

**ACCESS TO MODERN ENERGY, AIR POLLUTION AND GREENHOUSE GAS  
MITIGATION: INTER-LINKING THREE MAJOR ENERGY CHALLENGES FACING  
INDIA TODAY**

by

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## Abstract

The majority of the Indian population relies on traditional fuels such as biomass, and an estimated million people die prematurely in India due to poor air quality, both indoor and outdoor, annually. A major CO<sub>2</sub>-emitter, India has also committed to a low carbon development pathway. In this thesis, I study the problem of indoor and outdoor air pollution exposure in India, and its links to energy equity and climate mitigation.

First, I use national-scale household survey data to quantify changes in cooking habits and health. I show that electrification and complete transition to Liquefied Petroleum Gas (LPG) provide significant health and time-saving benefits, particularly for women, but using LPG together with biomass provides negligible benefits. Second, I use national-scale household energy use data to show that indoor exposures to fine particulate matter (PM<sub>2.5</sub>) in rural and low-income urban households exceed those in higher income urban households by an order of magnitude. Using a diffusion model for future energy use I show that comprehensive access to modern fuels *for all* is needed to drastically reduce indoor PM<sub>2.5</sub> exposures, and it would add minimally to current levels of GHG emissions, if non-Kyoto pollutants from traditional fuels are considered.

Third, I construct a multi-box atmospheric transport model for PM<sub>2.5</sub> to analyze the spatial and seasonal variation of *ambient* air pollution. I then use a national air pollution inventory to calculate source contribution to ambient PM<sub>2.5</sub> exposure. Residential biomass use dominates mortality burdens from ambient air pollution in India. I show that the informal sector (sources beyond the direct ambit of regulation including traditional household fuels) is responsible for 73% of deaths

attributable to ambient air pollution and 33% of nation-wide GHG (including non-Kyoto) emissions. Coal use in formal industry is the second leading contributor to mortality and is responsible for half of national GHG emissions. The significant contribution of informal sources to ambient air pollution and GHG emissions leads to the conclusion that a focus on formal sources (e.g. power and transport) alone is inadequate - the role of informal sources needs to be addressed to meet air quality and climate goals.

## **Lay Summary**

Emerging economies such as India face multiple energy challenges – providing affordable energy to everyone, reducing air pollution and forging a low carbon development pathway. In general, these issues are considered and treated disparately. However, their interconnected nature implies that policy action addressing one challenge, may have co-benefits or trade-offs in other areas. First, I study aspects of the transition from traditional to modern fuels in Indian households - equity implications in terms of gender, income and urban-rural location, and the impacts on indoor air pollution, health, and greenhouse gas emissions. Second, I construct an atmospheric transport model for fine particulate matter to estimate the spatial and seasonal distribution of ambient air pollution in India, and identify the sectors which can provide health and climate benefits. Household energy transition appears to play a crucial role in catalyzing development and gender equity, as well as contributing to better health and climate mitigation.

## **Preface**

This dissertation is my original, unpublished, and independent work. I identified the problem, conducted the research, analyzed the data and wrote the manuscripts. Dr. Milind Kandlikar edited the manuscripts and provided feedback at each stage. Dr. Hadi Dowlatabadi provided feedback at various stages.

Each chapter of this dissertation is a stand-alone paper, intended for journal publication, due to which there may be repetitive content, particularly in the background and literature review sections of each chapter. A version of Chapter 2 will be submitted for publication with Dr. Zia Mehrabi and Dr. Milind Kandlikar as co-authors. Versions of Chapters 4 and 5 will be submitted for publication with Dr. Milind Kandlikar and Dr. Chandra Venkataraman as co-authors. A version of Chapter 3 will be submitted for publication with Dr. Milind Kandlikar as the co-author.

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## List of Abbreviations

(A)LRI	(Acute) Lower Respiratory Infection
BC	Black carbon
CH <sub>4</sub>	Methane
CO	Carbon monoxide
CO <sub>2</sub>	Carbon dioxide
COPD	Chronic Obstructive Pulmonary Disorder
GHG	Greenhouse gas
ICS	Improved cookstove
IGP	Indo-Gangetic Plain
IHD	Ischemic Heart Disease
LPG	Liquefied Petroleum Gas
NMVOC	Non-methane volatile organic compound
N <sub>2</sub> O	Nitrous oxide
NO <sub>x</sub>	Oxides of nitrogen
OC	Organic carbon
SIA	Secondary inorganic aerosols
SO <sub>2</sub>	Sulfur dioxide
SOA	Secondary organic aerosols

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*To Ma.*

# Chapter 1: Introduction

## 1.1 Overview

Rapid economic development in India over the last few decades has led to exponential growth in energy consumption in the country. Total primary energy consumption in India doubled between 2000 and 2015 (IEA 2015) as GDP grew at an average annual rate of 7% and the population rose to 1.3 billion (CSO 2018). The agricultural sector's contribution to the economy has reduced to less than 18% over the last four decades, to give way to the services sector (Kanitkar et al. 2015). Economic restructuring has been accompanied by urbanization and consequent energy-intensive changes in lifestyles – car sales of the three largest automobile companies witnessed a three-fold increase between 2000 and 2010 (Verma 2015) and ownership of air conditioning units is expected to drive the rise in electricity consumption over the next decade (World Bank 2008b). India is the 2<sup>nd</sup> largest coal and 3<sup>rd</sup> largest oil consumer in the world (IEA 2015). And yet much of India's development needs remain unmet - a large section of the population still does not have access to electricity (23% of the population (NITI Aayog 2017)) or basic infrastructure such as roads (25% of villages) and schools (20% of villages), all of which need energy as input (Sreenivas 2014). Low cost energy is needed to invest in better energy access mechanisms and infrastructure, and to industrialize. The current government effort to stimulate the manufacturing sector in the country through the 'Make in India' campaign indicates a more energy-intensive economic future. The International Energy Agency estimates that the rise in energy demand in India will account for more than a quarter of the rise in global energy use by 2040 (IEA 2012) .

Coal has the largest share of the primary energy in India (at 44%), followed by biomass (24%) and oil (23%), with the remaining accounted for by natural gas (6%), renewables (2%) and nuclear (1%) (IEA 2015). Rising fossil energy consumption has gone hand in hand with carbon dioxide (CO<sub>2</sub>) emissions in India – India is currently the third largest CO<sub>2</sub> emitter and the country's leadership recognizes the shared global responsibility towards sustainable development. India's climate commitments for the period 2021-2030, in response to the 2016 Paris agreement within the UNFCCC, include reducing the emissions intensity of GDP by about a third over 2005 levels. Fossil fuel consumption not only affects the global environment but also regional air quality – average fine particulate matter (PM<sub>2.5</sub>) concentrations in India are some of the highest in the world, exceeding WHO air quality guidelines by a factor of 7 (WHO 2006; Cohen et al. 2017). The air pollution problem is particularly staggering in densely populated areas such as metropolitan cities and the northern Indo-Gangetic Plain (Brauer et al. 2012; CPCB 2011). An estimated million people lost their lives to air pollution-related diseases in India in 2015 (Cohen et al. 2017).

The per capita energy profile presents a stark contrast to national-level aggregate numbers – per capita energy consumption is only about a third of the world average and lower than developing countries in Africa and South-East Asia (IEA 2015); rural annual per capita electricity consumption is less than a tenth of the UN standard of decent living (Powell 2015). 304 million Indians lived without access to electricity as of 2012 and 500 million Indians relied on inefficient and polluting solid fuels for cooking (NITI Aayog 2017). To make modern energy services affordable and accessible, the Government of India subsidizes electricity connections and liquefied petroleum gas (LPG) for cooking, with a special focus on expanding energy services to

rural India. The National Energy Policy (2017) declared making clean cooking fuel and electricity available at affordable prices to all citizens as key components of poverty alleviation and economic growth. ‘Inclusive growth’ has been a key target for India (Planning Commission 2014; Planning Commission 2012) – it is broadly defined as the improvement in the living standards of all sections of the population, brought about by economic growth coupled with poverty alleviation.

India thus faces the triple challenge of providing energy to all while minimizing negative impacts on local and global environment. Improved energy access and economic growth come hand in hand with greater energy consumption which may result in trade-offs with climate mitigation and/or air quality improvement goals. In the face of multiple challenges, analyzing energy transition pathways that have impacts across the sectors of development, air quality and climate is important in developing a comprehensive view of policy impacts and is the goal of this thesis.

## **1.2 Energy and development: The household energy transition in India**

Affordable access to modern energy is essential to development. The UN’s 2030 Agenda for Sustainable Development recognizes access to clean and modern energy as one of 17 development goals that need urgent attention worldwide. Clean cooking fuels and electricity provide a number of health and developmental benefits – reducing air pollution from biomass burning and kerosene lamps, saving women’s time and effort spent in collecting firewood and educational benefits such as allowing study time in the evenings through electrification (Cabraal et al. 2005; Asian Development Bank 2010; ESMAP 2004).

The ongoing household energy transition in India has seen a general shift from traditional fuels such as biomass for cooking and kerosene for lighting to LPG and electricity. While the majority of urban India has access to electricity, complete rural electrification has been a challenge for successive governments, with 26% of rural households un-electrified as of 2012 (NITI Aayog 2017). On the clean cooking front, use of LPG has been generally restricted to middle and high-income urban households, with almost 90% of rural households using biomass for cooking in 2009 (Cheng & Urpelainen 2014), primarily due to affordability and supply issues (Viswanathan & Kavi Kumar 2005; Farsi et al. 2007; S. Pachauri & Jiang 2008) or cooking preferences based on the taste of food and cultural characteristics (Kowsari & Zerriffi 2011). LPG is more expensive, requiring a lump payment for each refill, compared to cooking alternatives such as firewood which are either collected and hence free, or can be bought in small quantities. LPG supply infrastructure is also deficient in rural India compared to urban India (IISD 2014).

Currently, the Pradhan Mantri Ujjala Yojana (PMUY) is the primary policy in place addressing the inequity in access to LPG – subsidized LPG connections are provided to women in below-poverty-line households. Updates from the field tell us that PMUY beneficiaries only satisfy part of their cooking energy requirements with LPG<sup>1</sup>. Stacking fuels, i.e., using different fuels in

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<sup>1</sup> *Pradhan Mantri Ujjwala Yojana: Smokeless kitchens are becoming a reality* 2018, Financial Express, New Delhi. Retrieved from <http://ezproxy.library.ubc.ca/login?url=https://search-proquest-com.ezproxy.library.ubc.ca/docview/2084794059?accountid=14656>

combination, is often practiced in households who cannot switch completely to clean fuels or have particular cooking preferences (Masera et al. 2000; Kowsari & Zerriffi 2011; Cheng & Urpelainen 2014). There are a few other clean cooking options in India but adoption rates are very low – they include improved biomass cookstoves, electricity, and piped natural gas. A review of the role of energy in development leads to the question of the nature of equity of past household energy transition in India, as well as equity implications in the future.

### **1.3 Household energy use and indoor air pollution**

The household energy transition to clean cooking and lighting fuels has significant positive impacts on indoor air quality. Burning solid fuels and kerosene lighting are the primary sources of indoor PM<sub>2.5</sub> exposure; almost four million deaths can be attributed to household biomass smoke in 2010 globally (Smith et al. 2014). The health impact of biomass is particularly significant for women who are primarily responsible for cooking activities - estimated mean daily concentration in kitchens in solid-fuel using households is 4 times that in living areas (Smith et al. 2014). LPG stoves lead to negligible PM<sub>2.5</sub> emissions - estimated intake (or amount inhaled) of PM<sub>2.5</sub> from LPG stoves is less than 1mg/day, which corresponds with WHO air quality guideline of about 0.6 mg/day (WHO 2006), while that from traditional biomass cookstoves is about 80 mg/day (Grieshop et al. 2011). High efficiency improved biomass

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*The Hindu Business Line: PMUY: A feather in the cap for pradhan and his team (2018).*

Chatham: Newstex. Retrieved from <http://ezproxy.library.ubc.ca/login?url=https://search-proquest-com.ezproxy.library.ubc.ca/docview/2083373761?accountid=14656>

cookstoves (ICS) are known to reduce PM<sub>2.5</sub> exposure but estimated PM<sub>2.5</sub> intake from ICS still exceeds the WHO air quality guidelines by an order of magnitude or more (Grieshop et al. 2011). Burnett et al.(2014) state that health risk reductions are achieved only at the level of WHO guideline, which implies that even small amount of biomass use through stacking or in improved cookstove may be harmful for health. Thus, the household energy transition might be particularly beneficial for women, and not all forms of transition may be equally beneficial.

#### **1.4 Ambient air pollution**

Ambient air pollution presents a significant challenge, particularly in densely populated areas in India and in winter, when meteorological conditions such as low mixing height are conducive for PM<sub>2.5</sub> to accumulate in air. Majority of metropolitan cities in India are ‘critical’ in terms of air quality (CPCB 2011) – the National Air Quality Index<sup>2</sup> for cities in the Indo-Gangetic Plain such as New Delhi and Lucknow, often indicates ‘Poor’ or ‘Very Poor’ air quality, and falls to ‘Severe’ every winter. The northern Indo-Gangetic Plain in general experiences higher levels of air pollution than the rest of the country (Brauer et al. 2012; Ram & Sarin 2011). The significance of sources of PM<sub>2.5</sub> varies across the country, with primary sources being biomass burning, thermal power, heavy industry and diesel transport (Guttikunda, Goel & Pant 2014; Guttikunda & Calori 2013) . Certain cities have taken air pollution mitigation measures such as odd-even license plate rationing scheme for cars in Delhi but the problem persists and worsens every winter. The impact of PM<sub>2.5</sub> on human health is determined by the amount of emitted PM<sub>2.5</sub> that is inhaled by the exposed population. Thus sources in proximity to a densely

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<sup>2</sup> categories: Good, Satisfactory, Moderately Polluted, Poor, Very Poor, Severe

populated area are more harmful for human health, and similarly with emissions from vehicular diesel exhausts which are in greater proximity to the population than the high stacks of thermal power plants; regions and months with low mixing heights and wind speed imply greater accumulation of particulate matter in the atmosphere; and low rainfall leads to less PM<sub>2.5</sub> washed out from air. A range of factors specific to the emission source and region in which the source is located – population density, seasonal meteorology, emission stack height - influence the impact of emissions on human health. Additionally, the distribution of sources themselves vary spatially - thermal power plants are large point sources of pollution located in specific locations and agricultural residue burning is a distinct challenge in the Indo-Gangetic Plain. The regional nature of the ambient air pollution challenge raises the question of which measures will be effective in terms of health risk reduction and where they need to be implemented.

## **1.5 Climate**

Coal and oil consumption in India increased at an annual rate of 6% and 5% respectively over the last decade (CSO 2017). Although India's per capita CO<sub>2</sub> emissions are only about 11% of that of the US<sup>3</sup> (Ebinger 2016), India's position in the three largest emitters and planned growth in the fossil fuel sector, make its carbon policy significant in the international climate scene. The Government of India recognizes the shared global responsibility of combating climate change, and at the same time recognizes the developmental needs of the nation and the crucial role of low-cost energy in economic growth. As part of its Intended Nationally Determined

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<sup>3</sup> at 1.9 tCO<sub>2</sub> in 2014 compared to 7.1 tCO<sub>2</sub> in China and 17 tCO<sub>2</sub> in the US.

Contributions (INDC), in response to the Paris Agreement of 2016, India put forth a number of climate action targets – reducing GDP emissions intensity by 33-35% by 2030 compared to 2005 levels; increasing installed renewable energy capacity to 175 GW by 2022 and nuclear capacity to 63 GW by 2032 so that 40% of total installed capacity is non fossil-fuel based; improving energy efficiency in buildings, transport and industry; and improvement in infrastructure such as railways and power grid that would improve energy efficiency (Government of India 2015). But in spite of huge planned expansions in renewable power, coal is expected to play a major role in the energy mix in the near future - the INDC lay out plans for high efficiency supercritical coal technology in the future. Official energy policy documents such as the Draft National Energy Policy (2017) recognize that climate change goals may be in conflict with other energy sector goals.

The focus of greenhouse gas (GHG) accounting and modelling studies has so far been on Kyoto pollutants (CO<sub>2</sub>, CH<sub>4</sub>, and N<sub>2</sub>O) (MOEF 2010; McKinsey & Company 2009; World Bank 2011; WWF-India/TERI 2013), but a host of other pollutants such as black carbon (BC) and non-methane volatile organic compounds (NMVOCs) have global warming impact (Bond 2007; Lam, Chen, et al. 2012; Venkataraman et al. 2016). The effectiveness of a climate policy action may be misjudged, if only CO<sub>2</sub> or Kyoto pollutants are included in estimating climate impact – sources of Kyoto and non-Kyoto emissions may be different and climate policy targeting Kyoto emissions may not be effective in reducing non-Kyoto emissions (Venkataraman et al. 2016).

The largest share of CO<sub>2</sub> emissions in India is from thermal power (38%), industry (cement and iron and steel) (22%), and agriculture (18%), followed by transport and residential sectors (about 7% each) (MOEF 2010). But this does not include products of incomplete combustion (PICs) of

biomass which could alter the sector-wise share of GHG emissions and consequently the climate mitigation impact of a policy option. There is a level of uncertainty associated with quantifying the climate impact of PICs such as black carbon, and yet despite this uncertainty, the warming impact of BC is certainly greater than CO<sub>2</sub> (Bond 2007).

Including non-Kyoto pollutants in GHG emission estimates brings residential biomass burning, generally considered carbon-neutral, into the focus of climate policy discussions and raises the question of whether air pollution and climate concerns can be addressed simultaneously through a transition to cleaner fuels, or if there is a trade-off between air pollution and climate action since cleaner cooking and lighting options are fossil fuel-based.

### **1.6 Dealing with India's energy trilemma: the overarching aim of this thesis**

The growing energy needs of a population place the need for low-cost energy at odds with global sustainability concerns about greenhouse gas emissions and local air quality considerations. The varied nature of energy challenges in India draws attention to the cross-impacts of any energy policy option. Policies targeting clean cooking gas access or particulate matter emissions from thermal power may not simply have an impact on the objectives they are intended for, but also across other sectors.

The overarching aim of this thesis is to explore the interconnections between multiple energy challenges - equity in energy access, indoor and ambient air pollution, and climate action - which so far have been treated as disparate and often conflicting issues, through a single unified lens.

Two significant themes emerge from my review of multiple energy challenges in India – firstly, household energy transition has ramifications across sectors. It not only plays a key role in development and air pollution, but also has implications for climate– by moving away from biomass and kerosene lighting and hence reducing non-Kyoto emissions, as well as through transitioning to LPG and electricity, both of which are fossil fuel-based. Secondly, the regional nature of air pollution implies that effective pollution control strategies may need to be tailored to specific regions and any national-level climate action may have distributional air pollution impact, being effective in some areas and not others. The thesis chapters are structured around these two themes and focus on one or more of the energy challenges discussed. Data used in this thesis are national-scale secondary data – they include survey data on population-level energy consumption and socio-economic indicators, inventory data on PM2.5 and GHG emissions, modelled meteorological data, and Census data from the Government of India.

## **1.7 Introduction to thesis chapters**

### **1.7.1 Chapter 2**

*Theme: Household energy transition*

*Focus: Gender equity and Respiratory health*

Research question: What are the quantifiable health and developmental benefits of household energy transition in India? Specifically, how are these benefits distributed a) among households that make different forms of energy transition - switch to efficient biomass cookstoves, partially adopt clean fuels or completely adopt clean fuels - and b) among men and women?

Data:

I use data from the India Human Development Survey (IHDS), a publicly available nationally representative dataset. In the IHDS, more than 40000 households in 1503 villages and 971 urban neighbourhoods were interviewed once in 2005 and re-interviewed in 2011. The IHDS provides a panel dataset in which the same households are interviewed in both years, thus allowing us to track the changes in a given household over time. The questionnaire was development-focused - the relevant variables for the purpose of this analysis are type of fuel and stove used, occurrence of cough and smoking habits of each household member, time of stove use, time spent by each household member collecting solid fuels, use of appliances such as refrigerator, and location of household.

Methodology:

I use mixed effects regression to quantify the benefits experienced by men and women in a household on making a cooking and/or lighting fuel transition. I focus on two impacts - respiratory health benefits, using occurrence of cough within 30 days of the interview as the health metric; and time savings, using two metrics - daily stove use time and time spent on collecting solid fuels.

### **1.7.2 Chapter 3**

*Theme: Household energy transition*

*Focus: Energy equity, Indoor air pollution, Climate*

Retrospective research question: How equitable has household energy transition been across urban and rural India and across income groups? How have indoor air quality and climate impacts been distributed as a result?

Prospective research question: What are the potential impacts of future household energy transition on energy equity, indoor air pollution and climate impacts across urban-rural and income groups?

Data:

I use consumer expenditure data from the National Sample Survey (NSS), for years 1987-88 (43<sup>rd</sup> round) and 2009-10 (66<sup>th</sup> round). In the NSS, households are interviewed every 5 years on socio-economic indicators such as monthly expenditure, fuel consumption and household demographics. Unlike the IHDS, the same set of households are not interviewed in each round of the survey, yielding a pooled cross-sectional dataset. In the 43<sup>rd</sup> round, more than 45,000 urban and 82,600 rural households were interviewed while in the 66<sup>th</sup> round, more than 41,000 urban and 59,000 rural households were interviewed. The relevant variables in the questionnaire for the purpose of this analysis are household size, monthly expenditure, primary cooking and lighting fuels used, and quantities and types of fuel used.

Methodology:

To address the retrospective research question, I conduct descriptive analysis of past NSS data and study the household energy transition and consequent impacts on indoor air quality and GHG emissions across urban and rural households, and across income groups.

To address the prospective research question, I model feasible household energy transition scenarios for 2030 and study the implications for energy equity, indoor air pollution and GHG emissions across urban and rural households and across income groups.

### **1.7.3 Chapter 4**

*Theme: Regional nature of air pollution*

*Focus: Indoor and outdoor air pollution exposure*

Research question: How can we quantify the dependence of the spatial and seasonal distribution of PM<sub>2.5</sub> exposure on population density and meteorological conditions across India?

Data:

I use modelled hourly district-wise meteorological data from the publicly available repository ‘Urbanemissions.info’ and Census 2011 data on district-wise population as inputs. For model validation purposes, I use PM<sub>2.5</sub> emissions data for 2015 from the spatially disaggregated emissions inventory developed by Sadavarte and Venkataraman, and Pandey et al. (Sadavarte & Venkataraman 2014; Pandey et al. 2014) to estimate the distribution of PM<sub>2.5</sub> concentrations across India.

Methodology:

I use intake fraction, i.e., the fraction of emissions inhaled by the exposed population, as the metric for exposure per unit emission, in order to study the role of population density and meteorology in determining exposure, independent of magnitude of emissions. I develop a multi-

box model for PM<sub>2.5</sub> transport in the atmosphere, based on the USEtox modeling framework and considering regional variations in population density and meteorology to determine ‘box’ boundaries within the model. Densely populated urban ‘boxes’ are nested within regional boxes, which are differentiated by mixing height values and proximity to the ocean, and are themselves nested within sub-continental ‘boxes’. The resulting nested box model framework allows estimation of region and month-specific intake fraction values.

#### **1.7.4 Chapter 5**

*Theme: Regional nature of air pollution*

*Focus: Ambient air pollution exposure and consequent mortality burden*

Research question: How are significant emission sources distributed spatially across India and what are their health impacts?

Data:

I use the emissions inventory developed by Sadavarte and Venkataraman and Pandey et al. (Sadavarte & Venkataraman 2014; Pandey et al. 2014). Emissions include PM<sub>2.5</sub> and GHG – Kyoto gases such as CO<sub>2</sub>, CH<sub>4</sub> and N<sub>2</sub>O, and non-Kyoto pollutants such as BC, OC, NMVOC, CO and SO<sub>2</sub>. Annual emissions for 2015 are available for residential, industry, transport and agricultural sectors, with emissions from certain sectors (agricultural residue burning, space heating and water heating) available on a monthly basis.

Methodology:

I employ the model developed in chapter 4 and use the emissions inventory to estimate the source-contribution to the spatial distribution of PM<sub>2.5</sub> exposure and consequent mortality burden.

### **1.7.5 Chapter 6: Conclusion**

In the concluding chapter, I situate the issues of traditional fuel use in households and ambient air pollution, within the context of nation-wide GHG emissions, in order to identify emission sectors that can provide both health and climate benefits.

### **1.8 Concluding remarks: Viewing multiple challenges through a single unified lens**

In general, household access to modern fuels, ambient air pollution and greenhouse gas emissions are viewed as distinct challenges. In this thesis, my attempt has been to bring together these distinct issues and examine the co-benefits and trade-offs of mitigating each of them through a single unified lens. As India strives to achieve its developmental, health and environmental goals, my endeavor in this thesis is to present an integrated picture of the energy challenges facing the country today.

## **Chapter 2: Quantifying the Gendered Benefits of India's Household Energy**

### **Transition**

#### **2.1 Introduction**

Access to modern energy services such as liquefied petroleum gas (LPG) for cooking and electricity contributes to people's well-being and improving their general quality of life. Studies, primarily using cross-sectional data, have shown that LPG and electricity provide a number of benefits including reducing the time spent collecting solid fuels, increasing the time available in the evenings to do productive work through lighting facilities and improving indoor air quality by moving away from polluting alternatives, among others (Cabraal et al. 2005; Asian Development Bank 2010; Khandker et al. 2013; ESMAP 2002; ESMAP 2004).

India has over 300 million people without access to electricity and over 800 million people who use biomass fuels for cooking (Government of India 2015), and the majority of this group resides in rural areas (S. Pachauri & Jiang 2008; S. Pachauri 2014; Ailawadi & Bhattacharyya 2006). Total electrification and access to clean cooking LPG has been a long-held policy goal of successive Indian governments, though progress has been slow. The ongoing transition in India from traditional solid fuels (such as wood fuel and dung) for cooking and kerosene for lighting towards LPG and electricity respectively, has been faster in urban India and among middle and high-income households. The share of households relying solely on electricity for lighting rose from 10% to 50% in urban India between 1987 and 2009, but only increased from 6% to 13% in rural India (Cheng & Urpelainen 2014). Similarly, the share of households relying exclusively on LPG

for cooking rose from 5% to 58% in urban India between 1987 and 2009 but only from 4% to 8% in rural India (Cheng & Urpelainen 2014). Even when households have access to modern energy sources they often practice ‘fuel stacking’, wherein they continue to use biomass for cooking after adopting LPG, and/or kerosene lamps along with electricity (Masera et al. 2000; Rajesh et al. 2003; Kowsari & Zerriffi 2011; S. Pachauri & Spreng 2003; Davis 1998).

A number of papers have quantified the developmental benefits of household energy transition using cross-sectional datasets on household fuel use patterns (Khandker et al. 2013; Khandker et al. 2009; ESMAP 2002; Aguirre 2014; Barnes et al. 2012) . While cross-sectional datasets provide information about energy consumption patterns across a population at a given time, they cannot easily control for variation in the unobserved characteristics of a population that influence the developmental indicator of interest, such as respiratory health. Panel datasets, which allow us to track the energy transition in the same set of households over time, can isolate the health and developmental effects of adopting clean fuels on individuals, by using households as their own ‘controls’. In this study I use the India Human Development Survey (IHDS) dataset collected at two points in time, 2005 and 2011 - to examine the shift in a household’s fuel and stove use pattern and to quantify the gender-related health and time-saving benefits of the energy transition experienced by households that made the transition. I focus on gender-related benefits since a well-known, but under-researched, and poorly quantified aspect of transition to clean fuels is the benefit it may specifically provide to women (Laxmi et al. 2003; Barnes et al. 2012).

The remainder of the paper is structured as follows. Section 2.2 provides a brief review of the literature on gendered direct and indirect benefits of switching away from solid fuel and kerosene

use, including those related to health, and household time budgets. Section 2.3 presents a descriptive analysis of the gendered dimensions of India's energy transition using IHDS panel data. Mixed effects regression models and data analysis are presented in section 2.4, with a focus on health outcomes (2.4.1) and time spent collecting fuel and cooking (2.4.2) for women. I conclude in section 2.5 with a discussion.

