHAL). The PMUY scheme, originally launched in 2016, initially aimed at providing 50 million LPG connections by 2019 and was later increased to 80 million connections by 2020, with the latter target already achieved ahead of schedule. The initiative provides an interest-free loan facility for the cost of an LPG stove and first refill and is targeted at households living below the poverty line. The Direct Benefit Transfer of LPG scheme, also known as PAHAL, was launched in stages in 2013 and expanded as a national scheme in 2015. This scheme is eligible for all consumers and it provides a subsidy for the purchase of LPG fuel. A "Give It Up" campaign launched by the government has persuaded 10 million households to opt out of the subsidy (IEA, 2021). It has been estimated that the expansion of clean cooking fuels, largely supported by these initiatives, has helped prevent more than 200 thousand premature deaths in the country between 2010 and 2019 (Health Effects Institute, 2020). Even with these schemes in place, household surveys reveal that cooking with biomass remains widespread. Although affordability, especially the large upfront payments for LPG, is a fundamental reason for the continued use of solid fuels, other barriers to access have also been identified, including volatile fuel supplies and prices and household incomes, long distances to LPG distributors, and cultural factors (Van Der Kroon et al., 2013). For instance, even as household incomes increase some still opt for using LPG along with biomass or other fuels because of their cooking preferences for certain dishes, a practice known as "fuel stacking" (using multiple fuels for the same purpose).

Health impacts of HAP

The prolonged exposure to HAP, especially $PM_{2.5}$ is associated with an increased risk of a wide range of health outcomes, including respiratory tract infections, exacerbations of inflammatory lung conditions, cardiac events, stroke, eye disease, tuberculosis, and cancer (Gordon, 2014). According to recent GBD estimates, the death rate due to HAP in India decreased by 64 % (95 % UI: 52–74 %) between 1990 and 2019. The total mortality burden, however, is still very high, amounting to 0.61 million deaths (95 % UI: 0.39–0.86) or 6.5 % (95 % UI: 4.3-9.0%) of total mortality in the country. The high exposure to smoke of pregnant women and young children is a particular matter of concern. Due to their developmental susceptibility early in life, air pollution exposure can have long-lasting detrimental effects on children's health and human capital formation (Backes et al., 2013). While AAP studies have measured exposure based on estimated levels of PM and other pollutants, most of the epidemiological studies on HAP that have been conducted in India have used qualitative indicators to characterise exposure, for instance, use of solid vs. clean cooking fuels, involvement in cooking, or proximity to the stove. Although the health burden of HAP in India is also quantified using global models such as the IER, several epidemiological studies for India are incorporated in the systematic reviews/meta-analyses for these global models (Gordon et al., 2018; Smith et al., 2014).

According to a recent study, the lower-income households in India not only bear the brunt of HAP due to their energy poverty as discussed above, but they are also disproportionately affected by exposure to air pollution from the household consumption of richer-income groups (Rao et al., 2021). As a result of this double burden, the poorest in India are estimated to be nine times more likely to die from air pollution, compared with the richest, considering each income group's relative contribution to air pollution.

Scenario analysis

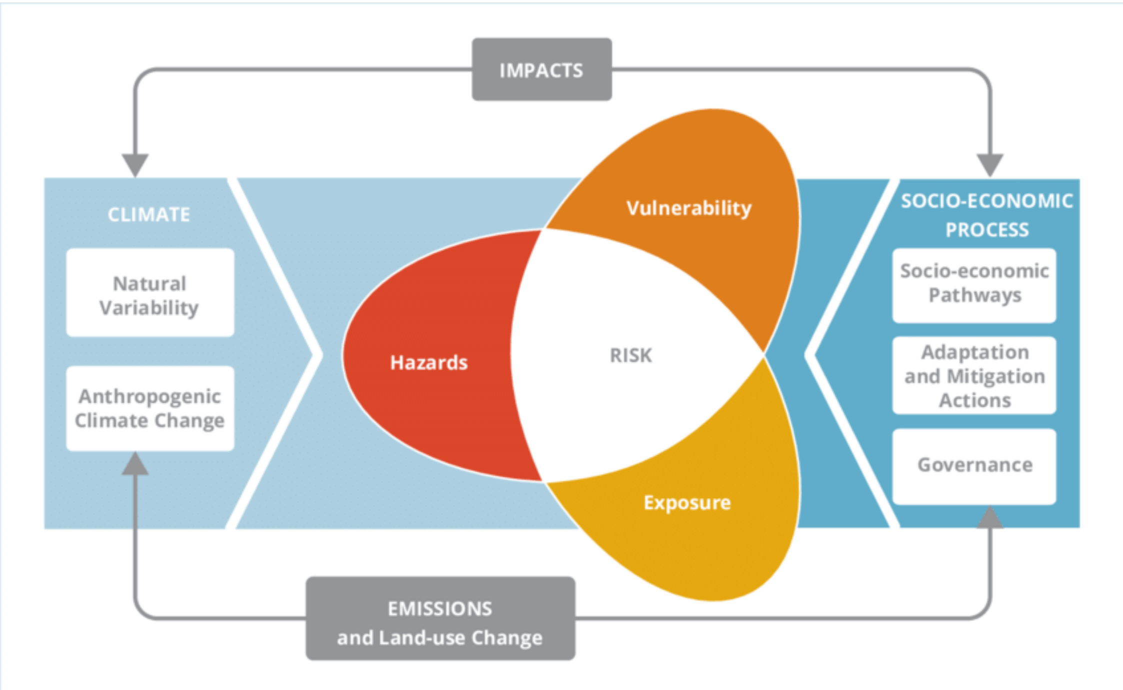
Projections of HAP and related health impacts have been more limited compared to AAP and most of the studies on AAP have not considered changes in HAP. One study investigated access to clean cooking in South Asia between 2010 and 2030 under four increasingly stringent climate change mitigation scenarios and different clean fuel and stove price support policies and quantified the associated mortality burden and the cost of support policies (Cameron et al., 2016). The authors found that in 2030 climate policy in line with a 66 % probability of reaching the 2°C target, without compensatory measures, will increase the average cost to cook with LPG by 38 %, making LPG unaffordable for 21 % of the population and potentially leading to 0.40 million (UI: 0.22- 0.44) premature deaths from solid fuel use compared to the business-as-usual. Climate policy with the provision of additional clean fuel and stove subsidies can reduce the number of premature deaths from HAP by 0.68 million (UI: 0.31- 0.84) compared to the business-as-usual but would cost governments between US$29 billion and US$38 billion depending on the choice of access policy instrument.

The recent scenarios developed by the IEA as described earlier (see section 1.5.3) also included projections of access to clean cooking fuel and the associated disease burden from energy-related HAP (IEA, 2021a). The authors project that in 2040 under the current policies scenario (STEPS) the total number of premature deaths from energy-related HAP will fall by only 0.1 million compared to 2019. Additional interventions both under the SDS and IVC scenarios (innovative subsidy schemes supporting the sustained use of LPG and eliminating fuel stacking; investments and incentives to expand infrastructure for LPG bottling and distribution and for the repair and replacement of broken stoves) are projected to lead to universal access to clean cooking by 2030 and thus reduce the mortality burden from HAP in 2040 by 0.5 million compared to 2019.

1.5.5 The role of socio-demographic factors in climate risk assessment

Within the IPCC framework, the risk of climate-related impacts results from the interaction of weather or climate-related hazards with vulnerability and exposure of human and natural systems (Figure 1.11). Vulnerability has been defined as "the propensity or predisposition to be adversely affected", which could refer to personal or group characteristics, while exposure has been formulated as the "presence (location) of people, livelihoods, environmental services and resources, infrastructure, or economic, social, or cultural assets in places that could be adversely affected by physical events" (IPCC, 2012, p.32). In this context, a realistic assessment of future health impacts of climate change requires not only advanced modelling of future environmental hazards (i.e. climate events or trends) but also consideration of potential interactions of these hazards with future socio-economic and demographic developments, which determine the vulnerability and exposure drivers of climate risks. This is particularly the case for LMICs such as India, which are not only recognised as highly vulnerable to climate risks (Watts et al., 2015) but also expected to experience dramatic socio-economic, health, and demographic transformations in the next decades.

Figure 1.11: Definition of climate risk within the IPCC framework



Source: Davis-Reddy and Vincent (2017)

The population in 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 grow from 31.3 % in 2011 to 52.8 % in 2050. These trends will have paramount implications for economic growth, energy use, and GHG emissions. However, they can also amplify potential climate risks since a larger population will be exposed to the expected climate hazards, many of which will be concentrated in urban areas (e.g. UHI effect, air pollution, floods). Furthermore, the rising levels of cardio-metabolic diseases and ageing of the population, associated with the undergoing demographic and epidemiological transitions in India, are likely to further amplify climate risks by increasing the share of those most vulnerable (Dandona et al., 2017). As India continues to develop economically there are likely to be also positive developments in the opposite direction – reduction in poverty and improvements in education, access to healthcare, water, sanitation, and clean energy. For instance, previous studies have shown that education has important mediating effects on climate hazards (Dimitrova and Muttarak, 2020; Lutz et al., 2014; O'Neill et al., 2020). 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 et al., 2015). Projections that explore these interactions at the sub-national level are particularly needed to help determine regional or local priorities for improving public health through mitigation or adaptation measures.

1.6 Overview of existing methodologies for forecasting environmental health impacts

What is Health Impact Assessment?

The most commonly used formulation of Health Impact Assessment (HIA) to date emerged from the Gothenburg Consensus meeting in 1999, which defined HIA "as a combination of procedures, methods, and tools, by which a policy, programme or project may be judged as to its potential effects on the health of the population, and the distribution of those effects within the population" (European Centre for Health Policy, 1999). Several other definitions have been proposed, but as highlighted by Veerman (2007) and Kemm (2003) the two defining characteristics of HIA are that (1) it seeks to predict the future consequences for health of a potential project, programme, or policy decisions and that (2) it seeks to inform decision-making on the basis of these predictions. Typically, HIA considers interventions outside of the health sector, which have unintended consequences on human health (Veerman, 2007).

The origins of HIA can be traced back to two prior developments. On the one part, HIA represents a natural development of Environmental Impact Assessment (IEA). IEA used to inform decision-makers about the consequences of development projects on the physical and chemical environment since the seventies. The aspect of health was first applied in EIAs of construction projects in low-income countries (e.g. construction of dams, irrigation schemes, etc.) when the large health consequences of such projects became apparent and was later expanded to EIA in high-income countries as well (Birley, 1995). A second movement that HIA is rooted in is related to the (social) determinants of health and healthy public policy (Lalonde, 1974) and the WHO Healthy Cities Initiative (Veerman, 2007). This tradition puts forward a holistic view of health, recognizing the importance of factors at the individual, communal, and macro-level that shape population health. Special emphasis is placed on the social, environmental, and behavioral determinants of health and their interactions.

HIA approaches can be classified into two broad disciplinary groups – one is based on epidemiology and toxicology, while the other – on social sciences. HIAs can also be distinguished by their application – they can be applied either to specific projects or to broader policies and strategies (Kemm, 2003). Given the different disciplinary roots of HIA and the diverse types of projects and policies that it applies to, it is not surprising that many different HIA methods have been developed. Although levels of detail and rigor in conducting a HIA vary depending on specific needs and available resources, most HIA processes share five key steps: screening, scoping, effect analysis, interaction with the policy process, and monitoring and evaluation. The screening phase involves judgment of the potential consequences of policy proposals on human health, on the one hand, and the potential of HIA to influence decision making, on the other. In the scoping phase, for HIAs deemed useful, the research question, the study design, and the partners to be involved are decided. Normally, these two stages benefit from the involvement of a wide range of stakeholders, including those whose health is likely to be affected by the proposed policy, programme, or project (European Centre for Health Policy, 1999). In the effect analysis phase, the nature and size of the health impacts are estimated along with their distribution across population groups. This is normally done by linking (i) predictions of how the proposed policies will affect the determinants of health with (ii) estimates of how changes in these determinants affect population health (Fehr et al., 2012). In doing so, HIA relies on evidence on causal links between exposure and outcomes (exposure-response relationships) from epidemiology and toxicology. Recommendations based on the assessment of health gains and losses of proposed actions are communicated to policy-makers and other stakeholders. If deemed necessary, this can lead to the further monitoring of the health impacts and relevant exposures and to an evaluation of the HIA (Veerman, 2007).

Quantitative HIAs

Quantitative HIA can complement qualitative analysis by offering several important advantages. First, quantitative HIA can provide a very specific numerical description of health effects compared to qualitative analysis only. This can help decision-makers in distinguishing between minor and major issues that need to be addressed, understanding trade-offs that policies may entail, and allocating resources accordingly. Second, quantification of negative and positive effects permits the use of economic instruments, for example, cost-effectiveness analysis, which can further aid decision-making. Quantitative impact estimates are likely to be more influential in policy discussions, in particular when these could be weighed against economic or other nominal benefits or costs of proposed policies (Fehr et al., 2012). However, the drawbacks that arise from quantification should also be considered. Quantification can lead to an unwarranted impression of accuracy and to the so-called "quantification bias", i.e. focusing only on issues and parameters where data are available (Fehr, 2010). Quantitative assessment alone cannot capture the manifold and complex drivers of health impacts since not all health effects are quantifiable. Therefore, due attention should be paid to all aspects of the decision-making process, whether these are qualitative or quantitative. Quantitative HIAs inevitably involve approximations and uncertainties, which are important to address and communicate. As Kemm (2003) concludes, quantitative HIAs do not offer certainty in their predictions, nor do they remove the need for judgment in decision-making. They could only reduce uncertainties and inform public debate and judgments that are for political decision-makers to make.

Projecting climate-related health impacts

As climate impact assessment is primarily a model-based exercise, HIAs of the potential disease burden of climate change are mainly quantitative. In comparison to other risk factors to human health, impacts of climate change on health outcomes are mediated by a diversity of causal pathways and typically involve a long delay between cause and effect (McMichael et al., 2004). Thus, climate related HIAs inevitably involve large uncertainties with respect to the magnitude, and distribution of future hazards, the size, characteristics and distribution of exposed population, and the future vulnerability of the exposed population. Therefore, HIAs of climate change needs to address many additional complexities compared to traditional HIA of projects and policies. One main difference with "traditional" HIAs is that the projected exposures (meteorological or other variables) are generated through global climate models or Integrated Assessment Models (IAMs) (Box 2). These projected exposures are then linked with ERFs from historical data to quantify human health impacts. ERFs describe how the likelihood of an adverse health effect (outcome) is related to an environmental hazard (exposure). There are three sources of exposure-outcome association, which are normally used in climate-related HIA: i) locally derived; ii) pooled from the literature (i.e. meta-analyses of epidemiological studies) or iii) mathematically modelled (Hess et al., 2016). ERFs derived from meta-analyses can provide more reliable risk estimates for projecting future health impacts than individual studies as they combine results from multiple studies. Meta-analyses can be particularly informative when based on systematic reviews that provide both quantitative (e.g. size of the cohort) and qualitative (e.g. the quality of the analyses) weight of studies (van den Brenk, 2018). As with other HIAs, studies on climate-related health impacts should draw from the most recent epidemiological evidence, preferably based on a similar population.

The extrapolation of short-term and historical associations between climate variation and health to the long-term and future effects of climate change is one of the principal sources of uncertainty in climate related HIAs. Therefore, a particular challenge in this type of HIAs is to consider and model potential autonomous or planned adaptations, which might change this association. This requires the need to account for interactions between the effects of climate change and other changes to human populations (e.g. investment in health infrastructure, level and equity in the distribution of wealth, education, housing, etc) (McMichael et al., 2004). Furthermore, the fact that future health impacts are based on observed causal associations means that not all probable health outcomes, with nevertheless large consequences (e.g. impact of sea level rise on displaced population), can be easily quantified and modelled (McMichael et al., 2004).

Box 2: Integrated Assessment Models

Integrated Assessment Models (IAMs) are scientific models that combine knowledge from multiple academic disciplines to arrive at a mathematical representation of the world. The main aim of IAMs is to support informed decision-making, normally in the context of climate change but also in relation to various other human-environment interactions. IAMs link the main features of human systems (e.g. society, economy, energy systems, land-use, agriculture) with natural systems (e.g. the biosphere and atmosphere) into a single "integrated" modelling framework. IAMs can either be "simple" – relying on simplified equations for comparing the costs and benefits of avoiding different levels of warming – or "complex" – modelling the detailed processes and relationships of the different human and environmental systems using linked "modules". Complex IAMs can be used to answer more general "what if" policy questions such as: *What will be the implications of not taking actions on climate change? What measures and actions are needed for the world to stay within the 1.5°C and 2°C climate mitigation targets?* or more specific ones such as: *What will happen if a universal price of \$100 per tonne of CO_2 emissions is set by 2030? How can climate change be mitigated if certain technologies such as carbon capture and storage are not available?* Importantly, IAMs do not aim at providing a prediction of the future but rather estimates under potential scenarios that can guide policy decisions between different choices. A main advantage of IAMs because of their complex linkages is the ability to trace feedbacks and tradeoffs between different policy decisions with regard to the economy, energy system, and environment. For instance, IAMs can explore co-benefits or unintended consequences of climate change mitigation policies in different sectors and geographic areas and thus, assess net costs and benefits of climate action. For more information see CarbonBrief (2018)

Modelling techniques for forecasting health impacts of climate change

A multitude of tools for health impact quantification have been developed, partly enabled by the increase in computing power in the last decades. Briggs et al. (2016) provide a comprehensive review and a taxonomy of existing methods for the quantitative evaluation of public health interventions related to non-communicable diseases (NCDs). The focus of their review is on economic evaluation, which includes quantification of health impacts as well and economic costs. Briggs´s taxonomy of quantitative health impact assessment models is presented in Table 3. Horizontally, the model structures are ordered based on the unit of analysis, ranging from population- (columns A and B) to individual-level models (columns C and D), and based on their ability to incorporate randomness. Vertically, the model structures are categorised depending on whether they include interaction elements (no interaction, interaction between entities within the model and between entities and the environment) and on how they treat time (untimed, timed, discrete time or continuous time). Briggs et al. (2016) summarise the main advantages and disadvantages of these different modelling structures. Here, we will briefly discuss the characteristics and some of the advantages and disadvantages of the methods we consider most relevant for forecasting health impacts and co-benefits of climate change mitigation. However, this is not an exhaustive review of all modeling structures that can be applied.

Table 1.1: Taxonomy of model structures

			A	B	C	D
			Cohort/aggregate-level/counts		**Individual-level**	
			Expected value, continuous state, deterministic	**Markovian, discrete state, stochastic**	**Markovian, discrete state**	**Non-Markovian, discrete state**
1	**No interaction**	**Untimed**	Decision tree rollback or comparative risk assessment	Simulation decision tree or comparative risk assessment	Individual sampling model: simulated patient-level decision tree or comparative risk assessment	
2		**Timed**	Markov model (deterministic)	Simulation Markov Model	Individual sampling model: Simulated patient-level Markov model	
3	**Interaction entity and the environment**	**Discrete time**	System dynamics (finite difference equations)	Discrete time Markov chain model	Discrete time individual event	Discrete time discrete event simulation

					history model	
4		**Continuous time**	System dynamics (ordinary differential equations)	Continues time Markov chain model	Continuous time individual event history model	Continuous time discrete event simulation
5	**Interaction between hetero-geneous entities**		x	X	X	Agent-based simulation

Source: adopted from (Briggs et al., 2016).

i) Comparative risk assessment

Comparative risk assessment (CRA) models (corresponding to sections A1, B1, C1 and D1 in Table 3) are aggregate-level model widely used in the HIA literature (Mueller et al., 2015; Nieuwenhuijsen et al., 2017). The Global Burden of Diseases, Injuries, and Risk Factors Study (GBD), which estimates levels and trends in exposure, attributable deaths, and attributable disability-adjusted life-years (DALYs) for a wide range of behavioural, environmental, occupational, and metabolic risks, is the largest global project using a CRA framework (GBD 2019 Diseases and Injuries Collaborators, 2020). CRA involves mapping alternative population health scenarios based on a different distribution of exposure to a risk factor over time and using Population Attributable Fractions (PAFs) to estimate the change in health outcome for each scenario (Murray et al., 2003). CRA models can be adapted to include a time component (see the section on multistate life tables below) or to simulate individuals when combined with microsimulation (see the section on microsimulation below). Although CRA models do not allow for interactions, they can be used to simulate age- and sex-specific effects of changes in population exposure to multiple risk factors and disease processes simultaneously (Briggs et al., 2016). Health inequalities can also be estimated with this approach by applying the same method to other population strata.

CRA is the most widely used method for quantifying health impacts and co-benefits of climate change mitigation (Rai et al., 2019; Silva et al., 2016) and guidelines for this specific application of the method have been previously published (Campbell-Lendrum and Woodruff, 2006; Hess et al., 2020, 2016; Kovats et al., 2003). Studies using this approach normally consider demographic change by incorporating population and mortality projections in the estimation of attributable mortality or disease burden. However, future mortality rates and population size are assumed to be equal across different (emission) scenarios, with only the proportion of attributable disease burden changing. Thus, this method can be misleading for long-term predictions or for locations with high exposures and associated hazard risks since it does not consider changes in mortality and population survival over time induced by changes in exposures (Miller and Hurley, 2003).

ii) Macrosimulation

Macrosimulation or multi-cohort method (row 2, column A, B) is an aggregate level Markov model[10] for projecting future population and population health, with the unit of analysis referring to entire populations or population sub-groups. Typically, two populations are modelled — the population of interest as it is, and an identical population that has been exposed to changes in the risk factors. Each of these populations can be modelled through a standard life table, where changes in exposure to a risk factor over time impact survivorship and all-cause mortality rates in the population (Miller and Hurley, 2003). The population is classified by sex and age group or other relevant characteristics (cohorts) and transition probabilities are repeatedly applied (for example, incidence or mortality hazards), which determine how cohorts move between states (alive and death) at specific time intervals.

Proportional multi-state life table (MSLT) is an extension of the multi-cohort method as it allows for the incorporation of morbid states and not only mortality outcomes. The MSLT is termed 'proportional' as it allows to model a number of diseases simultaneously while also allowing for co-morbidity (Barendregt et al., 1998). In the proportional MSLT model, two populations are simulated through a standard life table with all-cause mortality and sub-life tables for each one of the diseases causally related to the modelled risk factors. Transition

[10] A Markov model is a stochastic method used to model randomly changing systems. In a Markov model system behaviour is represented with a set of states and interstate transitions and probabilities between them, where the probability to move to a new state only depends on the current state, but not on any previous state. Markov models have applications in many fields, including medical research and health economics. An example of a simple Markov model in medical research is the modelling of health states that might be included in a study on a cancer intervention: progression-free, post-progression, and dead.

probabilities are repeatedly applied (for example, incidence or mortality hazards), which determine how cohorts move between health states (presence or absence of modelled diseases and death) at specific time intervals (for example, annually). The Potential Impact Fraction (PIF) is used to link changes in exposure to the determinant of health and incidence of related diseases (Zapata-Diomedi, 2017).

The multi-cohort method originally stems from demography and medical demography, where it is used for modeling the effects of morbidity, disability, and mortality on the size, composition, and structure of the population (Lhachimi, 2011). In comparison to CRA models, MSLT models allow for the simulation of more complex scenarios by incorporating multiple disease outcomes, the possibility of relapse, and outcomes over different time horizons (Briggs et al., 2016). However, this comes at the expense of increased data requirements since exposure, morbidity, and mortality data need to be age specific. Also, the model is more complex compared to CRA, which might decrease transparency and increase the probability of error (Veerman, 2007). On the other hand, MSLT models can be implemented in a spreadsheet, which increases their flexibility and transparency. An important advantage of MSLT models is that outcomes can be expressed not only in terms of the number of deaths or prevalence of a disease but also using summary metrics of population health such as Years of Life Lost (YLL), Healthy Life Expectancy (HLE), DALYS. These are more informative measurements of premature mortality, which allow to account for the extent to which lives are shortened by exposure to temperature and air pollution. The Markov model is considered especially useful for modeling processes that progress over time, such as chronic diseases, and has been applied in projection studies for diabetes (Murakami and Ohashi, 2001), cardiovascular diseases (Moran et al., 2010), and health outcomes related to physical activity such as IHD, stroke, type 2 diabetes, breast cancer and colon cancer (Cobiac et al., 2009).

iii) Microsimulation

Macro- and microsimulation models have certain features in common — both approaches represent a simplified, quantitative description of reality, which determines populations structure and health, and both rely on hypotheses about future values of model parameters (van Imhoff and Post, 1998). However, the two approaches also have major differences. Dynamic microsimulation techniques model individual life courses (rather than the total population), where transition probabilities guide shifts between different states (for example, exposed, unexposed, healthy, diseased, and dead). Microsimulation models (corresponding to sections C1-4 and D1-2 in Table 3) normally use a sample rather than the total population and rely on repeated random experiments rather than on average fractions (van Imhoff and Post, 1998). Microsimulations can be static or dynamic, depending on how population aging, and individual interactions are modeled. Static models usually take a cross-section of the population at a specific point in time and apply program rules to the individual units (Lambert et al., 1994). As opposed to dynamic microsimulation models, which alter the relevant population by applying deterministic probabilities that a certain event may or may not occur, static microsimulations use static aging techniques, which age the population by "reweighing" and "uprating" based on exogenous demographic or economic projections. If we assume that an individual is a combination of certain characteristics, by altering the weights of the individuals in the dataset static microsimulation models change the combination of these characteristics, but not the characteristics themselves. Static microsimulation techniques originate and have been mostly applied in economic studies evaluating the redistributive effects of taxes and benefits over the life-course (National Research Council, 1991).

In a dynamic microsimulation, each event (e.g. mortality, change in health status and socioeconomic status, fertility, migration, etc.) is modelled through a Monte Carlo process, which allows for the estimation of stochastic uncertainty (uncertainty resulting from two individuals being in the same situation, but having different outcomes by chance) and parametric uncertainty (uncertainty in the estimates of model parameters) (Briggs et al., 2016). The model is run either until a specific outcome occurs or until a certain length of time has elapsed. Results of the simulations can be aggregated at the population level or variations in results across individuals can be reported (Briggs et al., 2016). Dekkers (2015) compares in detail the static and dynamic types of microsimulations and argues that although they are technically different, the dynamic and static methods are very similar in terms of their simulation properties. Properties of static models are very similar to those of dynamic, in particular (i) if the number of dimensions that have to be modified to capture 'the future' is limited and (ii) if future types of individuals are present in the baseline dataset. Due to the common model properties and the lower data, development, maintenance, and time requirements of the static approach, Dekkers (2015) recommends the use of static models unless otherwise justified.

Microsimulation models, in general, are considered an appropriate technique for modelling a large number of individual attributes (e.g. age, sex, education, health status, activity, religion, etc.) and thus, analyzing the distribution of health effects within the population (e.g. by socio-economic status) (Veerman, 2007). Further advantages of microsimulation models include the fact that they can manage continuous covariates and can provide a much richer output. Since microsimulation models require detailed individual-level information they normally draw empirical data from sample surveys, either cross-sectional surveys or longitudinal panels (van Imhoff and Post, 1998). This highlights a major tradeoff between macro- and microsimulation models, namely information loss in macro-models versus high data requirements and larger influence of error terms in micro models (van Imhoff and Post, 1998).

iv) Agent-based models

An important feature that distinguishes an agent-based simulation (ABS) (row 5, column D on Table 3) from the methods previously described is that it allows for the probability of events occurring within the system that is modelled to change over time and as a result of interactions of individuals (agents) with other agents and with the environment (Briggs et al., 2016). This is done by modelling heterogeneous agents or groups of agents, whose behavioural responses depend on their characteristics, which can change over time as a result of interactions with the environment or other agents. Therefore, ABSs are particularly well suited for modelling multi-component interventions, feedback loops, and layers of complex, interacting components (Silverman, 2021). ABSs can offer a rich output, similar to microsimulations, and a more accurate representation of spatial effects, such as social networks (Squires, 2014). In addition, since ABSs can model explicitly individual-level decision-making, they can reveal unexpected emergent effects at the population level (Silverman, 2021). The main disadvantage of ABSs is the requirement of large amounts of data and processing power. Silverman (2021) describes in detail the advantages of using ABSs in public health research, in particular in relation to complex problems arising from various sources such as behavioural and social influence, and environmental interaction. In the climate-population literature, among others, ABSs have been applied in the study of the climate-agriculture-nutrition-health nexus (Lloyd et al., 2018) and climate-induced migration (Entwisle et al., 2016)

Chapter 2: RATIONALE

Over the last decades, socio-economic development in India has brought improvements in living standards and a range of health outcomes. The LE in the country has increased from 49.7 in 1970-1975 to 69.0 years in 2013-2017 (Government of India, 2020). However, two-thirds of Indian households continue to rely primarily on polluting solid fuels to meet their energy needs and, in absolute terms, the number of solid fuel users has remained largely unchanged in the past 30 years (Conibear, 2018). At the same time, the large growth in the economy, the industrial, power generation, and transport sectors, partly driven by rapid population growth and urbanisation, has resulted in high levels of CO_2 emissions and deterioration of ambient air quality (Dey et al., 2012; GBD MAPS Working Group, 2018). Exposure to air pollution is the second leading risk factor for disease burden in the country and AAP alone is estimated to shorten population LE by up to 4.3 years (Greenstone and Fan, 2018). Emissions of air pollutants are predicted to grow substantially in India over the next decades, but so are also other environmental health threats related to climate change as outlined in the previous chapter. Due to its current geography and climate and low adaptive capacity, India is recognised as one of the countries most vulnerable to the future impacts of climate change (Carabine et al., 2014). The interrelated nature of all these challenges — HAP, AAP, climate change, and development — provides an opportunity to devise policies that deliver on multiple sustainable development objectives. In particular, reduction in air pollutants and GHG emissions can improve population health and human capital, while minimising future risks of climate change. Current cost-benefit analyses of climate policies rarely consider the health implications of policies, even though co-impacts, especially those related to health, have been shown to significantly change the outcome of cost-benefit evaluations (Ürge-Vorsatz et al., 2014). Studies that assess the potential impacts of climate change on population health and the health co-benefits of climate change mitigation are needed to assist governments in their risk-benefit analysis. In low-income settings, studies that evaluate both the synergistic and opposing effects of climate policies, especially among the most vulnerable, are needed to ensure that development objectives are not compromised, and scarce public resources are spent efficiently. By demonstrating the localised health impacts and co-benefits for current generations, such studies can also legitimise governmental policy actions to the wider public and provide incentives for more ambitious mitigation measures.

This thesis will address the topic of health impacts of climate change and health co-benefits of climate change mitigation in India by focusing on two specific exposures – ambient temperatures and air pollution. This is motivated by the fact that increasing ambient temperatures are one of the main risk factors of climate change in the country, while AAP levels in India are some of the highest in the world. In this thesis, the terms 'AAP' and '$PM_{2.5}$' will be used interchangeably since $PM_{2.5}$ was applied as a proxy for the overall AAP exposure of the population. This is a common practice in the co-benefits literature since the disease burden of $PM_{2.5}$ exceeds those of other major pollutants. Climate change refers to long-term averages of weather conditions (e.g. several decades). However, this thesis also refers to "climate impacts" when discussing the association between mortality and shorter-term fluctuations in weather conditions in the recent past. This is because, as discussed in Chapter 1, this historical quantitative relationship is normally applied to future climate scenarios to project the potential disease burden of climate change.

This thesis aims to address some of the following research gaps in the literature established in the previous chapter:

a. The lack of robust population-specific ERFs on the association between ambient temperatures and air pollution and mortality is a major source of uncertainty in current health impact projection studies in India and South Asia, in general.
b. The HIA methodologies adopted by most projection studies in India do not comprehensively represent the interplay between future environmental hazards, population dynamics, and socio-economic developments.
c. Most assessments of air pollution health co-benefits from climate change mitigation to date have focused on mortality outcomes and on adult populations. This leads to an underestimation of the total co-benefits. Also, mortality metrics do not show the extent to which air pollution represents a significant shortening of human life as opposed to a relatively short advance of deaths of fragile individuals.
d. Existing studies of air pollution-related health co-benefits in India report population-specific impacts by state and age, but not by other relevant population characteristics such as sex, urban/rural residence, income, social group, or education.

e. Existing projection studies have largely focused on a single exposure pathway and rarely considered concurrent effects of multiple exposures.

The rest of this thesis is structured as follows: Chapter 3 introduces the specific objectives of the analyses, Chapter 4 describes the general methodology, Chapter 5 presents the three research articles that comprise this thesis. Research Article I and II have been published, while at the time of writing this thesis Research Article III has been submitted to a journal for review. Research Article II is complemented with two unpublished analyses on the total projected decrements in LE from $PM_{2.5}$ under the modelled scenarios (section 5.2.1) and on comparison of the applied dynamic health impact assessment method with the conventional CRA approach (5.2.2). Finally, Chapter 6 summarises and discusses the findings of this thesis and the uncertainty in the health impact projections. It also highlights policy implications and directions for future research.

Chapter 3: OBJECTIVES

The overall objectives of this thesis were twofold — first, to investigate the association between ambient temperature and mortality in South Asia, and second, to quantify future air pollution-related health co-benefits and trade-offs in India under different global climate change mitigation and complementary national policy scenarios. The specific objectives of this research are as follows:

Objective 1: To systematically review and quantitatively assess the current evidence on the association between ambient temperature and heat waves, and all-cause mortality in South Asia. **[Research Article I]**

Objective 2: To project the future localised (i.e. by state and urban-rural level) benefits in terms of LE gains and avoided premature mortality from reduced ambient $PM_{2.5}$ in India under global climate change mitigation scenarios in line with the Paris Agreement targets and national scenarios for maximum feasible air quality control. **[Research Article II]**

Objective 3: To project the future localised (i.e. by district and urban-rural level) net benefits for child linear growth from changes in AAP and HAP under a combination of scenarios for climate change mitigation, AAP control, and clean cooking access (CCA) **[Research Article III]**

In order to address these objectives, this thesis integrates conceptual and technical knowledge from various disciplines, spanning from environmental epidemiology and demography to economic, atmospheric, and climate modelling.

Chapter 4: GENERAL METHODOLOGY

The three studies undertaken during this PhD were based on three different methods (see Table 4.1). Research Articles II and III shared some common data sources and explored some of the same or similar scenarios. This section provides an overview of the general methodology applied to address each of the three research objectives, while detailed information on the methods, data sources, and scenarios used in each article can be found in Chapter 5.

To identify epidemiological studies on the association between ambient temperatures and heat waves, and all-cause mortality in South Asia a systematic search of four electronic databases — Pubmed, Web of Science, Scopus, Embase — was performed. The search was restricted to peer-reviewed articles published in English between January 1990 and August 2020. Two reviewers independently assessed full texts for eligibility, based on pre-defined inclusion and exclusion criteria, previously published in a PRISMA protocol (Dimitrova, A. and Tonne, 2018). The Navigation Guide methodology was applied in order to evaluate the quality and strength of the evidence for each exposure (Johnson et al., 2014). Those studies that were sufficiently compatible in terms of study design, outcome and exposure measures, and lag structure, were included in a random-effects point-wise meta-analysis. The meta-analysis was based on a novel approach that allows for combining nonlinear exposure-response associations without access to data from individual studies.

To quantify the health benefits from reduced ambient $PM_{2.5}$ in India under global climate change mitigation scenarios in line with the Paris Agreement targets and national scenarios for targeted ambient air quality control, a previously developed multidimensional population projection was linked with projections of gridded urban/rural $PM_{2.5}$ concentrations from the GAINS-MESSAGEix-GLOBIOM IAM. Assuming that the demographic projection reflects only socio-economic but not environmental drivers (i.e. air pollution) of population change over time, the population projection was re-run for each policy scenario by adjusting mortality rates to account for the risk of mortality associated with ambient $PM_{2.5}$ exposure, while keeping all other drivers of population change constant (i.e. fertility, education, and migration). This dynamic approach allowed us to account for changes in population survival over time, resulting in different mortality rates, size, and structure of the population for each scenario. We applied the GEMM for $PM_{2.5}$, which includes cohort studies at much higher concentration ranges and accounts for a larger set of causes of death than considered previously. In addition, we accounted for the differential risk of mortality by age, urban/rural residence, and state and developed and incorporated projections of changes in disease burden over time. The future impacts of ambient $PM_{2.5}$ exposure on mortality, LE, and population change were estimated as the difference between each policy scenario and the original demographic projection.

Table 4.1. Overview of methods, data and data sources analysed in in this PhD thesis.

Research Article	Method	Data	Data sources
I	- Systematic review and quality and strength of evidence assessment as per Navigation Guide methodology - Meta-analysis	- 27 studies included in qualitative synthesis - 5 studies included in quantitative synthesis	- 4 databases: Pubmed, Web of Science, Scopus, Embase - 8 countries covered
II	Population projection method	- Gridded projections of annual average $PM_{2.5}$ concentrations for urban and rural areas (2010-50) - Multi-dimentional demographic projection (age, sex, urban/rural residence, maternal education, state) (2010-50) - Global exposure mortality model (GEMM)	- GAINS-MESSAGEix-GLOBIOM IAM - K. C. et al. (2018) - Burnett et al. (2018) - GBD

		- Share of deaths from NCDs and LRIs (2015-17)	
III	Static microsimulation	- Height-for-age Z score and individual and household characteristics, including primary cooking fuel type (2015-16)	- India´s National Family Health Survey (NFHS-4)
		- Annual average gridded $PM_{2.5}$ concentrations (2009-16)	- Atmospheric Composition Analysis Group
		- Projections of clean fuel use and poverty levels (2010-50)	- MESSAGE-Access-GLOBIOM IAM
		- Multi-dimentional demographic projection (age, sex, urban/rural residence, maternal education, state) (2010-50)	- K. C. et al. (2018)

To project the future net benefits for child linear growth from changes in AAP and HAP under a combination of scenarios for climate change mitigation, AAP control, and CCA, we applied a static microsimulation. The analysis was performed in two stages. First, we empirically examined the association between early-life exposure to AAP (ambient $PM_{2.5}$) and HAP (type of fuel used for cooking) and stunting in a large nationally representative survey of children under-5 years in India (NFHS-4), using modelled ambient $PM_{2.5}$ concentrations and a binomial logistic regression. In the second stage, under each future scenario, we generated synthetic datasets with identical individuals as those in the stage I dataset. We adjusted the individual sample weights in those synthetic datasets to reproduce the changes in the demographic characteristics of children under-5 over time (age, sex, state, residence, maternal education) as forecasted by the multi-dimensional demographic projection. We linked the epidemiological model developed in stage I and the synthetic datasets with projections of ambient $PM_{2.5}$ concentrations, clean fuel use, and poverty levels from an IAM to project the prevalence of child stunting at the local level and for distinct population groups under four scenarios combining climate change mitigation, air quality control, and policies to support CCA.

Chapter 5: ORIGINAL RESEARCH ARTICLES

Research Article I: Association between ambient temperature and heat waves with mortality in South Asia: Systematic review and meta-analysis

Research Article II: Health impacts of fine particles under climate change mitigation, air quality control, and demographic change in India

Research Article II Additional Analyses:

(i) Total decrements of LE due to ambient $PM_{2.5}$

(ii) Comparison of the static and dynamic health impact assessment approaches

Research Article III: The impact of air pollution on child stunting in India – synergies and trade-offs between climate change mitigation, ambient air quality control, and clean cooking access

5.1 Association between ambient temperature and heat waves with mortality in South Asia: Systematic review and meta-analysis

Bibliographic reference

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Author contributions

AD designed the study, screened all titles and abstracts, assessed full texts for eligibility, conducted the quality and strength of evidence assessment, interpreted the results, wrote the original draft. VI assessed full texts for eligibility; XB developed and wrote the script for the meta-analysis, and advised on the quality assessment criteria; OR advised on the design of methods and quality assessment criteria; CM advised on the quality assessment criteria and assisted with the graphical presentation of the meta-analysis; JB advised on the quality assessment criteria and provided scientific input in the interpretation of the results; CT advised on the study design, screened a sample of the abstracts, crticially reviewed and edited the manuscript. All authors contributed to the submitted version of the manuscript and approved the final version.

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Review article

Association between ambient temperature and heat waves with mortality in South Asia: Systematic review and *meta*-analysis

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ABSTRACT

Background: South Asia is highly vulnerable to climate change and is projected to experience some of the highest increases in average annual temperatures throughout the century. Although the adverse impacts of ambient temperature on human health have been extensively documented in the literature, only a limited number of studies have focused on populations in this region.
Objectives: Our aim was to systematically review the current state and quality of available evidence on the direct relationship between ambient temperature and heat waves and all-cause mortality in South Asia.
Methods: The databases Pubmed, Web of Science, Scopus and Embase were searched from 1990 to 2020 for relevant observational quantitative studies. We applied the Navigation Guide methodology to assess the strength of the evidence and performed a *meta*-analysis based on a novel approach that allows for combining nonlinear exposure–response associations without access to data from individual studies.
Results: From the 6,759 screened papers, 27 were included in the qualitative synthesis and five in a *meta*-analysis. Studies reported an association of all-cause mortality with heat wave episodes and both high and low daily temperatures. The *meta*-analysis showed a U-shaped pattern, with increasing mortality for both high and low temperatures, but a statistically significant association was found only at higher temperatures — above 31° C for lag 0–1 days and above 34° C for lag 0–13 days. Effects were found to vary with cause of death, age, sex, location (urban vs. rural), level of education and socio-economic status, but the profile of vulnerabilities was somewhat inconsistent and based on a limited number of studies. Overall, the strength of the evidence for ambient temperature as a risk factor for all-cause mortality was judged as *limited* and for heat wave episodes as *inadequate*.
Conclusions: The evidence base on temperature impacts on mortality in South Asia is limited due to the small number of studies, their skewed geographical distribution and methodological weaknesses. Understanding the main determinants of the temperature-mortality association as well as how these may evolve in the future in a dynamic region such as South Asia will be an important area for future research. Studies on viable adaptation options to high temperatures for a region that is a hotspot for climate vulnerability, urbanisation and population growth are also needed.

1. Introduction

Expected increases in temperature and the intensity and frequency of heat waves due to climate change have become a matter of growing public health concern (IPCC, 2014; Watts et al., 2017; Ebi et al., 2018; Maycock et al., 2018; Watts, 2019). Along with other climatic changes such as precipitation and atmospheric circulation patterns, temperature increases can affect human health and wellbeing through various pathways, including heat stress, increases in wildfires, spread of vector-borne and water-borne diseases, crop failure and its potential impact on food prices, nutrition, incomes, population displacement and conflict (Watts et al., 2017; Ebi, Campbell-Lendrum and Wyns, 2018). One of the most direct, and therefore, well-studied mechanisms through which changes in average weather impact human health is ambient temperature.

An extensive body of epidemiological literature has documented the

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adverse impacts of ambient high and low temperatures and isolated events such as heat waves and cold spells (normally defined as a prolonged period of abnormally high/low temperatures, with the exact number of days and temperature thresholds varying by study design) on human health in terms of increases in cardiovascular (Moghadamnia et al., 2017), respiratory, and all-cause mortality (Oudin Åström, Bertil and Joacim, 2011; Yu et al., 2012; Ryti, Guo and Jaakkola, 2016), as well as increases in emergency department visits and hospital admissions (Mastrangelo et al., 2007; Phung et al., 2016). Most of these studies have been conducted in countries with temperate climates in the Global North (mostly North America and Europe) and more recently China (Chen, 2018; Han et al., 2017; Zhang et al., 2014). Evidence on the relationship between temperature and health risks in low- and middle- income countries (LMICs) and hot climates, albeit growing, is still limited, even though the highest temperature increases and the global hotspots of population growth and urbanisation will occur there (IPCC, 2014; UNDESA, 2018; European Commission, Joint Research Centre, 2018).

Although two recent reviews have summarised the body of literature on temperature and mortality for LMICs and tropical countries (Burkart et al., 2014a; Green et al., 2019), a comprehensive review on one of the most vulnerable geographical regions in the world — South Asia — is still lacking (Mora et al., 2017; Byers et al., 2018; Muthukumara et al., 2018). South Asia is recognised as being at high risk of climate impacts due to the combination of its climate and geography (occupying areas with high year-round temperatures and humidity), large and growing population, rapid urbanisation, relatively low adaptive capacity in terms of high levels of poverty and inequality, poor health infrastructure, scarcity of resources and livelihood dependence on agriculture, which implies large occupational exposure to outdoor temperature. With a population of about 1.8 billion (World Bank, 2019b), South Asia, which comprises Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka (World Bank definition), is the most densely populated and the second most populous region in the world (after East Asia&Pacific). The region accommodates the second highest number and proportion of people in extreme poverty (defined as living below $1 per day) (Islam, Newhouse, Yanez-Pagans, 2018) and 43% of its labour force works in agriculture (World Bank, 2019a).

South Asia has a diverse geography and climate, covering the glaciated and sparsely populated regions of the Himalayas, Karakoram, and Hindu Kush mountain, with annual average temperatures around 0 °C, as well as vast tropical and sub-tropical regions, with annual temperatures averaging between 25 °C and 30 °C (Mani et al., 2018). Given these characteristics, both high and low temperatures are likely to affect population health. Similar to other regions, South Asia has experienced a clear and considerable upward trend in annual average temperatures, albeit unevenly distributed geographically. Most pronounced increases over the period 1950–2010 have been observed in Western Afghanistan and southwestern Pakistan, ranging from 1.0 °C to 3.0 °C. Within the same decades, average annual temperatures have shifted upward by 1.0 °C to 1.5 °C in Southeastern India, western Sri Lanka, northern Pakistan, and eastern Nepal (Mani et al., 2018). These trends are projected to continue in the future. The Intergovernmental Panel on Climate Change (IPCC) indicates that, compared to the average in the 20th century, average annual temperatures in the region could rise by >2 °C over land by the mid-21st century, and exceed 3 °C over high latitudes, by the late 21st century under a high-emissions scenario (Carabine, 2014). Importantly, rising humidity, especially in regions with routinely warm and humid weather, can further amplify the health impacts of higher temperatures by compromising humanś' ability to dissipate heat through sweating (Gosling et al., 2009; Im, Pal and Eltahir, 2017).

The threat of aggravating heat is also reflected in the increasing death toll reported from extreme temperatures in the region according to the Emergency Events Database (EM-DAT) (See Fig. 1). Some of the most notable historical episodes, which claimed thousands of human and livestock lives, include: the severe heat waves reported around Odisha (eastern India) in 1998, in Andhra Pradesh (2003), Ahmadabad (2010) and other parts of Gujarat (western India), the 2008 Afghanistan blizzard, and the more recent 2015 heat wave, which hit large parts of India and Pakistan, resulting in about 3500 deaths (Im, Pal and Eltahir, 2017). These figures are likely to be conservative and underestimate the total health burden of extreme heat, given the lack of official surveillance and misreporting. Furthermore, they do not capture the impact of moderate non-extreme temperatures, which are much more frequent, and therefore, contribute considerably to total heat and cold-related deaths (Gasparrini et al., 2015).

Although geographic location, climate, and latitude are of crucial importance, the literature has shown the pattern and magnitude of temperature-mortality effects are also highly dependent on local contexts and strongly influenced by the interaction of non-atmospheric factors such as demographic, socio-economic, and lifestyle characteristics, underlying disease burdens of the population, features of the built environment, and others (Uejio et al., 2011; Xu et al., 2013; Zanobetti et al., 2013). For instance, it has been demonstrated that exposure–response functions can differ even for populations within the same geographic or climatic area (Michelozzi, 2006; Anderson & Bell, 2009; Hajat & Kosatky, 2010).

It is also well known that populations are usually well adapted to the most frequent and/or moderate temperatures in their local climates, which explains higher thresholds for heat-related mortality in warmer climates and lower thresholds for cold-related mortality in colder climates (Gosling et al., 2009). Studies have also reported that exposure–response functions can change over time, highlighting the scope for adaptation and acclimatization (Hondula et al., 2015; Kinney, 2018a; Petkova et al., 2014). However, the speed at which adaptation is likely to take place and whether it can outpace future temperature changes are poorly understood. Furthermore, the scope of further acclimatization and adaptation for populations living in hot, and especially hot and humid climates, where heat adaptations and lifestyle modifications already exist, is likely to be more limited (Hanna and Tait, 2015). According to a climate simulation study, under the current business-as-usual trajectory of carbon emissions, by the end of the century some of the population in South Asia may experience hot and humid temperatures that exceed the “upper limit on human survivability “(Im, Pal and Eltahir, 2017). In this context, it has been argued that the population in the region might need to rely mainly on technological and behavioural adaptations in the future (Hanna and Tait, 2015).

In the context of climate change and the vulnerabilities in South Asia it is crucial to provide a comprehensive analysis on the region-specific

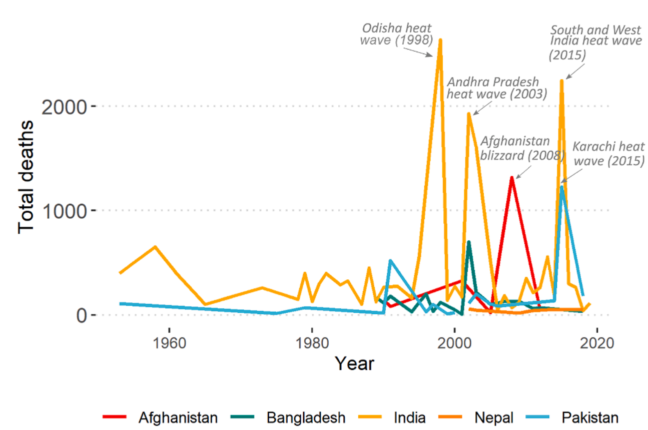

Fig. 1. Deaths from extreme temperature events in South Asia. Source: Own figure, EM-DAT database* (Centre for Research on the Epidemiology of Disasters CRED, 2019) *The data in the database are compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies. An extreme event is considered in the database only if >10 fatalities were reported. Annotations of major heat and cold events in the figure are added by the authors.

temperature-mortality effects in order to guide adaptation planning, inform targeted health interventions, and support sound and evidence-based health impact projections. To address this need and to establish the state of the available evidence, identify knowledge gaps, and highlight future research directions, we systematically reviewed the existing literature on temperature-related mortality in South Asia. Through a systematic review and a *meta*-analysis we investigated the following hypothesis: "Are ambient temperature (high and low), and heat wave events associated with increased all-cause mortality in the general population in South Asia?". We developed a "Population", "Exposure", "Comparator", and "Outcomes" and "study design" (PECOs) statement as follows:

- **Population:** the general population in South Asia (as defined by the World Bank in August 2018: Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka)
- **Exposure:** high and low ambient temperatures (defined as daily/weekly/monthly/annual mean/max/min temperatures or a composite index of temperature and other weather variable) and heat wave events.
- **Comparators:** A comparable population not exposed to the same temperature or heat wave event or the same population at a time when it was not exposed to the same ambient temperature or heat wave event.
- **Outcome:** all-cause or cause-specific mortality, Years of Life Lost (YLL), changes in life expectancy
- **Study design:** quantitative observational studies

We also perform more narrative review on the following exploratory research questions: i) "Are ambient temperatures (high and low), and heat wave events associated with increased cause-specific mortality in the general population in South Asia?", ii) Are certain population groups at higher risk of mortality from exposure to ambient temperature?", iii) At what time lags do temperature effects on mortality occur for the population in South Asia?"

We add to previous systematic reviews conducted for tropical regions (Burkart et al., 2014a), LMICs (Green et al., 2019) and India (Salve et al., 2018) by covering both effects from heat wave episodes and ambient temperature, assessing the strength and quality of the body of evidence, and including a *meta*-analysis of exposure–response functions based on a novel approach that allows combining nonlinear exposure–response associations without access to data from individual studies. We also identify key areas for future research.

2. Methods

2.1. Search strategy

We performed a systematic search of four electronic databases - Pubmed, Web of Science, Scopus, Embase – in order to identify epidemiological studies examining the direct relationship between ambient temperature and all-cause and cause-specific mortality in South Asia. We restricted the search to peer-reviewed articles published in English between January 1990 and August 2020. The search was initially run on 16 August 2018, and later updated on 13 August 2020. The systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines and was based on a registered review protocol accessible online (PROSPERO CRD42018105730) (Dimitrova and Tonne, 2018). To ensure that all relevant articles were identified, we screened bibliographic reference lists of all included studies manually. Example of an exact electronic search strategy is provided in Supplementary Table S1.

2.2. Selection of studies

We considered peer-reviewed studies published since 1990 in English, which examined any of the eight countries in the region as defined by the World Bank in August 2018 (Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka), South Asia as a whole, or studies on a global level, which included at least one country of the region. We included only quantitative observational studies, which present results for the general population. Epidemiological studies based on medical records were also included when these stemmed from a representative number of hospitals in a country or from the leading hospitals in an urban area, that has a catchment area representative of the target population. In terms of outcome measures, we included studies using mortality counts as well as alternative population health metrics such as YLL or life expectancy. We excluded studies investigating morbidity effects only or those investigating indirect effects of temperature on mortality, for example through changes in crop yields, forest fires, droughts and water shortages, and others. We did not apply restrictions on the type or the timeframe of effects and exposure measures (e.g., year-round hot or cold temperatures, heat waves or cold spells).

We included studies based on daily, weekly, monthly or annual temperatures, and those combining measures of temperature and humidity (apparent temperature, Humidex, Heat Index, Wet Bulb Globe Temperature, etc.). Since there is no standard definition of heat waves with respect to human health in the literature, we included all studies referring to heat wave episodes. We excluded studies looking only at seasonal effects on mortality without explicitly considering temperatures. Regarding types of study design, we considered time series studies, case-crossover studies as well as single episode analyses. Since the focus was on studies examining the quantitative association between ambient temperature and mortality, we excluded discussion articles, case studies, and articles featuring descriptive analysis only (See Table S2).

After we combined the search results and removed duplicates, one of the reviewers (AD) screened all the titles and abstracts and assessed their relevance against the inclusion criteria (see Table S2). To validate these results a second reviewer (CT) screened a sample of 20% of all retrieved titles and abstracts. Independent judgment of the two reviewers differed for 0.3% of the titles and abstracts, but perfect agreement on which studies should be selected was reached through discussion. Two reviewers (AD and VI) separately assessed full texts for eligibility, based on the pre-defined inclusion and exclusion criteria. In the case of discrepancies, disagreements were resolved with the involvement of a third senior investigator (CT).

2.3. Data extraction

Both investigators independently retrieved the main characteristics and results of the included studies using a standardised data extraction form. The following information was retrieved from each article: location and study period, study design, statistical methods and sensitivity analysis, inclusion of lagged effects, control of confounding and modifying factors, exposure and outcome measure(s) and their data source(s), observed temperature and humidity ranges, minimum mortality temperature (MMT), reported effect estimates, subgroup analysis, mortality displacement, key findings, and modeled or suggested adaptation strategies. We pilot tested the data extraction form to ensure accuracy and consistency during the entire process. Data collected by both reviewers were compared and any discrepancies were resolved through discussion and consensus. In several instances, study authors were contacted to obtain additional data necessary for the analysis or to clarify ambiguous information.

2.4. Assessment of evidence

We assessed the quality and strength of the evidence separately for the association between ambient temperature and all-cause mortality and heat wave events and all-cause mortality following the Navigation

Guide framework (Johnson et al., 2014; Woodruff and Sutton, 2014). The Navigation Guide methodology has been specifically developed for the assessment of the quality and strength of the evidence of research in the environmental health field (Johnson et al., 2014). The assessment proceeded in three stages: i) rating the Risk of Bias (RoB) for each individual study, ii) rating the quality of the evidence across all studies, and iii) rating the strength, or certainty, of the evidence across all studies.

