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The Contribution of Household Fuels to Ambient Air Pollution in India

A Comparison of Recent Estimates

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Executive Summary

What is the single largest source of air pollution exposure in India? You would be perhaps surprised to find that the answer, with a near consensus in the published scientific literature, is neither transportation nor stubble burning. Instead, it seems to be the millions of households across the country burning solid fuels like firewood in their homes for cooking, heating and other energy services. The resulting pollution not only has an enormous health impact on the households themselves, but it likely accounts for a quarter to a third of ambient air pollution across the country. Working towards ensuring universal access to cleaner fuels like LPG should therefore be one of the pillars of India's pollution control efforts.

When families burn solid fuels (like wood, dung and agricultural waste) in their homes, various kinds of air pollutants are generated. One of the many pollutants emitted by this combustion of solid fuels is fine particulate matter ($PM_{2.5}$, particulate matter with aerodynamic diameter <2.5 μm). Exposure to $PM_{2.5}$ has been shown to cause a range of serious health problems, including respiratory and heart disease, and can lead to early death.

Household air pollution (HAP) is the term given to emissions of $PM_{2.5}$ that are generated from household solid fuel burning. People are exposed to HAP in homes where solid fuels are burned. Exposure to HAP *indoors*, near the source of the pollution, is estimated to result in approximately 800,000 premature deaths per year in India alone. HAP emitted indoors goes outdoors and is a leading contributor to outdoor ambient air pollution. Other major sources of ambient air pollution in India include road transport, the industrial sector, open biomass burning, coal-fed power plants, brick kilns, and construction dust. Exposure to all *ambient* $PM_{2.5}$ is estimated to result in approximately one million premature deaths annually in India.

There have been seven published scientific studies to date that model the proportion of ambient air pollution in India and associated deaths caused by HAP. From these studies, we find that HAP causes at least 22% and as much as 52% of ambient $PM_{2.5}$ in India (see Figure 1). The median estimate from these studies is about 30%. Other sources like transportation, power plants, and industries are estimated to contribute less towards ambient $PM_{2.5}$ than HAP (Figure 1). Of course, within cities, especially highly polluted ones like Delhi, sources like transportation and construction dust can contribute more locally.

There is a wide range of estimates in the literature. This spread results from differences in (1) the way that air pollution models account for specific types of air pollution and chemistry (aerosol and trace gas chemistry, meteorology, and other $PM_{2.5}$ formation factors); (2) the resolution of the model (geographic grid size), and (3) the years considered in the model. The definition of residential emissions also differs between studies, with emission inventories including varying combinations of cooking, heating, and lighting emissions, and some that also couple commercial emissions with residential emissions. Such differences in inputs and modeling methods are not unusual in scientific studies.

Even the lowest of the estimates of contribution of HAP to ambient air pollution indicates that household sources contribute to a significant portion of the large public health burden from ambient air pollution. Across all studies, HAP contribution to average air pollution exposure in India is estimated to be about 60% higher than all coal use, 4x higher than open burning, and 11x higher than transportation in India. Critically, this is in addition to the substantial risk households experience directly from the combustion of these fuels. Put another way, in addition to the 800,000 premature deaths annually due to indoor exposure to HAP, approximately another 300,000 (30% of one million) can be attributed to HAP due to outdoor exposure. Cleaning up household fuel use thus both directly benefits those exposed to HAP and has broader population benefits by reducing ambient air pollution.

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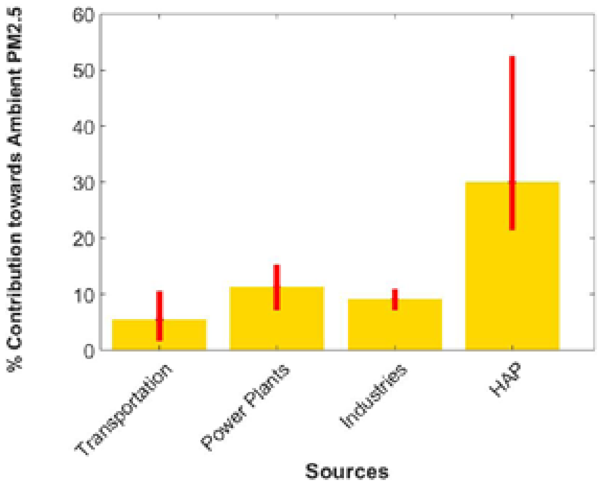

FIGURE 1: Percentage contribution towards ambient $PM_{2.5}$ in India. The height of the bars shows the median value of contribution among the published studies over India. The range encompasses the highest and lowest estimates among the published studies.