## **2.2 Gendered benefits of electrification and clean cooking fuel**

As in many other parts of the developing world, women in India spend a greater proportion of their time on household work than men, almost 7 times as much (OECD<sup>4</sup>), and bear much of the responsibility for cooking, cleaning and childcare (Barnes et al. 2012). Direct benefits of modern energy access for women include increases in welfare, appliance use, longer hours for home businesses in the evening, all enabled by electrification, as well as time saved from collecting and cooking with solid fuels when households switch to LPG. However, indirect benefits of modern energy services such as improvement in education and health can also be substantial (Cabraal et al. 2005). A key indirect benefit is positive respiratory health impacts due to reduced exposure to air pollutants as households' transition away from solid fuels and kerosene lamp. Other indirect benefits include improvement in educational attainment due to lighting and reduced fertility levels as evidenced in rural Bhutan and Ivory Coast (Asian Development Bank 2010; Peters & Vance 2011).

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<sup>4</sup> <https://stats.oecd.org/index.aspx?queryid=54757>

*Smoke Inhalation:* Smoke from burning biomass and kerosene lamps indoors contributes significantly to high particulate matter exposure in households and contains fine particles, also known as PM<sub>2.5</sub> (particles with aerodynamic diameter less than 2.5 µm) that are known to be respiratory irritants and carcinogenic by nature (Naeher et al. 2010; Bruce et al. 2002; Gordon et al. 2014; Lam, Smith, et al. 2012; Muyanja et al. 2017). Incomplete combustion of biomass in most traditional stoves along with poor ventilation exacerbates the problem of indoor air pollution. Since women are responsible for cooking in most households and children spend more time at home, women and children are particularly vulnerable to diseases caused by indoor air pollution (Gordon et al. 2014; Bruce et al. 2002). 24-h average exposure concentrations for respirable particulate matter in wood-using households in a study conducted in rural India was estimated<sup>5</sup> at 226µg/m<sup>3</sup> for cooks, who are primarily women, while for non-cooks it was 172µg/m<sup>3</sup> (Balakrishnan et al. 2002). In LPG-using households in the same study, mean daily exposure concentrations were similar for cooks and non-cooks at 76-79 µg/m<sup>3</sup>. In the Global Burden of Diseases assessment of the impact of household solid fuel exposure (Smith et al. 2014), estimated average national daily exposure to PM<sub>2.5</sub> in solid fuel-using households in India is higher in women, at 337µg/m<sup>3</sup> compared to 204µg/m<sup>3</sup> in men. Switching to cleaner fuel like LPG improves indoor quality dramatically –personal exposure concentrations for cooks during cooking time in wood-using households was measured at 1200-1307µg/m<sup>3</sup>, compared to 60-83 µg/m<sup>3</sup> attributed to cooking with LPG (Ellegard 1996; Balakrishnan et al. 2002).

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<sup>5</sup> through a combination of measurements from personal and household samplers and time-activity records from 400 households in rural Tamil Nadu (India)

*Health Outcomes:* A number of studies show an association between high particulate matter exposure and adverse cardiovascular and pulmonary health impacts (Gordon et al. 2014; Smith et al. 2014). Household exposure to specifically biomass smoke is linked with higher risk of chronic obstructive pulmonary disease (COPD) and acute lower respiratory infection (ALRI) (Naeher et al. 2010; Bruce et al. 2002; Ezzati & Kammen 2001; Smith et al. 2005; Liu et al. 2007; Dennis et al. 2016; Johnson et al. 2011), causing almost three million annual premature deaths globally (Smith et al. 2014). The odds of developing COPD due to biomass smoke is 20% higher for women than men (Smith et al. 2014). Similarly, the likelihood of ARI and ALRI incidence in women exposed to fuelwood smoke indoors is twice as high as that in men (Ezzati & Kammen 2001). Household biomass usage also shows statistically significant association with cough, reduced lung function, and hypopharyngeal and lung cancers (Ellegard 1996; Mbatchou Ngahane et al. 2015; Sapkota et al. 2008; Smith et al. 2014). Respiratory symptoms like cough are associated with carbon monoxide (CO) exposure due to household air pollution (Naeher et al. 2010; D. Pope et al. 2015). For example, the RESPIRE study, or Randomized Exposure Study of Pollution Indoors and Respiratory Effects, shows that ICS (with chimney) intervention in rural Guatemala reduced CO exposure in households post-intervention by 50-60% and ICS adoption is associated with a reduced risk of wheeze, a chronic airway symptom, in women (Smith-Sivertsen et al. 2009), but not reduced incidence of pneumonia in children (Smith et al. 2011).

Kerosene wick lamps also contribute significantly to particulate matter concentrations indoors (Apple et al. 2010; Lam, Chen, et al. 2012; Muyanja et al. 2017), though there are fewer studies investigating the health impact of specifically using kerosene for lighting and cooking. Kerosene

combustion generates known carcinogens such as formaldehyde and polycyclic aromatic compounds and studies indicate that kerosene use is linked with reduced lung function and asthma in children and women (Lam, Chen, et al. 2012), tuberculosis in women (Pokhrel et al. 2010) and ALRI in children (Savitha et al. 2007).

*Time spent by women:* Surveys show that rural Indian households spend about 1-2 hours a day collecting firewood (including traveling to the collection location) and about 3 hours on cooking<sup>6</sup>, with women and girl children bearing most of the responsibility (Laxmi et al. 2003; ESMAP 2004). Although collecting firewood is unpaid work, the opportunity cost of time spent collecting fuel is high, as it has implications for school hours missed by children and significantly poor quality of life for women as they regularly travel long distances and carry heavy loads of fuelwood (Laxmi et al. 2003). The Asian Development Bank estimates that when rural households in Bhutan switch from firewood to a clean alternative like electricity, women are seen to benefit more than men, saving 27.6 minutes a day in firewood collection time compared to 21.6 minutes for men (Asian Development Bank 2010). Survey results show that Indian households using LPG also spend about 24 minutes less on cooking compared to households using firewood (ESMAP 2004).

*Education:* Electrification has been shown to have a positive impact on education outcomes. Studies from around the world., viz., from Peru (Aguirre 2014), India (Khandker et al. 2012), Philippines (ESMAP 2002), Bangladesh (Khandker et al. 2009) and South Africa (Martins 2005) show a positive impact on school enrolment and study time at home among school-going children

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<sup>6</sup> Further analysis of time spent on cooking activities provided in Section 4.2

due to electrification. A modelling study for rural Assam, where only 25% of households were electrified, showed that improvement in electrification by 1% could potentially increase literacy rate by 0.17% (Kanagawa & Nakata 2008). Studies also show that electrification may have a greater positive impact on educational outcomes for girls compared to boys - in one study school enrolment increased by 6% and 7.4%, and average number of schooling years by 0.3 and 0.5 years for boys and girls respectively in rural India (Khandker et al. 2012); rural electrification in Bhutan had a significant impact on literacy rate and completed school years only in girls, contributing 0.56 years of additional school years (Asian Development Bank 2010).

*Economic benefits:* In general, economic benefits of household energy transition, including those specific to women are difficult to quantify. The use of shadow wages for time saved on collecting fuels is debatable since most of the collection work is done by women and children in rural households, where employment opportunities are limited and time saved may not be used for income-generating activity (García-Frapolli et al. 2010). Khandker et al. show that a 17% increase in employment hours for women in rural India following electrification, along with increases in non-farm income (2012), and a 12% increase in income in rural Bangladesh (2009), though greater benefits accrue to wealthier households in both studies. In a study in rural India, Aklin et al. (2017) find no evidence of impact of electrification on socioeconomic development indicators such as business creation, savings or time spent working or studying. Kooijman-van Dijk (2012) concludes that the impact of electrification on income depends on the access to markets for rural businesses, and that energy is necessary but not sufficient for increasing income-generating activities.

### **2.3 Dataset and descriptive analysis**

The IHDS is a nationally representative survey covering topics within development including education, health, gender relations (University of Maryland & National Council of Applied Economic Research, New Delhi n.d.). Data was collected in 2005 (November 2004 - October 2005) through interviews with households, and about 85% were re-interviewed in 2011-12 (January 2011-March 2013), providing a useful panel dataset to track changes in the same households over time. The publicly available dataset covers 40,018 households in both years, with about 30% urban households.

Panel data captures changes in households across time and health and time saving effects have distinct indicators in the IHDS dataset used in this study, like occurrence of cough in household members within 30 days of the interview and time spent cooking and collecting fuels, respectively<sup>7</sup>. In this study, I restrict my analysis to the impact of household energy transition, i.e., switch to cleaner fuels for cooking and the use of electricity for lighting and appliances, on respiratory health and on time saved cooking and collecting fuel, using data for 2005 and 2011. Other measures such as time spent studying are confounded by changes in the ages of children in a household making it harder to attribute educational outcomes to electrification. Both measures – health and time saved – are particularly significant for women who are primarily responsible for collecting fuel and cooking in households.

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<sup>7</sup> Further explanation of the variables provided in Section 4.

Figure 2.1 shows the cooking and lighting energy transitions in interviewed households between 2005 and 2011. The data confirm that clean cooking energy transition has been faster in urban India<sup>8</sup> in comparison with rural India. About 16% of urban households interviewed made a complete transition from solid fuel use to exclusively using LPG between 2005 and 2011, and 50% of urban households exclusively used LPG for cooking by 2011. While 6% of solid fuel-using urban households partially adopted LPG/kerosene between 2005 and 2011, i.e., used LPG and/or kerosene in addition to solid fuels, another 7% of urban households reverted to solid fuel use – equal proportions moved from exclusively using LPG to stacking solid fuels with LPG and from stacking solid fuels with kerosene to only using solid fuels. In the case of rural households, 87% used solid fuels in both years, and only 5% of rural households exclusively adopted LPG/kerosene between 2005 and 2011, with 20% partially adopting clean cooking fuel. In fact, 12% of rural households, moved from stacking solid fuels with kerosene for cooking to exclusively using solid fuels.

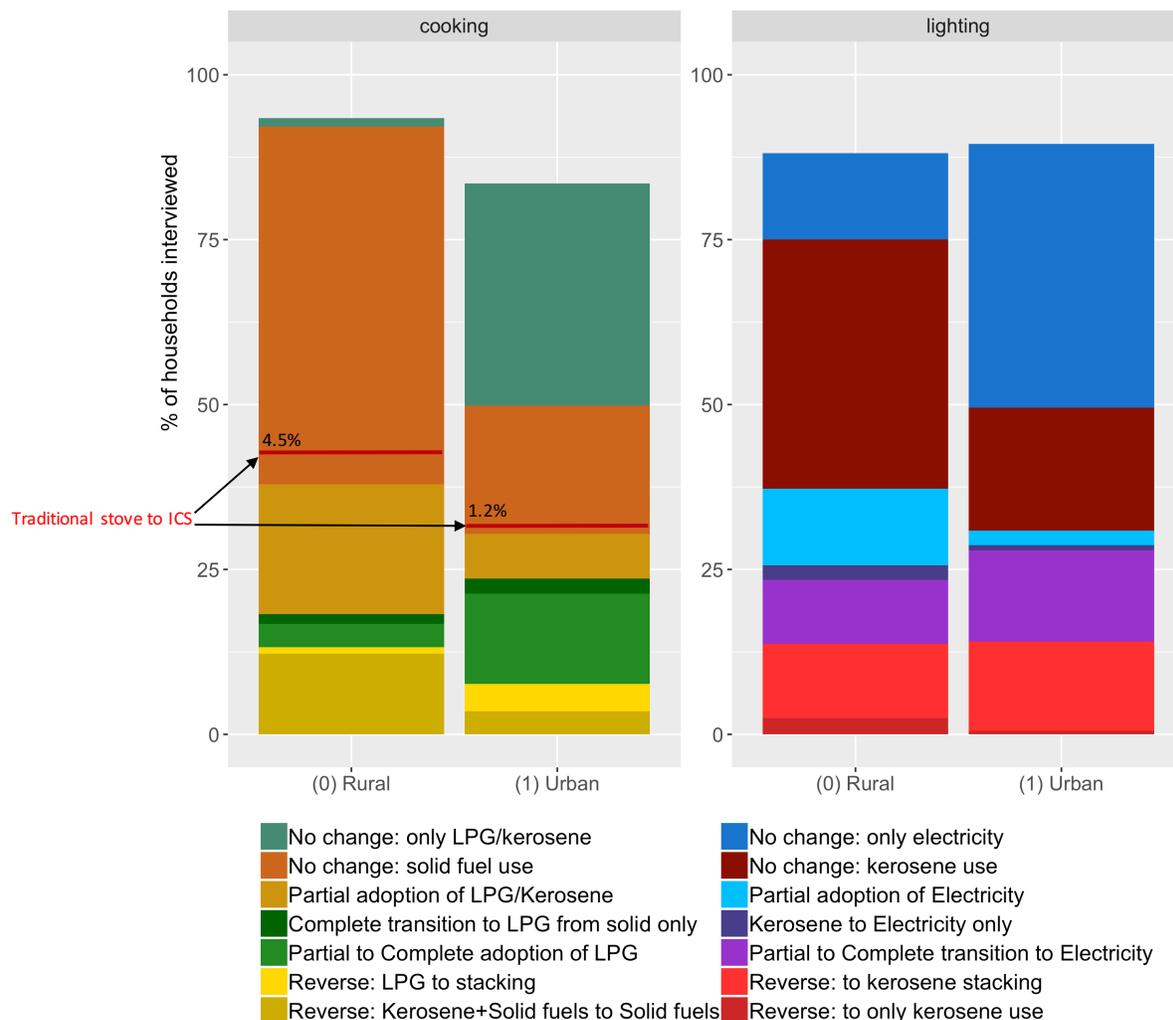
The IHDS dataset shows that kerosene use as a primary cooking fuel is negligible and kerosene is not a distinct ‘rung’ in the energy ladder, rather it is used to stack with solid fuels for cooking. The Government of India has taken steps to limit the availability of subsidized kerosene for household consumption since a sizeable portion of it is estimated to be diverted illegally, for further resale or

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<sup>8</sup> urban areas defined by the Census of India as Statutory Towns with a municipality or Census Towns with a minimum population of 5000, population density > 400 p./sq.km and 75% of population involved in the non-agricultural sector (Census of India 2011)

to adulterate diesel (Gangopadhyay et al. 2005; Ailawadi & Bhattacharyya 2006). This has reduced the appeal of kerosene as a primary cooking fuel option since larger quantities are needed for cooking compared to lighting (N. D. Rao 2012).

Kerosene use for lighting, either as the sole lighting fuel or as supplemental to electricity, is common in both urban and rural households – 33% of urban and 64% of rural households used kerosene in 2011. About 40% of urban households solely relied on electricity for lighting in both years, with an additional 15% making a complete transition to electricity between 2005 and 2011. However, about 13.5% of urban households reverted to using kerosene for supplemental lighting by 2011. In the case of rural households (with only 13% solely using electricity for lighting in both years), 12% made a complete transition to the exclusive use of electricity between 2005 and 2011 and 11.5% gained access to electricity but still used kerosene for supplemental lighting, while 11% reverted from using only electricity in 2005 to partially meeting lighting needs with kerosene in 2011.



**Figure 2.1** IHDS data: Household energy transition from 2005 to 2011

(Note: rural/urban households do not add up to 100% due to missing energy use data; urban households account for 30% of total households interviewed in both years) \*ICS: Improved biomass cookstove

Not represented here: 1.4% rural households transitioned from using ICS in 2005 to traditional cookstoves in 2011

## 2.4 Data analysis and modelling

I use mixed effects regression to estimate the developmental impact of energy transition in households during the six years between 2005 and 2011. Panel datasets such as the IHDS dataset record observations for the same set of individuals and households at multiple points in time so

that each household or individual can be used as their own control, comparing developmental outcomes of interest before and after energy transition. Mixed effects models include fixed effects, the systematic variation in discrete levels of household or individual-level variables over time (for example, whether a household uses solid fuels or not), and random effects that are probabilistic by nature and take into consideration correlations that arise from repeated measurements within a unit (Seltman 2010). In surveys such as the IHDS where data collected have an inherent hierarchical structure, i.e., individuals within households, and households within districts/states are interviewed, mixed effects models help account for the correlation between individuals in the same household or households within the same district/states. Multilevel or mixed effects models allow us to include differences between groups (households or districts/states), instead of assuming that data within groups (for example, the occurrence of cough in individuals within the same household) are uncorrelated (Gelman & Hill 2007).

In Equation 2.1 below for each individual  $i$  in household  $j$  and time period  $t$ , the relationship between the outcome variable of interest  $O_{ijt}$  and each explanatory variable  $EV_e$  (either an individual or household level predictor) is expressed through the coefficient  $\beta_k$  that represents the fixed effect of  $k$  different ‘levels’ of each explanatory variable.

$$O_{ijt} = \beta_{0j} + \sum_{ek} \beta_{ek} EV_{ek} + u_{jt} + e_{ijt} \quad \text{..... Equation 2.1}$$

where  $O_{ijt}$  = the response variable of each individual  $i$  in each household  $j$  at time  $t$ ,

$\beta_{0j}$  = intercept associated with each household  $j$

$\beta_{ek}$  = fixed effect associated with each level of the predictor variable  $EV_e$  with  $k$  levels

$EV_{ek}$  = predictor variable  $e$  with  $k$  levels specific to individual  $i$  in household  $j$  at time  $t$

$e_{ijt}$  = residual associated with each observation

$u_{jt}$  = variability among households or the random effect

Regression analysis is conducted using STATA and Appendix A Section A.1 presents a descriptive summary of each outcome variable.

The impact of household energy transition on two gender-specific outcome variables is analyzed at the individual level: respiratory health and time saved.

1. Respiratory health: I use mixed effects logistic regression with the occurrence of cough in non-smoking household members as the dichotomous dependent variable and model the log odds of the dependent variable as a linear combination of explanatory variables. Household members are asked to recall if they had a cough within 30 days of the interview, as part of the ‘Short Term Morbidity’ questionnaire. Interviews were conducted across the year in 2005 and 2011 and seasonal variation in cough is considered by including a dummy season variable. Household-level random effects, nested within State-level random effects, allow accounting for correlations between individuals in the same households and among households within the same state due to unobserved characteristics across households and States. State-level random effects are expected to capture any geographical patterns in the incidence of cough (apart from urban-rural disparity which is considered through a dummy variable), either due to differences in ambient air quality or public health provisioning.

## 2. Time saved:

- a. Time saved from using solid fuels in terms of daily stove use hours: I use linear mixed effects regression to model daily stove use as a function of household variables, assuming household-level random effects. More than 98% of interviewed households, rural or urban, have female cooks, and I assume that time spent cooking is time spent by women.
  
- b. Time spent by individuals in the household collecting fuels: I use log-linear mixed effects regression to model solid fuel collection time in rural households, as a function of household, age and gender variables. I assume household-level random effects, nested within district-level random effects, to account for the geographical variation in the availability of firewood, which may occur on a smaller spatial scale (i.e. districts) than State-level.

### **2.4.1 Respiratory health**

The occurrence of cough has been used as an indicator of the respiratory health impact of exposure to air pollution in a number of studies (D. Pope et al. 2015; Gordon et al. 2014; Johnson et al. 2011; Diaz et al. 2007). I use the occurrence of cough within 30 days of the interview as an indicator of respiratory health in household members, and calculate the impact of energy transition on the odds of occurrence of cough in non-smoking adult household members (to avoid confounding effects of smoking on cough). The impact of household energy transition on the outcome variable is expected to be different: first, for urban and rural households, since urban

areas can have higher ambient levels of pollution; second, for different gender and age categories since adult women are responsible for most cooking activities and so exposed to indoor smoke in greater numbers and magnitude. In order to examine the impact of household energy transition for household members whose exposures have remained relatively constant across the years, I restrict my analysis to household members who were adults in 2005 and 2011, to minimize changes in periods of indoor exposure due to transition into and out of school. Of non-smoking adults who reported their cough status in the IHDS, 20% of women and 11% of men in solid fuel-using households reported having a cough, while 11% of women and 6% of men in non-solid fuel-using households reported a cough.

There are four explanatory variables of interest:

1. *Cooking energy transition within a household*: An energy transition dummy variable is used to represent whether households use only solid fuels, stack solid fuels with LPG or exclusively use LPG. This allows a comparison of the impacts of complete and partial transition to modern energy services on outcome variables.
2. *Transition in stove type*: A variable representing stove type used helps estimate whether a transition to improved biomass cookstoves with chimney (ICS) from a traditional biomass cookstove (without chimney) provides a significant benefit in health and time savings.  
I combine 1. and 2. in a single categorical variable - 'Cooking'.
3. *Use of kerosene for lighting*: A transition to or away from kerosene as a primary lighting fuel or as supplemental fuel with electricity.
4. Changes in the *electrification* status of a household between 2005 and 2011  
I combine 3. and 4. in a single categorical variable - 'Electricity'.

Surveyed household characteristics such as daily stove use hours, interview month, and income per capita act as control variables in the regression. Household infrastructure characteristics that might influence the occurrence of cough but are constant for a given household across the years, such as whether a household has a common cooking and living space (a single room) or whether the kitchen area is vented or not, are accounted for in the household-level random effect variable. The state-level random effect variable is expected to capture any geographic variations in ambient air quality and/or public health facilities available to residents. For example, states in the northern Indo-Gangetic Plain of India, due to meteorology and high population densities, generally experience higher levels of ambient air pollution than most other parts of the country.

The mixed effects logistic equation for the occurrence of cough in each individual  $i$  in household  $j$  and year  $t$  is as follows:

$$\begin{aligned} \log \text{odds} (\text{cough})_{ijt} &= \beta_{0j} + \sum_k \beta_{1k} \text{Cooking} * \text{Rural} * \text{Age\_Gender} \\ &+ \sum_k \beta_{3k} \text{Electricity} * \text{Rural} + \beta_4 \text{Quarter} + \beta_5 \text{Hours} + \beta_6 \log(\text{Income}) \\ &+ \beta_4 \text{Passive} + u_{jt} + u_{kt} + e_{ijt} \end{aligned}$$

.....Equation 2.2

where,

$k$  = discrete levels of interaction between explanatory variables

$\beta_{0j}$  = intercept associated with each household  $j$

*Cooking* (0= No solid fuels, 1=Solid fuels with LPG for cooking in traditional cookstoves without chimney, 2= Only solid fuels in traditional cookstoves without chimney, 3= Only solid fuels in improved cookstoves with chimney)

*Electricity* (0 = No electricity used, only kerosene for lighting, 1= Electricity used with/without kerosene lighting)

*Rural* (0=Urban, 1= Rural)

*Age\_Gender* = (>15 years female, >15 years male)

*Quarter* = (1= Dec-Feb (winter); 2= Mar-May (spring/summer); 3= Jun-Aug (monsoon); 4= Sep-Nov (post-monsoon/pre-winter))

*Hours* = daily stove use hours

*Passive* = (0= not exposed to passive smoke due to other household members; 1=exposed to passive smoke)

$u_{jt}$  and  $u_{kt}$  are the variances across households and states respectively, or the random effects with household-level nested within State-level random effects.

In logistic regression, the outcome variable (i.e. probability of cough) is modelled in the form of log odds:

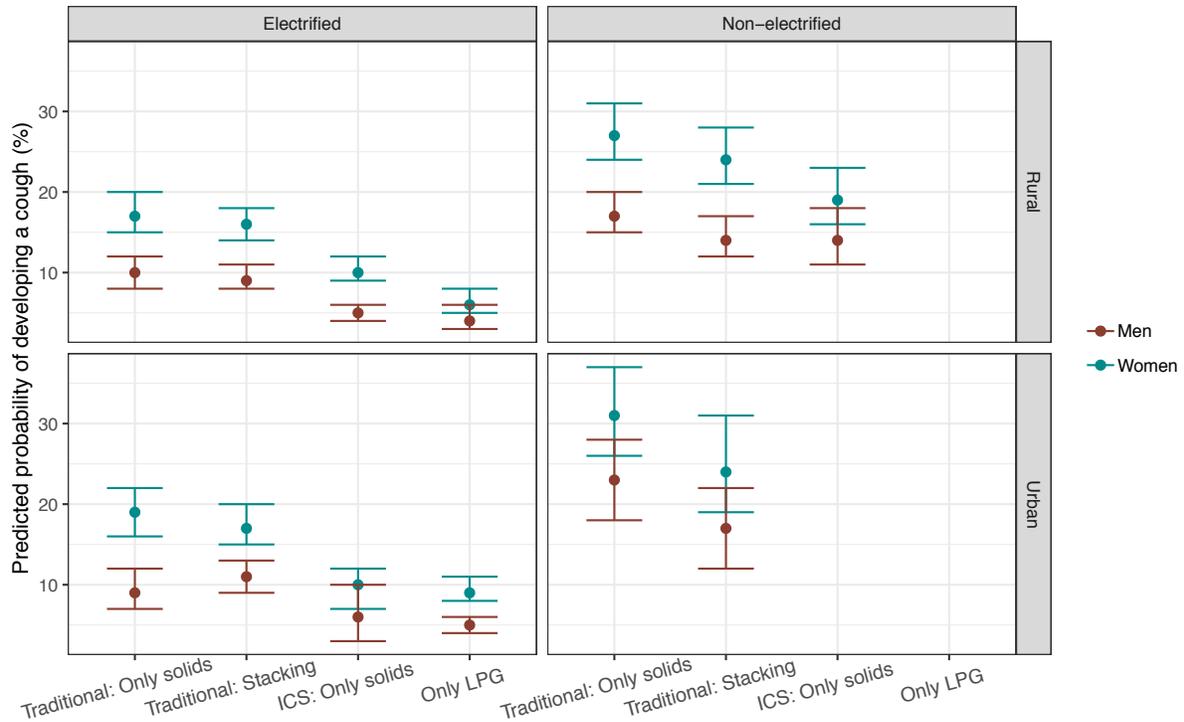
$$\log\left(\frac{p}{1-p}\right) = O_{ijt} \quad \text{.....Equation 2.3}$$

where  $O_{ijt}$  is the predicted response variable at an individual level and  $p$  is the predicted probability of developing cough. Equation (2.3) can be rearranged to calculate the predicted probability of developing a cough from the regression outcome as:

$$p = \frac{e^{-O_{ijt}}}{1 + e^{-O_{ijt}}}$$

In Figure 2.2, I present the mean predicted probabilities of cough and corresponding 95% confidence intervals (CI) for categories of interest in this study. Only individuals not exposed to passive smoke from other members in their household are considered since regression results show that passive smoking is associated with a 14% (95% CI: 9% - 19%) increase in odds of developing a cough. The mean predicted probabilities are calculated considering both the fixed effects of explanatory variables and random variability across households and states, while estimated confidence intervals reflect the uncertainty in fixed effects estimations. There are less than 10 observations in the following groups: only LPG-using non-electrified rural or urban households; and ICS-using non-electrified urban households (see Appendix A Section A.1 for the number of interviewed individuals by group). I exclude these groups in the discussion of impacts of household energy transition.

Post-hoc pairwise comparisons (t-tests) across categories of interest that have overlapping confidence intervals indicate which categories of individuals have a statistically significant difference (at 95% confidence level) in terms of the predicted probability of cough. Results from pairwise comparison and post-estimation diagnostics can be found in the Appendix A Section A.2.



**Figure 2.2** Predicted probabilities of cough in men and women with 95% CI  
 \*'Traditional': traditional cookstove without chimney; 'ICS': Improved cookstove with chimney. Only non-smoking individuals not exposed to passive smoke from other household members are included.

- i) *Cough in women vs. men:* Predicted probabilities of cough in women are 30%-60% higher than men in solid-fuel using households, with the differences between gender categories statistically significant at 95% confidence level across electrified and non-electrified households. Predicted probabilities of cough in LPG-using rural households are similar for men and women. In urban electrified households, male members of solid fuel-using households have similar predicted probability of developing a cough compared to women in LPG-using households, implying the health risk posed by solid fuels specifically to women.
- ii) Complete transition to LPG: A complete transition away from solid fuels is associated with a 45-65% reduction in the probability of developing a cough in non-smoking adult men

and women. The effect can be observed in electrified rural and urban households – in non-electrified households that exclusively use LPG there are less than 5 data points for adult males or females in both rural and urban groups.