2.4.1. Assessment of the risk of bias in individual studies

We assessed the quality of individual studies using the Office of Health Assessment and Translation (OHAT) Risk of Bias Rating Tool for Human and Animal Studies. Since OHAT does not specifically consider time series environmental health study designs, in collaboration with subject-matter experts (CT, XB, OR, JB) we adapted some of its domains to better tailor it to our research question (See Table S3). We evaluated each study against the following six domains of Risk of Bias (RoB): selection, confounding, exposure assessment, outcome assessment, selective reporting and other bias (appropriateness of statistical methods). For each of these possible sources of bias we rated the RoB as *definitely low, probably low, probably high* and *definitely high*. The rating scale is based on a conservative approach, where insufficient information to judge the risk of bias for specific domain results in a rating of *probably high* risk of bias. The two reviewers (AD, VI) independently performed the risk of bias assessment and discussed results with the other coauthors in case consensus could not be reached. Following the Navigation Guide Methodology, we considered an individual study to have a *definitely low* or *probably low* RoB if all domains of assessment were rated as *definitely low* or *probably low*. Due to the very limited number of studies the results of the RoB assessment were not used to exclude studies from the quantitative synthesis.

2.4.2. Assessment of the quality of the evidence across studies

We rated the overall quality of the evidence for studies on ambient temperature and heat wave episodes separately. Rating categories included *high, moderate*, or *low*. Following the approach in the Navigation Guide, we initially rated the body of evidence as *moderate* and then "downgraded" or "upgraded" this rating based on eight factors. The downgrading factors included risk of bias across studies, indirectness, inconsistency, imprecision, publication bias, and the upgrading factors consisted of size of the effect, dose response pattern and possibility of confounding minimizing effects. We assessed the RoB across studies based on the RoB rating of individual studies, as outlined above. As recommended in the Navigation Guide, the RoB across studies was judged on the basis of each study, but with more weight placed on high quality studies.

2.4.3. Assessment of the strength of the evidence across studies

We also rated the strength of the body of evidence, separately for ambient temperature and heat wave episodes, based on the following four considerations outlined in the Navigation Guide: i) quality of the body of evidence (i.e., rating from previous assessment stage), ii) direction of effect, iii) confidence in the effect (likelihood that a new study would change our conclusions) and iv) any other attributes of the data that might affect certainty.

2.5. Meta-analysis

From the studies included in the review, we selected those that were sufficiently compatible in terms of study design, outcome and exposure measures, and lag structure, in order to conduct a *meta*-analysis of the association between temperature and mortality. After screening all studies, we identified that the most common choice of study design, outcome and exposure variables, and lag structure was the following: time series studies using daily all-cause mortality and daily mean temperature and reporting effects for lag 0–1 and lag 0–13 days. Hence, we limited our choice to studies with these characteristics (Burkart et al., 2011; Fu et al., 2018; Hashizume et al., 2009; Ingole et al., 2017; McMichael et al., 2008). For studies that included a plot of the temperature-mortality association, we extracted numerical representation of the exposure–response curves and their confidence intervals at every 0.5 increment of the temperature values using the web-based tool WebPlotDigitizer (Rohatgi, 2014). Authors of two studies that did not include such visualizations were contacted to acquire the necessary data. We also extracted the following data: i) average number of daily deaths, ii) number of days analysed in the study and iii) range of the distribution of exposure variables. The analysis was performed separately for the exposure response curves at lag 0–1 days and lag 0–13 days. Since the reference value used across studies differed (in most cases this was the MMT), recalculation of the curves and standard errors using a common reference value was necessary before combining the curves. We set the reference values for re-centering the curves to be equal to the average MMT across the included studies. This corresponded to 24.5 °C for the exposure response curves at lag 0–1 days and 26.5°C at lag 0–13 days. Even though the selected studies include locations within different climatic zones, they have comparable temperature distributions and all of them included the reference temperature values for the *meta*-analysis. Although the estimates across a single exposure–response curve are correlated because they share the same reference category, without available data on these correlations, it is not possible to compute the standard errors that would result from re-centering the curve to another reference value. To overcome this challenge and calculate the standard errors after re-centering the curves without access to the individual-level data, we applied the recently developed methodology by Basagaña (2019). Using the extracted data described above, the method allows to simulate individual datasets in order to change the reference category and approximate the confidence intervals (Basagaña, 2019). In brief, the approach consists in the generation of a dataset, which has an identical number of observations as the original one and upon analysis produces a good approximation of the exposure–response function and confidence interval reported by the study. A more detailed description of the methodology, including a reproducible example with R software code, is available in the publication Basagaña (2019). After calculating the standard errors and the exposure–response estimates at each temperature increment, we combined the non-linear exposure–response curves of the individual studies using a *meta*-smoothing approach (Schwartz and Zanobetti, 2000). The latter method consisted of conducting a random-effects point-wise *meta*-analysis for each exposure level (Schwartz and Zanobetti, 2000). The analysis was performed using the R (version 3.6.1) package '*metafor*' (Viechtbauer, 2010). The datasets and the R software code for conducting the analysis are available in the Supplementary Material of this publication.

3. Results

3.1. Literature search

We identified a total of 10, 713 references from the electronic databases' search and through other sources, after removal of duplicate entries. After screening these for relevance based on title and abstract, we selected 50 articles for in-depth review. A detailed evaluation of the content against the inclusion criteria resulted in 27 studies being included in the final analysis. The flow diagram in Fig. 2 illustrates in detail the literature search and the selection process.

3.2. Characteristics of included studies

Among the included studies, about half (n = 15; 56%) examined the effects of both heat and cold on mortality, five (19%) focused only on heat effects and one on cold effects, while nine studies (33%) assessed the association of heat waves with mortality and one addressed the

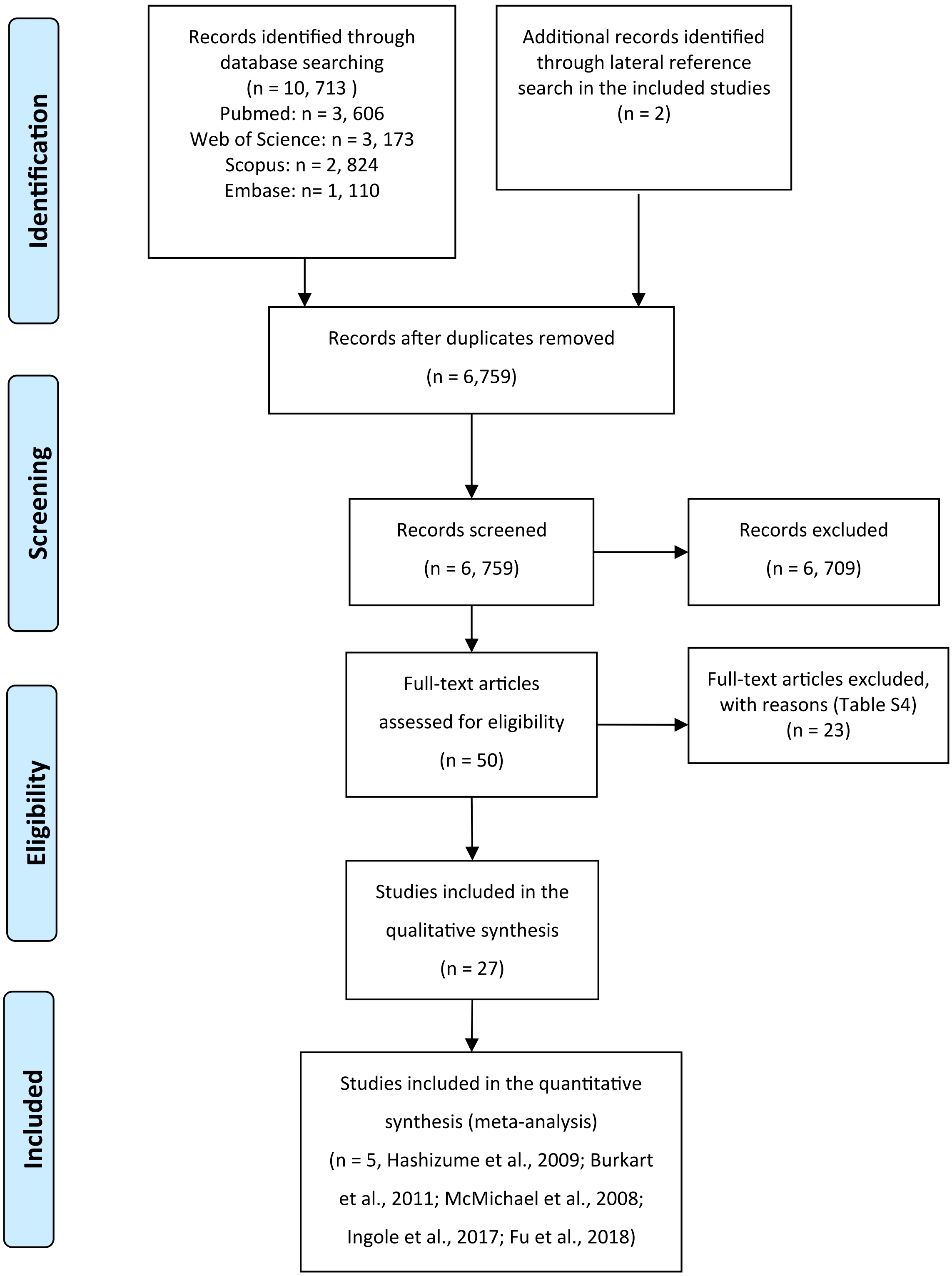

Fig. 2. Flow diagram of literature search and study selection process.

association between cold spells and mortality (See Table 1 for a more detailed description). The studies used diverse approaches for defining hot and cold temperature effects — based on the MMT, a specific percentile of the temperature distribution, an arbitrary temperature threshold, the season (summer/winter months), deviation of temperatures from their annual average, or simply based on the pattern of the temperature-mortality relationship. The definition of heat waves was not uniform across studies. Five used the conventional approach of considering both the duration and intensity of a heat wave (Mazdiyasni et al., 2017; Nissan et al., 2017; Nori-Sarma et al., 2019a; Singh et al., 2019; Nori-Sarma et al., 2019b), while the rest considered only its intensity. Four studies used the heat wave definition by the India Meteorological Department (IMD) based only on maximum temperature thresholds (Azhar et al., 2014; Murari et al., 2015; Nori-Sarma et al., 2019a; Nori-Sarma et al., 2019b) and one study did not provide a specific definition, but analysed maximum temperatures and heat-induced

Table 1
Characteristics of reviewed studies and main findings.

Reference	Methods						Exposure	Outcome	Main findings
	Study population and location	Category of effect	Study period	Study design and statistical method	Lag structure	Control variables (confounders and effect modifiers)	Measure and source	Measure and source	
Rural areas									
Alam et al. (2012)	General population Abhoynagar, Bangladesh	Heat and cold effects (continuous temperature)	1983–2009	Time series analysis, Poisson generalized additive model (GAM)	Lag 0–1 week, lag 0–2 week, lag 0–3 week	Time trend, seasonal pattern	Average weekly mean temperature Bangladesh Meteorological Department	All-cause mortality (n = 4,850) ICDRR, B́s Sample Vital Registration System (SVRS) in Abhoynagar subdistrict	Weekly mean temperatures (lag 0) below the 25th percentile and between the 25th (23 °C) and 75th percentiles (29.6 °C) were associated with increased mortality risk, particularly in females and adults aged 20–59 years by 2.3–2.4% (CI: 4.4, 0.1) for every 1 °C decrease. Temperature above the 75th percentile (29.6 °C) did not increase the risk.
Hashizume et al. (2009)	General population Matlab, Bangladesh	Heat and cold effects (continuous temperature)	1994–2002	Time series analysis, Poisson generalized linear model	Lag 0–1 days, lag 0–13 days (cumulative)	Year, season, day of the week, public holiday	Daily mean temperature Bangladesh Meteorological Department	All-cause mortality excluding external causes (n = 13, 270) and cause-specific mortality (cardiovascular, respiratory, perinatal, infectious and parasitic mortality and others) ICDRR, B́s Health and Demographic Surveillance System (HDSS) in Matlab	Every 1 °C decrease in mean temperature (lag 0–13) was associated with a 3.2% (95% CI 0.9, 5.5) increase in all-cause mortality. There was no clear heat effect on all-cause mortality for any of the lags examined. Heat effect was observed only for cardiovascular mortality (lag 0–1), mortality from infectious diseases (lag 0–13) and mortality in elderly people (lag 0–1).
Sewe et al. (2018)	General population 22 villages in Pune district, India	Heat and cold effects (continuous temperature)	2003–2012	Time series analysis, Quasi-Poisson distributed-lag non-linear models (DLNM)	Lag 0–14 (separate)	Trend, season, day of the week, indicator for “heaping days”	Daily max temperature National Oceanic and Atmospheric Administration (NOAA)	All-cause mortality (daily mean number of deaths: 0.9, n = 2,958) Vadu HDSS	Heat (lag 0–14) was associated with YLL (26.03 YLL; 95% CI: −0.36, 52.42 at the 95th percentile, 39 °C compared to 30 °C), but there was no evidence of an association with cold.
Ingole et al. (2017)	General population aged 15 and older 22 villages in Pune district, India	Heat and cold effects (summer and winter months)	2004 – 2013	Case-crossover study, Quasi-Poisson regression (1st stage analysis) and Conditional logistic regression model (2nd stage analysis)	Lag 0–1 days and lag 0–13 days (cumulative)	Season, time trend, education, occupation and ownership of agricultural land; potential temporal confounders and time-invariant confounders controlled for “by design”	Daily mean temperature National Oceanic and Atmospheric Administration NOAA and India Meteorological Department	All-cause mortality (n = 3,079) Vadu HDSS	Temperature above a threshold of 31 °C was associated with total mortality (OR 1.48, CI: 1.05, 2.09) per 1 °C increase in daily mean temperature. Odds ratios were higher among females, those with low education, those owing larger agricultural land, and farmers. In winter, per 1 °C decrease in mean temperature, OR for total mortality was 1.06 (CI = 1.00–1.12) in lag 0–13 days, with higher risk observed

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Table 1 (*continued*)

Reference	Methods Study population and location	Category of effect	Study period	Study design and statistical method	Lag structure	Control variables (confounders and effect modifiers)	Exposure Measure and source	Outcome Measure and source	Main findings
									among people occupied in housework.
Ingole et al. (2012)	General population 22 villages in Pune district, India	Heat and cold effects (continuous temperature)	Jan 2003 - May 2010	Time series analysis, Poission regression model	lag 0–1 days, lag 2–6 days, lag 7–13 days (cumulative)	Season, time trends	Daily mean temperature India Meteorological Department	All-cause mortality (n = 1 ,662) Vadu HDSS	Both high and low temperatures were associated with all-cause mortality over all age groups, with children aged 5 years or below being particularly affected. In the age group 20–59, 1 °C increase in temperature was associated with 9.4% increase in RR (95%CI: 3.6, 15.5) for lag 0–1 and 1 °C decrease in temperature with RR= − 9.5 (95%CI: −15.5, − 3.2) for lag 2–6.
Ingole et al. (2015)	General population aged 12+ 22 villages in Pune district, India	Heat and cold effects (continuous temperature)	Jan 2003 to Dec 2012	Time series analysis, Quasi-Poisson model and Logistic regression model	Lag 0–1 days, lag 0–4 days (cumulative)	Day of week, time trend	Daily maximum temperature India Meteorological Department	All-cause mortality (n = 2,302) and cause-specific mortality (infectious diseases, non-infectious diseases and mortality from external causes) Vadu HDSS	Heat was significantly associated with total mortality (RR = 1.33; 95% CI: 1.07, 1.60) and mortality from non-infectious diseases (RR = 1.57; CI: 1.18, 2.10) for lag 0–1. Men and people in the age group 12–59 showed elevated risk for total mortality. No association between total and cause-specific mortality was found for cold temperature.
Lindeboom et al. (2012)	General population Matlab, Bangladesh	Heat and cold effects (continuous temperature)	1983–2009	Time series analysis, Poisson generalized additive model (GAM)	Lag 0–21 days, (separate)	Time trend, season, public holiday, festivals, cyclones	Daily mean temperature, daily max temperature and daily min temperature Bangladesh Meteorological Department	All-cause mortality (n = 48,238) ICDRR, B́s (HDSS) in Matlab	1.4% (95 %CI: 0.7, 2.0) increase in mortality with every 1 °C decrease in mean temperature below 29.2 °C, and 0.2% (95% CI:0.1,0.3) increase in mortality with every 1 °C increase in mean temperature above 29.2 °C for lag 0. Elderly, aged 60 years and above, were most affected at lower temperatures, with a 5.4% (95% CI: −7.0, −3.5) increase in mortality with every 1 °C decrease in temperature below 23 °C (combined lag 0 and lag 1–5).
Babalola et al. (2018)	Infants and children under 5 years	Heat and cold effects (continuous temperature)	1982 – 2008	Time series analysis, OLS regression	Lag 0 months and lag 0–1 months	Month, age and gender	Monthly mean temperature, monthly max temperature Bangladesh	All-cause mortality (n = 49,426) ICDRR, B́s HDSS in Matlab	Each 1 °C increase in mean monthly temperature reduced monthly mortality by 3.7 (SE 1.5, p < 0.05)

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Table 1 (*continued*)

Reference	Methods Study population and location	Category of effect	Study period	Study design and statistical method	Lag structure	Control variables (confounders and effect modifiers)	Exposure Measure and source	Outcome Measure and source	Main findings
	Matlab, Bangladesh			with ARIMA errors			Meteorological Department		points. Effect sizes of mean monthly temperature were larger for neonates at 1.1 (SE 0.5, $p < 0.05$) than for post neonates at 0.9 (SE 0.3, $p < 0.05$) reductions in mortality per 1 °C.
Urban areas									
Hajat et al. (2005)	General population Delhi, India	Heat effects (continuous temperature)	1991–1994	Time series analysis, Poisson generalized linear model	Lag 0 days, lag 0–1 week, lag 0–4 weeks (cumulative)	Season, time trend, relative humidity, rainfall, particulate air pollution, day of the week, public holidays	Daily mean temperature India Meteorological Department	All-cause mortality, excluding violent deaths (mean daily number of deaths: 25, n ~ 36,500) and cause-specific mortality (cardiovascular, respiratory and other non-violent deaths) data from the New Delhi Municipal Committee (NDMC) provided by the World Bank	All-cause mortality increased by 3.2% (95%CI: 1.8, 4.5) per 1 °C increase in temperature above 20 °C (lag 0–7 days). Cardiovascular mortality increased by 4.3% (95%CI: 1.1, 7.6) per 1 °C increase in temperature above 20 °C and respiratory by 4.5% (95%CI: 0.0, 9.2) over the same lag. Heat effects were sustained up to 3–4 weeks for non-respiratory deaths. Children aged 0–14 years and elderly faced the highest risk, for children sustained up to 4 weeks.
McMichael (2008)	General population Delhi, India	Heat and cold effects (continuous temperature)	1991–1994	Time series analysis, Poisson generalized linear model	Lag 0–1 days, lag 0–13 days (cumulative)	Season, daily relative humidity, day of the week, public holidays, daily, particulate pollution concentration	Daily mean temperature India Meteorological Department	All-cause mortality, excluding external causes (mean daily number of deaths: 25, n ~ 36,500) and cause-specific mortality (cardio-respiratory and non-cardio-respiratory) data from the NDMC provided by the World Bank	All non-external causes of death increased by 3.9% (95%CI: 2.8, 5.1) for each 1 °C increase in temperature above 29 °C (95%CI: 8, 30) for lag 0–1 days and by 2.8% (95%CI: 0.7, 4.9) for each 1 °C decrease in temperature below 19 °C (95%CI:.–39) for lag 0–14 days. Cardiorespiratory mortality was found to increase by 203% (95%CI: 41.2, 553) for each 1 °C below a cold threshold of 12 °C (95%CI:. –13) and by 3.94% (95%CI: 2.38–5.53) above a heat threshold of 17 °C (95%CI: 12,19). Non-cardio-respiratory mortality increased by 2.7% (95%CI: 0.21, 5.16) for each 1 °C below 19 °C (.–30) and by 4.3% (95%CI: 2.89, 5.72) for each 1 °C above 30 °C (95% CI: 27, 31).

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Table 1 (*continued*)

Reference	Methods Study population and location	Category of effect	Study period	Study design and statistical method	Lag structure	Control variables (confounders and effect modifiers)	Exposure Measure and source	Outcome Measure and source	Main findings
Desai et al. (2015)	General population Surat, India	Heat effects (summer months)	2001–2012	Time series analysis, Studentś *t*-test, correlation analysis (lag 0, lag 1.)	Lag time correlation for one, two, three- and four-days lag	NA	Daily max T and heat index (HI) Tutiempo Network, S.L website, based on data exchanged under the World Meteorological Organization (WMO) World Weather Watch Program, local weather station	All-cause mortality (n = 36,167) Birth and Death Registration Department of Surat Municipal Corporation (SMC)	Daily mean number of deaths were 11% higher for days with maximum temperature above 40 °C compared to days with maximum temperature below 35 °C. Mean number of deaths were 9% higher during danger-level heat-risk days (HI = 41–54 °C) and 8% higher during high risk/ extreme danger heat days (HI = 41–54 °C), respectively, compared to mean number of deaths during less risky or caution days (HI = 27–31 °C).
Rathi et al. (2017)	General population Surat, India	Heat effects (summer months)	2014 – 2015 (March to May)	Time series analysis Analysis of variance, Student *t*-test, Turkeýs multiple comparison post hoc test, Pearson correlation analysis	Lag time correlation for one, two, three- and four-days lag	NA	Daily max temperature, heat index (HI) Tutiempo Network, S.L website, based on data exchanged under the WMO World Weather Watch Program, local weather station	all-cause mortality (n = 9,237) Health Department of SMC	The mean daily number of deaths for days with maximum temperature below 35 °C was 48.0 ± 7.7, which was 20% lower compared to the mean daily number of deaths for days with maximum temperature above or equal to 40 °C (57.3 ± 7.2).
Azhar (2014)	General population Ahmedabad India	Heat wave event	May 2010	Heat-episode analysis 7-day moving average; monthly rate ratio analysis; month-wise correlation	NA	NA	Daily max and monthly max temperature **Heat wave definition:** An excess of 5 °C over a normal daily historical maximum temperature (30-year average) of<40 °C; or an excess of 4 °C over a normal historical maximum temperature of>40 °C. If the actual maximum temperature is above 45 °C,a heatwave is declared irrespective of the normal historical maximum Temperature. Indian Meteorology Department's Meteorological Aerodrome Report, station at Ahmedabad airport	all-cause mortality (n = 4,462) Death records of Ahmedabad Municipal Corporation (AMC) Office of the Registrar of Births and Deaths	Excess mortality in May 2010 was estimated to be 1,344 deaths, or 43.1% above the reference period (May 2009 and May 2011). Mortality rate ratios for heatwave days (May 19–25, 2010) in 2010 were 1.76 (95% CI: 1.67, 1.83) compared to reference period 1 (May 12–18, 2010) and 2.12 (95% CI: 2.03, 2.21) compared to reference period 2 (May 19–25 from 2009 and 2011). The gender distribution highlights significantly more female deaths in the summer months and in the heatwave period.
Ghumman and Horney (2016)	General population Karachi, Pakistan	Heat wave event	June 2015	Heat-episode analysis Risk difference	NA	NA	Daily max temperature AccuWeather, State College, Pennsylvania USA	Deaths attributable to heat wave (n = 1,220) Official death certificates	Residents of Karachi were approximately 17 times as likely to die of a heat-related cause of death during June

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Table 1 (*continued*)

Reference	Methods Study population and location	Category of effect	Study period	Study design and statistical method	Lag structure	Control variables (confounders and effect modifiers)	Exposure Measure and source	Outcome Measure and source	Main findings
				and rate ratio calculation				from public and private hospitals	2015 (RR = 17.68; 95% CI: 13.8, 22.53) when compared with the reference period of June 2014. An excess risk of mortality from heat-related illness was found among the poor and those with lower levels of education during the 2015 heatwave period when compared with the reference period.
Hess et al. (2018)	General population Ahmedabad (Gujarat), India	Heat wave events	1 April to 30 June for 2007–2010 and 2014–15	Heat-episode analysis Distributed Lag Nonlinear Model	Up to 5 days lag	NA	Daily max temperature Meteorological Aviation Report (METAR) system	All-cause mortality Registrar of Births and Deaths office of AMC	Before the Heat Action Plan (HAP), the RR of mortality increased monotonically over 40 °C with maximum effect (RR of 2.34; 95% CI 1.98, 2.76) at 47 °C, lag 0. After the HAP, the RR also increased monotonically over 40 °C, but with a substantially lower maximum effect (RR of 1.25; 1.02, 1.53) estimated at 47 °C.
Nori-Sarma et al. (2019a)	General population (Mumbai ≥ 35 years old) Five cities in Northwest India: Jaipur, Churu, Idar, Himmatnag-ar, Mumbai	Heat wave episodes and continuous temperature	2000–2012	Time series analysis Generalized linear model for heat wave analysis and over-dispersed Poisson regression for continuous temperature analysis	NA	Day of the week, time trend, daily max temperature for a community at a specific lag (same day or previous day), adjusted dewpoint temperature, population offset	Daily max temperature, dewpoint temperature **Heat wave definitions:** 1) ≥ 2 consecutive days with daily maximum temperature (Tmax) higher than the community's 97th percentile Tmax. 2) Modified IMD definition: hill stations - Tmax of 5–6 °C or more above "normal" baseline temperature (over entire temperature record); plains stations - Tmax of 4–5 °C or more above "normal" baseline temperature (over entire temperature record) India Meteorological Department, NOAA's Global Summary of the Day (GSOD)	All-cause mortality (n = 389,665) Local municipal governments	Overall, across the four communities, mortality risk is estimated at 18.11% higher [95% interval – 5.31%, 47.33%] on 97PoT heatwave days compared to non-heatwave days. Using the IMD heatwave definition, estimated risk of mortality is 15.46% [−0.929%, 34.556%] comparing heatwave days to non-heatwave days. Limited evidence of effect modification by heatwave characteristics (intensity, duration, and timing in season) was found, but central estimates suggest more harmful heatwaves later in the warm season.
Nori-Sarma et al. (2019b)	General population (Mumbai ≥ 35 years old) Five cities in	Heat wave episodes	Jaipur (2005–2012); Churu (2003–2012); Idar and Himmatnagar	Time series analysis Propensity Score Matching, Quasi-	lag 0–14	time trend; seasonal and cyclical variation; days of the week; adjusted dew point temperature	Daily max temperature **Heat wave definitions:** 1) IMD heat wave definition; 2) > 2 days exceeding the 90th T	All-cause mortality (n = 389,665) Local municipal governments	There is a wide variation in the RR associated with heat waves depending on the criteria used for defining heat waves. RR of mortality

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Table 1 (*continued*)

Reference	Methods Study population and location	Category of effect	Study period	Study design and statistical method	Lag structure	Control variables (confounders and effect modifiers)	Exposure Measure and source	Outcome Measure and source	Main findings
	Northwest India: Jaipur, Churu, Idar, Himmatnag-ar, Mumbai		(2006–2012); Mumbai (2000–2012)	Poisson regression model			percentile; 3) > 3 days exceeding the 90th T percentile; 4) > 4 days exceeding the 90th T percentile; 5) > 2 days exceeding the 92.5th T percentile; 6) > 3 days exceeding the 92.5th T percentile; 7) > 4 days exceeding the 92.5th T percentile; 8) > 2 days exceeding the 95th T percentile; 9) > 3 days exceeding the 95th T percentile; 10) > 4 days exceeding the 95th T percentile; 11) > 2 days exceeding the 97.5th T percentile; 12) > 3 days exceeding the 97.5th T percentile; 13) > 4 days exceeding the 97.5th T percentile; India Meteorological Department, NOAA's GSOD		ranged from 1.28 [95% CI:1.11, 1.46] in Churu under the 95%_2d heat wave definition to 1.03 [95% CI: 0.87, 1.23] in Idar and Himmatnagar under the 95%_4d definition. Some heat wave definitions were associated with a high RR; but lower attributable mortality because few days on record match those criteria. Heat waves that occur later in the season have a higher impact on health (higher RR) than those that occur earlier in the season.
Singh et al. (2019)	General population Varanasi, India	Continuous temperature (summer, winter, other months), heat wave episodes and cold spells	2009–2016	Time series analysis Semipara-metric quasi-Poisson regression model	A restricted distributed lag model up to 7 days' lag with polynomial of degree two and single lag model up to 7 days lag	Time trend, relative humidity, ambient air pollution and days of the week.	Daily min, max and mean temperature, diurnal temperature variations (DTV) **Heat wave definition:** an event during summer with daily mean temperature remaining equal to or above the 95th percentile of annual mean temperature (≥34.5 °C) for at least 3 consecutive days **Cold spell definition:** an event during winter with daily mean temperatures equal to or below the 5th percentile of annual mean temperature (≤14.7 °C) for at least 3 consecutive days [moving average lag (0–2)]. India Meteorological Department	All-cause mortality (n = 64,712) Municipal Corporation of Varanasi	During summer, a unit increase in daily temperature was associated with 5.6% increase in all-cause mortality (95% CI: 4.69, 6.53%). During winter, a unit decrease in daily temperature was associated with 1.5% increase in all-cause mortality (95% CI: 0.88, 2.18%). Increase in all-cause mortality was highest for people ≥ 65 years of age (−2.71% in winter to 6.83% in summer) and gradually reduced with the decrease in age, except for 0–4 years age group. Higher mortality found for non-institutional deaths (those dying outside the hospital) compared to institutional deaths (those dying within the hospital). RR of 1.13 (95% CI: 1.04, 1.22) for heat wave days vs. non-heat wave days and RR of 1.06 (95% CI: 0.98, 1.14)

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Table 1 (*continued*)

Reference	Methods Study population and location	Category of effect	Study period	Study design and statistical method	Lag structure	Control variables (confounders and effect modifiers)	Exposure Measure and source	Outcome Measure and source	Main findings
									for cold spell days vs. non-cold spell days. Higher RR for heat waves for females (RR 1.22, 95% CI: 1.09–1.37) compared to males (RR 1.09, 95% CI: 0.99–1.20), no significant difference for cold spells. Highest RR for heat waves for age group <4 years (RR 1.39, 95% CI: 1.16–1.69), and for cold spells – 45–64 years age group (RR 1.17, 95% CI: 1.03–1.33). The DTV showed a negative association with all-cause mortality.
Dutta et al. (2020)	General population Bhubaneswar city (Odisha), India	Continuous temperature (summer months)	March to July (2007 – 2014)	Time series analysis Generalized Additive Model with quasi-Poisson distribution, DLNM	Lag 0 and lag 0–1 days	lLLong-term trend, seasonality, day of the year, day of the week, relative humidity	Daily max and daily min temperature Bhubaneswar Meteorological Centre of the Indian Meteorological Department	All-cause mortality (n = 16,033) Bhubaneswar Municipal Corporation	Two 'thresholds' of max temperatures were identified, beyond which mortality increases – lower at 36.2 °C and upper at 40.5 °C. Every degree rise of T-max above 36.2 °C increased the mortality risk by 2% (RR: 1.02; 95% CI 1.01, 1.03) and each degree rise of T-max above 40.5 °C increased it by 6% (RR: 1.0616, 95% CI: 1.03, 1.09). Daily T-max had significantly more effect on daily all-cause mortality rates when the minimum T-min was above its median value (25.6 °C) as compared to when it was below the median.
Urban and rural areas									
Burkart et al. (2014b)	General population Bangladesh	Heat and cold effects (continuous temperature)	2003–2007	Time series analysis, Semi-parametric Poisson DLNM	Lag 0–1 days, lag 0–4 days for children and youths (cumulative)	Time trend, season, and day of the week	Daily mean values of the universal thermal climate index (UTCI) Bangladesh Meteorological Department	All-cause mortality, excluding accidental and maternity-related deaths and deaths of infants younger than 1 year of age (n = 22,840) and cause-specific mortality (cardiovascular and infectious diseases) ICDRR, B́s SVRS in Bangladesh	All-cause mortality and mortality from cardiovascular and infectious diseases were positively associated with UTCI below and above a threshold, ranging between 34 and 35 °C UTCI. All-cause mortality increased by 31.3% (95%CI: 24.5 – 44.3) per 1 °C increase in UTCI above breakpoint (lag 0–1). Heat effects were strongly

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Table 1 (*continued*)

Reference	Methods Study population and location	Category of effect	Study period	Study design and statistical method	Lag structure	Control variables (confounders and effect modifiers)	Exposure Measure and source	Outcome Measure and source	Main findings
									pronounced for the elderly, for males, and for those living in urban and high socio-economic status areas.
Burkart et al. (2011)	General population Bangladesh	Heat and cold effects (continuous temperature)	2003–2007	Time series analysis, Poisson generalized additive model	Lag 0–1 days, lag 0–6 days and lag 0–13 days (cumulative)	Time trend, season, day of the month	Heat Index (HI), physiological equivalent temperature (PET), universal thermal climate index (UTCI) Bangladesh Meteorological Department	All-cause mortality, excluding accidental, maternity related and infant mortality (n = 21, 655) and cause-specific mortality (cardiovascular mortality) ICDRR,B́s SVRS in Bangladesh	Mortality increased by 4.4% (95%CI: +/-5.4) per 1 °C increase in temperature above a specific threshold in rural areas and 13.7% (95% CI: +/-10.9) in urban areas (lag 0–1). Mortality increased by 2.6 (95%CI: +/-0.6) per 1 °C decrease in temperature below threshold in rural areas and by 3.3% (95%CI: +/-1.8) in urban areas (lag 0–13), respectively. A heat effect on cardiovascular mortality was only observed in urban areas.
Fu et al. (2018)	General population India	Heat and cold effects (continuous temperature)	2001–2013	Case-crossover study, DLNM	Lag 0–21 days (cumulative)	Potential temporal confounders and time-invariant confounders controlled for “by design”	Daily mean temperature India Meteorological Department	All-cause mortality at all ages, excluding injury and ill-defined medical causes (n = 411,613) and cause-specific mortality (ischemic heart disease, respiratory diseases, malaria and cancer among adults aged 30–69) India’s Million Death Study, Sample Registration System, Registrar General of India	For all medical causes and ages, moderately cold temperature was associated with a higher attributable risk (OR) (6.3%, 95% CI: 1.1, 11.1) than extremely cold, moderately hot, and extremely hot temperatures, each of which were<0.6%. The risk related to moderately cold temperature was most pronounced for the population aged 30–69 years and 70 + . For cause-specific deaths at ages 30–69 years, moderately cold temperature was associated with attributable risks of 27.2% (95% CI: 11.4, 40.2) for stroke, 9.7% (95% CI: 3.7 to 15.3) for IHD, and 6.5% (95% CI: 3.5, 9.2) for respiratory diseases.
Burkart and Kinney (2017)	General population Bangladesh	Cold effects (continuous temperature and seasonal temperature)	2003–2007	Time series analysis, Poisson GAM and Poisson DLNM	Lag 0–1 days, lag 0–2 days, lag 0–4 days, lag 0–7 days, lag 0–14 days and lag 0–21 days (cumulative)	Time trend, season, day of the month	Daily mean temperature, daily max temperature, daily min temperature, diurnal temperature range (DTR) Bangladesh Meteorological Department	All-cause mortality, excluding external causes and maternity-related deaths (n = 25, 226) ICDRR, B́s SVRS in Bangladesh	During the winter season, mortality increased with 1.7% (95% CI = 0.86–2.54%) per 1 °C decrease in temperature (lag 0–1 days). Heat effects observed during the summer

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Table 1 (*continued*)

Reference	Methods Study population and location	Category of effect	Study period	Study design and statistical method	Lag structure	Control variables (confounders and effect modifiers)	Exposure Measure and source	Outcome Measure and source	Main findings
									season were stronger than over the entire year.
Shrestha et al. (2017)	General population Nepal	Heat and cold effects (continuous variable)	2009–2014	Time series analysis Generalized linear model (GLM) with log link function (Poisson model)	3-day prior moving average for all-cause mortality; 7-day geometrical decay effect for water- and vector- borne mortality	Seasonal dummy variables, day of week (Saturday) and secular trend, humidity, wind [for all-cause mortality]; wind, time trend [for water- and vector- borne mortality]	Daily average temperature weekly data of the number of days of occurrence of extreme events Department of Hydrology and Meteorology (DHM), Kathmandu, 16 meteorological stations in the country	All-cause mortality (n = 10,000) and cause-specific mortality (vector-bore and water-borne diseases) inpatient records from 22 hospitals in Nepal	All-cause mortality increased by 1.4% per 1 °C increase in the absolute difference of average temperature with its overall average (20 °C) (3-day prior moving average) (parameter estimate: 0.014, 95% CI: 0.002, 0.026). All-cause mortality also increased with decreasing temperature relative to overall average condition (20 °C). Mortality from water-borne and vector-borne diseases increased by 3.7% per 1 °C rise in daily average temperature (7-day geometrical decay effect). Association between mortality from water-borne and vector-borne diseases and extremely cold days (<4.6 °C) was also reported, as well as between mortality from water borne and renal diseases and extremely hot days (above 95 percentile of maximum temperature).
Mazdiyasni et al. (2017)	General population India	Heat wave episodes	1960–2009	Annual time series analysis Correlation analysis, Kolmogorov-Smirnov test; Man-Kendall Test and Conditional probabilistic model	NA	NA	Daily mean and max temperature (summer months) **Heat wave definition:** Three or more consecutive days of temperatures above the 85th percentile of the hottest month for each specific location. Four different heatwave properties are assessed: (i) accumulated heatwave intensity, (ii) annual heatwave count, (iii) mean heatwave duration, and (iv) heatwave days. India Meteorological Department	heat-related mortality (n = 10, 619) India Meteorological Department, annual reports	The increase in summer mean temperature in India over 1960–2009 corresponds to a 146% increase in the probability of heat-related mortality events of >100 people.
Murari et al. (2014)	General population Four states in India: Delhi, Rajasthan,	Heat wave episodes	1997–2009	Annual Time series analysis OLS regression	NA	NA	Annual number of severe heat wave days (HWD) **Heat wave definition:** If the maximum	Heat wave-induced mortality (number of deaths not reported) Mortality records,	Positive significant association (90% CI) between annual mortality rates and annual number of

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Table 1 (*continued*)

Reference	Methods Study population and location	Category of effect	Study period	Study design and statistical method	Lag structure	Control variables (confounders and effect modifiers)	Exposure Measure and source	Outcome Measure and source	Main findings
	Maharashtra and Orissa						temperature of a day exceeds 45° C, irrespective of the normal maximum temperature of a region, that day is defined as a severe HWD. In case a day's maximum temperature is<45° C, that day is defined as a severe HWD when (1) the day's maximum temperature is at least 7° C greater than the normal temperature, and (2) the maximum temperature of that day is above 40° C. Three different heat wave properties are characterised: (i) severe heat wave intensity, (ii) duration and (iii) frequency India Meteorological Department	obtained from the Ministry of Home Affairs (Government of India)	severe HWDs is found for Delhi (3.1, SE: +/-1.45), Rajasthan (5.6, SE:+/-1.46), and Maharashtra (2.3, SE:+/-1.46).
Nissan et al. (2017)	General population Bangladesh	Heat wave episodes	1989–2011	Time series analysis Generalized additive regression models	NA	NA	Daily max temperature, max and min day-and-night temperature, daily max heat index, daily max and min heat index, daily average temperature, average heat index **Heat wave definition:** Definitions of six heat wave indices are proposed and assessed, incorporating a range of conditions known to be important for heat stress: day- and nighttimes temperatures, humidity, and duration. According to all indices, a heat-wave day is declared on the third consecutive day on which one (or two) variables exceed the 95th percentile of daily values. [Calculated according to the formulation used by the U.S. National Weather Service] Bangladesh Meteorological Department	All-cause mortality, excluding maternal and accidental deaths (n = 25,223) ICDRR, B́s Sample Vital Registration System (SVRS) in Bangladesh	All proposed indices are a statistically significant predictor of mortality in Bangladesh, with effect estimates ranging between 10.4% and 24.0% increase in mortality during heat wave vs. non-heat wave days. The study findings recommend using the day-and-night index, which defines a heat wave as elevated day- and night-time temperatures above the 95th percentile for 3 consecutive days (22.3% increase in mortality, CI: 8.2, 38.2). The proposed definition is deemed appropriate for preparedness measures in a heat early warning system (HEWS) because it is both related to human health outcomes and forecastable.

mortality (Ghumman and Horney, 2016).

In terms of geographical coverage, 63% (n = 17) of the selected studies focused on India, eight on Bangladesh and one on Pakistan and Nepal, respectively. It is important to note that no epidemiological studies on the association between ambient temperature and mortality were identified for half of the countries in the region, namely Afghanistan, Bhutan, Maldives, and Sri Lanka. Eight of the studies included in this review (30%) focused solely on rural populations and eleven (40.7%) on urban, while eight studies (30%) evaluated the association between ambient temperature or heat waves and mortality for the general population in a country (including urban and rural areas). All the included studies on ambient temperature and heat waves are summarised in Table 1.

In total, the included studies analysed >1.5 million deaths. However, eleven (41%) of the selected articles were based on identical populations, analysed over the same or an overlapping period. The most extensive datasets were provided by the Matlabs Health and Demographic Surveillance System (HDSS) (around 49 thousand deaths), which is the oldest field site in the region dating back to 1966 and maintained by the International Centre for Diarrheal Disease Research, Bangladesh (ICDRR,B), and India's Million Death Study (around 412 thousand deaths), which is based on one of the largest Sample Vital Registration Systems (SVRS) in the world. Other data sources included several smaller HDSSs, ICDRR,Bs SVRS in Bangladesh, inpatient hospital records, death records from municipal registrars and heat-related mortality statistics compiled by the IMD. Apart from all-cause mortality, eight studies reported effects of temperature on cause-specific mortality, with the most commonly examined causes being cardiovascular, respiratory, and infectious disease mortality. Outcomes related to perinatal mortality, ischemic heart disease, cancer, malaria, parasitic, vector-borne and water-borne diseases, and external causes were also assessed. Some studies on heat waves analysed specifically heat-attributable deaths (Murari et al., 2015; Ghumman and Horney, 2016; Mazdiyasni et al., 2017)

Most selected articles (n = 24; 89%) examined the effects of short-term variations of temperature on mortality, thus measuring heat and/or cold exposure as daily temperature. However, several studies applied a different timeframe for assessing temperature-mortality effects: Alam et al. (2012) analysed effects based on weekly mean temperature "to minimise fluctuations due to small number" of observations, Babalola et al. (2018) used monthly mean and maximum temperature as a unit of analysis to investigate effects on infant and child mortality, while Murari et al. (2015) and Mazdiyasni et al. (2017) analysed annual (summer) mortality and occurrences of heat waves and heat wave days. The majority of articles considering continuous temperature effects (n = 11; 55%) used mean temperature as it was demonstrated to be a better predictor of the temperature-mortality relationship compared to maximum and minimum temperatures, or because it permitted better comparability with other studies. Several studies (n = 9; 45%) used maximum and minimum daily temperature, in some cases as a sensitivity analysis. Five articles evaluated the combined effect of other meteorological parameters such as humidity, wind speed, and mean radiant temperature with temperature by using an index (Heat Index, Universal Thermal Climate Index, Physiological Equivalent Temperature). Two studies also investigated the impact of temperature variability, i.e., the difference between daily maximum and minimum temperatures, or diurnal range. Excluding studies on heat waves, three of the selected articles limited their analysis to summer months and two to summer and winter months to isolate heat and cold effects. Also, the indices adopted by Nissan et al. (2017) incorporated relative humidity and day-time as well as night-time conditions.

About 80% of the studies used data from local stations obtained from a national meteorological department. Two studies relied on climatic records from weather websites provided from the World Meteorological Organization (WMO) under the World Weather Watch Program, one from a weather website, whose exact source we could not trace, and four on data from the National Oceanic and Atmospheric Administration (NOAA), which are collected from local airports. The period analysed in the time series studies ranged from several months to 49 years (Mazdiyasni et al. 2017).

Different approaches were used to determine a threshold for hot and cold effects and to quantify the temperature-mortality association. In general, threshold values were determined based on a specific percentile of the temperature data, through visual inspection of the temperature-mortality plots, or using statistical procedures such as maximum likelihood estimation. Four of the studies on heat waves selected thresholds based on an existing national heat wave definition and four based on a specific percentile of the data. MMTs in the included studies were highly dependent on the temperature and mortality measures, the health outcome of interest, the statistical analysis (non-linear, semi-linear or linear models) and the considered lag structure. Therefore, it is difficult to draw comparisons of the threshold values across studies directly. For articles using mean daily temperature and all-cause daily death counts the temperature threshold values below which mortality started to rise ranged from 19 °C to 30 °C for lags 0–13 and lag 0–14 (cold effects). The threshold above which deaths started to increase ranged from 20 °C to 31 °C for lag 0–1 days (heat effects). Outcomes were reported using a variety of metrics such as relative risk (RR), odds ratio (OR), percentage change in mortality, regression coefficients, and probability of a certain number of deaths.

As expected, there were wide variations in observed temperature ranges across studies and locations. For the articles reporting these, daily maximum temperatures varied between 37.8 °C and 46.2 °C (n = 9), daily minimum temperatures between 8.6 °C and 28.5 °C (n = 6) and daily mean temperatures were in the range of 13.2 °C and 35.6 °C (n = 10). These temperature ranges corresponded to the diverse climatic conditions in the region. Study locations covered eight main climatic zones based on the Koeppen-Geiger climate classification and were dominated by four main climatic zones: tropical wet and dry, humid subtropical, warm semi-arid and warm desert (see Fig. 3). Areas in the tropical zone, found along the southern parts of India and in Bangladesh, experience mostly hot summers and receive heavy rainfall during the monsoon periods. The humid subtropical zone, which spans the Indo-Gangetic plains, is also characterized by hot summers, but cooler winters. The warm semi-arid climate, found in some parts of India, tends to have hot summers and warm to cool winters, with very little precipitation. Finally, the warm desert climatic zone, found in the northern edge of India and most of Pakistan, is characterized by extreme temperature variations, with hot summers and cool or cold winters, and minimal precipitation.

Concerning study design, articles evaluating the impact of heat and/or cold on mortality were based either on time series or case-crossover design. As previously noted by Basu (2009) and demonstrated in several studies on temperature and mortality, study results should be similar irrespective of whether they are based on time series or case-crossover design. Studies investigating heat wave effects were based either on episode analysis, comparing deaths in a heat wave vs. matched non-heat wave period/days, or on time series analysis, regressing daily or annual mortality with heat wave/non-heat wave days or an annual number of heat waves.

Most time series studies included season and time trend as confounding variables in their models, using smoothing functions with specified degrees of freedom, while several studies considered additional confounders such as day of the week, public holidays, humidity, rainfall, and particulate air pollution. Control for most of these confounders was not necessary for case-control/case crossover studies since they controlled for potential temporal confounders "by design", i.e., by matching control days by day of the week and month across years. Also, in the case of case-crossover studies as well as time series controlling for trend, biases due to individual characteristics such as genetics, behaviours and physiological differences are also inherently accounted for by study design.

The majority of included time series studies also examined harvesting and delayed effects of non-optimum temperature exposure and reported cumulative impacts over periods prior to the mortality event, with the considered lag structure ranging from a single day for high temperatures to 28 days for low temperatures. Harvesting or mortality displacement effects are characterised as excess mortality over the first few days of relatively high temperature being offset by reduced mortality in the following days of lower temperatures. Analysing harvesting is essential for determining the full magnitude of the public health issue, since its presence indicates that frail individuals were the only major population subgroup affected by the exposure and that their deaths were brought forward by a certain number of days (Gasparrini, Armstrong and Kenward, 2010; Hajat and Kosatky, 2010).

3.3. Assessment of the risk of bias in individual studies

We found substantial variation in the quality of the included articles as shown in the summary table for all studies (Table 2) and in the summary tables for individual assessments (Supplementary Table S5-S31). We identified measurement of exposure, measurement of outcome, and appropriateness of statistical method as the most common weakness in the quality of the body of evidence. In particular, twelve studies were judged to have *definitely high* or *probably high risk* of exposure measurement bias. These low ratings were related to the use of weekly or monthly temperature observations as opposed to daily time series, which might attenuate the true temperature effect or capture seasonal effects rather than true temperature effects, as well as large spatial aggregation of exposure data, which might conceal local temperature effects on mortality, and lack of sufficient information on data source and quality control of the data. Fourteen studies were rated as having a *definitely high* or *probably high risk* of measurement bias due to the use of data from unofficial sources with low reliability (e.g. newspapers, unofficial reports) or the use of municipal and vital registry data, which is considered as incomplete and under-representative for the countries in the region as large number of people die outside hospitals and without being registered (Setel et al., 2007; Jha, 2014; Mikkelsen et al., 2015). Seven of the studies were judged to have *definitely high* or *probably high risk* of bias for using an inappropriate statistical method. In most cases this was related to the use of statistical methods not appropriate for count data (e.g. OLS regression, Pearson correlation coefficient, ANOVA analysis, *t*-test, etc.) or inference of a causal association based on inappropriate study design or method.

Four of the included studies were identified as being at *probably high risk* of selection bias. Eight of the studies did not control for some of the primary confounders (seasonality or time trend) or any confounders at all and were, therefore, rated as being at *definitely high* or *probably high risk* of confounding bias based on our assessment criteria. One study was evaluated as being at *definitely high* risk of bias due to inconsistencies in reporting.

Seven of the overall 20 studies that examined risk of mortality with continuous exposure to ambient temperature, were judged to have *definitely low* or *probably low risk* of bias across all the risk of bias domains. In contrast, all the nine studies focusing on the mortality risk of heat wave episodes received *probably high* or *definitely high risk* of bias rating for one or more of the domains.

3.4. Synthesis of findings on primary research question

3.4.1. Synthesis of findings on temperature and all-cause mortality

Included studies suggest that both hot and cold temperatures are associated with mortality in the South Asian population. However, results across studies were not homogenous in terms of the direction (increasing mortality with decreasing or increasing temperatures beyond cold and heat thresholds) and magnitude of effects. Furthermore, estimates from the *meta*-analysis confirm evidence of impacts for high temperatures only.

From the eight studies, which analysed the susceptibility of rural populations to non-optimum temperature, six found an association between cold temperature and mortality, while five found a heat effect. All studies on urban areas apart from two focused solely on heat effects and showed evidence for heat-related mortality, while two documented both heat and cold-related mortality (McMichael et al., 2008; Singh et al., 2019). Burkart et al. (2011) specifically examined and contrasted the temperature effects for urban and rural areas in Bangladesh. Although they observed an increase in mortality at high and low temperatures for both rural and urban areas, urban areas were found to exhibit generally stronger and longer lasting heat effects. The other four studies (Burkart et al., 2014b; Burkart and Kinney, 2017; Fu et al., 2018; Shrestha et al., 2017), which examined the relationship between temperature and excess mortality at a national scale, also ascertained both heat and cold effects. Overall, studies in India found that substantial health impacts occur even at temperatures lower than those specified in the national heat wave definition.

Results across studies also varied considerably in terms of the magnitude of the observed heat and cold effects. The heterogeneity of studies in terms of outcome and exposure metrics, temperature thresholds and lags examined did not permit direct comparison of effect estimates across studies. The mortality increases due to elevated daily mean temperatures in the included studies using linear approximation ranged from 0.2% to 3.2% per 1° C increase in temperature above a MMT threshold ($n = 5$), while for cold effects excess mortality was in the range of 1.4% – 3.2% per 1° C decrease in temperature below a MMT threshold ($n = 4$). While Burkart et al. (2011); Ingole et al. (2017); McMichael et al. (2008) found heat effects to outweigh cold effects in Vadu, Bangladesh, and Delhi, and Ingole et al. (2012) observed comparable effects of heat and cold in Vadu, Lindeboom et al. (2012) and Fu et al. (2018) found stronger effects for cold and moderately cold temperatures compared to hot temperatures in Matlab and India, respectively. Some inconsistencies in the reported results across studies may be partly attributed to differences in methodology and model specification (e.g., statistical method, adjustment for confounders, lag structure and thresholds used), but also specific characteristics of the locations or the populations that might determine vulnerability. Four of the twenty studies on ambient temperature and all-cause mortality were judged to have probably high or definitely high risk of bias by at least two of the assessment criteria.

Only five of the studies on all-cause mortality and ambient temperature were judged as homogenous enough to be combined in one *meta*-analysis. Only two of these were judged to have probably high or definitely high risk of bias based on one of the assessment criteria. Fig. 4 shows the pooled estimates of the association at every 0.5° C increment of temperature with reference to a common threshold of 24.5° C (lag 0–1) and 26.5° C (lag 0–13). Since not all studies cover the same temperature range, the colour shades and the legend underneath indicate how many and which studies specifically contribute to the pooled effect estimates at different temperature increments. The pooled RR estimates at different temperatures represent the *meta*-analysed RR estimates of individual curves at these points. The *meta*-analysis shows a U-shaped temperature-mortality relationship, with a temperature band of minimum mortality of 22° C – 25° C for lag 0–1 days and 25° C – 28° C for lag 0–13 days, respectively. However, a statistically significant association was found only at temperatures above the upper limits of these bands, i.e. indicating heat effects. In particular, a significant positive association can be observed at temperatures above 31° C for lag 0–1 days and above 34° C for lag 0–13 days. For lag 0–1 days, 10° C increase in temperature above 25° C was associated with a 22% (RR = 1.22, 95% CI: 1.10–1.36) increase in the risk of mortality, with the RR increasing steeply at higher temperatures. For lag 0–13 days, 5.5° C increase in temperature above 26.5° C was associated with a 23% (RR = 1.23, 95% CI: 1.11–1.37) increase in the risk of mortality, with the effect increasing even more steeply at the higher range of the exposure, but the precision of estimates decreasing due to the small number of studies reporting effects at these ranges.

3.4.2. Synthesis of findings on heat wave events and all-cause mortality

All nine studies, which examined the effect of heat waves on all-cause mortality find a positive association. Six of these studies refer directly to all-cause mortality, while three studies refer to all-cause mortality indirectly, by considering heat wave-induced, heat-related or heat-attributable mortality. Since none of the studies provides specific information on which causes of death were classified as "heat-related", we consider them as a proxy of all-cause mortality, but note that the selection criteria in these studies are likely to be arbitrary and to exclude unreported deaths or indirect causes of death. The reported RR of all-cause mortality during a heat wave vs. non-heat wave period/days in studies ranges between 1.03 and 2.34 (Hess et al., 2018; Nori-Sarma et al., 2019a; Singh et al., 2019). Nori-Sarma et al. (2019a) demonstrates that the estimated RR from heat waves depends considerably on the exact definition of heat waves, which highlights the difficulty of comparing results across studies with very heterogenous definitions.

Several studies report results using alternative effect estimates to risk ratios. For example, Azhar et al. (2014) report a 43.1% increase in all-cause deaths during the 2010 Ahmedabad heat wave compared to the reference period. Mazdiyasni et al. (2017) find that the increase in summer mean temperature in India over 1960–2009 corresponded to a 146% increase in the probability of heat-related mortality events of >100 people. Ghumman and Horney (2016) find that residents of Karachi were approximately 17 times as likely to die of a heat-related cause of death during the June 2015 heatwave when compared to a reference period of June 2014. Although all studies find a positive association between mortality and heat wave episodes, the different methodological approaches, study designs, definitions of heat waves and heat wave-related mortality do not allow for a direct comparison of effect estimates across studies. Five of the nine studies on heat waves were judged to have probably high or definitely high risk of bias by at least two of the assessment criteria, with three of them by five of the assessment criteria.

3.5. Additional analyses

3.5.1. Temperature and cause-specific mortality

Five studies reported a pronounced heat effect on cardiovascular disease (CVD) mortality, with effects ranging from 1.9% increase in mortality with every 1 °C increase in temperature above specific threshold in Delhi (Hajat et al., 2005) to 62.9% in Bangladesh (Hashizume et al., 2009). Burkart et al. (2011, 2014b) found severe heat effects on CVD mortality particularly in urban areas as opposed to rural areas. The analysis of Burkart et al. (2014b) also revealed a higher risk of heat-related CVD mortality among males than females. In comparison, only two studies reported cold effects on CVD mortality, but these were much weaker, 1% and 9.9%, respectively (Burkart et al., 2011; Hashizume, 2009). Fu et al. (2018) also documented both a cold and heat association of temperature with Ischemic Heart Disease (IHD)-related mortality.

Temperature effects on respiratory mortality were also mixed. Hashizume et al. (2009) reported strong cold effects (17.5% increase in mortality for each 1 °C decrease in temperature below a threshold), but no heat effects, while Hajat et al. (2005b) and Fu et al. (2018) demonstrated both heat and cold effects.