India needs to act on each of the major sources for air pollution levels to come closer to the national standards. Given that the median estimate of contribution of HAP to ambient $PM_{2.5}$ is 30% and the lowest estimate is 22%,, reducing emissions from household solid fuel use should be a top priority for the Indian government. The Pradhan Mantri Ujjwala Yojana (PMUY) is an important policy effort in this direction. However, it is essential to look to further expand the access of LPG to more beneficiaries, and work towards ensuring sustained use of LPG by households that have already joined the programme. We should also redouble efforts—most likely, ensuring access to reliable electricity— to substitute for other household pollution sources, such as bathwater heating and kerosene lighting. Averting 1.1 million premature deaths annually need us to take bold strides towards universal access to cleaner residential fuels.

1. Introduction

Billions of people worldwide rely on unclean and unhealthy household energy sources for cooking, lighting and heating – despite major progress in recent decades to address global poverty and development. About 40% of humanity uses wood, agricultural residues (such as rice straw), coal and other solid fuels for daily cooking (Bonjour et al., 2013). The figure is likely even higher if other energy services, such as lighting and heating, are considered. A recent study (Lacey et al., 2017) estimates that complete phase out of solid fuel usage globally has the potential to avoid 10.5 (5.5-10.8) million premature deaths from 2010-2050. In India alone, about 160 million households rely on solid fuels for their household energy needs (Venkataraman et al., 2010). When these fuels are burned, they emit fine particles ($PM_{2.5}$), carbon monoxide (CO), and a range of other often toxic products of incomplete combustion. Exposure[1] to “household air pollution” (HAP)—smoke from burning solid fuels in the home—results in an estimated 800,000 premature deaths every year in India (Dandona et al., 2017). Ambient, or outdoor, $PM_{2.5}$ exposure in India causes approximately one million premature deaths annually (Cohen et al., 2017). In combination, exposure to household and ambient air pollution form the second largest risk factor for ill-health in the country, after poor child and maternal nutrition (Dandona et al., 2017; Wang and GBD-Collaborators, 2016).

Perhaps not surprisingly, HAP contributes to ambient air pollution, and ambient air pollution affects indoor air quality. Ambient air pollution arises from a variety of sources, including vehicles, power plants, industrial processes, and crop waste burning. Pollutants from these additional sources may infiltrate into the households and contribute to household exposure (Baumgartner et al., 2014). Household fuel burning also impacts ambient air quality. Until recently, the household contribution to ambient air pollution was under-recognized and poorly characterized. The full impact of HAP is thus composed of the exposures to HAP 1) inside and around a given house and 2) from the household contribution to ambient air pollution.

To the best of our knowledge, there have been seven independent published estimates of the fraction of ambient air pollution due to household fuel combustion,

1 See Box 1 for an overview of terminology

BOX 1: Defining air pollution and air pollution emissions, emissions inventories, concentrations, and exposures

Air pollution is a mixture of gases and particles that come from a variety of sources, including industry, automobiles, household fuel use, and burning of agricultural fields ("open burning"). There are hundreds of substances in the air, but very few of them can be easily and regularly measured. One that is often measured is particulate matter with an aerodynamic diameter of less than 2.5 μm, or $PM_{2.5}$. $PM_{2.5}$ is so small that it cannot be seen unaided. It is much smaller than a grain of sand, or even the width of a human hair. Exposure to $PM_{2.5}$ is associated with adverse health outcomes, including pulmonary and cardiovascular diseases. Many countries around the world regulate $PM_{2.5}$. It is commonly measured as part of government air monitoring networks and during research studies. In areas where measurements are not possible, levels of $PM_{2.5}$ can be estimated using mathematical models, such as chemical transport models (See Box 2).