- iii) Partial transition from solid fuel use to LPG: There is no positive health impact associated with stacking solid fuels with LPG, compared to using only solid fuels (see Appendix A Section A.2 for significance testing) – predicted probabilities of developing a cough are similar in households that stack fuels and households that use only solid fuels, implying that even using solid fuels as secondary fuel is harmful for women. This indicates that 6% of households who transitioned into partial LPG adoption, along with 2% of households that reversed from using only LPG to stacking it with solid fuels, are likely to experience adverse health impacts in spite of using LPG. Although not statistically significant, mean predicted probabilities of cough are lower for the ‘stacking’ group compared to ‘only solid fuels’ in non-electrified rural and urban households. However, there are fewer than 30 observations in non-electrified ‘stacking’ groups.
- iv) Switch from traditional stove to improved cookstove with chimney (ICS): Overall, adoption rates of improved cookstoves with chimneys are low - about 4.5% of rural households and 1.2% of urban households transitioned from traditional to improved cookstoves between 2005 and 2011, while 1.4% of rural households transitioned back from ICS to traditional cookstoves. In rural and electrified urban households, switching the primary stove type from traditional without chimney to improved cookstove with chimney reduces the probability of cough in women by about 30-40%. A similar effect is seen in men in rural India but only in electrified households.

v) Switch from kerosene for lighting to electricity: Electrification reduces the probability of developing cough by about 35-50% in both men and women in rural and urban households, either through a complete or partial transition away from kerosene for lighting. The recorded quantity of kerosene used for lighting is not a statistically significant factor and use of kerosene for supplemental lighting is not associated with an increased probability of cough.

## 2.4.2 Time savings

### 2.4.2.1 Time spent cooking

I use the hours of daily stove use as an indicator of time spent cooking by women. Daily stove hours recorded in the dataset include total stove use time, which includes boiling water, making tea, and other minor uses. The average daily stove use hours in urban and rural households is roughly 3 hours and 3.2 hours respectively. The explanatory variables of interest include cooking energy transition within a household and transition in stove type as described above. The number of meals cooked daily, interview month and household size are control variables in the regression.

For each household  $j$  in time  $t$ , daily stove use is modelled using a linear mixed effects regression as follows:

$$Hours_{jt} = \beta_0 + \sum_k \beta_{1k} Cooking * Rural + \beta_4 Meals + \beta_5 Hhsize + \beta_6 Quarter + u_{jt} + e_{jt}$$

.....Equation 2.4

$k$  = discrete levels of interaction between explanatory variables

$\beta_{0j}$  = intercept associated with each household  $j$

*Cooking* = (0= No solid fuels, 1=Solid fuels with LPG for cooking in traditional cookstoves without chimney, 2= Only solid fuels in traditional cookstoves without chimney, 3= Only solid fuels in improved cookstoves with chimney)

*Rural* = (0=Urban, 1= Rural)

*Quarter* = (1= Dec-Feb (winter); 2= Mar-May (spring/summer); 3= Jun-Aug (monsoon); 4= Sep-Nov (post-monsoon/pre-winter))

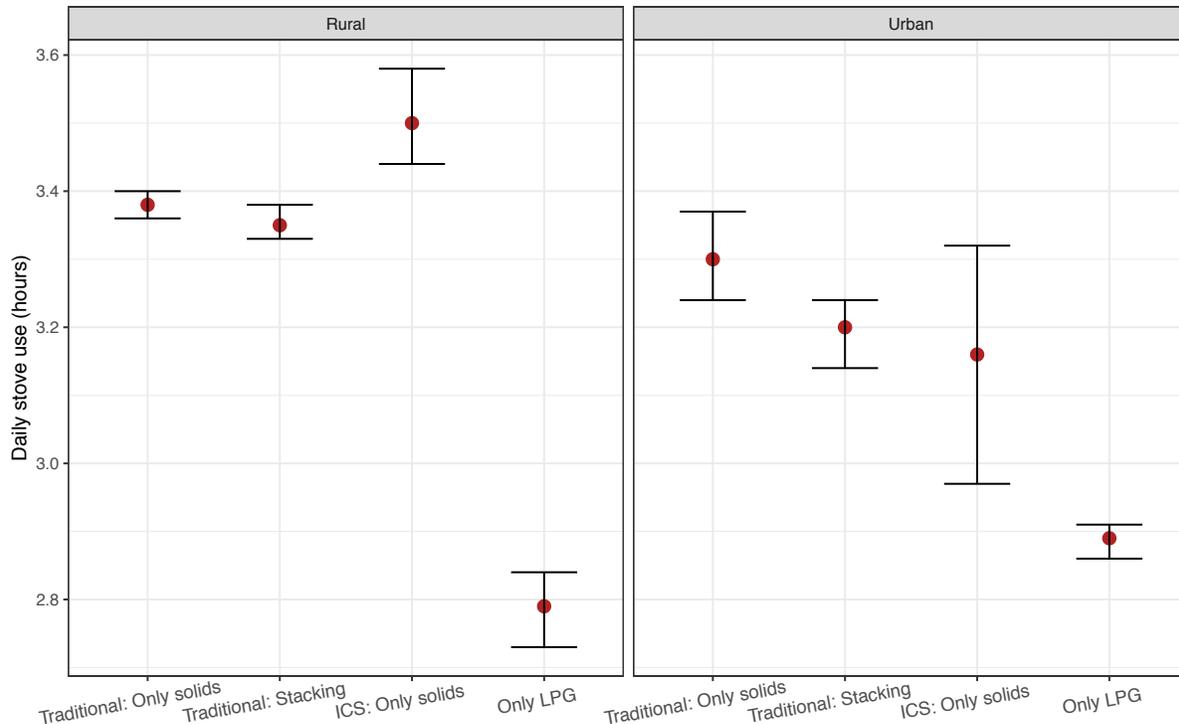
*Hhsize* = number of household members

*Meals* = number of meals cooked per day

*Hours* = daily stove use hours

$u_{jt}$  is the variance across households or the random effects included.

As in Section 2.4.1, I present the predicted daily stove use hours (estimated as the outcome of the regression equation) and the 95% confidence intervals reflecting the uncertainty in fixed effects in Figure 2.3. Post-hoc pairwise comparisons (t-tests) are conducted across categories of interest that have overlapping confidence intervals to test for statistical significance (at 95% confidence level) in differences in stove use time. Results of statistical tests are included in Appendix A Section A.3.



**Figure 2.3** Predicted daily stove use in households and 95% confidence interval  
 \*'Traditional' = traditional cookstove without chimney; 'ICS' = Improved cookstove with chimney (ICS used by less than 5% of urban households interviewed in both years)

Partial transition to LPG is associated with only a small reduction in stove use time (about 5 minutes in rural households only), whereas a complete transition to LPG from solid fuels reduces stove time by 18% (about 37 minutes) and 12% (about 24 minutes) in rural and urban households respectively. Use of improved cookstoves is not associated with any change in stove use time compared to traditional cookstove in urban households, while in rural households it leads to an increase in daily stove use time by about 6 minutes.

### 2.4.2.2 Time spent collecting fuel

Most urban households that use firewood purchase it from markets - the IHDS dataset shows that in 2011 only about 4% of urban households collected it from their own land and another 5% from locations apart from their own land. On the other hand, about 75% of rural households collect firewood, with about 36% traveling to collect it. In rural households that collect solid fuels in both years, women spend almost twice as much time as men, and on average 37 minutes daily, collecting fuel, while the average time spent by children in interviewed households is only 3-7 minutes per day. Figure 2.4 shows the proportion of interviewed households in 2011 by their source of firewood – whether firewood is purchased and/or collected from the household’s own land or collected from other places.

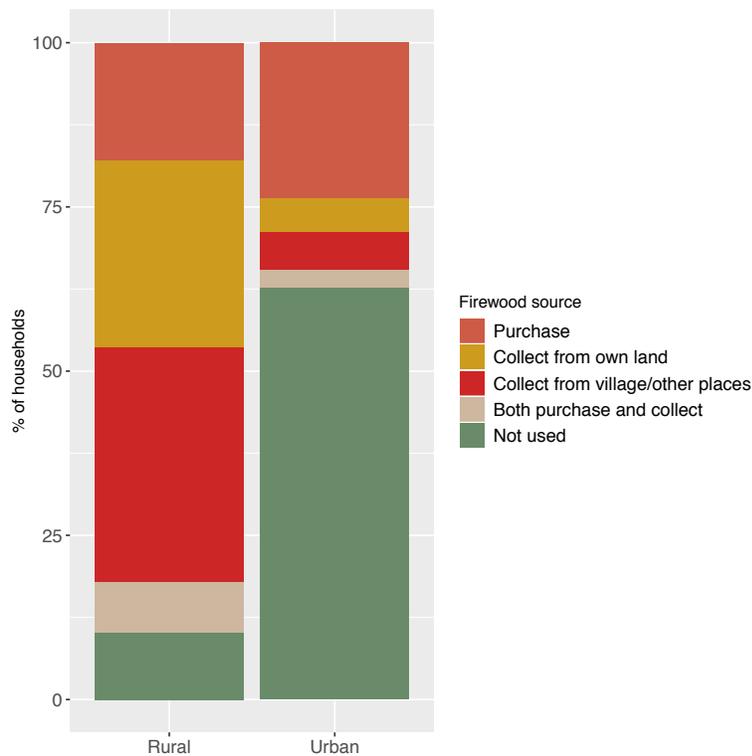


Figure 2.4 Source of firewood in rural and urban households in 2011.

Spending time to collect firewood is specifically a rural challenge and I focus my analysis on rural households. The explanatory variables of interest are, as described above, cooking energy transition within a household and transition in stove type. The mode of firewood collection (whether collected from the household's own land or from other places or both purchased and collected), hours of stove use daily, income per capita and household size are control variables in the regression. I consider variability due to household-level characteristics as well as district level as random effects to account for local geographical variation in firewood availability.

For each rural household  $j$  in time  $t$ , fuel collection time is modelled using log-linear mixed effects regression as follows:

$$\log(\text{Collection})_{jt} = \beta_{0j} + \sum_k \beta_{1k} \text{Cooking} * \text{Age\_Gender} \\ + \beta_3 \text{Source} + \beta_4 \text{Hours} + \beta_5 \text{Hhsize} + \beta_6 \log\left(\frac{\text{Income}}{\text{capita}}\right) + u_{jt} + u_{dt} + e_{jt}$$

.....Equation 2.5

$k$  and  $l$  = discrete levels of interaction between explanatory variables

$\beta_{0j}$  = intercept associated with each household  $j$

$\text{Cooking}$  = (1=Solid fuels with LPG for cooking in traditional cookstoves without chimney, 2= Only solid fuels in traditional cookstoves without chimney, 3= Only solid fuels in improved cookstoves with chimney)

$\text{Age\_Gender}$  = (>15 female, >15 male)

$\text{Rural}$  = (0=Urban, 1= Rural)

*Quarter* = (1= Dec-Feb (winter); 2= Mar-May (spring/summer); 3= Jun-Aug (monsoon); 4= Sep-Nov (post-monsoon/pre-winter))

*Source* = (Collect from own land, Collect from other places, Both purchase and collect)

*Hhsize* = number of household members

*Hours* = daily stove use hours

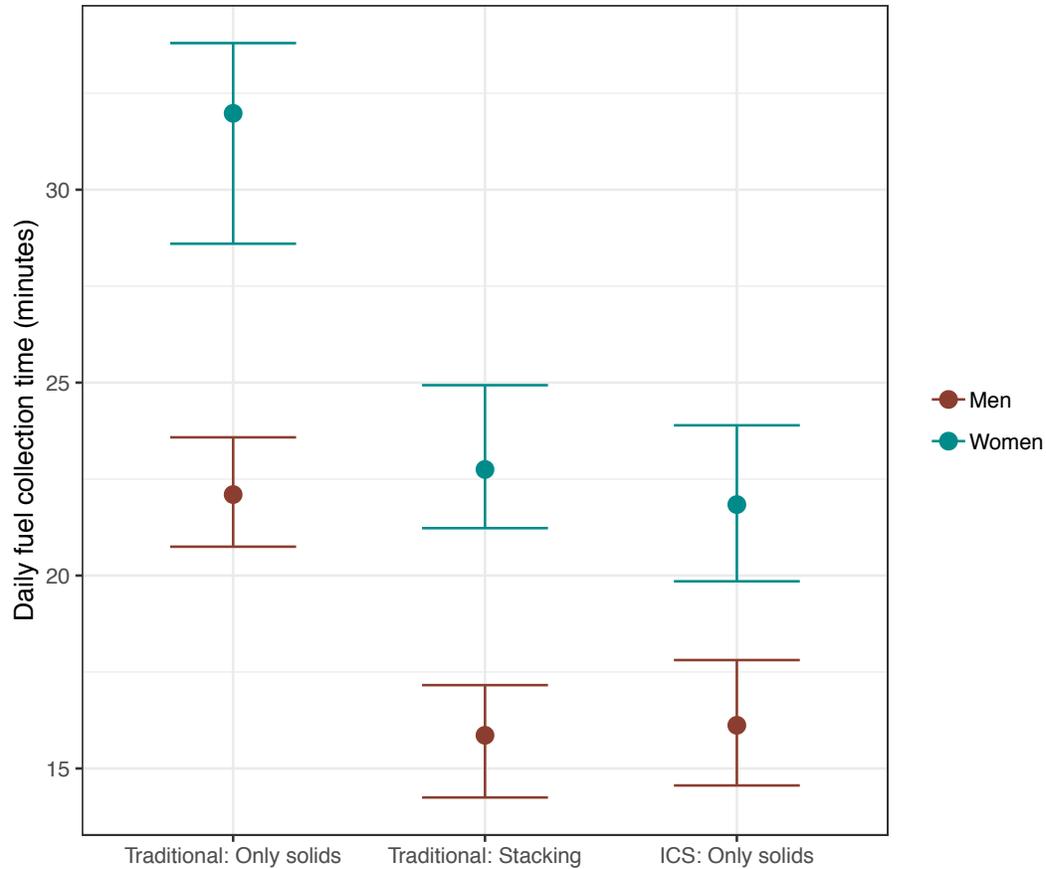
$u_{jt}$  and  $u_{dt}$  are the variances across households and districts respectively or the random effects with household-level nested within district-level random effects.

In log-linear regression, the response variable is modelled in logarithmic form.

$$\mathbf{\log(collection\ time)} = \mathbf{O_{ijt}}$$

.....Equation 2.6

I exponentiate the outcome of the regression model and multiply with Duan's smearing factor (D) (Duan 1983) to get predicted fuel collection time ( $collection\ time = e^{O_{ijt}} * D$ ) and present the predicted mean daily fuel collection time in minutes for household groups of interest, with the 95% confidence intervals reflecting the uncertainty in fixed effects estimates in Figure 2.5 (See Appendix Section A.4 for intra-class correlation values and smearing factor calculation).



**Figure 2.5** Predicted daily fuel collection time (minutes) for men and women in rural households  
 \*'Traditional' = traditional cookstove without chimney; 'ICS' = Improved cookstove with chimney

Full transition to LPG from a traditional cookstove saves, on a daily basis, 32 minutes of fuel collection time for women and 22 minutes of fuel collection time for men. A partial transition to LPG or a transition from traditional to improved cookstoves saves about 6-9 minutes daily in fuel collection time for adult men and women in rural households.

## 2.5 Results and Discussion

A household's decision to rely solely or partially on modern energy services is expected to affect women's health and time disproportionately since women are responsible for most cooking and fuel collection activities. The 2011 IHDS dataset shows that more than 98% of cooks in both urban and rural households are women. This work indicates that the greatest benefits to health are made possible from a full conversion to LPG for cooking in rural India, which can reduce the likelihood of developing a cough by almost 65% in women. Similarly, electrification has significant positive impact on respiratory health – it can reduce the probability of developing a cough by up to 50% in households. However, this finding is predicated on the assumption that electrified households primarily rely on electricity for lighting, with little or no kerosene use for lighting. One limitation of this analysis is that the trade-offs between the adopting LPG and additional household income required to afford clean fuel are not discussed – while LPG may bring health and developmental benefits, it is more expensive compared to firewood, which is often collected for free. This implies that there may need to be trade-offs with other expenditures in the household budget or extra work hours.

The exposure–response relationship curve between PM<sub>2.5</sub> exposure and cardiovascular disease mortality risk is steep at levels of exposure corresponding to 0-20 mg PM<sub>2.5</sub> inhaled daily and flattens out at higher levels of exposure (C. A. Pope et al. 2009). Grieshop et al. (2011) estimate the intake from LPG stoves at less than 1mg/day, while that from traditional cookstoves is almost two orders of magnitude higher. Exposure to PM<sub>2.5</sub> when solid fuels are used along with LPG is thus sufficient to cause adverse health impacts. My findings are consistent with this – partial

adoption of LPG (i.e. stacking solid fuels with LPG) does not reduce the probability of developing a cough.

This study also finds a reduction in the occurrence of cough as a result of transition to ICS, and contributes to an emerging picture of the effect of ICS on human health. Modelling studies (Grieshop et al. 2011) show that relative to traditional stoves, ICS can reduce exposures by 75% and 94%, with and without chimneys respectively. A number of recent field trials (for e.g. (Aung et al. 2016; Dutta et al. 2007; Sambandam et al. 2015)) also show reductions in PM<sub>2.5</sub> exposure, although usage of ICS tends to drop over time (Pillarisetti et al. 2014), so the benefits might be short-lived (Hanna et al. 2012). For this study, there are two points to consider: first, the IHDS dataset only includes ICS with chimneys, which result in considerably lower PM<sub>2.5</sub> emissions than ICS without chimneys and thus might provide greater respiratory health benefits; two, the dataset does not provide information on which year ICS were adopted in households, and I might be observing the short-term health benefits ICS may provide.

This work shows that LPG for cooking is associated with significantly less cooking time (by 37 minutes) compared to using solid fuels in traditional cookstoves. When this is combined with the average reduction in time for collecting fuels (32 minutes), rural women stand to gain roughly an hour every day from a complete transition. A partial transition to LPG offers far lower time saving benefits in cooking, and a ~30% reduction (~15 minutes) in a household's firewood collection time. The potential time saving benefits of improved cookstoves are not evident in terms of reducing actual cooking time – in fact, rural households spend 6 extra minutes on switching from traditional stoves to ICS. ICS reduces household fuel collection time by about 30% (~15 minutes),

implying lesser use of firewood. In laboratory settings and under proper usage conditions, ICS are known to reduce fuel requirements but evidence from actual usage conditions is disputed - in rural India and Ghana, there is no evidence that ICS reduce firewood requirements (Hanna et al. 2012; Burwen & Levine 2012; Aung et al. 2016), while in Senegal, ICS are associated with a 15-30% reduction in firewood usage per meal compared to traditional stoves, but no statistically significant reduction in fuel collection time (Bensch & Peters 2012).

Continued use of firewood either through stacking with LPG or in cleaner improved cookstoves might offer incremental benefits through reduced fuel collection time, or lower exposure to particular matter when households switch to ICS; however, a complete transition to LPG and electricity offers significantly greater benefits to women in terms of improving respiratory health and reducing time spent on cooking activities.

## **Chapter 3: Quantifying the Equity, Indoor Air Quality and Climate**

### **Implications of India's Household Energy Transition**

#### **3.1 Introduction**

Rapid economic growth, urbanization and changes in lifestyles have led to a transition in the Indian household energy sector - away from traditional solid fuels like firewood, dung and coal, and towards modern energy services like liquefied petroleum gas (LPG) and electricity. Residential electricity and LPG consumption in India grew at 10% and 9% respectively in 2015-2016, with annual increase in consumption higher than previous years (CSO 2017). The household sector accounts for a substantial part of national final energy consumption - 88% of LPG and 24% of final electricity consumption can be attributed to the residential sector (CSO 2017). However, India still houses 300 million people who do not have access to electricity and about 800 million people who rely on solid fuels for cooking (Government of India 2015), the majority of these energy-deprived households being low-income and/or residing in rural areas (Ailawadi & Bhattacharyya 2006; S. Pachauri & Jiang 2008; S. Pachauri 2014). Access to clean energy plays a key role in poverty eradication, improving the general quality of life and improved health. And yet, both LPG and electricity are fossil fuel-based and have implications for rising greenhouse gas (GHG) emissions in India.

LPG and electricity are 'cleaner' household fuels - burning solid fuels is inefficient and polluting and is widely known to adversely affect indoor air quality and health. Incomplete combustion of biomass and kerosene in lamps releases fine particulate matter. PM<sub>2.5</sub> – particles less than 2.5

microns in diameter - are especially harmful to respiratory and cardiovascular health (Po et al. 2011; Lam, Smith, et al. 2012; Bruce et al. 2000; Gordon et al. 2014). The negative impacts of solid fuels are particularly significant for women and children who spend more time collecting fuelwood as well as indoors (Smith et al. 2014; Ezzati & Kammen 2001). PM<sub>2.5</sub> also includes pollutants like black carbon which has significantly higher global warming potential than CO<sub>2</sub> (Lam, Chen, et al. 2012; Venkataraman et al. 2016; Bond 2004). Analyses of different cookstove technologies have shown that kerosene and LPG stoves may have both health and climate benefits – they lead to lower particulate matter exposure and help avoid products of incomplete combustion (PICs) which are global warming pollutants (Grieshop et al. 2011). Modern energy services provide a number of other developmental benefits such as reliable lighting for evening study hours and savings in women’s time spent collecting solid fuels (Cabraal et al. 2005; Asian Development Bank 2010; Khandker et al. 2013; ESMAP 2002; ESMAP 2004). On the other hand, in India modern energy services like LPG and electricity are fossil-fuel centric - coal contributes towards about 75% of electricity generation (Ebinger 2016). As the share of such energy services surpasses traditional biomass use, the fuel transition will also contribute towards household CO<sub>2</sub> emissions (van Ruijven et al. 2011; Cameron et al. 2016).

The Government of India has emphasized on prioritizing improved and accelerated access to LPG and electricity (Government of India 2015). Government schemes like the Pradhan Mantri Ujjwala Yojana (PMUY) and Power for All aim to provide accelerated access to LPG and universal

electrification, respectively, by 2019 through subsidized connections<sup>9</sup> to poor households. India's Intended Nationally Determined Contributions (INDC) for the period 2021-2030, as outlined in response to the Paris Agreement under the United Nations Framework Convention on Climate Change (2016), emphasizes on the need for inclusive economic development, concurrent with a 'low carbon path to progress' (Government of India 2015). This paper uses a co-benefits approach – analyzing indoor air quality and GHG emission impacts of household energy transition pathways for 2030 and assessing whether future energy transition pathways in India can improve indoor air quality while helping realize climate goals at a household level.

Here I analyze India's household energy transition in a retrospective, as well as a prospective manner. I use household-level data from a nation-wide consumer expenditure survey (National Sample Survey) for the years 1987-88 and 2009-2010 to represent the transition in types and quantities of household fuel across urban-rural populations and income groups. I calculate shifts in GHG emissions, including CO<sub>2</sub> and other short-lived climate pollutants such as black carbon (BC) and non-methane volatile organic compounds (NMVOC), as well as in emission and intake of PM<sub>2.5</sub> by households across income classes.

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<sup>9</sup> An LPG connection refers to providing the initial cost of a cylinder, set-up equipment such as regulator and connecting pipe, and administrative fees (\$70). Under the PMUY scheme households are expected to purchase LPG at government subsidized rates.

I use the retrospective data to prospectively model five near-term fuel transition scenarios (to 2030) based on varying levels of adoption of clean fuels and technologies such as LPG, electricity and improved cookstoves, and particularly focusing on rural energy transition. In addition to household consumption scenarios, changes in the fuel mix of India's electricity supply as well as the efficiency of India's electricity grid are incorporated to evaluate the climate and indoor air quality outcomes of India's household fuel transition pathways. I estimate indoor air quality benefits and greenhouse emission co-benefits for these pathways, accounting for different household energy consumption scenarios, power grid efficiency and renewables' share in power generation. The results allow an examination of the role that new technologies and government policy can play in maximizing co-benefits for climate and health across income classes. The remainder of the paper is structured as follows. Section 3.2 provides a brief overview of household energy consumption in India, with a focus on emissions of GHGs and indoor air pollution. Section 3.3 presents a retrospective assessment of the effect of India's household energy transition from 1987-2009 on GHG emissions and exposure to indoor air pollution. In section 3.4, I model five near-term (2030) household energy transition scenarios to examine the possible role of government policies on equitable access to energy, GHG emissions, air pollution exposure. I conclude in section 3.5 with my findings.

### **3.2 India's household energy transition**

Studies on household fuel consumption patterns in India have approached the topic on different scales - at macro or national level as well as micro or household level. While a macro-level analysis, allows the study of both direct and indirect household energy use (S. Pachauri & Spreng 2002; Das & Paul 2014), household-level data, such as from the National Sample Survey (NSS)

in India, captures the heterogeneity amongst household groups. It enables us to make distinctions in consumption patterns between urban and rural households, as well as among household groups by: income, geographical location and other characteristics like household size. Clean fuel adoption has been more rapid in India's urban areas; however within urban and rural populations there are vast differences in income and lifestyles and consequent differences in energy consumption patterns, with LPG and electricity use being more widespread in higher income households (Gangopadhyay et al. 2005; S. Pachauri & Jiang 2008; Reddy 2003; Viswanathan & Kavi Kumar 2005). A number of studies find that increasing per capita expenditure is the biggest driver of rising household energy requirements (S. Pachauri & Spreng 2002; Lenzen et al. 2006) as well as clean cooking fuel choice (Reddy 1995; M. N. Rao & Reddy 2007; Farsi et al. 2007). Despite a general transition to modern energy services over the last few decades, households often practise 'fuel stacking', i.e., instead of giving up traditional fuels, they use a combination of traditional and modern fuels, primarily due to unaffordable and/or unreliable supply, or even cultural preferences (Masera et al. 2000; Kowsari & Zerriffi 2011). More than 60% of rural households and about 40% of urban households used both kerosene and electricity in 2009-2010, while about 15% of rural households and 10% of urban households used both LPG and biomass (Cheng & Urpelainen 2014). In fact, LPG and biomass stacking grew in Indian households between 1987 and 2009 (Cheng & Urpelainen 2014), implying that households are adopting modern energy services, but often only partially.

Modern energy services provide a number of direct and indirect developmental benefits – direct benefits include reduction in firewood collection time due to a transition to LPG and longer hours of productive work in the evening due to electrification, while a significant indirect benefit is

improvement in indoor air quality as households move away from biomass burning and kerosene lamps (Cabraal et al. 2005; Asian Development Bank 2010; Khandker et al. 2012; Barnes et al. 2012). Both kerosene lamps and biomass burning contribute significantly to high indoor PM<sub>2.5</sub> exposure - personal exposure in wood-using Indian households is estimated to be two orders of magnitude higher than in those that use LPG (Balakrishnan et al. 2002; Grieshop et al. 2011). Balakrishnan et al. (2002) estimate 24-hour mean exposures for women and men in wood-using households in rural India to be 232 $\mu\text{g}/\text{m}^3$  and 172 $\mu\text{g}/\text{m}^3$  respectively, which is well above the WHO interim target guideline (ITG-I) of 75 $\mu\text{g}/\text{m}^3$  for 24-hour PM<sub>2.5</sub> concentrations (WHO 2006). This is consistent with average national 24-h exposure estimates by Smith et al. (2014) of 337 $\mu\text{g}/\text{m}^3$  for women, 285 $\mu\text{g}/\text{m}^3$  for children and 204 $\mu\text{g}/\text{m}^3$  for men. Kerosene wick lamps are known to result in indoor PM<sub>2.5</sub> concentrations that exceed the WHO guidelines by an order of magnitude as well (Apple et al. 2010; Lam, Chen, et al. 2012; Muyanja et al. 2017). High exposure to PM<sub>2.5</sub> has a number of adverse cardiovascular and pulmonary impacts – it is associated with chronic obstructive pulmonary disorder, acute respiratory tract infections and chronic cough (Naeher et al. 2010; Bruce et al. 2002; Smith et al. 2005; Liu et al. 2007; Dennis et al. 2016; Johnson et al. 2011; Ellegard 1996; Mbatchou Ngahane et al. 2015), with higher risks for women than men (Ezzati & Kammen 2001; Smith et al. 2014).

Studies on household-level fuel transition and corresponding climate impacts focus primarily on CO<sub>2</sub> emissions (Ahmad et al. 2015; S. Pachauri 2014; van Ruijven et al. 2011). Pachauri et al. (2014) conclude that growth in access to electricity in India between 1983 and 2009 is responsible for 39-53% of the rise in household CO<sub>2</sub> emissions from electricity use, but only 3-4% of the rise in national CO<sub>2</sub> emissions in this period. van Ruijven et al. (2011) developed a model that shows

that a more equitable income distribution and higher electrification rates in India may have developmental and air quality advantages, but would lead to higher electricity consumption and consequently, CO<sub>2</sub> emissions. Cameron et al. (2016) model LPG adoption and the cost of access for different carbon tax scenarios, concluding that trade-offs between access to modern fuel and CO<sub>2</sub> mitigation can be large, particularly for the urban poor and rural rich who are more vulnerable to price changes. However, transition to clean cooking fuel and electricity may also provide climate benefits since short-lived climate forcers (like black carbon) add to GHG emissions.