Regarding mortality from infectious diseases, both Burkart et al. (2014) and Hashizume et al. (2009) showed marked heat effects, with 83.4% (lag 0–13 days) and 10.4% increase in mortality above a

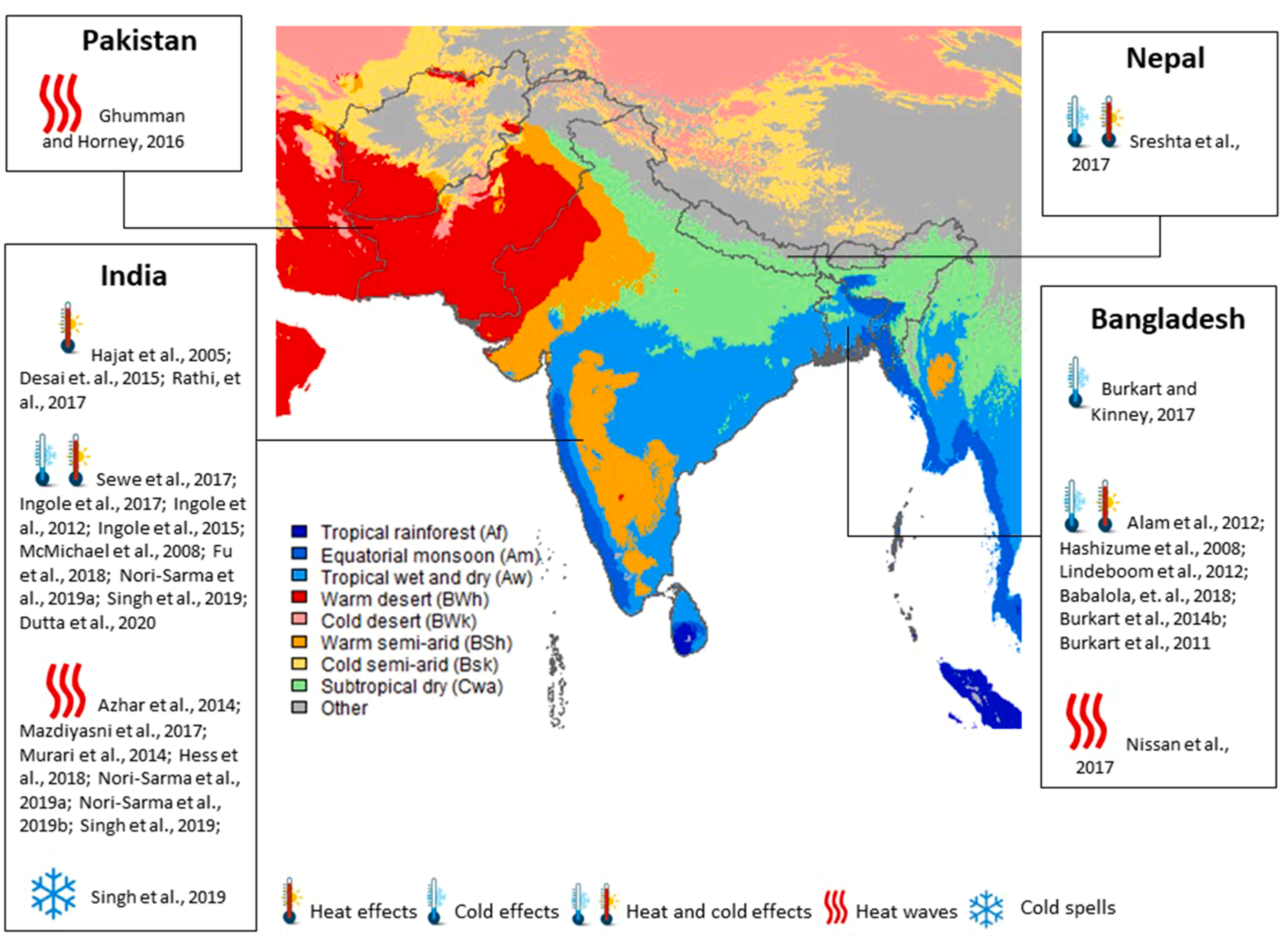

Fig. 3. Map of the climatic zones and the number of studies conducted in each country by category of effect. Source: Own figure, climatic zones based on Köppen-Geiger climate classification maps (Beck et al., 2018).

Table 2
Summary of the results of the risk of bias assessment in individual studies.

Study	Selection bias	Confounding	Exposure assessment	Outcome assessment	Selective reporting	Other bias
Studies on ambient temperatures (n = 20)						
Alam et al. (2012)	PL	PL	DH	PL	PL	PL
Hashizume et al. (2008)	PL	DL	PL	PL	PL	DL
Sewe et al. (2017)	DL	DL	PL	DL	PL	DL
McMichael et al. (2008)	PL	DL	PL	DH	PL	DL
Burkart et al. (2014b)	PL	DL	PH	PL	PL	DL
Burkart et al. (2011)	DL	DL	PH	DL	PL	DL
Ingole et al. (2017)	PL	DL	PL	PL	PL	DL
Ingole et al. (2012)	DL	PL	PL	DL	PL	DL
Ingole et al. (2015)	PL	DL	PL	PL	PL	DL
Hajat et al. (2005)	PL	DL	PL	PH	PL	DL
Fu et al. (2018)	PL	DL	PL	PL	PL	DL
Lindeboom et al. (2012)	PL	DL	PL	PL	PL	DL
Desai et al. (2015)	PH	DH	PH	PH	DH	DH
Burkart and Kinney (2017)	DL	DL	PH	DL	PL	DL
Babalola et al. (2018)	DL	PH	DH	DL	PL	PH
Rathi et al. (2017)	PL	PH	PH	PH	PL	DH
Sreshta et al. (2017)	PL	DL	PH	PH	PL	DL
Dutta et al. (2019)	PL	DL	PL	PH	PL	PL
Nori-Sarma et al. (2019a)*	PL	DL	DL	PH	PL	DL
Singh et al. (2019)*	DL	DL	PL	PH	PL	DL
Studies on heatwave episodes (n = 9)						
Azhar et al. (2014)	DL	PH	PL	PH	PL	DH
Ghumman and Horney (2016)	PH	PH	PH	PH	PL	DH
Mazdiyasni et al. (2017)	PH	PH	DH	DH	PL	DH
Murari et. al (2014)	PH	PH	PH	DH	PL	DH
Nissan et. al (2017)	PL	DL	PH	PL	PL	DL
Hess et al. (2018)	PL	PH	PL	PH	PL	PL
Nori-Sarma et al. (2019a)	PL	DL	DL	PH	PL	DL
Nori-Sarma et al. (2019b) *	PL	DL	PL	PH	PL	DL
Singh et al. (2019) *	DL	DL	PL	PH	PL	DL

DL = Definitely Low RoB; PL = Probably Low RoB; PH = Probably High RoB; DH = Definitely High RoB;
*The study examined both effects of heat wave episodes and continues temperature, therefore they have been included twice in the table.
The underlined studies are those included in the *meta*-analysis.

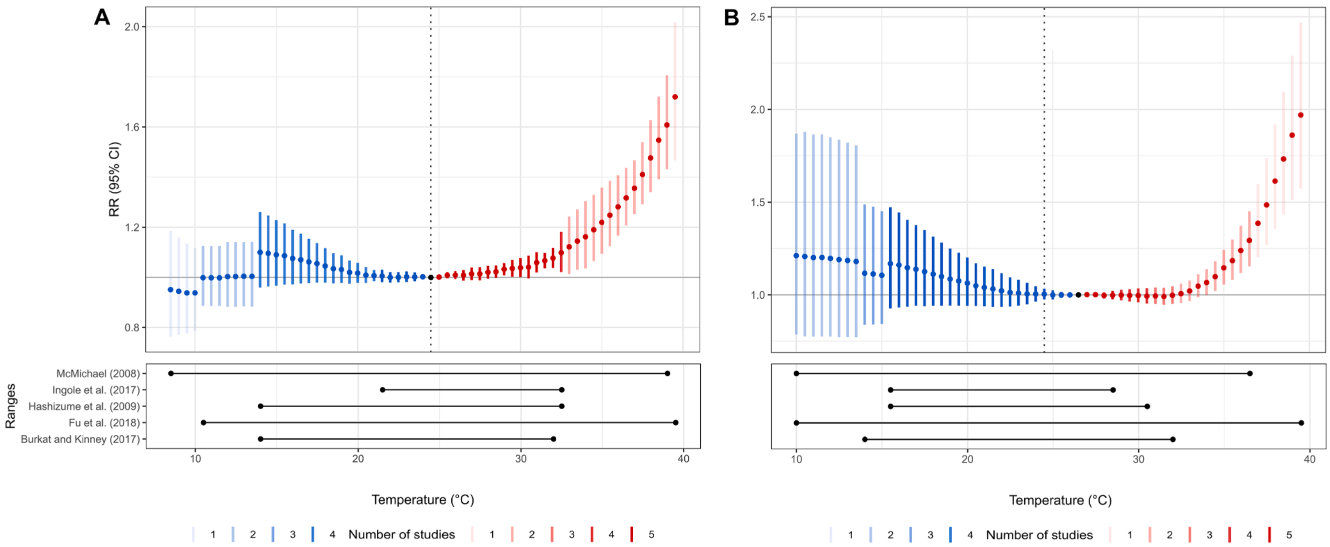

Fig. 4. Pooled estimates of the temperature-all-cause mortality association at (A) lag 0–1 days and (B) lag 0–13 days. Studies included in the *meta*-analysis: Burkart and Kinney (2017), Fu et al. (2018), Hashizume et al. (2009), Ingole et al. (2017), McMichael et al. (2008).

threshold per 1 °C in (equivalent) temperature, respectively. As opposed to the higher risk of heat-related all-cause and cardiovascular mortality observed in urban areas, Burkart et al. (2014) found a significant increase in infectious disease mortality only for rural areas. Ingole et al. (2015) did not find any association of deaths from infectious causes with heat or cold, considering delayed effects of up to 4 days.

With respect to the other examined causes of death, strong cold effects were found for perinatal mortality (Hashizume et al., 2009). Modest increases in risk of malaria deaths were observed at 14 °C – 20 °C (Fu et al., 2018). Statistically significant positive associations were shown for temperature and water- and vector-borne disease mortality (Shrestha et al., 2017) and no association was found for temperature with external causes of death (Ingole et al., 2015) and cancer (Fu et al., 2018).

3.5.2. *Lagged effects and mortality displacement*

Most of the studies also investigated the lag structure and some also the temporal displacement of heat and cold effects. In most studies hot temperatures were shown to have a more immediate effect, lasting from 1 to 6 days, but several studies (n = 4) showed heat effects over a sustained period of time (up to 21 days). Studies reported sustained impacts of cold temperatures over 4 to 14 days after exposure. The duration of temperature effects seemed to differ considerably across causes of death, age and sex. For instance, Burkart et al. (2014) reported more delayed heat effects in children and younger adults, and Hajat et al. (2005b) demonstrated more sustained risks for children and non-respiratory diseases. Babalola et al. (2018), who considered monthly infant mortality, found evidence for cold effects for lag 0 months. None of the five studies, which focused on mortality related to heat waves, formally modeled delayed effects of exposure. Azhar et al. (2014) assessed possible delayed effects graphically but did not find any evidence for these. Considering this methodological shortcoming, one cannot exclude that the reported excess mortality in the included heat wave studies represents, at least to a certain extent, a harvesting effect rather than a substantial increase in mortality. However, it has been shown that the more extreme weather events are, the smaller the harvesting effect is (Saha, Davis and Hondula, 2014).

3.5.3. *Vulnerable populations*

The identification of specific segments of the population most vulnerable to non-optimum temperatures has been of specific interest in most of the included studies as in climate-related research in general. However, results across studies do not provide a homogenous picture regarding vulnerabilities, and this is true even for studies based on the same population, but using different study design and/or statistical method. Most of the reviewed studies explored only vulnerabilities based on age and sex and cause of death, possibly due to the lack of sufficient data on socio-economic and other characteristics. Only Burkart et al. (2014) and Ingole et al. (2017) also analysed differences due to other individual or intra-population characteristics such as socio-economic status, education, occupation, housing, or level of urbanisation. Cold effects have been shown to be most pronounced among infants and children younger than 5 years (Ingole et al., 2012; Babalola et al., 2018) or <15 years (Hashizume, 2009), the elderly (Lindeboom et al., 2012; Ingole et al., 2017; Fu et al., 2018), adults aged 20–69 (Alam et al., 2012; Fu et al., 2018), and those employed in housework (Ingole et al., 2017). Alam et al. (2012) found cold to exert a stronger effect on females, while Ingole et al. (2017, 2012) and Singh et al. (2019) did not find any gender differences. Stronger heat effects were demonstrated for children aged 0–14 (Hajat et al., 2005; Sewe et al., 2018; Singh et al., 2019), adults aged 20–59 (Ingole et al., 2012) and the elderly (Burkart et al., 2014b; Singh et al., 2019). However, no such association was found by Ingole et al. (2015) for the elderly (60 and older) in Vadu HDSS. Burkart et al. (2014) and Ingole et al. (2015) showed that males in Bangladesh, particularly the elderly, and males in Vadu HDSS appear to face increased mortality risk on hot days. However, Ingole et al. (2017) demonstrated the opposite for women in Vadu (results were not statistically significant), and Ingole et al. (2012) did not find any significant association by gender. In terms of socio-economic factors, findings from Burkart et al. (2014) suggest a more pronounced risk of heat-related all-cause mortality for people living in urban and in high socio-economic status areas, especially among the elderly, as compared to rural and low socio-economic status areas. The higher heat-related risks for urban areas in Bangladesh were also demonstrated in a previous study by Burkart et al. (2011). Singh et al. (2019) report higher mortality for non-institutional deaths (those dying outside a hospital) compared to institutional deaths (those dying within a hospital), which the authors broadly attribute to lower socio-economic status. In a study conducted at the individual level in a rural setting in western India, stronger heat effects were observed among farmers, those with low educational attainment as well as those owing more agricultural land (Ingole et al., 2012).

Only a few studies on heat wave episodes investigated the role of non-atmospheric factors on the temperature-mortality relationship. Both Azhar et al. (2014) and Singh et al. (2019) report a higher RR of mortality from heat waves for females compared to males. Analysis of the deadly heat wave in Karachi, Pakistan during 2015, revealed excess risk of heat-related mortality among the poor and those with lower levels of education, but no effect of fasting during Ramadan was found as initially hypothesised.

3.6. Quality of the evidence

Table 3 summarizes the overall quality of the evidence on the association between ambient temperature and heat wave episodes and all-cause mortality for the general population in the countries in South Asia. We downgraded the overall quality of the evidence for studies on ambient temperature by the criterion on imprecision as several studies had large confidence intervals and two did not report any confidence intervals. We downgraded the overall quality of the evidence for studies on heat wave episodes for three of the criteria: risk of bias – due to the substantial risk of bias across studies, indirectness – due to ambiguity of outcome definition and imprecision – due to several studies having large confidence intervals and one not reporting any confidence intervals. We upgraded the quality of the evidence on ambient temperature since most studies reported a broadly consistent dose–response pattern, with risk of mortality increasing with increases and decreases of ambient temperatures beyond a certain threshold. The resulting overall quality of the evidence was judged as *moderate* for studies on ambient temperature and *low* for studies on heat wave episodes.

3.7. Strength of the evidence

Table 3 also summarizes the rating of the strength of the body of evidence. Our judgements were based on the following considerations:

- Quality of the body of evidence: *moderate* for studies on ambient temperature and *low* for studies on heat waves (as explained above).
- Direction of effect estimates was largely as expected – risk of mortality increasing with higher and lower ambient temperature beyond a threshold and with more frequent or intense heat wave episodes.
- Confidence in effect estimate: unlikely that a new study on ambient temperature and all-cause mortality would have an effect estimate that would make the results null or statistically insignificant. For heat wave exposure, due to the methodological deficiencies of the studies it cannot be ruled out that new studies might show different effects.
- Other compelling attributes of the data that may influence certainty: for ambient temperature studies, differences in exposure measurement, statistical methods, and contextual factors (completeness in mortality counts, population exposure level, vulnerability and physical and physiological adaptation) make interpretation and comparison difficult. Similarly, the included heat wave episode studies are very heterogenous in terms of heat wave definitions, consideration of lagged effects and mortality displacement, study design and contextual factors (completeness in mortality counts, population exposure level and vulnerability, physical and physiological adaptation), which makes interpretation less certain and clear. For both ambient temperature and heat wave exposure, evidence is based only on a few countries in the regions, with the vast majority of countries not being represented.

We compared these considerations to the strength of evidence definitions specified in the Navigation Guide (Table S32) and concluded that for high and low ambient temperatures there was *sufficient* human evidence that exposure affects all-cause mortality in South Asia and for heat waves – *limited* evidence.

4. Discussion

4.1. Summary of evidence

Our systematic review and *meta*-analysis resulted in five main findings. First, we found only a limited number of studies (n = 27), which have attempted to quantify the mortality effects of temperature and heat waves in South Asia. Studies were limited geographically, with half of the countries in the region not represented and two countries covered by only one study. Seven populations were analyzed more than once (e.g. four separate analyses based on the Vadu population, three based on the Matlab population, three on the total population of Bangladesh and two on Delhi, Surat, Ahmedabad and five Indian cities). Second, as summarised in Table 4 below, the strength of the evidence on ambient temperature as a risk factor for all-cause mortality was *sufficient* and on heat wave episodes — *limited*. The latter rating is not to suggest that heat waves are not a risk a factor for all-cause mortality in South Asia, but rather reflects the lack of a sufficient number of robust studies in a region with very heterogenous contexts and a challenging environment for health data collection. Third, individual studies reported an association of all-cause mortality with both high and low temperatures and heat waves for the population in South Asia. However, our *meta*-analysis, indicated evidence of an association for high temperatures only, both at shorter and longer lags, possibly due to the very small number (n = 5) and skewed geographical representation of the included studies. In particular, steep supra-linear increase in risk was observed at temperatures above 31° C for lag 0–1 days and above 34° C for lag 0–13 days, with the risk being higher for longer lags. Fourth, in terms of cause-specific mortality, studies found evidence for both heat and cold effects on CVD, IHD and respiratory mortality. Heat effects were also identified for mortality related to infectious diseases and water- and vector-borne diseases, while cold effects were also found for perinatal mortality. Lastly, the profile of vulnerabilities identified in the reviewed studies is fragmented and sometimes conflicting, possibly due to differences in contexts, heterogeneity in study designs and limitations in data collection.

4.2. Comparison with other systematic reviews

Results from the *meta*-analysis are in contrast to findings from other systematic reviews on LMICs (Burkart et al., 2014a; Amegah, Rezza and Jaakkola, 2016), and evidence from higher income low-latitude countries in Europe and North America (The Eurowinter Group, 1997; Gasparrini et al., 2015), which found mortality effects for both hot and cold temperatures. The presence of cold effects in South Asia is plausible and, similar to populations in moderate climates, might be related to poor physiological and physical adaptation to cold weather, for instance, concerning thermal efficiency of housing and clothing (The Eurowinter Group, 1997; Healy, 2003; Burkart and Kinney, 2017) and relative perceptions of risk and vulnerability (Sperber and Weitzman, 1997). Other mechanisms have also been suggested to explain the somewhat counterintuitive cold effects on mortality in tropical and sub-tropical climates: the higher proportion of moderately cold than extremely cold or hot days (Fu et al., 2018), the importance of relative rather than absolute drop in temperatures (Burkart et al., 2014a; Guo et al., 2016), and insufficient control for seasonal confounding (Kinney et al., 2015). For instance, influenza outbreaks (Burkart et al., 2014a; Yang et al., 2009) and household air pollution due to biomass use for cooking and heating, could affect cold-related mortality due to their potential seasonal variations (Egondi et al., 2012; Ingole et al., 2017), but these have been poorly investigated in the included studies and in LMICs in general, possibly due to lack of routine data. Possible explanations for why we did not observe cold-related increase in mortality risk despite observations from individual studies in this review and evidence from the literature include the small number and limited geographical coverage of studies included in the *meta*-analysis as well as their large within-study standard errors at the

Table 3
Summary of the assessment of the quality and strength of the evidence on ambient temperature and heat wave events as a risk factor for all-cause mortality.

Reference	Ambient temperature (n = 20)		Heat wave events (n = 9)	
	Rating	Basis	Rating	Basis
Quality of evidence assessment				
i. Downgrade considerations				
Risk of bias across studies	0	Among all, one study with large sample size judged to have low risk of bias.	−1	There is a substantial risk of bias across most studies.
Indirectness	0	All-cause mortality was appropriate outcome, studies conducted in the population of interest, mostly direct measures of exposure.	−1	Three of the studies used “heat-related mortality”/” heat-induced mortality”/” heat-attributable mortality”, which was not well defined and is not directly comparable to the outcome of interest.
Inconsistency	0	The magnitude of effect estimates likely to differ because of differences in study methods (study design, statistical methods, lag structure considered, method for determining MMT) and not be driven by unexpected heterogeneity.	0	Effect estimates likely to differ because of differences in study methods (study design, statistical methods, study definition of heat waves) and not be driven by unexpected heterogeneity.
Imprecision	−1	Three studies had wide confidence intervals and two did not provide any confidence interval estimates.	−1	Two studies had wide confidence intervals and one did not provide any confidence interval estimates.
Publication bias	0	No evidence for publication bias for studies that would meet our inclusion criteria.	0	No evidence for publication bias for studies that would meet our inclusion criteria.
ii. Upgrade considerations				
Size of the effect	0	Effect sizes are small in most studies.	0	Confounding alone cannot be ruled out as an explanation for large effect estimates.
Dose response pattern	1	Most studies report broadly similar dose–response pattern, with risk of mortality increasing with increases and decreases of ambient temperatures beyond a certain threshold.	0	Dose response relationship is difficult to compare across studies due to differences in contexts, study designs and methods used.
Confounding minimises effect	0	No evidence found to suggest that possible residual confounders would reduce effect estimates.	0	No evidence found to suggest that possible residual confounders would reduce effect estimate.
iii. Summary of the quality assessment				
Overall quality of evidence starts: *Moderate*	*Moderate*	Moderate + (1) +(-1) = Moderate. Downgrading/upgrading resulted in moderate rating for the quality of evidence.	*Low*	Moderate + (-1) + (-1) + (-1) = Low. Downgrading changed the quality from moderate to low.
Summary of findings	n/a	Overall moderate quality of the evidence of higher risk of all-cause mortality for high and low ambient temperature exposure.	n/a	Overall low quality of the evidence of higher risk of all-cause mortality during heat wave episodes.
Strength of evidence assessment				
Quality of evidence	*Moderate*		*Low*	
Direction of effect estimates	n/a	Direction largely as expected: higher risk of mortality at high and low ambient temperatures.	n/a	Direction largely as expected: higher risk of mortality during heat wave episodes.
Confidence in effect estimate	n/a	Studies on ambient temperature measure directly the outcome of interest, direction of effect is largely consistent, majority score low on risk of bias, in particular one study with a large sample size, but several studies have large confidence intervals or do not report confidence intervals at all. It is unlikely that a new study on ambient temperature and all-cause mortality would have an effect estimate that would make the results null or statistically insignificant.	n/a	Most studies have high RoB, do not measure directly the outcome of interest and not all potential confounders are controlled for. Due to these methodological deficiencies it cannot be ruled out that new studies might show different effect estimates.
Other aspects	n/a	Differences in exposure measurement, statistical methods, and contextual factors, including completeness in mortality counts, population exposure level and vulnerability, differences in physical and physiological adaptation across study populations make interpretation and comparison difficult.	n/a	Differences in heat wave definitions, consideration of lagged effects and mortality displacement, study design, contextual factors, including completeness in mortality counts, population exposure level and vulnerability, physical and physiological adaptation across study populations make interpretation and comparison difficult.
Overall strength of evidence	*Sufficient*	We found sufficient evidence that ambient low and high temperatures are positively associated with all-cause mortality for the population in South Asia, where chance, bias, and confounding can be ruled out with reasonable confidence. The available evidence includes results from one or more well-designed, well conducted studies, and the conclusion is unlikely to be strongly affected by the results of future studies. Due to lack of comparability across studies quantitative estimates can only be interpreted in broad terms.	*Limited*	We found limited evidence that heat wave exposure is associated with all-cause mortality for the population in South Asia. A positive association is observed between exposure and outcome; however, chance, bias, and confounding cannot be ruled out with reasonable confidence. Confidence in the association is constrained by the limited number and size of studies and the low quality of individual studies. Further studies, particularly with more rigorous control for confounding, high quality outcome data and consideration of temporal aspects of the association may allow an assessment of effects.

lower temperature range. Further studies with large sample sizes and using comparable and advanced methodologies are necessary in order to understand better the direction and magnitude of temperature effects on mortality in the region, particularly for the six countries with limited or no epidemiological studies, namely Pakistan, Nepal, Afghanistan, Bhutan, Maldives, and Sri Lanka.

Interestingly, two of the included studies found only cold but no heat effects on mortality (Alam et al., 2012; Hashizume et al., 2009). Since both of them were conducted in rural areas (humid sub-tropical areas of Bangladesh), these results might be partly explained by the lower density, higher vegetation cover, and associated lack of urban heat island (UHI) in the study areas. However, other factors such as the population-specific acclimatization and adaptation to hot and cold weather, the demographic and health profile of the study populations as well as insufficient control for confounding cannot be excluded as possible explanations.

Our findings on cause-specific mortality are in line with systematic reviews on other tropical and sub-tropical regions and LMICs (Burkart et al., 2014a; Amegah, Rezza and Jaakkola, 2016; Green et al., 2019). Impacts of temperature on cardiovascular and respiratory mortality are some of the most well documented in the epidemiological literature. Cardiovascular impacts have been related to a range of physiological

Table 4
Summary of findings.

Summary of finding	Studies contributing to the findings	Certainty in the evidence (Navigation Guide)	Brief rationale of the rating around the certainty of the evidence
Ambient temperature: Positive association of all-cause mortality with temperatures below and above a MMT threshold.	Alam et al. (2012); Hashizume et al. (2009); Sewe et al. (2018); McMichael (2008);Burkart et al. (2014b) ; Burkart et al. (2011); Ingole et al. (2017, 2012, 2015); Hajat et al. (2005); Fu et al. (2018); Lindeboom et al. (2012); Desai et al. (2015); Burkart and Kinney (2017); Babalola et al. (2018); Rathi et al. (2017); Shrestha et al. (2017); Dutta et al. (2020); Nori-Sarma et al. (2019a); Singh et al. (2019)	**Sufficient**	Findings based on studies of large sample size and mostly of good quality. Overall, direction of effect was consistent across studies, but there was a lack of estimate comparability due to methodological differences. Evidence of an exposure–response pattern was found. Studies were very skewed geographically.
Heat wave episodes: Heat waves are associated with increases n all-cause mortality	Azhar (2014); Ghumman and Horney (2016); Mazdiyasni et al. (2017); Murari et al. (2014);Nissan et al. (2017); Hess et al. (2018); Nori-Sarma et al. (2019a); Singh et al. (2019); Nori-Sarma et al. (2019b)	**Limited**	Findings are consistent, but based on a small number of studies, many of which score high on risk of bias and have methodological weaknesses, thus chance cannot be ruled out. Studies were very skewed geographically and effect estimates were not comparable due to differences in study design and methods.

changes in the human body such as increased plasma viscosity, blood pressure, and elevated cholesterol levels (Basu, 2009; Moghadamnia et al., 2017; Zhang et al., 2014; Zhang et al., 2014). Cold has been associated with an increased risk of respiratory infections through bronchoconstriction and changes in immunological reactions (Gasparrini et al., 2015), while physiological stress of heat on the respiratory systems is less well understood (Seltenrich, 2015). Several causes of death, which have been associated with temperature in other epidemiological studies, namely deaths from cerebrovascular diseases (Stafoggia et al., 2006), diabetes (Seposo, Dang and Honda, 2017), pre-existing psychiatric disorders (Stafoggia et al., 2006) and adverse birth outcomes (Son et al., 2019), were not investigated in any of the included studies.

4.3. Vulnerabilities and modifying factors

The studies included in this review identified infants, children, the elderly, adults and people occupied in housework as more vulnerable to the impacts of low temperatures and children, adults, farmers, people with low educational attainment, and those owning agricultural land or living in urban areas as more susceptible to the impacts of high temperatures. Overall, women and people with lower socio-economic status were reported as more susceptible to the impacts of heat waves. However, evidence on certain vulnerabilities is often based on single studies and findings for some sub-groups (especially gender and age groups) are inconsistent, which warrants further investigation. Furthermore, some of the underlying factors shaping vulnerabilities are poorly understood and many questions are still to be elucidated — for instance, are people in urban areas more affected by heat because of higher exposure (e.g., UHI effect) or because of differences in age and disease patterns (Burkart et al., 2014b)? Are adults at higher risk because they are more involved in outdoor occupational activities? Are gender differences in vulnerability due to physiological predispositions, occupational differences or differences in treatment seeking behaviour? Are less educated people at higher risk because of occupation, their health status, access to resources (water, housing, information, health care, etc.), or heat-health awareness? How does personal perception of risk shape vulnerabilities? Answering these questions would require better understanding of contextual factors that moderate vulnerabilities.

Besides population characteristics, the built environment, in particular, building features, urban form, and density of green spaces, has also been shown to be an important determinant of temperature-related health risks (Scovronick & Armstrong, 2012; Dang et al., 2017; Lu et al., 2018; Horrison & Amirtham, 2016), but its modifying effect in the included studies and in LMICs in general has not been well investigated (Pramanik and Punia, 2019). One of the studies in this review (Alam, et al. 2012) hypothesised that differences in thermal efficiency of housing might be a possible explanation of the more marked effects of low temperatures on mortality in Matlab as opposed to Abhoyangar. However, Ingole et al. (2017) did not find mortality outcomes in the summer months in Vadu HDSS to be related to housing characteristics.

In terms of vulnerabilities, another important knowledge gap to be addressed are the temperature effects for the population living in substandard housing conditions in the region. 30.4% of the urban population in South Asia lives in informal settlements, with this share being particularly high in some countries such as Afghanistan (62.7%), Bangladesh (55.1%), Nepal (54.3%) and Pakistan (45.5%) (World Bank, 2014). Populations living in informal housing might be particularly vulnerable to non-optimum temperatures due to overcrowding, the poor quality and limited insulation of the housing, but also as a result of other interrelated factors such as poverty, lack of access to health care, sanitation and information on heat wave risks, limited access to clean drinking water and electricity, and restricted household ventilation. Two studies investigating how heat varies within the cities of Nairobi, Kenya and Ahmadabad, India, respectively, demonstrated higher local temperature exposure in informal settlements compared to other city areas, with average difference between 5 to almost 10 °F in the case of Nairobi (Scott et al., 2017; Wang et al., 2019). We found only one study globally, which has investigated the temperature effects on mortality in informal settlements, but this was based in Nairobi (Egondi et al. 2012). Clearly, the lack of routinely collected health data for populations in informal settlements hinders scientific studies. To overcome this, Scovronick et al. (2015) provide an overview of available data sources and epidemiological designs with modest data requirements, which could potentially be deployed for investigating the association between weather and health in these understudied populations.

Comprehensive analysis of vulnerabilities and their determinants could help identify more targeted and cost-effective adaptation strategies, which is particularly important for low income settings. Research in this direction can benefit from different study designs (e.g. case studies, mixed methods, personal temperature measures, etc.) as well as insights from other disciplines than public health such as exposure science, sociology, behaviour studies, economics, architecture, urban design, etc. (Maller and Strengers, 2011; Milà et al., 2020).

4.4. Adaptation and policy implications

The role of adaptation for minimising health impacts of non-optimum temperatures is poorly investigated in the reviewed articles. Nevertheless, the included studies propose a range of interventions based on their findings. Most of these are related to increasing public awareness of the problem through public messaging or health education campaigns; encouraging preventative measures (e.g. wearing light, bright-coloured and sun-protective clothing, avoiding physical activity or outdoor work during the hottest hours, staying hydrated), especially among the elderly, outdoor workers and those with existing cardiovascular, respiratory and other chronic diseases; enhancing response capacity and coordination of public health centers; distribution of electric fans; setting-up of cooling centers — air conditioned sites designated as shelters during extreme heat (Widerynski et al., 2016), and introducing early warning systems.

We note that some of the proposed technological cooling interventions are to be viewed with caution due to their limited scope and undesirable consequences. Although studies have shown the protective effect of the use of air conditioning units during heat waves (Barreca et al., 2016) and air conditioning is growing rapidly in South Asia, this solution still remains out of reach for the majority of the population due to its high operational costs (Mastrucci et al., 2019). Increased use of air conditioning units in urban areas is also shown to contribute to increase in outdoor temperatures by one degree or more (Lundgren and Kjellstrom, 2013), it leads to increased risk of power outages as a result of higher pressure on energy grids and, most importantly, it further contributes to climate change through upsurge in electricity consumption (Gupta et al., 2012). Use of electric fans has often been proposed as a more affordable alternative to air conditioning in low resource settings. However, a 2012 Cochrane systematic review showed that the benefits of using electric fans during heat waves are uncertain and may actually increase mortality risk, especially if ambient temperature is above body temperature (35° C), by contributing to an increased rate of dehydration and increased convective heat gain (Gupta et al., 2012).

A few formal evaluations of heat-health warning systems have been conducted so far, and they appear to show a notable reduction in excess mortality following a heat wave (Ebi et al., 2004; Martínez-Solanas and Basagaña, 2019). The first Heat Action Plan, including an early heat warning system, in South Asia was implemented in the city of Ahmedabad, in India's western province of Gujarat, following the deadly heat wave of May 2010. According to a pilot formal evaluation of the plan, it has been effective in averting 1190 (95%CI 162–2218) average annualized deaths two years after its implementation (Hess et al., 2018). Following the experience of Ahmedabad, the government is currently working with over 100 cities and districts within 23 states towards scaling up heat action plans and early warning systems across India (Pradesh et al., 2019). In light of the findings in this review, which demonstrated that temperature thresholds can differ substantially between regions in the same country and that health effects may occur at a temperature below those specified in national heat wave definitions, there is a need for more local epidemiological studies to establish appropriate temperature thresholds, which can inform such early warning systems.

Beyond the more immediate and upfront interventions mentioned above, long-term strategies for reducing temperature vulnerabilities are rarely discussed in the included studies. Evidence from other studies shows that improvement of public infrastructure, expansion of public transport, and reduction of the UHI effects through increase in tree canopy, deployment of heat-reflective surfaces on roofs and roads have the potential to decrease heat stress, especially in densely built urban and *peri*-urban areas (Rizwan, Dennis and Liu, 2008; Garg et al., 2016; Deilami, Kamruzzaman and Liu, 2018). Previous research has suggested that addressing broader development challenges such as economic diversification and shifting of labour away from the agricultural sector (Green et al., 2019), improvement in educational attainment (Lutz, Muttarak and Striessnig, 2014), expansion of essential healthcare, set-up of other social protection programmes and provision of access to electricity (Mastrucci et al., 2019) could be important for decreasing the human cost of climate-related threats.

4.5. Potential interactive effects of temperature and particulate or ozone air pollution

Another important avenue for future research is to explore the potential interactions between temperature or heat waves and particulate or ozone air pollution on mortality. Ambient air pollution is a major public health concern in the region: the 2015 iteration of the Global Burden of Disease project estimated that almost 60% of deaths attributable to $PM_{2.5}$ globally happened in South Asia (Cohen et al., 2017). McMichael et al. (2008) included particulate air pollution in their model for Delhi but found a minimal impact on the temperature effect estimate, while Singh et al. (2019) observed that the associations between mortality and extreme temperature in Varanasi, India are substantially confounded by different air pollutants, in particular PM_{10}. There is emerging evidence that the adverse effects of hot temperature or heat waves on human health can be amplified by high air pollution levels, and vice versa – the harmful effects of air pollution are enhanced by high temperature (Analitis et al., 2018; Burkart et al., 2014b; Kinney, 2018b). Various mechanisms have been identified as a possible explanation of these synergistic effects. Hot days might be associated with higher emissions of certain pollutants since ozone and secondary particles are generated faster in the atmosphere in the presence of sunlight and higher temperatures (Ebi and McGregor, 2008; Kinney, 2018b). Behavioural responses to hot temperatures, e.g., increased use of (air-conditioned) cars, can also increase emissions of air pollutants. Physiological stress in the body due to extreme heat may also make individuals more sensitive to air pollution exposure and allergens, or vice versa (Gordon, 2003; Ren et al., 2011). However, not all studies have identified synergistic effects of temperature and air pollution (Basu, Feng and Ostro, 2008; Zanobetti and Schwartz, 2008) and further research is warranted, particularly in South Asia.

4.6. Need for improved environmental and health monitoring

We identified the lack of reliable and regularly collected data on mortality and temperature as a major obstacle for conducting analysis in the region. Comprehensive analysis of temperature-related mortality requires daily all-cause or cause-specific mortality data, which are not readily available for most countries in South Asia. Similar to most LMICs, majority of deaths in countries of the region occur at home and remain undocumented or without a medically certified cause of death, hence the reliance on HDSSs and SVRSs for studying premature mortality (Jha et al., 2006). All countries in the region have some form of a vital registration system (UN DESA, 2010), but these have been rated as poorly functioning with the exception of the Maldives and Sri Lanka (Mikkelsen et al., 2015). Continued efforts to strengthen vital registration systems are important not only for mapping vulnerabilities due to temperatures but also to other climate-related health impacts.

4.7. Strengths and limitations

This review covered a region highly vulnerable to climate change but relatively understudied. Our review synthesises evidence from studies on ambient temperature, heat waves, and studies with different methodological approaches: a more inclusive approach than previous reviews (Green et al., 2019). We assessed the overall quality and strength of the evidence following the Navigation Guide, specifically developed for environmental health research. Finally, we used a new, flexible statistical approach, which allowed us to pool estimates of non-linear exposure response functions and calculate MMT across studies without having access to individual study data. In contrast, previous *meta*-analyses based on summary results from the literature relied on more simplified methods that did not account for non-linear and delayed effects.

Our study also has some limitations. The considerable heterogeneity of the included studies in terms of study design, lagged effects, outcome and exposure metrics, and the overlap of populations across publications limited the number of studies that could be included in the *meta*-analysis. Furthermore, although we tried to select studies with comparable designs, differences across studies remained: one study in the *meta*-analysis reported effects stratified by season as opposed to year-round effects (Ingole et al., 2017) and one reported cold effects for lag 0–14 instead of lag 0–13 days (Burkart and Kinney, 2017). A *meta*-regression could have elucidated differences due to methods, exposure measures, latitude, temperature thresholds, and others, but was not possible given the small number of eligible studies. Half of the studies included in the review and three in the *meta*-analysis were conducted in India. Therefore, generalizability of our findings might be somewhat limited since the countries in the region differ in terms of their climate, geography and topology, as well as culture, demography, economic development, and other population characteristics. This review has focused on excess mortality associated with temperature variability and extreme temperatures, not accounting for other potential health effects related to non-fatal conditions and psychological stress (Carleton, 2017; Pailler and Tsaneva, 2018).

Finally, we may have missed some relevant publications since the review did not cover research published in other languages than English. Also, given the policy relevance of this topic and the scientific practices in the region, it is likely that relevant publications in the grey literature have been excluded (e.g. reports from government or non-profit or international organisations). However, it is highly unlikely that their inclusion would appreciably change the conclusions in this review since high quality quantitative epidemiological studies are mainly published in peer-reviewed journals.

4.8. Conclusions

We found a limited number of studies, which have attempted to quantify the mortality effects of temperature in South Asia. The existing body of evidence, focused mainly on India and Bangladesh, points to excess mortality associated with hot and cold temperatures as well as heat waves, but our *meta*-analysis based on five of the included time series studies confirmed evidence for high temperatures only. More evidence is needed to reduce uncertainty in the shape and size of the temperature-mortality association in a region that is a hotspot for climate vulnerability and experiencing rapid population growth and urbanisation. In particular, a better understanding of the modifying factors of the temperature-mortality relationship is necessary to inform targeted interventions in the region. In light of slow progress in achieving greenhouse gas emission reduction targets, more evidence on viable adaptation options for the population in South Asia is particularly important. More robust exposure–response functions are also essential for health impact assessments of temperature-related mortality and morbidity burdens under different climate change mitigation or adaptation scenarios to inform decision making.

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Declaration of Competing Interest

The authors declared that there is no conflict of interest.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2020.106170.

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Supplementary Material

Table S1. Example of the full search strategy, used in Embase.

Search	EMBASE
#1 Exposure terms	('temperature*':ti,ab,kw OR 'weather':ti,ab,kw OR 'season*':ti,ab,kw OR 'heat wave':ti,ab,kw OR 'heatwave*':ti,ab,kw OR 'heat*':ti,ab,kw OR 'humidex':ti,ab,kw OR 'climate*':ti,ab,kw OR 'climatic':ti,ab,kw OR 'wet bulb':ti,ab,kw)
#2 Outcome terms	('mortality':ti,ab,kw OR 'death*':ti,ab,kw OR 'years of life lost':ti,ab,kw OR 'life expectancy':ti,ab,kw OR 'yll':ti,ab,kw OR 'hyperthermia':ti,ab,kw OR 'heat stroke':ti,ab,kw OR 'thermal stress':ti,ab,kw)
#3 South Asia country terms	('afghanistan':ti,ab,kw OR 'bangladesh':ti,ab,kw OR 'bhutan':ti,ab,kw OR 'india':ti,ab,kw OR 'maldives':ti,ab,kw OR 'nepal':ti,ab,kw OR 'pakistan':ti,ab,kw OR 'sri lanka':ti,ab,kw OR 'south asia':ti,ab,kw)
#6 Studies published over 1990–2018	[1990-2018]/py AND [english]/lim AND [1-1-1990]/sd NOT [16-8-2018]/sd

Table S2. Study inclusion and exclusion criteria.

	Inclusion criteria	Exclusion criteria
Literature type	- Peer-reviewed papers reporting empirical observational studies	- Commentaries, discussion articles, editorials, literature reviews, case studies, articles with descriptive analysis only - News reports and book chapters - Non-peer-reviewed literature
Population	- Human	- Non-human
	- General population in the South Asia region, country in the South Asia region, city, county/state or rural areas	- Patients from a specific hospital
	- Patients from a representative number of hospitals in a area, that has a catchment area representative of the target population	- Patients from private clinics or a hospital that are not representative for the country population
Exposure measure	- Temperature (daily/weekly, monthly/annual)	- No measure of temperature and/or heatwave exposure
	- Composite indices of temperature and other weather variables such as humidity, radiation, wind speed, etc	
	- Heatwave event	
Outcome measure	- All-cause or cause-specific mortality counts	- Morbidity outcomes
	- Years of Life Lost (YLL)	
	- Life expectancy	
Country of study	- South Asia as classified by the World Bank (Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka)	- Countries in any other regions as classified by the World Bank
Year of publication	- 1990 (incl.)– 13th August 2020	- Prior to 1990
Language of publication	- English	- Languages other than English

Table S3. Instructions for the Risk of Bias Assessment in individual studies

Adapted from: Office of Health Assessment and Translation (OHAT) Risk of Bias Rating Tool for Human and Animal Studies

	Judgement criteria
Selection: Did selection of study participants result in appropriate comparison groups?	
Definitely Low risk of bias	□ There is direct evidence that inclusion of deaths in each time period (e.g. day/week/month) is not based on any factor associated with exposure (ie. Inclusion of deaths varies during summer/holidays). <u>Example:</u> There is evidence that deaths were consistently counted each time period.
Probably Low risk of bias	□ There is indirect evidence that inclusion of deaths in each time period (e.g. day/week/month) is not based on any factor associated with exposure <u>Example</u>: There is no direct evidence that deaths were consistently counted each time period. However, for data collected through a routine and established surveillance systems (e.g. HDSS, SVRS, vital registry, census data and municipal data) there is no reason to suspect important temporal variation in inclusion of deaths.
Probably High risk of bias	□ There is indirect evidence that the inclusion of deaths in each time period (e.g. day/week/month) is based on some factor associated with exposure. OR □ There is insufficient information provided about the consistency of inclusion of deaths over the study period (record “NR” as basis for answer). <u>Example:</u> There is no evidence that inclusion of deaths was consistent across time periods. However, for data collected through unofficial sources (e.g. newspapers) the possibility of an important variation in inclusion of deaths linked exposure cannot be excluded.
Definitely High risk of bias	□ There is direct evidence that the inclusion of deaths is based on some factor associated with exposure. <u>Example</u>: There is evidence that the identification of deaths varied with exposure (e.g. plots of time series showing unusual patterns).
Confounding: Did the study design or analysis account for important confounding and modifying variables?	
Definitely Low risk of bias	□ There is direct evidence that appropriate adjustments or explicit considerations were made for primary covariates and confounders in the final analyses through the use of statistical models to reduce research-specific bias including standardization, matching, adjustment in multivariable model, stratification, propensity scoring, or other methods that were appropriately justified. AND □ There is direct evidence that primary covariates and confounders were assessed using valid and reliable measurements, AND □ There is direct evidence that other exposures anticipated to bias results were not present or were appropriately measured and adjusted for

	Example: The study controlled for primary confounders (time trend and season) and other potential confounders (e.g., day of the week, air pollution, latitude, public holiday.) using valid and reliable measurements and appropriate methods.
Probably Low risk of bias	□ There is indirect evidence that appropriate adjustments were made, OR □ It is deemed that not considering or only considering a partial list of covariates or confounders in the final analyses would not appreciably bias results. AND □ There is evidence (direct or indirect) that primary covariates and confounders were assessed using valid and reliable measurements, OR □ It is deemed that the measures used would not appreciably bias results (i.e., the authors justified the validity of the measures from previously published research), AND □ There is evidence (direct or indirect) that other co-exposures anticipated to bias results were not present or were appropriately adjusted for, OR □ It is deemed that co-exposures present would not appreciably bias results. Example: The study controlled for primary confounders (time trend and season) through the use of statistical models or by design, but did not control for other potential confounders.
Probably High risk of bias	□ The study did not account for any or accounted for some but not all of the primary confounders AND □ This lack of accounting may have introduced substantial bias, OR □ There is indirect evidence that primary covariates and confounders were assessed using measurements of unknown validity, OR □ There is insufficient information provided about the measurement techniques used to assess primary covariates and confounders (record “NR” as basis for answer). Example: The study adjusted for confounders deemed as primary by topic experts – time trend and season, but an inadequate method was used to do so.
Definitely High risk of bias	□ The study did not account for any or evaluate important potential confounders AND □ There is direct evidence that this lack of accounting may have introduced substantial bias OR □ There is direct evidence that primary covariates and confounders were assessed using non valid measurements. Example: The study did not adjust for any of the confounders deemed as primary by topic experts – time trend and season.
Exposure assessment: Can we be confident in the exposure characterization?	

Definitely Low risk of bias	□ There is direct evidence that the exposure was consistently assessed using well-established methods that directly measure exposure, OR □ Exposure was assessed using indirect measures (e.g., questionnaire or occupational exposure assessment by a certified industrial hygienist) that have been validated or empirically shown to be consistent with methods that directly measure exposure (i.e., inter-methods validation: one method vs. another). AND □ Quality control procedure on the temperature series has been carried out, e.g. data have been explored for missing values and these have been handled in the initial data processing (employing rules, algorithms or models to impute missing values). AND □ If there are missing observations from the time series, there is evidence that missingness is not related to exposure (e.g missing data during unusual weather) Example: Daily temperature data obtained from a nearby local weather station or other reliable source. If online data were used these have been validated against background data.
Probably Low risk of bias	□ There is indirect evidence that exposure was consistently assessed using well established methods that directly measure exposure, OR □ Exposure was assessed using indirect measures that have been validated or empirically shown to be consistent with methods that directly measure exposure (i.e., inter-method validation).
Probably High risk of bias	□ There is indirect evidence that the exposure was assessed using poorly validated methods that directly measure exposure, OR □ There is direct evidence that the exposure was assessed using indirect measures that have not been validated or empirically shown to be consistent with methods that directly measure exposure, OR □ There is insufficient information provided about the exposure assessment, including validity and reliability, but no evidence for concern about the method used.
Definitely High risk of bias	□ There is direct evidence that the exposure was assessed using methods with poor validity, OR □ Evidence of exposure misclassification Example: The study did not used daily data, but weekly, monthly, yearly data etc.
Outcome assessment: Can we be confident in the outcome assessment?	
Definitely Low risk of bias	□ Outcome data on all cause mortality stem from a reliable data source AND □ Studies provide evidence of quality assurance of outcome data Example: Outcome data were collected through routine and long-term surveillance systems (e.g. HDSS, SVRS) and there is evidence that date of death was correctly recorded and not falsified, e.g. showing counts in the time series and checking for unrealistic patterns.
Probably Low risk of bias	□ There is indirect evidence that the outcome was assessed using acceptable methods, OR

	□ It is deemed that the outcome assessment methods used would not appreciably bias results. Example: Outcome data were collected through routine and long-term surveillance systems (e.g. HDSS, SVRS) the outcome assessment method can be deemed adequate, but there is no direct evidence that date of death was correctly recorded and not falsified.
Probably High risk of bias	□ There is indirect evidence that the outcome assessment method is an insensitive instrument. OR □ There is insufficient information provided to judge that deaths were correctly recorded (record "NR" as basis for answer). Example: There is no direct evidence that the outcome was assessed using acceptable methods. However, since vital registries in all of the countries in the region are considered by experts as poorly functioning and not reliable (Mikkelsen et al., 2015), the outcome assessment method will be deemed as "probably high risk of bias" when based on these sources.
Definitely High risk of bias	□ There is direct evidence that the outcome assessment method is an insensitive instrument. Example: Outcome data stem from unofficial sources (e.g. newspapers, media, unofficial reports), which are very likely to show inaccurate data.
Selective reporting: Were all measured outcomes reported?	
Definitely Low risk of bias	□ There is direct evidence that all of the study's measured outcomes (primary and secondary) outlined in the protocol, methods, abstract, and/or introduction (that are relevant for the evaluation) have been reported. This would include outcomes reported with sufficient detail to be included in meta-analysis or fully tabulated during data extraction and analyses had been planned in advance.
Probably Low risk of bias	□ There is indirect evidence that all of the study's measured outcomes (primary and secondary) outlined in the protocol, methods, abstract, and/or introduction (that are relevant for the evaluation) have been reported, OR □ Analyses that had not been planned in advance (i.e., retrospective unplanned subgroup analyses) are clearly indicated as such and it is deemed that the unplanned analyses were appropriate and selective reporting would not appreciably bias results (e.g., appropriate analyses of an unexpected effect). This would include outcomes reported with insufficient detail such as only reporting that results were statistically significant (or not).
Probably High risk of bias	□ There is indirect evidence that all of the study's measured outcomes (primary and secondary) outlined in the protocol, methods, abstract, and/or introduction (that are relevant for the evaluation) have not been reported, OR □ There is indirect evidence that unplanned analyses were included that may appreciably bias results, OR □ There is insufficient information provided about selective outcome reporting (record "NR" as basis for answer).

Definitely High risk of bias	□ There is direct evidence that all of the study's measured outcomes (primary and secondary) outlined in the protocol, methods, abstract, and/or introduction (that are relevant for the evaluation) have not been reported. In addition to not reporting outcomes, this would include reporting outcomes based on composite score without individual outcome components or outcomes reported using measurements, analysis methods or subsets of the data (e.g., subscales) that were not pre-specified or reporting outcomes not pre-specified, or that unplanned analyses were included that would appreciably bias results.
Other bias: Were statistical methods appropriate?	
Definitely Low risk of bias	□ There is direct evidence that the statistical method used was appropriate. <u>Example:</u> The selected statistical model is appropriate and its suitability and robustness has been checked (e.g. initially fitting a smooth function to explore the shape of the temperature-mortality relationship, comparing model fit statistics of smoothed functions and adjusted linear approximations, checking the robustness of the model, analyzing the relationship of interest within strata of the confounder, etc.)
Probably Low risk of bias	□ There is indirect evidence that the statistical method used was appropriate. <u>Example:</u> There is no direct evidence for the suitability or robustness of the model. However, the selected model seems appropriate.
Probably High risk of bias	□ There is indirect evidence that the statistical method used was not appropriate. OR □ There is insufficient information (e.g., not reported or "NR") provided to judge the appropriateness of the statistical method. <u>Example:</u> Reporting results when it is likely that two or more of the explanatory variables included in the model are highly correlated (although there is no direct evidence), which might cause multicollinearity problems. Reporting of statistical tests that require normally distributed data (e.g., t-test or ANOVA) when using count data (e.g. number of deaths per day); also using Pearson correlation instead of Spearman for count data.
Definitely High risk of bias	□ There is direct evidence that the statistical method used was not appropriate for addressing the research question. <u>Example:</u> Inferring a causal relationship between temperature and mortality when performing a correlation analysis only.

Table S4. Reasons for study exclusion at the stage of the full text review.

Reason for exclusion	Studies (Author, year)
Not published in a peer reviewed journal/Conference abstracts/Book chapters	Kovats and Wilkinson (2004); Aakanksha; Hudda, V.; Nithiyanandam, (2017); Dholakia, H.H., and A Garg (2018); Raju (2018)
Not reporting outcomes related to mortality, YLL or life expectancy	Mall et al. (2017); Aakanksha; Hudda, V.; Nithiyanandam, (2017); Sun et al., (2019)
Not reporting empirical study results	Dear (2009); Azhar et al. (2014b); The Lancet, (2018); Sun et al., (2019)
No measure of ambient temperature and/or heatwave exposure	Burkart et al. (2011); Becker, (2002); Cecinati et al., (2019); Banerjee and Maharaj, (2020)
Correction of an earlier published version of an already included study	The PLOS ONE Staff (2014)
Presents only descriptive analysis	Chaudhury et al. (2000); Ray-Bennett, (2018); Mahapatra et al., (2018); Vittal et al., (2020)
Not representative of the general population	Mall et al. (2017); van der Linden et al., (2019)
Duplicate	Azhar et al. (2014a)
Not specific to South Asian countries	Takahashi et al. (2007); Gasparrini et al., (2017)

Table S5. Risk of bias assessment summary for Alam et al. (2012)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data comes from a Sample Vital Registration System (SVRS) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Probably low risk	The study controlled for all the primary confounders (time trend and seasonal pattern).
Possibility of detection bias (exposure)	Definitely high risk	The study used weekly temperature data for measuring exposure, which might attenuate the true temperature effect. Also, no quality control of the temperature data is reported.
Possibility of detection bias (outcome: all-cause mortality)	Probably low risk	Outcome data are based on a SVRS, which it is routine and long-term and, thus, likely to be more reliable than other data collection systems. However, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Probably low risk	Poisson generalized additive model (GAM) is an appropriate method for analyzing time series count data. However, no tests or sensitivity analysis for checking the appropriateness of the model is reported. Hence, there is only indirect evidence that the method is appropriate.