Health studies focus on emissions, concentrations, and/or exposures to $PM_{2.5}$. Emissions are expressed in release of a pollutant per unit time, per activity, or per unit fuel burned (for instance, milligrams of $PM_{2.5}$ per gram of wood or coal combusted, or grams of $PM_{2.5}$ per minute, or grams of $PM_{2.5}$ per vehicle mile travelled). Emissions inventories are databases of emissions – often at the state, national, or regional level – for a variety of air pollutants from a range of sectors (industry, transport, residential, power generation, etc). These inventories are often based on available measurement data and knowledge about each sector's polluting activities at a given time. They are calculated by multiplying activity data by emission factors for each of the source categories, and often for subcategories such as types of combustion (e.g. coal, oil, natural gas) and traffic (e.g. light- and heavy-duty vehicles). Multiple institutions around the world work extensively on developing separate emission inventories. There is no benchmark to which the emission inventories developed by these institutions can be compared to decide the best available inventory

Concentrations are typically measured in terms of mass of pollutant per volume air. Concentrations change as emitted pollutants interact with the environment. Air pollution exposure is often measured in the same units as concentrations but takes into account whether and how people come in contact with pollutants. For example, a small fire on a distant mountaintop, far from where people live, may lead to a high measured concentration at that mountaintop, but may have little impact on people's exposure, since they are far away from the pollution, which is heavily diluted before it reaches them. Conversely, a cooking fire in a home may lead to both a high concentration of air pollutants and a high level of exposure among those in the house.

starting with the first study in 2014 (Chafe et al., 2014). These estimates vary in geographic scope – some are global, while others focus on specific regions or countries. In India, estimates of the fraction of ambient air pollution attributable to HAP range from 22-52%. In contrast, other major sources like transportation, power plants, and industries are estimated to contribute 2-10%, 8-15%, 8-11% respectively Each independent estimate uses a combination of different datasets, assumptions, time periods, study domains, and other inputs.

The purpose of this policy paper is to explore the large variation in the estimates for India and to note commonalities and differences between the estimates. In Section 2, we introduce the seven studies and their estimates of the contribution of HAP to ambient PM2.5 exposure. In Section 3, we delve deeper into the comparisons between these estimates, and outline the sources of differences. Section 4 discusses the policy implications, and concludes.

2. Contribution of HAP to ambient $PM_{2.5}$

HAP is created when families burn solid fuels for cooking, lighting, space and water heating. These emissions contribute to air pollution exposure near where fuels are used and then escape through openings in the home, such as windows, doors, eaves, and chimneys, worsening ambient air quality. Some households burn solid fuels outdoors, and the emissions directly impact ambient $PM_{2.5}$ concentrations (Lam et al., 2017). $PM_{2.5}$ is emitted directly from household fuel combustion and contributes both "primary $PM_{2.5}$" including black carbon (BC) and organic

BOX 2: What is a chemical transport model (CTM) and what does it estimate?

A chemical transport model (CTM) is a complex simulation of air quality that predicts pollutant concentrations for a given space and time using a set of inputs. These inputs include emissions, meteorological conditions, and chemical and physical processes. The model includes a set of numerical equations that simulate chemical reactions taking place in the atmosphere.

Chemical transport models can be classified as Eulerian or Lagrangian. Eulerian CTMs describe the composition of the atmosphere within a fixed space along which air flows. Lagrangian models describe the composition moving with the air flow. These models employ different methods of incorporating physical and chemical parameters such as precipitation microphysics, longwave and shortwave radiation, land surface classification, convective parameterization, gas-phase chemistry, photolysis, aerosols, natural dust inventory, initial and boundary conditions for chemistry, aerosols and meteorology.

Chemical transport models can be characterized as global or regional models according to their processing extent. As simulating chemical transport models is computationally intensive and expensive, global chemical transport models are simulated at a coarse spatial resolution, and are often not able to account for changes in meteorology, topography etc. at a local scale. Regional chemical transport models, however, are simulated locally over a more limited geographic domain, often at higher spatial resolution.

carbon (OC) and "secondary $PM_{2.5}$" formed as emissions of sulfur dioxide (SO_2), nitrogen oxides, volatile organic compounds, and semi-volatile organic compounds react in the air downwind from the stove (Fleming et al., 2018; Reece et al., 2017).