A few previous studies account for non-CO<sub>2</sub> global warming pollutants, but they are either a technology-specific analysis of climate and air quality synergies (Grieshop et al. 2011) or fuel-specific analysis of the climate impacts of household energy transition (Singh et al. 2017). There are three key differences between previous work and this study. First, I conduct a nation-wide empirical assessment of household energy transition, integrating the net climate impact of GHGs (accounting for both Kyoto and non-Kyoto warming agents) and indoor air quality. Second, I analyze GHGs and indoor air quality consequences of the household energy transition across the income spectrum. Third, I use historical data to project future scenarios of household energy transition and analyze potential air quality and climate cross-impacts.

### **3.3 Equity, Indoor air quality and Climate impacts of India's household fuel transition (1987-2009)**

#### **3.3.1 Household energy transition across income classes**

The National Sample Survey (NSS) provides India-wide socio-economic data at a household level. Data is collected through interviews on a range of expenditure items including fuel, along with household characteristics like household size, monthly expenditure on each item, etc. I use data from the 43<sup>rd</sup> (July 1987- June 1988) and 66<sup>th</sup> (July 2009- June 2010) rounds<sup>10</sup>, to examine the household energy transition over a span of 22 years. The NSS dataset also records quantities of fuel used per household by fuel type and so can be used for calculating GHG and PM2.5 emissions from direct fuel use in the household.

Urban and rural households were divided into 10 income groups corresponding to per capita expenditure deciles in the urban and rural populations, where expenditure is used as a proxy variable for income (Figures B.1 and B.2 in Appendix B Section B.1 show details of fuel transition across income groups). The NSS data shows that while urban India experienced an almost complete transition to electrification by 2009, low-income and middle-income rural households

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<sup>10</sup> The number of urban and rural households in the 43<sup>rd</sup> survey sample is more than 45,000 and 82,600 respectively, which represent about 33.5 million urban and 109.5 million rural households. The 66<sup>th</sup> round covers more than 41,000 urban and 59,000 rural households, which represents about 68.1 million urban and 162.5 million rural households. Household weights provided in each dataset are used to represent all Indian households.

formed the majority of those without access to electricity (about 25% of all Indian households). 53% of rural households in the bottom 30% and 35% in the middle 30% used kerosene as their primary lighting fuel. Firewood dominated as the primary choice for cooking fuel in rural households in 1987 (80%) as well as 2009 (76%) while 65% of urban India, primarily middle and high-income households, adopted LPG by 2009 (up from 22% in 1987). Strikingly, the adoption of LPG in the highest income class in rural areas (43% of the income group) is roughly equal to that of the second lowest urban income class (37%), even though the rural group's mean consumption levels are 3 times greater, indicating a very strong urban bias in the supply and use of LPG.

Average per capita useful energy consumption by fuel type and by income decile was calculated using fuel energy density and assumed stove efficiency values from the literature (Fig B.4 in Appendix B). Energy consumption in middle and high-income urban households was dominated by electricity use, while cooking energy requirement saturated in 2009 in these households at a monthly value of about 84MJ per capita<sup>11</sup>. In 2009, individuals in the top 10% of urban households used almost five times as much useful modern energy (LPG and electricity) as those in the the bottom 10%, while individuals in the top 10% of rural households used 37 times as much as the bottom 10% in rural areas. The data also show that inequity in modern energy access is greater than inequity in income, particularly in rural India. The calculated Gini coefficient for per capita

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<sup>11</sup> Details on dividing reported kerosene consumption into cooking and lighting uses are provided in Appendix B Section B.2.

modern energy use is 0.53 and 0.69 in urban and rural households respectively, which is considerably higher than the corresponding values of Gini coefficient for income per capita which are 0.41 and 0.31. Urban consumers use more electricity than rural counterparts in all income deciles, but the gap rises dramatically at the highest income levels. In addition to the presence of a general transition in primary cooking fuel used among urban and high-income rural households, many households use multiple fuels simultaneously (*aka* fuel stacking) (see Figure B.3 in Appendix B for fuel stacking by income group). Among households that adopted LPG for cooking by 2009, the share of LPG in useful cooking energy ranged from 87-99% in urban households and 32-78% in rural households, with LPG's share rising with income and firewood and kerosene as supplemental cooking fuels. Kerosene use as a primary cooking fuel has declined over the years – the Government of India discourages the use of kerosene as a cooking fuel by restricting the quantities of subsidized kerosene available, since a substantial portion is sold through the black market for adulteration of other fuels (Gangopadhyay et al. 2005; Clarke 2014).

### **3.3.2 Greenhouse gas emissions**

Fuel consumption data allow GHG emission calculations at the household level, including gases covered under the Kyoto protocol- CO<sub>2</sub>, CH<sub>4</sub>, and N<sub>2</sub>O - as well as 'non-Kyoto' emissions – CO, BC, NMVOC, OC and SO<sub>2</sub> (see Appendix B Section B.2 for emission factors for fuels and 100-year global warming potentials (GWP) used). Although there is a level of uncertainty associated with non-Kyoto emissions, uncertainty analyses show that the global warming impact of particles such as BC is significantly higher than CO<sub>2</sub> (Bond 2007). GHG emission profiles assume average power grid transmission and distribution losses (excluding theft) to be 25% (Buckley 2015) and biomass sustainability to be 70% (Singh et al. 2017; van Ruijven et al. 2011).

Total Kyoto and non-Kyoto emissions in rural and urban households in each year are calculated as follows:

1. For cooking fuel and kerosene use in lamps:

$$Emissions = \sum_{hfp} Fuel\ consumption\ (MJ)_{hf} \times Emission\ factor\ \left(\frac{g}{MJ}\right)_{fp} \times GWP_p$$

.....Equation 3.1

where h is each household, f is a fuel-technology combination and p is a pollutant. Emission factor gives the emissions of a pollutant p per unit consumption of fuel f. For the purpose of this analysis, emission factor of CO<sub>2</sub> from biomass is assumed to be 30% of its value from literature, to account for 70% renewability. Cooking fuel emission factors are collated from (Grieshop et al. 2011; Pandey et al. 2014; Smith et al. 2000) and the GAINS database ([http://gains.iiasa.ac.at/models/gains\\_models3.html](http://gains.iiasa.ac.at/models/gains_models3.html)) for South Asia.

2. For electricity:

$$Emissions = \sum_{hfp} \left( \frac{Electricity\ use\ (kWh)_h}{\eta} \right) \times Power\ share_f \times Emission\ factor\ \left(\frac{g}{kWh}\right)_{fp} \times GWP_p$$

.....Equation 3.2

where h is each household,  $\eta$  is the power grid efficiency, f is the power plant type by fuel, and p is the pollutant. Power share<sub>f</sub> is the generation share of power plant type f in 1987 and 2009 obtained from (CEA 2011). All emission factors are collated from (CEA 2011; Sadavarte & Venkataraman 2014) and GAINS database for South Asia.

Calculated nation-wide Kyoto emissions from household fuel use in 2009 were 368 Mt CO<sub>2</sub>eq, which is about 21% of estimated nation-wide Kyoto emissions from all sectors in 2007 (MOEF 2010). Of this, household electricity consumption in 2009 accounted for 146 Mt CO<sub>2</sub>eq (or about 10% of total emissions in 2007 *ibid*. This estimate is consistent with Pachauri et al.'s (2014) estimate of 159 Mt CO<sub>2</sub> from household electricity use or 10% of total emissions in 2011. Including non-Kyoto emissions increases total household carbon equivalent emissions in 2009 by about 60%. Firewood accounted for about 50% of total household emissions (Kyoto and non-Kyoto) while kerosene lighting and electricity each accounted for about 20%. Secondary kerosene use for supplemental lighting contributed an additional 9% to total household emissions. Non-Kyoto emissions are key to this accounting and contribute 95% of emissions from kerosene lighting and 55% of firewood emissions. Total (Kyoto and non-Kyoto) household GHG emissions in rural India (79% in 2009) are higher than in urban India (21% in 2009), with firewood contributing the majority of emissions, both in 1987 and 2009 (see Table 3.1). This is true even if firewood is considered 100% renewable.

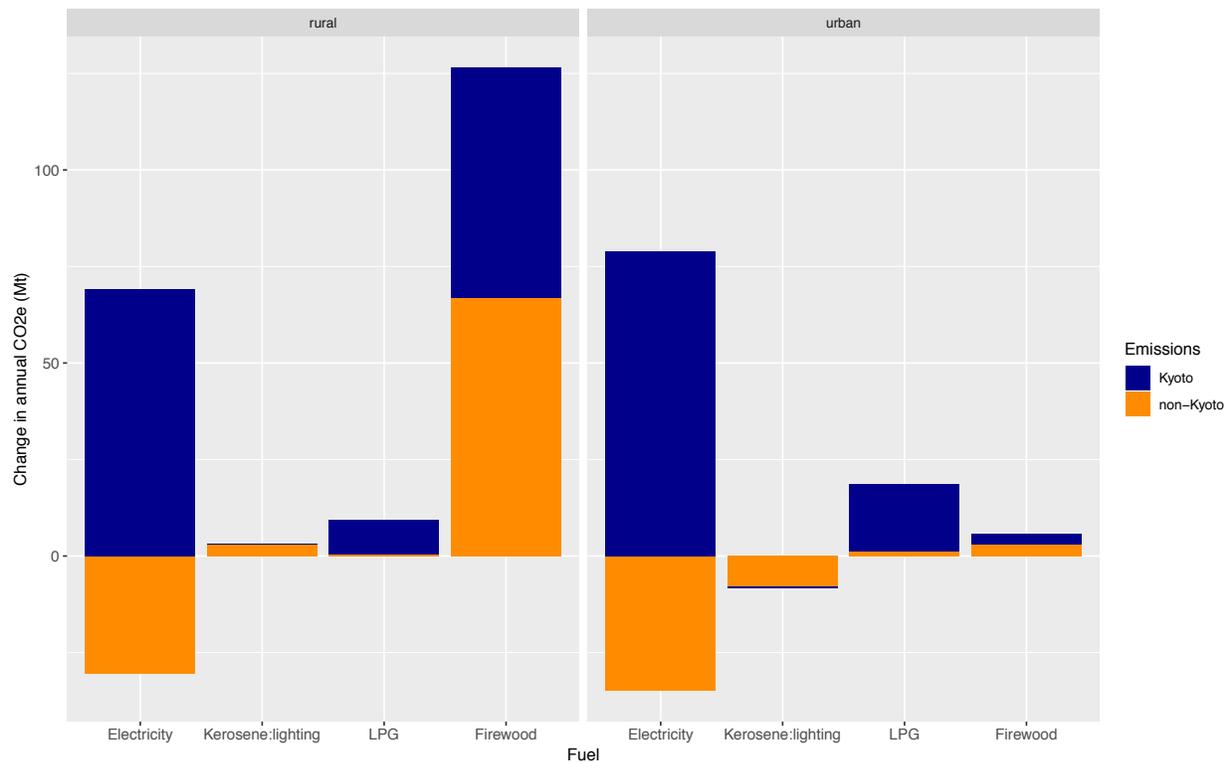
	% of total household emissions		Share of Kyoto/non-Kyoto emissions from each fuel	
	Rural	Urban	Kyoto	non-Kyoto
Firewood	43%	4%	45%	55%
Kerosene lighting (primary and supplemental)	25%	4%	5%	95%
LPG	1%	3%	94%	6%

	% of total household emissions		Share of Kyoto/non-Kyoto emissions from each fuel	
	Rural	Urban	Kyoto	non-Kyoto
Electricity	8%	10%	178%	-78%
Total	77%*	21%		

**Table 3.1** Household cooking and lighting fuels: Contribution to household GHG emissions in 2009

*\*(coke, coal and charcoal contributed an additional 2% to rural GHG emissions)*

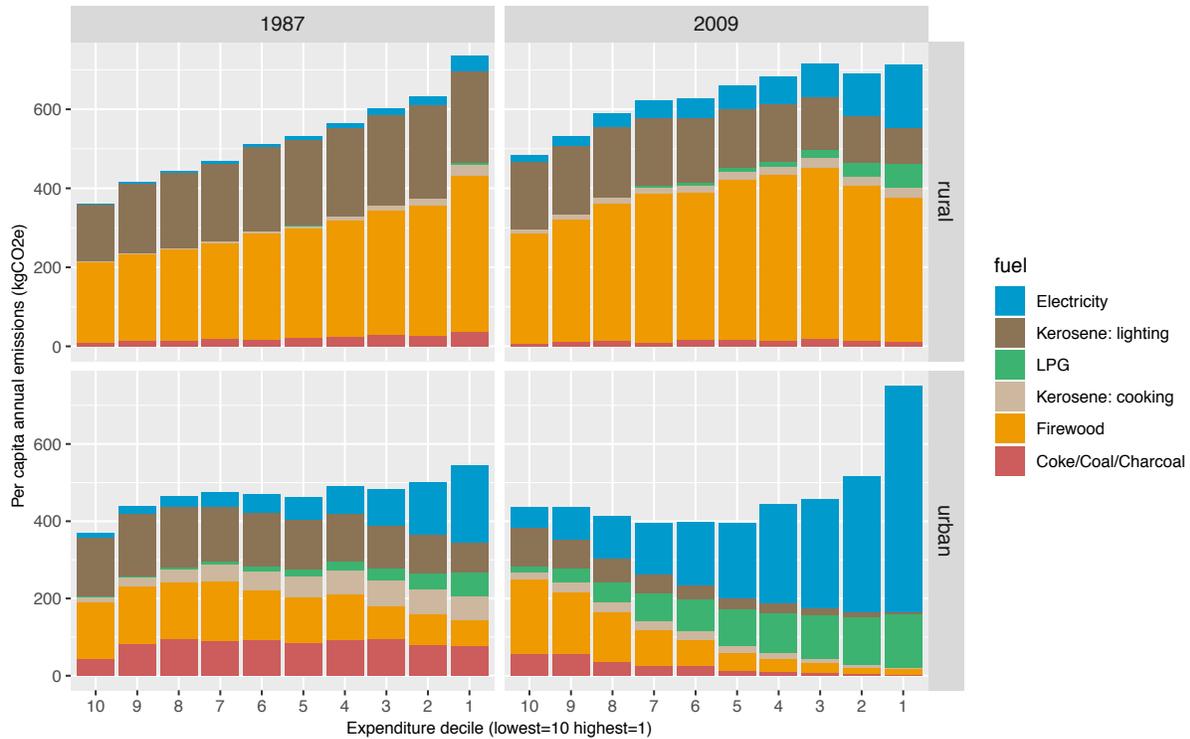
Between 1987 and 2009, total household GHG emissions rose by 48% (Figure 3.1). Increase in non-Kyoto emissions from rural firewood use from 1987 and 2009 is almost equivalent to increase in Kyoto emissions, implying that accounting for only Kyoto emissions is significant underestimate of the impact of firewood usage on climate. In urban households, electricity consumption is the most significant contributor to rising GHG emissions. The negative bar for non-Kyoto emissions from electricity use in both years is driven by the SO<sub>2</sub> emissions from thermal power plants, implying adverse air quality impacts, in spite of providing climate advantages.



**Figure 3.1** Change in total annual household Kyoto and non-Kyoto emissions (1987-2009)

Figure 3.2 shows the change in per capita GHG emission profiles across income groups between 1987 and 2009. In urban households, emissions from kerosene lighting and firewood have dramatically reduced, particularly in middle and high-income groups, while emissions from per capita electricity use have risen exponentially. LPG emissions have stabilized in the high-income households as subsidized LPG supply is capped at 12 cylinders annually. In rural households, per capita firewood emissions have risen, except in the top decile where LPG displaced some firewood. Emissions reduction from kerosene lighting in the top rural decile led to a 3% reduction in total per capita emissions (cooking fuel emissions remaining constant) in spite of a rise in electricity consumption, indicating that a complete transition away from kerosene lighting can play

a significant role in reducing the climate impact of household fuel use. The relationship between emissions and income is stronger in urban India where emissions are driven by rising electricity consumption; in rural India emissions are primarily due to firewood usage, with electricity consumption gaining significance in the top 2 deciles.



**Figure 3.2** Annual per capita CO<sub>2</sub>eq (Kyoto+non-Kyoto) emissions from direct household fuel use in rural and urban India (1987-2009)

### 3.3.3 Air quality and exposure to indoor PM<sub>2.5</sub>

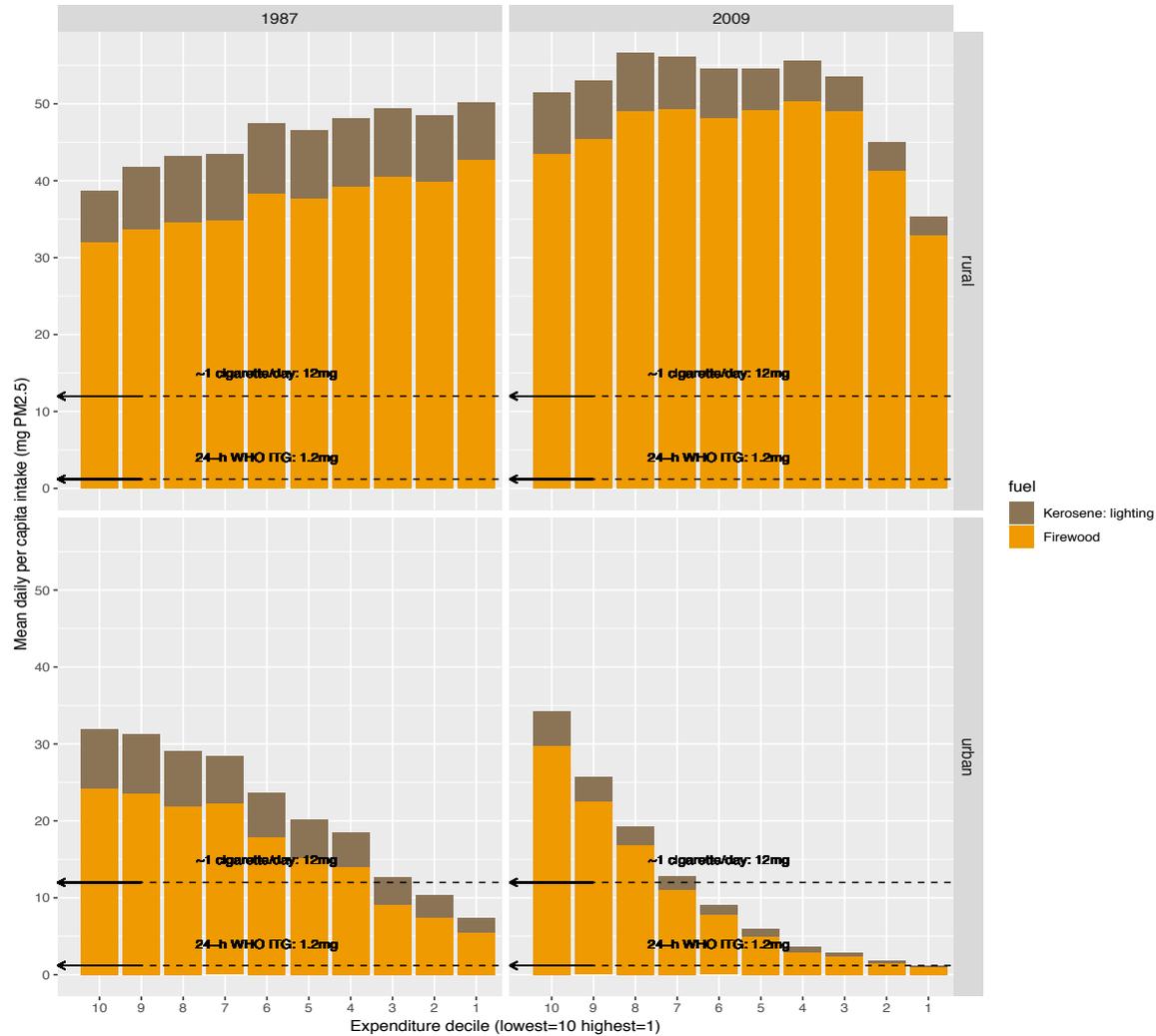
Daily exposure to PM<sub>2.5</sub> is calculated as below:

$$\text{Daily PM}_{2.5} \text{ intake per capita} = f_{TE} * \frac{BR}{(V * k_{ex} * m)} * \sum_f emf_f \left( \frac{mg}{MJ} \right) * FU_f (MJ)$$

..... Equation 3.3

where,  $f_{TE}$  = fraction of time exposed or spent indoors=90%; BR = breathing rate in  $m^3/day=16m^3/day$ ; V= volume of air per person in  $m^3=30m^3$  and  $k_{ex}$  = exchange rate between indoor and outdoor air=14/hour corresponding to high occupancy and high air exchange between indoor and outdoors (Fantke et al. 2017); m= mixing factor = 1 (Humbert et al. 2011);  $emf_f$  = emission factor of fuel f and FU= daily fuel use in MJ.  $V*k_{ex}$  is assumed to be constant across income groups – high-income households may have higher volume of air available per person but can be expected to be more airtight than low-income households. I calculate an iF of 1430 ppm, which is within the range of estimates (1300-2400 ppm) of daily intake from unvented cookstoves described in Grieshop et al. (2011) and consistent with iF of 1600 ppm calculated by Fantke et al. (2017) for high occupancy and high air exchange indoor settings typical of India.

Figure 3.3 below shows average per capita PM2.5 intake across income groups in 1987 and 2009. PM2.5 exposure is driven by firewood usage – in rural households PM2.5 exposure has increased over the years and rises with income, except in the top 20% where LPG adoption and a shift away from kerosene lamps has reduced exposure. However, mean PM2.5 exposure in 2009 was well above the 24-hour WHO ITG-I of  $75\mu g/m^3$  (WHO 2006) across income groups in rural households and low/middle income urban households, with the household fuel transition making a notable difference only in high (top 3 deciles) income urban households.



**Figure 3.3** Mean daily per capita PM<sub>2.5</sub> intake in urban and rural households (24-hour WHO Interim Target Guideline (ITG)=75 $\mu\text{g}/\text{m}^3$  (WHO 2006) or 1.2mg/day at average breathing rate of 16m<sup>3</sup>/day (Fantke et al. 2017); inhaled PM<sub>2.5</sub>/cigarette=12mg (C. A. Pope et al. 2009))

### 3.4 Climate and indoor exposure outcomes for scenarios of future energy use (2030)

This section estimates the climate impact and indoor exposure to PM<sub>2.5</sub> of potential fuel transition pathways to 2030 for urban and rural households. Five household energy consumption scenarios are defined in order to examine the effect of government policies. Fuel consumption patterns from 2009 are used with projections of per capita expenditure, population and household size to 2030,

and assumptions about future energy access trends to quantify energy consumption by fuel type in households. Details are provided in the Appendix B Section B.3. In addition to household consumption scenarios, changes in the fuel use of India's electricity supply as well as the efficiency of India's electricity grid are incorporated to evaluate the climate and indoor air quality outcomes of India's household fuel transition pathways.

### **3.4.1 Household fuel consumption scenarios**

#### **Scenario 1: Business-As-Usual (BAU) 2030**

The BAU 2030 scenario assumes that urban and rural patterns of cooking fuel and electricity consumption change with per capita income and that these follow the past pattern of energy expenditures, with no additional policies addressing the GHG content of electricity or the power grid efficiency. No additional effort in increasing rural availability of LPG or improving the quantum of electricity supply, is made i.e., fuel use patterns follow projected trends in population and income growth. The price of fuels is assumed to remain constant relative to 2009 income levels and cultural preferences for a specific fuel type are not considered.

The 2009 NSS data is used to model three key fuel consumption parameters - the share of households electrified, per capita electricity consumption and the share of LPG in per capita cooking energy requirements - as functions of the mean per capita expenditure for each income decile in rural and urban households. Rural and urban households are considered separately to account for the different trends of fuel consumption in each category. Sigmoid or S-shaped curves, such as the Gompertz and Richard's curves have been used to model make future projections of electrification (World Bank 2008b) and electricity consumption (Mohamed & Bodger 2005)

respectively. Gompertz, Richards and Logistic functions differ in terms of their point of inflexion and shape parameters. A logistic curve is symmetrical about the point of inflexion (point where rate of growth starts decreasing), the Gompertz model allows asymmetry about the point of inflexion, while the Richards function allows flexibility in the position of point of inflexion through a shape parameter (Höök et al. 2011; Teleken et al. 2017). I use the ‘grofit’ package in R to select the best fitting sigmoid growth curve – Gompertz curve for electrification and rural LPG adoption, and Richards curve for electricity use and urban LPG adoption. All parameters and model details are provided in Appendix B Section B.3. I also assume for all scenarios that un-electrified households in 2030 use 4 litres of kerosene a month for lighting (N. D. Rao 2012), and that no electrified household in 2030 uses kerosene for lighting.

Shares of cooking fuels and cooking energy requirements per capita are considered specific to income groups - wealthier households are smaller in size and per capita cooking requirements are higher. As per capita expenditure rises, the household fuel mix curve for cooking of a particular income decile shifts rightward to reflect this increase. I assume that per capita consumption of LPG and electricity in rural and urban households are capped at the 2009 level of the highest income group, i.e., households in the top rural decile do not increase LPG/electricity consumption with increase in income (LPG meets a maximum of 38% of rural household fuel requirements in the top decile), either due to barriers to supply of these fuels or other factors, while the highest income urban household deciles have reached saturation in terms of per capita electricity and LPG demand. The saturation levels of LPG adoption and electricity use in rural households are raised in the following scenarios, assuming that physical availability of LPG and electricity, currently a

constraint in rural areas, will improve by 2030 (See Appendix B Section B.3 for further details). Firewood's share in the cooking energy requirements is adjusted according to LPG adoption.

LPG and electricity consumption from 2016 and 2015 respectively help validate the aggregate BAU outcomes. BAU estimates for LPG consumption in India in 2016 are lower than government estimates for domestic LPG supply in 2016 by 10% (MoPNG 2017). NSS consumption figures are generally lower than national accounts data (CSO 2015b; Kulshreshtha & Kar 2005); additionally a portion of the subsidized domestic LPG supply is diverted illegally for commercial purposes. BAU electricity consumption estimates for 2015 exceed national-level government estimates for domestic electricity consumption (CSO 2017) by 24%. However, modelled BAU estimates are based on NSS data which include imputed values for electricity consumption based on expenditure and market price, and so are expected to capture illegal electricity consumption, unlike official reported government estimates.

**Sub-scenario 1a) BAU with PMUY (Pradhan Mantri Ujjala Yojana):** In the BAU scenario the share of LPG is only about 25% of a household's cooking requirements in low income (bottom 30%) rural households. I model a sub-scenario to account for the PMUY which aims to enable greater use of LPG in the poorest households. Under the PMUY scheme, launched in 2016, the Indian government provides subsidized LPG connections to poor households in order to remove the barrier of high upfront costs of clean cooking fuel. While government figures show that more than 40 million new LPG connections have been distributed through this scheme in 2 years, LPG consumption under PMUY has not grown in tandem with growth in customer base, as the

subsidized cost of fuel is still too high for poor households<sup>12</sup>. According to government figures, households under this scheme use 3.5-4 cylinders annually<sup>13</sup>. The PMUY scheme is modelled as a subset of the BAU scenario for 2030 by assuming a minimum of 4.5 kg of LPG used each month by each of the bottom 3 rural deciles (3.8 cylinders annually); this accounts for about 35% of each household's fuel requirements, which is 10% greater than BAU levels.

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<sup>12</sup> *Pradhan Mantri Ujjwala Yojana: Smokeless kitchens are becoming a reality (2018)*. Financial Express. Retrieved from <http://ezproxy.library.ubc.ca/login?url=https://search-proquest-com.ezproxy.library.ubc.ca/docview/2084794059?accountid=14656>

*The Hindu Business Line: PMUY: A feather in the cap for pradhan and his team (2018)*. Chatham: Newstex. Retrieved from <http://ezproxy.library.ubc.ca/login?url=https://search-proquest-com.ezproxy.library.ubc.ca/docview/2083373761?accountid=14656>

<sup>13</sup> *The Hindu Business Line: The silent LPG revolution (2018)*. Chatham: Newstex. Retrieved from <http://ezproxy.library.ubc.ca/login?url=https://search-proquest-com.ezproxy.library.ubc.ca/docview/2001162669?accountid=14656>

### **Scenario 2: Medium effort: Rural LPG and electricity**

In scenario 2, the BAU scenario is modified to include rural LPG and electricity supply increases, along with universal electrification in rural and urban households, and the elimination of all kerosene use for lighting. In this and following scenarios (3, 4 and 5) where universal electrification is assumed, households that would have been excluded from the modelled share of electrified households in each income group in the BAU scenario are assigned a fixed amount of electricity/month (30 kWh<sup>14</sup>). I assume that availability and reliability of supply of LPG and electricity in rural India improves between 2009 and 2030 and thus rural households in the top decile increase their consumption of LPG and electricity beyond those projected in the BAU scenario. Relative to BAU scenario LPG and electricity supply thus increase by 38% and 30% of the total rural supply respectively. These changes correspond to a saturation level of 60% of a rural household's cooking energy requirements in the top decile being met with LPG, as well as a doubling of per capita electricity use in the top rural decile. Urban households follow similar LPG adoption and electricity consumption trends as in BAU scenario.