Table S6. Risk of bias assessment summary for Hashizume et al. (2009)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data comes from a Health and Demographic Surveillance System (HDSS) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study controlled for all the primary confounders (time trend and season) and also for day of the week and public holiday.
Possibility of detection bias (exposure)	Probably low risk	The study used daily temperature data for measuring exposure. Data was obtained from official sources – the Bangladesh Meteorological Department. However, it is not specified whether a quality control procedure was carried out and if the data have been explored for missing values.
Possibility of detection bias (outcome: all-cause mortality)	Probably low risk	Outcome data are based on a HDSS, which it is routine and long-term and, thus, likely to be more reliable than other data collection systems. However, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	Poisson generalized linear model is an appropriate method for analyzing time series count data. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S7. Risk of bias assessment summary for Azhar et al. (2014a)

Source of bias	**Rating**	**Support for the judgement**
Possibility of selection bias	Definitely low risk	The daily mortality time series that are presented on Figure 1 show a reasonable distribution, hence providing evidence that inclusion of deaths in each time period is not based on any factor associated with the exposure.
No/Inadequate control of confounding	Probably high risk	The study did not account for any of the primary of additional confounders.
Possibility of detection bias (exposure)	Probably low risk	The study used daily temperature data for measuring exposure. Data was obtained from official sources – the Indian Meteorology Department. However, it is not specified whether a quality control procedure was carried out.
Possibility of detection bias (outcome: all-cause mortality)	Probably high risk	Death records from the Ahmedabad Municipal Corporation Office of the Registrar of Births and Death are used. Given the probably low reliability of vital registry and municipal data from countries in the region, there is a possibility that not all deaths in the study period have been captured, which can affect the final study results.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely high risk	The study makes inferences about the association between temperature and mortality based on correlation analysis. Also, Pearson correlation is not an appropriate method to use for count data

Table S8. Risk of bias assessment summary for Sewe et al. (2018)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Definitely low risk	The daily mortality time series that are presented on Figure S1 show a reasonable distribution, hence providing evidence that inclusion of deaths in each time period is not based on any factor associated with the exposure.
No/Inadequate control of confounding	Definitely low risk	The study controlled for all the primary confounders (time trend and season) and also for day of the week and “heaping days”.
Possibility of detection bias (exposure)	Probably low risk	The study used daily temperature data for measuring exposure. Data was obtained from the nearest weather station for each study site. However, it is not specified whether a quality control procedure was carried out.
Possibility of detection bias (outcome: all-cause mortality)	Definitely low risk	Outcome data are based on a HDSS, which is a routine and long-term and, thus, likely to be more reliable than other data collection systems. Plots of daily death counts are included in Figure S1, which show a reasonable distribution and hence, provide direct evidence that outcome was correctly measured.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	Quasi-Poisson distributed-lag non-linear model (DLNM) is an appropriate method for analyzing time series count data. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S9. Risk of bias assessment summary for McMichael et al.(2008)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data comes from official sources (the New Delhi Municipal Committee) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study controlled for all the primary confounders (secular trend and season) and also for daily relative humidity, day of week, public holidays, daily particulate pollution concentration.
Possibility of detection bias (exposure)	Probably low risk	The study used daily temperature data for measuring exposure. Data was obtained from local meteorological stations (India Meteorological Department). Appropriate quality control procedure on the time series data has been carried out. However, there is no evidence that the 71 days with missing observations for Delhi are not related to unusual weather or to holidays.
Possibility of detection bias (outcome: all-cause mortality)	Definitely high risk	Municipal data is used for measuring mortality counts. Given the probably low reliability of vital registry and municipal data from countries in the region, there is a possibility that not all deaths in the study period have been captured, which can affect the final study results. Also, there is some direct evidence that the outcome assessment method is insensitive. Table 1 shows that only 13 % of total deaths in the series were in the age group 65+ and almost 50 % in the age group 0-14, which is very unbalanced even for a LMIC and points to problems with incompleteness of data. *"There was limited information on the quality of the death registration data, but there are likely to have been problems with completeness and with certification of cause of death, particularly in the Indian and Thai cities."* Also, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	Poisson generalized linear model is an appropriate method for analyzing time series count data. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S10. Risk of bias assessment summary for Burkart et al. (2013)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data comes from a Sample Vital Registration System (SVRS) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study controlled for all the primary confounders (time trend and season) and also for day of the month.
Possibility of detection bias (exposure)	Probably high risk	The study used daily temperature data for measuring exposure. Data was obtained from local meteorological stations (Bangladesh Meteorological Department). Appropriate quality control procedure on the time series data has been carried out. However, average mean temperature was aggregated for the whole country and regional meteorological variations were not considered, which might conceal true temperature-mortality associations in some locations. Also, there is no evidence that the missing observations in the data (17 %) are not related to unusual weather or to holidays.
Possibility of detection bias (outcome: all-cause mortality)	Probably low risk	Outcome data are based on a SVRS, which it is routine and long-term and, thus, likely to be more reliable than other data collection systems. However, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	Poisson distributed lag non-linear model (DLNM) is an appropriate method for analyzing time series count data. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S11. Risk of bias assessment summary for Burkart et al. (2011)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Definitely low risk	The daily mortality time series that are presented on Figure S1 show a reasonable distribution, hence providing evidence that inclusion of deaths in each time period is not based on any factor associated with the exposure.
No/Inadequate control of confounding	Definitely low risk	The study controlled for all the primary confounders (time trend and season) and also for day of the month.
Possibility of detection bias (exposure)	Probably high risk	The study used daily temperature data for measuring exposure. Data was obtained from 26 local meteorological stations (Bangladesh Meteorological Department) and used to calculate spatial average daily mean temperature values. Appropriate quality control procedure on the time series data has been carried out. However, average mean temperature was aggregated for the whole country and regional meteorological variations were not considered, which might conceal true temperature-mortality associations in some locations. Also, there is no evidence that the missing observations in the data (17 %) are not related to unusual weather or to holidays.
Possibility of detection bias (outcome: all-cause mortality)	Definitely low risk	Outcome data are based on a HDSS, which is a routine and long-term and, thus, likely to be more reliable than other data collection systems. Plots of daily death counts are included in Figure S1, which show a reasonable distribution and hence, provide direct evidence that outcome was correctly measured.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	Poisson generalized additive model (GAM) is an appropriate method for analyzing time series count data. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S12. Risk of bias assessment summary for Ingole et al. (2017)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data comes from a Health and Demographic Surveillance System (HDSS) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study used a case-cross-over study design, where controls for each case were selected for the same year, month and day of the week as the case. Also, a cubic spline function was used to adjust for season and time trend. Hence, the study controlled for the primary confounders and for day of the week.
Possibility of detection bias (exposure)	Probably low risk	The study used daily temperature data for measuring exposure. Data was obtained from the National Oceanic and Atmospheric Administration and it was validated against data from the local meteorological office of the Indian Meteorological Department, showing good agreement. However, it is not specified whether other quality control procedure was carried out.
Possibility of detection bias (outcome: all-cause mortality)	Probably low risk	Outcome data are based on a HDSS, which it is routine and long-term and, thus, likely to be more reliable than other data collection systems. However, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	Quasi-Poisson regression and conditional logistic regression model used in a case-crossover study design are an appropriate method for analyzing time series count data. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S13. Risk of bias assessment summary for Ingole et al. (2012)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Definitely low risk	The daily mortality time series that are presented on Figure 1 show a reasonable distribution, hence providing evidence that inclusion of deaths in each time period is not based on any factor associated with the exposure.
No/Inadequate control of confounding	Probably low risk	The study controlled for the primary confounders only – season and time trend.
Possibility of detection bias (exposure)	Probably low risk	The study used daily temperature data for measuring exposure. Data was obtained from a local meteorological office of the Indian Meteorological Department. However, it is not specified whether a quality control procedure was carried out.
Possibility of detection bias (outcome: all-cause mortality)	Definitely low risk	Outcome data are based on a HDSS, which is a routine and long-term and, thus, likely to be more reliable than other data collection systems. Plots of daily death counts are included in Figure S1, which show a reasonable distribution and hence, provide direct evidence that outcome was correctly measured.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	A Poisson regression model is an appropriate method for analyzing time series count data. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S14. Risk of bias assessment summary for Ingole et al. (2015)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with the exposure. Since the data comes from a Health and Demographic Surveillance System (HDSS) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study controlled for only the primary confounders –seasonality, time trend and in addition – day of the week.
Possibility of detection bias (exposure)	Probably low risk	The study used daily temperature data for measuring exposure. Data was obtained from a local meteorological office of the Indian Meteorological Department. However, it is not specified whether a quality control procedure was carried out.
Possibility of detection bias (outcome: all-cause mortality)	Probably low risk	Outcome data are based on a HDSS, which it is routine and long-term and, thus, likely to be more reliable than other data collection systems. However, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	Quasi-Poisson regression is an appropriate method for analyzing time series count data. Sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S15. Risk of bias assessment summary for Hajat et al. (2005)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with the exposure. Since the data comes from official sources (the New Delhi Municipal Committee) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study controlled for all the primary confounders (time trend and season) and also for relative humidity, rainfall, particulate air pollution, day of the week and public holidays.
Possibility of detection bias (exposure)	Probably low risk	The study used daily temperature data for measuring exposure. Data was obtained from a local meteorological station. However, it is not specified whether a quality control procedure was carried out.
Possibility of detection bias (outcome: all-cause mortality)	Probably high risk	Municipal data is used for measuring mortality counts. Given the probably low reliability of vital registry and municipal data from countries in the region, there is a possibility that not all deaths in the study period have been captured, which can affect the final study results. Also, it is hard to confirm to what extent the mortality data used is representative for the whole city: *"the Delhi data relate to one of three districts in the National Capital Territory and include approximately 25% of the deaths in the city as a whole".* The study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	Poisson generalized linear regression is an appropriate method for analyzing time series count data. Sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S16. Risk of bias assessment summary for Fu et al. (2018)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with the exposure. Since the data comes from India´s Sample Registration System we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study used a case-cross-over study design, where controls for each case were matched to the same day of the week within the same month as when the death occurred. In addition, the study used DLNM, thus controlling at the same time for seasonality and long-term trend. Hence, the study controlled for all the primary confounders (time trend and season), but also for day of the week by design.
Possibility of detection bias (exposure)	Probably low risk	The study used daily temperature data for measuring exposure. Data was obtained from the India Meteorological Department. However, it is not specified whether a quality control procedure was carried out.
Possibility of detection bias (outcome: all-cause mortality)	Probably low risk	Outcome data are based on a Sample Registration System, which is routine and long-term and, thus, likely to be more reliable than other data collection systems. However, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	Distributed-lag nonlinear model (DLNM) within a case-crossover study design is an appropriate method for analyzing time series count data. Sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S17. Risk of bias assessment summary for Ghumman and Horney (2016)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably high risk	The study compares number of deaths in June 2015 (heat wave period) to number of deaths in June 2014 (chosen as a reference period). However, the authors point out as a limitation: *"Due to the large number of excess deaths, the burden of record keeping during a public health emergency, and the decision to use only death certificates with complete information, these data are almost certainly an underestimate of total mortality."* Hence, we cannot exclude the likelihood that counted deaths depended on some factor associated with the exposure.
No/Inadequate control of confounding	Probably high risk	The study did not control for any of the primary confounders.
Possibility of detection bias (exposure)	Probably high risk	The study used daily temperature data for measuring exposure. Data was obtained from an online source: AccuWeather.com (AccuWeather; State College, Pennsylvania USA). However, it is not clear whether the data has been collected from local meteorological stations or validated with local data.
Possibility of detection bias (outcome: all-cause mortality)	Probably high risk	Data are obtained from medical certificates from 7 leading public and private hospitals in the city: *"A record of deaths attributable to the heat wave by attending medical personnel in seven public hospitals and private clinics were obtained via an in-person examination of the death certificates by a trained physician"; "Mortality data were collected by a trained physician who examined death certificates at hospitals and private clinics; however, those who died at home or in other facilities not visited are also not included".* It is not defined what is meant by "deaths attributable to heat wave" and "deaths with a primary cause of death of heat-related illness", data likely to be an underestimate if only deaths from heatstroke are considered and if deaths happening outside hospitals are not counted. Also, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely high risk	The study makes inferences about the association between temperature and mortality risk based only on calculation of risk difference and rate ratios for total number of deaths during a heatwave period and a reference period, without adjusting for any confounders.

Table S18. Risk of bias assessment summary for Mazdiyasni et al. (2017)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably high risk	Mortality data were obtained from *"the India Meteorological Department and from annual reports, which compiled information from newspaper and other sources about mortality during specific extreme heat events*". Since these are unofficial sources, the possibility that the number of deaths measured each day depended on some factor associated with the exposure (daily temperature) cannot be excluded.
No/Inadequate control of confounding	Probably high risk	The study did not adjust for any of the primary confounders.
Possibility of detection bias (exposure)	Definitely high risk	The study used daily temperature data from 395 local stations of the India Meteorological Department in order to estimate mean summer temperature and heatwave days. Averaging temperature values over all summer months might attenuate the true temperature effect. Also, temperature data were aggregated for the whole country, which might conceal true temperature-mortality effects for some locations. It is not specified whether a quality control procedure was carried out.
Possibility of detection bias (outcome: all-cause mortality)	Definitely high risk	Data are obtained from unofficial sources, which are highly unlikely to capture mortality during specific extreme heatwave events. No information is provided on where the data in newspapers and annual reports were compiled from.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are reported. Analysis of the underlying mechanisms of the temperature effects related to income were not pre-specified in the abstract or the methods section, but these are appropriate and selective reporting is not likely to bias the final results.
Other bias (Inappropriate statistical methods)	Definitely high risk	The study uses Pearson correlation of annual mortality and mean annual summer temperature and a probabilistic model to infer causality.

Table S19. Risk of bias assessment summary for Lindeboom et al. (2012)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with the exposure. Since the data comes from India´s ICDRR,B´s Health and Demographic Surveillance System (HDSS) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study controlled for all the primary confounders (time trend and season) and also for public holiday, festivals and cyclone.
Possibility of detection bias (exposure)	Probably low risk	The study used daily temperature data for measuring exposure. Data was obtained from a local meteorological office of the Indian Meteorological Department. Missing values have been replaced through linear interpolation. However, there is no evidence that missing values are not related to the days excluded (holidays or days with unusual weather).
Possibility of detection bias (outcome: all-cause mortality)	Probably low risk	Outcome data are based on a HDSS, which it is routine and long-term and, thus, likely to be more reliable than other data collection systems. However, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	Poisson generalized additive model (GAM) is an appropriate method for analyzing time series count data. Sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S20. Risk of bias assessment summary for Desai et al. (2015)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably high risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. The mortality data of the city were obtained from the Birth and Death Registration Department of SMC. Before data analysis, non-resident Surat city deaths were excluded from the data set through sorting the place of residence (town/village). It is not clear why non-resident deaths were excluded. If there was a reason that on days with high temperature there were more visitors/migrants (e.g. seasonal work), this might potentially lead to selection bias.
No/Inadequate control of confounding	Definitely high risk	The study did not adjust for any of the primary confounders.
Possibility of detection bias (exposure)	Probably high risk	Daily maximum temperature data were obtained from Tutiempo Network, S.L website. It is not specified in the paper whether the data originate from official weather stations or if it has been validated with such data. Days with missing data for temperature and/or humidity were excluded from the analysis and there is no evidence that missing values are not related to the days excluded (holidays or days with unusual weather).
Possibility of detection bias (outcome: all-cause mortality)	Probably high risk	Death records from the Birth and Death Registration Department of SMC are used. Given the probably low reliability of vital registry and municipal data from countries in the region, there is a possibility that not all deaths in the study period have been captured, which can affect the final study results. Also, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Definitely high risk	In the methods section the study specifies that they use unconstrained distributed lag model to assess mortality displacement, but in the results section only correlation analysis with mortality and temperature/humidity at different lags is reported. Also, in the abstract and methods section the study states that it analyzes the whole period 2001-2012, but correlation analysis is performed only for the year 2010.
Other bias (Inappropriate statistical methods)	Definitely high risk	The study makes inferences about the association between temperature and mortality based on correlation analysis. Also, Pearson correlation is not an appropriate method to use for count data.

Table S21. Risk of bias assessment summary for Burkart and Kinney (2017)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Definitely low risk	The daily mortality time series that are presented on Figure 1 show a reasonable distribution, hence providing evidence that inclusion of deaths in each time period is not based on any factor associated with the exposure
No/Inadequate control of confounding	Definitely low risk	The study controlled for all the primary confounders (time trend and season) and also for day of the month.
Possibility of detection bias (exposure)	Probably high risk	The study used daily temperature data for measuring exposure. Data was obtained from 26 meteorological stations (Bangladesh Meteorological Department) if at least 75% of the measurements for a day were available. Average mean temperature was aggregated for the whole country and regional meteorological variations were not considered, which might conceal true temperature-mortality associations in some locations. Also, number of days with missing values is not reported.
Possibility of detection bias (outcome: all-cause mortality)	Definitely low risk	Outcome data are based on a SVRS, which is a routine and long-term surveillance system and, thus likely to be more reliable than other data collection systems. Plots of daily death counts are included in Figure 1, which show a reasonable distribution and hence, provide direct evidence that outcome was correctly measured.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Other bias (Inappropriate statistical methods)	Definitely low risk	Poisson generalized additive model (GAM) and Poisson Distributed Lag Nonlinear Model (DLNM) are appropriate methods for analyzing time series count data. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S22. Risk of bias assessment summary for Babalola et al. (2018)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Definitely low risk	The monthly mortality counts that are presented on Table S1 show a reasonable distribution, hence providing evidence that inclusion of deaths in each time period is not based on any factor associated with the exposure
No/Inadequate control of confounding	Probably high risk	The study adjusted for only one of the primary confounders, namely, season (by adjusting for month).
Possibility of detection bias (exposure)	Definitely high risk	The study used monthly temperature data for measuring exposure, which might attenuate the true temperature effect or capture seasonal effects rather than true temperature effects. Also, no quality control of the temperature data is reported.
Possibility of detection bias (outcome: all-cause mortality)	Definitely low risk	Outcome data are based on a HDSS, which is a routine and long-term and, thus, likely to be more reliable than other data collection systems. Monthly mortality counts are included in Table S1 and these show a reasonable distribution and hence, provide direct evidence that outcome was correctly measured.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Inappropriate statistical methods	Probably high risk	The use of Pearson correlation and linear regression is not appropriate for count data.

Table S23. Risk of bias assessment summary for Rathi et al. (2017)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data are collected through a routine and established surveillance system (the Health Department of Surat Municipal Corporation) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Probably high risk	The study did not adjust for any of the primary confounders.
Possibility of detection bias (exposure)	Probably high risk	Daily maximum temperature data were obtained from Tutiempo Network, S.L website. It is not specified in the paper whether the data originate from official weather stations or if it has been validated against such data. Days with missing data for temperature and/or humidity were excluded from the analysis and there is no evidence that missing values are not related to the days excluded (holidays or days with unusual weather).
Possibility of detection bias (outcome: all-cause mortality)	Probably high risk	Death records from the Birth and Death Registration Department of SMC are used. Given the probably low reliability of vital registry and municipal data from countries in the region, there is a possibility that not all deaths in the study period have been captured, which can affect the final study results. Also, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Inappropriate statistical methods	Definitely high risk	The study makes inferences about the association between temperature and mortality based on correlation analysis. Also, Pearson correlation is not an appropriate method to use for count data.

Table S24. Risk of bias assessment summary for Murari et al. (2015)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably high risk	Data on heat-wave induced mortality are obtained from the Ministry of Home Affairs (Government of India) for Delhi, Rajasthan, Maharashtra and Orissa. Since it is not specified how heat-related mortality is classified and measured, the possibility that the number of deaths measured each day depended on some factor associated with the exposure (daily temperature) cannot be excluded
No/Inadequate control of confounding	Probably high risk	The study did not adjust for any of the primary confounders.
Possibility of detection bias (exposure)	Probably high risk	The study used daily gridded temperature data for calculating number of heat waves per year. Data were obtained from a 395 meteorological stations of the Indian Meteorological Department. Gridded daily temperature data were aggregated for each of the states, which might conceal true temperature-mortality associations in some locations. Sheppard's angular distance weighting Algorithm is an interpolation method.
Possibility of detection bias (outcome: all-cause mortality)	Definitely high risk	Data on heat-wave induced mortality are obtained from the Ministry of Home Affairs (Government of India) for Delhi, Rajasthan, Maharashtra and Orissa. Since it is not specified how heat-related mortality is specified, the possibility that not all deaths in the study period have been captured cannot be excluded. Also, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Inappropriate statistical methods	Definitely high risk	The study performed a linear regression of number of heatwave days per year and annual mortality rates 1985-1999 to infer a causal association between the heatwave episodes and mortality.

Table S25. Risk of bias assessment summary for Nissan et al. (2017)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data are collected through a routine and established surveillance system (a Sample Vital Registration System) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study adjusted for all primary and some additional confounders - day of the week and month, seasonal cycle, and long-term trend.
Possibility of detection bias (exposure)	Probably high risk	Daily minimum and maximum temperature for 35 weather stations across Bangladesh were obtained from the Bangladesh Meteorological Department. Anomalous values, identified by flagging repeated values and time steps where Tmin exceeded Tmax, were checked manually. Outliers were either replaced with missing values or were corrected where obvious data-entry errors had occurred. However, station values were averaged to create daily time series of temperature for the whole country, which might conceal true temperature-mortality associations in some locations. Also, for days with missing data that were excluded from the analysis there is no evidence that missing values are not related to the days excluded (holidays or days with unusual weather).
Possibility of detection bias (outcome: all-cause mortality)	Probably low risk	Outcome data are based on a SVRS, which it is routine and long-term and, thus, likely to be more reliable than other data collection systems. However, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Inappropriate statistical methods	Definitely low risk	A generalized additive regression model is an appropriate method for analyzing time series count data. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S26. Risk of bias assessment summary for Shrestha et al. (2017)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data are collected through a routine and established surveillance system (hospital records) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study did adjust for primary confounders - seasonal dummy variables and secular trend. - and for day of week (Saturday) to account holiday effect.
Possibility of detection bias (exposure)	Probably high risk	Daily temperature data for 16 meteorological stations in the country were obtained from Department of Hydrology and Meteorology. However, it seems station values were averaged to create daily time series of temperature for the whole country, which might conceal true temperature-mortality associations in some locations. Also, it is not specified whether a quality control procedure was carried out.
Possibility of detection bias (outcome: all-cause mortality)	Probably high risk	Outcome data were obtained from inpatient records from 22 hospitals (public, teaching, private) in Nepal. The possibility that not all deaths are captured, i.e. those which happened outside hospitals, cannot be excluded. Also, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Inappropriate statistical methods	Definitely low risk	A generalized linear model with log link function (Poisson model) is an appropriate method for analyzing time series count data. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S27. Risk of bias assessment summary for Hess et al. (2018)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data are collected through a routine and established surveillance system (Registrar of Births and Deaths office of AMC) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Probably high risk	The study did not adjust for any of the primary confounders.
Possibility of detection bias (exposure)	Probably low risk	Daily max temperature data were obtained from the Meteorological Aviation Report (METAR) system, from a weather station located at Ahmedabad's Sardar Vallabai Patel International Airport. However, it is not specified whether a quality control procedure was carried out and if the data have been explored for missing values
Possibility of detection bias (outcome: all-cause mortality)	Probably high risk	Outcome data collected from local municipal governments are used. Given the probably low reliability of vital registry and municipal data from countries in the region, there is a possibility that not all deaths in the study period have been captured, which can affect the final study results. Also, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Inappropriate statistical methods	Probably low risk	Distributed lag non-linear model (DLNM) is an appropriate method for analysis time series temperature data. However, the study does not adjust for any potential confounders and no comprehensive sensitivity analysis is performed.

Table S28. Risk of bias assessment summary for Nori-Sarma et al. (2019a)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data are collected through a routine and established surveillance system (local municipal governments) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study adjusted for the primary confounders and for day of week.
Possibility of detection bias (exposure)	Definitely low risk	The study used daily max temperature data for measuring exposure. Data was obtained from the India Meteorological Department and supplemented with data from the National Oceanic and Atmospheric Administration's (NOAA) Global Summary of the Day (GSOD). Very good agreement between the two datasets is demonstrated.
Possibility of detection bias (outcome: all-cause mortality)	Probably high risk	Outcome data collected from local municipal governments are used. Given the probably low reliability of vital registry and municipal data from countries in the region, there is a possibility that not all deaths in the study period have been captured, which can affect the final study results. Also, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Inappropriate statistical methods	Definitely low risk	The generalized linear and the over-dispersed Poisson regression models are appropriate methods for analyzing time series count data in relation to heatwave and continuous temperature, respectively. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S29. Risk of bias assessment summary for Nori-Sarma et al. (2019b)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data are collected through a routine and established surveillance system (local municipal governments) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study used Propensity Score Matching to control for confounding factors such as time trend, seasonal and cyclical variations, calendar effects, including day of the week, weekend versus weekday, and adjusted dew point temperature. Thus, all main confounders and additional confounders were controlled for.
Possibility of detection bias (exposure)	Probably low risk	The study used daily max temperature data for measuring exposure. Data was obtained from the India Meteorological Department and supplemented with data from the National Oceanic and Atmospheric Administration's (NOAA) Global Summary of the Day (GSOD). However, it is not specified if quality control procedure was carried out (e.g. agreement between the datasets)
Possibility of detection bias (outcome: all-cause mortality)	Probably high risk	Outcome data collected from local municipal governments are used. Given the probably low reliability of vital registry and municipal data from countries in the region, there is a possibility that not all deaths in the study period have been captured, which can affect the final study results. Also, the study does not provide quality assurance of the outcome data.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Inappropriate statistical methods	Definitely low risk	Propensity Score Matching and Quasi-Poisson regression are appropriate methods for analyzing time series count data in relation to heatwave days. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S30. Risk of bias assessment summary for Singh et al. (2019)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Definitely low risk	The daily mortality counts that are presented on Fig 1 show a reasonable distribution, hence providing evidence that inclusion of deaths in each time period is not based on any factor associated with the exposure
No/Inadequate control of confounding	Definitely low risk	The study did adjust for primary confounders - seasonal dummy variables and time trend, and for ambient air pollution, relative humidity and day of the week.
Possibility of detection bias (exposure)	Probably low risk	The study used daily min, max and mean temperature, diurnal temperature variations. Data was obtained from the India Meteorological Department. However, it is not specified whether a quality control procedure was carried out and if the data have been explored for missing values.
Possibility of detection bias (outcome: all-cause mortality)	Probably high risk	Data from the Municipal Corporation of Varanasi are used for measuring mortality counts. Given the probably low reliability of vital registry and municipal data from countries in the region, there is a possibility that not all deaths in the study period have been captured, which can affect the final study results.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Inappropriate statistical methods	Definitely low risk	Semipara-metric quasi-Poisson regression model is appropriate for analyzing time series count data in relation to continuous temperature and heatwave days. Different sensitivity analyses of the model were performed, which provide direct evidence that the used method was appropriate.

Table S31. Risk of bias assessment summary for Dutta et al. (2020)

Source of bias	Rating	Support for the judgement
Possibility of selection bias	Probably low risk	There is no direct evidence that inclusion of deaths in each time period is not based on any factor associated with exposure. Since the data are collected through a routine and established surveillance system (local municipal governments) we assume the risk of bias is probably low.
No/Inadequate control of confounding	Definitely low risk	The study did adjust for primary confounders - time trend and seasonality, and for day of the year, day of the week and relative humidity.
Possibility of detection bias (exposure)	Probably low risk	The study used daily max and daily min temperature, which were obtained from the Bhubaneswar Meteorological Centre of the Indian Meteorological Department. However, it is not specified whether a quality control procedure was carried out and if the data have been explored for missing values.
Possibility of detection bias (outcome: all-cause mortality)	Probably high risk	Data from the Bhubaneswar Municipal Corporation are used for measuring mortality counts. Given the probably low reliability of vital registry and municipal data from countries in the region, there is a possibility that not all deaths in the study period have been captured, which can affect the final study results.
Possibility of reporting bias	Probably low risk	All the outcomes that the study pre-specified in the abstract and methods sections are explicitly reported. However, there is no previously published study protocol to compare reported outcomes with pre-specified analysis.
Inappropriate statistical methods	Probably low risk	Distributed Lag Non-linear Model model is appropriate for analyzing time series count data in relation to continuous temperature and heatwave days. However, no sensitivity analyses of the model were performed.

Table S32. Strength of evidence definitions for human evidence according to the Navigation Guide (Johnson et al., 2014).

Strength rating	Definition
Sufficient evidence of toxicity	A positive relationship is observed between exposure and outcome, where chance, bias, and confounding can be ruled out with reasonable confidence. The available evidence includes results from one or more well-designed, well conducted studies, and the conclusion is "unlikely to be strongly affected by the results of future studies."
Limited evidence of toxicity	A positive relationship is observed between exposure and outcome, where chance, bias, and confounding cannot be ruled out with reasonable confidence. Confidence in the relationship is constrained by factors such as "the number, size, or quality of individual studies" or "inconsistency of findings across individual studies." As more information becomes available, the observed effect could change, and this change may be large enough to alter the conclusion.
Inadequate evidence of toxicity	"The available evidence is insufficient to assess effects" of the exposure. The evidence is insufficient because of "the limited number or size of studies," low quality of individual studies, or "inconsistency of findings across individual studies." More information may allow an assessment of effects.
Evidence of lack of toxicity	No relationship is observed between exposure and outcome; and chance, bias, and confounding can be ruled out with reasonable confidence. The available evidence includes consistent results from more than one well-designed, well conducted study at the full range of exposure levels that humans are known to encounter, and the conclusion is unlikely to be strongly affected by the results of future studies. The conclusion is limited to the age at exposure and/or other conditions and levels of exposure studied.

R code for conducting the meta-analysis

Changing the reference temperature

```
# Functions to generate random numbers following
# over-dispersed Poisson distributions
# based on using a standard negative binomial,
# but choosing the scale parameter to give the desired mean/variance
# ratio at the given value of the mean.

rpois.od<-function (n, lambda,d=1) {
    if (d==1)
       rpois(n, lambda)
    else
       rnbinom(n, size=(lambda/(d-1)), mu=lambda)
}

## Function to reproduce a given curve by generating overdispersed Poisson
## data for a given overdispersion

reproduceCurves=function(cases,days,predvar,overdis,df,cen) {
  # This function is for studies that calculated RRs taking one value as
  #   the reference. In other words, there are no confidence intervals for
  #   the reference value (or, equivalently, its s.e. is zero)

  if (days[1]>0) {
    vec.cases=rpois.od(days[1],cases[1],d=overdis)
    vec.predvar=rep(predvar[1],days[1])
  } else {
    vec.cases=NA
    vec.predvar=predvar[1]
  }
  for (i in 2:length(cases)) {
    if (days[i]>0) {
      vec.cases=c(vec.cases,rpois.od(days[i],cases[i],d=overdis))
      vec.predvar=c(vec.predvar,rep(predvar[i],days[i]))
    } else {
      vec.cases=c(vec.cases,NA)
      vec.predvar=c(vec.predvar,predvar[i])
    }
  }
  dsim=data.frame(cases=vec.cases,predvar=vec.predvar)
  modglm=glm(cases~ns(predvar,df),data=dsim,family="quasipoisson")
  X=model.matrix(modglm)

  Xcen=matrix(X[which(dsim$predvar==cen)[1],],byrow=T,ncol=7,nrow=dim(X)[1])
  b=coef(modglm)
  V=vcov(modglm)
  RR=exp((X-Xcen)%*%b)
  vv=sqrt(diag((X-Xcen) %*% V %*% t((X-Xcen))))
  RRlow=exp(log(RR)-1.96*vv)
  RRhi=exp(log(RR)+1.96*vv)
  ddpreds=data.frame(predvar=dsim$predvar[!is.na(dsim$cases)],logrr=log(RR),l
ogrr.low=log(RR)-1.96*vv,
    se=vv )
  ddpreds.short=ddpreds[!duplicated(ddpreds$predvar),]
  ddpreds.short=merge(ddpreds.short,data.frame(predvar=seq(range(vec.predvar)
[1],range(vec.predvar)[2],by=.5)),by="predvar",all.y=T)
```

```
}


reproduceCurvesScaled=function(cases,days,predvar,overdis,df,cen) {
  # This function is for studies that calculated RRs by scaling the predicted
  #   counts with the counts at the reference value. In this case, they repor
t
  #   confidence intervals for the reference value (or, equivalently, s.e.
  #   greater than zero for the reference value)

  if (days[1]>0) {
    vec.cases=rpois.od(days[1],cases[1],d=overdis)
    vec.predvar=rep(predvar[1],days[1])
  } else {
    vec.cases=NA
    vec.predvar=predvar[1]
  }
  for (i in 2:length(cases)) {
    if (days[i]>0) {
      vec.cases=c(vec.cases,rpois.od(days[i],cases[i],d=overdis))
      vec.predvar=c(vec.predvar,rep(predvar[i],days[i]))
    } else {
      vec.cases=c(vec.cases,NA)
      vec.predvar=c(vec.predvar,predvar[i])
    }
  }
  dsim=data.frame(cases=vec.cases,predvar=vec.predvar)
  modglm=glm(cases~ns(predvar,df),data=dsim,family="quasipoisson")
  dat.pred=data.frame(predvar=seq(min(predvar),max(predvar),by=0.5))
  preds=predict(modglm,newdata=dat.pred,se.fit=T)
  ddpreds.short=data.frame(predvar=dat.pred$predvar,logrr=preds$fit,se=preds$
se.fit)
}



changeRefTemp = function(predvar,logrrs,ses,cen,avgDailyCases,ndays,avgTemp,n
ewCen,scaled=0) {
  # predvar: vector of temperatures where you want to predict for that study
  # logrrs: vector of the same length as predvar, with corresponding log(RR)
  # ses: vector of the same length as predvar, with standard errors
  # avgDailyCases: average number of daily cases in the study
  # ndays: number of days in the study
  # avgTemp: average temperature in the study
  # newCen: new temperature at which we want to center the curve


  # Calculate average of logRR. I make the assumption it will be the
  #  place in which number of deaths is equal to the average number of deaths
  pos=which(predvar==newCen)
  RRaux=exp(logrrs-logrrs[pos])
  cases=avgDailyCases*RRaux
  # value of temperature at which the curve for RRs is centered in the study
  cen= predvar[which(predvar==cen)]
  # df to fit the curve
  df=6

  # Number of days with a given temperature. I assume temperature is normally
  #   distributed with the mean provided. I derive sd from the range of
```

```
  #   temperatures provided in predvar. Assume range=8*sd

  sdTemp=(max(predvar)-min(predvar))/8
  temps=rnorm(n=ndays,mean=avgTemp,sd=sdTemp)

  days=as.numeric(table(cut(temps, c(predvar[1]-1,predvar) )))
  # ensure there are days in the entire range
  days[days==0]=3

  # Find the optimal overdispersion parameter to reproduce the curve and
  #   standard errors

  overdis.vec=c(seq(1,1.9,by=.1),2:30)
  search.vec=vector()
  if (scaled==1) {
    for (i in 1:length(overdis.vec)) {
      res=reproduceCurvesScaled(cases=cases,days=days,predvar=predvar,overdis
=overdis.vec[i],df=df,cen=cen)
      search.vec[i]=sqrt(sum((res$se - ses)^2,na.rm=T))
    }
  } else {
    for (i in 1:length(overdis.vec)) {
      res=reproduceCurves(cases=cases,days=days,predvar=predvar,overdis=overd
is.vec[i],df=df,cen=cen)
      search.vec[i]=sqrt(sum((res$se - ses)^2,na.rm=T))
    }
  }
  overdis=overdis.vec[which.min(search.vec)]

  # now simulate the data several times, change the centering value,
  #   and average the results

  nsim=50

  logrrs.cen=matrix(NA,nrow=length(predvar),ncol=nsim)
  ses.cen=matrix(NA,nrow=length(predvar),ncol=nsim)

  for (i.sim in 1:nsim) {
    vec.cases=rpois.od(days[1],cases[1],d=overdis)
    vec.predvar=rep(predvar[1],days[1])
    for (i in 2:length(cases)) {
      vec.cases=c(vec.cases,rpois.od(days[i],cases[i],d=overdis))
      vec.predvar=c(vec.predvar,rep(predvar[i],days[i]))
    }
    dsim=data.frame(cases=vec.cases,predvar=vec.predvar)
    modglm=glm(cases~ns(predvar,df=df),data=dsim,family="quasipoisson")
    X=model.matrix(modglm)
    Xcen=matrix(X[which(dsim$predvar==newCen)[1],],byrow=T,ncol=df+1,nrow=dim
(X)[1])
    b=coef(modglm)
    V=vcov(modglm)
    logRR=(X-Xcen)%*%b
    vv=sqrt(diag((X-Xcen) %*% V %*% t((X-Xcen))))

    ddpreds=data.frame(predvar=dsim$predvar,logrr=logRR,se=vv )
    ddpreds.short=ddpreds[!duplicated(ddpreds$predvar),]

    logrrs.cen[,i.sim]=ddpreds.short$logrr
    ses.cen[,i.sim]=ddpreds.short$se
```

```
  }

  logRRcen=apply(logrrs.cen,1,mean)
  secen=apply(ses.cen,1,mean)

  return(list(logRRcen=logRRcen,secen=secen))

}
```

Meta-analysis at lag 0-1 days

```
library(dplyr)
library(tidyr)
library(tidyverse)
library(viridis)
library(cowplot)


# First, run the "changeRefTemp.r" file to use the functions defined there

source("changeRefTemp.r")

Lag_0_1 <- read.csv("lag_0-1.csv",sep=";",dec=",")
Lag_0_1=Lag_0_1[1:315,1:6]

#Set all the characters as numeric
Lag_0_1 <- within(Lag_0_1, {
  T <- as.numeric(gsub(",", ".", as.character(T)) )

})

summary(Lag_0_1)
Lag_0_1 <- round(Lag_0_1,2)

#Take exponential of the RR estimates in study 2 (Ingole(2017))

Lag_0_1[Lag_0_1$Study=="2",c("RR", "RR_low", "RR_high")] <- exp(Lag_0_1[Lag_0
_1$Study=="2",c("RR", "RR_low", "RR_high")])
Lag_0_1 <- round(Lag_0_1,4)

#Divide all RR values in the study 6 by McMichael (estimate refers to percent
age increase in mortality above average) by 100 to get the RR values
Lag_0_1[Lag_0_1$Study=="6",c("RR", "RR_low", "RR_high")] <- Lag_0_1[Lag_0_1$S
tudy=="6",c("RR", "RR_low", "RR_high")] /100
Lag_0_1 <- round(Lag_0_1,4)

#  Select a new reference T (start by selecting, for example, the average MMT
from all studies). Create a new column with a new reference T for all studies
meant_MMT<- mean(Lag_0_1$MMT)
Lag_0_1$MMT_new <- meant_MMT

# Note: We need to know where the curve is centered, sometimes it is the MMT,
but sometimes not (e.g. Study 3 or 6)
```

```
Lag_0_1$cen=Lag_0_1$MMT
Lag_0_1$cen[Lag_0_1$Study==3]=27
Lag_0_1$cen[Lag_0_1$Study==6]=28


#Recalculate the table based on the new reference T
# For logRR just done by subtracting the value at the new reference
# For se, need the more complicated approach

# RR
Lag_0_1$logRR=log(Lag_0_1$RR)
Lag_0_1$se= (log(Lag_0_1$RR)-log(Lag_0_1$RR_low))/1.96

Lag_0_1_new=Lag_0_1
Lag_0_1_new$isNewCen=Lag_0_1_new$T==Lag_0_1_new$MMT_new

Lag_0_1_new$RRref=NA
for (i in c(1:3,5:6)) {
  Lag_0_1_new$RRref[Lag_0_1_new$Study==i]=rep(Lag_0_1_new$RR[Lag_0_1_new$Stud
y==i & Lag_0_1_new$isNewCen==T],length(Lag_0_1_new$RRref[Lag_0_1_new$Study==i
]))
}

Lag_0_1_new$RRcen=Lag_0_1_new$RR/Lag_0_1_new$RRref
Lag_0_1_new$logRRcen=log(Lag_0_1_new$RRcen)

# Standard errors

# Study 1 scaled results against the mean daily mortality  (Fig 2 legend)
#   but the s.e. are not 0 at the reference temp. Then, I'm guessing they jus
t
#   divided the predicted number of cases for each temperature by the mean mo
rtality
#   and they did the same with the standard errors. In that case, the s.e.
#   does not change by changing the reference category

Lag_0_1_new$secen=NA

# The field "scaled" indicates if the RR is calculated by dividing predicted
#  counts by counts at reference value, and therefore they provid s.e.>0 fore
#  the reference value (scale=1). Otherwise, they take one value as reference
#  value and the s.e. for the reference category is 0 (scale=0)

# One could add avgTemp to auxinfo, and then take this value when avgTemp is
#  defined below

auxinfo=data.frame(Study=c(1,2,3,5,6),ndays=c(3286,1220,1461,4747,1460),
                   avgDailyCases=c(4,.8,17.3,86.7,25),scaled=c(1,1,0,0,1),avg
Temp=c(24,27.9,24,25.4,25))

library(splines)
for (i in c(1:3,5:6)) {
  dati=Lag_0_1_new[Lag_0_1_new$Study==i,]
  dati=dati[!is.na(dati$RR),]
  predvar=dati$T
  logrrs=log(dati$RR)
  ses=((log(dati$RR)-log(dati$RR_low))/1.96)
  cen=dati$cen
  avgDailyCases=auxinfo$avgDailyCases[auxinfo$Study==i]
```

```
  ndays=auxinfo$ndays[auxinfo$Study==i]
  scaled=auxinfo$scaled[auxinfo$Study==i]
  # this can be replaced by the true mean temp if this info is available in a
uxinfo
  if (scaled==1) avgTemp=predvar[which.min(ses)] else avgTemp=mean(predvar)
  newCen=Lag_0_1_new$MMT_new[1]
  vals=changeRefTemp(predvar=predvar,logrrs=logrrs,ses=ses,cen=cen,
                     avgDailyCases=avgDailyCases,ndays=ndays,avgTemp=avgTemp,
newCen=newCen,scaled=scaled)
  Lag_0_1_new$secen[Lag_0_1_new$Study==i & !is.na(Lag_0_1_new$RR)]=vals$secen
}

Lag_0_1_new <- mutate(Lag_0_1_new, se = round(se,4))



# Now one needs to use Lag_0_1_new$logRRcen and Lag_0_1_new$secen in the
#  meta-analysis

# Perform the meta-analysis for each T (using a loop)
library(metafor)

meta_analyse_temp <- function(df){

  # Run meta-regression
  meta <- suppressWarnings(rma(yi= logRRcen, sei= secen, data=df, method="DL"
))

  # Retrieve results
  tibble(Temp = unique(df$T),
         k = meta$k,
         beta = meta$beta,
         se = meta$se,
         zval = meta$zval,
         pval = meta$pval,
         ci.lb = meta$ci.lb,
         ci.ub = meta$ci.ub,
         tau2 = meta$tau2)
}

# Find and exclude the values where secen=0

Lag_0_1_new <- filter(Lag_0_1_new, secen!=0|is.na(secen))

#Lag_0_1_new[Lag_0_1_new$logRRcen == 0, "logRRcen"] <- 1

results <- Lag_0_1_new %>%
  split(.$T) %>%
  map_df(meta_analyse_temp)

results <-
  bind_rows(results,
            data.frame(Temp = 24.5, beta = 0, ci.lb = 0, ci.ub = 0, k = 5))

results <- mutate(results, k = as.character(k),
                  col = case_when(Temp == 24.5 ~ "Reference",
                                  Temp < 24.5 ~ "Cold",
                                  Temp > 24.5 ~ "Heat"))
```

```
mainplot <- results %>%
  mutate_at(vars(beta, ci.lb, ci.ub), exp) %>%
  ggplot() +
  geom_hline(yintercept = 1, colour = "grey70") +
  geom_vline(xintercept = 24.5, colour = "grey10", lty = "dotted") +
  geom_point(aes(x = Temp, beta, colour = col)) +
  geom_linerange(aes(x = Temp, ymin = ci.lb, ymax = ci.ub, alpha = k, colour
= col), lwd = 1) +
  xlab("Temperature (°C)")+
  ylab("RR (95% CI)")+
  labs(k = "Number of included studies") +
  # scale_colour_brewer(palette = "Reds") +
  # scale_colour_viridis(end = 0.9, discrete = T, direction = -1) +
  scale_alpha_discrete(range = c(0.25, 1)) +
  scale_colour_manual(values = c("#1A62D0", "#DB0202", "black")) +
  theme_bw(base_size=11) +
  theme(legend.position = "bottom") +
  guides(colour = "none", alpha = "none") +
  NULL
legend0 <- ggplot() + theme_void(base_size=11)

legend1 <- results %>%
  mutate_at(vars(beta, ci.lb, ci.ub), exp) %>%
  ggplot() +
  geom_hline(yintercept = 1, colour = "grey70") +
  geom_point(aes(x = Temp, beta), colour = "#1A62D0") +
  geom_linerange(aes(x = Temp, ymin = ci.lb, ymax = ci.ub, alpha = k), lwd =
1,
                 colour = "#1A62D0") +
  xlab("Temperature (°C)")+
  ylab("RR (95% CI)")+
  labs(k = "Number of studies") +
  # scale_colour_brewer(palette = "Reds") +
  # scale_colour_viridis(end = 0.9, discrete = T, direction = -1) +
  scale_alpha_discrete(range = c(0.25, 1)) +
  # scale_colour_manual(values = c("#1A62D0", "#DB0202", "black")) +
  theme_bw(base_size=11) +
  theme(legend.position = "bottom") +
  labs(alpha = "")
legend1 <- get_legend(legend1)


legend2 <- results %>%
  mutate_at(vars(beta, ci.lb, ci.ub), exp) %>%
  ggplot() +
  geom_hline(yintercept = 1, colour = "grey70") +
  geom_point(aes(x = Temp, beta), colour = "#DB0202") +
  geom_linerange(aes(x = Temp, ymin = ci.lb, ymax = ci.ub, alpha = k), lwd =
1,
                 colour = "#DB0202") +
  xlab("Temperature (°C)")+
  ylab("RR (95% CI)")+
  # scale_colour_brewer(palette = "Reds") +
  # scale_colour_viridis(end = 0.9, discrete = T, direction = -1) +
  scale_alpha_discrete(range = c(0.25, 1)) +
  # scale_colour_manual(values = c("#1A62D0", "#DB0202", "black")) +
  theme_bw(base_size=11) +
```

```
  theme(legend.position = "bottom") +
  labs(alpha = "Number of studies")

legend2 <- get_legend(legend2)

# rel_widths =  c(0.35, 0.35, 0.8, 0.2)
complot_1 <-

  plot_grid(mainplot,
                   plot_grid(legend0, legend1, legend2, legend0,
                             nrow = 1, rel_widths =  c(0.28, 0.075, 0.75, 0
.0)),
                   ncol = 1, rel_heights = c(0.9, 0.1))
#cowplot::ggsave(complot, filename = "lag_0-1.png", dpi = 500, width = 7, hei
ght = 5)
ggsave(complot_1, filename = "lag_0-1.png", dpi = 500, width = 7, height = 5)
```

Meta-analysis at lag 0-13 days

```
# First, run the "changeRefTemp.r" file to use the functions defined there

source("changeRefTemp.r")

#Lag_0_1 <- read_excel("lag 0-1.xlsx")
Lag_0_13 <- read.csv("lag_0-13.csv",sep=";",dec=",")
Lag_0_13=Lag_0_13[1:300,1:6]

#Set all the characters as numeric
Lag_0_13 <- within(Lag_0_13, {
  T <- as.numeric(gsub(",", ".", as.character(T)) )
})

summary(Lag_0_13)
Lag_0_13 <- round(Lag_0_13,2)

#Take exponential of the RR estimates in study 2 (Ingole(2017))

Lag_0_13[Lag_0_13$ID=="2",c("RR", "RR_low", "RR_high")] <- exp(Lag_0_13[Lag_0
_13$ID=="2",c("RR", "RR_low", "RR_high")])
Lag_0_13 <- round(Lag_0_13,4)

#Divide all values in the study 6 by McMichael (refers to percentage increase
in mortality above average) by 100 to get the RR values
Lag_0_13[Lag_0_13$ID=="6",c("RR", "RR_low", "RR_high")] <- Lag_0_13[Lag_0_13$
ID=="6",c("RR", "RR_low", "RR_high")] /100
Lag_0_13 <- round(Lag_0_13,4)

#  Select a new reference T (start by selecting, for example, the average MMT
from all studies). Create a new column with a new reference T for all studies
meant_MMT<- mean(Lag_0_13$MMT)
Lag_0_13$MMT_new <- meant_MMT

# Note: We actually need to know where the curve is centered (sometimes it is
#   the MMT, but sometimes it is not (e.g. Study 3 or 6)
```

```
Lag_0_13$cen=Lag_0_13$MMT
Lag_0_13$cen[Lag_0_13$ID==1]=24
Lag_0_13$cen[Lag_0_13$ID==2]=21.5
Lag_0_13$cen[Lag_0_13$ID==3]=27
Lag_0_13$cen[Lag_0_13$ID==6]=26


#Recalculate the table based on the new reference T
# For logRR just done by subtracting the value at the new reference
# For se, need the more complicated approach

# RR
Lag_0_13$logRR=log(Lag_0_13$RR)
Lag_0_13$se= (log(Lag_0_13$RR)-log(Lag_0_13$RR_low))/1.96

Lag_0_13_new=Lag_0_13
Lag_0_13_new$isNewCen=Lag_0_13_new$T==Lag_0_13_new$MMT_new

Lag_0_13_new$RRref=NA
for (i in c(1:3,5:6)) {
  Lag_0_13_new$RRref[Lag_0_13_new$ID==i]=rep(Lag_0_13_new$RR[Lag_0_13_new$ID=
=i & Lag_0_13_new$isNewCen==T],length(Lag_0_13_new$RRref[Lag_0_13_new$ID==i])
)
}

Lag_0_13_new$RRcen=Lag_0_13_new$RR/Lag_0_13_new$RRref
Lag_0_13_new$logRRcen=log(Lag_0_13_new$RRcen)

# Standard errors

# Study 1 scaled results against the mean daily mortality  (Fig 2 legend)
#   but the s.e. are not 0 at the reference temp. Then, I'm guessing they jus
t
#   divided the predicted number of cases for each temperature by the mean mo
rtality
#   and they did the same with the standard errors. In that case, the s.e.
#   does not change by changing the reference category

Lag_0_13_new$secen=NA

# The field "scaled" indicates if the RR is calculated by dividing predicted
#  counts by counts at reference value, and therefore they provid s.e.>0 for
#  the reference value (scale=1). Otherwise, they take one value as reference
#  value and the s.e. for the reference category is 0 (scale=0)

# One could add avgTemp to auxinfo, and then take this value when avgTemp is
#  defined below

auxinfo=data.frame(ID=c(1,2,3,5,6),ndays=c(3286,1133,1461,4747,1460),
                   avgDailyCases=c(4,.9,17.3,86.7,25),scaled=c(1,0,0,0,1),avg
Temp=c(24,21.4,24,25.4,25))

library(splines)
for (i in c(1:3,5:6)) {
  dati=Lag_0_13_new[Lag_0_13_new$ID==i,]
  dati=dati[!is.na(dati$RR),]
  predvar=dati$T
  logrrs=log(dati$RR)
```

```
  ses=((log(dati$RR)-log(dati$RR_low))/1.96)
  cen=dati$cen
  avgDailyCases=auxinfo$avgDailyCases[auxinfo$ID==i]
  ndays=auxinfo$ndays[auxinfo$ID==i]
  scaled=auxinfo$scaled[auxinfo$ID==i]
  # this can be replaced by the true mean temp if this info is available in a
uxinfo
  if (scaled==1) avgTemp=predvar[which.min(ses)] else avgTemp=mean(predvar)
  newCen=Lag_0_13_new$MMT_new[1]
  vals=changeRefTemp(predvar=predvar,logrrs=logrrs,ses=ses,cen=cen,
                   avgDailyCases=avgDailyCases,ndays=ndays,avgTemp=avgTemp,
newCen=newCen,scaled=scaled)
  Lag_0_13_new$secen[Lag_0_13_new$ID==i & !is.na(Lag_0_13_new$RR)]=vals$secen
}

Lag_0_13_new <- mutate(Lag_0_13_new, se = round(se,4))



# Now one need to use Lag_0_13_new$logRRcen and Lag_0_13_new$secen in the
#  meta-analysis

# Perform the meta-analysis for each T (using a loop)
library(metafor)

meta_analyse_temp <- function(df){

  # Run meta-regression
  meta <- suppressWarnings(rma(yi= logRRcen, sei= secen, data=df, method="DL"
))

  # Retrieve results
  tibble(Temp = unique(df$T),
         k = meta$k,
         beta = meta$beta,
         se = meta$se,
         zval = meta$zval,
         pval = meta$pval,
         ci.lb = meta$ci.lb,
         ci.ub = meta$ci.ub,
         tau2 = meta$tau2)
}

# Find and exclude the values where secen=0

Lag_0_13_new <- filter(Lag_0_13_new, secen!=0|is.na(secen))



results <- Lag_0_13_new %>%
  split(.$T) %>%
  map_df(meta_analyse_temp)

results <-
  bind_rows(results,
            data.frame(Temp = 26.5, beta = 0, ci.lb = 0, ci.ub = 0, k = 5))

results <- mutate(results, k = as.character(k),
                  col = case_when(Temp == 26.5 ~ "Reference",
```

```
                                  Temp < 26.5 ~ "Cold",
                                  Temp > 26.5 ~ "Heat"))


mainplot <- results %>%
  mutate_at(vars(beta, ci.lb, ci.ub), exp) %>%
  ggplot() +
  geom_hline(yintercept = 1, colour = "grey70") +
  geom_vline(xintercept = 26.5, colour = "grey10", lty = "dotted") +
  geom_point(aes(x = Temp, beta, colour = col)) +
  geom_linerange(aes(x = Temp, ymin = ci.lb, ymax = ci.ub, alpha = k, colour
= col), lwd = 1) +
  xlab("Temperature (°C)")+
  ylab("RR (95% CI)")+
  labs(k = "Number of included studies") +
  # scale_colour_brewer(palette = "Reds") +
  # scale_colour_viridis(end = 0.9, discrete = T, direction = -1) +
  scale_alpha_discrete(range = c(0.25, 1)) +
  scale_colour_manual(values = c("#1A62D0", "#DB0202", "black")) +
  theme_bw(base_size=11) +
  theme(legend.position = "bottom") +
  guides(colour = "none", alpha = "none") +
  NULL
legend0 <- ggplot() + theme_void(base_size=11)

legend1 <- results %>%
  mutate_at(vars(beta, ci.lb, ci.ub), exp) %>%
  ggplot() +
  geom_hline(yintercept = 1, colour = "grey70") +
  geom_point(aes(x = Temp, beta), colour = "#1A62D0") +
  geom_linerange(aes(x = Temp, ymin = ci.lb, ymax = ci.ub, alpha = k), lwd =
1,
                 colour = "#1A62D0") +
  xlab("Temperature (°C)")+
  ylab("RR (95% CI)")+
  labs(k = "Number of studies") +
  # scale_colour_brewer(palette = "Reds") +
  # scale_colour_viridis(end = 0.9, discrete = T, direction = -1) +
  scale_alpha_discrete(range = c(0.25, 1)) +
  # scale_colour_manual(values = c("#1A62D0", "#DB0202", "black")) +
  theme_bw(base_size=11) +
  theme(legend.position = "bottom") +
  labs(alpha = "")
legend1 <- get_legend(legend1)


legend2 <- results %>%
  mutate_at(vars(beta, ci.lb, ci.ub), exp) %>%
  ggplot() +
  geom_hline(yintercept = 1, colour = "grey70") +
  geom_point(aes(x = Temp, beta), colour = "#DB0202") +
  geom_linerange(aes(x = Temp, ymin = ci.lb, ymax = ci.ub, alpha = k), lwd =
1,
                 colour = "#DB0202") +
  xlab("Temperature (°C)")+
  ylab("RR (95% CI)")+
  # scale_colour_brewer(palette = "Reds") +
  # scale_colour_viridis(end = 0.9, discrete = T, direction = -1) +
  scale_alpha_discrete(range = c(0.25, 1)) +
```

```
  # scale_colour_manual(values = c("#1A62D0", "#DB0202", "black")) +
  theme_bw(base_size=11) +
  theme(legend.position = "bottom") +
  labs(alpha = "Number of studies")

legend2 <- get_legend(legend2)

#rel_widths = c(0.04, 0.51, 0.25, 0.2)
par(bg = 'white')

complot_2 <- plot_grid(mainplot,  plot_grid(legend0, legend1, legend2, legend
0,
                               nrow = 1, rel_widths =  c(0.09, 0.25, 0.5, 0.0
)
                              ),
                     ncol = 1, rel_heights = c(0.9, 0.1))

ggsave(complot_2,  filename = "sysplot.png", dpi = 500, width = 7, height = 5
)

p <- plot_grid(complot_1, complot_2, labels = "AUTO")
save_plot("meta-results.png", p, ncol = 2)
```

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Author contributions

AD, GM and GK designed the study and developed the method. GK, RP and S KC provided modelled input data. S KC provided assistance with the use of the MSDem package in R. AD coordinated the work, performed the analysis, drafted the manuscript and produced the figures. CT crticially reviewed and edited the manuscript. All co-authors provided feedback on and contributed to the submitted version of the manuscript.