Seven modelling studies (Chafe *et al.*, 2014; Lelieveld *et al.*, 2015[2]; Butt *et al.*, 2016; Silva *et al.*, 2016; www.urbanemissions.info; Conibear *et al.*, 2018; GBD-MAPS Working Group, 2018) have estimated that, for India, HAP contributes to between 22-52% of ambient $PM_{2.5}$ exposure. These studies used either global or regional chemical transport models (CTM, See Box 2) paired with source-specific emission inventory data (see Box 1 for discussion on emission inventories) to apportion total ambient $PM_{2.5}$ to specific sources. These source categories vary by emission inventory but often include household/residential, industry, power generation, traffic/on-road vehicles, agricultural biomass burning, brick kilns, the more general category of all "anthropogenic" emissions, and dust (sometimes divided into crustal or anthropogenic). Each of these studies estimates exposure by weighting the distribution of pollutant concentrations by the population distribution in the country.

Figure 2 depicts the percent of ambient $PM_{2.5}$ that can be attributed to HAP as estimated by these studies. This range of estimates can be hard to interpret for lay audiences and may lead to disagreement among policymakers on (1) where HAP control falls amongst other emissions control strategies and on (2) the magnitude of expected implications of PM control policies. The next section will seek to clarify the sources of these differences.

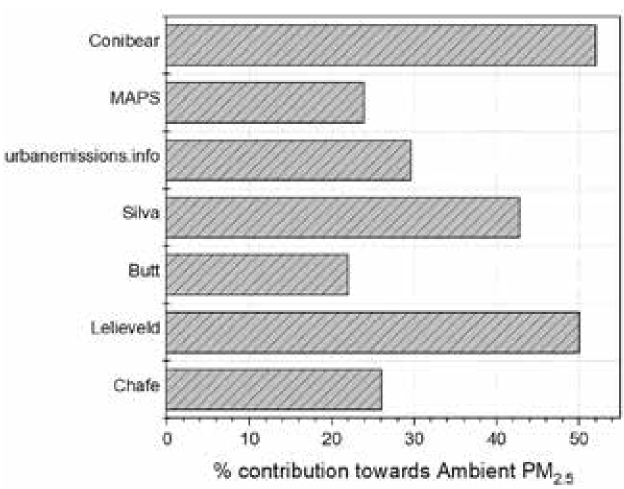

FIGURE 2: Contribution of HAP towards ambient $PM_{2.5}$ as estimated by the seven studies. All estimates except Lelieveld and Butt are population-weighted.

2 Lelieveld *et al.,* 2015 includes the impact of both $PM_{2.5}$ and O_3 on premature mortality burden.

3. Comparing existing estimates

This section explains the similarities and differences between the seven studies' assessment of the contribution of HAP to ambient air pollution in India. We identify the seven studies as Chafe (Chafe et al., 2014), Lelieveld (Lelieveld et al., 2015), Butt (Butt et al., 2016), Silva (Silva et al., 2016), urbanemissions.info (urbanemisssions.info), MAPS (GBD- MAPS Working Group, 2018; Venkataraman et al., 2018), and Conibear (Conibear et al., 2018).

All seven studies use different CTMs with disparate emissions inventories, model configurations and meteorological inputs. This is not unusual, as air pollution models are developed by a variety of research groups and organizations to answer different questions, using different data inputs, over different time periods, and with different spatial resolutions. We note that the estimates presented in each of the studies would likely vary if the input data were changed or tweaked relative to the configuration used in the respective study. For example, if researchers coordinated meteorological inputs or defined emissions categories differently, the estimates of the contribution of HAP to ambient air pollution would change. The magnitude of these changes is difficult to predict. Variability among the presented CTM results are distinct from model error, which occurs due to propagation of internal error in the model equations, error in the meteorological data, and error in formulations of emission inventory. It should also be noted that specific model configurations may make perfectly aligning input variables impossible to administer due to different spatial resolution, source classes, included species, etc.

Given the challenges in interpreting the findings from these seven studies, we detail below how changing each of the major driving factors could introduce variability among the estimates. It should be noted that these challenges prevail during inter-comparison of all the possible model outputs and is not entirely specific to estimation of the fraction contribution of HAP towards ambient $PM_{2.5}$. These challenges call for large model inter-comparison initiatives to detect the sensitivity of model inputs as in (Ding et al., 2017; Trombetti et al., 2018) or generation of cumulative ensemble from the wide range of variation in the estimated output variable (Meehl et al., 2000).