### **Scenario 3: Strong push: Rural LPG and electricity**

In scenario 3, there are no barriers in physical availability of rural LPG and electricity (modelled through higher saturation level in growth equations and universal electrification). LPG and electricity use by rural households is determined by their income levels (using expenditure as a

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<sup>14</sup> The Government of India aims to provide a minimum of 1 kWh/day to each household as part of its inclusive growth targets for 2030 (Planning Commission 2014).

proxy), with no restrictions on availability or reliability of supply. Kerosene use for lighting is eliminated. Given the widespread availability of firewood in rural areas, I assume that a maximum of 90% of rural households' energy requirements being met with LPG. As a result, total rural LPG and electricity consumption increase by 70% and 50% respectively. Urban households follow the similar LPG adoption and electricity consumption trend as in BAU scenario.

**Scenario 4: Sustainable Development Goals (SDG) or All LPG-cooking scenario:**

In scenario 4, all solid fuel use is replaced with LPG, irrespective of affordability, along with universal electrification and no barriers to electricity supply. There is no kerosene used for lighting and no solid fuels used for cooking. This is an ideal scenario where clean household energy for all as a sustainable development goal has been achieved. This leads to a 192% increase in rural LPG supply and only 5% increase in urban LPG supply relative to BAU scenario, with electricity use patterns in rural and urban households similar to Scenario 3.

**Scenario 5: Multi-fuel scenario with the following assumptions:**

- A complete transition from solid fuels to induction stove cooking in urban India
- Replacement of traditional biomass cook stoves to improved cook stoves (ICS) in rural India,
- Universal access to electricity and the elimination of kerosene from lighting.
- Urban and rural households follow the same pattern of LPG adoption as in the BAU scenario – there is no additional effort to improve LPG supply or promote its adoption as a clean fuel. Additionally, 20% of urban households (the top 2 income deciles) switch to piped natural gas (PNG) for cooking.

Induction stoves, although requiring specific cooking vessels, are non-polluting devices that can be used by households with a reliable electricity connection. They are efficient, safe, long-lasting and low-cost (average cost of 20-30 USD for the stove and even less when ordered in bulk, with monthly electricity cost lower than subsidized LPG) (Smith & Sagar 2014). PNG is a relatively new primarily urban commodity, being part of the city gas distribution sector. As of 2011, there were 2.6 million households with PNG connections but the ability of gas distribution companies to pass on price increases to consumers (Sen 2015) and cost of PNG currently being slightly higher than subsidized LPG (3%)<sup>15</sup>, does not currently enable this to be an option for the urban poor. The WWF-TERI modelling study for 2030 (WWF-India & TERI 2013) assumes a similar transition pathway for its alternate renewable energy scenario.

### **3.4.2 Transition pathway models**

Fuel transition pathways are modelled using two key variables related to changes to the Indian electricity grid - grid efficiency and renewable energy's share in power. These variables in addition to the five future scenarios for household fuel consumption described in section 3.4.1 drive the analysis.

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<sup>15</sup> [http://www.business-standard.com/article/economy-policy/png-costlier-than-subsidised-lpg-as-cooking-fuel-115041000365\\_1.html](http://www.business-standard.com/article/economy-policy/png-costlier-than-subsidised-lpg-as-cooking-fuel-115041000365_1.html)

Moreover, the security deposit for 14.2kg LPG cylinder is Rs. 1150-1450 (\$16-20), depending on the state while the cost of a PNG connection is Rs. 6000 (\$85).

	Grid efficiency	Renewable energy share (incl. hydro)
2009 value	75% <sup>1</sup>	15.6% <sup>2</sup>
Alternate model value for 2030	85%	25%

**Table 3.2** Grid variables used in scenario analysis

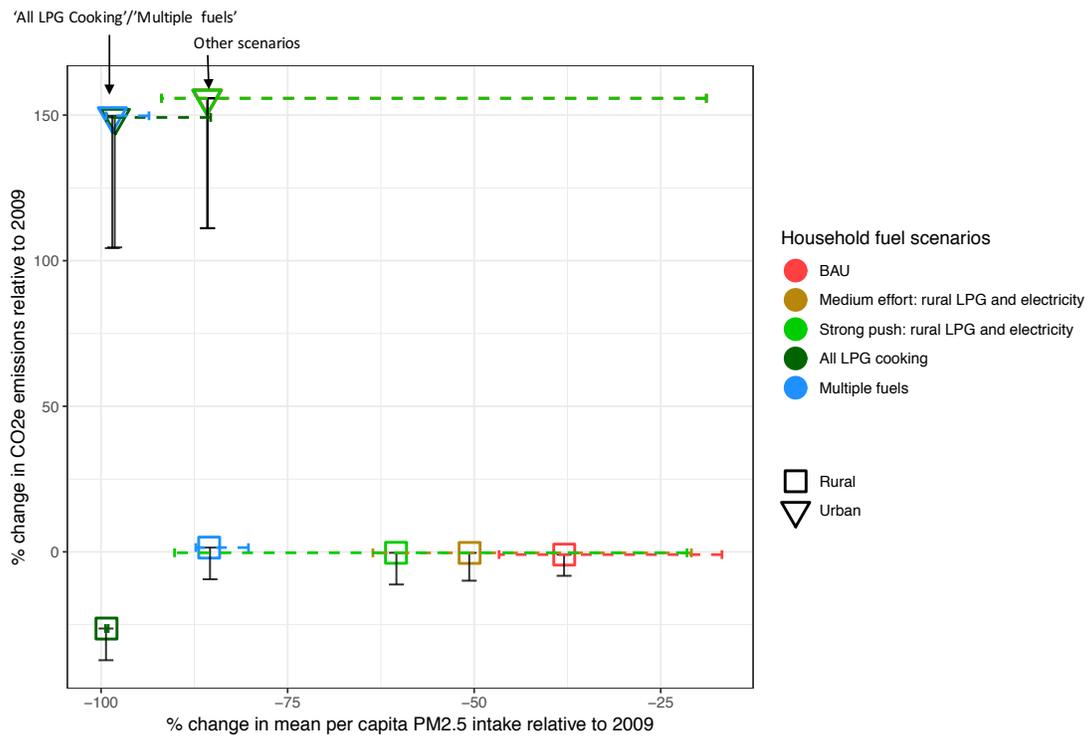
<sup>1</sup>(Buckley 2015) <sup>2</sup>(CEA 2011)

The model’s alternate values for grid efficiency and renewable power in 2030 are based on current government targets. The Government of India’s Restructured-Accelerated Power Development and Reforms scheme aims to reduce annual transmission and distribution losses to 15%, leading up to a scenario with power grid efficiency as 85%. Renewables, including hydropower, accounted for 17% of power generation in 2015 (CSO 2015a) and given the Government of India’s latest Renewable Purchase Obligation target for 2022 as 22% (excluding hydro), I assume an alternate conservative value of 25% renewable power for 2030. GHG emissions are calculated using equations (3.1) and (3.2) stated in section 3.3.2 and PM2.5 intake per person is calculated using equation (3.3) in section 3.3.3.

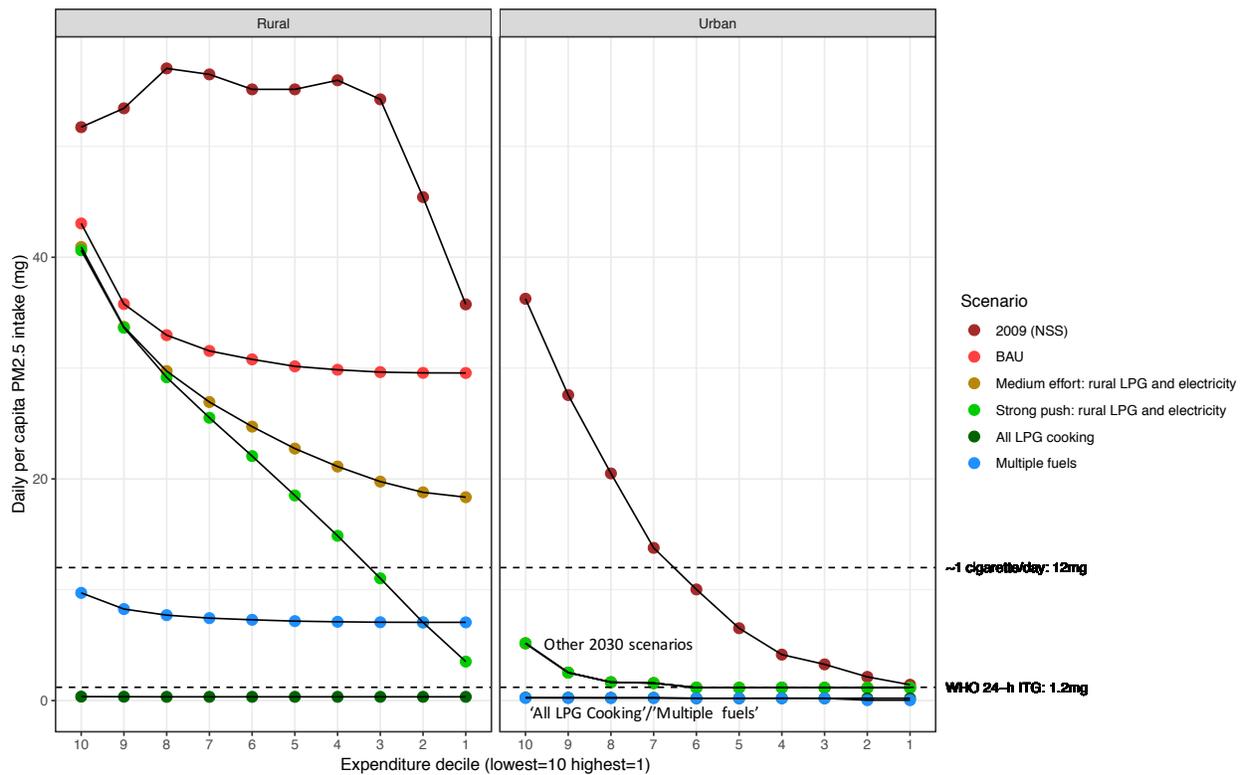
Nation-wide household GHG emissions are projected to increase by 32% relative to 2009 in the BAU scenario for 2030 (see Appendix B Figures B.7 and B.8 for per household and urban-rural breakdown of projected change in emissions), with estimates varying from 2-33% in other scenarios. If only Kyoto emissions are considered and the potential non-Kyoto emission reductions from transitioning away from kerosene lighting and firewood are excluded, the projected increase in the BAU scenario relative to 2009 is 155%, driven by LPG adoption and electricity

consumption. Alternate high LPG adoption and universal electrification scenarios, for the same grid parameter assumptions, show even higher rise in Kyoto emissions, implying a trade-off between climate and clean energy access. Including non-Kyoto emissions shows that high LPG adoption and universal electrification in fact reduces non-Kyoto emissions from firewood and kerosene lighting, thus indeed providing a climate benefit (Figure B.9 in Appendix B shows Kyoto and net emissions from the scenarios).

Figure 3.4 shows the change in net GHG and mean per capita PM<sub>2.5</sub> intake for each household fuel scenario for rural and urban households, assuming grid efficiency and renewables' share in power remain at 2009 levels – vertical error bars show the range of estimated GHG reductions for increasing grid efficiency to 85% and/or renewables' share in power to 25%. Horizontal error bars in figure 3.4 show the range of projected reduction in mean per capita intake across income groups. Figure 3.5 expands on the inequity in indoor exposure reduction across scenarios and shows the mean daily per capita PM<sub>2.5</sub> intake for each income group in each scenario.



**Figure 3.4** Transition pathways to 2030: Climate (Kyoto + non-Kyoto) and indoor air quality co-benefits in urban and rural households  
*(Note: 100% decline implies a complete reduction relative to 2009)*



**Figure 3.5** Household fuel transition pathways: Equity in indoor air quality benefits

### 3.5 Results and Discussion

The 2030 BAU scenario for household energy consumption estimates a 1-8% decrease in GHG (Kyoto + non-Kyoto) emissions in rural households and 110-156% increase in urban households,

depending on grid efficiency and renewables' share in power<sup>16</sup>. The emissions reduction in rural households in the BAU scenario is driven primarily by a transition away from kerosene lighting and consequent reduction in non-Kyoto emissions. In the BAU PMUY sub-scenario, the additional transition from firewood to LPG by low-income rural households leads to a further reduction of 1.5% in rural GHG emissions<sup>17</sup>. In urban households, widespread adoption of LPG in the BAU projections results in all urban households, except the bottom 20%, meeting the 24-hour WHO ITG-I PM2.5 exposure threshold value of 75 µg/m<sup>3</sup>, while in rural households, persistent use of firewood does not significantly improve indoor air quality across the income spectrum. The BAU PMUY sub-scenario, through greater LPG usage in bottom 30% of rural households, reduces PM2.5 exposure in these households by 16% relative to BAU without the PMUY scheme. The resultant exposure values, at an average of 35 mg PM2.5/day are still high, but now comparable to those of middle/high income rural households.

Projected GHG emissions in Scenarios 2 and 3, with medium and high LPG adoption respectively in rural households and universal electrification, are within a range of 2-3% of emissions in BAU scenario. Greater LPG use and additional electricity consumption due to universal electrification in rural households do not lead to significant changes in net GHG emissions. Mean per capita

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<sup>16</sup> If only Kyoto gases are considered, in the BAU scenario for 2030 GHG emissions in rural households increase by 60-85% and those in urban households increase by 200-279% relative to 2009.

<sup>17</sup> Assuming biomass is 70% renewable (Singh et al. 2017), and including non-Kyoto emissions.

PM2.5 intake is lower in these scenarios compared to BAU scenario, but largely for middle-income and high-income rural households who can afford to transition from firewood to LPG.

Scenario 4 (All LPG-cooking) offers the greatest climate and health benefits. Universal LPG and electricity adoption across urban and rural households leads to a rise of only 2-11% in GHG emissions, or even a decrease of about 7%, relative to 2009, depending on grid efficiency and renewables' share in power, while indoor PM2.5 exposure is reduced to below 75  $\mu\text{g}/\text{m}^3$  across urban and rural households. Compared to the BAU scenario for 2030, this All LPG-cooking scenario leads to 21% lower GHG (Kyoto+non-Kyoto) emissions.

Scenario 5 or Multi-fuel scenario is similar to BAU and scenarios 2 and 3 in terms of climate impact but offers greater and more equitable health benefits, as all wood-using rural and urban households move from traditional to improved cookstoves and solid fuels to induction cooking respectively. Switching to ICS, however, does not reduce PM2.5 exposure to below the WHO threshold value of 75  $\mu\text{g}/\text{m}^3$  in rural areas.

Higher levels of clean fuel (LPG and PNG) use and electricity consumption scenarios (Scenarios 2, 3 and 5) do not have a large effect on the range of GHG emissions increase estimated in the BAU scenario. One exception is when all households use only LPG for cooking (Scenario 4); this leads to emission *reductions* for rural households by 26-37% relative to 2009, predominantly due to reduction of non-Kyoto emissions from firewood and kerosene lighting. Improving grid efficiency (to 85%) and renewables' share (to 25%) in any household fuel scenario leads to a decrease of about 9-12% in rural GHG emissions and about 50% in urban GHG emissions relative

to keeping both parameters at 2009 levels. Across scenarios, projected emission reductions are a function of the transition away from firewood, lower power grid losses and lower share of coal in power.

The multi-fuel scenario where urban households switch from solid fuels to electricity for cooking offers similar health and climate benefits to urban households as would a complete switch to LPG. In rural India, improved cookstoves (ICS) offer lower benefits than those that result from switching to LPG. The estimated per-capita intake in ICS households of about 10mg/day from ICS is far higher than that implied by WHO guidelines (about 0.6 mg/day). Relative to switching to LPG, ICS also leads to about 30% higher GHG emissions in rural households, assuming biomass is 70% renewable (Singh et al. 2017) and including non-Kyoto emissions.

One of the limitations of this work is that the uncertainty in renewability of biomass (assumed to be 70% here) and global warming potential of non-Kyoto pollutants is not analyzed. Additionally, in modelling energy transition scenarios for 2030, examining the role of cultural preferences or social pressure to use a specific fuel was beyond the scope of this chapter.

From this analysis, the greatest health and climate benefits are achieved through a complete transition to LPG and electricity – moving away from firewood and kerosene lighting offers significant climate benefits, particularly in terms of non-Kyoto emission reductions. Using firewood in improved cookstoves in rural households can reduce PM<sub>2.5</sub> exposure compared to traditional cookstoves by more than 70%, but it is still estimated to exceed the 24-hour WHO ITG-I guideline of 75 µg/m<sup>3</sup>. Greater access to clean fuels in 2030 – higher levels of LPG

adoption and electricity use in rural households in scenarios 2 and 3 – does not significantly affect GHG emissions relative to lower levels of clean fuel access in BAU scenario. Increasing the physical availability or supply of LPG (as in scenarios 2 and 3), without addressing affordability will largely benefit middle-income and high-income rural households and provide unequitable health benefits and limited climate benefits, as poorer households continue to use firewood. Subsidy schemes like the PMUY aim to make LPG more affordable by reducing upfront costs without further subsidizing the fuel; but LPG use affords minimal climate and health benefits if it meets only part of the cooking energy requirements of low-income households. Government efforts should focus on both affordability and improving the quantum and reliability of supply of clean fuels like LPG and electricity.

## **Chapter 4: A spatially and seasonally disaggregated approach to characterizing intake fraction of primary and sulfate PM<sub>2.5</sub> emissions in India**

### **4.1 Introduction**

Exposure to fine particulate matter, that is particulate matter less than 2.5 microns in diameter (PM<sub>2.5</sub>), is associated with respiratory and cardiovascular diseases and premature mortality (Gordon et al. 2014; Smith et al. 2014; Burnett et al. 2014). Average annual PM<sub>2.5</sub> concentrations in India are among the highest in the world, estimated at about 91µg/m<sup>3</sup> in 2017 (Health Effects Institute 2019); by comparison, the WHO annual interim and final target guidelines are 35µg/m<sup>3</sup> and 10µg/m<sup>3</sup> respectively (WHO 2006)<sup>18</sup>. According to the Global Burden of Diseases assessment, air pollution is the leading risk factor for death in South Asia – and India accounted for 26% of the 4.2 million deaths in that can be attributed to air pollution in 2015 globally (Lim et al. 2012; Cohen et al. 2017).

Air pollution is a significant challenge particularly in densely populated areas in India – the Central Pollution Control Board categorizes 75% of metropolitan cities in India as 'critical' in terms of air quality (CPCB 2011). However, the challenge of air pollution is not specific to large metropolitan regions – modelled annual mean particulate matter concentrations in the densely populated Indo-

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<sup>18</sup> Interim guidelines are intended to be provisional targets for highly polluted areas, as part of a progressive pollution reduction plan towards final guidelines.

Gangetic Plain (IGP), that includes the capital New Delhi, range between 50 -150  $\mu\text{g}/\text{m}^3$  and are generally two to four times the concentrations in other parts of India (Brauer et al. 2012; Venkataraman et al. 2018; Upadhyay et al. 2018). Satellite-derived PM<sub>2.5</sub> concentrations, based on aerosol optical depth measurements, show a similar spatial distribution of PM<sub>2.5</sub> concentration (Dey et al. 2012; Guttikunda, Goel & Pant 2014). Among the most densely populated cities in India, measured mean annual PM<sub>2.5</sub> concentrations are the highest for cities in the IGP, Delhi and Kolkata (80-115 $\mu\text{g}/\text{m}^3$ ), compared to others - e.g., Hyderabad, Mumbai and Chennai (37-54 $\mu\text{g}/\text{m}^3$ ) (Sreekanth et al. 2018).

Studies on the characterization of PM<sub>2.5</sub> concentration by source have focused on cities such as Delhi (Guttikunda & Calori 2013; Bisht et al. 2015; Nagar et al. 2017), Hyderabad (Guttikunda & Kopakka 2014), Kanpur (Behera et al. 2013; Ram & Sarin 2011) and Kolkata (Gurjar et al. 2016; Chatterjee et al. 2012), with a few in rural areas (Begam et al. 2016) and in 'hill stations' (A. Kumar & Sarin 2010). Given the regional nature of ambient air pollution, the spatial distribution of PM<sub>2.5</sub> exposure by source is important for understanding the significance of each emission source in influencing regional air quality and consequent human exposure and health effects. Two studies, one by Upadhyay et al. (2018) and another by Venkataraman et al. (2018), simulate the emission sector-contribution to PM<sub>2.5</sub> concentrations across India. But neither differentiate between primary PM<sub>2.5</sub>, emitted directly from a source, and secondary PM<sub>2.5</sub>, formed from precursor gases emitted by various sources. Control of secondary PM<sub>2.5</sub> such as sulfates and nitrates might need different mitigation action compared to primary PM<sub>2.5</sub> such as reduction of SO<sub>2</sub> emissions from thermal power plants through flue gas desulfurization (Guttikunda & Jawahar 2014) and catalytic reduction of NO<sub>x</sub> using ammonia in vehicle exhaust .

The risk posed by PM<sub>2.5</sub> to human health depends on the level of exposure of the surrounding population. Toxicology studies suggest that health effects of PM<sub>2.5</sub> depend on size (ultrafine particles being more harmful) and chemical composition (black carbon, sulfates and transition metals have specific adverse effects). However, due to lack of sufficient evidence air quality standards simply specify recommendations for PM<sub>2.5</sub> concentrations, which play a critical role in determining exposure (Cassee et al. 2013). Apart from the quantity of emissions from a source, the significance of a source in terms of its exposure contribution is determined by a range of factors such as its proximity to population and meteorological conditions. In this paper, I develop a model that specifies the exposure impact of a source, regardless of its level of emissions, considering spatially-dependent characteristics such as population and meteorology and source characteristics such as emission stack height. Intake fraction (iF) is a commonly used metric to quantify the relationship between emissions and exposure. iF is defined as the fraction of emitted pollutant inhaled by an exposed population (Bennett et al. 2002). It is a dimensionless quantity often expressed as ppm or parts per million and represents the exposure to a pollutant per unit emission.

iF has been used to estimate source and location-specific exposure to PM<sub>2.5</sub> in a number of empirical studies (Navarro et al. 2016; Ries et al. 2009; Marshall et al. 2003; Greco et al. 2007; Levy et al. 2003). A simple box-model framework, where regional atmospheric domains are considered enclosed within compartments, has been used to calculate intake fraction values (Apte et al. 2012; Humbert et al. 2011; Fantke et al. 2017) and can provide reasonable estimates compared to empirically derived iF values from measured concentrations (Marshall et al. 2005). The spatial and temporal distribution of iF can provide relevant information about the variability

in exposure per unit emission due to a specific source, and along with emissions data, help compare exposure from different sources. Exposure estimates combined with dose-response relationships can help in understanding health risks associated with specific emission sources and aid in focusing policy efforts so as to maximize human health benefit per unit emissions reduction (Evans et al. 2002; Apte et al. 2011).

The aim of this work is to estimate spatially disaggregated and source-specific iF of PM<sub>2.5</sub> sources in India through a simple model-based characterization of PM<sub>2.5</sub> transport and deposition. I model the emission-to-exposure pathways outlined in the USEtox life cycle assessment model (Bijster et al. 2017), and evaluate intake fractions for the entire population of India aggregated at the district level, the local-scale administrative unit in India. The remainder of the paper is structured as follows: in section 4.2, I review the concept of intake fraction, including past efforts at modeling geographically distributed PM<sub>2.5</sub> intake fractions. Section 4.3 outlines the structure of the model framework and Section 4.4 explains the model framework for indoor and outdoor population exposure in detail, as well as describes the data inputs. Section 4.5 describes the model equations (with details in Appendix C Section C.3) and Section 4.6 describes model validation (4.6.1) and sensitivity analyses (4.6.2). I conclude with a discussion of the implications of this work in Section 4.7.

## **4.2 Intake fraction as an exposure metric**

Intake fraction of a pollutant such as primary PM<sub>2.5</sub> from an emissions source is determined by population density, proximity of the population to the sources of emissions (horizontal distance from the source as well as vertical distance represented by emission stack height), and

meteorological conditions such as wind speed and atmospheric boundary layer mixing height (Evans et al. 2002; Levy et al. 2002; Nigge 2001). iF estimates can vary widely; Marshall et al. (2003) state that an expected value of iF for primary pollutants from outdoor sources in urban areas can range between 1-100ppm. Intake fraction values in literature vary across sources and location as shown in Table 4.1. iF estimates from power plants in China are about an order of magnitude higher than the US, primarily driven by population density, not just close to the emission site but beyond 500km of the source (Zhou et al. 2006). This implies that regional population density, and not simply the population density close to the source, plays a role in determining the intake fraction of a pollutant.

Estimated iF	Particle type	Emission source	Location	Study
6.6-24 ppm	Primary PM2.5	Urban wood smoke in winter	Vancouver (Canada)	(Ries et al. 2009)
34-85 ppm	Primary non-reactive compounds	Vehicular emissions	California	(Marshall et al. 2003)
7-21 ppm	Primary non-reactive compounds	Vehicular emissions	Urban US	(Marshall et al. 2005)
0.12-25 ppm	Primary PM2.5	Mobile sources	US	(Greco et al. 2007; Evans et al. 2002; Levy et al. 2002; Levy et al. 2003)
0.05-10 ppm	Secondary PM2.5: sulfate			
0.0-1.3 ppm	Secondary PM2.5: nitrate			

Estimated iF	Particle type	Emission source	Location	Study
0.6-2.2 ppm	Primary PM2.5	Power plants	US	(Evans et al. 2002; Levy et al. 2003)
0.13-0.2 ppm	Secondary PM2.5: sulfate			
0.025-0.06 ppm	Secondary PM2.5: nitrate			
2.8-19 ppm	Primary PM2.5	Power plants	China	(Zhou et al. 2003)
0.7-7 ppm	Secondary sulfate and nitrate			

**Table 4.1** Estimates of source-specific intake fraction from literature

**4.2.1 Modeling intake fraction**

Intake fraction can be mathematically expressed as follows (Levy et al. 2002):

$$iF = P * BR * \frac{C}{E} \quad \text{..... Equation 4.1}$$

where P= population, BR= breathing rate of an individual in m<sup>3</sup>/day, C= average daily incremental concentration attributable to a pollutant and E= average emissions rate of the pollutant per day. In estimating human exposure to a pollutant, intake fraction combines the ‘fate’ or equilibrium mass of a pollutant in a given environment and population exposure into a single metric to represent the fraction of emitted pollutant mass that is inhaled by the exposed population. Equation (4.1) can be rearranged to get,

$$iF = \left( V * \frac{C}{E} \right) * \left( P * \frac{BR}{V} \right) = FF * XF \quad \text{..... Equation 4.2}$$

where  $V$  = volume of air in the environment,  $FF$  is the ‘fate factor’ or the fraction of emitted pollutant mass per unit time that remains in the environment, and  $XF$  is the exposure factor, or the fraction of air in the environment inhaled by the exposed population per unit time.

Levy et al. (2002) state that a simple regression model with relevant parameters such as population density, mixing height and wind speed, can be used to calculate  $iF$  values for power plants and mobile sources that are reasonably consistent with outputs from complex dispersion models. Marshall et al. (2005) find that mean intake fraction values calculated using a simple one-compartment model that uses demographic data on population and area and meteorological data on wind speed and mixing height are consistent with those calculated using an empirical model based on measured concentrations.