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Health impacts of fine particles under climate change mitigation, air quality control, and demographic change in India

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Abstract

Despite low per capita emissions, with over a billion population, India is pivotal for climate change mitigation globally, ranking as the third largest emitter of greenhouse gases. We linked a previously published multidimensional population projection with emission projections from an integrated assessment model to quantify the localised (i.e. state-level) health benefits from reduced ambient fine particulate matter in India under global climate change mitigation scenarios in line with the Paris Agreement targets and national scenarios for maximum feasible air quality control. We incorporated assumptions about future demographic, urbanisation and epidemiological trends and accounted for model feedbacks. Our results indicate that compared to a business-as-usual scenario, pursuit of aspirational climate change mitigation targets can avert up to 8.0 million premature deaths and add up to 0.7 years to life expectancy (LE) at birth due to cleaner air by 2050. Combining aggressive climate change mitigation efforts with maximum feasible air quality control can add 1.6 years to LE. Holding demographic change constant, we find that climate change mitigation and air quality control will contribute slightly more to increases in LE in urban areas than in rural areas and in states with lower socio-economic development.

Abbreviations

CO_2	carbon dioxide
GAINS	greenhousegas air pollution interaction and synergies
GBD	global burden of disease
GEMM	global exposure mortality model
GHGs	greenhouse gases
NAAQS	Indian national ambient air quality standard
INDC	intended nationally determined contributions
LE	life expectancy
LRIs	lower respiratory infections
MFR	maximum feasible reduction
NCDs	noncommunicable diseases
NPi	national policy implementation
$PM_{2.5}$	fine particulate matter

1. Introduction

Socio-economic development in India has been accompanied by gains in life expectancy (LE) and improvements in a range of health outcomes over the past decades (Samir *et al* 2018). However, these developments have occurred in parallel with growing environmental challenges, including rising CO_2 emissions and deterioration of air quality (Dey *et al* 2012, GBD MAPS Working Group 2018). Currently, 99.9% of the Indian population lives in areas exceeding the World Health Organization's Air Quality Guideline for annual mean concentrations of ambient fine particulate matter ($PM_{2.5}$) of 10 μgm^{-3} (GBD MAPS Working Group 2018), and the country hosts 13 out of 20 of the world's most polluted cities (Purohit *et al* 2019).

$PM_{2.5}$ (particulate matter with diameter ⩽2.5 μm) comprises a complex mixture of solid and liquid aerosols arising from natural sources (e.g. wind-blown dust, sea salt and biogenic sources) and anthropogenic activities (WHO 2016). Residential energy use has been identified as the dominant contributing sector in India (Lelieveld *et al* 2015, Conibear *et al* 2018a, Purohit *et al* 2019). Both short-term and long-term exposure to $PM_{2.5}$ have been associated with adverse health impacts that can occur even at very low levels (WHO 2016). In India, air pollution was ranked as the second most important contributor to mortality and morbidity in 2017, after malnutrition and dietary risks (IHME 2019) and $PM_{2.5}$ was estimated to account for 12.5% of total deaths (Balakrishnan *et al* 2019). Estimates of the annual premature mortality burden from ambient $PM_{2.5}$ in India range between 392 thousand and 2.2 million (Burnett *et al* 2018, Conibear *et al* 2018a), with differences explained by variations in ambient $PM_{2.5}$ estimates, baseline health and population data, $PM_{2.5}$-mortality functions and methodological approaches.

Climate change and air quality have an important potential for co-control since emissions of CO_2 and many health-damaging air pollutants such as nitrogen oxides, sulphur dioxide and particulate matter are generated through many of the same combustion processes (Li *et al* 2018). While the health impacts from reductions in CO_2 emissions involve large uncertainties and occur over long-time horizons and on a global scale, those from improved air quality are more immediate and localized (Nemet *et al* 2010, West *et al* 2013). Thus, health co-benefits of climate change mitigation due to air pollution reduction can serve as a catalyst for more stringent climate policy and provide an incentive for stronger cooperation, especially from low- and middle-income countries, where air pollution levels and the associated benefits of improving air quality are high, but the perceived responsibility for climate action may be limited due to low current and past per capita emissions (Nemet *et al* 2010, The World Bank 2020). In this respect, India is pivotal for climate change mitigation globally, being the third largest emitter of GHGs (CarbonBrief 2019).

Global modelling studies based on the Representative Concentration Pathways and the Paris Agreement have demonstrated that India can reap some of the largest medium-term (i.e. by 2050) health co-benefits from lower $PM_{2.5}$ concentrations with ambitious climate change mitigation (West *et al* 2013, Silva *et al* 2016, Rafaj *et al* 2018 Vandyck *et al* 2018) and these can fully compensate the mitigation costs even under most aspirational scenarios (Markandya *et al* 2018, Sampedro *et al* 2020). Chowdhury *et al* (2018) projected reductions in premature mortality from $PM_{2.5}$ in India in 2050 compared to 2010 across a range of climate change and socio-economic scenarios and despite trends in population growth and aging. Studies focusing specifically on air quality policies in India project increases in $PM_{2.5}$ concentrations and associated premature mortality by 2050 under business-as-usual scenarios, while demonstrating a large scope for minimizing this burden under more stringent air quality control measures (Sanderson *et al* 2013, International Energy Agency 2016, Venkataraman *et al* 2017, Chowdhury *et al* 2018, Conibear *et al* 2018b, Limaye *et al* 2019, Purohit *et al* 2019). However, even under most aspirational scenarios several studies suggest the $PM_{2.5}$-mortality burden will not fall below present levels as a result of population growth and aging offsetting reductions in air pollution emissions (International Energy Agency 2016, GBD MAPS Working Group 2018, Conibear *et al* 2018b). While previous projection studies have considered demographic change, a major gap in the current literature is the failure to account for the feedback effects of changes in air pollution on future mortality rates and population, i.e. studies assume the same future mortality rate and population under alternative $PM_{2.5}$ scenarios. This can be misleading, especially for long-term projections in settings with high air pollution (Miller and Hurley 2003). Sanderson *et al* (2013) incorporated the feedback effects of changes in air pollution on future mortality rates under different air quality control, but not mitigation, scenarios at the national level. A more comprehensive modelling framework is needed to quantify the health co-benefits of climate change mitigation at the sub-national level accounting for these feedbacks while also incorporating newly available epidemiological evidence and more advanced demographic projections.

We advance on previous studies in several ways by (a) estimating future health co-benefits related to $PM_{2.5}$ dynamically by accounting for changes in population and mortality rates induced by changes in $PM_{2.5}$ levels; (b) calculating co-benefits from $PM_{2.5}$ reduction on LE and on avoidable premature mortality in the context of the Paris Agreement and at more spatially disaggregated levels (e.g. by state and urban and rural residence); and (c) exploring synergies between global climate change mitigation and national air quality control at the local level. The main contribution of this study is the consistent and dynamic integration of future trends in demographics, urbanization, and disease burdens in the health impact assessment, which allows us to isolate the impacts of air pollution on mortality from population aging effects and to account for the feedback effects of $PM_{2.5}$ exposure on population survival over time. As demographic change is a main determinant of future trajectories of exposure and vulnerability to environmental hazards, comprehensive modelling of the interplay of population dynamics and air pollution can support more realistic health impact assessments and better informed decision making.

The paper is organized as follows: section 2 describes the different models and datasets and how they are linked; sections 3.1 and 3.2 report the health co-benefits in terms of LE gains and avoided premature deaths across scenarios compared to the business-as-usual, and section 3.3 reports results according to region. In section 3.4, we show the implications of changing $PM_{2.5}$ exposure on population size. In section 4, we discuss the relevance and implications of our findings. We focus on $PM_{2.5}$ because of the well-established literature linking exposure to mortality, and because its mortality burden exceeds those of other major pollutants in India such as ozone (Balakrishnan *et al* 2019). We use the term premature mortality to refer to deaths brought forward in time due to air pollution exposure across all ages and avoidable premature mortality to refer to deaths that can be averted with respect to the business-as-usual scenario.

Table 1. Scenario descriptions.

Scenario	Description
NPi	National Policies until 2030, no climate policy after 2030
INDC	National Policies until 2020, after which implementation of Intended Nationally Determined Contributions (INDCs) 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 2 °C—MFR 1.5 °C—MFR	Same as above, but combined with the implementation of measures for maximum feasible reduction of air pollution in India

2. Material and methods

2.1. Scenario definition

Table 1 describes the modelled scenarios. These have been developed in the MESSAGEix-GLOBIOM global energy-economy framework (International Institute for Applied Systems Analysis 2019) as part of the CD-LINKS (Linking Climate and Development Policies—Leveraging International Networks and Knowledge Sharing) project (CD-LINKS 2019). The National Policy implementation (NPi), or business-as-usual scenario, specifies the implementation of currently announced targets for climate, energy, environment (air pollution) and development policies up to 2030 in all countries and equivalent effort to no climate policy beyond 2030 (based on a policy database for G20 countries with a cut-off year of 2015 (New Climate Institute 2020)). The Intended Nationally Determined Contributions (INDC) scenario assumes that policy commitments specified in countries' INDCs are implemented by 2030, but no further intensification of emission reduction commitments beyond this point is undertaken. The more aspirational scenarios of 2°C and 1.5°C 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 (cumulative 2011–2100 global CO_2 budget of 1000 $GtCO_2$ and 400 $GtCO_2$ for the 2°C and 1.5°C targets, respectively (McCollum *et al* 2018)). These scenarios have been implemented in MESSAGE-GLOBIOM based on global cost-effective pathways for staying within the specified global CO_2 budgets as well as national objectives and capabilities for implementing mid-century emissions strategies. The NPi, INDC, 2°C and 1.5°C scenarios are combined in GAINS with a set of air pollution measures assuming a compliance with the current air pollution legislation in each country. The three additional scenarios correspond to the CO_2 emission mitigation pathways described above, but are complemented with implementation of explicit control measures for maximum feasible reduction of air pollutants in India, hereafter referred to as MFR (Rafaj *et al* 2018, Purohit *et al* 2019). The energy use by fuel type and the sector-specific $PM_{2.5}$ emissions under each scenario can be found in figures SI.1–2 (available online at stacks.iop.org/ERL/16/054025/mmedia).

2.2. Ambient $PM_{2.5}$ concentrations

Projections of anthropogenic emissions, as well as historical and future (2010–2050) gridded annual ambient $PM_{2.5}$ concentrations (figure 1) under each modelled scenario for India were derived from the GAINS model. These were based on regionalised economic activities of different types either developed in MESSAGEix-GLOBIOM (energy supply and demand, transport) or derived from the GAINS databases (industrial production, agriculture). To arrive at the $PM_{2.5}$ emissions in each scenario, a few hundred end-of-pipe national air quality control measures in the industry, power plant, household and agricultural sectors were applied in GAINS. For MFR variants these refer to the best available technical measures to capture SO_2, NO_x, VOCs, NH_3 and PM emissions at their sources before they enter the atmosphere and without structural changes in the economy or energy systems (see table SI.1 for an illustrative list). Comparison of modelled concentrations against observational data shows relatively good agreement (figure SI.3).

To determine population-weighted concentrations for urban and rural areas, the gridded $PM_{2.5}$ concentrations were intersected with urban polygon shapes from Global Rural-Urban Mapping Project (NASA 2020), gridded population data from the Joint Research Centre, and from WorldPop (2020).

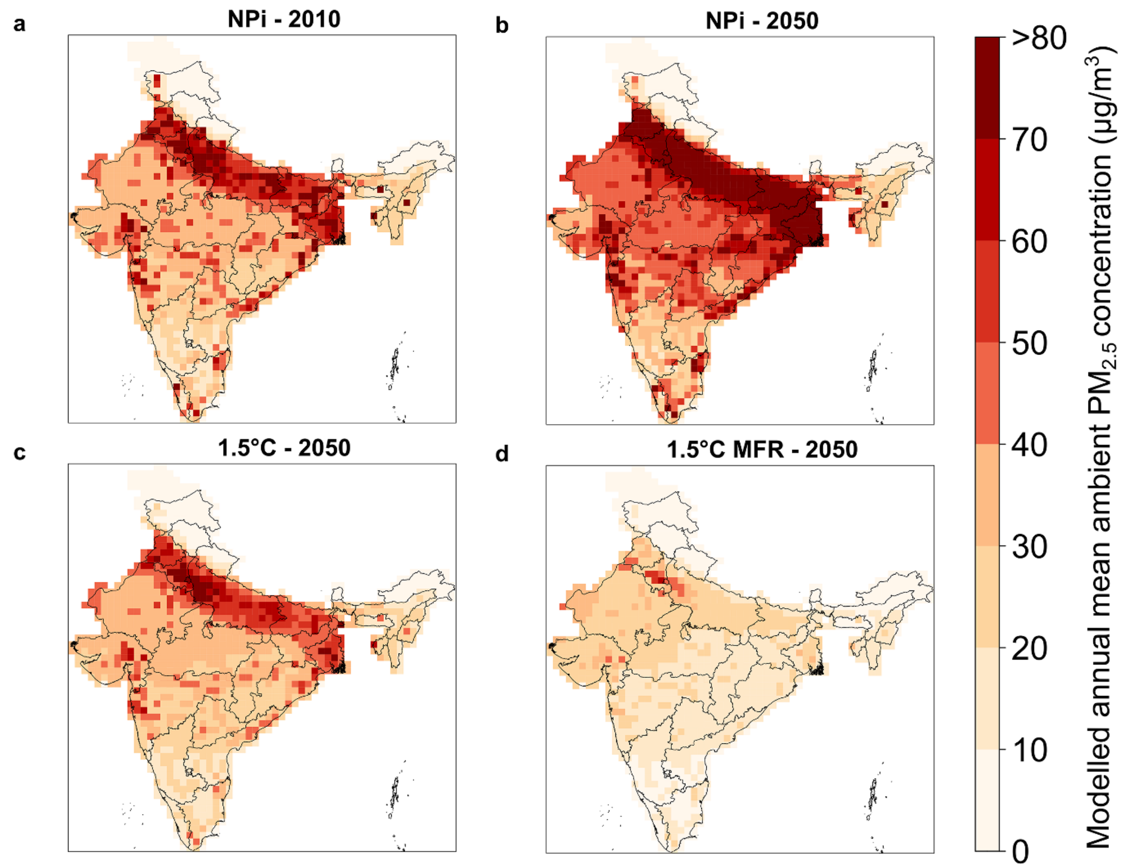

Figure 1. Modelled annual mean ambient $PM_{2.5}$ concentrations (μg m^{-3}) over the Indian landmass for scenario (a) NPi, 2010, (b) NPi, 2050, (c) 1.5 °C, 2050 and (d) 1.5 °C—MFR, 2050.

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 was adjusted to ensure consistency with percent rural area classification in the 2001 Indian census.

The projected $PM_{2.5}$ exposures under each scenario can be found in figure SI.4 and more details on the methods—in section S1.1 of the supplementary material.

2.3. Demographic projection

To estimate how changes in air pollution will affect future LE, age-specific mortality, as well as the structure and size of the population, we used the five-dimensional population projection for India developed by Samir *et al* (2018), which projects India's population by state, urban/rural place of residence, age, sex and level of education, using sub-group specific fertility, mortality, education and migration rates. The initial data for the population projection has been derived from the two most recent Indian censuses (2001 and 2011) and vital rates from the India Sample Vital Registration System (1999–2013). The urban–rural designation applied in the population projection differs from the one used for the exposure assessment described above as it also considers population density and share of employment in non-agricultural work. Further explanation of the method and data sources used in the population projection can be found in the supplementary material (section S1.2) and in the appendix of Samir *et al* (2018).

2.4. Exposure response function

To quantify the mortality impacts of exposure to outdoor $PM_{2.5}$ due to Noncummunicable Diseases (NCDs) and Lower Respiratory Infections (LRIs), we apply the Global Exposure Mortality Model (GEMM) (Burnett *et al* 2018) (figure SI.5):

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

where HR denotes the mortality hazard ratio (relative risk of mortality at any concentration compared to the counterfactual of 2.4 μg m^{-3}) for a specific annual exposure to $PM_{2.5,}$ z is population-weighted $PM_{2.5}$ exposure $z = \max(0, \mathrm{PM2.5} - 2.4\ \mathrm{mg}\ /\mathrm{m}^{-3})$ and θ, z, α, μ are age-specific and disease-specific parameters. The counterfactual was selected as the lowest observed concentration in any of the 41 observational studies, included in the GEMM development; below the counterfactual, GEMM assumes no change in the hazard ratio.

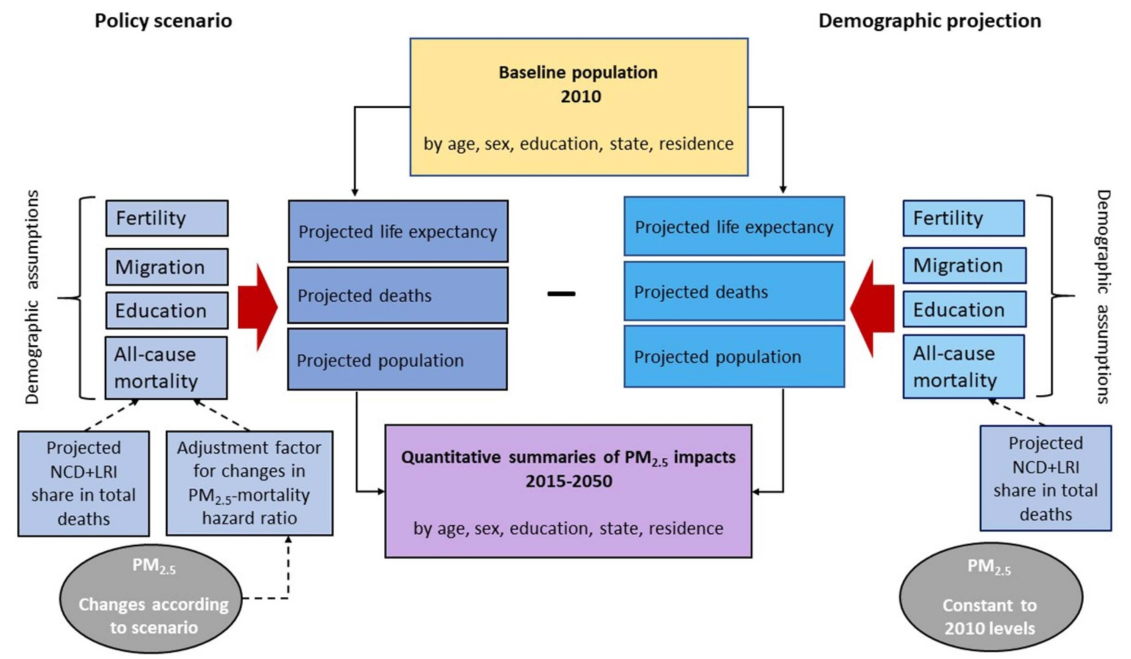

Figure 2. Schematic model of the dynamic health impact assessment approach.

2.5. Projection of future disease burden

To account for future trends in disease patterns in India, we modelled the burden of NCDs and LRIs deaths based on the projected changes in LE at birth from the demographic projection. We used sex- and age-specific (5 years age groups) data on the percentage of all deaths due to NCDs and LRIs for 31 of the states and union territories in India for 2015–2017 from the Global Burden of Disease (GBD) project (Indian Council of Medical Research, Public Health Foundation of India and IHME 2017). We assumed that if a state reached the LE at birth in 2050 that another state had in 2015, it will also have the same age- and sex-specific percentage of deaths due to NCDs and LRIs as the other state in 2015. Thus, for each state and sex, we matched projected LE at birth in the year 2050 with the state with the closest LE at birth in 2015 (within 3 years band) and assigned the 2050 NCDs and LRIs mortality burden accordingly. The values for all the years in-between were interpolated. States with the highest LE at birth that could not be matched with past LE in any state were matched to other countries in Southern Asia with similar LE at birth (table SI.2).

2.6. Health impact estimation

We linked all models described above in an integrated framework, using a dynamic health impact assessment approach (see figures 2 and SI.6). Firstly, we presume that the future mortality assumptions in the demographic projection reflect only future socio-economic prospects, but not the impact of changes in air pollution (Miller and Hurley 2003). We then re-ran the population projection for each emission scenario, adjusting age-specific mortality rates for each state and urban/rural residence at every 5 year period from 2010 to 2050 to the changes in risk of mortality associated with the changing $PM_{2.5}$ concentrations over time:

$$m^{\text{scen}}_{a,r,s}(t) = m^{\text{base}}_{a,r,s}(t) \times \text{Share}_{\text{NCD+LRI}} \frac{\text{HR}_{a,r,s}(t)}{\text{HR}_{a,r,s}(2010)} + m^{\text{base}}_{a,r,s}(t) \times \left(1 - m^{\text{base}}_{a,r,s}(t) \times \text{Share}_{\text{NCD+LRI}}\right).$$

$$a = \text{age},\ r = \text{residence},\ s = \text{state}$$

where $m^{\text{scen}}_{a,r,s}$ indicates the age-, urban/rural residence- and state-specific mortality rate in the respective emission scenario and $m^{\text{base}}_{a,r,s}$ in the population projection. $\text{Share}_{\text{NCD+LRI}}$ is the projected age-, sex- and state-specific share of NCDs and LRIs in all-cause mortality. $\text{HR}_{a,r,s}$ denotes the age-specific hazard ratio associated with the $PM_{2.5}$ exposure in each domain (urban/rural residence and state). Rescaling the mortality rates in this way, without changing any other demographic drivers in the projection (i.e. fertility, migration), entails distinct LEs, number of deaths, and population size under each scenario that can be attributed to the differences in $PM_{2.5}$ exposure levels.

The health impact estimation was based on aggregated population-weighted concentrations for urban and rural areas in each state, respectively. The population projections under each scenario were implemented in R using version 0.0.4.1 of the MSDem (multi-state demography) package (Wurzer and Samir 2018). In the following sections we compare the projected LE at birth, total number of deaths and population under each of the scenarios with

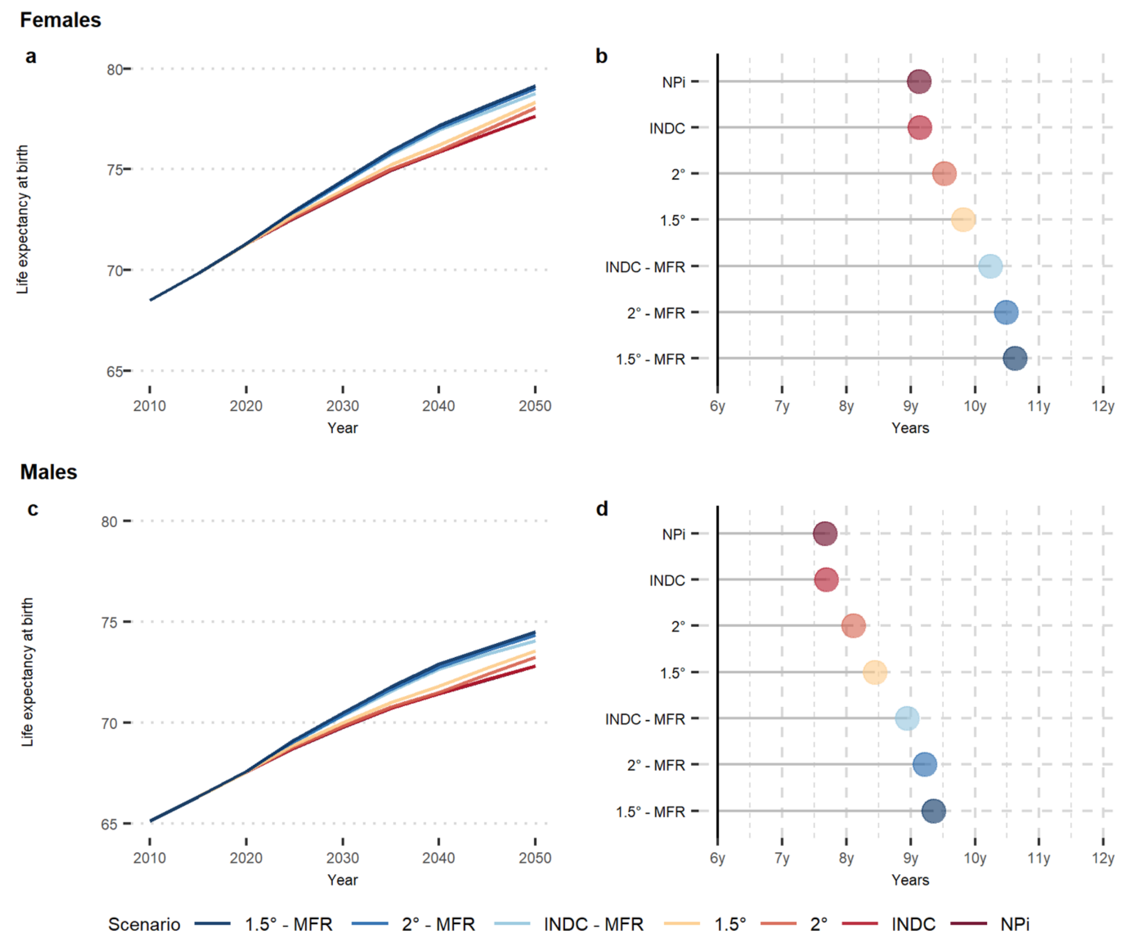

Figure 3. Projected changes in LE at birth from 2010 to 2050 ((a) females and (c) males) and total gains in LE between 2010 and 2050 ((b) females and (d) males) under climate change mitigation and air quality control scenarios according to sex.

those in the demographic projection that assumes 2010 constant $PM_{2.5}$ levels. We also draw comparison across scenarios to illustrate the potential health co-benefits of stricter climate change mitigation against the NPi.

3. Results

3.1. Gains in life expectancy

Figure 3 and table SI.4 show the projected gains in LE up to 2050 for each scenario. In the period 2010–2050 LE at birth for both females and males in India is projected to increase under all scenarios. These increases reflect the underlying assumption of improving LE in the demographic projection as well as the impacts of changing $PM_{2.5}$ levels. There are substantial differences in the projected LE trajectories across emission scenarios as a result of deaths being brought forward in time or delayed due to changes in $PM_{2.5}$ 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 LE at birth between 2010 and 2050 is projected to be 9.1 years for females and 7.6 years for males (LE at birth in 2010 was 68.5 years for females and 65.1 for males). Pursuit of carbon emission targets can bring substantial health co-benefits through cleaner air by adding 0.4 (under 2°C) or 0.7 (under 1.5°C) years to the average (both sexes) projected LE in 2050. These LE gains account for 4.2% and 7.4% of the total increases in LE under each of these scenarios, respectively.

The results in figure 3 demonstrate that under the 1.5°C—MFR scenario increases in LE at birth between 2010 and 2050 would be 1.6 years higher compared to the NPi scenario (15.5% of the total increase in LE at birth between 2010 and 2050). There was essentially no difference in LE gains between the INDC and NPi scenarios.

Under all scenarios total increases in LE between 2010 and 2050 are projected to be larger for women than for men and for rural residents than for urban (figure 4(a)). Comparing LE changes across scenarios with those of the demographic projection allows us to isolate the impacts of changing $PM_{2.5}$ levels on LE from those of the underlying demographic assumptions (figure 4(b)). Holding demographic changes constant, the relative impact of climate change mitigation and air quality control is almost the same for men and women,

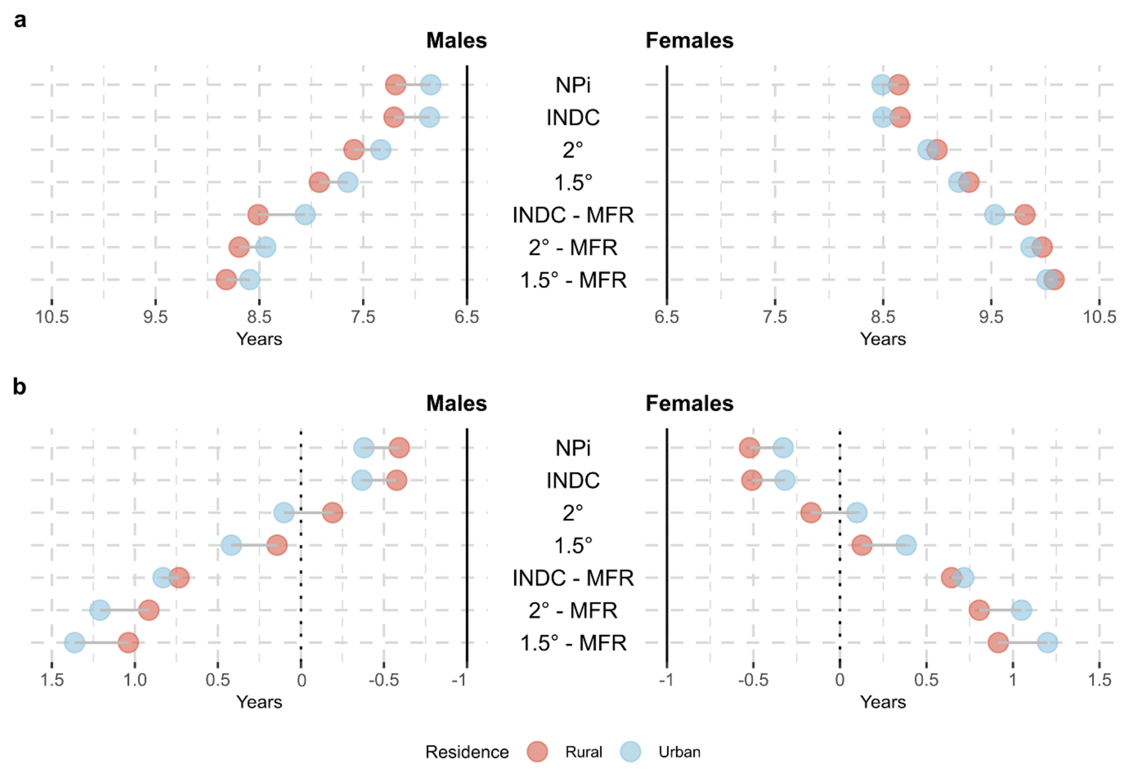

Figure 4. Projected changes in LE at birth (from 2010 to 2050) in years under different climate change mitigation and air quality control scenarios according to sex and urban/rural residence (a) due to changes in demographic assumptions and changes in $PM_{2.5}$ concentrations and (b) only due to changes in $PM_{2.5}$ concentrations.

which is expected considering that there are no sex-differentiated hazard ratios in GEMM. However, improvements in $PM_{2.5}$ levels associated with these measures contribute more to LE increases for urban residents.

3.2. Avoidable premature deaths due to $PM_{2.5}$ reductions

Our projections indicate that number of premature deaths due to $PM_{2.5}$ exposure will increase by 5.6 million and 5.3 million between 2010 and 2050 under the NPi and INDC scenarios, respectively (figure 5 and table SI.5). Taking ambitious action to prevent climate change can generate clear health co-benefits: under the 2° scenario we project the number of premature deaths from $PM_{2.5}$ in the period 2010–2050 to be 3.9 million lower compared to the NPi scenario and 8.0 million lower under the 1.5°C scenario. Combining climate change mitigation efforts with measures targeting air pollution can bring the largest reduction in premature mortality due to $PM_{2.5}$ exposure: 2.6–4.8 times larger in magnitude than the avoided premature mortality through climate change mitigation alone. Compared to the NPi scenarios, aggressive GHG emission reductions plus air quality control can avert up to 20.8 million premature deaths by 2050, with larger benefits among rural residents (11.2 million in rural vs. 9.5 million in urban areas). Even under current national mitigation commitments (scenario INDC), targeted air quality control can avert substantial premature deaths by 2050, comparable in magnitude to avoidable premature deaths from $PM_{2.5}$ under 2 °C—MFR scenario (10.9 million under INDC-MFR compared to 13.3 million under 2 °C—MFR, see table SI.5).

Our results indicate that without any further policy action between 2010 and 2050 premature deaths due to $PM_{2.5}$ exposure will increase the most in rural areas, but with aggressive climate action and air quality control they can be reduced the most in urban areas (figures 5(b) and (c)).

The reduction in premature deaths from lower $PM_{2.5}$ concentrations occur mainly among those aged 50–70 (47.4% of the reduction in premature deaths over 2010–2050 under the 1.5°C—MFR scenario) and 70–90 (43.5% of the reduction premature deaths over 2010–2050 under the 1.5°C—MFR scenario) as shown in figure 6. Under all scenarios coupling mitigation efforts with targeted air quality control, premature deaths across all age groups are projected to fall in the period 2010–2050 apart from the oldest (90+). In contrast, in the NPi, INDC and 2°C scenarios, premature deaths from $PM_{2.5}$ are expected to increase for all age groups, but the eldest (90+).

3.3. Regional differences

State-level analyses revealed some regional variations in projected LEs (figure 7). LE gains from CO_2 and

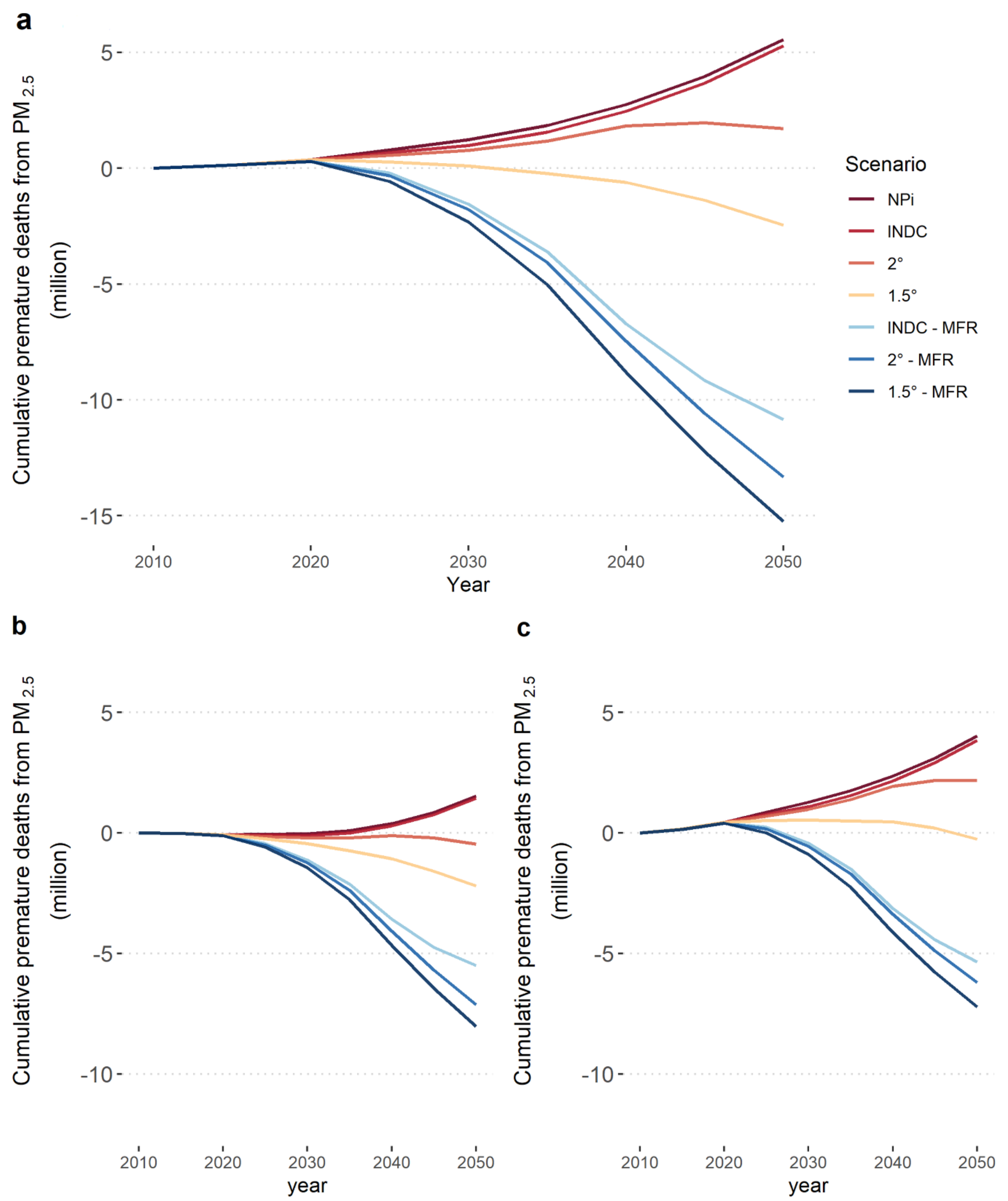

Figure 5. Projected change in the cumulative number of premature deaths due to $PM_{2.5}$ exposure under modelled scenarios (2010–2050) for (a) India; (b) all urban areas; (c) all rural areas. Note: Deaths are calculated relative to the demographic projection, assuming 2010 $PM_{2.5}$ levels remain constant for India.

$PM_{2.5}$ emission controls were negatively correlated with baseline LE at birth and positively correlated with baseline $PM_{2.5}$ levels across states (figure 8). States with the highest potential gains in longevity through improvements in air quality were situated around the Indo-Gangetic Plain and East India, in particular West Bengal, Jharkhand, Bihar, Odisha, Uttar Pradesh and Chhattisgarh (figures 7, 8 and SI.7).

These states are at multiple disadvantages — they are highly polluted and are projected to experience the largest increases in $PM_{2.5}$ with climate change (NPi scenario); they are some of the most populated, have relatively low LE and have a large share of households using solid fuels for heating and cooking. Nevertheless, differences in overall state-level health inequalities across scenarios were small based on the coefficient of variation and absolute and relative LE gap between states (table SI.7).

To explore the relative importance of climate policy versus air pollution control at state-level, we compared gains in LE relative to NPi scenario between the INDC-MFR and 1.5 °C-MFR scenarios, which only differ in the climate change mitigation

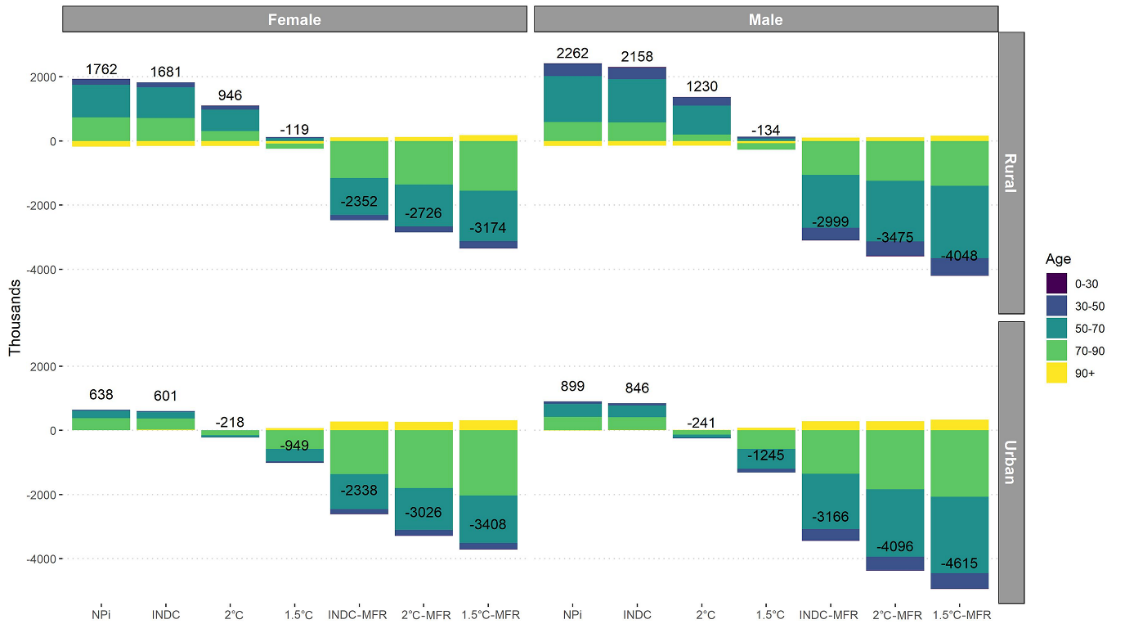

Figure 6. Projected change in premature deaths (in thousands) due to $PM_{2.5}$ exposure from 2010 to 2050 for each scenario according to sex and urban/rural residence.
Note: Deaths are calculated relative to the demographic projection, assuming 2010 $PM_{2.5}$ levels remain constant

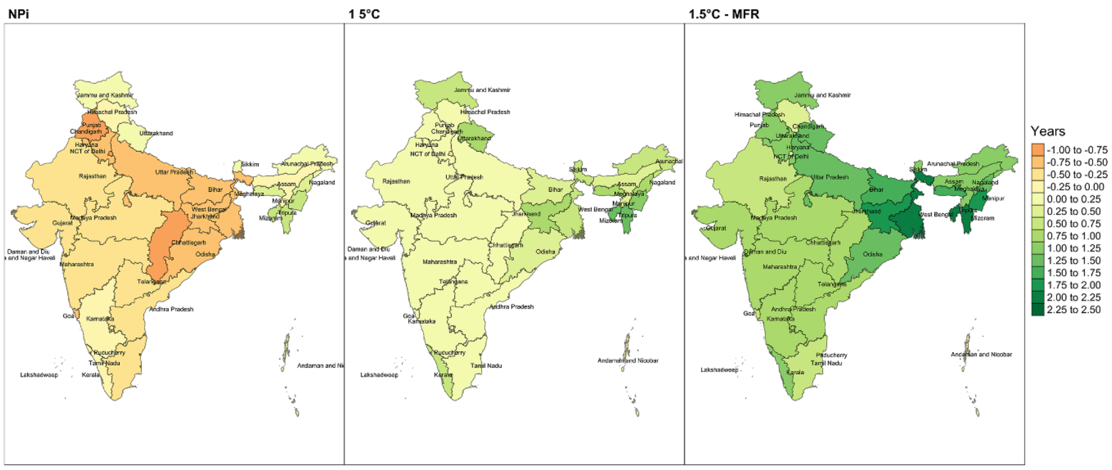

Figure 7. Difference in LE at birth in 2050 between scenarios NPi, 1.5 °C and 1.5 °C—MFR relative to the demographic projection.
Note: Estimates calculated as population-weighted values for females, males and urban and rural residents

ambition. Although air quality policies seem to dominate the LE gains for India overall, we find that the cleaner energy transition as envisioned in the 1.5 °C-MFR scenario can double these potential gains in many urban regions, especially those in Northeast India, where the overall $PM_{2.5}$ burden is the largest (table SI.8).

3.4. Implications for population size

In our dynamic method, $PM_{2.5}$ levels affect population survival in each specific age interval; i.e. deaths due to $PM_{2.5}$ in a population subgroup (sharing the same characteristics such as age, sex, education, residence) in one projection period will affect the shape and size of the population in subsequent periods. Therefore, the different emission scenarios modelled resulted in distinct total population sizes and structures. In the most aspirational scenario, the total population in 2050 is projected to be 16.2 million larger compared to the NPi scenario (table SI.9). Differences in population survival will also slightly affect the structure of the population. For instance, the percentage of the population aged 65+, which was 5.5% in 2010, is projected to reach 15.9% in 2050 under the NPi scenario and 16.5% under the 1.5°C—MFR scenario.

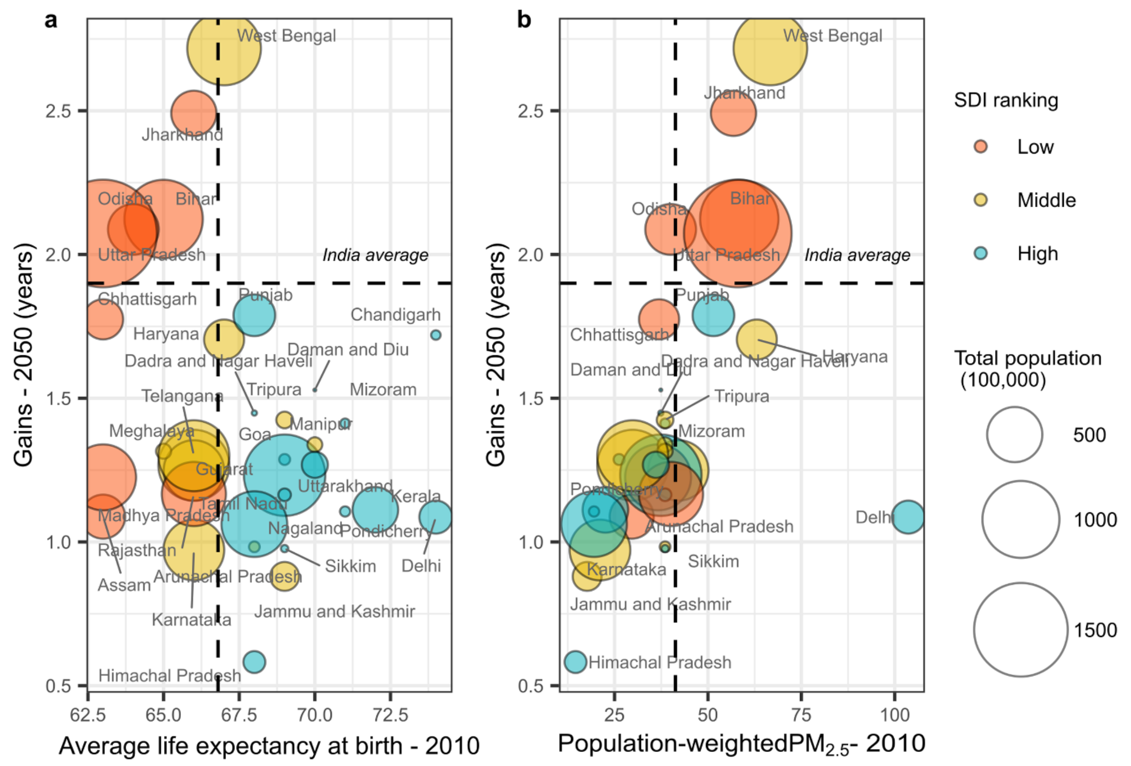

Figure 8. Gains in LE at birth in 2050 (1.5°C—MFR scenario compared to NPi scenario) against (a) LE at birth in 2010 and (b) population-weighted $PM_{2.5}$ in 2010.
Note: Size of the circles indicates baseline population size (in 100 000) and colour indicates state ranking based on the Socio-demographic Index (SDI) levels as calculated by GBD 2017 (Balakrishnan *et al* 2019), which is based on lag-distributed per-capita income, mean education in people aged 15 years or older, and total fertility rate in people younger than 25 years. LE at birth and gains in LE are calculated as a population-weighted average of female and male LE at birth.

4. Discussion

Our study estimates gains in LE and avoidable premature deaths from reduced fine particle concentrations in India under different climate change mitigation scenarios using an integrated framework that incorporates demographic dynamics. Most prior research on future health benefits of air quality improvement has relied on more static methods that assume future population structure and mortality rates are independent from changes in exposure. In contrast, we assessed the feedback effects of air pollution on LE and population size and structure, a largely neglected aspect in the co-benefits literature. We find compelling evidence for the health co-benefits related to air quality improvement under the aspirational 2°C and 1.5°C climate change mitigation targets laid out in the Paris Agreement. In particular, a child born in India under these low emission pathways in 2050 could expect to live on average 0.4 or 0.7 years longer, respectively, than if she were born in a world following a business-as-usual trajectory. Furthermore, meeting the Paris Agreement targets has the potential to avert between 3.9 million and 8.0 million premature deaths due to $PM_{2.5}$ exposure in the country over the period 2010–2050 compared to the NPi scenario. These immediate and localised health co-benefits of cleaner air provide a strong incentive for climate action from the third largest CO_2 emitting nation.

Our results indicate that with maximum and coordinated efforts of both climate change mitigation and end-of-pipe air quality control, LE increases between 2010 and 2050 could be 1.6 years higher compared to the NPi scenario, which is far beyond current estimates of the LE impacts of tobacco or all cancer in South Asia (Apte *et al* 2018). Avoided premature deaths between 2010 and 2050 can amount to 20.8 million. 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. A previous study demonstrated that the economic costs of MFR policies in India would still be extremely low compared to the economic benefits of cleaner air associated with higher productivity through reduction in mortality and work absenteeism (Sanderson *et al* 2013) and this has been confirmed for climate change mitigation efforts (Markandya *et al* 2018). Although our results suggest that targeted air pollution control might be more effective in reducing premature mortality from $PM_{2.5}$, stronger coordination with climate change mitigation is indispensable considering the multiple additional health, socio-economic and environmental benefits of limiting climate change. Furthermore, we show that purely technical end-of-pipe emission control measures without a large-scale transformation in the energy system would have much more limited scope for reducing the health burden of $PM_{2.5}$ throughout the most highly affected areas in Delhi and in Northeastern India. In addition, it has been recently demonstrated that these one-way solutions would be associated with higher implementation costs (Purohit *et al* 2019).

In line with recent scenario-based studies (GBD MAPS Working Group 2018, Karambelas *et al* 2018), we find that without climate change mitigation efforts premature deaths from $PM_{2.5}$ will increase the most in rural areas. Despite their lower ambient air pollution levels, rural areas have higher $PM_{2.5}$ related health burden due to their larger population and lower baseline LE compared to urban areas. Previous studies estimate the total mortality burden of air pollution in rural areas to be three to five times larger than in urban areas (GBD MAPS Working Group 2018, Karambelas *et al* 2018). Holding demographic change constant, we find that climate change mitigation can contribute slightly more to LE increases and avoided premature deaths for urban residents over the period 2010–2050, likely due to larger improvements in $PM_{2.5}$. We note that our results likely underestimate impacts at highly polluted urban areas due to the logarithmic form of the exposure-response function at concentrations above 84 μgm^{-3}, implying impacts at lower exposures increase more rapidly compared to higher exposures, and the fact that we average concentrations across urban grid cells. Quantifying the health impacts at grid level would have involved an additional set of assumptions regarding spatial distribution of future population growth and mortality. Modelling not only improvements in outdoor but also indoor air quality associated with decreasing use of solid fuels for household energy would likely demonstrate even greater health co-benefits in rural areas, especially in some less-developed states, where the proportion of people using solid fuels for heating and cooking is as high as 75% (Balakrishnan *et al* 2019). For instance, one study estimated that household air pollution in India shortens the average lifespan by 0.7 years (Balakrishnan *et al* 2019). We do not find substantial differences in health co-benefits according to sex; however, this could change when accounting for changes in indoor air pollution levels, which mostly affect children and women in India (Balakrishnan *et al* 2019).

In agreement with previous studies (Chowdhury *et al* 2018, Balakrishnan *et al* 2019, Limaye *et al* 2019, Purohit *et al* 2019) we find that regions with lower socio-economic development, especially those along the Indo-Gangetic Plain, would reap the largest benefits with relation to LE gains and avoided premature mortality from reaching stringent targets on emissions. Although these regions have a lower incidence of NCDs, they have large health burdens because of their larger population size, lower LE and higher $PM_{2.5}$ concentrations (Purohit *et al* 2019). These heterogeneous regional effects have important implications for geographical equity in health and economic and social development.

Our results should be interpreted in light of the following main limitations. Firstly, the GEMM function considers only health impacts in adults, but in many regions in India mortality from LRIs in children is high, and childhood mortality has been shown to contribute to about 10% of the loss in LE in India (Apte *et al* 2018). Hence, our estimates should be considered as a lower bound of potential LE gains from improving air quality. Secondly, we did not consider possible climate-change-induced meteorological impacts on $PM_{2.5}$ concentrations as well as the feedback effects of stricter air quality control on the climate (although these are likely to be smaller and more local compared to changes in GHG emissions). Although uncertainties in estimating these are still very large, especially at the regional and local level, a previous study (Chowdhury *et al* 2018) estimated that climate change might diminish the rise in surface $PM_{2.5}$ over India by 7%–17% through its effects on local meteorology. Lastly, quantitative uncertainty analysis of our results was beyond the scope of this study due to the complexity of the linked models and lack of uncertainty bounds for important parameters, e.g. in the population projection, integrated assessment model and air pollution model. Uncertainty in our model will likely stem from assumptions and parameters related to (a) baseline populations, emissions and disease burden data; (b) the integrated assessment model, (c) the GAINS model, (d) the demographic projection model, (e) the disease burden projection, (f) the GEMM model and its extrapolation in the future, beyond observed $PM_{2.5}$ ranges, and to settings with very different population and air pollution characteristics, (g) the calculation of health impacts at aggregate level (state and urban/rural residence) and (h) the assumption of constant air pollution in the demographic projection. 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 providing insights regarding the range of potential health implications of global and national policy decisions.

Our integrated and dynamic approach allowed us to: (a) report the impacts of air pollution on mortality independent of demographic change; and (b) explore feedback effects of climate change mitigation and $PM_{2.5}$ emissions control on future population size and structure. In contrast to previous studies, which report an increasing burden of $PM_{2.5}$-related mortality even with reduction in emissions (International Energy Agency 2016, GBD MAPS Working Group 2018, Conibear *et al* 2018b), we find that emission controls can reduce the number of premature deaths from $PM_{2.5}$ in India. These contrasting results can be explained by differences in the definition of premature deaths as well as overall methodological approach. Our results also suggest that while most aspirational policies will contribute to improving LE, this will also have the effect of increasing population size and the proportion of the population at older ages. Larger populations can in turn produce additional feedback mechanisms on the climate system through higher energy use and CO_2 emissions, which should be examined in future studies. Two policy questions that arise in this respect are (a) whether changes in population size and structure delivered by reduction in premature mortality from climate change mitigation and air quality control can make meeting CO_2 reduction targets more challenging and (b) if the productivity gains from lower mortality and morbidity will outweigh the higher social and healthcare costs of sustaining a larger elderly population. While public policy strives to improve population health and prolong LE, it is important, especially in a dynamic country such as India, that this progress is accompanied by measures for reducing the carbon footprint of individuals and decoupling increases in GHG emissions and air pollutants from economic growth.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Supplementary Information: Health impacts of fine particles under climate change mitigation, air quality control, and demographic change in India

S1. Input data and methods

S1.1. Ambient $PM_{2.5}$ concentrations

Air quality implications in the scenarios analysed in this paper are based on over 1000 technical control measures simulated by GAINS, which include structural measures and end-of-pipe solutions such as improved cook stoves, flue-gas desulfurization, ban on open burning of agricultural residues, improved emission standards for vehicles, etc. The measures for reducing precursor emissions simulated by GAINS refer to application of technologies, commercially available in India today; non-technical options such as changes in behaviour and preferences were not modelled. A more complete list of assumed control measures/policies under the current legislation as well for the MFR scenarios can be found in Purohit et. al (2019).

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 (states) of the country. Modelling of 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 sources: (i) primary ambient PM emitted directly to the atmosphere from anthropogenic sources, (ii) secondary PM formed in the atmosphere through chemical reactions of precursors gasses such as SO_2, NO_x and NH_3, (iii) PM 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).

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 (NASA, 2020), 250m gridded population data from the Joint Research Centre, and 100x100m gridded population data from WorldPop (WorldPop, 2020). 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 were 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; however, as shown previously the population-weighted mean will not be affected by increases in the absolute population size but rather by changes in population distribution relative to the distribution of particles (e.g. internal migration) (Stedman et al., 2002).

Fig. SI.4 depicts the modeled average annual-population-weighted $PM_{2.5}$ exposure over time under each emission scenario for India overall and separately for all urban and rural areas. In 2010, simulated $PM_{2.5}$ exposure was 67.7 μg/m^3 for urban areas, 36.2 μg/m^3 for rural areas and 41.3 μg/m^3 for the whole of India. With only implementation of current legislation (NPi scenario) by 2050 $PM_{2.5}$ concentrations over the Indian landmass are projected to steadily increase and reach 57.4 μg/m^3 (39.0 % increase), driven by larger increases in rural areas (34.7 %) than in urban areas (20.0 %) (See Table SI.3). India´s current emission pledges under the Paris Agreement (INDC scenario) will have negligible impact on this upward trajectory.