Model configuration and model type

The models used in the seven studies employ different methods of incorporating physical and chemical processes (see Box 2) necessary to predict time-varying $PM_{2.5}$ concentrations. Therefore, their performance depends on the choice of (1) simulation timestep, (2) horizontal and vertical resolutions of initial and boundary conditions for chemistry, aerosols and (3) meteorology. Most atmospheric CTMs underestimate $PM_{2.5}$ concentrations over India, which necessitates correction using remote sensing and in-situ, locally-available ground-based data (Brauer et al., 2012; Chowdhury et al., 2018).

Studies urbanemissions.info, MAPS and Conibear used regional CTMs. Regional CTMs are often optimized to suit local conditions better. Therefore, these three studies are expected to provide more accurate estimates of $PM_{2.5}$ exposure for India; the relative share of HAP to ambient $PM_{2.5}$ is thus expected to be different from Leileveld, Butt and Silva who use global CTMs'. However, this hypothesis needs to be verified for Indian conditions through rigorous inter-model comparison studies (Dore et al., 2015; Prank et al., 2016). On the other hand, aerosol transport across regions and geographic boundaries is better captured in the global CTMs (as used in Lelieveld, Butt and Silva) by virtue of their larger geographic extent. Limiting transport of pollution, as the regional models do, may lead to underestimation of ambient $PM_{2.5}$ (thereby enhancing the relative share of HAP).

It should be noted that choosing a different model of the same type as employed in the study will also introduce variability due to differences in how models are configured. Similarly, meteorological data (listed in Table 1) used in the models modulates the life-cycle of simulated aerosols (i.e. transport pattern, atmospheric processes and removal via wet and dry deposition). Changing the meteorological inputs would also change model estimates. This may be attributed to inter-annual variation of meteorological parameters and sources of meteorological data. For example, using meteorological parameters from two different years will provide two distinct outputs. Similarly, using meteorological inputs for the same year but from different data sources would provide different output.

Each of the above-mentioned studies utilize emission inventories and meteorological data for different years,

TABLE 1: DETAILED INFORMATION OF THE STUDIES WHICH WERE COMPARED IN THIS STUDY

	Study Name, Year	Model Used	Meteorology used to force	Model Horizontal resolution	Secondary particle formation included?	Emission Inventory used	Emission sources considered	Residential emission considered	% of ambient PM2.5 from HAP**
Chafe	Chafe et al., 2014	TM5-FASST	ECMWF, 2010	regional scale, (concerned estimate is provided for South Asia)	Yes	GAINS	Natural, industry, land transport, residential and commercial energy, power generation, biomass burning, agriculture	Cooking	26 (P)
Lelieveld	Lelieveld et al., 2015	ECHAM5	ECHAM, 2010	1.1º x 1.1º	Yes	EDGAR	Natural, industry, land transport, residential and commercial energy, power generation, biomass burning, agriculture	Space heating, cooking, emission from local and commercial energy use from small combustion sources, diesel generator sets	Up to 50
Butt	Butt et al., 2016	GLOMAP	ECMWF, 2000	2.8º x 2.8º	Yes	Various sources	Energy sources and distribution, industry, land transport, maritime transport, residential and commercial, agricultural waste burning	Space heating, cooking, emission from local and commercial energy use from small combustion sources	22
Silva	Silva et al., 2016	MOZART-4	GEOS,2005	0.5º x 0.67º	Yes	RCP	Residential and commercial, energy, industry, land transport, shipping and aviation	Space heating, cooking, emission from local and commercial energy use from small combustion sources	42.8 (P)
Urbanemissions. info	www. urbanemissions. info	WRF-CAMx	NCEP,2013	0.25º x 0.25º	Yes	Various sources	Residential (cooking, heating, and lighting), all industries (including power, bricks), all transport (road, rail, air, and water), natural and resuspended dust, open fires, seasalt and lightning, open waste burning, and some miscellaneous sources	Cooking, space heating, water heating, lighting	29.6 (P)
MAPS	GBD-MAPS Working Group, 2018	GEOS-Chem	GEOS,2015	0.5º x 0.67º	Yes	Various sources	Residential biomass, total coal, industrial coal, powerplant coal, open burning, transportation, brick production, distributed diesel, anthropogenic dust and total dust	Cooking, space heating water heating, lighting	23.9 (P)
Conibear	Conibear et al., 2018	WRF-Chem	NCEP,2014	30km x 30km	Yes	EDGAR-HTAP	Agricultural, biomass burning, dust, power generation, industrial non power, residential energy use and land transport.	small scale supplemental engines for residential, commercial, agricultural, solid waste and wastewater treatment plants, Cooking, space heating water heating, lighting	52 (P)