A box- or compartment model is the simplest representation of the atmospheric domain where concentrations are assumed to be uniform within the simulated atmospheric domain (Seinfeld & Pandis 2006a). Previous studies have used a compartment model – either a single compartment (Ries et al. 2009; Marshall et al. 2005; Apte et al. 2012) or multiple linked compartments (Humbert et al. 2011; Fantke et al. 2017) to estimate  $iF$  values specific to regions or regional archetypes. Apte et al. (2012) use a simple one-compartment box model to calculate the intra-urban  $iF$ , i.e., the fraction of emissions within a city inhaled by the city residents, associated with ground sources for 3646 cities. The average intra-urban  $iF$  is calculated to be 39ppm, while that for an average Indian city is 60ppm.

The USEtox model, a UNEP/SETAC life cycle assessment initiative, aims to characterize the health impact of emissions, using a multi-compartment framework to model fate, exposure and effects of pollutants (Bijster et al. 2017). Humbert et al. (2011) use the USEtox modeling framework to estimate intake fractions of PM<sub>2.5</sub> specific to regional archetypes (urban and rural areas) and emission stack heights, by parameterizing population density, wind speed and mixing height. In their work, outdoor urban and rural iFs for South Asia are estimated at 29ppm and 4.6ppm respectively. Fantke et al. (2017) extended the model by Humbert et al. (2011) to include exchange between indoor and outdoor air and calculate iF values for indoor and outdoor sources in world regions including the 3646 cities evaluated in Apte et al.(2012). They estimate an average iF of 70ppm and 6.28ppm for ground-level outdoor emissions in cities and rural areas respectively in India, and 1600 ppm for indoor emissions in high air exchange and high occupancy settings typical of India.

In both these models, a typical city is considered the innermost compartment enclosed by a single regional or rural compartment, which is spatially of national or continental scale. The regional scale is considered uniform in terms of population density and meteorological parameters and the system of equations for *each* city is solved independently to calculate intake fraction values. There are two reasons for why these assumptions may mislead in the Indian case. First, population density varies substantially across India – the Indo-Gangetic Plain is densely populated (area-weighted mean population density across districts is 920 p/sq.km.) compared to the less populated regions in north-eastern India (16-80 p./sq.km in the states of Arunachal Pradesh, Mizoram and Sikkim) and central India (180-200 p./sq.km in Rajasthan and Chhattisgarh). Additionally, meteorology and in particular the mixing height varies across the country and seasonally – ranging

between 80 - 500m in December and 220 -1120m in June, with the Indo-Gangetic Plain seeing lower mixing heights than central India, particularly during winter (see Appendix C Section C.1 for maps of population density and mixing height). Intake fraction of city emissions thus are determined not only by city-specific parameters such as population density and meteorology, but also by the conditions in the region surrounding the city. For a heterogeneous country such as India, a more spatially and temporally disaggregated approach is needed.

Here I develop a simple atmospheric transport model with minimal run time and low level of complexity, to estimate spatially and seasonally disaggregated iF values and analyze the role of population density and meteorology in determining PM<sub>2.5</sub> exposure. I adapt the USEtox framework as a starting point to account for variation in population density and meteorological parameters (e.g. mixing height and precipitation) across India. I divide the country into multiple regional zones of similar population density and mixing heights, each of which include distinct urban (or densely populated) areas and build a model to estimate iF values from ambient exposure to PM<sub>2.5</sub>. The ambient exposure model is combined with a model of indoor exposures, and a regionally specific model for human exposure to PM<sub>2.5</sub> across the country is developed. Previous work of Humbert et al. (2011) and Fantke et al. (2017) also did not account for secondary aerosol formation from precursor gases. In this work I also model, in a simplified form, the production of and exposure to secondary sulfate aerosols.

#### **4.2.2 Primary vs. secondary pollutants**

PM<sub>2.5</sub> in the atmosphere includes both primary pollutants directly emitted by different sources (comprising of black carbon (BC), organic matter (OM) and crustal matter), and secondary

particles, formed through transformation of precursor gases. Secondary PM<sub>2.5</sub> consists of secondary inorganic aerosols (SIA), such as SO<sub>4</sub><sup>2-</sup>, NO<sub>3</sub><sup>-1</sup> and NH<sub>4</sub><sup>+1</sup> formed in the atmosphere from precursor gases SO<sub>2</sub>, NO<sub>x</sub> and NH<sub>3</sub> respectively, and secondary organic aerosols (SOA) formed through condensation or nucleation from gaseous phase volatile organic compounds (VOCs). Evaluation of the chemical transformation processes involved in the formation of nitrate, ammonium and SOA PM<sub>2.5</sub> is complex due to volatility of compounds, uncertainties in the gas-phase chemistry and varying rates of reactions of different compounds. The chemical conversion of SO<sub>2</sub> to SO<sub>4</sub><sup>2-</sup> is, however, well-defined and modeled (Venkataraman et al. 1999; Venkataraman et al. 2001; Seinfeld & Pandis 2006b), with the reaction being the most important in cloudwater (Seinfeld & Pandis 2006b), and SO<sub>4</sub><sup>2-</sup> ions form the bulk of SIA (R. Kumar et al. 2006; A. Kumar & Sarin 2010; Behera & M. Sharma 2010). The formation of SO<sub>4</sub><sup>2-</sup> from SO<sub>2</sub> is parameterized in this model since the chemistry is well-understood. Measured data on other secondary PM<sub>2.5</sub> (SOA, nitrates and ammonium) from previous studies is presented to estimate the fraction of total PM<sub>2.5</sub> concentration captured by this model's results, which include primary PM<sub>2.5</sub> and sulfates.

### **4.3 Model framework**

Under steady state conditions, the mass of pollutants within a 'box' representing an atmospheric domain is constant and the rate of inflow of emissions is equal to the rate of loss, through processes of advection, deposition and chemical transformation. I assume that primary PM<sub>2.5</sub> does not undergo chemical transformation in the box. The rate of advection and deposition of particulate matter are proportional to its equilibrium mass in the box and can be expressed as products of a rate coefficient  $k$  and mass. Loss through deposition includes dry deposition, the transfer of

particles from the atmosphere to surfaces in the absence of rain, and wet deposition, removal of particulate matter by precipitation. In a multi-box model like the USEtox (Bijster et al. 2017), all boxes are at steady state, and the mass balance condition holds true for each box by definition. The mass balance equations for multiple compartments can be written using rate coefficients in matrix notation as:

$$E + Km = 0 \quad \text{.....Equation 4.3}$$

where E is the emission rate and m is the equilibrium mass in a compartment, and K is the matrix of rate coefficients for advection and deposition. (See Section 4.5 for further information on rate coefficients and Appendix C Sections C.2 and C.3 for detailed equations).

The rate coefficient matrix K is used to calculate the fate factor matrix FF, which represents the fraction of a unit emission in each source compartment (each column in FF) that flows out to other compartments (each row in FF), with diagonal elements (source=destination) representing total loss from a compartment as:

$$FF = K^{-1} \quad \text{.....Equation 4.4}$$

The iF matrix, representing the fraction of emission in each box breathed in by the populations in other boxes, where each column represents a source compartment and each row represents a destination compartment, is calculated as:

$$iF = FF * XF \quad \text{.....Equation 4.5}$$

XF is the exposure factor matrix or the fraction of air in each compartment breathed in by the exposed population per day; it is calculated as:

$$XF_i = P_i * BR / V_i \quad \text{.....Equation 4.6}$$

where  $P_i$  and  $V_i$  are the population and volume of each compartment  $i$  respectively and BR=breathing rate of an individual (assumed to be  $16 \text{ m}^3/\text{day}$  in this model (Fantke et al. 2017)).

Intake fraction values calculated are assumed to be an emission-weighted average for a given compartment –  $iF$  values specific to stack height (ground, low stack and high stack) are calculated using Humbert et al.'s (2011) methodology outlined in Appendix C Section C.4.

Equilibrium concentrations in each compartment can be calculated using the fate factor matrix:

$$C_i = (\sum_s FF_{s,i} * E_s) / V_i \quad \text{..... Equation 4.7}$$

where  $C_i$  is the concentration in compartment  $i$ ,  $FF_{s,i}$  represents the fate of emissions from compartment  $s$  in compartment  $i$ ,  $E_s$  is the rate of emissions in compartment  $s$  and  $V_i$  is the volume of compartment  $i$ .

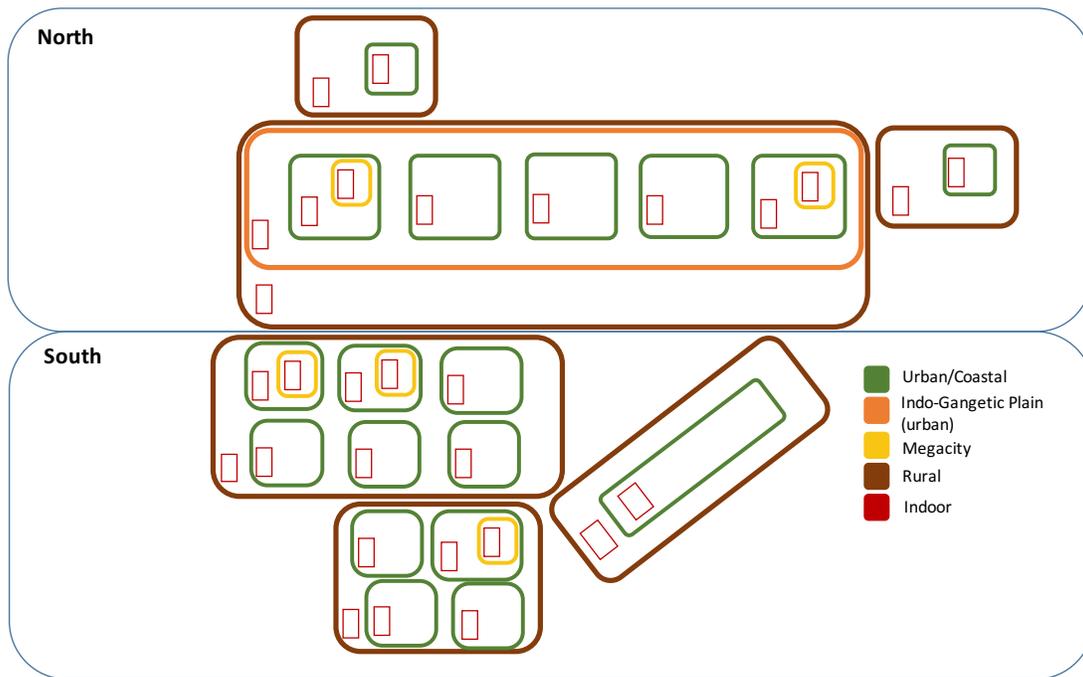
#### 4.4 Model set-up

The modeling framework developed has multiple nested compartments. At the highest level of spatial aggregation, the model has two sub-continental boxes – one corresponding to peninsular India, including proximate marine regions, to account for air exchange between coastal districts and the ocean (South), and another corresponding to the northern landlocked region of the sub-continent (North). For modelling simplicity, I assume that all air in the first sub-continental box, after exchanging air with enclosed rural boxes, flows into the second one, and vice-versa. Mixing height of continental boxes is assumed to be the maximum of the enclosed boxes. Each sub-continental region is split into smaller rural compartments, each of which incorporates distinct urban compartments, some of which also enclose high-density urban compartments.

The two continental boxes North and South (outermost blue boxes in Figure 4.1) encompass and exchange air with 6 ‘rural’ boxes (brown boxes in Figure 4.1), characterized by a population density of less than 400 people/km<sup>2</sup> and a spatial scale of 2E+05-1E+06 km<sup>2</sup>. Each rural box encompasses one or more urban (population density > 400 people/km<sup>2</sup>) and/or coastal boxes (boxes which exchange air with the sea). A total of 19 urban or coastal boxes<sup>19</sup> (green or orange boxes in Figure 4.1 and of spatial scale 5E+03-3E+05 km<sup>2</sup>) are enclosed by the 6 rural boxes. The densely populated Indo-Gangetic Plain forms its own ‘urban’ box (orange box in Figure 4.1) and further encloses five urban boxes. Additionally, nested within the urban boxes are five high-density urban boxes with population density >4000 p/km<sup>2</sup> and of spatial scale 2E+02-6E+02 km<sup>2</sup> (yellow boxes in Figure 4.1). Each rural, urban and high-density urban box includes an indoor box (innermost red boxes in Figure 4.1 and 4E+01-3E+03 km<sup>2</sup> in area) that captures indoor exposures. The resulting nested model has a hierarchical structure with 5 categories of boxes - continental, rural, urban/coastal, high-density urban, and indoor. A graphical representation of compartment set-up in the model is shown in Figure 4.1.

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<sup>19</sup> 13 inland urban boxes; 6 coastal boxes, of which 4 are urban and 2 are rural



**Figure 4.1** Depiction of compartments in this model  
*(continental boxes: 2 outermost blue; rural boxes: 6 brown; urban/coastal boxes: 18 green and 1 orange (Indo-Gangetic Plain); high density urban boxes: 5 yellow; indoor boxes: innermost red in each compartment)*

Districts are the most salient administrative jurisdiction in India<sup>20</sup>, with both population and meteorological data being available at the district level. Thus, each box in this model consists of one or more districts, with the districts assigned to one of 30 model boxes (6 rural boxes, 19 urban boxes, and 5 high density urban boxes) based on simple classification rules. See Appendix C Section C.1 Figure C.2 for a map of districts classified into compartments.

<sup>20</sup> India is currently divided into 36 sub-national jurisdictions (29 states and 7 union territories), which are further sub-divided into a total of 640 districts.

#### **4.4.1 Classification of districts into model ‘boxes’**

Intake fraction values are more strongly sensitive to population density compared to meteorological variables (Humbert et al. 2011; Zhou et al. 2006), so districts are first grouped into population density classes (Table 4.2). Then mixing height is used as a grouping variable and rural regions are assigned into model compartments - districts in extreme mixing height classes are not grouped together. I also examine distribution of wind speed and rainfall across India – southern peninsular India (states of Kerala, Tamil Nadu and southern Karnataka) experience higher wind speed and higher rainfall compared to the remaining land area in the South continental box, and hence forms its own rural region. Thus the boundaries of each rural box are determined by meteorological parameters of mixing height, wind speed and rainfall. See Appendix C Section C.1 Figure C.1 for maps of population density and meteorology.

Additionally, the following assumptions were made:

- Districts in the North continental box are not grouped together with those in the South continental box to account for air exchange with sea.
- Coastal districts in the South continental box are grouped distinctly from inland districts, provided population density and mixing height classification conditions are met. Air exchange between coastal boxes and the sea is accounted for by assuming a ‘mirror’ sea box of same area and wind speed as the coastal land box and adding this area onto the enclosing rural box.

Table 4.2 describes the categories of ‘boxes’ in the modelling framework:

Box Type	Spatial Scale (km <sup>2</sup> )	Population Characteristic (p/km <sup>2</sup> )	No. of boxes	Notes
Continental	~ 2E+06	None	2	'South' continental box includes marine area of 4.6E+05 km <sup>2</sup> (Fantke et al. 2017)
Rural	~2E+05- 1E+06	< 400 <sup>1</sup>	6	
Urban: Class I	~5E+03- 8E+04	400 – 1200 <sup>2</sup>	14	
Urban: Class II		1200 – 4000	5	All enclosed within the IGP class I urban box

Box Type	Spatial Scale (km <sup>2</sup> )	Population Characteristic (p/km <sup>2</sup> )	No. of boxes	Notes
High-Density Urban	~2E+02- 6E+02	> 4000 <sup>3</sup>	5	Delhi, Kolkata, Mumbai, Hyderabad, Chennai are nested within urban compartments <sup>4</sup>
Indoor	~4E+01- 3E+03	Specific to surrounding rural/urban/high-density urban box	30	

**Table 4.2** ‘Boxes’ in the modelling framework

<sup>1</sup>definition of ‘rural’ districts by Census 2011 (population density of 53% districts < 400 p./km<sup>2</sup>). <sup>2</sup>90% of districts in India are under 1200 p./km<sup>2</sup>. <sup>3</sup>Average population density of a global city is 8300 p/sq.km (Humbert et al. 2011). South West and New Delhi districts fall within 4000-8300 and are included within the high density urban class. <sup>4</sup>Bangalore (pop. den=4300 p/km<sup>2</sup>) forms its own urban compartment enclosed by rural area

#### 4.4.2 Data used in classification

Open access district-wise GIS maps for India are obtained under the Creative Commons license from the DataMeet community<sup>21</sup>. District-level data on population and area are from Census 2011. Meteorological data for 2015, available by hour and district, are from the publicly available data

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<sup>21</sup> (<https://github.com/datameet/maps/tree/master/Districts>)

repository Urbanemissions.info (Guttikunda et al. n.d.) and are aggregated to monthly values. The district-level meteorological data is a result of processing global NCEP Reanalysis data through the WRF mesoscale meteorological model<sup>22</sup>. The dataset includes surface wind speed, wind direction, precipitation, temperature, and mixing height. All variables are significant inputs in determining dispersion of pollution in the atmosphere.

In order to validate the model with past efforts, model results are compared with those from the Global Burden of Disease Major Air Pollution Sources (GBD-MAPS) study (GBD MAPS Working Group 2018). The GBD-MAPS study uses the emissions inventory developed by Sadavarte et al. and Pandey and Venkataraman for 2015 (Sadavarte & Venkataraman 2014; Pandey et al. 2014) as inputs for the atmospheric chemical transport model GEOS-CHEM to estimate ambient PM<sub>2.5</sub> concentrations. It combines modelled output with satellite-based data on aerosol optical depth and surface measurements from more than 400 stations in India to generate estimates for ambient PM<sub>2.5</sub> concentration at a spatial scale of 11km X 11km. I use intake fraction values from this model to estimate PM<sub>2.5</sub> concentrations in each model compartment, using the same emissions inventory employed by the GBD study. The inventory used includes PM<sub>2.5</sub> and SO<sub>2</sub> emissions; emissions are available for the following sectors: thermal power, heavy industry

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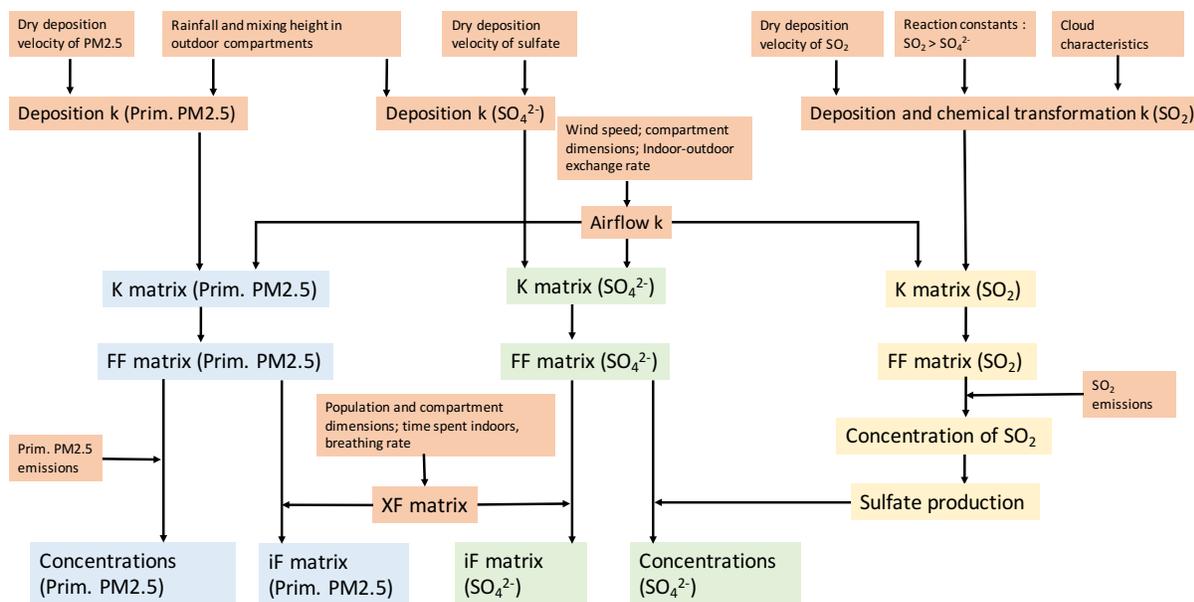
<sup>22</sup> NCEP Reanalysis data is assimilated from observations and modelling and is publicly available through the NOAA, while the WRF or the Weather Research & Forecasting model can generate predictions for atmospheric conditions at a smaller spatial scale than global models, ranging from a few metres to thousands of kilometres.

(iron and steel, fertilizer, cement), light industry, informal industries, brick kilns, transport (railways and on-road gasoline and diesel), agriculture (residue burning and diesel in tractors and pump sets), and residential (cooking with biomass, kerosene and LPG, kerosene lighting, diesel generator sets, water heating and space heating). Monthly emissions are available for space heating, water heating and agricultural residue burning, and annual emissions from other sectors are equally split into monthly emissions. Emission sources are split into indoor (residential sector) and outdoor, and assigned stack height values of 'ground', 'low' and 'high' (details in Appendix C Section C.4).

#### **4.5 Model equations**

In order to calculate the  $iF$  matrix for model compartments, 2 matrices are needed – Fate factor (FF) and Exposure Factor (XF) (see equation 4.5 in Section 4.3). The XF matrix is calculated as a function of population density and mixing height of each compartment (equation 4.6 in Section 4.3). The FF matrix is calculated as the inverse of the rate coefficients matrix  $K$  (equation 4.4 in Section 4.3). I construct the rate coefficients matrix  $K$ , using the rate coefficients ( $k_i$ ) for airflow and deposition, yielding a matrix with 62 rows and 62 columns (32 outdoor boxes and 30 indoor boxes). Each column in the  $K$  matrix represents a source compartment and each row represents a destination compartment, so that diagonal elements represent the total loss of PM<sub>2.5</sub> from a compartment (sum of rate constants for airflow to other compartments and deposition) and all other elements represent the airflow from a source compartment (column) into a destination compartment (row). The concentration of primary PM<sub>2.5</sub> in each compartment is calculated as in equation 4.7 in Section 4.3, using the FF matrix, emissions from each source compartment and dimensions of each destination compartment.

The flowchart in Figure 4.2 shows the pathway to estimating PM2.5 and sulfate iF and concentrations in this model. All airflow rate coefficients are derived with the USEtox model as the reference for outdoor compartments (Bijster et al. 2017), Fantke et al.'s model (Fantke et al. 2017) as the basis for indoor compartments and Venkataraman et al.'s work for sulfate formation pathway (Venkataraman et al. 1999; Venkataraman et al. 2001), while wet deposition rate coefficients are from Jolliett and Hauschild (Jolliet & Hauschild 2005). The orange boxes in Figure 4.2 represent the key inputs needed for calculating model outputs; the blue, green and yellow boxes represent the model outputs (intermediate and final) for primary PM2.5, sulfate and sulfur dioxide respectively. Details on calculations of rate coefficients are included in Appendix C Section C.3 and details on constant terms used in each equation are provided in Appendix C Section C.2.



**Figure 4.2** Pathway for model calculations: Concentrations and iF of primary PM2.5 and sulfates (*k* are the rate constants for airflow, deposition and chemical transformation that form the rate coefficients matrix *K*)

This section first describes how the rate coefficients matrix  $K$  for primary PM<sub>2.5</sub> is constructed (Section 4.5.1) and then describes how secondary sulfate formation is modelled (Section 4.5.2). Section 4.5.3 provides an estimated range for the fractional contribution of other secondary aerosols (inorganic and organic) to total PM<sub>2.5</sub> from previous studies.

#### 4.5.1 Primary PM<sub>2.5</sub>

Indoor compartments transfer PM<sub>2.5</sub> through deposition ( $k_{\text{dep\_indoors}}$ ) and outflow of air to enclosing outdoor compartment ( $k_{\text{indoor-outdoor}}$ ), and through inflow of air from outdoor compartments ( $k_{\text{outdoor-indoor}}$ ). Constant values for  $k_{\text{dep\_indoors}}$  and  $k_{\text{indoor-outdoor}}$  are assumed, specific to average structural house characteristics in India (Rosenbaum et al. 2015), and  $k_{\text{outdoor-indoor}}$  is modelled as a function of indoor and outdoor compartment dimensions (see Appendix C Section C.2). I assume a breathing rate of 16 m<sup>3</sup>/day and 90% of time spent indoors for the base model run (Fantke et al. 2017).

The innermost outdoor boxes within a rural box, i.e., urban or high-density urban boxes, exchange air with the enclosing rural or urban boxes respectively; the rate constant for outward airflow ( $k_{\text{airflow}}$ ) is given by the inverse of residence time in the box and is a function of area and wind speed in the box. For all other outdoor boxes,  $k_{\text{airflow}}$  is given by the sum of airflow to compartments within and the outer enclosing compartment. All equations for airflow rate coefficients and derivations of equations are provided in Appendix C Section C.3.1. Apart from airflow out, outdoor compartments also transfer PM<sub>2.5</sub> through deposition ( $k_{\text{mean deposition}}$ ), which is a combination of dry deposition ( $k_{\text{dry}}$ ) and wet deposition ( $k_{\text{wet}}$ ) processes (see Appendix C Section C.3.2 for calculation of  $k_{\text{mean deposition}}$ ).  $k_{\text{dry}}$  is a function of assumed constant dry deposition velocity

of primary PM<sub>2.5</sub> and mixing height of a compartment;  $k_{\text{wet}}$  depends on average mixing height and rainfall in a compartment, and assumed constants for average duration of dry and wet periods and aerosol collection efficiency of rain (see Appendix C Section C.3.2 for details). Table 4.3 gives the total loss rate coefficients for indoor and outdoor compartments.

iF dependence on emission stack height: For primary PM<sub>2.5</sub>, the iF matrix gives the average iF, weighted over emissions from different stack heights. The share of PM<sub>2.5</sub> emissions from high, low and ground stacks in each compartment is calculated using the available emissions inventory (Sadavarte & Venkataraman 2014; Pandey et al. 2014) (see Appendix C Section C.4.1 for stack categories of emission sources). Ratios of iF for stack height categories ‘ground’, ‘low’, and ‘high’ ( $X = iF_{\text{ground}}/iF_{\text{low}}$  and  $Y = iF_{\text{low}}/iF_{\text{high}}$ ) (Humbert et al. 2011), specific to regional archetypes defined by population density, are then used to calculate stack-height specific iF values for urban and rural compartments (see Appendix C Section C.4.2 for equations). The values of X and Y used are: X = 2.9 for urban and 1.9 for rural compartments, and Y = 1.3 for urban and 1.2 for rural compartments.

#### **4.5.2 Sulfate aerosols**

Formation of secondary PM<sub>2.5</sub> in the form of particles containing sulfate ions is modeled in three steps based on the work by Venkataraman et al. (1999; 2001).

a) Estimating the equilibrium concentration of SO<sub>2</sub> in each compartment:

In this model, SO<sub>2</sub> is removed from an outdoor compartment through airflow, dry deposition, gaseous stage conversion to SO<sub>4</sub><sup>2-</sup> ion through reaction with hydroxyl radicals (rate constant =

$K_{OH}$ ) and through delivery to clouds (rate constant =  $k_{cloud}$ ), a fraction of which transforms into  $SO_4^{2-}$  ion ( $F_{cc} * k_{cloud}$ ) (Venkataraman et al. 1999; Venkataraman et al. 2001; Seinfeld & Pandis 2006b). See Appendix C Section C.3.3 for details on the sulfate formation pathway and Appendix C Section C.3.4 for equations of sulfate formation in clouds. Wet deposition of  $SO_2$  is ignored since it accounts for less than 10% of removal (Venkataraman et al. 1999). For indoor  $SO_2$  emissions, only airflow and deposition are considered as removal mechanisms. Table 4.3 gives the rate coefficients of  $SO_2$  removal from outdoor ( $k_{tot\_outdoor}$ ) and indoor ( $k_{tot\_indoor}$ ) compartments.

Rate coefficients for dry deposition and airflow ( $k_{dry}$  and  $k_{airflow}$ ) are calculated as outlined for primary  $PM_{2.5}$  above (dry deposition velocity of  $SO_2$  provided in Appendix C Section C.2). From the rate coefficients matrix I calculate the fate factor matrix, and the equilibrium concentration of  $SO_2$  in each compartment using the methodology outlined in Section 4.3.

b) Estimating sulfate ion formation:

The equilibrium mass of  $SO_2$  in outdoor compartments oxidizes to form sulfate ions in the gaseous phase, through its reaction with hydroxyl radicals (see Appendix C Section C.3.3 for equations), and in the aqueous phase primarily through reactions with  $O_2$ ,  $O_3$  and  $H_2O_2$ , when an air parcel containing  $SO_2$  reaches clouds (see Appendix C Sections C.3.3 and C.3.4).

c) Equilibrium concentration of sulfate ions:

In this model  $SO_4^{2-}$  formed in each compartment from gaseous and aqueous phase reactions of  $SO_2$  undergoes similar removal processes as primary  $PM_{2.5}$  through airflow and dry and wet deposition. I construct a rate coefficients matrix (dry deposition velocity of sulfate in Appendix C

Section C.2) and calculate FF and iF matrices and equilibrium concentration of  $\text{SO}_4^{2-}$  using the method described in Section 4.3.