Under global mitigation efforts in line with the 2°C target, $PM_{2.5}$ levels in India are projected to continue increasing steadily up to 2040 before starting to decline afterwards. These air quality improvements are mainly driven by slight reductions in average population-weighted $PM_{2.5}$ levels in urban areas by 2050 (-7.0 %), offsetting the increases in rural areas (9.7 %). More aggressive CO_2 reductions in accordance with the 1.5°C target generate steady declines in $PM_{2.5}$ levels over time (2010-2050) both for urban (-20.3 %) and rural areas (-9.9 %) and ensure that the India-wide average is below National Ambient Air Quality Standard (NAAQS) of 40 μg/m^3.

The largest improvements in air quality over this period, however, are achieved in the scenarios combining climate change mitigation efforts with maximum feasible control of air pollutants (MFR scenarios), with population-weighted concentrations reaching 22.0 μg/m^3 in the 2°C - MFR and 19.7 μg/m^3 in the 1.5°C - MFR scenario, levels considerably below the India-wide NAAQ standard of 40 μg/m^3 and the World Health Organisation´s Interim target of 35 μg/m^3. In contrast to the climate mitigation scenarios, the $PM_{2.5}$ reductions in the MFR scenarios are almost equally distributed across urban and rural areas, ranging between -49.3 % and -57.3 %. As shown in Fig.1 there were large heterogeneities in $PM_{2.5}$ levels across India in 2010, with the regions along the Indo-Gangetic Plain recording some of the highest $PM_{2.5}$ levels. The potential future reductions across states are also not uniform. Climate action, especially when combined with air quality control measures, has the potential to substantially improve air quality across all regions, but most notably for the states in the Indo-Gangetic Plain. The projected differences in reductions across regions are related to state-specific level of decarbonization of industry, elimination of fossil fuels from the energy mix, transition in demand patterns in the household and transport sectors.

S1.2. Demographic projection

The cohort-component model by KC et. al (2018) projects India´s population by state, rural/urban place of residence, age, sex and level of education, using differential fertility, mortality and migration rates. Compared to the conventional approach of only considering the age and sex structure of the population at national level, this projection model accounts explicitly for other sources of population heterogeneity, which notably affect population forecasts. The definition of urban inhabitants used in the projection is in accordance with the 2011 Census definition. 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 and Lutz, 2017). The main future assumptions in the model are as follows: declining education-specific fertility pathways for urban and rural types of residence, with total fertility rate (TFR) converging to 1.75 in urban and 2.08 in rural areas; increasing sex-specific life expectancy (LE) at birth, with average rate of gains in LE at birth converging to 0.75 years per five years for males and 1 year for females; no international migration, constant age- and sex-specific migration rates. The assumptions in the demographic projection as well as the population and socio-economic development trajectories embedded in all the emission scenarios are in line with the 'middle-of-the-road' storyline of the Shared Socioeconomic Pathways (SSP2)(Riahi et al., 2017).

Section S2. Figures and tables

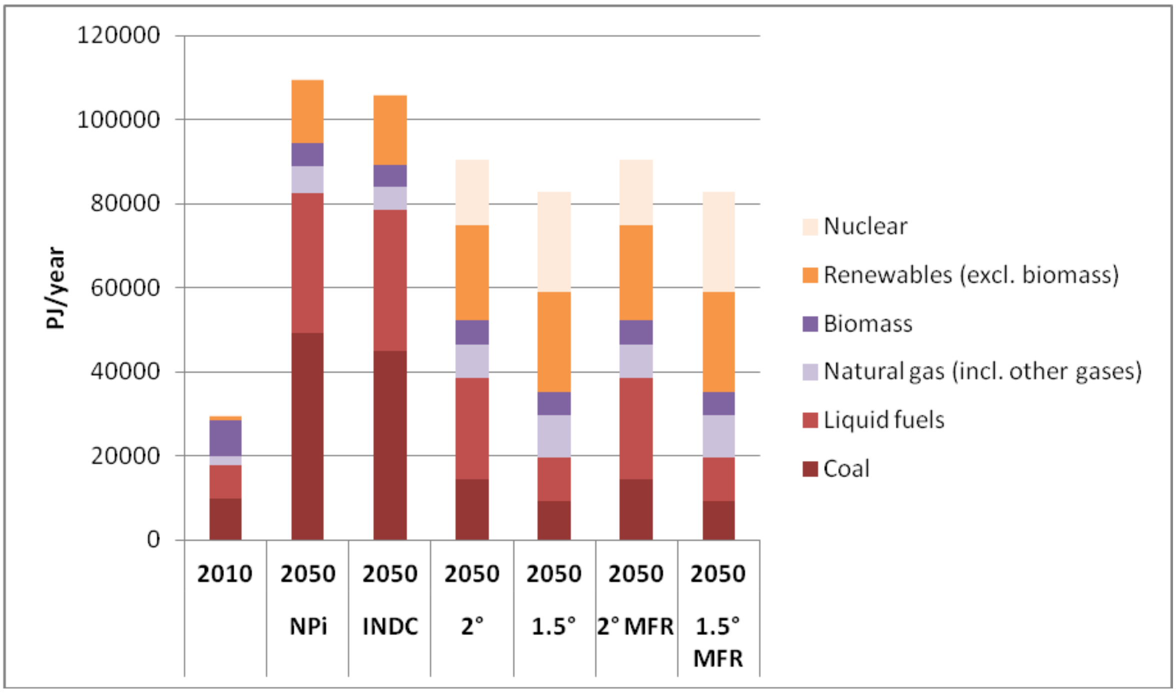

Fig. SI.1: Energy use by key fuel type at the national level – 2010, 2050 by scenario
Note: Baseline and future fuel use are exogenous to GAINS and derived from CD-LINKS scenarios

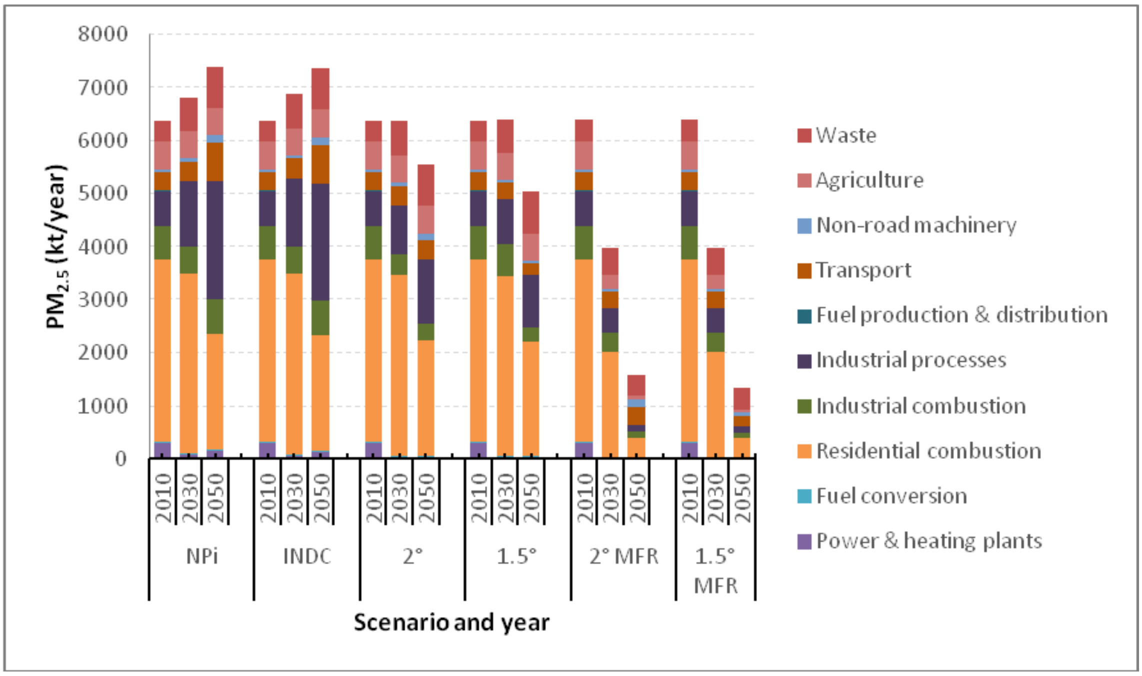

Fig. SI.2: Sector-specific $PM_{2.5}$ emissions by scenario and year at the national level

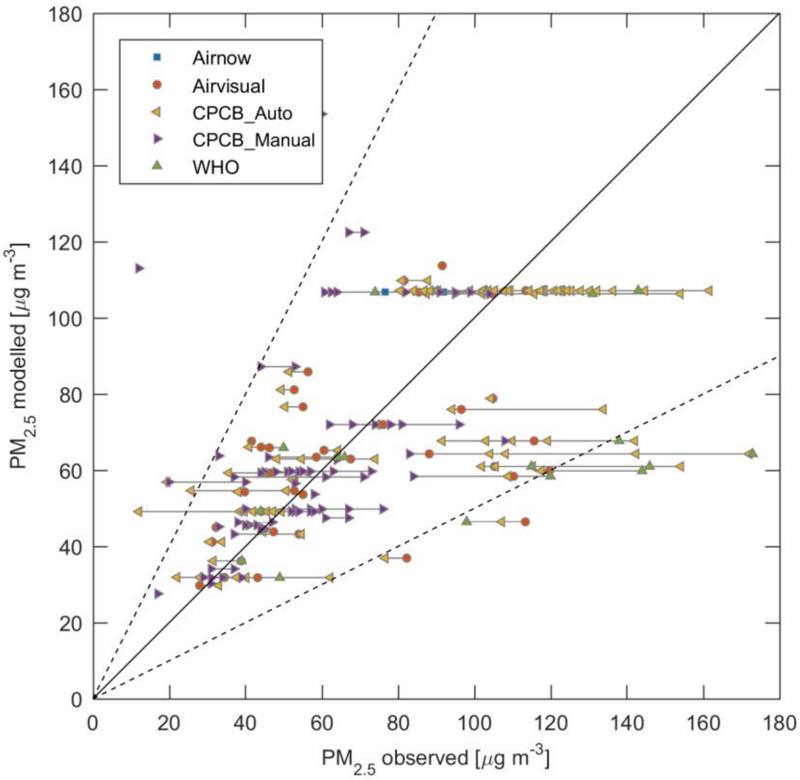

Fig. SI.3: Comparison of 2015 modelled $PM_{2.5}$ concentrations calculated with the GAINS model (NPi scenario) with observations collected from ground based sources (2014-2018).
Note: Readings from different stations in the same city, as well as from different years for the same city, are connected with lines to show spatio-temporal variability within a city. CPCB_Auto: Central Pollution Control Board – Automatic stations; CPCB_Manual: Central Pollution Control Board – Manual stations; WHO: WHO AAP database 2018

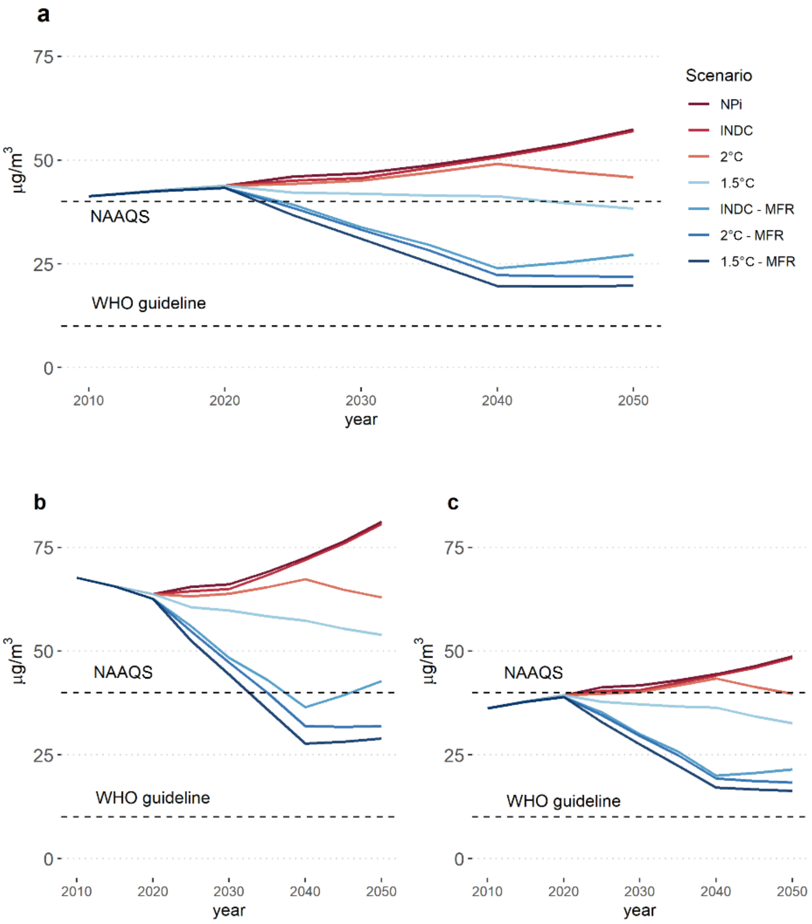

Fig. SI.4: Projected population-weighted ambient $PM_{2.5}$ concentrations through 2050 under all modelled scenarios averaged over (a) India; (b) all urban areas in India; (c) all rural areas in India. Dotted lines represent annual average $PM_{2.5}$ levels set in the World Health Organisation´s Air Quality Guideline and the Indian National Ambient Air Quality Standard (NAAQS), respectively.

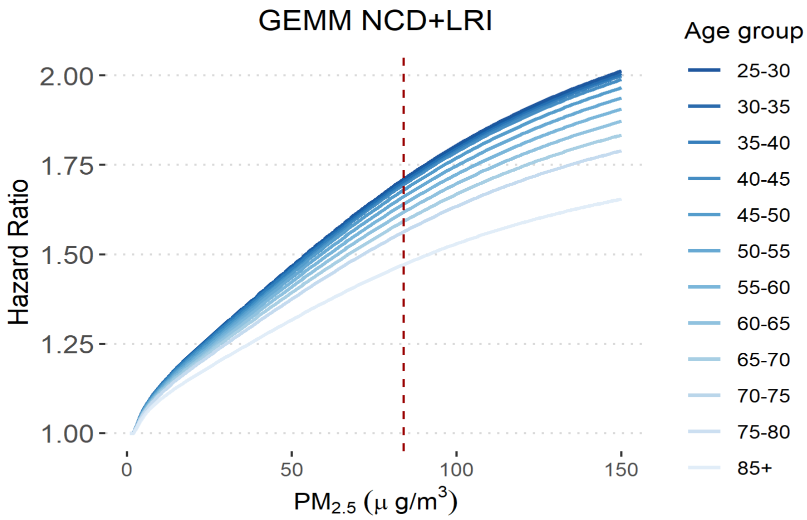

Fig. SI.5: Age-specific GEMM hazard ratio over $PM_{2.5}$ range for NCDs and LRIs. Note: Curves beyond the dashed line represent extrapolations.

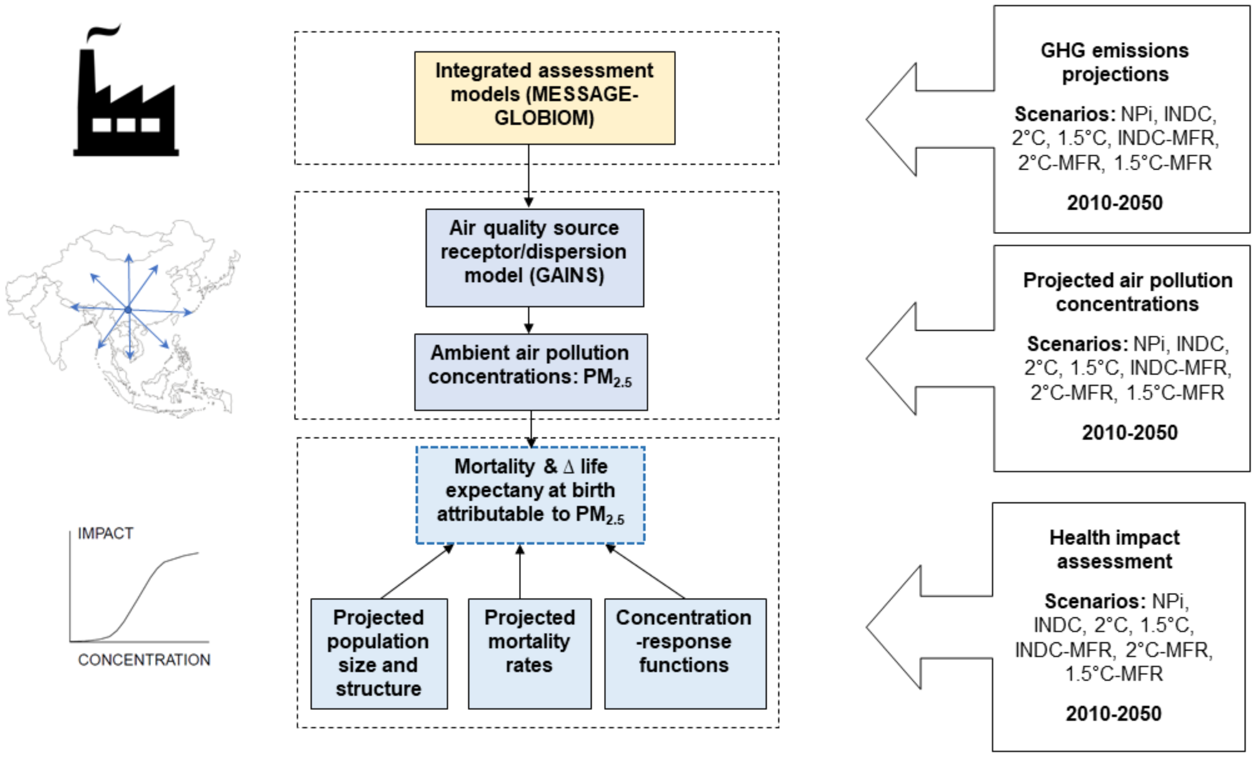

Fig. SI.6: Proposed health impact assessment framework.

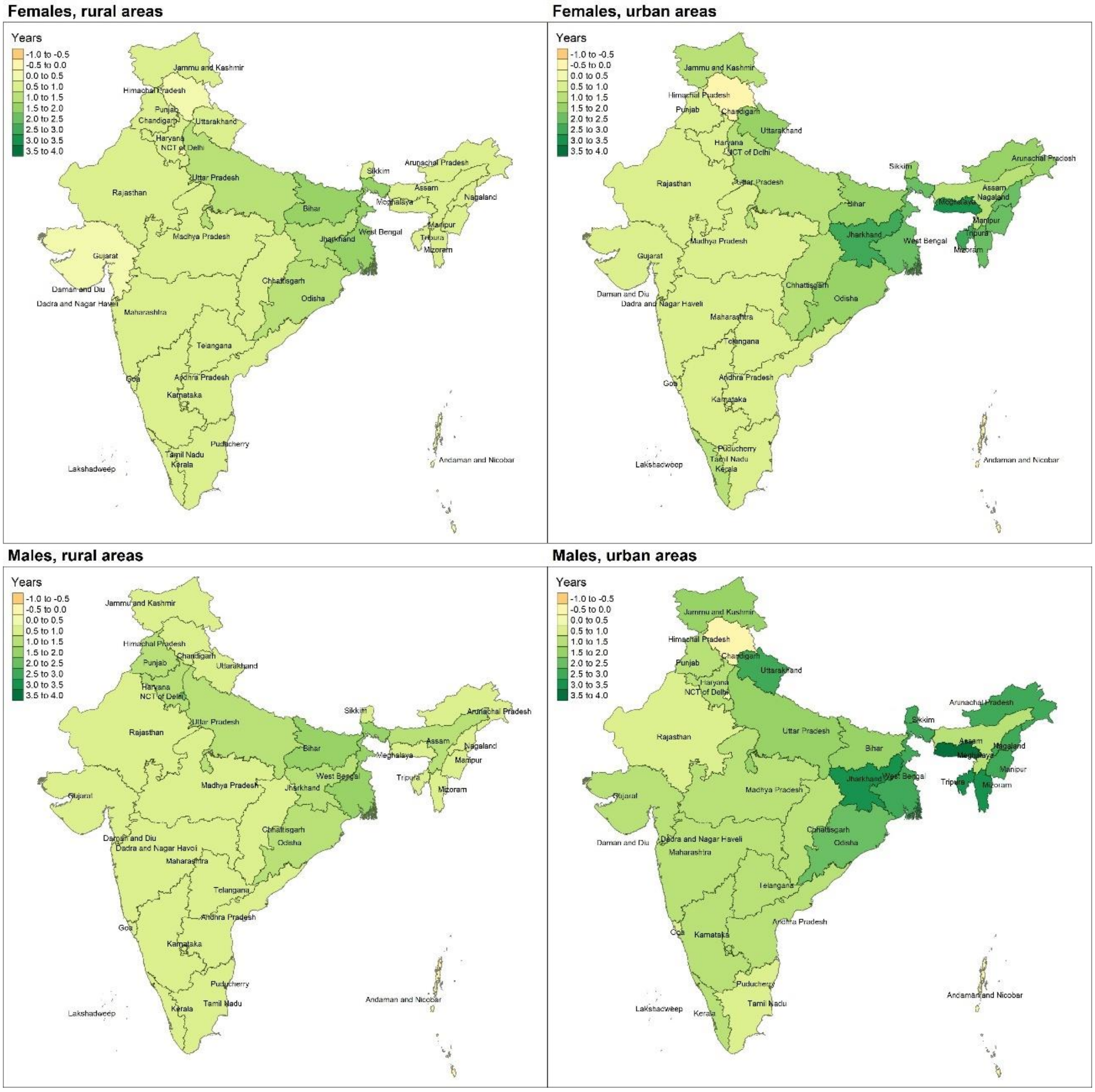

Fig. SI.7: Difference in life expectancy at birth in 2050 between the demographic projection and scenario* 1.5°C - MFR *according to sex and urban/rural residence

Table SI.1: List of policies and measures assumed under current air pollution legislation (CLE) and maximum feasible reduction (MFR). Adapted with permission from International Institute for Applied Systems Analysis and Council on Energy and Water (2019)

CLE *Power Plants*	*MFR* *Power Plants*
▪ Complete move towards supercritical technologies in coal power plants	▪ High-efficiency PM controls at power plants
▪ Reverse bidding of solar and wind power plants ▪ Flue gas desulphurisation for SO2 ▪ Selective catalytic reduction (SCR) and selective non-catalytic reduction (SNCR) for NOx	▪ Selective catalytic reduction at existing and new oil and gas power plants
Industry	*Industry*
▪ Full compliance with the PAT-I5 and PAT-II cycle	▪ High-efficiency PM controls for boilers
▪ Zig-zag or vertical shaft kilns for all new brick production installations	▪ More stringent PM controls for furnaces
▪ New emission standards for SO2 and NOx for five industries (ceramics, foundries with furnaces based on fuel, glass foundries, lime kilns, and reheating furnaces)	▪ Combustion modification and selective catalytic reduction in oil and gas boilers and furnaces
▪ Ban of coke and furnace oil in industry in the NCR districts	▪ Stringent emission controls for industrial processes, including: o Ferrous and non-ferrous industries o Refineries o Coke plants o Carbon black production o Fertiliser plants o Brick kilns (by increasing capacity of tunnel kilns)
	▪ Improved control of flaring in refineries

	▪ Suppressing fugitive emissions during coal handling
Mobile sector	***Households***
▪ BS VI controls (all road vehicles) from 2020 onwards	▪ Annual inspection and maintenance of residential oil boilers
▪ Bharat (Trem) Stage IV controls (non-road machinery) from 2020 onwards, and Stage V from 2024	▪ Replacement of wick kerosene lamps with hurricane lanterns
▪ FAME scheme 1: Incentives for increasing the adoption of electric vehicles and push to remove infrastructure barriers in India	▪ Nationwide ban on open burning of solid waste (trash)
Agriculture and other sectors	***Agriculture and other sectors***
▪ Ban of open burning of waste (trash) in Indian cities and crop residue burning in NCR districts	▪ Improved enforcement of bans on burning of agricultural waste
▪ Solid Waste Management Rules 2016	▪ Improved manure management in livestock production
	▪ Efficient use of urea-based mineral fertilisers
	▪ Suppressing dust emissions from storage and handling of agricultural crops
	▪ Low-till farming, alternative cereal harvesting

Table SI.2: List of Indian states with 2050 LE at birth (ex_0) matching with 2015 LE at birth of other Indian states or countries in South Asia.

A. **Females**

State	2015 ex_0	2050 ex_0	State/country with matching ex_0
Assam	66	75	Mizoram
Chhattisgarh	66	74	Pondicherry
Madhya Pradesh	66	75	Mizoram
Uttar Pradesh	66	75	Mizoram
Odisha	67	76	Kerala
Meghalaya	69	76	Kerala
Jharkhand	69	77	Delhi
Rajasthan	69	77	Delhi
Bihar	68	76	Kerala
Andhra Pradesh	70	80	Chandigarh
Gujarat	70	77	Delhi
Haryana	70	79	Chandigarh
Karnataka	70	77	Delhi
West Bengal	70	76	Kerala
Arunachal Pradesh	71	80	Chandigarh
Himachal Pradesh	71	80	Chandigarh
Tamil Nadu	71	80	Chandigarh
Dadra and Nagar Haveli	73	82	Chandigarh
Punjab	73	83	Maldives
Maharashtra	72	81	Chandigarh
Sikkim	72	82	Chandigarh
Goa	73	83	Maldives
Nagaland	73	83	Maldives
Jammu and Kashmir	73	83	Maldives
Manipur	73	84	Maldives
Tripura	73	84	Maldives
Uttarakhand	73	83	Maldives
Pondicherry	74	83	Maldives
Daman and Diu	75	86	Maldives
Mizoram	75	85	Maldives
Kerala	76	84	Maldives
Delhi	78	88	Maldives
Chandigarh	79	88	Maldives

Note: Matching in ex0 with other states in India was performed within 3 years tolerance range, and with countries in South Asia within 6 years tolerance range.

B. Males

State	2015 ex_0	2050 ex_0	State/country with matching ex_0
Assam	63	69	Nagaland
Chhattisgarh	63	69	Nagaland
Madhya Pradesh	63	70	Pondicherry
Uttar Pradesh	63	71	Kerala
Odisha	64	71	Kerala
Meghalaya	64	71	Kerala
Jharkhand	65	72	Kerala
Rajasthan	65	72	Kerala
Bihar	66	73	Delhi
Andhra Pradesh	66	75	Chandigarh
Gujarat	66	72	Kerala
Haryana	66	74	Delhi
Karnataka	66	73	Delhi
West Bengal	67	72	Kerala
Arunachal Pradesh	67	75	Chandigarh
Himachal Pradesh	68	74	Delhi
Tamil Nadu	68	75	Chandigarh
Dadra and Nagar Haveli	68	77	Chandigarh
Punjab	68	77	Chandigarh
Maharashtra	69	76	Chandigarh
Sikkim	69	77	Chandigarh
Goa	69	77	Chandigarh
Nagaland	69	78	Chandigarh
Jammu and Kashmir	70	79	Maldives
Manipur	70	79	Maldives
Tripura	70	79	Maldives
Uttarakhand	70	79	Maldives
Pondicherry	70	78	Chandigarh
Daman and Diu	71	80	Maldives
Mizoram	71	79	Maldives
Kerala	71	78	Chandigarh
Delhi	74	82	Maldives
Chandigarh	75	82	Maldives

Note: Matching in ex0 with other states in India was performed within 3 years tolerance range, and with countries in South Asia within 6 years tolerance range.

Table SI.3: Change in population-weighted annual mean $PM_{2.5}$ concentrations between 2010 and 2050 according to urban/rural residence and scenario

		NPi	INDC	2°C	1.5°C	INDC-MFR	2°C – MFR	1.5°C - MFR
India	**2010**	41.3	41.3	41.3	41.3	41.3	41.3	41.3
	2050	57.4	57.0	45.9	38.3	27.2	22.0	19.7
	% Δ	38.8%	37.8%	11.0%	-7.4%	-34.2%	-46.9%	-52.4%
Urban areas	**2010**	67.7	67.7	67.7	67.7	67.7	67.7	67.7
	2050	81.2	80.7	63.0	53.9	42.8	31.9	28.9
	% Δ	20.0%	19.2%	-7.0%	-20.3%	-36.7%	-52.9%	-57.3%
Rural areas	**2010**	36.2	36.2	36.2	36.2	36.2	36.2	36.2
	2050	48.8	48.3	39.7	32.6	21.5	18.4	16.4
	% Δ	34.7%	33.6%	9.7%	-9.9%	-40.6%	-49.3%	-54.8%

Table SI.4: Change in life expectancy at birth for all of India between 2010 and 2050 according to sex, urban/rural residence and scenario

A. Females

		NPi	INDC	2°C	1.5°C	INDC-MFR	2°C - MFR	1.5°C - MFR
India	**2010**	68.5	68.5	68.5	68.5	68.5	68.5	68.5
	2050	77.7	77.7	78.0	78.3	78.7	79.0	79.1
	Total change 2010-2050 (years)	9.1	9.2	9.5	9.8	10.2	10.5	10.6
Urban areas	**2010**	71.1	71.1	71.1	71.1	71.1	71.1	71.1
	2050	79.6	79.6	80.0	80.3	80.6	80.9	81.1
	Total change (years)	8.5	8.5	8.9	9.2	9.5	9.9	10.0
Rural areas	**2010**	67.1	67.1	67.1	67.1	67.1	67.1	67.1
	2050	75.7	75.7	76.1	76.4	76.9	77.0	77.2
	Total change (years)	8.6	8.7	9.0	9.3	9.8	10.0	10.1

B. Males

		NPi	INDC	2°C	1.5°C	INDC-MFR	2°C - MFR	1.5°C - MFR
India	**2010**	65.1	65.1	65.1	65.1	65.1	65.1	65.1
	2050	72.8	72.8	73.2	73.6	74.1	74.4	74.5
	Total change 2010-2050 (years)	7.6	7.7	8.1	8.4	9.0	9.3	9.4
Urban areas	**2010**	68.0	68.0	68.0	68.0	68.0	68.0	68.0
	2050	74.8	74.8	75.3	75.6	76.1	76.5	76.6
	Total change (years)	6.8	6.8	7.3	7.6	8.1	8.5	8.6
Rural areas	**2010**	63.6	63.6	63.6	63.6	63.6	63.6	63.6
	2050	70.7	70.8	71.2	71.5	72.1	72.3	72.4
	Total change (years)	7.2	7.2	7.6	7.9	8.5	8.7	8.9

Table SI.5: Change in cumulative number of premature deaths due to $PM_{2.5}$ exposure (in millions) between 2010 to 2050 relative to the demographic projection, assuming 2010 $PM_{2.5}$ levels remain constant

	Year	NPi	INDC	2°C	1.5°C	INDC-MFR	2°C - MFR	1.5°C - MFR
India	2010	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	2030	1.2	1.0	0.8	0.1	-1.6	-1.8	-2.3
	2050	5.6	5.3	1.7	-2.4	-10.9	-13.3	-15.2
Urban areas	2010	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	2030	0.0	-0.1	-0.2	-0.4	-1.1	-1.2	-1.4
	2050	1.5	1.4	-0.5	-2.2	-5.5	-7.1	-8.0
Rural areas	2010	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	2030	1.3	1.1	1.0	0.5	-0.4	-0.5	-0.9
	2050	4.0	3.8	2.2	-0.3	-5.4	-6.2	-7.2

Table SI.6: Change in cumulative number of avoidable premature deaths due to $PM_{2.5}$ exposure between 2010 and 2050 relative to NPi scenario (in millions)

	Year	INDC	2°C	1.5°C	INDC-MFR	2°C - MFR	1.5°C - MFR
India	2010	0.0	0.0	0.0	0.0	0.0	0.0
	2030	-0.2	-0.5	-1.1	-2.8	-3.0	-3.5
	2050	-0.3	-3.8	-8.0	-16.4	-18.9	-20.8
Urban areas	2010	0.0	0.0	0.0	0.0	0.0	0.0
	2030	-0.1	-0.2	-0.4	-1.1	-1.2	-1.4
	2050	-0.1	-2.0	-3.7	-7.0	-8.7	-9.6
Rural areas	2010	0.0	0.0	0.0	0.0	0.0	0.0
	2030	-0.2	-0.3	-0.7	-1.7	-1.8	-2.2
	2050	-0.2	-1.8	-4.3	-9.4	-10.2	-11.2

Table SI.7: Indicators of inequalities in life expectancy at birth in 2050 according to sex and scenario

A. **Females**

Scenario	Mean average e_{x0}	Maximum average e_{x0}	Minimum average e_{x0}	Standard deviation (sd)	Coefficient of variation (CV) *	Absolute e_{x0} gap**	Relative e_{x0} gap***
NPi	80.4	87.5	73.5	4.1	0.1	14.0	1.2
INDC	80.4	87.5	73.5	4.1	0.1	14.0	1.2
2°C	80.7	88.0	74.1	4.0	0.0	13.9	1.2
1.5°C	81.0	88.2	74.5	4.0	0.0	13.7	1.2
INDC-MFR	81.2	81.2	74.9	3.8	0.0	13.4	1.2
2°C - MFR	81.5	88.8	75.1	3.9	0.0	13.8	1.2
1.5°C - MFR	81.6	88.9	75.2	3.9	0.0	13.8	1.2

B. **Males**

Scenario	Mean average e_{x0}	Maximum average e_{x0}	Minimum average e_{x0}	Standard deviation (sd)	Coefficient of variation (CV) *	Absolute ex0 gap**	Relative e_{x0} gap***
NPi	75.2	81.2	68.4	3.8	0.1	12.7	1.2
INDC	75.3	81.2	68.5	3.8	0.1	12.7	1.2
2°C	75.7	81.8	69.1	3.8	0.0	12.7	1.2
1.5°C	75.9	82.1	69.5	3.7	0.0	12.6	1.2
INDC-MFR	76.3	82.2	70.0	3.6	0.0	12.2	1.2
2°C - MFR	76.6	82.9	70.2	3.6	0.0	12.7	1.2
1.5°C - MFR	76.7	83.1	70.3	3.6	0.0	12.8	1.2

* The Coefficient of Variation (CV) is a normalised measure of dispersion and it is defined as the ratio of the standard deviation to the average value of the distribution (ref).

** Refers to the difference in e_{x0} between the regions with highest and lowest e_{x0}.

*** Refers to the ratio of e_{x0} between the regions with highest and lowest e_{x0}.

Table SI.8: Comparison of gains in life expectancy at birth between 1.5°C-MFR scenario and scenario INDC-MFR according to sex, urban/rural residence and state

	Females		Males	
State	**Rural areas**	**Urban areas**	**Rural areas**	**Urban areas**
Andhra Pradesh	1.2	1.3	1.2	1.3
Arunachal Pradesh	1.2	2.0	1.2	2.1
Assam	1.2	1.3	1.2	1.3
Bihar	1.2	1.3	1.2	1.3
Chandigarh	1.6	1.9	1.3	1.8
Chhattisgarh	1.2	1.3	1.2	1.3
Daman and Diu	1.1	1.4	1.1	1.3
Delhi	2.0	2.2	2.3	2.1
Dadra and Nagar Haveli	1.0	1.4	1.1	1.3
Goa	1.2	1.9	1.3	1.9
Gujarat	1.2	1.5	1.2	1.5
Himachal Pradesh	1.4	0.8	1.4	1.5
Haryana	1.3	2.0	1.3	2.0
Jharkhand	1.2	1.3	1.2	1.3
Jammu and Kashmir	1.4	1.7	1.4	1.7
Karnataka	1.2	1.4	1.2	1.4
Kerala	1.4	2.6	1.4	2.6
Maharashtra	1.2	1.3	1.2	1.3
Meghalaya	1.2	2.1	1.2	2.1
Manipur	1.2	2.1	1.2	2.1
Madhya Pradesh	1.2	1.3	1.2	1.3
Mizoram	1.2	2.1	1.2	2.1
Nagaland	1.2	2.1	1.2	2.1
Odisha	1.2	1.3	1.2	1.3
Punjab	1.3	1.8	1.3	1.8
Pondicherry	1.4	1.7	1.4	1.7
Rajasthan	1.2	1.4	1.2	1.5
Sikkim	1.2	2.1	1.2	2.1
Tamil Nadu	1.3	1.7	1.3	1.7
Tripura	1.2	2.1	1.2	2.1
Uttar Pradesh	1.2	1.3	1.2	1.3
Uttarakhand	1.3	1.6	1.3	1.6
West Bengal	1.3	1.3	1.3	1.3

Note: Numbers indicate the ratio of gains in life expectancy at birth (2010-2050 relative to NPi) between 1.5°C-MFR and INCD-MFR scenarios.

***Table SI.9**: Difference in total population size compared to NPi scenario for India (in millions)*

Scenario	Population size over NPi
INDC	0.3
2°C	2.0
1.5°C	5.3
INDC – MFR	13.1
2°C – MFR	14.5
1.5°C - MFR	16.2

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5.2.1 Total decrements in LE due to ambient $PM_{2.5}$

For purposes of comparability with others studies, we also estimate the total loss in LE due to ambient $PM_{2.5}$ across all scenarios modelled in Research Article II by comparing results with a counterfactual scenario, assuming a theoretical minimum risk exposure level (TMREL), below which there is no evidence of $PM_{2.5}$ impacts on mortality (Burnett et al., 2018).

Method

To estimate LE and population size under the TMREL of ambient $PM_{2.5}$, we adjusted the age-, residence- and state-specific mortality rates to eliminate $PM_{2.5}$ as health risk factor as follows:

$$m_{a,r,s}^{scen}(t) = \left(\frac{m_{a,r,s}^{base}(t) * Share_{NCD+LRI}}{HR_{a,r,s}(2010)}\right) + m_{a,r,s}^{base}(t) * (1 - m_{a,r,s}^{base}(t) * Share_{NCD+LRI})$$

Based on these new probabilities of death, we reconstructed the state-specific life tables to calculate the hypothetical future life expectancies in the absence of ambient $PM_{2.5}$. Since all other assumptions of population change remain unchanged, we attribute the difference between LE in the demographic projection and the LE under the $PM_{2.5}$ TMREL as the loss of LE due to $PM_{2.5}$ exposure. This approach is similar to the one used by the GBD (Balakrishnan et al., 2019).

Results

We find that $PM_{2.5}$ levels in 2010 reduced LE in India by 2.3 years, with state-level decrements ranging between 1.2 and 5.6 years (Figure 5.1). This estimate falls within the range of outputs from other modeling studies in India (0.9-4.3 years (Table 5.1)). The largest LE losses in 2010 occurred in urban populations (women: 2.7 urban vs 2.0 years rural, men: 3.0 urban vs 2.2 rural years). We estimated that under the NPi scenario loss in LE due to $PM_{2.5}$ in India can reach ~3 years, while pursuit of most aspirational policy (1.5° – MFR) can reduce it to ~1.4 years (Table 5.2). In terms of population size, we find that bringing ambient $PM_{2.5}$ to the TMREL of 2.4 $\mu g/m^3$, India´s population would be almost 40.1 million above the business-as-usual projections (Figure 5.2). Furthermore, when ambient $PM_{2.5}$ is completely eliminated as a health risk factor, the share of the elderly population (age 65+), is projected to reach 17.5 % from 5.5 % in 2010.

Figure 5.1: Loss in LE at birth from $PM_{2.5}$ in 2010 compared to the TMREL of 2.4 μg/m³.

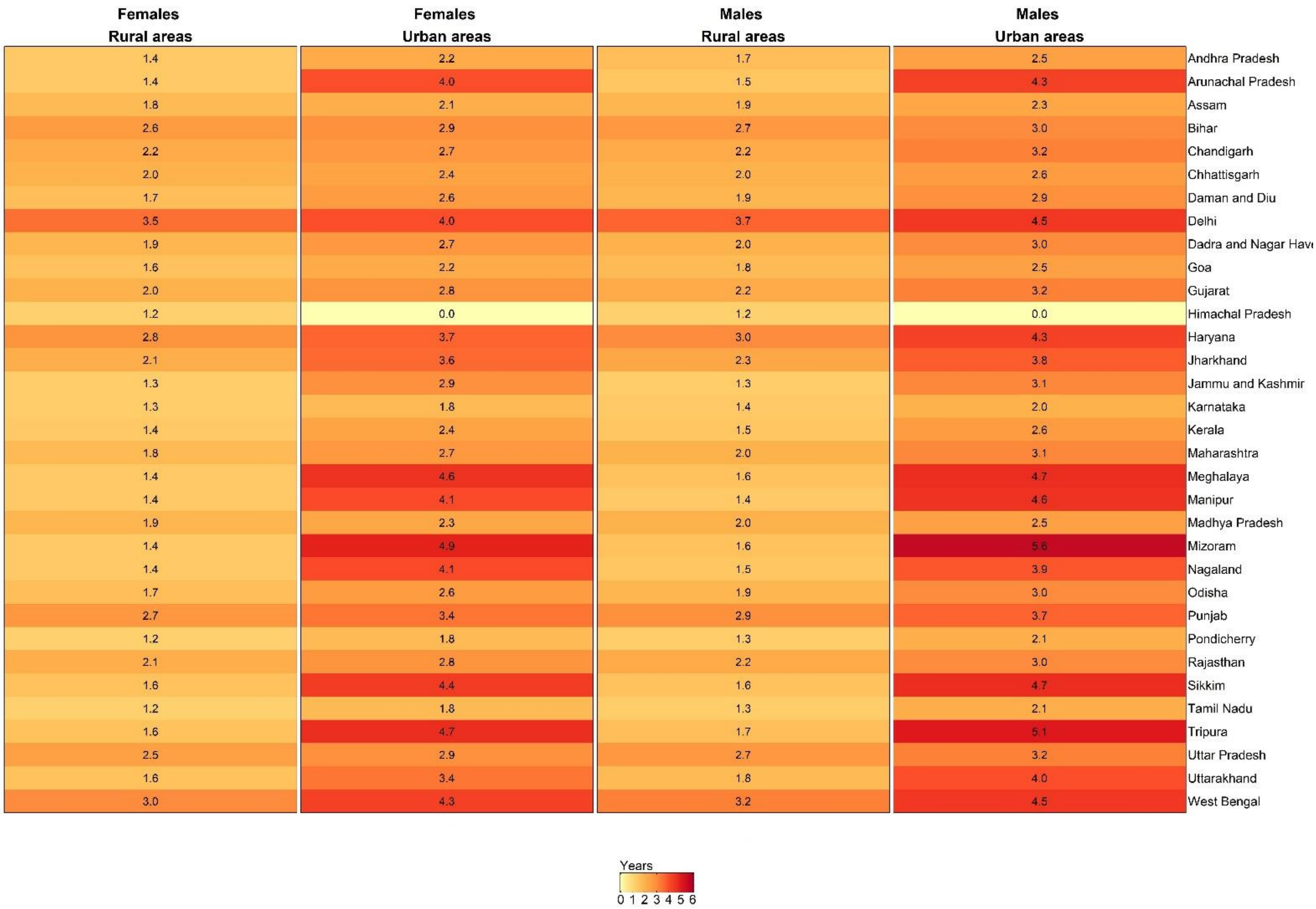


Figure 5.2: India´s total projected population under all modelled ambient $PM_{2.5}$ scenarios, including a counterfactual scenario, assuming a TMREL of 2.4 μg/m³.

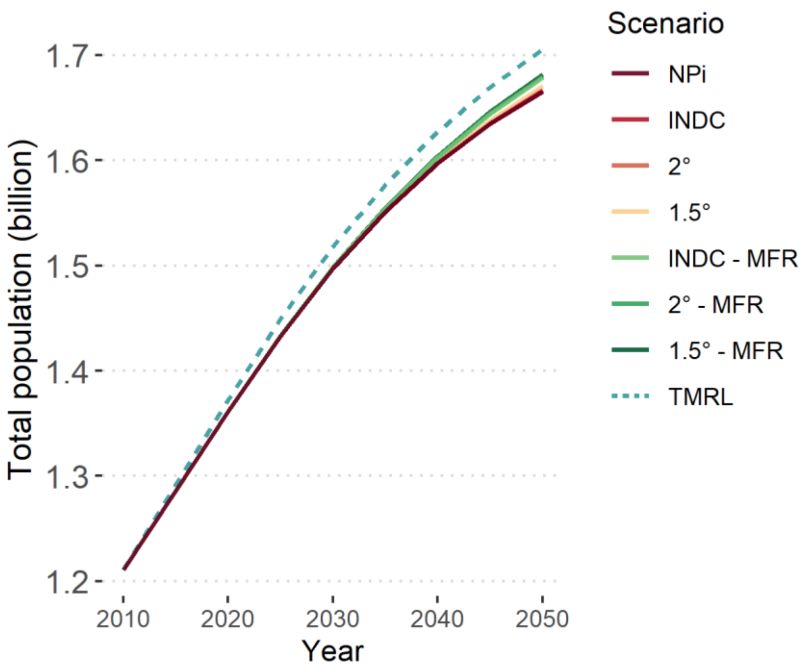


Table 5.1: Comparison of methods and $PM_{2.5}$-attributable loss in LE from this study with other studies on India

Study	Year	Air pollutant	LLE (years)	TMREL for $PM_{2.5}$	Exposure-response function	Modelled mortality causes	Method
Balakrishnan et al. (2019)	2017	ambient $PM_{2.5}$	0.9	2.4 - 5.9 μg/m³	IER	ALRIs (infants); IHD, stroke, COPD, lung, cancer, and diabetes(adults)	Cause-deleted life table approach; reporting separate impact of ambient $PM_{2.5}$ and HAP, avoiding overestimation due to exposure to both
Apte et al. (2018)	2015	ambient $PM_{2.5}$	1.53	2.4 - 5.9 μg/m³	IER	ALRIs (infants); IHD, stroke, COPD, lung, cancer (adults)	Cause-deleted life table approach

Guo et al. (2018)	2010	ambient $PM_{2.5}$	1.98	2.4 - 5.9 μg/m³	IER	ALRIs (infants); IHD, stroke, COPD, lung, cancer (adults)	Summation of the number of deaths at each age group multiplied by the number of years remaining (i.e. e0 for India)
This study	2010	ambient $PM_{2.5}$	2.3	2.4 μg/m³	GEMM	NCDs, LRIs (adults)	Cause-deleted life table approach
Ghude et. al (2016)	2010	ambient $PM_{2.5}$	3.4	NA	Pope et al. (2009)	all-cause mortality (all ages)	Applying a linear unit $PM_{2.5}$-LLE association from high-income countries
Lelieveld et al. (2020)	2015	ambient O_3 and $PM_{2.5}$	3.85	2.4 μg/m³	GEMM and Jerrett et al. (2009)	LRIs, COPD, IHD, stroke, and LC, other NCDs (adults)	Based on calculations of $PM_{2.5}$- and O_3-attributable YLL, normalised by population size and multiplied by reference maximum LE of 91.9
Greenstone and Fan (2018)	2011	ambient $PM_{2.5}$	4.3	10μg/m³ (WHO standard)	Chen, et al. (2013)	all-cause mortality	Applying an association of particulate matter and LE derived from a quasi-experimental empirical study based on China's Huai River policy

Note: IER – Integrated Exposure Response function, GEMM -Global Exposure Mortality Model, (A)LRIs – (Acute) Lower Respiratory Infections, COPD - Chronic Obstructive Pulmonary Disease, IHD – Ischemic Heart Disease, LC – Lung Cancer, NCDs – Non-communicable Diseases, LLE – Loss in Life Expectancy at Birth

Table 5.2: Decrements in LE at birth due to $PM_{2.5}$ exposure above the TMREL for India by residence and sex under all modelled scenarios

C. Females

		NPi	INDC	2°C	1.5°C	INDC-MFR	2°C - MFR	1.5°C - MFR
India	**2010**	2.2	2.2	2.2	2.2	2.2	2.2	2.2
	2050	2.7	2.7	2.4	2.1	1.7	1.4	1.3
Urban areas	**2010**	2.7	2.7	2.7	2.7	2.7	2.7	2.7
	2050	2.8	2.8	2.4	2.1	1.8	1.5	1.3
Rural areas	**2010**	2	2	2	2	2	2	2
	2050	2.6	2.6	2.2	1.9	1.4	1.3	1.1

D. Males

		NPi	INDC	2°C	1.5°C	INDC-MFR	2°C - MFR	1.5°C - MFR
India	**2010**	2.4	2.4	2.4	2.4	2.4	2.4	2.4
	2050	3.3	3.3	2.9	2.5	2	1.7	1.6
Urban areas	**2010**	3	3	3	3	3	3	3
	2050	3.5	3.5	3	2.7	2.2	1.8	1.7
Rural areas	**2010**	2.2	2.2	2.2	2.2	2.2	2.2	2.2
	2050	3.1	3	2.6	2.3	1.7	1.5	1.4

5.2.2 Comparison of the static and dynamic health impact assessment approaches

Motivation

We were interested in comparing the results of the dynamic estimation of the health burden of $PM_{2.5}$ used in Research Article II with the static health impact assessment approach (CRA) that most of the existing projection studies on air pollution and temperatures 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. 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 (a TMREL of 2.4 $\mu g/m^3$ in the GEMM). In this approach, future mortality rates and population estimates are based on assumptions of future demographics only and do not change across emission scenarios, but only the proportion of deaths that can be attributed to air pollution changes, hence the term "static" that we use. This method can be misleading for long term predictions since it does not consider changes in mortality and population survival induced by changes in exposure. For instance, using the static approach total number of deaths in a high and low emission scenario will be the same but a larger share of these deaths will be attributed to air pollution in the high emission than in the low emission scenario. Furthermore, summing up avoidable premature deaths from air pollution over time with this approach would not be appropriate, because population survival in one period would have affected future population size, structure, and deaths.

Method

For comparison between the static and the dynamic approach we selected only one of the air pollution scenarios modelled in Article II, namely the INDC scenario. First, we projected total attributable deaths due to ambient $PM_{2.5}$ based on the static approach described above, using age-, sex-, urban-rural and state-specific mortality and population estimates from the demographic projection and hazard risk estimates based on the GEMM and the projected population-weighted exposures under the INDC scenario. Second, we also projected the total deaths that could be attributed to ambient $PM_{2.5}$ using the dynamic approach. For this purpose, we ran the population projection and estimated future changes in LE and deaths under a counterfactual scenario of TMREL to $PM_{2.5}$ (<2.4 μg/m3), beyond which no health effects are assumed[11]. In other words, this is a hypothetical scenario where AAP 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:

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

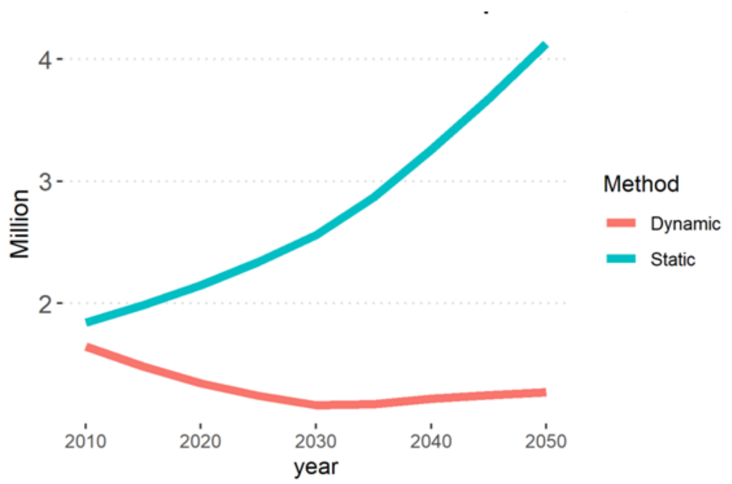
We then compared the total projected mortality under this counterfactual scenario with the projected mortality under the INDC scenario as described in Research Article II[12]. While comparison of the INDC scenario with the demographic projection provides estimates of the health impacts due to changes in $PM_{2.5}$ after 2010, the comparison of the INDC scenario with the counterfactual scenario shows total health impacts attributable to $PM_{2.5}$. By estimating total mortality burden due to $PM_{2.5}$ under the dynamic approach in this way we were able to compare it with attributable number of deaths calculated for the same scenario with the static approach.

Results

The static and dynamic methods produce very different results in terms of total number of attributable deaths. Although the two estimates are very similar in the base year (2010), the further one goes in time, the higher their difference becomes, with attributable deaths in the static approach increasing over time and in the dynamic — decreasing and stabalising (Figure 5.2). In 2050, attributable deaths in the static model are three times higher than in the dynamic one. The outcomes of the dynamic method seem counterintuitive at first since they show reduction in the mortality burden of air pollution against a trend of increasing concentrations.

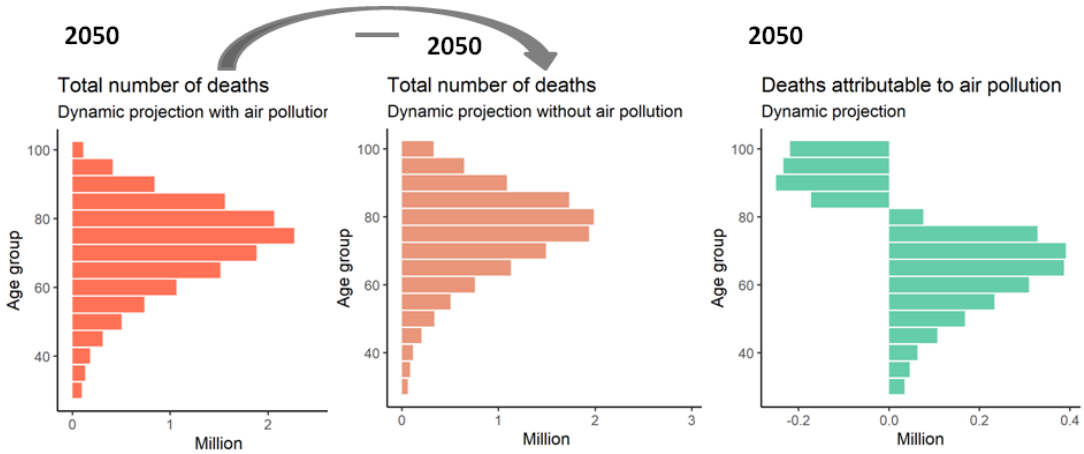
[11] Based on the GEMM model described above.
[12] Note that in this illustrative example cause-specifc mortality was not considered as in section 5.2.1

Figure 5.2: Deaths attributable to air pollution 2010-2050, INDC scenario, based on the two estimation methods



The reason behind this surprising result becomes clear when looking at the age distribution of number of deaths estimated through the dynamic method. Attributable deaths are estimated as the age-specific difference in total deaths between a counterfactual scenario without air pollution (risk-deleted mortality) and the INDC scenario with increasing air pollution (mortality adjusted to changes in risk factor). Since LE at birth in the counterfactual scenario without air pollution will be higher, deaths will be delayed in time and will take place mainly among the elder age groups. Conversely, in the scenario with increasing air pollution

Figure 5.3: Estimation of deaths attributable to air pollution in dynamic method.



$$m^{2050}Pop^{2050}\frac{HR(PM2.5\ exposure\ \ 2050)}{HR\ (PM2.5\ exposure\ \ 2010)} \qquad \frac{m^{2050}Pop^{2050}}{HR\ (PM2.5\ exposure\ \ 2010)}$$

(INDC scenario) LE would be lower, which will bring deaths forward in time. Thus, subtraction of age-specific number of deaths between the two scenarios results in negative numbers for the older age groups. Thus, the summation of total number of deaths due to ambient $PM_{2.5}$ across all age groups diminishes over time, explaining the declining trend in attributable deaths in the dynamic method (Figure 5.3). The static model does not reflect at all these changes in mortality and the structure of the population, induced by changes in exposure. As a direct function of population size, mortality rate and the exposure, attributable deaths in this method increase over time.

Discussion

We compared two different methodologies — dynamic and static — for projecting health impact 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 continues to be the norm. 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 as a risk factor (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. Comparison of the two methods using such metric was, however, beyond the scope of this thesis.