** P in parenthesis if the estimates are population weighted.

which does not allow direct comparison among the estimates. For example, Silva simulated their CTM using 2005 meteorology and emission data while Conibear ran simulations using 2014 meteorology and 2010 emission inventory. Direct comparison between these two studies would have to consider multiple factors, including the change in the population using solid fuel in India (from 73% to 62% between 2005 and 2010) and changes in meteorological factors like wind speed , mean temperature and relative humidity between 2005 and 2010.

Another major model property that may lead to varied results is the model grid size or horizontal resolution. Models that simulate at finer resolutions in higher detail are computationally intense, but allow more resolved analyses. For example, models that simulate at coarse resolutions are usually incapable of identifying pollution hotspots or the distribution of populations within urban regions, which may affect the mean of population-weighted estimates. There are studies which indicate that the choice of model resolution may not necessarily be the leading cause of uncertainty(Lelieveld et al., 2015).

These uncertainties are not presented to undermine the utility or value of these models. Rather, we emphasize the relative consistency of estimates given the heterogeneity in emissions inventories, time scales, and geographic resolutions evaluated. The overall strength of the association indicates the importance of household sources as a contributor to ambient air pollution over India.

Table 1 lists the horizontal resolution at which the models are simulated. Though the TM5 model used in Chafe is simulated at 1° x 1 ° resolution the study reports results at regional (South Asia) level. As the results are population-weighted, and India accounted for 77% of the South Asia regional population in 2010, the authors claim the fraction contribution of HAP towards ambient $PM_{2.5}$ in South Asia as indicative of the proportion for India.[3] Lelieveld applies a model grid of 1.1°, and aggregates emissions to this resolution from the global EDGAR inventory at 0.1° (~10km). Studies urbanemissions.info and Conibear, which simulate at 25km × 25km and 30km × 30km resolution respectively, are best equipped to capture the spatial heterogeneity in $PM_{2.5}$ pollution and hence the heterogeneity in the contribution of HAP towards ambient $PM_{2.5}$ levels.

Emission Inventories

The selection of an emissions inventory plays a major role in determining how accurately models simulate ambient $PM_{2.5}$ concentrations over the Indian region. Use of inventories which fail to incorporate detail of household activities (e.g. type and duration of solid fuel used in each household) in the Indian region may result in large uncertainty. There is also significant heterogeneity in how sources get categorized and grouped (discussed in more detail below).

It is expected that the emission inventories designed in India (Pandey et al., 2014; Pandey and Venkataraman, 2014; Sadavarte and Venkataraman, 2014) incorporate much finer detail than global emission inventories, which are not as explicit. For example, recent Indian inventories take into account space and water heating behaviors observed in parts of India where it has been assumed non-existent in other inventories. It is difficult to compare how different emission inventories perform over India until a single CTM is run each of these, to estimate PM2.5 and subsequently validate against in-situ measurement data. This is a massive task, well beyond the scope of this review. It will, however, be undertaken under National Carbonaceous Aerosol Program of MoEFCC (Ministry of Environment Forest and Climate Change).

The studies reviewed here used a variety of emissions inventories with different classifications of the residential sector. Some inventories, like those used in Lelieveld, Butt and Silva, use the term 'residential and commercial sector,' which defines HAP emissions to be originating both from households as well as from the commercial sector. They take into consideration that both of these types of activities use similar fuels for similar purposes. For example, Lelieveld uses an emissions inventory which includes small commercial combustion for space heating and cooking, diesel generator sets, and biomass for uses other than cooking. These inclusions add about 5% more emissions on top of those from households. Similarly, the emission inventory used in Conibear for residential energy combines emissions from small scale supplemental engines for residential,

3 The countries included in South Asia regional grouping are Afghanistan, Bangladesh, Bhutan, India, Nepal, Pakistan. Population total for this region for 2010 was 1.591 billion. Proportion that lived in India was 77%, or 1.231 billion. The claims are verified by additional calculations undertaken for this review.