I assume that sulfate formation in model compartments occurs at the same height irrespective of stack height of  $\text{SO}_2$  emissions, since the primary sulfate pathway is the in-cloud transformation of  $\text{SO}_2$ .

Description	Total removal rate coefficients for compartments
Rate constant for loss of PM2.5 in indoor compartments	$k_{\text{indoors}} = k_{\text{dep\_indoors}} + k_{\text{indoor-outdoor}}$
Rate constant for loss of PM2.5 in outdoor compartments	$k_{\text{tot}} = k_{\text{airflow out}} + k_{\text{mean deposition}}$
Rate constant for loss of $\text{SO}_2$ in outdoor compartments	$k_{\text{SO}_2\_outdoor} = k_{\text{dry}} + k_{\text{airflow}} + K_{\text{OH}} + (F_{\text{cc}} * k_{\text{cloud}})$
Rate constant for loss of $\text{SO}_2$ in indoor compartments	$k_{\text{SO}_2\_indoor} = k_{\text{dep\_indoor}} + k_{\text{indoor} > \text{outdoor}}$

**Table 4.3** Rate coefficients for total removal of PM2.5 and  $\text{SO}_2$  from model compartments (see Appendix C Section C.3 for derivations)

### 4.5.3 Other secondary aerosols

The contributions of nitrate and ammonium individually to total measured PM<sub>2.5</sub> concentrations are in the range of 1-11% from six previous studies in urban locations<sup>23</sup> (M. Z. Chowdhury 2004; Behera & M. Sharma 2010; Rengarajan et al. 2011; Ram & Sarin 2011; R. Kumar et al. 2006; Chatterjee et al. 2012) and one in a rural location (Mount Abu) (A. Kumar & Sarin 2010). Location-specific ratios of secondary inorganic aerosols (SIA) to primary PM<sub>2.5</sub> from previous studies in India are presented in Appendix C Table C.7. I derive a mean of 8.4% for aggregate nitrate and ammonium SIA contribution to total PM<sub>2.5</sub> concentrations, although greater ammonium concentrations in rural areas is likely due to agricultural emissions (Witkowska et al. 2016).

Estimating SOA is more difficult due to uncertainties in emissions of precursor hydrocarbons and the wide range of secondary compounds formed through condensation of hydrocarbons (Nagar et al. 2017; Guo et al. 2017). SOA estimates show a wider variation - 12-14% in winter and 6% in summer in Delhi (Nagar et al. 2017; Pipal et al. 2014), 18% in winter and 12% in summer in Kanpur (Behera & M. Sharma 2010), 3-7% in north India (Guo et al. 2017), 7.5 - 30% in Agra in winter (Pipal et al. 2014; T. Pachauri et al. 2013) and 11% in the Bay of Bengal in summer (Shohel et al. 2018). I assume that SOA contributes 10-15% of total PM<sub>2.5</sub> contributions.

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<sup>23</sup> Delhi, Kolkata, Mumbai, Chandigarh, Ahmedabad and Kanpur

Thus, modelled values for PM<sub>2.5</sub> concentrations, which include primary PM<sub>2.5</sub> and sulfates, can be expected to account for about 80% of total PM<sub>2.5</sub> concentrations, considering the range of nitrate and ammonium and SOA in literature.

#### **4.6 Model validation and Sensitivity analysis**

The modeling framework adopted is transparent and of low complexity, and highlights the seasonal and spatial differences in iF and PM<sub>2.5</sub> concentrations. Two things are examined in this section – one, how iF estimates from this model, taking regional variations in population density and seasonal meteorology into account, compare to a high level aggregate model; and two, how model estimates of PM<sub>2.5</sub> concentrations, using an India-wide inventory of PM<sub>2.5</sub> and SO<sub>2</sub> emissions, compare with results from a more complex dispersion modeling framework and/or observations. Two different validation exercises are performed by comparing the model output to prior modeling studies. First, indoor and outdoor intake fraction values for primary PM<sub>2.5</sub> predicted by this model are compared with past work done by Fantke et al (2017). I expect modelled iF values to differ from Fantke et al.'s study, particularly in regions which vary considerably from nation-wide mean values of population density and meteorological parameters assumed by Fantke et al. Second, model results for primary and secondary PM<sub>2.5</sub> concentration are compared with data synthesis done by the GBD-MAPS study (GBD MAPS Working Group 2018). The GBD-MAPS study estimates PM<sub>2.5</sub> concentrations across India in the following steps: it first uses the emissions inventory used in this paper (Sadavarte & Venkataraman 2014; Pandey et al. 2014), as input in the atmospheric chemical transport model GEOS-CHEM to model the spatial distribution of PM<sub>2.5</sub> exposure across India; it then combines these estimates with satellite-based data on aerosol optical depth and surface measurements from more than 400 stations in India

to generate estimates for ambient PM<sub>2.5</sub> concentrations. I expect modelled concentration estimates, which include primary and secondary sulfate PM<sub>2.5</sub>, to capture about 80% of ambient concentrations, particularly in areas with low influence from unaccounted pollution sources, i.e. marine sources and neighbouring countries' emissions.

The majority of model parameters are derived from the meteorological, census and emissions inventory databases, and are not easily amenable to conventional sensitivity analyses. The sensitivity of model outputs to four key sets of parametric assumptions in the model are analyzed:

1. indoor box characteristics (occupancy and air exchange rate with outdoor box),
2. exposure characteristics (time period of indoor exposure and breathing rate of individuals),
3. deposition rate (dry deposition velocities of primary PM<sub>2.5</sub>, sulfate PM<sub>2.5</sub> and SO<sub>2</sub>; aerosol washout rate of PM<sub>2.5</sub> by precipitation), and
4. the dependence of sulfate formation on the characteristics of clouds over India.

The following base case is considered (see Section 4.6.3 for details):

Variable class	Variable	Assumed value
Indoor box	Occupancy	High = 30m <sup>3</sup> /person
	Air exchange rate with outdoors	High = 14 hr <sup>-1</sup>
Exposure	Time spent indoors	90%
	Breathing rate of individuals	16 m <sup>3</sup> /day

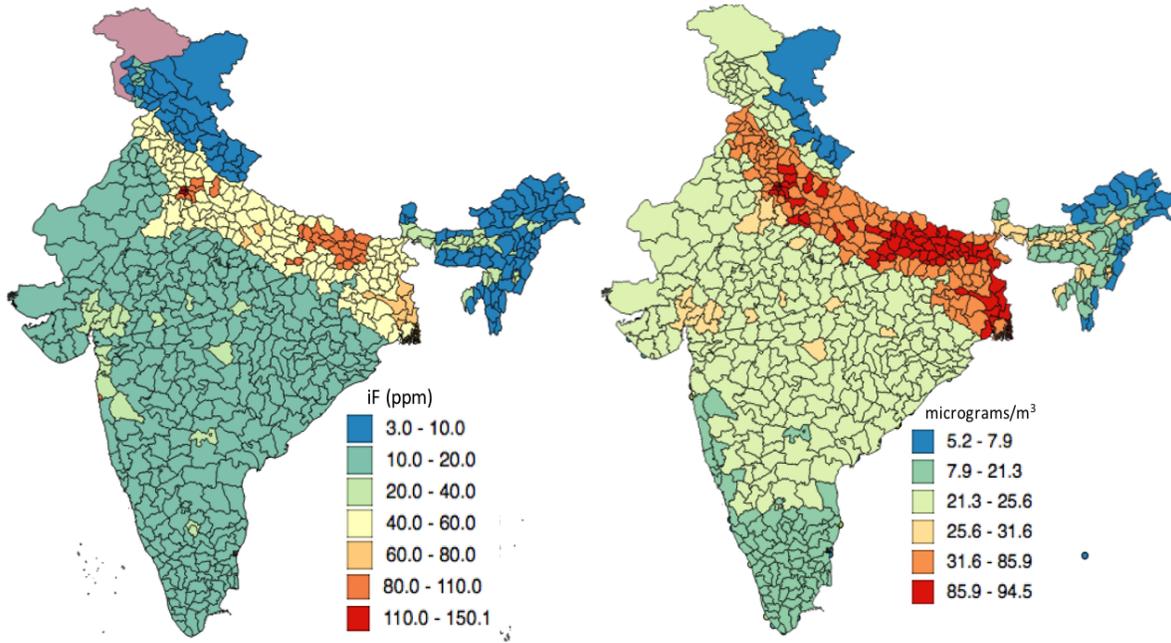
Variable class	Variable	Assumed value
Deposition	Dry deposition velocity of primary PM2.5	0.1 cm/s
	Dry deposition velocity of SO <sub>2</sub>	0.6 cm/s
	Dry deposition velocity of secondary sulfate	0.2 cm/s
	Aerosol washout ratio by precipitation	2E+05
Cloud conditions	pH	5
	Residence time in clouds	40 minutes
	Time period between cloud encounters	34 hours

**Table 4.4** Assumed values for the base case model run

I run the model for the base case and perform sensitivity analyses for these four classes of variables.

The key model outputs are iF and concentrations of PM2.5 (primary and sulfate). iF of sulfate PM2.5 is half of primary PM2.5 across the country due to greater dry deposition velocities of sulfate particles. iF of SO<sub>2</sub> depends on sulfate formation from SO<sub>2</sub> in clouds and the seasonal variation in cloud cover (derived from MODIS data – see Appendix C Section C.2). Figure 4.3 shows the spatial variation of estimated mean annual iF of primary PM2.5 and PM2.5 concentrations (primary PM2.5 + sulfate) across India. iF values for primary PM2.5 range from 3 ppm, in rural areas of the sparsely populated far north or north eastern parts of the country, to 150 ppm in densely populated cities of the northern Indo-Gangetic Plain (IGP) such as Delhi. Intake fraction values in the IGP are high in general due to high population density and low winter

atmospheric mixing height in the region. Annual mean PM<sub>2.5</sub> concentrations are the highest in the densely population northern IGP and lowest in the far north/north eastern parts of India and in the peninsular South surrounded by sea. The average sulfate to primary PM<sub>2.5</sub> ratio is 0.53.



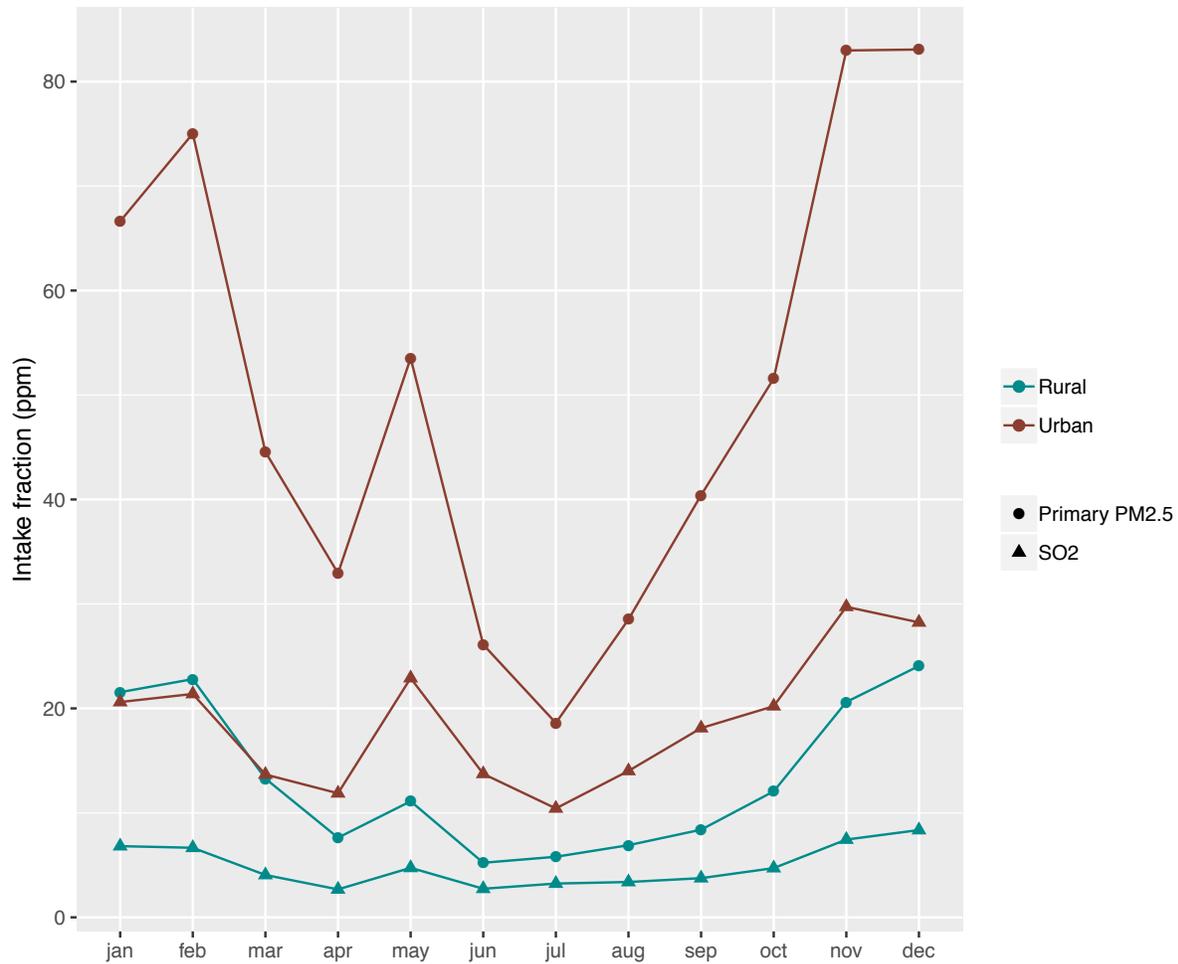
**Figure 4.3** Spatial variation in mean annual intake fraction (iF) of primary PM<sub>2.5</sub> and modelled PM<sub>2.5</sub> concentrations (primary + sulfate)

#### 4.6.1 Model comparison for intake fraction

The mean intake fraction (assuming the base case noted above) for ambient primary PM<sub>2.5</sub> sources in urban and rural areas is estimated as 51 ppm (sd = 29.0 ppm) and 14ppm (sd = 4.6ppm) respectively. For secondary sulfate emissions, the estimated mean iF for urban and rural areas are 28.1 ppm (sd=15.8 ppm) and 7.8 ppm (sd=2.6 ppm) respectively. The estimated mean iF for SO<sub>2</sub> emissions in urban and rural areas are 18.74 ppm (sd=6.26 ppm) and 4.88 ppm (sd=1.95 ppm) respectively. Intake fractions for indoor exposure are much greater. The mean rural indoor intake

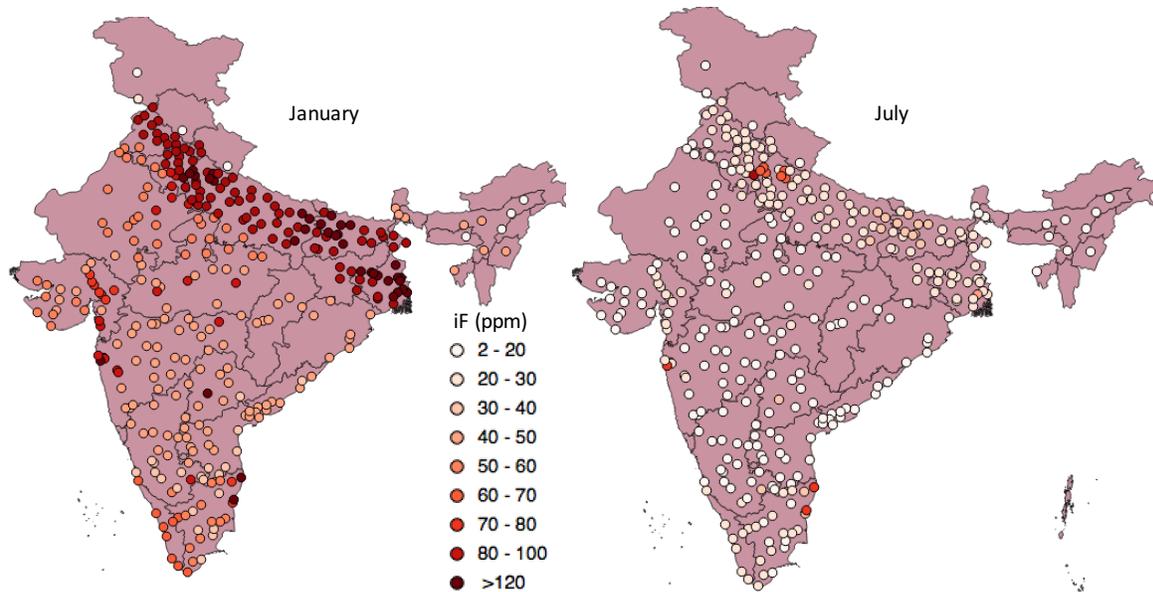
fraction is 1429 ppm (1420 – 1434 ppm), while the mean urban indoor intake fraction is 1466 ppm (1426 – 1565 ppm).

Outdoor intake fraction values, particularly urban iF, show strong seasonal as well as spatial differences, due to variation in population density and meteorology (mixing height, wind speed and precipitation). Figure 4.4 shows the monthly variation in mean outdoor iF of primary PM<sub>2.5</sub> and SO<sub>2</sub>. Outdoor intake fraction values are the lowest during the monsoon (June-August) when higher levels of precipitation lead to greater wet deposition of PM<sub>2.5</sub>, and highest during winter (November – February) when low levels of mixing heights, wind speed and precipitation lead to presence of stagnant air masses and high concentrations of air-borne pollutants. Except in southern peninsular India where the monsoon begins early (end-May), the rest of the country experiences very low monthly rainfall in May, which leads to the relatively high iF in May in Figure 4.4. This is particularly prominent in urban India (population density > 400 p./sq.km.), driven by the Indo-Gangetic Plain recording the least rainfall in May in the year. Average rainfall in the region in May is 1.7 mm, while average monthly rainfall is higher in the rest of the year – 4-22mm during winter (Nov-Feb), 40-60mm in spring/autumn (March/April/September/October) and 38-308mm during the monsoon.



**Figure 4.4** Seasonality in modelled iF for urban and rural locations in India  
*(Note: 'urban' is defined as districts with population density > 400 p./sq.km.)*

Figure 4.5 shows ground-level iF estimates from this model for 337 cities (the cities considered in the study by Fantke et al.(2017)) for the months of January and July – on average modelled January iF values are higher than July values by a factor of 3, with the least difference observed in southern India, where January values are 30% higher than July.



**Figure 4.5** Model estimates for ground-level intake fraction (iF) for 337 cities: January and July

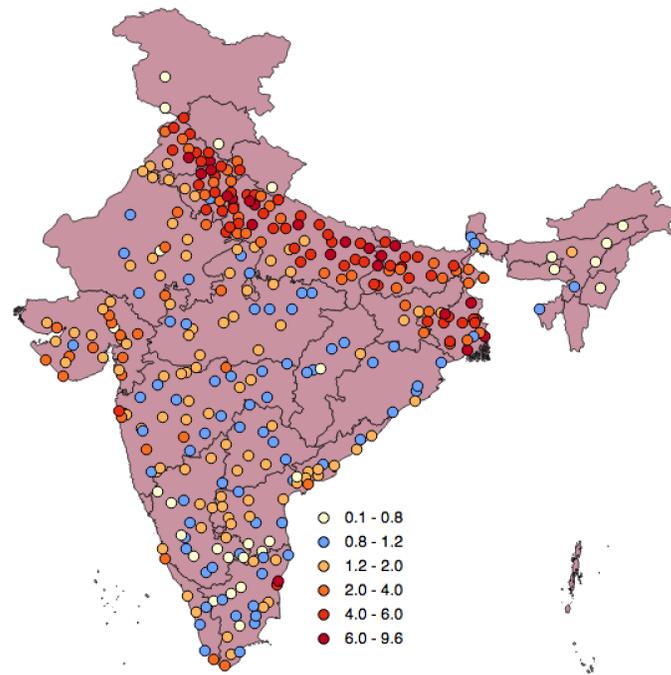
Modelled intake fraction estimates for primary PM<sub>2.5</sub> are compared to estimates by Fantke et al. (2017) for 337 cities in India. The comparison for average indoor and outdoor iF for urban and rural India, and for source stack height categories: ground-level, low and high is shown in Table 4.5, along with the range of modelled iF obtained from sensitivity analysis (see Section 4.6.3 for details). Model estimates for mean outdoor urban and rural iF are higher by 27% and 78% respectively and estimates for January are 2-5 times higher than mean annual estimates by Fantke et al.(2017), while those for July are about 25% lower.

	Indoor		Outdoor					
	Urban	Rural	Urban			Rural		
Stack height category			Ground	Low	High	Ground	Low	High
This model (range)	754-12677	754-12652	50-167	17-57	13-44	11-52	6-27	5-23
This model (base case)	1466	1429	92	32	24.5	22	11.5	9.5
(Fantke et al. 2017)	1483	1420	70	24	19	6.3	2.2	1.7

**Table 4.5** Modelled iF (ppm) compared to Fantke et al.'s (2017) study

Figure 4.6 shows the ratio of ground-level iF values from this model to those from Fantke et al.'s study (2017) for 337 cities in India. Modeled intake fractions show the largest deviation for cities in the IGP - the Normalized Mean Bias (NMB) relative to Fantke et al.'s values is 2.85 (see Appendix C Section C.5.2 for details) - and the least deviation in South India (NMB=0.07). These findings are consistent with the differences in the two approaches. Fantke et al. assume that the rural areas surrounding all cities have a uniform population density (100 people/km<sup>2</sup>), a uniform mixing height (1000m) and uniform rainfall (60mm/month). In this model, the regions surrounding urban areas vary considerably in terms of population density and meteorology; the average rural population density is higher, at 237 people/km<sup>2</sup>, and rural mixing heights vary between 150m to 1170 m depending on season and location in this model. Further, the densely populated IGP, has

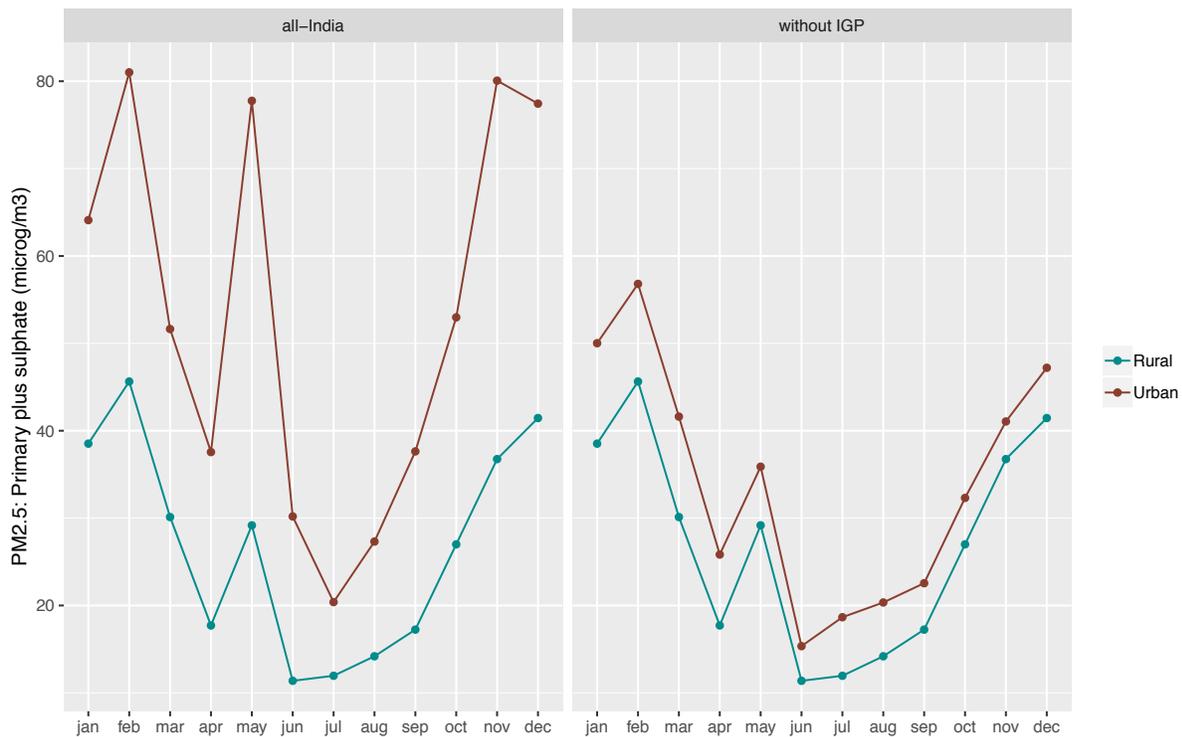
a higher population density (mean= 760 people/km<sup>2</sup>) and lower levels of precipitation relative to other parts of the country, leading to considerably higher intake of emissions (see Appendix C Section C.5.1 for a map showing spatial variation in these parameters across regions).



**Figure 4.6** Ratio of modelled ground-level iF compared to Fantke et al.'s study (2017) for 337 cities in India

#### **4.6.2 Model validation for PM<sub>2.5</sub> concentrations**

The model estimates for mean monthly concentration of PM<sub>2.5</sub> (primary PM<sub>2.5</sub> + secondary sulfate) in urban and rural India are shown in Figure 4.7. Figure 4.7 shows both all-India and India minus the Indo-Gangetic Plain, to highlight the high concentrations of PM<sub>2.5</sub> in the IGP. In particular, high concentrations of PM<sub>2.5</sub> in the IGP are driven by seasonal agricultural residue burning in both May and in October/November. Overall, agricultural residue burning is the second most significant source of PM<sub>2.5</sub> in the region after cooking with biomass.