5.3 The impact of air pollution on child stunting in India – synergies and trade-offs between climate change mitigation, ambient air quality control, and clean cooking access

The impact of air pollution on child stunting in India – synergies and trade-offs between climate change mitigation, ambient air quality control, and clean cooking access

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Abstract

Background: Many children in India face the double burden of high exposure to ambient (AAP) and household air pollution (HAP), which can affect child linear growth. Although climate change mitigation is expected to decrease AAP, climate policies could increase the cost of clean cooking fuels. We aimed to project the future air pollution related burden of child stunting in India, accounting for synergies and trade-offs between climate policy, AAP control, and a clean cooking access support intervention.

Methods: We linked data from a nationally representative survey (NFHS-4) with satellite-based estimates of fine particulate matter ($PM_{2.5}$) and used a Binomial Logistic regression to quantify the association between in-utero exposure to ambient $PM_{2.5}$, cooking fuel type, and stunting among children under-5 years. Ambient $PM_{2.5}$ and clean cooking access were projected up to 2050 with an integrated assessment model under four scenarios combining climate change mitigation (2°C target) with national policies for AAP control and subsidised access to clean cooking. We developed a static microsimulation model to quantify the potential impacts on child stunting due to changes in both outdoor and indoor air pollution under each scenario, accounting for differential effects of air pollution across population groups and for socio-economic and demographic change over time.

Findings: In-utero exposure to ambient $PM_{2·5}$ significantly increased the odds of stunting (Odds Ratio (OR): 1·04, 95%CI: 1·04-1·05 per 10 μg/m^3 $PM_{2·5}$) and clean compared to polluting cooking fuel decreased the odds (OR: 0·81, 95%CI: 0·79-0·84) in confounder-adjusted models. The positive effects on child linear growth from reductions in AAP under the 2°C Paris Agreement target could be fully offset by the negative effects of mitigation through reduced clean cooking access. Targeted AAP control or subsidised access to clean cooking could shift this trade-off to result in net benefits of 2·8 (95% uncertainty interval [UI]: 1·4, 4·2) or 6·5 (UI: 6·3, 6·9) million cumulative prevented cases of child stunting between 2020-50 compared to business-as-usual. Implementation of integrated climate, air quality, and energy access interventions had a synergistic impact, reducing cumulative number of stunted children by 12·1 (UI: 10·7, 13·7) million compared to business-as-usual, with the largest health benefits experienced by the most disadvantaged children and geographic regions.

Interpretation: Findings underscore the importance of complementing climate change mitigation efforts with targeted air pollution and energy access policies to concurrently deliver on carbon mitigation, air pollution, energy poverty and health goals in India.

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Key words: stunting, air pollution, India, climate change mitigation

Research in context

Evidence before this study

Most assessments of air pollution health co-benefits from climate change mitigation to date have focused on mortality outcomes and on adult populations. These estimates underestimate the health burden from air pollution by not accounting for the multitude of relevant morbidity impacts. The potential lifelong consequences for future generations of children are still very poorly reflected in particular, even though these populations will bear a disproportionate share of the disease burden from environmental change. Furthermore, existing health co-benefit projections are based on comparative risk assessment or life table methods, which do not allow for more detailed analysis of health inequalities across socio-demographic groups and geographical areas. Lastly, the health co-benefits literature has largely focused on single exposure pathways and rarely considered concurrent effects of multiple exposures. A few microsimulation models analysing health outcomes under air pollution control have been developed for some high-income countries, but models focusing on health co-benefits from climate change mitigation and on Low and Middle-Income countries are still lacking. We searched PubMed with the search terms ("co-benefits" OR "air pollution" OR "particulate matter" OR "PM" OR "cooking fuel") AND ("stunting" OR "height" OR "growth" OR "HAZ") AND ("climate" OR "mitigation" OR "projection" OR "forecast") AND ("India") for articles published in any language up to July 1, 2021. Our search returned no published articles on the topic.

Added value of this study

We quantified the impacts of climate change mitigation and complementary policy interventions on reducing the burden of child stunting from air pollution in India. We focused on an important health outcome, with significant long-term human capital and economic consequences at the individual, household, and national level, not previously included in co-benefits analysis. Our analysis makes use of a large nationally representative, individual-level dataset and advanced analytical techniques, which allowed us to incorporate population-specific exposure response functions, differential impacts across population groups and geographical areas, and to consider simultaneous effects of indoor and outdoor air pollution. We used a static microsimulation, an integrated assessment model, and a multi-dimensional demographic projection in this first study to provide a detailed assessment of some of the counteracting and synergistic effects of climate change mitigation, ambient air quality, energy access, and socio-economic change on child health.

Implications of all the available evidence

While delivering on the Paris Agreement is projected to lead to a moderate decrease in exposure to ambient air pollution in India, household air pollution exposure is expected to increase due to reduced affordability of clean cooking fuels. This study showed that the benefits for child linear growth from reduced ambient air pollution under climate change mitigation in line with the Paris Agreement could be completely offset by projected increases in household air pollution without additional policy action. Appreciable co-benefits for child growth can be realised when global mitigation measures are accompanied by additional targeted end-of-pipe air quality control or policies to increase access to clean cooking. Child health benefits would be maximised with the coordinated implementation of climate, air quality, and energy access policies, with the largest health benefits among the most disadvantaged children. Findings from this study can help inform multisectoral national policies to protect child health while meeting the Paris Agreement targets.

Introduction

The 25 million children born annually in India are exposed to some of the highest levels of ambient air pollution (AAP) in the world, several-fold greater than current WHO guidelines. With 56 % of households in the country relying on highly polluting solid fuels to meet household energy needs, many children bear the double health burden of both high AAP and household air pollution (HAP)(International Institute for Population Sciences (IIPS) and ICF, 2017). Air pollution (both AAP and HAP) is currently recognised as the second leading risk factor for disease burden and mortality in India, surpassed only by malnutrition (IHME, 2019). A recent India Disease Burden study attributed 4·8 % (95% UI 3·6-6·0) of all under-5 deaths in the country to AAP and 4·0 % (95% UI 3·0-5·1) to HAP (India State-Level Disease Burden Initiative Child Mortality Collaborators, 2020). Exposure to air pollutants in-utero and early in life can be especially detrimental for children´s health because of their biological vulnerability and rapid development resulting in a range of adverse health outcomes (Perera, 2017; Backes et al., 2013). These include adverse birth outcomes, including low birth weight and pre-term birth, respiratory diseases such as pneumonia, asthma and bronchitis, impaired cognitive and neurological development. In addition to these well-established health outcomes, there is accumulating evidence that in-utero and early life exposure to AAP and HAP are also associated with child linear growth retardation (Zhu et al., 2015; Yuan et al., 2019; Bruce et al., 2013; Pun et al., 2021).

Stunting, defined as being too short for one´s age, is a largely irreversible linear growth impairment that can have severe long-lasting impacts on child health and human capital formation. In childhood, stunting is associated with poor cognitive development (Poveda et al., 2021) and a higher risk of mortality and susceptibility to infectious diseases such as pneumonia and diarrhoea. Later in life stunting can lead to lower productivity and earnings and increased risk of metabolic diseases (Prendergast and Humphrey, 2014). Although the biological mechanisms underlying the effects of air pollution on stunting are yet to be fully understood, it is recognised that these start during the in-utero period. Particles or their components can reach beyond the lungs of pregnant women to induce systemic inflammation or oxidative stress, leading to poor foetal growth (Backes et al., 2013). Postnatally, environmental exposure to air pollution may compound the adverse effects of poor nutrition and pathogens on immune development and function, resulting in a cycle of recurrent disease and malnutrition (Dewey and Mayers, 2011). More specifically, recurrent respiratory infections caused by air pollution may lead to suppressed appetite, impaired absorption of nutrients, increased nutrient losses and diversion of nutrients towards immune response and away from growth (Dewey and Mayers, 2011). Several observational studies from India, where child undernutrition is among the highest in the world, reported consistent results for the association between child stunting and early-life exposure to AAP (Singh et al., 2019; Spears et al., 2019) and HAP, defined as use of unclean cooking fuels, compared with cleaner alternatives (Islam et al., 2021; Fenske et al., 2013; Tielsch et al., 2009). The epidemiological evidence linking AAP and HAP with prenatal (small for gestational age) or postnatal (low height-for-age z-score) stunting has been summarised by several meta-analyses (Zhu et al., 2015; Yuan et al., 2019; Bruce et al., 2013; Pun et al., 2021). According to the most recent pooled estimates a 10 μg/m^3 increase in ambient $PM_{2 \cdot 5}$ over the entire pregnancy increased the odds of prenatal stunting by 8 % (95% CI: 3–13 %)(Pun et al., 2021), while postnatal exposure to HAP from solid fuel use compared to cleaner fuels increased the risk of postnatal stunting by 19 % (95% CI: 10-29 %).

Previous studies have shown that reductions in greenhouse gas (GHG) emissions in line with climate change mitigation targets can bring substantial AAP improvements and health benefits in India, so-called co-benefits (West et al., 2013; Silva et al., 2016; Vandyck et al., 2018; Markandya et al., 2018; Sampedro et al., 2020; Chowdhury et al., 2018), and even more so when combined with stricter national measures for air quality control (Dimitrova et al., 2021). However, scenario analysis from six different Integrated Assessment Models (IAMs), which quantified the interactions between climate change mitigation and energy access suggest that stringent climate policy might significantly slow down the transition to clean cooking fuels by affecting energy prices (McCollum et al., 2018). Thus, climate change mitigation is likely to have opposing effects on the levels of AAP and HAP exposure and the associated health and developmental outcomes for future generations of children.

We used a novel analytical method and outputs from an IAM and a multi-dimensional demographic projection to investigate, for the first time, how the synergies and trade-offs between climate change mitigation, targeted ambient $PM_{2 \cdot 5}$ control and energy access support policies could affect future child stunting in India.

Methods

Study design

Our analysis proceeded in two stages. First, we examined the association between early-life exposure to AAP, as measured by ambient $PM_{2 \cdot 5}$, and HAP, as measured by type of fuel used for cooking, and stunting in a large dataset of children under-5 years in India.

In the second stage, we developed a static microsimulation model of child stunting based on the survey data, a multi-dimensional population projection and projections of ambient $PM_{2·5}$ concentrations, clean fuel use and poverty levels from an IAM. We used the model to project the prevalence of child stunting at local level and for distinct population groups under four scenarios combining climate change mitigation, air quality control and policies to support clean cooking access (CCA). A detailed description of the data sources and methods is provided in the appendix.

Stage one: Epidemiological analysis

We used nationally representative anthropometric and household data of children under-5 from India´s 2015-16 National Family Health Survey (NFHS-4). The outcome variable in our analysis was child stunting, defined as height-for-age z- score (HAZ) below minus two standard deviations from the median of the WHO Child Growth Standards. We linked the individual data with high resolution annual average $PM_{2·5}$ concentrations for the period 2009-2016 from the Atmospheric Composition Analysis Group (Hammer et al., 2020). The data are based on satellite observations and chemical transport modelling and calibrated against available ground-based measurements (Hammer et al., 2020). Each child was assigned average $PM_{2·5}$ exposure for the in-utero period based on the location of their household cluster, date of birth and pregnancy duration. For pregnancies spanning two years, a month-weighted average was constructed (appendix 1.1).

As a proxy of exposure to HAP, we used primary cooking fuel type as reported by each household in the survey data. We analysed the effect on child stunting of cooking with clean fuels (electricity, Liquefied Petroleum Gas (LPG), natural gas and biogas) compared to high-polluting fuels (kerosene, coal, charcoal, wood, straw, crop waste and dung). We fitted a Binomial Logistic regression with a random intercept for administrative district and penalized spline for age to estimate the effects of both $PM_{2·5}$ exposure in-utero and type of cooking fuel on child stunting, adjusting for confounders and accounting for interaction effects between exposures and socio-economic variables (see appendix 1.1). We performed a series of model specification checks by including a larger set of covariates in the model, adjusting for seasonality, and estimating effects of life-course $PM_{2·5}$ exposure (appendix 1.1).

Stage two: Projections

Scenarios We developed four hypothetical pathways for India to deliver on the Paris Agreement target and compared them to a reference scenario (Table 1). “NPi without access policy” specifies a business-as-usual pathway of global GHG emissions based on currently announced climate policies till 2030, current AAP legislation and no additional support for CCA. We explore four mitigation pathways, which differ from the NPi in that they assume the implementation of a carbon price of US$40 per ton CO_2 equivalent in the year 2020 that increases at the social discount rate through until the end of the century. These pathways are consistent with a >66% chance of limiting global mean temperature increases to 2°C relative to pre-industrial levels throughout the end of the century. The four mitigation pathways differ between each other only with respect to the AAP control and compensatory energy access policies implemented at the national level. The 2°C scenarios assume compliance with current air pollution legislation only, while the 2°C MFR (Maximum Feasible Reduction) scenarios model implementation of additional few hundred end-of-pipe national air quality control measures in industrial, power generation, household, and agricultural sectors. The “no access” scenarios assume no counterbalancing price support policies on clean fuels and stoves, while the two “access” scenarios model a universal subsidy covering 15% of the cost of LPG cooking stoves and 75% of the cost of LPG fuel.

The AAP and CCA scenarios were developed independently in the MESSAGE-GLOBIOM global energy-economy IAM framework (IIASA, 2021) based on the same national CO_2 budget constraints and projections of population growth, urbanisation and various regionalised economic activities. The AAP projections were generated within the Greenhouse-Gas Air Pollution Interaction and Synergies (GAINS) module, while the clean access transitions were modelled within the Access household fuel-choice module of MESSAGE-GLOBIOM. More details on the climate-energy modelling and the linkages of the different modules can be found elsewhere (Cameron et al., 2016; Purohit et al., 2019).

Static microsimulation For each year and scenario, we generated datasets with individuals with identical characteristics to those in the stage one dataset. We applied a reweighting

<table>
<tr><th>Scenario</th><th>Climate Change Mitigation</th><th>Ambient Air Pollution Control</th><th>Clean Cooking Access</th></tr>
<tr><td>NPi without access policy</td><td>National Policies for climate, energy, environment and development until 2030, no climate policy after 2030.</td><td rowspan="3">Current air pollution legislation</td><td>No additional clean cooking access support policy</td></tr>
<tr><td>2° C without access policy</td><td rowspan="4">National Policies until 2020, after which mitigation measures in line with a >66% chance of staying below 2°C throughout 21st century.</td><td>No additional clean cooking access support policy</td></tr>
<tr><td>2° C with access policy</td><td>15 % LPG cooking stove & 75 % LPG cost subsidies available to all households</td></tr>
<tr><td>2° C MFR without access policy</td><td rowspan="2">Maximum Feasible Reduction (MFR) of air pollution</td><td>No additional clean cooking access support policy</td></tr>
<tr><td>2° C MFR with access policy</td><td>15 % LPG cooking stove & 75 % LPG cost subsidies available to all households</td></tr>
</table>

***Table 1*: Scenarios description**
NPi – National Policy Implementation, MFR – Maximum Feasible Reduction

procedure to reproduce the changes in the demographic characteristics of children under-5 over time (age, sex, state, residence, maternal education) as forecasted by a multi-dimensional demographic projection for India (K. C. et al., 2018). The population projection assumes a continuation of past demographic trends, leading to a decline in fertility and in child mortality, improvement in educational attainment and increase in urbanisation (Table S2). In each simulated dataset we altered the individual $PM_{2 \cdot 5}$ exposure during pregnancy, the income category and the primary cooking fuel of the household based on the projections from the IAM, keeping other covariates fixed.

Gridded annual mean $PM_{2 \cdot 5}$ concentrations under each scenario were obtained separately for urban and rural locations for the period 2010-2050 from the GAINS model and matched with the simulated datasets based on the geographic coordinates and urban-rural designation of NFHS-4 clusters. In-utero $PM_{2.5}$ exposure for each individual in our simulated datasets was then calculated, assuming no change in pregnancy duration and the seasonality of births.

We used data on changes in poverty levels and uptake of clean cooking fuels under the policy pathways described above, generated in the MESSAGE-Access household fuel-choice model (Cameron et al., 2016). Data were available for the whole of India and distinguished energy use patterns of four socio-economic groups based on rural-urban residence and daily per-capita expenditure threshold (PPP$2 per day in rural and PPP$5 per day in urban areas (PPP, Purchasing Power Parity)). We translated aggregate level projections into individual cooking fuel choices based on several assumptions. First, due the aggregate level of income and clean fuel projections we assumed the same rate of poverty reduction and uptake of cleaner cooking fuels for all regions. Second, since NFHS-4 includes data on relative poverty only (i.e., a composite wealth index), for each future year and scenario we generated an indicator of absolute poverty based on the household wealth index and the projected population distribution in each poverty category from the IAM. Third, we ranked fuel preferences following the theory of the “energy ladder” and assumed that as households´ economic status improves they tend to gradually shift to cleaner fuels (Van Der Kroon et al., 2013) (appendix 1.2). To also account for the importance of socio-demographic factors in determining household fuel choice, we conditioned transition to clean cooking on maternal educational level. For example, as energy access increased over time, we selected households which used kerosene and ranked highest on maternal education to transition to cleaner fuels first; after all kerosene users had transitioned, we selected those using charcoal and ranked highest on maternal education to transition, and so on until the projected share of clean fuel users for a specific socio-demographic group from MESSAGE-Access was reached. This procedure was done separately for each year, scenario, state, residence, and income group. We used the regression model specified in the epidemiologic analysis (Stage one) to predict the probability of stunting under the specified scenarios for each individual in the dataset. The adjusted sampling weights were then applied to estimate the stunting prevalence in the population under each scenario.

We performed posterior simulations to derive 95 % UIs (appendix 1.3). Lack of confidence bounds in the projections of ambient $PM_{2·5}$, access to clean cooking fuels, income, and population change limited our ability to incorporate these uncertainties in our final estimates. We performed a sensitivity analysis by re-running the simulations after calibration of modelled $PM_{2·5}$ concentrations in GAINS with those from the Atmospheric Composition Analysis Group (appendix 1.4).

Results

Epidemiological analysis

203,870 children from the NFHS-4 dataset were included in our final sample, after removing missing observations, children that had died or were reallocated since their birth. Summary statistics for the exposure variables and other covariates by stunting status are presented in Table S1. Children in our sample were on average exposed to 73·6 μg/m^3

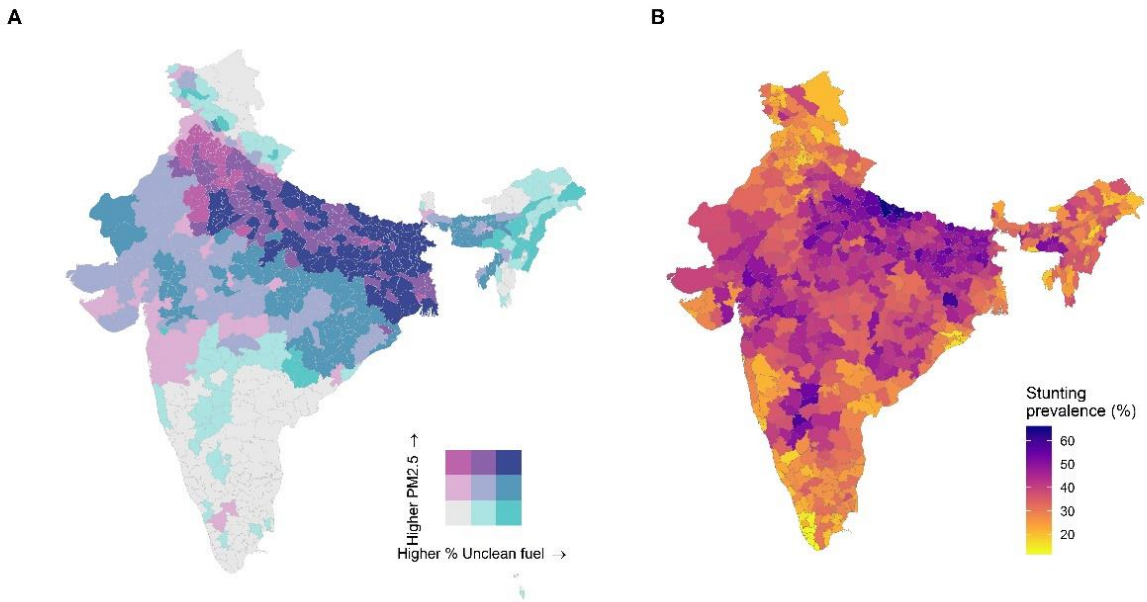

***Figure 1*: Map of India showing (a) children's district-level mean ambient $PM_{2·5}$ exposure in-utero (μg/m^3) and households using unclean cooking fuel (%) in 2015, and (b) district-level prevalence of stunting among children under-5 in 2015.**

All values are weighted using sampling weights of NFHS-4.

$PM_{2·5}$ in-utero, while 67 % of them lived in households without CCA. There were large regional variations in AAP and HAP exposure as well as in stunting prevalence (Figure1). After adjustment for confounders, our model showed that in-utero exposure to ambient $PM_{2·5}$ significantly increased the odds of child stunting (OR: 1·04, 95% CI: 1·03-1·05 per 10 μg/m^3 increase in $PM_{2·5}$), while clean compared to polluting cooking fuel decreased the odds of stunting (OR: 0·81, 95% CI: 0·79-0·84) (Table S3). We observed modification of the effect of in-utero $PM_{2·5}$ exposure on stunting by sex, residence (urban/rural), maternal education, caste, and household income. The effect of CCA was modified by sex and caste. In particular, female children, those living in urban areas, born to less educated mothers, belonging to more disadvantaged castes and to lower income households were more susceptible to the harmful effects of $PM_{2·5}$ on linear growth. Conversely, the beneficial effects of CCA on child stunting were more pronounced for children that were female and that did not belong to socially disadvantaged castes. Similar to Spears et al. (2019), we did not find evidence for a non-linear association between $PM_{2·5}$ in-utero exposure and child stunting. Seasonal effects of $PM_{2·5}$ exposure in-utero were not detected after adjusting for month of birth, and inclusion of the additional co-variates had minimal effect on the exposure effect estimates (Figure S1). As we used annual $PM_{2·5}$ data in the analysis, we could not test the effect of $PM_{2·5}$ exposure in different trimester periods on child stunting. In-utero exposure to ambient $PM_{2·5}$ was more strongly associated with child linear growth than life-course exposure (in-utero and after birth) (Figure S1).

Projections of impacts on stunting

Projected in-utero ambient $PM_{2·5}$ exposure and the share of population with CCA by residence and year are shown in Table 2. Under all scenarios ambient $PM_{2·5}$ is projected to decrease and CCA to increase over time. The largest reductions in ambient $PM_{2·5}$ are observed in the scenarios where climate change mitigation is accompanied by end-of-pipe AAP controls, while population access to clean cooking is maximised in those modelling the adoption of additional access support policies. The projected characteristics of children under-5, which are identical across all modelled scenarios, are shown in Table S2.

Scenario	Year	Average in-utero $PM_{2\cdot5}$ ($\mu g/m^3$)		Share of children living in households with CCA (%)	
		Rural	**Urban**	**Rural**	**Urban**
	2015	75	70	17	73
NPi without access policy	2030	50	61	53	90
	2050	57	73	65	95
2° C without access policy	2030	48	59	36	80
	2050	49	60	49	90
2° C with access policy	2030	48	59	77	96
	2050	49	60	90	97
2° C MFR without access policy	2030	39	48	36	80
	2050	22	30	49	90
2° C MFR with access policy	2030	39	48	77	96
	2050	22	30	90	97

Table 2: **Baseline and projected exposure variables according to scenario and year**
The 2015 values for CCA and in-utero $PM_{2\cdot5}$ are calculated based on the NFHS-4 data and the Atmospheric Composition Analysis Group data, respectively, applying sample weights. All future values are based on modelled CCA and $PM_{2\cdot5}$ concentrations, applying adjusted sample weights to account for changes in demographics, urbanisation and maternal education over time.

Figure 2 and Table S4 show the cumulative (2020-50) preventable number of stunted children over time under each intervention scenario compared to NPi and disaggregated by the contribution of changes in AAP and HAP. In the 2°C scenario without access policy, the increase in child stunting from higher HAP (+ 4 million) is larger than the reduction in the burden from AAP (-1·2 million), leading to an overall higher cumulative number of stunted children compared to NPi (2·9 million, UI: 2·8, 3·0). However, accompanying the 2°C mitigation efforts with additional AAP control or CCA support is projected to reduce the overall burden of child stunting from air pollution compared to NPi. Implementation of national policies for maximum feasible reduction of AAP can help prevent 2.8 (UI: 1·4, 4·2) million cases of child stunting between 2020-50, while compensatory subsidies for LPG cooking fuel and stoves can avert growth faltering in 6·5 (UI: 6·3, 6·9) million children. The joint implementation of the two policies along with mitigation efforts will have synergistic effects for child growth and prevent linear growth impairment in 12·1 (UI: 10·7, 13·7) million children overall compared to NPi.

Table S5 and S11 show the projected stunting prevalence over time and across scenarios with the uncalibrated and calibrated ambient $PM_{2\cdot5}$ data. Sensitivity analysis with calibration of the modelled data did not notably affect our final results (S12).

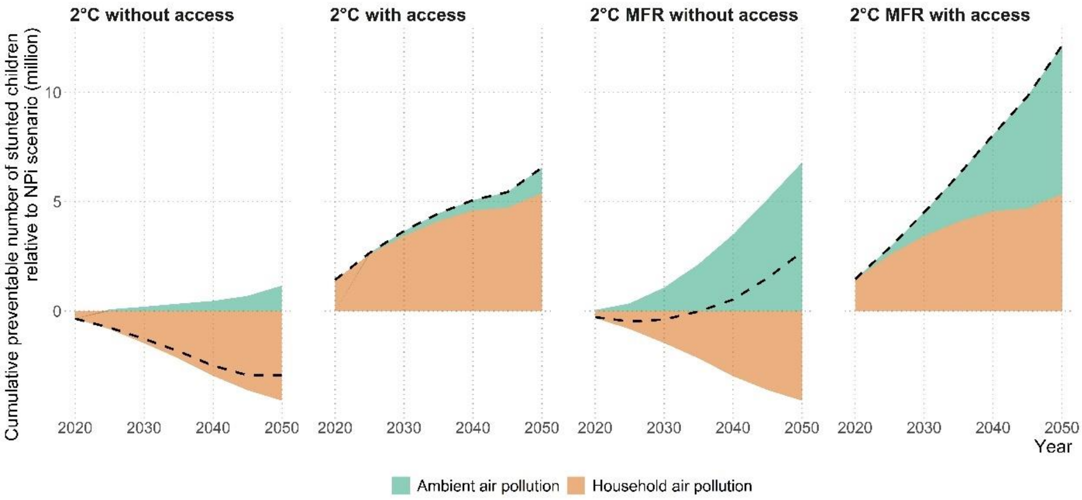

***Figure 2*: Cumulative preventable number of stunted children (in million) from changes in household air pollution (orange), ambient air pollution (green) and household and ambient air pollution combined (dashed black line) according to mitigation scenario and year relative to NPi scenario.**

The benefits of the most aspirational scenario (2°C MFR with access policy) compared to NPi differed by population groups (Figure 3 and Tables S6-S10). While all children benefited from improvements in indoor and outdoor air quality under the 2°C MFR with access policy scenario compared to NPi, child linear growth improved the most among more disadvantaged groups with the highest prevalence of stunting in 2015. Larger difference in the prevalence of child stunting in 2050 between the 2°C MFR with access policy and the NPi were estimated for children living in poorer households (- 6·3 % compared to – 2·3 % for richer households), belonging to a scheduled caste or tribe (- 3·6 % compared to – 1·6 % for those from other castes) or having an uneducated mother (- 5·8 % compared to - 2·2 % for those with highest maternal education). The benefits of the 2°C MFR with access policy scenario in 2050 were similar for both sexes and for urban and rural residents, thus only marginally reducing existing disparities in child stunting among these groups.

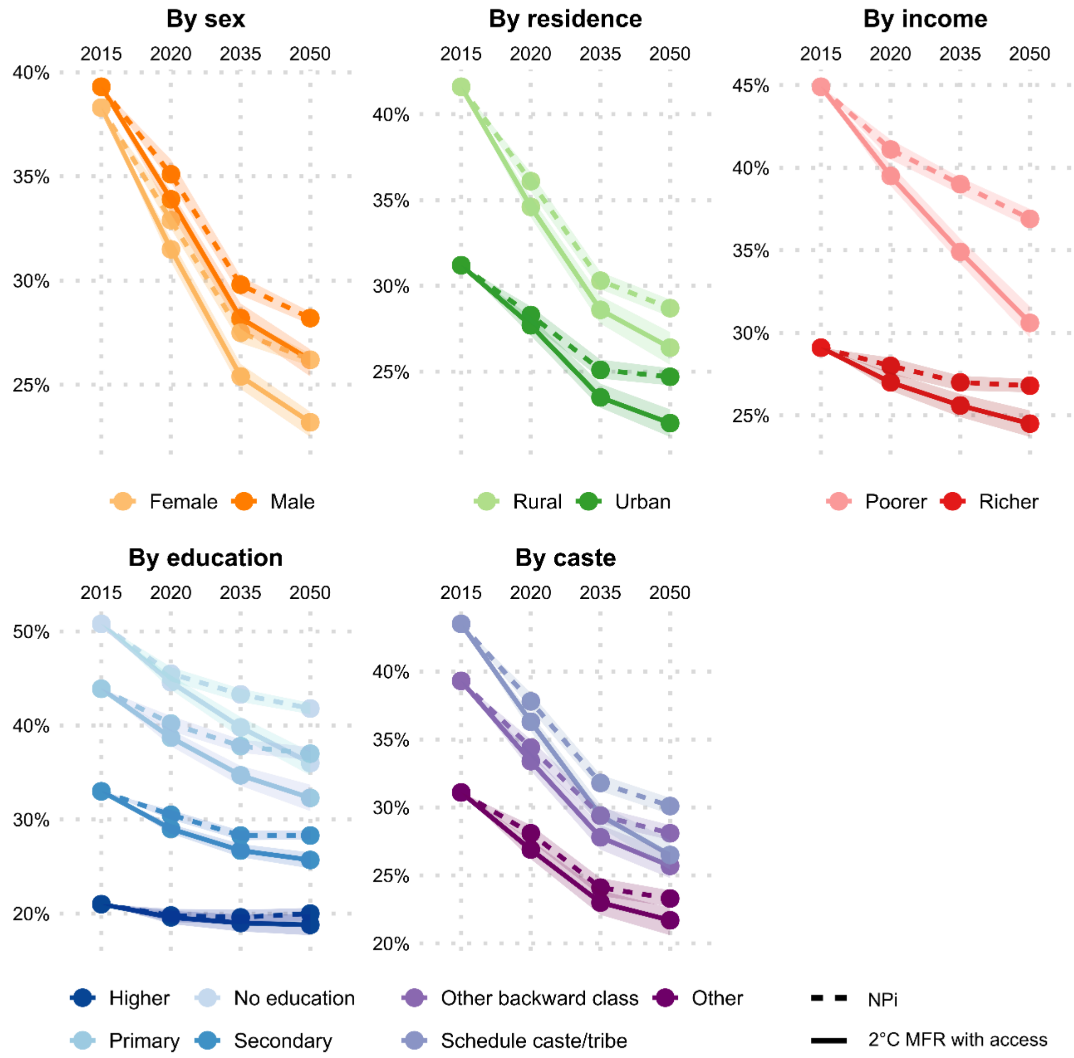

***Figure 3*: Projected trends in stunting prevalence (children under-5) by population sub-group under NPi and 2°C MFR with access policy scenarios**

Similarly, implementation of the 2°C MFR with access policy scenario was projected to reduce stunting prevalence in the districts with the highest burden of child stunting in 2015, especially in North-eastern India and around the Indo-Gangetic Plain (Figure 4). In 2050, largest reductions in the prevalence of child stunting were recorded in the Purbi Singhbhum and Saraikela Kharsawan districts in Jharkhand (- 6 %) and in the districts within the National Capital Territory of Delhi (-7 %), almost three times higher than the India average (-2·5%) (Figure 4).

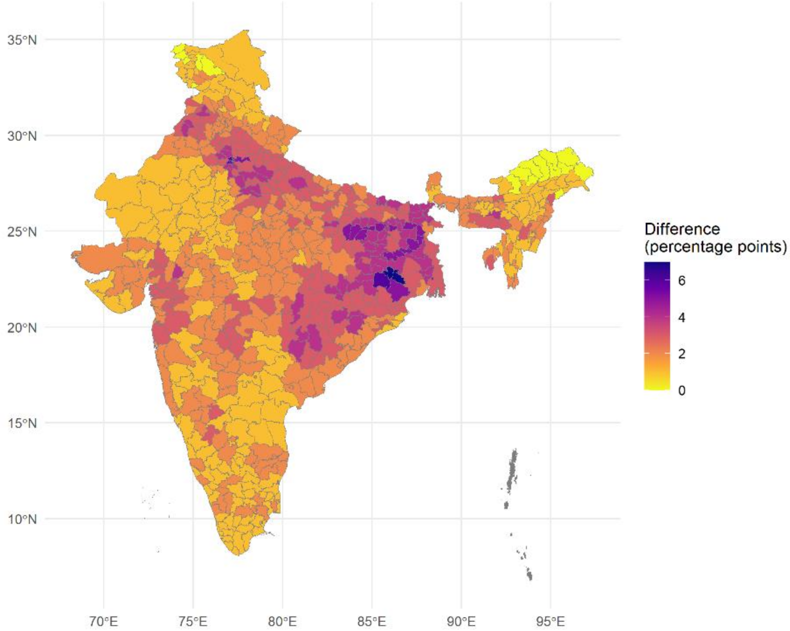

Figure 4: **Percent difference in projected prevalence of child stunting in 2050 between the 2°C MFR with access policy and NPi scenarios according to administrative district.**

Discussion

We used a static microsimulation model to assess the potential impacts of changes in AAP and HAP on child linear growth impairment in India under four policy scenarios for delivering on the Paris Agreement climate change mitigation target. Our analysis resulted in several key findings. First, the slower transition to clean cooking fuels under climate change mitigation could fully cancel out projected benefits for child linear growth due to reduced AAP without additional policies. Second, net benefit for health would result if stringent climate policy were complemented by either national end-of-pipe air quality control or policies to support clean cooking access. These policies would prevent stunting in 2·8 (UI: 1·4, 4·2) million and 6·5 (UI: 6·3, 6·9) million children between 2020-2050, respectively, compared to the business-as-usual. Third, optimal results for child growth can be achieved when mitigation action is combined with both complementary policies (stunting avoided in 12·2 (UI: 10·7, 13·7) million children). This policy pathway will also provide an opportunity to reduce inequalities in health and human capital early in life by benefiting the most underprivileged children – those with lowest household income, maternal education, and social status. In terms of geographical impacts, we estimated that the implementation of integrated climate, air quality and energy access policies would help reduce stunting where it is currently most prevalent – the regions along the Indo-Gigantic Plain and in north-eastern India. Due to the high concentrations of ambient $PM_{2.5}$

and the high levels of poverty and hence reliance of unclean cooking fuels, children growing up in these regions are likely to particularly benefit from the combined ambient air pollution controls and CCA policies.

We used a novel health impact modelling approach, which allows for an in-depth assessment of the interactions of complex population-environment dynamics and multiple exposure pathways on human health, not captured by comparative risk assessment methods. A particular advantage of the applied static microsimulation model is the more modest modelling and computational requirements compared to dynamic microsimulations and agent-based models, which still allow for comprehensive evaluation of the distributional effects of policies. We identified a number of socio-economic effect modifiers for the two exposure variables in the first stage of the analysis - sex, residence, maternal education, caste, and household income for in-utero $PM_{2\cdot5}$ exposure and sex and caste for CCA. The static microsimulation approach allowed us to reflect these heterogenous individual effects in the health impact assessment without the full computational burden of a dynamic microsimulation. By using a re-weighting procedure, we were able to account for changes in many important socio-demographic characteristics of the population – age, sex, urban residence, region, and maternal education – without having to perform a multidimensional demographic projection. The combination of static microsimulation with integrated assessment models and demographic projections offers a flexible and efficient approach for meeting the increasing demand of policy makers for projections that assess long-term health impacts and differential population vulnerabilities related to climate change.

Overall, our findings underscore the importance of complementing climate change mitigation efforts with targeted air pollution and energy access policies to improve child health in India. We identified population groups and regions where combined policies could deliver the largest health benefits, which could be valuable for more targeted national- or local-level efforts to improve air quality and clean cooking access. As highlighted by previous studies, health benefits of these combined policies crucially depend on effective enforcement and overcoming of legal, financial, social and other barriers for their sustained implementation (Peng et al., 2020).

Our analysis has a number of limitations. First, although the ambient $PM_{2 \cdot 5}$ and the CCA projections in our model were developed within the same IAM, they were not fully integrated. The effect of clean energy uptake on ambient $PM_{2 \cdot 5}$ exposure was not considered, leading to a possible underestimation in the reductions in ambient $PM_{2 \cdot 5}$. Chowdhury et. al. (2019) showed that complete mitigation of biomass emissions from cooking in 2015 would have reduced ambient $PM_{2 \cdot 5}$ concentrations in India by 17.5%. The likely underestimation in our analysis would be smaller since the difference in CCA in our mitigation scenarios with and without access in 2050 was 29% rather than 100%. Ambient $PM_{2 \cdot 5}$ reductions from end-of-pipe air quality control on indoor air quality were not reflected in the MFR scenarios since we used CCA as a proxy of indoor air pollution exposure. The adoption of more efficient biomass cookstoves modelled in the MFR scenarios was also not implemented as NFHS does not include data on type of cooking stove. However, this effect is likely to be small as improved biomass cookstoves have resulted in minimal health benefits (Sambandam et al., 2015). Second, we did not explicitly model fuel stacking due to lack of data on use of multiple fuels in NFHS-4. Fuel stacking is a well-documented behavioural response to volatile fuel supplies and prices, household incomes, or a result of cultural preferences (Van Der Kroon et al., 2013). Accounting for fuel stacking would likely lead to somewhat smaller estimated benefits of CCA policies on child stunting given that some households might not use clean fuels exclusively. Third, projected trends in poverty and clean fuel use were available only at aggregate level from the IAM. Differences in trends in income and CCA across states in our model thus only reflect disparities in 2015. As higher resolution energy, population and income projections from IAMs and demographic models become available in the future, more refined geographical variations in health impacts could be assessed. Finally, the population, energy and income projections in our model also do not reflect the catastrophic effects that COVID-19 has recently had on population health, the economy of India, and clean energy access. Although the full impacts of the crisis are still to be fully evaluated, research has suggested that the pandemic might slow down the transition to clean cooking fuels and other development objectives in the country (Ravindra et al., 2021) and affect global investments in emission reductions (Reilly et al., 2021).

Future extensions of this modelling approach could focus on incorporating dynamic feedback effects and behavioural responses such as the effects of air pollution on child survival over time or the influence of child stunting on educational attainment and adult survival later in life. In addition, an extension of this model could also evaluate the balance of costs between scenarios. Both the end-of-pipe air quality measures and the CCA subsidies presented here entail additional policy costs besides mitigation finance. However, previous research has shown that avoided premature mortality through climate change mitigation or MFR in India will considerably outweigh the potential implementation costs (Sanderson et al., 2013; Markandya et al., 2018). Furthermore, as highlighted previously, additional finance to cover subsidies for universal CCA could be mobilised through effort-sharing international climate regimes (Cameron et al., 2016). Besides these, the anticipated improvements in child linear growth, both through the air pollution co-benefits analysed here and through the avoided impacts from climate change via income and food prices previously demonstrated (Lloyd et al., 2018), represent a human capital investment, which is likely to bring to substantial savings through higher productivity, reduced morbidity, work absenteeism and associated health care costs.

Contributers

AD, GM and CT designed the study; AD and GM developed the method; GK, PR, SP and S KC provided modelled input data for the microsimulations; SO provided support in the statistical analysis and the uncertainty analysis; DR provided scientific input in the interpretation of the results; AD coordinated the work, performed the analysis, drafted the manuscript and produced the figures; all co-authors provided feedback on and contributed to the submitted version of the manuscript.

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Supplementary Appendix
The impact of air pollution on child stunting in India – synergies and trade-offs between climate change mitigation ambient air quality control and clean cooking access interventions

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1. Detailed information on data and methodology

1.1 Epidemiological analysis

Observed population data NFHS is a nation-wide, multi-round, two-stage stratified survey conducted in a representative sample of women of reproductive age[1]. Using NFHS´s child anthropometric data, we defined stunting as height-for-age z score (HAZ) below minus two standard deviations from the median of the WHO Child Growth Standards. To avoid exposure misspecification, we excluded observations for households, which were visitors or were not residing at the site at the time of birth of the child.

Baseline ambient $PM_{2.5}$ and clean cooking access data Due to the lack of direct ground-based $PM_{2.5}$ observations for India, we retrieved high resolution annual average $PM_{2.5}$ concentrations (0.01 ° x 0.01°) for the period 2009-2016 from the Atmospheric Composition Analysis Group (ACAG)[2]. The data are based on satellite observations and chemical transport modelling and calibrated against available ground-based measurements[2]. Each child in our sample was assigned average $PM_{2.5}$ exposure in-utero based on their date of birth, pregnancy duration and the geo-location of their household cluster. For pregnancy spanning two years, a month-weighted average was constructed as follows:

$$PM_{2.5in-utero} = \frac{PM_{2.5y_{concep}} * \left(12 - month_{preg\ start}\right) + PM_{2.5y_{birth}} * month_{birth}}{preg\ duration}$$

Where $PM_{2.5in-utero}$ stands for $PM_{2.5}$ exposure in the in-utero period, $PM_{2.5y_{concep}}$ – for annual average $PM_{2.5}$ exposure in the year of conception of the child, $PM_{2.5y_{birth}}$ – for annual average $PM_{2.5}$ exposure in the year of birth of the child, $preg\ duration$ – for duration of the pregnancy and $month_{preg\ start}$ and $month_{birth}$ – for the month of the start of the pregnancy and the month of birth, respectively.

As a proxy of exposure to HAP we used the type of primary coking fuel of the households in the survey data. We assumed households used the same fuel at the time of birth of the child as reported at the time of interview as previous studies have shown that cooking fuel transitions are relatively slow. We analysed the effect on child stunting of cooking with clean cooking fuels (electricity, LPG, natural gas and biogas) compared to high-polluting fuels (kerosene, coal, charcoal, wood, straw, crop waste and dung).

Statistical analysis We estimated the effect of $PM_{2.5}$ exposure in-utero and type of cooking fuel using a Binomial Logistic regression, with random intercept for administrative district (63 districts) to account for clustering. Similar to Spear *et al.* (2019) [3], we did not use the NFHS-4 sampling weights in our statistical models. Based on the literature, we identified and adjusted for the following confounders: age and sex of the child, age, education and caste of the mother, household income category (based on the household wealth index as shown in the next section) and urban-rural

residence. Following the NFHS methodology, we re-calculate the wealth index using Principal Component Analysis but excluding type of cooking fuel use.
We included a penalized spline for age and interaction terms between $PM_{2.5}$ in-utero with sex of the child, urban-rural residence, maternal education, household income category and caste and interaction terms between clean fuel use with sex of the child and caste in order to account for differential vulnerabilities to air pollution across different socio-demographic groups. The analysis was performed with R (version 3.6.1), using the package *mgcv*[4].

Our final model had the following form:

$$\ln\left(\frac{\Pr(stunted_i = 1)}{\Pr(stunted_i = 0)}\right) = \beta_0 + \beta_1 PM_{2.5\ i} + \beta_2 PM_{2.5\ i} * Sex_i + \beta_3 PM_{2.5\ i} * Residence_i + \beta_4 PM_{2.5\ i} * EducMother_i + \beta_5 PM_{2.5\ i} * IncomeGroup_i + \beta_6 PM_{2.5\ i} * Caste_i + \beta_7 s(Age_i,\ 8df) + \beta_8 Sex_i + \beta_9 AgeMother_i + \beta_{10} EducMother_i + \beta_{11} Caste_i + \beta_{12} CleanFuel_i + \beta_{13} CleanFuel_i * Sex_i + \beta_{14} CleanFuel_i * Caste_i + \beta_{15} IncomeGroup_i + \beta_{16} Residence_i + s(district_i)$$

1.2 Microsimulation model

AAP projections Gridded annual mean $PM_{2.5}$ concentrations at 0.5° x 0.5° resolution under each scenario were generated from the GAINS model for the period 2010-2050. $PM_{2.5}$ concentrations were estimated separately for urban and rural areas by intersecting the gridded $PM_{2.5}$ data with urban polygons[5] and gridded population data[6]. Each individual in our dataset was allocated year- and scenario-specific $PM_{2.5}$ exposure by matching the GPS coordinates and urban-rural designation of their clusters with those in the modelled data. For the 10.5 % (n=2,686) of clusters where the NFHS-4 and the modelled urban-rural classification differed, the NFHS-4 classification of clusters was preserved. In-utero $PM_{2.5}$ exposure was calculated for each individual, assuming no change in the seasonality of births and pregnancy duration.

Clean cooking fuel projections We used previously published data on the uptake of clean cooking fuels under the modelled scenarios generated in the MESSAGE-Access household fuel-choice model[7]. In brief, the model determines demand for clean cooking fuels for different socio-economic groups on the basis of fuel prices and household preferences and financial means[7]. The data were available for the whole of India and distinguished energy use patterns of four socio-economic groups based on rural-urban residence and daily per-capita expenditure thresholds (PPP$2 per day in rural and PPP$5 per day in urban areas). We also used projections of changes in the population distribution according to each of these groups generated with the MESSAGE-Access model. These projections were identical for each policy scenario and in line with the ‘middle-of-the-road’ storyline of the Shared Socioeconomic Pathways (SSP2)[8].

Since NFHS-4 includes data on relative poverty only (i.e. wealth index summarising household ownership of various assets), we linked each child in the NFHS-4 survey with the modelled CCA data by firstly generating an indicator of absolute poverty for the base year and for each future period. We first ranked individuals in the dataset based on their household wealth score and then assigned them an income group by applying the absolute poverty thresholds such that the distribution of the population in each category matched the population distribution in the absolute poverty projections from the model. This approach also allowed us to account for changes in the socio-economic position of households over time. Income projections were available only at the national-level; we therefore assumed the same rate of uptake of cleaner cooking fuels for all regions.

Having defined an income group for each individual, we translated the aggregate level projections into individual cooking fuel choices in our dataset. A common simplified model for explaining household fuel choices in low income countries assumes that as households´ economic status improves they tend to gradually shift to cleaner fuels i.e. ascending a metaphorical "energy ladder"[9]. Beyond income and fuel prices, studies have also found that socio-demographic factors such as education and sex of the head of the household and household size are also important determinants of household fuel choice[9]. We accounted for some of these empirical observations in our model by conditioning household adoption of clean cooking fuels on their current fuel use and maternal educational level. Based on the theory of the "energy ladder", we ranked fuel preferences in the following order: dung/crop/ waste, wood, charcoal, coal, kerosene, gas, LPG, biogas, electricity. As an example, as energy access increased over time we selected households´ which use kerosene and rank highest on maternal education to transition to cleaner fuels first, after all kerosene users have transitioned, we selected those using charcoal on the basis of maternal education to transition, and so on until the projected share of clean fuel users for a specific socio-demographic group from MESSAGE-Access was reached. This procedure was done separately for each year, scenario, state, residence and income group. Since NFHS-4 includes data only on primary cooking fuel we could not account for multiple fuel use, which is a widespread household behaviour[9].

Static microsimulation procedure We developed a static microsimulation model to quantify the potential impacts on child stunting due to the projected changes in ambient $PM_{2.5}$ and clean cooking access under each scenario, accounting for differential effects across population groups and for socio-economic and demographic change over time. For each five-years period we generated a dataset of individuals identical to the ones in NFHS-4 dataset. To account for demographic change, we updated the simulated population each future period by modifying the individual sampling weights to reflect changes in the total population and the weighted characteristics of children (e.g. sex, age, state, urban/rural residence, education of the mother) from an existing advanced population projection model. The individual sampling weights from the survey were re-scaled as follows:

$$w_{i,y,a,s,e,r,t} = w_{i,2015,a,s,e,r,t} * \frac{P_{y,a,s,e,r,t}}{P_{2015,a,s,e,r,t}}$$

Where $w_{i,y,a,s,e,r,t}$ stands for the sampling weight of individual i in year y, with age a and sex s, maternal educational level e, living in residence r and state t; $w_{i,2015,a,s,e,r,t}$ is the sampling weight of an individual with the same characteristics in 2015, $P_{2015,a,s,e,r,t}$ and $P_{y,a,s,e,r,t}$ are the size of the total population in 2015 and in the future year y, respectively, with the same age, sex, maternal education, residence and state characteristics as individual i.

To estimate the potential reduction in child stunting due AAP and HAP that could be achieved under the scenarios described previously we ran simulations with the micro-datasets with altered exposures and sampling weights. We also accounted for economic development over time by altering each year the household income category variable based on the MESSAGE-Access projections and the household wealth index as described above. Simulations on the "aged" microdata were performed as follows: for each future year and scenario the effect estimates from the multivariable model specified above were used to predict the probability of stunting for each child under the new exposure patterns for AAP and clean fuel uptake, keeping other individual characteristics constant. The individual outcomes were then averaged, applying the altered sampling weights, to estimate the population level prevalence of stunting under each scenario. Finally, results were compared between the mitigation scenarios and the NPi scenario, where only the exposure variables between them differ, in order to isolate the effect of changes in AAP and clean cooking access on child stunting. The cumulative prevented number of stunted children for a certain year was calculated for each scenario by adding up the number of prevented cases of child stunting in the respective year with the number in all preceding years.

In order to disentangle the contribution of AAP and HAP to changes in the burden of child stunting over time we ran additional simulations for each scenario. In the first set of simulations we only altered individual AAP exposure, income category and sampling weight, keeping household fuel use constant to the baseline year. Comparing results of these simulations with the simulations where all variables were altered, allowed us to isolate the impacts of changes in HAP on child stunting. Conversely, the impacts of changes in AAP on child stunting were isolated by running simulations where only individual household fuel type, income category and sampling weight were altered, keeping AAP exposure constant to the baseline year, and comparing results with the simulations where all variables were altered.

1.3 Quantification of uncertainty

We quantified the uncertainty in the estimated average stunting probability for the whole population by performing posterior simulations of the model parameters and computing the desired population average probabilities. Specifically, we simulated 500 draws from the approximate multivariate normal distribution of the parameters with the estimated mean and variance-covariance matrix from the model. Predicted probabilities were computed for each draw of simulated parameters and each individual. Population average probabilities were then computed for each draw accounting for the sampling weights. The upper and lower bounds of the confidence intervals were estimated by calculating the 2.5th and 97.5th percentiles of the sample of average probabilities. Uncertainty in our results is also likely to stem from the modelling and projections of ambient $PM_{2.5}$, access to clean cooking fuels, income, and population change. However, the lack of confidence bounds in these projections did not allow us to incorporate these set of uncertainties**.**

1.4 Sensitivity analysis

Annual ambient $PM_{2.5}$ concentrations from the model used in the first stage (ACAG) and the second stage of the analysis (GAINS) were available for the years 2010 and 2015. Comparison of the two models showed substantial differences across space, in particular for rural areas and regions in (Figure S2).

We did not perform data calibration in the main analysis since i) both datasets were based on different models, with their own assumptions and uncertainties, which made it difficult to identify a superior model and ii) the geographical resolution of the two models was very different, thus making a direct comparison difficult. However, as a sensitivity analysis we ran the simulations again after calibrating the modelled $PM_{2.5}$ concentrations in GAINS with the data from ACAG. We selected the ACAG data for the calibration as their model was already calibrated against historical monitoring data. We calibrated the two datasets by calculating the mean residence- and district-specific difference in $PM_{2.5}$ concentrations between the two models for the years 2010 and 2015 and then applied this offsetting factor to additively correct the projected GAINS time series for each cluster:

$$PM_{2.5}^{calibrated}(y,s,r,d,c) = \frac{1}{n_{c\,(r,d)}}\sum\nolimits_{n_{c\,(r,d)}} \frac{PM_{2.5\,(2010)}^{ACAGmodel}+PM_{2.5\,(2015)}^{ACAGmodel}}{2} - \frac{PM_{2.5\,(2010)}^{GAINSmodel}+PM_{2.5\,(2015)}^{GAINSmodel}}{2} + PM_{2.5}^{GAINSmodel}(y,s,r,d,c)$$

Where y- stands for year, s- for scenario, r- for urban/rural residence, d- for district and c- for cluster. This correction forces the mean bias at each residence and district to be zero, using bias detected from the two years period for each district and residence. The main underlying assumption in this data calibration method is that model bias remains stationary in time. As shown on table S11 and S12, the calibration resulted in slightly different stunting prevalence rates across scenarios compared to the original simulations. However, this did not lead to substantial differences in our final results (0.1 percentage points difference in projected prevalence of stunting due to air pollution for all scenarios), possibly due to the linear exposure response function between stunting and $PM_{2.5}$ and the fact that deviation between the prevalence rates in the calibrated and uncalibrated models was of almost equal size for each scenario, thus cancelling out when results from the NPi and any of the other mitigation scenarios are subtracted.

2. Supplementary Tables S1-S12

Table S1. Characteristics of children under-5 by stunting status, India, 2015-16

Summary Statistics	Not Stunted (N = 125108)	Stunted (N = 78762)
$PM_{2.5}$ in-utero†		
mean (sd)	66.78 (30.62)	73.15 (31.26)
Use of clean fuel for cooking		
n (%)	40,595 (32%)	15,775 (20%)
Child sex		
Female (%)	61,234 (49%)	37,141 (47%)
Child age in months		
mean (sd)	28.39 (17.55)	32.20 (15.68)
Urban residence		
n (%)	31,610 (25%)	14,563 (18%)
Mother´s age at birth		
mean (sd)	27.22 (5.09)	27.45 (5.27)
Mother´s educational level		
No education (%)	32,546 (26%)	31,864 (40%)
Primary education (%)	16,875 (13%)	12,906 (16%)
Secondary education (%)	61,581 (49%)	30,182 (38%)
Higher education (%)	14,106 (11%)	3,810 (5%)
Mother´s social group‡		
Schedule caste or schedule tribe (%)	46,718 (39%)	33,227 (44%)
Other backward class (%)	47,921 (40%)	31,690 (42%)
Other (Other 'general' caste or "Don´t know") (%)	25,181 (21%)	11,316 (15%)
Wealth quintile of household		
Poorest (%)	23,054 (18%)	22,812 (29%)
Poor (%)	24,680 (20%)	19,290 (24%)
Middle (%)	25,014 (20%)	15,327 (19%)
Rich (%)	25,337 (20%)	12,193 (15%)
Richest (%)	27,023 (22%)	9,140 (12%)
Income group		
Above absolute poverty threshold (%)	53,886 (43%)	22,008 (28%)
Below absolute poverty threshold (%)	71,222 (57%)	56,754 (72%)

Note: Sample means, standard deviations and proportions are computed without adjustment for sampling weights.

† Missing data n =1569 (< 1%)

‡ Missing data n = 7817 (3.8 %)

Table S2. Projected characteristics of children under-5 by year, India, 2030-50

Summary Statistics	2020	2030	2050
Child sex			
Female	48 %	47.7 %	47.5 %
Male	52 %	52.3 %	52.5 %
Child age in months			
mean (sd)	16.9 (4.9)	16.9 (4.6)	16.8 (4.4)
Residence			
Urban	28 %	31.5 %	36 %
Rural	72 %	68.5 %	64 %
Mother´s educational level			
No education	22 %	9.5 %	1.1 %
Primary education	13.7 %	10.9 %	4.8 %
Secondary education	52.8 %	64.6 %	74.8 %
Higher education	11.5 %	15 %	19.4 %
Wealth quintile of household			
Poorest	19.8 %	15.4 %	11.3 %
Poor	20.3 %	19 %	17.6 %
Middle	19.9 %	20.5 %	20.9 %
Rich	20.5 %	22.5 %	24.3 %
Richest	29.5 %	22.6 %	25.9 %
Income group			
Above absolute poverty threshold (%)	45.1 %	19.9 %	0.5 %
Below absolute poverty threshold (%)	54.9 %	80.1 %	95.1 %
Total projected number of children under-5	117 million	104 million	94 million

Note: These projections are identical across all modelled scenarios. Sample means, standard deviations and proportions are computed using the adjusted sampling weights. The total projected number of children under-5 refers to India and not the synthetic datasets.