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commercial, agricultural, solid waste and wastewater treatment plants with emissions from households. The estimates from Lelieveld, Silva[4], Butt and Conibear thus consider sources beyond household sources and tend to provide a higher estimate of contribution of HAP towards ambient $PM_{2.5}$.

In contrast, the estimates from Chafe, Urbanemissions, and MAPS focus more explicitly on household-level emissions. Chafe uses the cooking emissions only from the residential sector of the GAINS emission inventory and do not consider end uses from other household energy services. Urbanemissions.info and MAPS use emissions inventories which include only conventional sources like cooking, water heating, space heating and lighting activities in the residential sector.

A detailed inter-emission inventory comparison may help better understand how these additional sources (besides the conventional household sources) impact estimates of the contribution of household emissions to ambient air pollution[5]. For example, the EDGAR HTAP_v2.2 emission inventory used in the Conibear study has larger residential sector emissions than in MAPS : 1.2x higher $PM_{2.5}$ emissions, 4x higher SO_2 emission, 3x higher NO_x emission and 1.3x higher NMVOC emission. This results in residential emission contributing to about 56% of total primary $PM_{2.5}$ emissions as compared to 44% in MAPS. .

4. Policy perspectives

Regardless of the variations in model types, configurations and the emission inventories used in the abovementioned seven studies, all of them identify residential emissions as a leading contributor to ambient $PM_{2.5}$ in India, with a median estimate of 30%. Even the lowest estimate of the contribution of HAP to ambient air pollution indicates that household sources contribute to a significant portion of the large premature mortality burden from exposure from ambient air pollution. Across all studies, HAP contribution to premature mortality burden is (median (range)) 58% (38-83) higher than that due to all coal use, 303% (248-372) higher than open burning, and 1056% (914-1245) higher than due to transportation in India (GBD-MAPS Working Group, 2018). This is, as mentioned above, in addition to the risk households experience directly from the combustion of these fuels. Cleaning up household fuel use thus both directly benefits those exposed to HAP and has broader population benefits by reducing ambient air pollution.

These findings necessitate immediate action and demand formulation of extensive policies to reduce HAP. Starting in 2015, the Government of India (Ministry of Power, Government of India, 2014; Ministry of Petroleum and Natural Gas Government of India, 2016) embarked upon an ambitious program to tackle HAP, promoting use of liquefied petroleum gas (LPG) for cooking. It will soon be possible to discern the impacts of this policy on outdoor air pollution levels in India using quantitative information from the government, but additional substitution of clean burning fuels for other residential uses like heating needs to be warranted. In states with low Socio-Demographic Index (SDI) like Bihar, Uttar Pradesh, Madhya Pradesh, Orissa, Jharkhand, Rajasthan, Chattisgarh and Assam where about 72.1% (71.1-73) of people use solid fuels for cooking (Balakrishnan et al., 2019) and the annual ambient $PM_{2.5}$ is around 125.3(87.5-167.3)$\mu g/m^3$(Balakrishnan et al., 2019) these mitigation programs are expected to harbor major health benefits. In addition, increased attention to enhancing usage of such fuels in addition to access may be needed(Smith, 2018; Smith and Pillarisetti, 2017).

There is value in continuing to explore methods to refine model output. Primary among these is the uncertainty in emission inventories (Li et al., 2017; Zhao et al., 2011), which we believe can be improved by gathering more refined energy service utilization data – for instance, better data on primary and secondary fuel use[5] through the use of nationally representative surveys. These activities are being promoted globally through the World Health Organization's efforts to harmonize household energy surveys[6]. Such activities will help add nuance to our understanding of energy use at more highly resolved spatial scales and contribute to more accurate emissions inventories, in addition to enabling better tracking of progress on meeting energy-related Sustainable Development Goals.