Table S3. Association between cluster-level $PM_{2.5}$ exposure during pregnancy and household clean cooking fuel use with child stunting

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$PM_{2.5}$ in-utero (per 10 ug/m^3)	1.04*** (1.04, 1.05)	1.04*** (1.03, 1.05)	1.06*** (1.05, 1.06)	1.06*** (1.05, 1.07)	1.04*** (1.03, 1.05)	**1.05*** (1.04, 1.06)**
Clean cooking fuel use (ref. = Unclean cooking fuel use)	0.81*** (0.79, 0.84)	0.81*** (0.79, 0.84)	0.81*** (0.79, 0.83)	0.81*** (0.79, 0.83)	0.81*** (0.79, 0.83)	**0.73*** (0.69, 0.77)**
Male child (ref. = Female)	1.09*** (1.07, 1.12)	1.09*** (1.07, 1.12)	1.1*** (1.07, 1.12)	1.1*** (1.08, 1.12)	1.1*** (1.08, 1.12)	**1.17*** (1.12, 1.23)**

Age of mother	0.99*** (0.99, 1)	0.99*** (0.99, 1)	0.99*** (0.99, 1)	0.99*** (0.99, 0.99)	0.99*** (0.99, 0.99)	**0.99*** (0.99, 1)**
Highest educational level of mother (ref. = No education)						
Primary	0.88*** (0.85, 0.9)	0.88*** (0.85, 0.9)	0.97 (0.89, 1.04)	0.95 (0.88, 1.03)	0.95 (0.88, 1.03)	**0.95 (0.88, 1.03)**
Secondary	0.69*** (0.67, 0.71)	0.69*** (0.67, 0.71)	0.82*** (0.78, 0.88)	0.79*** (0.74, 0.84)	0.78*** (0.73, 0.83)	**0.78*** (0.73, 0.83)**
Tertiary	0.48*** (0.46, 0.5)	0.48*** (0.46, 0.5)	0.65*** (0.59, 0.72)	0.6*** (0.53, 0.66)	0.59*** (0.53, 0.66)	**0.59*** (0.53, 0.66)**
Urban residence (ref. = Rural residence)	0.87*** (0.84, 0.89)	0.77*** (0.73, 0.82)	0.75*** (0.7, 0.8)	0.77*** (0.72, 0.82)	0.76*** (0.71, 0.81)	**0.76*** (0.71, 0.81)**
Higher income group (ref. = Lower income group)	0.71*** (0.69, 0.73)	0.71*** (0.69, 0.72)	0.71*** (0.69, 0.72)	0.81*** (0.77, 0.86)	0.8*** (0.75, 0.85)	**0.8*** (0.75, 0.85)**
Social Group (ref. = Other						
Scheduled caste or scheduled tribe	1.27*** (1.24, 1.31)	1.27*** (1.24, 1.31)	1.27*** (1.23, 1.31)	1.27*** (1.23, 1.3)	1.06 (0.98, 1.13)	**1.03 (0.96, 1.11)**
Other backward caste	1.14*** (1.11, 1.17)	1.14*** (1.11, 1.17)	1.13*** (1.1, 1.17)	1.13*** (1.1, 1.16)	1.04 (0.97, 1.12)	**1 (0.93, 1.08)**
$PM_{2.5}$ in-utero (per 10 ug/m^3): Urban residence		1.02*** (1.01, 1.02)	1.02*** (1.01, 1.03)	1.02*** (1.01, 1.03)	1.02*** (1.01, 1.03)	**1.02*** (1.01, 1.03)**
$PM_{2.5}$ in-utero (per 10 ug/m^3): Highest educational level of mother (ref. = $PM_{2.5}$ in-utero (per 10 ug/m^3): No education)						
$PM_{2.5}$ in-utero: Primary			0.99* (0.98, 1)	0.99* (0.98, 1)	0.99* (0.98, 1)	**0.99* (0.98, 1)**
$PM_{2.5}$ in-utero: Secondary			0.98*** (0.97, 0.98)	0.98*** (0.98, 0.99)	0.98*** (0.98, 0.99)	**0.98*** (0.98, 0.99)**
$PM_{2.5}$ in-utero: Tertiary			0.96*** (0.95, 0.97)	0.97*** (0.96, 0.99)	0.97*** (0.96, 0.99)	**0.98*** (0.96, 0.99)**
$PM_{2.5}$ in-utero (per 10 ug/m^3): Higher income group (ref. = $PM_{2.5}$ in-utero (per 10 ug/m^3): Lower income group)				0.98*** (0.97, 0.99)	0.98*** (0.97, 0.99)	**0.98*** (0.97, 0.99)**
$PM_{2.5}$ in-utero (per 10 ug/m^3): Social Group						

(ref. = $PM_{2.5}$ in-utero (per 10 ug/m^3): Other)						
$PM_{2.5}$ in-utero: Scheduled caste or scheduled tribe					1.03*** (1.02, 1.04)	**1.03*** (1.02, 1.04)**
$PM_{2.5}$ in-utero: Other backward caste					1.01** (1, 1.02)	**1.01**(1, 1.02)**
$PM_{2.5}$ in-utero (per 10 ug/m^3): Male Child (ref. = $PM_{2.5}$ in-utero (per 10 ug/m^3): Female child)						**0.99*** (0.98, 0.99)**
Clean cooking fuel use: Social Group (ref. = Unclean cooking fuel use: Other)						
Clean cooking fuel use: Scheduled caste or scheduled tribe						**1.09** (1.02, 1.16)**
Clean cooking fuel use: Other backward caste						**1.11*** (1.05, 1.18)**
Clean cooking fuel use: Male child (ref. = Unclean cooking fuel use: Female child)						**1.05* (1.01, 1.1)**
Spline for child age in months	Yes	Yes	Yes	Yes	Yes	Yes
District random effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column presents a Binomial Logistic regression model with the child's stunting as the dependent variable and with a random intercept for administrative district. The highlighted model is the one used in the projections. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05

Table S4. Cumulative number of preventable or excess cases of child stunting (in million, 95% UI) from changes in household and ambient air pollution combined for all of India according to mitigation scenario and year relative to NPi scenario.

Year	2°C without access	2°C with access	2°C MFR without access	2°C MFR with access
2020	-0.3 (-0.3, -0.3)	1.4 (1.4, 1.5)	-0.3 (-0.2, -0.3)	1.4 (1.4, 1.5)
2025	-0.8 (-0.7, -0.8)	2.7 (2.6, 2.8,)	-0.5 (-0.4, -0.5)	2.9 (2.9, 3)
2030	-1.3 (-1.2, -1.3)	3.6 (3.5, 3.8)	-0.4 (-0.2, -0.6)	4.5 (4.3, 4.8)
2035	-1.8 (-1.8, -1.9)	4.4 (4.3, 4.6)	0 (-0.4, 0.4)	6.2 (5.8, 6.7)
2040	-2.5 (-2.4, -2.5)	5.1 (4.9, 5.3)	0.6 (0, 1.3)	8 (7.4, 8.9)
2045	-2.9 (-2.9, -2.9)	5.4 (5.3, 5.7)	1.6 (0.6, 2.6)	9.8 (8.8, 11)
2050	-2.9 (-2.8, -3)	6.5 (6.3, 6.9)	2.8 (1.4, 4.2)	12.1 (10.7, 13.7)

Note: Positive values indicate preventable cases relative to the NPi scenario, while negative values show excess cases relative to the NPi scenario

Table S5. Projected prevalence of child (<5 years) stunting (%, 95% UI) in India, by year and scenario

Year	NPi	2°C without access	2°C with access	2°C MFR without access	2°C MFR with access
2020	33.9 (33.5, 34.4)	34.2 (33.7, 34.7)	32.7 (32.2, 33.2)	34.2 (33.7, 34.7)	32.7 (32.2, 33.2)
2025	31.8 (31.4, 32.3)	32.2 (31.7, 32.7)	30.7 (30.2, 31.2)	32 (31.5, 32.5)	30.5 (30, 31)
2030	29.9 (29.4, 30.3)	30.3 (29.9, 30.8)	28.9 (28.4, 29.4)	29.7 (29.2, 30.4)	28.3 (27.7, 28.9)
2035	28.6 (28.2, 29.1)	29.2 (28.7, 29.7)	27.8 (27.4, 28.3)	28.2 (27.6, 28.9)	26.9 (26.2, 27.6)
2040	27.7 (27.2, 28.1)	28.3 (27.9, 28.8)	27 (26.5, 27.5)	27.1 (26.3, 27.8)	25.8 (25, 26.5)
2045	26.9 (26.5, 27.4)	27.4 (26.9, 27.8)	26.6 (26.1, 27)	25.9 (25.1, 26.7)	25.1 (24.3, 25.9)
2050	27.3 (26.9, 27.7)	27.3 (26.8, 27.8)	26.1 (25.6, 26.6)	26 (25.1, 26.8)	24.8 (24, 25.6)

Table S6. Projected prevalence of child (<5 years) stunting in India (%, 95% UI) by sex, year and scenario

Sex	Year	2°C MFR with access	NPi
Female	2015	38.3	38.3
Female	2020	31.5 (30.9, 32)	32.9 (32.5, 33.6)
Female	2035	25.4 (24.8, 26)	27.5 (27, 28.2)
Female	2050	23.2 (22.5, 23.7)	26.2 (25.9, 26.5)
Male	2015	39.3	39.3
Male	2020	33.9 (33.2, 34.3)	35.1 (34.7, 35.8)
Male	2035	28.2 (27.7, 28.9)	29.8 (29.3, 30.2)
Male	2050	26.2 (25.4, 26.7)	28.2 (27.9, 28.5)

Table S7. Projected prevalence of child (<5 years) stunting (%, 95% UI) in India by residence, year and scenario

Residence	Year	2°C MFR with access	NPi
Rural	2015	41.6	41.6
Rural	2020	34.6 (34, 35.2)	36.1 (35.5, 36.6)
Rural	2035	28.6 (27.8, 29.4)	30.3 (29.8, 30.8)
Rural	2050	26.4 (25.4, 27.3)	28.7 (28.2, 29.2)
Urban	2015	31.2	31.2
Urban	2020	27.7 (27.1, 28.2)	28.3 (27.8, 28.8)
Urban	2035	23.5 (22.9, 24.3)	25.1 (24.6, 25.7)
Urban	2050	22 (21.2, 22.8)	24.7 (24.2, 25.2)

Table S8. Projected prevalence of child (<5 years) stunting (%, 95% UI) in India by income category, year and scenario

Income category	Year	2°C MFR with access	NPi
Poorer	2015	44.9	44.9
Poorer	2020	39.5 (38.9, 40.2)	41.1 (40.5, 41.7)
Poorer	2035	34.9 (34.2, 35.7)	39 (38.4, 39.4)
Poorer	2050	30.6 (29.7, 31.6)	36.9 (36.4, 37.5)
Richer	2015	29.1	29.1
Richer	2020	27 (26.5, 27.6)	28 (27.5, 28.5)
Richer	2035	25.6 (24.9, 26.3)	27 (26.5, 27.4)
Richer	2050	24.5 (23.7, 25.3)	26.8 (26.4, 27.2)

Table S9. Projected prevalence of child (<5 years) stunting (%, 95% UI) in India by maternal education, year and scenario

Maternal education	Year	2°C MFR with access	NPi
No education	2015	50.8	50.8
No education	2020	44.6 (43.8, 45.3)	45.5 (44.7, 46.2)
No education	2035	39.8 (38.7, 40.9)	43.3 (42.5, 43.9)
No education	2050	36 (34.7, 37.2)	41.8 (41.2, 42.4)
Primary	2015	43.9	43.9
Primary	2020	38.7 (37.8, 39.5)	40.2 (39.4, 41)
Primary	2035	34.7 (33.6, 35.7)	37.8 (37.1, 38.5)
Primary	2050	32.3 (30.9, 33.7)	37 (36.3, 37.7)
Secondary	2015	33	33
Secondary	2020	29 (28.5, 29.5)	30.5 (30, 31)
Secondary	2035	26.7 (26, 27.4)	28.3 (27.8, 28.8)
Secondary	2050	25.7 (24.8, 26.5)	28.3 (27.9, 28.8)
Higher	2015	21	21
Higher	2020	19.6 (18.9, 20.3)	19.8 (19.1, 20.5)
Higher	2035	19 (18.1, 19.9)	19.6 (18.9, 20.4)
Higher	2050	18.8 (17.7, 19.9)	20 (19.3, 20.6)

Table S10. Projected prevalence of child (<5 years) stunting (%, 95% UI) in India by caste, year and scenario

Caste	Year	2°C MFR with access	NPi
Other backward class	2015	39.3	39.3
Other backward class	2020	33.4 (32.7, 34)	34.4 (33.8, 35)
Other backward class	2035	27.8 (26.9, 28.7)	29.4 (28.8, 30)
Other backward class	2050	25.7 (24.8, 26.7)	28.1 (27.6, 28.7)
Other	2015	31.1	31.1

Other	2020	26.9 (26.2, 27.6)	28.1 (27.5, 28.7)
Other	2035	23 (22.1, 23.9)	24.1 (23.5, 24.8)
Other	2050	21.7 (20.6, 22.6)	23.3 (22.7, 23.9)
Schedule caste/tribe	2015	43.5	43.5
Schedule caste/tribe	2020	36.3 (35.6, 36.9)	37.8 (37.2, 38.4)
Schedule caste/tribe	2035	29.4 (28.5, 30.2)	31.8 (31.2, 32.4)
Schedule caste/tribe	2050	26.5 (25.4, 27.6)	30.1 (29.5, 30.7)

Table S11. Projected prevalence of child (<5 years) stunting (%, 95% UI) in India, by year and scenario based on calibrated $PM_{2.5}$ exposure

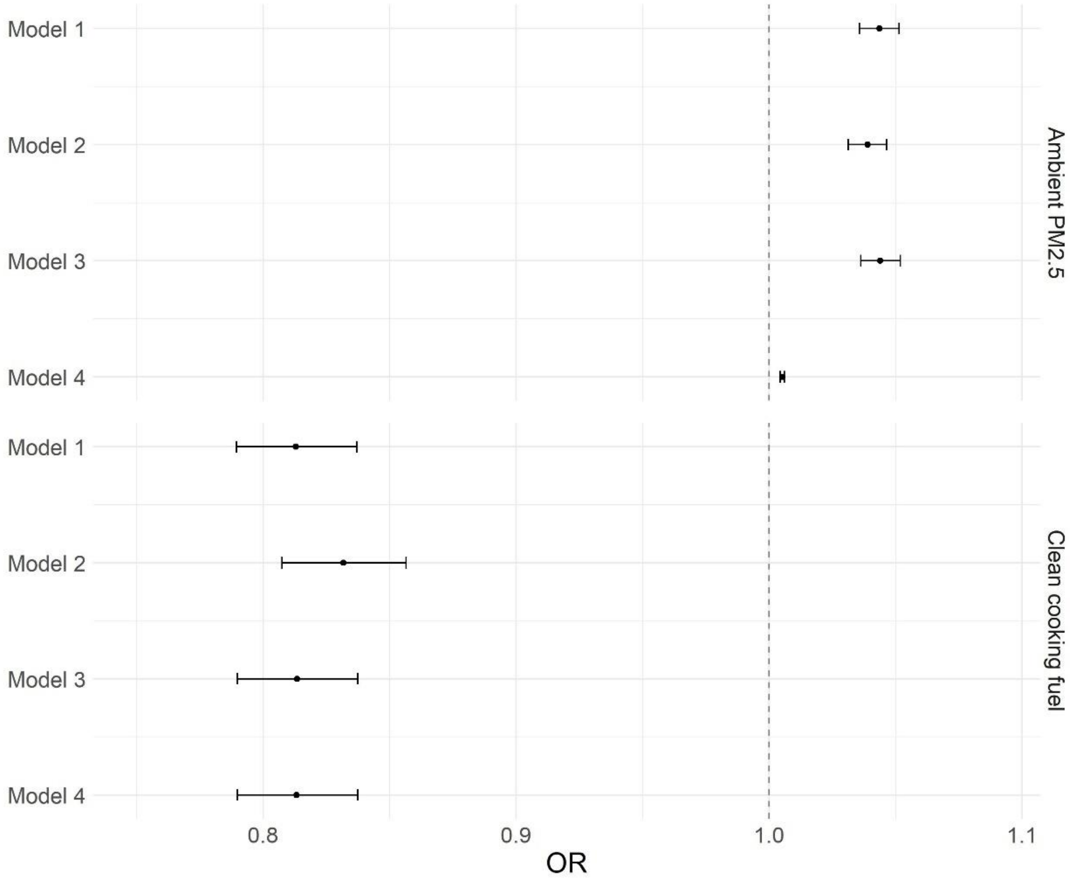
Year	NPi	2°C without access	2°C with access	2°C MFR without access	2°C MFR with access
2020	35.8 (35.5, 36.1)	36.1 (35.8, 36.4)	34.6 (34.2, 34.9)	36.1 (35.8, 36.4)	34.6 (34.2, 34.9)
2025	33.5 (33.2, 33.8)	33.8 (33.5, 34.1)	32.3 (32, 32.7)	33.6 (33.3, 33.9)	32.1 (31.8, 32.5)
2030	31.2 (30.9, 31.5)	31.7 (31.4, 32)	30.3 (29.9, 30.6)	31.1 (30.7, 31.5)	29.7 (29.2, 30.1)
2035	29.8 (29.5, 30.2)	30.4 (30.1, 30.7)	29 (28.6, 29.4)	29.4 (29, 29.8)	28.1 (27.6, 28.5)
2040	28.7 (28.3, 29.1)	29.4 (29.1, 29.8)	28.1 (27.7, 28.5)	28.1 (27.6, 28.6)	26.8 (26.3, 27.3)
2045	27.9 (27.5, 28.4)	28.4 (28, 28.8)	27.6 (27.1, 28)	26.9 (26.3, 27.4)	26.1 (25.5, 26.6)
2050	28.3 (27.8, 28.7)	28.2 (27.9, 28.6)	27 (26.6, 27.5)	26.9 (26.3, 27.5)	25.7 (25.1, 26.3)

Table S12. Difference in projected prevalence of child (<5 years) stunting in India between NPi and mitigation scenarios based on calibrated and uncalibrated $PM_{2.5}$ exposure in percentage points

	Model with calibrated PM2.5 exposure				Model with uncalibrated PM2.5 exposure			
Year	2°C without access	2°C with access	2°C MFR without access	2°C MFR with access	2°C without access	2°C with access	2°C MFR without access	2°C MFR with access
2020	-0.3	1.2	-0.3	1.2	-0.3	1.2	-0.3	1.2
2025	-0.3	1.2	-0.1	1.4	-0.4	1.1	-0.2	1.3
2030	-0.5	0.9	0.1	1.5	-0.4	1	0.2	1.6
2035	-0.6	0.8	0.4	1.7	-0.6	0.8	0.4	1.7
2040	-0.7	0.6	0.6	1.9	-0.6	0.7	0.6	1.9
2045	-0.5	0.3	1	1.8	-0.5	0.3	1	1.8
2050	0.1	1.3	1.4	2.6	0	1.2	1.3	2.5

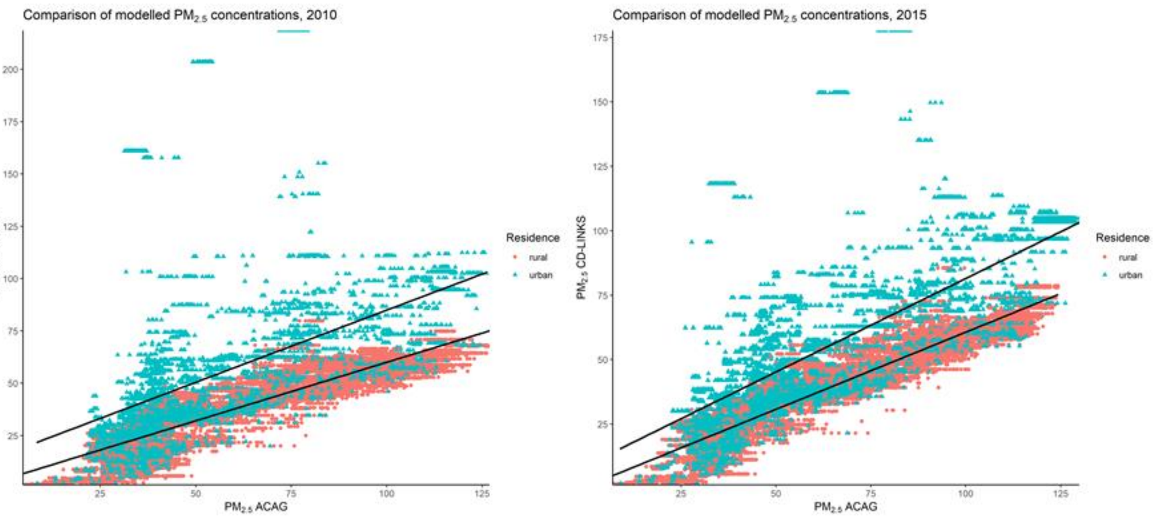
3. Supplementary Figures S1-S2

Figure S1. Model specification checks



Note: **Model 1** is identical to Model 1 in Table S3 (main model without interaction terms); **Model 2** is identical to Model 1, but controls additionally for the following co-variates: birth order of the child, multiple birth, mother´s age, short maternal stature, male household head and number of children under-5 in the family; **Model 3** is identical to Model 1, but controls additionally for month of birth of the child; **Model 4** is identical to Model 1, but ambient life-course $PM_{2.5}$ exposure (averaged $PM_{2.5}$ exposure over the in-utero and after birth period) instead of in-utero exposure is used as a dependent variable.

Figure S2. Comparison of $PM_{2.5}$ concentrations modelled in GAINS ($PM_{2.5}$ CD-LINKS) and ACAG ($PM_{2.5}$ ACAG) for 2010 and 2015



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Chapter 6: DISCUSSION AND CONCLUSIONS

6.1 Main findings and contribution to current knowledge

This thesis explored some of the health implications of climate change and co-benefits of climate change mitigation in India by taking ambient temperatures and air pollution as case studies. The research questions posed in the introduction were addressed in three thematic chapters. The first thematic chapter systematically reviewed and meta-analysed the association between ambient temperatures/heatwaves and mortality in South Asia, while the other two projected air pollution-related health co-benefits of climate change mitigation in India in terms of gains in LE, avoided premature deaths, and prevented cases of child stunting. The main findings of each of the three studies with respect to the pre-specified objectives are summarised below.

The first study systematically reviewed and quantitatively assessed the current evidence on the association between ambient temperature and heat waves, and all-cause mortality in South Asia. First, individual studies reported high and low ambient temperatures and heatwaves as a risk factor for all-cause mortality. Second, the strength of the evidence on ambient temperature as a risk factor for all-cause mortality was judged as *sufficient* and on heat wave episodes — as *limited*. This was mainly due to the limited number of studies (n=27), their skewed geographical distribution, and methodological weaknesses. Third, the meta-analysis on daily ambient temperature and risk of mortality resulted in a U-shaped ERF, with increasing mortality for both high and low temperatures, but a statistically significant association only at higher temperatures – above 31°C for lag 0-1 day and above 34°C for lag 0–13 days. Lastly, temperature effects varied with the cause of death, age, sex, location (urban vs. rural), level of education, and socioeconomic status, but overall evidence of vulnerabilities was fragmented and inconsistent across studies.

The second study projected the future localised (i.e. state and urban-rural level) health co-benefits from reduced ambient $PM_{2.5}$ in India under global climate change mitigation scenarios in line with the Paris Agreement targets and national scenarios for maximum feasible air quality control. First, we found that reduction of ambient $PM_{2.5}$ under the aspirational 2°C and 1.5°C climate change mitigation targets laid out in the Paris Agreement can lengthen LE at birth in India in 2050 by 0.4 and 0.7 years, respectively, compared to the business-as-usual. Additionally, meeting these targets can prevent between 3.9 million and 8.0 million premature deaths overall in the period 2010-50. Second, complementing the Paris Agreement targets with maximum feasible end-of-pipe air quality control can result in up to 1.6 years of gains in LE and up to 20.8 million averted deaths between 2010 and 2050 compared to the business-as-usual. Third, the largest gains in LE from cleaner air due to climate change mitigation and air quality control will occur in urban areas and in states with lower socio-economic development. Fourth, we investigated total loss in LE under each scenario and found that loss in LE from ambient $PM_{2.5}$ in India could increase from 2.3 years in 2010 to 3 years in 2050 without any climate mitigation or stricter air quality control, a matter of concern, considering India´s low ranking in LE globally (United Nations Development Programme, 2019). However, it was shown that this loss could be reduced to 1.4 years under the most aspirational scenario, which is comparable to current $PM_{2.5}$ decrements in LE in North America (Lelieveld et al 2020). Finally, the higher LE in the modelled aspirational scenarios also results in larger population size and proportion of the elderly in the total population compared to the business-as-usual, with potential implications for energy and resource use, and social planning.

The third study projected the future localised (i.e. district and urban-rural level) net benefits for child linear growth from changes in AAP and HAP under a combination of scenarios for climate change mitigation, AAP control, and CCA. First, the increase in child stunting from higher HAP (+ 4 million) under the 2°C Paris Agreement target is projected to outweigh the reduction in the burden from AAP (-1.2 million) in the period 2020-50, leading to an overall higher cumulative number of stunted children compared to the business-as-usual (2.9 million, UI: 2·8, 3·0). Second, complementing the 2°C mitigation efforts either with maximum feasible control of AAP or compensatory LPG stove and fuel subsidies is projected to reduce the overall burden of child stunting from air pollution by 2.8 (UI: 1.4, 4.2) or 6.5 (UI: 6.3, 6.9) million, respectively, compared to the business-as-usual. Third, complementing mitigation efforts with both targeted air quality control and CCA support will produce a synergistic impact by averting 12.1 (UI: 10.7, 13.7) million cases of child stunting. Finally, this synergistic effect will help reduce health inequalities early in life by benefitting the most disadvantaged children and geographic regions.

6.2 Contribution to current research

The analyses undertaken in this thesis contributed to the advancement of the research field on the health impacts of climate change and co-benefits of climate change mitigation in several ways, which are summarised below.

Research Article I

An important element in estimating the potential disease burden from climate change is the availability of robust and setting-specific ERFs. As daily temperature and mortality data series are still missing for many countries in South Asia due to underdeveloped monitoring systems, population-specific ERFs cannot always be estimated. Where such ERFs exist, they are often based on populations of small size and using observations from a limited number of years. These gaps either hinder the development of future temperature-related projections or add a large uncertainty to projected estimates. The first article included in this thesis provided meta-analysed estimates from the best available time-series studies on temperature and all-cause mortality in the region. This meta-analysis addresses an important data gap and supports future health impact assessment studies in a "data-scarce" region, which is a hotspot of climate change and urgently needs such projections for future planning. Furthermore, our systematic review complements other existing reviews (Burkart et al., 2014; Green et al., 2019; Salve et al., 2018) by assessing the strength and quality of the body of evidence, which is of central importance when informing policy and programming decisions. Methodologically, we demonstrated the application of a novel meta-analytic method for combining ERFs without access to individual study data. The study also summarised research gaps and needs of particular policy priority, namely the role of modifying factors, vulnerable population groups, and interactive effects with other environmental exposures.

Research Article II

As India has low historical emissions of GHGs, wider development impacts of climate change mitigation (co-benefits) are recognised as the main policy motive for cooperation in climate negotiations (Dubash, 2013). The second article included in this thesis demonstrated the health co-benefits of climate change mitigation related to the largest environmental contributor to the disease burden currently in the country, namely air pollution. Although prior co-benefit studies on India exist, we reported impacts for distinct population groups (age, sex, urban-rural residence) and at a lower aggregation than previously estimated (state level). In addition, health co-benefit estimates were reported as gains in LE, which is a more informative summary measure of population health than premature mortality. By modelling both climate change mitigation policies and targeted air quality control, we demonstrated a wider set of tools available for reducing the high burden of air pollution in the country. Most co-benefits studies rarely consider such interactive effects or compare global mitigation with national policy measures. Results demonstrated that targeted air quality control policies matter more for reducing the burden of air pollution than climate change mitigation, but not for all regions in the country. These findings suggest that although climate mitigation can support public health policy, it might not be sufficient for addressing public health challenges. Our findings also revealed an unexpected effect of climate change mitigation on population size and structure, which has not been reported before or considered in integrated modelling. Methodologically, we linked in a consistent way a multi-dimensional demographic projection and an IAM and accounted for feedback effects of air pollution on population survival over time, thus providing more realistic estimates on the interplay between exposure and population dynamics over time. This has previously been applied only by one study on India, but under different scenarios and using more aggregate country-level data (Sanderson et al., 2013). Furthermore, we provided updated estimates using the latest ERF based on an unprecedented number of cohort studies and covering a higher exposure-response range.

Research Article III

Climate change mitigation can produce not only unintended positive impacts but also pose trade-offs with other policy objectives. The third article included in this thesis investigated the potential trade-offs between climate change mitigation and clean energy access for child linear growth in addition to the positive co-benefits of AAP reduction. One study has previously investigated this trade-off, but for South Asia overall and considering only mortality from HAP, but no morbidity or AAP impacts (Cameron et al., 2016). Integrated assessments of such co-benefits and trade-offs can better support decision-making and inform complementary adaptation policies in advance. Furthermore, responding to the accumulating evidence on the association between early-life exposure to HAP and AAP and child linear growth retardation, this is the first study to attempt to project the future impacts of air pollution on child stunning. Lastly, the study demonstrated the application of a novel health impact modelling approach, which allows for the integration of complex population-environment interactions, multiple exposures pathways, and differential population vulnerabilities. A few dynamic microsimulation models analysing health outcomes under air pollution control scenarios have been developed for some high-income countries (Pimpin et al., 2018; Symonds et al., 2019). However, the author is not aware of other studies using a microsimulation approach to project future health impacts of air pollution in LMICs. Particular advantages of the approach compared to a dynamic microsimulation are the lower data, time, and computer processing requirements.

6.3 Uncertainty

Uncertainty is a major concern when projecting any future impacts of climate change due to the inherent complexity and uncertainty of the modelled processes. Comprehensive uncertainty analysis for HIAs is generally desirable to better support quantitative risk assessments. Quantitative uncertainty analysis was not undertaken in Research Article II due to the complexity of the applied method, while Research Article III reported uncertainty bounds related to parameters in the ERF only. The lack of uncertainty bounds for other important parameters in the HIA such as the modelled air pollution concentrations, income, energy access, and population projections, hindered a more complete treatment of uncertainty in our estimates. Here, the main uncertainties in the model and how they can potentially be addressed in the future are discussed qualitatively.

The uncertainty in the final estimates from our modeling studies (Research Article II and Research Article III) stem from the following key sources: (i) baseline and projected GHG emissions, clean fuel use, and income data from the IAM (ii) projected ambient $PM_{2.5}$ concentrations from the GAINS air pollution model, (iii) the ERFs and their extrapolation to future populations, (vi) baseline and projected population and disease burden data. Each of these uncertainties flows from one model component to the next, thus producing a cascading effect (Figure 6.1).

Large uncertainties in the air pollutant pre-cursors, clean energy access, and income projections in our models stem from the IAM used to simulate the future climate, economy, and energy systems (MESSAGE-GLOBIOM). Since IAMs are "simplified, stylised numerical approaches to represent enormously complex physical and social systems" they are built on a large number of assumptions (Clarke et al., 2015, p.422). These include many

Figure 6.1: The cascading effects of uncertainty for assessing the future impacts of co-benefits of climate change mitigation.

Source: Adapted from Gosling et al. (2009)

input assumptions regarding changes in population, resources, technology, baseline economic growth, and mitigation policy. IAMs do not structurally represent many dynamic and deeply uncertain social and political processes, which can influence how the world evolves such as habits, social customs, political shocks, disruptive innovation, or socio-economic shocks such as the COVID-19 pandemic. Since IAMs use Neoclassical economic theory as the basis for decision making, they assume fully functioning markets and competitive market behavior as well as rational, welfare-maximizing individuals with perfect foresight (Clarke et al., 2015). Furthermore, although climate change mitigation targets can be reached in a large variety of ways, most IAMs, including MESSAGE-GLOBIOM, are based on the minimisation of aggregate economic costs. Another main limitation of IAMs is that only abatement costs are considered, while the economic costs and benefits of climate damages and co-benefits of efforts to limit warming are normally not reflected. When interpreting the results of the two modelling studies included in this PhD thesis it is also important to bear in mind the political-economy constraints and assumptions that MESSAGE-GLOBIOM implies, and more specifically the use of an economy-wide global carbon price when developing future emission pathways to meet temperature limits. A complete review of the assumptions and uncertainties related to IAMs is provided in Chapter 2 of the IPCC´s 1.5C report (Forster et al., 2018). One way in which uncertainty in IAMs can be managed is by comparing findings from different models and based on different assumptions about the future. Since each IAM has its specific characteristics and assumptions, areas of consensus provide more robust evidence for policymaking. Concerning the projections used in this thesis, the inadequacy of current NDCs to set the world on a 2°C trajectory and achieve notable air pollution co-benefits, is a robust finding across different IAMs (IPCC, 2018; Rafaj et al., 2021).

Additional uncertainty in our estimates stems from the air quality module of the IAM considered in this thesis, GAINS. This uncertainty is related to the reduced-form source-receptor relationships used to quantify the spatial response of $PM_{2.5}$ concentrations to changes in precursor emissions, the downscaling technique used to calculate ambient concentrations at higher spatial resolution (urban/rural), the baseline activity and technology data and assumptions on the applications and effectiveness of technical measures. Despite these limitations, a comparison of observational $PM_{2.5}$ data for India with modelled data has shown relatively good agreement (Chapter 5). In Research Article III, projected concentrations in GAINS differed from modelled concentrations in the epidemiological stage of the analysis. However, it was demonstrated that calibration of the projected data with baseline data did not affect our findings.

As discussed in section 1.5.3, air pollution ERFs may differ among areas and populations due to a range of factors such as differences in concentration ranges, the composition and toxicity of air pollutants, population structure, baseline health status, and time-activity patterns of the population, quality, and access to health care. In the absence of regional epidemiological studies on the relationship between long-term exposure to $PM_{2.5}$ and mortality, in Research Article II we were restricted to use available ERFs from cohort studies conducted in other parts of the world. However, unlike most existing studies on India, we used the latest available ERF, which covers a larger exposure range, thus providing more certainty in the shape of the function at higher concentrations. Epidemiological studies on air pollution and mortality from India and other LMICs will be needed to provide more robust evidence for future HIAs. In Research Article III a population-specific ERF for the association between in-utero $PM_{2.5}$ exposure and child stunting was derived, thus partly reducing overall uncertainty. It should be mentioned, however, that ERFs can also change over time due to socioeconomic, demographic, behavioral, and political changes (Madaniyazi et al., 2015). While some projections studies on the mortality impacts of temperature changes account for this by incorporating assumptions on adaptation, this aspect is generally not considered in air pollution studies.

The uncertainty in the population modelling stems from uncertainty in the baseline disease burden and population data as well as in the projections of future disease burdens and size, characteristics, and geographic distribution of the population. We aimed to minimize uncertainties in the baseline population data by relying on official government census data (Research Article II) and a large population-representative survey (Research Article III). However, in the absence of cause-specific mortality data in the region, especially at the regional and urban/rural level, we were restricted by the assumptions of the available modelled data from the India State-level GBD. Furthermore, the population projections integrated in the two HIA studies are based on some of the most advanced methods to date and are consistently used by the climate modelling community. However, since the assumptions of demographic drivers are partly based on past trends and on expert consultation, uncertainty related to unexpected socio-economic developments is inevitable. We selected to model a middle-of-the-road scenario for population change in order to ensure consistency between projections of exposed population and population projections driving the energy, land, and resource demand in the IAM. Future studies can incorporate uncertainty in the main drivers of population change by considering the alternate demographic pathways embedded in the SSPs or estimates from other population projection models. Retrospective validation of the macro- and microsimulation can also be undertaken in the future. Such an exercise was currently not possible due to the lack of comparable data from past censuses and from the NFHS.

Due to the large uncertainties inherent in our model, the findings of this PhD thesis should not be considered as predictions or policy blueprints. The quantitative estimates, however, provide an indication of the magnitude of expected health impacts based on the best available evidence and enable informed comparisons of alternate policy portfolios against one another. As such, the scenarios analyses presented in this thesis could help judge which policy actions can reduce the health burden of air pollution in India the most and make choices that avoid future carbon lock-ins.

6.4 Policy implications

Ambient temperatures

The findings of this doctoral thesis confirmed that both high and low ambient temperatures are risk factors for mortality in India. However, the very steep increase in mortality risk at higher temperatures and the projected increase in the frequency, intensity, and duration of heatwaves in the country suggest that particular attention should be placed on adaptation measures to high temperatures. Such measures could include public awareness of the health risks of high temperatures through public messaging or health education campaigns; encouragement of individual preventative measures (e.g. hydration, appropriate clothing, reduced physical activity or outdoor work during intense heat); distribution of electric fans; setting-up of public cooling centres to be used during extreme heat, implementation of outdoor occupational heat standards. The planned development of heat action plans and early warning systems across India should continue and be expanded to a larger number of urban as well as rural areas. Adaptation measures should specifically target the elderly, outdoor workers, people with pre-existing cardiovascular, respiratory, and other chronic diseases, as well as populations living in informal housing. Enhancement of response capacity and coordination of public health centres should also be an important priority. Given the limits of these upfront interventions, long-term strategies to reduce temperature vulnerabilities should also be devised in collaboration with different policy departments, urban planners, scientists, labour, and civil society organisations. These could include infrastructural improvements such as an expansion of public transport, increase in the tree canopy, deployment of heat-reflective surfaces on roofs and roads, but also restructuring of agricultural labour and reductions in potential drivers of vulnerability such as poverty and inequality in access to healthcare and education. Considering the limits to physical adaptation to extreme temperatures and humidity, ultimately increase in ambition of climate change mitigation commitments through the reduction in GHG emissions should be the safest and preferred course of action to avoid impacts of high ambient temperatures on population health in the country.

Climate action and air pollution co-benefits

Current global and India-specific commitments under the Paris accord are insufficient to meet the envisioned temperature targets of 1.5° C or 2°C. Based on currently announced measures increases in GHG emissions are expected to lead to a temperature rise in excess of 3°C by the end of this century (United Nations Environment Programme, 2020). India still has not submitted its NDCs with updated 2030 targets. Not only are India´s current NDC pledges inconsistent with the Paris Agreement 1.5°C temperature limit, but they will also not bring any improvements in population LE and the number of deaths from reduced AAP. The inadequacy of current actions represents a missed opportunity to improve public health. By raising its ambition in line with the 2°C and 1.5°C climate change mitigation targets laid out in the Paris Agreement, India will not only prevent irreversible health damages for future generations but will also realise local near-term health benefits by substantially increasing the LE and mortality from AAP. Stricter mitigation policies will help reduce some of the large health inequalities in the country by bringing larger reductions in the mortality burden and LE loss from air pollution in less wealthy regions. Such a course of action will also make economic sense since the monetised health benefits have been consistently shown to exceed the mitigation costs. Concrete actions that could be implemented, potentially with international support, include scale-up of fiscal incentives for renewable energies, reduction in coal production and expansion of coal plants to avoid fossil fuel lock-in, transfer of subsidies from fossil to non-fossil sources, or introduction of a tax on electricity generated from coal to reflect the value of health damages. Overall, India as well as other countries should more clearly embrace such public health co-benefits in climate policies and explicitly include health considerations in the updated round of their NDCs, as recommended by the WHO (WHO, 2020). Dialogue and consultation with scientists, health professionals, economists, energy and transport experts, and close collaboration of different policy departments can help streamline such health co-benefits in the NDCs and in different areas of policy. Better aligning climate with health policy can also serve governments by providing greater public support for their actions.

The need for complementary policies

India can better tailor mitigation policies to its development objectives through the implementation of complementary policy measures that maximise co-benefits and minimise potential trade-offs. We showed that the application of the full spectrum of end-of-pipe air quality controls in line with the most efficient, feasible, and currently available technologies on the market will more than double gains in LE from mitigation action alone. Such policies include installation of high-efficiency PM controls at power plants, stringent emission controls for industrial processes, improved enforcement of bans on burning of agricultural waste, improved emission standards for vehicles.

Since mitigation policies might increase the cost of some transition fuels such as LPG, counterbalancing policies should be put in place for supporting clean energy access, especially among the most disadvantaged. Provision of price support policies for LPG cooking stoves and fuel can prevent switching to cheaper polluting fuels, reduce exposure to harmful household air pollutants and improve health, especially among women and children. We showed, in particular, that combining climate change mitigation either with counterbalancing clean cooking fuel policy or end-of-pipe air quality control can help reduce the large projected burden of child stunting in the country. Design of mitigation policies with both complementary measures is recommended due to the potential of synergistic effects and the large impact on the reduction of health inequalities early in life. This is of particular policy relevance as reduction of child stunting can, in the future, reduce the burden and healthcare costs from cardiovascular diseases, improve human capital formation and increase earnings and productivity. Although not investigated here, other maternal and child health outcomes that are sensitive to both HAP and AAP and have a large public health significance, such as pre-term birth, pneumonia, and other LRIs are likely to similarly benefit from such complementary policies. Additional financial resources to cover the expenses of such policies could be mobilised through effort-sharing international climate regimes. Finally, as the success of any of these complementary policies hinges upon effective enforcement and sustained implementation, it would require careful planning, coordination of multiple policy departments, and identification of any legal, financial, social, and other barriers.

6.5 Directions for future research

The studies carried out in the course of this doctoral thesis have identified important knowledge gaps and opened up a wide range of new research questions, which are discussed in this section.

- **Robust and population-specific ERFs**

A major limitation in existing air pollution co-benefit studies in India and other regions with high air pollution levels is the uncertainty in the shape of the ERF linking long-term exposure to ambient $PM_{2.5}$ and mortality. As discussed in Chapter 1.5 of this thesis the most commonly used ERF in the literature is based on the strong assumption of equal toxicity of $PM_{2.5}$ per total inhaled dose from different sources. The non-linear shape of this function has major implications for HIAs and policy in settings with high air pollution levels such as India since it implies the need for significant reductions in ambient $PM_{2.5}$ below current levels to achieve any notable reductions in the attributable mortality burden of this pollutant (Conibear, 2018). Although in Research Article II included in this thesis we used a more recent ERF covering a wider exposure range, large uncertainties remain due to the extrapolation of the ERF to very different settings and populations. Furthermore, the lack of agreement between these two ERFs, especially in terms of functional form and age groups and causes of death considered, is shown to lead to very large differences in the estimates of the final attributable burden to ambient $PM_{2.5}$ (Burnett et al., 2018). Thus, future epidemiological studies conducted in India will be crucial to reduce this uncertainty and provide more consistent policy messages. Recently, the first India-based study on short-term exposure to ambient $PM_{2.5}$ exposure and risk of non-accidental mortality in Delhi was released, suggesting a non-linear exposure-response curve and smaller effects than those observed in western Europe and the USA (Krishna et al., 2021). Larger cohort studies investigating long-term exposures both in urban and rural areas are warranted to complement these findings. Although the co-benefits analyses in this doctoral thesis focused only on the risk of mortality related to exposure to ambient $PM_{2.5}$, there is also a lack of population-specific ERFs for other air pollutants such as ground-level O_3 and NO_2.

A larger number of studies characterising the temperature-mortality association in India and other countries in the region are also needed. Although a meta-analysis of existing studies in the region was performed in Study I, the small number of research articles resulted in relatively large confidence intervals in the final estimates. A meta-regression to identify study-level factors that might drive heterogeneities in effects was also not possible due to the scarceness of eligible studies. Local epidemiological studies (based on certain cities or rural areas) with good quality health and temperature data can support the design of more effective and efficient adaptation measures, for instance, temperature thresholds at which heat action plans are to be activated, location and characteristics of the most vulnerable populations in the area. On the other hand, large-scale country-level studies can support the estimation of more robust ERFs and hence HIAs. These can help demonstrate the magnitude of current and future vulnerabilities to heat stress at the national level, where decision power regarding mitigation policies is mainly concentrated. Such large-scale studies can also help guide adaptation measures for administrative districts with too limited resources for conducting their analysis. Importantly, a major barrier for conducting epidemiological studies on temperature or air pollution exposure in the region is the poor vital statistics system and the lack of other reliable, regularly collected, and publicly available mortality and morbidity data.

Population-specific evidence on the associations between air pollution and ambient temperatures with non-fatal outcomes such as hospital admissions, doctor visits or work absenteeism can also support future HIAs and cost-benefit analyses. Due to the lack of such ERFs, most studies on India are limited to reporting only mortality impacts of different GHG emission scenarios, thus substantially underestimating the full health burden and associated economic costs of air pollution and temperature increases. Moreover, studies that examine in more detail the role of socio-economic and other mediating factors (e.g. education, sex, income, access to healthcare, housing) on the association between air pollution or temperature exposures and mortality or morbidity will be particularly valuable for future HIAs and for informing adaptation policies in the country.

- **Development of advanced HIA methodologies that can incorporate interactions of multiple exposures and heterogenous effects across population groups**

Most existing health impact projections related to climate change tend to focus on a single exposure pathway and report aggregate population-level effects. However, climate impacts are mediated by a diversity of often complex causal pathways and populations might be exposed to several risk factors simultaneously such as high AAP, prolonged heatwaves, more frequent wildfires, and food insecurity. Simply adding up independently projected health impacts leads to double counting and does not account for potential synergistic effects. Projections of aggregate population-level impacts, on the other hand, do not provide information on the distributional effects of policies. Comprehensive mitigation and adaptation planning require an understanding of the interactive effects of multiple exposures and differential population impacts (e.g. sex, income, urban-rural residence) at different geographical scales. As demonstrated in section 1.6 of this thesis, a broad range of mature and well-established methods beyond CRA are available for investigating such complexities. Where the large research and data requirements for such methods is a barrier, development of easy-to-use tools and open-source and portable models similar to the dynamic microsimulations "The Lives Saved Tool" or "DYNAMIS-POP" might be particularly valuable for supporting policy decisions (Bollinger et al., 2021; Spielauer and Dupriez, 2019). The static microsimulation developed as part of this thesis also incorporates such complexities, while having more modest modelling and computational requirements than dynamic microsimulation or ABSs. This model could potentially be expanded in the future to account for the burden of other health outcomes sensitive to HAP and AAP, to incorporate other climate feedbacks on child stunting or dynamic feedbacks on population change.

- **Integrated assessment of health co-benefits and trade-offs**

Similar to impacts of climate change, projections of health co-benefits have also been mostly restricted to a single exposure, in most cases air pollution. While the especially high health burden from air pollution in India justifies this choice, new methods and studies that examine, quantify, and potentially monetise multiple co-benefits of climate change mitigation can strengthen the case for climate action and increase policy ambition. An example is a recently published paper by Hamilton et al. (2021) that projected the combined national-level co-benefits related to air pollution, diet, and physical activity for nine high emission countries, including India, under the NDCs and the 2°C Paris Agreement target. The study, however, did not account for the interaction effects between changing dietary risks and changing physical activity or active travel and air pollution. Less studied co-benefits of climate change mitigation for India that could be additionally explored include green spaces, the UHI effect, noise pollution, improved road safety, employment, energy security, and food and water security. Furthermore, studies that consider health co-benefits and trade-offs in a unified framework, including their interactions and feedbacks, are rare. As highlighted previously, more research in this domain might be especially important for LMICs such as India, where resources are scarce and development objectives remain the main priority. Such research undertakings would require frameworks and collaboration of scientists from multiple disciplines, including public health, climate, and atmospheric science, economics, demography, energy modelling, and agronomy.

- **Consideration of demographic and socio-economic dynamics and improved integration of knowledge in the climate-population-health domain**

Similar to other LMICs, India is undergoing important societal transformations, including a fall in fertility, increase in LE, improvements in educational and income levels, rapid rural-to-urban migration, increase in the burden of NCDs, increase in the quality and access to healthcare services. As discussed in section 1.5.5 of this thesis, these factors will be crucial in determining exposure and vulnerabilities to future environmental risk factors. Some studies, for instance, have found larger sensitivity in their estimates in relation to socio-economic development trajectories than ERFs (Hodges et al., 2015) or even emission pathways (Lloyd, 2020). Current projections of health impacts, however, consider socio-economic developments to a very limited extent. A potential reason for this is the need for the integration of knowledge from very different disciplines and the use of more advanced methodologies. Interdisciplinary studies examining the interplay of environmental threats and socio-economic dynamics will be valuable in providing a more comprehensive assessment of future risks. Furthermore, modelling of more easily modifiable socio-economic factors (e.g. access to education, health care) under different policy scenarios can provide insights into potential adaptation strategies.

The interdisciplinary nature of this thesis opened interesting lines of research also in the field of demography. Future studies can expand on the population projection model applied in this thesis to incorporate the combined impacts of outdoor and indoor air pollution, ambient temperature increases, and other environmental stressors on LE. There are a number of recent studies linking both temperatures and air pollution with adverse birth outcomes and infertility (Carré et al., 2017; Cho, 2020; Conforti et al., 2018; Jensen et al., 2021). Indirect influences of climate change on fertility through reproductive choices have also been reported by empirical studies (Eissler et al., 2019; Sellers and Gray, 2019; Simon, 2017). Thus, in future work, the impact of climate change not only on mortality but also fertility can be explored. Future research can investigate how environmental stressors in the country (e.g. temperature increases, floods) might affect also migration flows and the health and wellbeing of affected populations. Finally, another emerging topic in this domain is how adverse climate-related health outcomes such as malnutrition, infectious disease outbreaks, or weather and climate disasters can affect social stability (Sellers et al., 2019).

- **Participatory HIAs of climate change mitigation policies**

Another important avenue for future research is the development of participatory HIAs in relation to climate change mitigation. Although health co-benefits are shown to be one of the largest and most important categories of co-benefits, these are in general still rarely considered in climate policy and are poorly, if at all, reflected in NDCs. The involvement of policymakers, civil society organisations, and other relevant stakeholders at an early stage of the development of HIAs can help ensure that the modelled assumptions and scenarios are feasible, transparent, publicly acceptable, and responsive to policy needs. Furthermore, participatory HIAs can help raise public awareness of the relevance of climate change for the health of current and future generations and the urgent need for action. Wider awareness can in turn promote ownership and strengthen support for national mitigation commitments.

Despite their invaluable contribution in the field of climate change, one key criticism of IAMs themselves is the insufficient or non-existent involvement of policymakers and other stakeholder groups in modelling activities (Doukas et al., 2018). Many of the assumptions embedded in IAMs are often formalised without stakeholder consultations and not clearly presented to policymakers along with modelling results. The lack of flexibility of the formalised frameworks for modelling the large diversity of available policy instruments has also been criticised (Doukas et al., 2018). In this context, uptake of participatory approaches, not only in the design of HIAs of mitigation policies but also in the development of the IAMs that they are often based on, will be a crucial step for ensuring that future research can effectively contribute to the climate action talks and inform policymaking processes.

6.6 Concluding remarks

Although India might have a lower historical responsibility for mitigating climate change, the future health and prosperity of its population will depend on the provision of clean, affordable, and reliable energy. Failing to rapidly decarbonise its growing economy, India will endanger the health and wellbeing of future generations, potentially undermining some gains in LE and other development progress over the last years. By focusing on ambient temperatures and heatwaves, in particular, this thesis demonstrated that the country is highly vulnerable to climate change. On the other hand, the scenario analyses undertaken as part of the thesis showed that mitigation actions, especially when complemented with targeted pollution and social support policies, could provide an opportunity to improve the health of not only future but also current generations by reducing the large health burden of air pollution in the country. This doctoral thesis, therefore, strengthened the case that, when carefully planned, ambitious climate change mitigation in line with the Paris Agreement can help accelerate progress on India´s development objectives and the sustainable development goals.

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Appendix

This section includes other activities that the PhD candidate has been involved in during her PhD research.

A) Other co-authored papers

Ortega N., Curto A., **Dimitrova A.**, Nunes J., Rasella D., Sacoor C., Tonne C. (2021) Health and Environmental Impacts of Replacing Kerosene-Based Lighting with Renewable Electricity in Eastern Africa. Energy for Sustainable Development 63, 16-23. https://doi.org/10.1016/j.esd.2021.05.004

Tonne C., Adair L., Adlakha D., Anguelovski I., Belesova K.,Berger M., Brelsford C., Dadvand P., **Dimitrova A.**, Giles-Corti B., Heinz A., Mehran N., Nieuwenhuijsen M., Pelletier F., Ranzani O., Rodenstein M., Rybski D., Samavati S., Satterthwaite D., Schöndorf J., Schreckenberg, D. Stollmann J., Taubenböck H., Tiwarit G., van Wee B., MazdaAdli M., (2021) Defining pathways to healthy sustainable urban development, Environment International. 146, 106236. doi: 10.1016/j.envint.2020.106236

Milà C., Curto A., **Dimitrova A.**, Sreekanth V., Kinra S., Marshall JD., Tonne C., (2020) Identifying predictors of personal exposure to air temperature in peri-urban India, Science of the Total Environment. Elsevier B.V., 707, p. 136114. doi: 10.1016/j.scitotenv.2019.136114.

Vijendra, I., **Dimitrova A.**, Sampedro J., Sacoor C., Acacio S., Juvekar J., Roy S., Basagana S., Ballester J., Anto J., Tonne C. Local mortality impacts due to future air pollution under climate change scenarios in Mozambique, India, and Spain [submitted for publication]

B) Presentations at scientific conferences

Oral presentations:

Impacts of climate change mitigation and clean cooking access on future childhood stunting in India. *International Society for Environmental Epidemiology (ISEE).* Aug **2021**.

Association between ambient temperature and heatwaves and mortality in South Asia – Systematic Review and Meta-analysis. *Gobeshona Global Conference: Research into Action on Locally-Led Adaptation*. Jan **2021**.

Association between ambient temperature and heatwaves and mortality in South Asia – Systematic Review and Meta-analysis. *British Society for Population Studies (BSPS).* Jul **2020**.

The future health impacts of long-term exposure to air pollution in India under climate change, demographic change and urbanization. *The 6th Stochastic Modeling Techniques and Data Analysis International Conference*. Barcelona, Spain. June **2020**.

The future health impacts of long-term exposure to air pollution in India. *UNU Summer Academy on World Risk and Adaptation Futures*. Accra, Ghana. Oct **2019**.

The future health impacts of long-term exposure to ambient air pollution in India. *IIASA YSSP Final Colloquium*. Vienna, Austria. Aug **2019**.

The future health impacts of long-term exposure to ambient air pollution in India. *British Society for Population Studies (BSPS)*. Leeds, UK. Jul **2019**.

The health impacts of the urban heat island effect — projections for two peri-urban areas in India. *Symposium on Urbanization and health: identifying pathways to healthy sustainable urban development.* Hannover, Germany. Oct **2018**.

Poster presentations:

The future health impacts of long-term exposure to air pollution in India under climate change, demographic change and urbanization. *ISEE*. **2020**.

Systematic Review and Meta-analysis of the association between ambient temperature and heatwaves and mortality in South Asia. *ISEE*. Utrecht, the Netherlands. Aug **2019**.

C) Reviews for Peer-Reviewed Scientific Journals

Mitigation and Adaptation Strategies for Global Change (x1)

Environment International (x1)

Environmental Research Letters (x1)

Environmental Research and Public Health (x1)

D) Additional Activities

- Responsible for the organisation of the Air Pollution and Urban Environment research seminars at ISGlobal for the period 2018-2020
- Academic courses and training:
  Fundamentals of Epidemiology. ISGlobal and UPF. 2018.
  Hands-on Tutorial on a Modelling Framework for Projections of Climate Change Impacts on Health. ISEE. 2019
  Numbers for Policy: Practical problems in Quantification. Universitat Oberta de Catalunya. 2019
  Smoothing Demographic Data & Data Visialization. Max Planck Institute for Demographic Research. 2020
  Causal Inference; Machine Learning. RECSM Summer School. 2021