Second, modelers may find value in comparing and refining CTM output. CTM output should be evaluated against available ground-based measurements to better

4 Silva estimates ambient $PM_{2.5}$ from anthropogenic sources and does not consider natural dust and sea salt. Thus, the fraction of HAP that they attribute to ambient $PM_{2.5}$ is potentially exaggerated.

5 Primary fuel indicates the major/dominant fuel used in the households (for cooking, heating and lighting), secondary fuel indicates the alternate fuel used for household purposes

6 http://www.who.int/airpollution/household/harmonized-survey/en/

understand their reliability. With respect to estimates of the contribution of HAP to ambient $PM_{2.5}$, we cannot fully understand the effects of employing diverse modeling techniques until simulation of multiple chemical transport models are performed with a single emission inventory. To understand the effect of emission inventories, a single atmospheric chemistry model should be run with each of the different emission inventory estimates. Running a single atmospheric chemistry model in this way would allow us to understand the role of emission inventories in arriving at the estimate of contribution of HAP towards ambient $PM_{2.5.}$ Additionally, observational source apportionment studies should be used to validate the source apportionment information obtained from a CTM to obtain confidence on use of the CTM in such studies. Furthermore, to tune the performance of the CTMs in estimating the contribution of HAP towards ambient $PM_{2.5}$, emission inventories should be updated with subtle information at household level (like isolating household emissions by gathering data on primary and secondary fuel use at household level and focusing on better understanding energy use by household energy service), this must be formulated with help of national and representative surveys.

MAPS depict spatial heterogeneity of contribution of HAP towards ambient $PM_{2.5.}$ The study establishes that the percentage contribution of HAP towards ambient $PM_{2.5}$ is higher in the eastern and north-eastern states of India like Bihar (~38%), West Bengal (~32%), Uttar Pradesh (~32%) and Assam (~30%) than in states in southern and western India like Telengana (~21%), Goa (~12%) and Gujarat (~10%). Overall, the large range (22%-52%) of estimates of the contribution of HAP to ambient air pollution published in the 7 studies performed thus far may be confusing for the policy makers to interpret. Put another way, consider a state in east India, like West Bengal which has an annual $PM_{2.5}$ exposure of 80μg/m^3, if the policy makers target achieving the Indian Standard of 40μg/m^3 and they adopt Conibear for framing their policies, then just mitigating the HAP by ensuring 100% clean fuel (like using cookstove powered by solar panels, we acknowledge that LPG usage may not result in zero household emission, however the introductory initiative in India is correctly undertaken by sheathing the solid fuel using community with LPG) use for household purposes would get the job done, but conversely if the policy makers adopt MAPS as the reference, just mitigating HAP would reduce the ambient $PM_{2.5}$ exposure to 55μg/m^3, which implies that subsequent mitigation measures should be applied to other sectors to achieve the goal of attaining the Indian Standard of 40μg/m^3. Hence the range in these seven studies show that HAP should be a sector of great concern for policymakers intent on improving air quality in India, especially to obtain the Indian National Ambient Air Quality Standard of 40μg/m^3 or WHO-Interim Targets. As models and emissions inventories are refined, we suggest the median estimate from available studies, i.e. ~30%, as a reasonable overall estimate of the amount of ambient $PM_{2.5}$ exposures that are due to household emissions in India.

As a next step, we call for energy, air pollution, and health researchers to harmonize the estimates of the contribution of HAP to ambient $PM_{2.5}$ by collaborating on a publicly-available, standard format for emissions inventories that quantifies sectoral emissions as consistently and as precisely as possible. Specifically, household emissions should be separated from commercial emissions, to the extent possible; and household emissions should then be further divided into emissions from household cooking, household heating, household lighting, and household water heating. Estimates should be internationally-comparable and informed by both local data sources and by international data repositories and projections, such as those published by the International Energy Agency. Given that such a large proportion of India's fine particulate air pollution originates from the daily use of solid fuels to cook food and heat homes, it is imperative that policymakers focus attention and resources on programs and strategies that will empower households to choose cleaner methods of meeting their basic energy needs. Seven studies have shown that household air pollution is a source of India's particulate air pollution crisis that can no longer be downplayed or ignored. New policies are urgently needed to enable households to switch away from solid fuels and thus reduce the contribution of household air pollution to India's ambient air pollution.

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