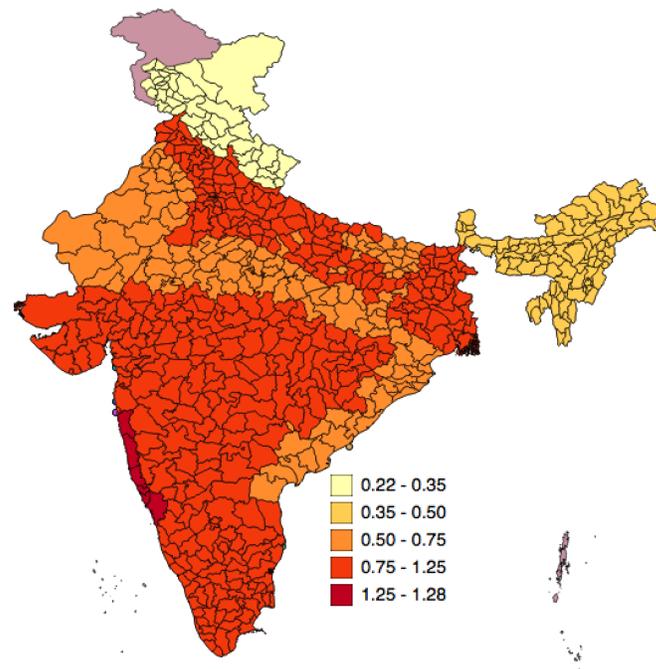


**Figure 4.7** Modelled PM2.5 concentrations: all-India and without IGP

*\*To highlight the significance of agricultural residue burning in northern India in May and Oct-Nov (Note: the IGP is densely populated and classified as 'urban' in spite of including agricultural areas)*

Modelled PM2.5 concentrations (primary PM2.5 + secondary sulfate) are compared to simulated total PM2.5 concentrations from the GBD-MAPS study which includes primary aerosols, secondary  $\text{SO}_4^{2-}$ ,  $\text{NO}_3^-$ ,  $\text{NH}_4^+$  and secondary organic aerosols; the concentrations from this model can be expected to account for up to 80% of PM2.5 concentrations in GBD-MAPS study. PM2.5 concentrations from GBD-MAPS that are available at  $0.1^\circ \times 0.1^\circ$  resolution are aggregated to the level of model compartments for comparison with this model. Figure 4.8 shows the ratio of modelled mean annual concentration to average modelled annual PM2.5 concentrations for 2015 from the GBD study. This model considerably underestimates concentrations in the north and

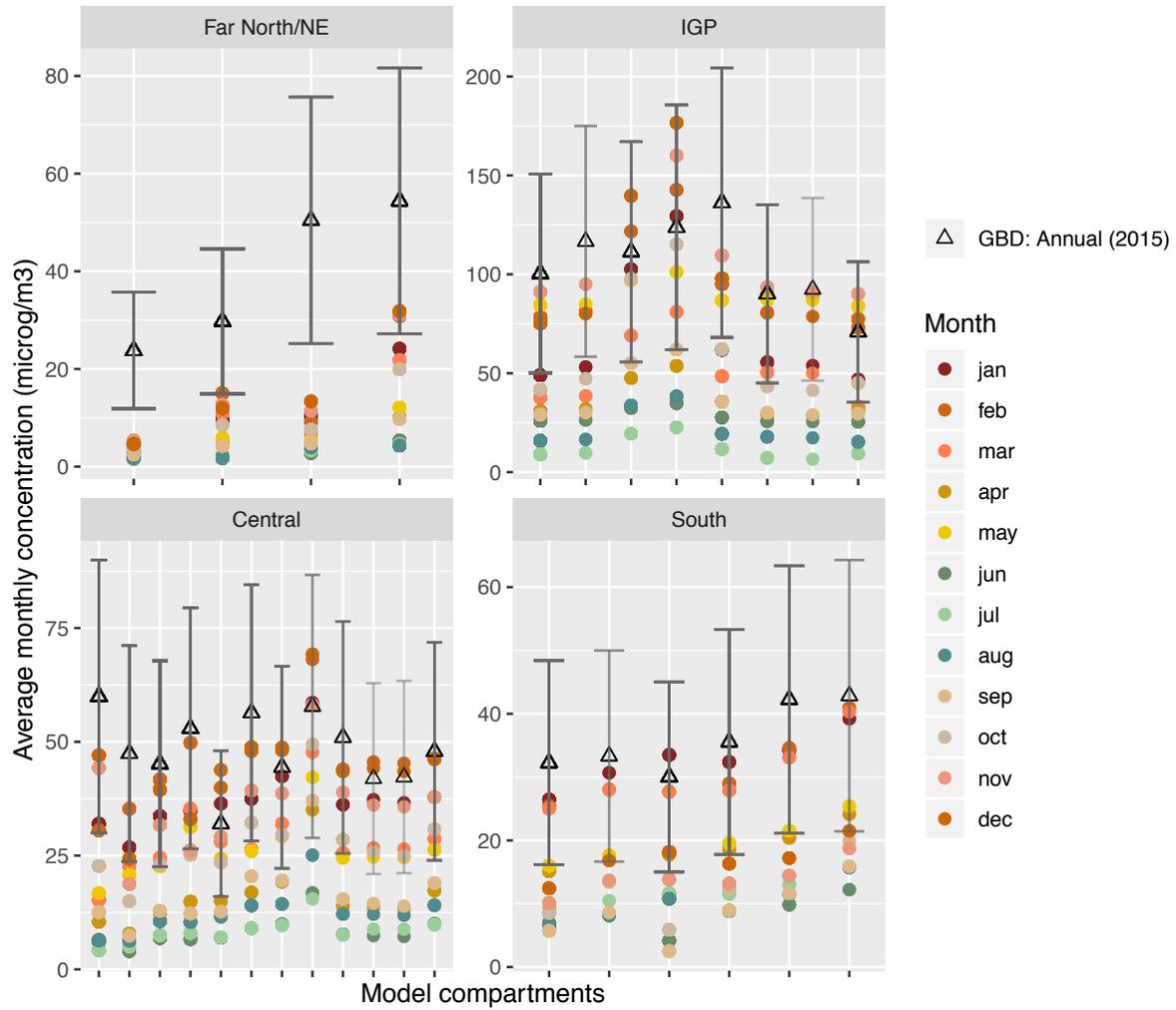
north-eastern region (average ratio between 0.22 and 0.35), while the average ratio is between 0.5 and 1.28 for the other regions. Normalized Mean Bias (NMB) relative to GBD concentrations for 2015 is 27% (details in Appendix C Section C.5.3). I also calculate NMB relative to GBD concentrations by geographical region (Far North/NE, IGP, Central, South) and population class by district (1 = <400, 2= 400-1200, 3 = 1200-4000, 4 = >4000 p./sq.km.). The bias is lowest in densely populated regions - population class 4 of IGP (4%) and the South (-13%), and population classes 3 and 4 in Central India (13%) - while it ranges from -27% to -17% for the rest of the country except the Far North/North East compartment, where NMB is -65% to -60%.



**Figure 4.8** Ratio of modelled PM2.5 concentrations (primary PM2.5 + secondary sulfate) to simulated total PM2.5 concentrations from Global Burden of Diseases study  
(GBD concentrations aggregated to model compartment level)

On comparing the spatial pattern of modelled concentrations to those from the GBD study, the model successfully captures the highest concentrations in the IGP, followed by central India (about 40% of IGP concentrations) and then southern India (about 25% of IGP concentrations). Concentrations along the western border of India (in the state of Rajasthan) relative to IGP are underestimated and this is possibly due to the exclusion of neighbouring countries' (Pakistan in this case) emissions.

Figure 4.9 shows modelled monthly values of PM<sub>2.5</sub> concentrations (primary + SO<sub>4</sub><sup>2-</sup>) compared to total PM<sub>2.5</sub> concentration values from the GBD study (for 2015) by geographical region. The error-bars in figure 4.9 show a range of +/- 50% around the GBD 2015 values each model compartment. Modelled winter concentrations are closer to GBD estimates, compared to monsoon (June- August) concentrations which are the lowest in the year.



**Figure 4.9** Modelled monthly PM<sub>2.5</sub> (primary + sulfate) concentrations compared to Global Burden of Diseases 2015 estimates  
*GBD estimates are aggregated to compartment level. Note: the y-axis scale for each panel is different.*

### 4.6.3 Sensitivity Analysis

The modelled iF values depend on two matrices – Fate Factor (FF) matrix and Exposure Factor matrix (XF). The sensitivity of iF to FF parameters– indoor box<sup>24</sup> and deposition characteristics - and XF parameters – time period of exposure and breathing rate of individuals - is studied. In addition, I test the sensitivity of sulfate formation to assumed cloud characteristics (see Table 4.6 for a summary of results and Appendix C Figure C.5 for graphical representation of results).

Variable class	Variable	Base case value	Alternate value	Deviation from base case iF
Indoor box	Occupancy	High=30m <sup>3</sup> /person	Medium=67m <sup>3</sup> /person	iF (indoor mean) = +775%
	Air exchange rate with outdoors	High = 14 hr <sup>-1</sup>	Medium = 0.62 hr <sup>-1</sup>	iF (outdoor mean) = - 12%
Exposure	Time spent indoors	90%	Case 1: 80%/18 m <sup>3</sup> /day	iF (outdoor PM2.5/SO2 mean) = +13%
	Breathing rate of individuals	16 m <sup>3</sup> /day	Case 2: 95%/8 m <sup>3</sup> /day	iF (indoor mean) = no change iF(outdoor/indoor means) = -50%

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<sup>24</sup> Outdoor box characteristics primarily depend on meteorological data and Census data on district dimensions as input and sensitivity analysis on input databases is not conducted.

Variable class	Variable	Base case value	Alternate value	Deviation from base case iF
Deposition	Dry deposition velocity of primary PM2.5	0.1 cm/s	+50%/-50%	iF (outdoor urban) = -23%/+78%
	Dry deposition velocity of SO <sub>2</sub>	0.6 cm/s		iF (outdoor rural) = -36%/+150%
	Dry deposition velocity of secondary sulfate	0.2 cm/s		iF (SO <sub>2</sub> urban) = -26%/+74%
				iF (SO <sub>2</sub> rural) = -40%/+140%
	Aerosol washout ratio by precipitation	2E+05	(2E+05*5)/ (2E+05/5)	
Cloud conditions*	pH	5	6.5/7	iF (SO <sub>2</sub> urban) = -74%/+174%
	Residence time in clouds	40 minutes	12 minutes	iF (SO <sub>2</sub> rural) = -80%/+180%
	Time period between cloud encounters	34 hours	12 hours/56 hours	

**Table 4.6** Summary of results for sensitivity analysis

\* See Appendix C Table C.11 for detailed results

#### 4.6.3.1 Sensitivity of iF to FF parameters: indoor box and deposition rates

The sensitivity of model output to two key indoor box parameters is examined – occupancy ( $V$ =volume of air available to each individual) and indoor-outdoor air exchange rate (see Appendix C Section C.2 for indoor parameters used in the model). The base case assumes high occupancy ( $V=30\text{m}^3/\text{person}$ ) and high air exchange rate ( $14\text{ hr}^{-1}$ ) (Fantke et al. 2017). Medium occupancy ( $V=67\text{m}^3/\text{person}$ ) and medium air exchange rate ( $0.62\text{ hr}^{-1}$ ) conditions (Fantke et al. 2017), which may be more representative of urban middle/high income households, lead to an increase in indoor iF from 1448 ppm (base case mean) to 12675 ppm. However, indoor solid fuel use and kerosene lighting is more prevalent in rural and low income urban households (Ailawadi & Bhattacharyya 2006; S. Pachauri & Jiang 2008), where base case model assumptions for occupancy and air exchange rate seem appropriate. Medium air exchange rate assumptions also lead to a 12% reduction in outdoor iF due to reduced transfer of outdoor air indoors.

The FF matrix depends on loss of PM<sub>2.5</sub> through dry and wet deposition. The base case assumes mean values of aerosol washout rate ( $2\text{E}+05$ ) and dry deposition velocities of primary PM<sub>2.5</sub> ( $0.1\text{cm/s}$ ), sulfate PM<sub>2.5</sub> ( $0.2\text{cm/s}$ ) and SO<sub>2</sub> ( $0.6\text{cm/s}$ ) from literature (see Appendix C Section C.2). The sensitivity of model output to the range of values for dry and wet deposition suggested in literature is examined: +/-50% for dry deposition velocities (Xu & Carmichael 1998; Jitto et al. 2007; Zhang 2001; Wesely et al. 1985);  $(2\text{E}+05)*5$  and  $(2\text{E}+05)/5$  for aerosol washout rate (Bidleman 1988). Considering the base case mean iF value of 51ppm for urban and 14ppm for rural emissions, urban iF changes by -23% to 78%, and rural iF varies by -36% to 150% with greater or lesser deposition.

#### **4.6.3.2 Sensitivity of iF to XF parameters: time spent indoors and breathing rate**

I conduct a sensitivity analysis for intake fraction values to the fraction of daily time spent indoors ( $f_{\text{indoor}}$ ) and breathing rates of individuals (BR), currently assumed to be 0.9 and  $16\text{m}^3/\text{day}$  (Fantke et al. 2017). Two cases are considered: one,  $f_{\text{indoor}} = 0.8$ , to estimate exposure for workers who spend a greater fraction of their day outside of their homes and assume that any time spent outside of homes are spent outdoors, and  $\text{BR}=18\text{m}^3/\text{day}$  to represent active adults who have higher inhalation rates (Klepeis & Nazaroff 2006; C. A. Pope et al. 2009); two,  $f_{\text{indoor}}= 0.95$  and  $\text{BR}=8\text{m}^3/\text{day}$  to represent children and inactive women who spend majority of their day at home (Klepeis & Nazaroff 2006) . For active adult workers, intake fraction of outdoor emissions is estimated to be higher by 13% compared to the base case, while indoor iF remains unchanged due to the combined effect of less time spent indoors and higher breathing rate. On the other hand, outdoor and indoor iF for children/inactive females who spend most of their time at home are estimated at half of the base case, primarily driven by lower breathing rates.

#### **4.6.3.3 Sensitivity of sulfate yield to cloud characteristics**

Modelled sulfate concentrations are half of the primary PM<sub>2.5</sub> concentrations on average, with the aqueous phase reaction of  $\text{SO}_2$  in clouds as the primary pathway to  $\text{SO}_4^{2-}$  formation. Thus, assumptions about cloud conditions have a significant impact on sulfate yield. I conduct a sensitivity analysis for three key cloud parameters: cloud pH (values ranging from 5 to 7), residence time of sulfate in clouds (12 minutes for cumulonimbus and 40 minutes for cumulus, stratocumulus and stratus clouds (Venkataraman et al. 2001)) and time period between cloud encounters (12-56 hours (Venkataraman et al. 2001)).

In the base case, a global average cloud pH of 5 is assumed (Meng & Seinfeld 1994; Venkataraman et al. 2001); studies in India indicate a pH of 5.2-7.2 (Kulshrestha et al. 2003; Khemani et al. 1987; Tiwari et al. 2012) during the monsoon. Other assumptions include an average period of 34 hours between cloud encounters and the in-cloud sulfate residence time for cumulus, stratocumulus and stratus clouds (40 minutes) (Venkataraman et al. 2001); cloud type over India is primarily dominated by stratocumulus and stratus clouds, followed by cumulus and deep convection clouds (Gupta & Kapoor 2011). For the base case assumptions the mean modelled sulfate concentrations are  $17.3 \mu\text{g}/\text{m}^3$  (urban) and  $10.2 \mu\text{g}/\text{m}^3$  (rural).

Sensitivity analysis results show that higher cloud pH leads to lower  $\text{SO}_4^{2-}$  yield and concentrations – a shift in pH from 5 to 6.5 reduces  $\text{SO}_4^{2-}$  concentrations by 39%. Assuming a lower in-cloud residence time of 12 minutes, typical of cumulonimbus clouds, reduces  $\text{SO}_4^{2-}$  concentrations by 17%. Greater time period between cloud encounters (56 hours) reduces  $\text{SO}_4^{2-}$  concentrations by 30%, while if cloud encounters are more frequent (every 12 hours)  $\text{SO}_4^{2-}$  concentrations increase by 70%. Overall, the average modelled sulfate concentrations over India can range between 3.4-29.6  $\mu\text{g}/\text{m}^3$  (urban) and 2.0-17.1  $\mu\text{g}/\text{m}^3$  (rural) (see Appendix C Section C.5.4 for results of sensitivity analysis).

#### **4.7 Discussion**

The simple atmospheric transport model developed to estimate the location-specific PM<sub>2.5</sub> intake fraction (iF) for indoor and outdoor emissions in India reveals several patterns about exposure to primary PM<sub>2.5</sub> and secondary sulfate particles. First, outdoor iF values show strong spatial

variability – with high intake fractions in the densely populated Indo-Gangetic Plain (IGP), even in relatively smaller towns and cities (mean modelled iF value in the IGP is 88ppm compared to 21ppm in the rest of the country). Second, outdoor iF is higher in the winter, when mixing height is low, than in the other seasons when mixing height and/or precipitation levels are higher. Modelled iFs in India range from 6ppm (rural mean) and 24ppm (urban mean) in monsoon (June-August) to 23ppm (rural mean) and 75ppm (urban mean) in winter (December-February). Third, indoor exposure is two to three orders of magnitude greater than outdoor exposure. Both indoor and outdoor exposures depend on assumptions about breathing rates of individuals; outdoor exposure also depends on parametric assumptions about deposition. Fourth, on average secondary sulfate aerosol concentrations are about half of primary PM<sub>2.5</sub> concentrations; iF of sulfur dioxide varies between 4ppm and 30ppm across India and across seasons, and is strongly dependent on assumed cloud characteristics.

On comparing the model results with the study by Fantke et al. (2017), in which a nationwide uniform regional box encloses city ‘boxes’, the distinct impact of variation in population density and meteorology on iF values can be observed. Model estimates for the densely populated IGP are higher by more than a factor of two, due to the demographic and meteorological features specific to the region.

Model estimates for PM<sub>2.5</sub> concentrations, which include primary PM<sub>2.5</sub> and secondary sulfate emissions (about 80% of total PM<sub>2.5</sub>), are in general agreement with the simulated total PM<sub>2.5</sub> concentrations for 2015 from the Global Burden of Diseases (GBD) study (GBD MAPS Working Group 2018), except in the Far North/North-Eastern parts of the country, where the model underestimates concentrations by more than 65%; this is likely because this model considers PM<sub>2.5</sub> emissions from within India, and ignores emissions in neighbouring countries in the

vicinity such as Bangladesh in the North-East due to unavailability of detailed disaggregated regional emissions data. On comparing monthly values to annual PM<sub>2.5</sub> concentrations from the GBD study, modelled winter concentrations are observed to be close to the GBD estimates whereas concentrations during the monsoon are lower due to greater washout of PM<sub>2.5</sub> through rainfall and higher mixing heights than winter.

I acknowledge that emissions from marine sources in coastal areas are excluded from the emissions inventory used and are not part of modelled PM<sub>2.5</sub> concentrations. Some limitations of this modelling framework include: not considering the seasonal impact, particularly of the monsoons, on the fraction of time spent indoors or moisture content of biomass burnt. I also assume constant values of O<sub>3</sub>, H<sub>2</sub>O<sub>2</sub>, Fe and Mn concentrations as well as cloud pH across the year.

Overall, the model aids in understanding the spatial distribution of PM<sub>2.5</sub> exposure in India, as a function of regional population density and meteorology. Further work would involve an analysis of source and location-specific exposure to determine where regional policy efforts should be focused in order to provide the greatest human health benefits.

## **Chapter 5: Mortality burden and PM2.5 exposure due to ambient air pollution: a spatially and seasonally resolved source-specific analysis**

### **5.1 Introduction**

India ranks 2<sup>nd</sup>, after China, in terms of premature mortality attributed to ambient air pollution (more than 673,000 estimated deaths in 2017) (Health Effects Institute 2019). Fine particulate matter (PM2.5) concentration is the most commonly used indicator of air pollution levels (Cohen et al. 2017; Lim et al. 2012). Ambient PM2.5 concentrations in India show strong spatial variation - they are the highest in densely populated areas such as the northern Indo-Gangetic Plain (D. Sharma & Kulshrestha 2014; Brauer et al. 2012) and in large cities (Nesamani 2010; Guttikunda et al. 2014). PM2.5 exposure is also distinctly higher in some regions during winter months due to meteorological conditions such low atmospheric mixing height (Guttikunda & Gurjar 2011; Bisht et al. 2015).

The literature finds that primary sources of ambient PM2.5 emissions vary regionally. For example, biomass burning is seen as the most significant source in Agra (Villalobos et al. 2015; Agarwal et al. 2017), power plants in Vishakapatnam (Guttikunda, Goel, Mohan, et al. 2014), industries (steel, textiles, paper, agricultural processing, pharmaceuticals, paint manufacturing) in Hyderabad (Guttikunda & Kopakka 2014), while transport, power plants and brick kilns are of equal importance in Delhi (Guttikunda & Calori 2013). However, source contribution to PM2.5 *exposure* depends on emission ‘stack’ height, apart from population density and meteorology (Humbert et al. 2011). For example, while power plants and transport emissions might be

comparable in terms of total mass in cities, vehicular sources in proximity to the population may have a greater human health impact. Thus, efforts to tackle regional pollution issues would be better directed if the locally significant sources in terms of exposure are identified. Studies on attribution of PM<sub>2.5</sub> concentrations by source are so far limited to specific cities – Agra (Agarwal et al. 2017), Delhi (Bisht et al. 2015; Guttikunda & Calori 2013; M. Z. Chowdhury 2004), Mumbai and Kolkata (M. Z. Chowdhury 2004), Chennai and Vishakapatnam (Guttikunda, Goel, Mohan, et al. 2014) and Hyderabad (Guttikunda 2008; Guttikunda & Kopakka 2014), with two studies analyzing the source-contribution to ambient PM<sub>2.5</sub> concentrations at a national and state level (Venkataraman et al. 2018; Upadhyay et al. 2018). A national and regional scale attribution of PM<sub>2.5</sub> exposure to sources would help identify differences in policy efforts needed in different locations.

This study contributes to the literature by presenting a spatially and seasonally-resolved national scale analysis of ambient PM<sub>2.5</sub> exposure by source type, and consequent mortality burdens. The rest of the paper is organized as follows. Section 5.2 provides an overview of the data and model used in estimating PM<sub>2.5</sub> exposure, and Section 5.3 describes the methodology followed.

Source-specific ambient PM<sub>2.5</sub> inhaled is estimated using modelled location and season-specific intake fraction of PM<sub>2.5</sub> (the fraction of emitted PM<sub>2.5</sub> inhaled by the exposed population) from the atmospheric transport model developed in this thesis, and an economy-wide emissions inventory for 2015 (section 5.4). This includes the quantification of source-contributions, at a regional level (section 5.4.3) and in major cities (section 5.4.4), to PM<sub>2.5</sub> inhaled by the population. In Section 5.5, the nation-wide and regional mortality burden due to the ambient air pollution impact of each source is calculated to help identify emission sectors that contribute

significantly to PM<sub>2.5</sub> exposure and consequent health impacts. Section 5.6 ends with a discussion of results.

## **5.2 Data and model overview**

Data on anthropogenic PM<sub>2.5</sub> emissions for 2015 are obtained from the inventory developed by Venkataraman and co-workers (Sadavarte & Venkataraman 2014; Pandey et al. 2014). The inventory on PM<sub>2.5</sub> emissions classifies sources into four key categories: industry, residential, transport and agriculture sectors. Industrial emissions include thermal power, heavy industry (iron and steel, fertilizer, cement, mining), light industry and small-scale industries (such as dairy and brick kilns). Household emission sources include cooking (with biomass, kerosene and gas), kerosene lighting, diesel generator sets, and biomass use for water and space heating. Transport comprises on-road gasoline and diesel, and diesel in railways, while agricultural emissions include residue burning and diesel use in tractors and pump sets. Emissions are calculated at a grid of resolution 0.25 x 0.25 degrees. Monthly emissions are available for agricultural residue burning, space heating and water heating; for the remaining sectors, annual emissions are equally divided into months for the purpose of seasonal analysis of PM<sub>2.5</sub> exposures.

The PM<sub>2.5</sub> transport model developed in the previous chapter (Chapter 4) is used to estimate PM<sub>2.5</sub> intake fraction specific to emission sources across regions. In the multi-box framework used, the atmospheric domain over India is modeled as a set of multiple nested boxes, delineated by district level population density and airflow characteristics such as mixing height and proximity to sea. PM<sub>2.5</sub> transport between boxes, each of which is assumed to be well-mixed, is modelled considering one-dimensional air exchange between nested boxes and deposition

(through dry and wet processes). At equilibrium, the mass of primary PM<sub>2.5</sub> in any box is constant, and total inflow of pollutants is equal to total outflow. Steady state ‘fate’ factors, i.e. the fraction of a unit emission originating in a given box that ends up in other boxes, and exposure factors, i.e. the fraction of air in a box that is breathed in by the population residing in that box, are multiplied to yield intake fraction values. Sources are divided into residential and outdoor emissions with three stack heights (‘ground’, ‘low’ and ‘high’) in modelling intake fraction values (details in Appendix C).

In addition to estimating intake of primary PM<sub>2.5</sub>, the formation of secondary PM<sub>2.5</sub> in the form of sulfate aerosols, from SO<sub>2</sub> emissions, is modelled. As mentioned in Chapter 4, modelling the formation of other secondary aerosols is more complex due to uncertainties in chemical reactions, while sulfate formation chemistry is well-defined and sulfates form the bulk of secondary inorganic aerosols. In this model, SO<sub>2</sub> emissions are transferred from compartments through advection and dry deposition, and chemical transformation of SO<sub>2</sub> emissions to form sulfate ions: through gaseous phase reaction with hydroxyl radicals, and through dissolution in clouds and consequent reaction with O<sub>2</sub>, O<sub>3</sub> and H<sub>2</sub>O<sub>2</sub> are modelled. These secondary PM<sub>2.5</sub> in the form of sulfate ions then undergo the same physical processes as primary PM<sub>2.5</sub> to yield steady-state intake fraction values for secondary PM<sub>2.5</sub> in each box in the model. Details on the model can be found in Chapter 4<sup>25</sup>.

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<sup>25</sup> Model inputs include district-level demographic and meteorological data. There are 640 districts in India, with an average population of 382 p./sq.km. (ranging from 1 p./sq.km in

### 5.3 Method

The emissions inventory described above is used to calculate location and source-specific PM<sub>2.5</sub> intake, i.e., PM<sub>2.5</sub> inhaled by the entire population. Modelled iF values are location, month and emission stack height-specific. PM<sub>2.5</sub> intake (mg/day) is calculated by multiplying the modelled iF values (for primary PM<sub>2.5</sub> and SO<sub>2</sub>) with emissions of PM<sub>2.5</sub> and SO<sub>2</sub> from the inventory. Exposure contribution of each emission source is measured by estimating the total intake, i.e., the portion of total emitted PM<sub>2.5</sub> from the source that is inhaled by the population. Using the metric of total PM<sub>2.5</sub> inhaled by the population informs us of the population impact of a source – sources in more densely populated regions can be expected to have greater exposure significance in terms of their population health impact, than those in sparsely populated regions even if their emissions are comparable. As noted in Chapter 2, dose-response relationships between PM<sub>2.5</sub> exposure and health impacts are steep at low levels of exposure (C.A. Pope et al. 2009), which shows that even low levels of PM<sub>2.5</sub> exposure can be harmful for health.

The mortality burden due to each pollution source is estimated following Cohen et al. (2017) and Upadhyay et al. (2018). Modelled average annual PM<sub>2.5</sub> concentrations are associated with the

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Dibang Valley, Arunachal Pradesh, to 36,155 p./sq.km in North East Delhi). Meteorological maps are obtained from the DataMeet community, demographic data are from Census 2011 and hourly meteorological data for 2015 from the publicly available data repository Urbanemissions.info (Guttikunda et al. n.d.).

relative risk to four diseases (Ischemic Heart Disease (IHD), Chronic Obstructive Pulmonary Disorder (COPD), lung cancer and stroke) (Apte et al. 2015). The mortality burden due to ambient air pollution, adjusted to State-level baseline mortality rates (S. Chowdhury & Dey 2016) is then calculated as follows, and attributed to specific sources. This helps identify sources on which policy efforts can be focused on and that would provide the greatest health benefits in India. Nation-wide premature mortality burden due to four diseases (IHD, COPD, Lung cancer and Stroke) caused by air pollution is calculated as:

$$\sum_{ij} M = \sum_{ij} Y \times \sum_{ij} (RR - 1) / RR \times \sum_i P \quad \dots\dots\dots \text{Equation 5.1}$$

where  $M$  = Mortality burden (number of deaths) due to disease  $j$  in district  $i$ ,  
 $Y$  = state-specific baseline mortality rate of disease  $j$  in district  $i$  (S. Chowdhury & Dey 2016)  
 $RR$  = relative risk due to disease  $j$  in district  $i$ . This is estimated using a look-up table associating annual average PM<sub>2.5</sub> concentrations with relative risk, calculated using the Integrated Exposure-Response function developed for the Global Burden of Diseases study (Apte et al. 2015)  
 $P$  = population of district  $i$  from Census 2011. For IHD and Stroke, relative risk corresponding to annual average PM<sub>2.5</sub> concentration levels are available for five-year interval age groups above 25 (corresponding age data available from Census 2011), while relative risk is not differentiated by age for COPD and lung cancer.

I begin by estimating the mortality burden due to total PM<sub>2.5</sub> exposure from all emission sources, and then exclude each emission source from the exposure calculations and estimate

mortality. The difference between the two can be attributed to the additional mortality burden due to each emission source.

#### **5.4 Source contribution to PM<sub>2.5</sub> exposure**

In presenting the results of this model emission sources in the inventory are categorized into formal (heavy and light industries, thermal power and transport) and informal (residential, agriculture and small-scale industries) categories. This classification is done on the basis of ease of monitoring and regulation. Small-scale industries (such as brick kilns) can have substantial impacts on air quality for a host of reasons - they are numerous, widely dispersed and are thus difficult to monitor and regulate (Blackman 2000). They are often more pollution-intensive than formal sources, and tend to not use pollution control equipment or employ trained workers (Chattopadhyay et al. 2010). Residential and agricultural sources have similar features; they are both numerous and spatially distributed, and similarly difficult to monitor and regulate.

Consequently, most regulatory effort in India focuses on formal sources of air pollution, despite growing knowledge of the impact of small-scale industrial (Croitoru & Sarraf 2012; Guttikunda & Goel 2013) and agricultural sources (Sinha et al. 2014) on local and regional air quality.

Classifying sources and their health effects into formal and informal categories helps understand the extent to which current regulation addresses the air pollution problem.

##### **5.4.1 Indoor exposure**

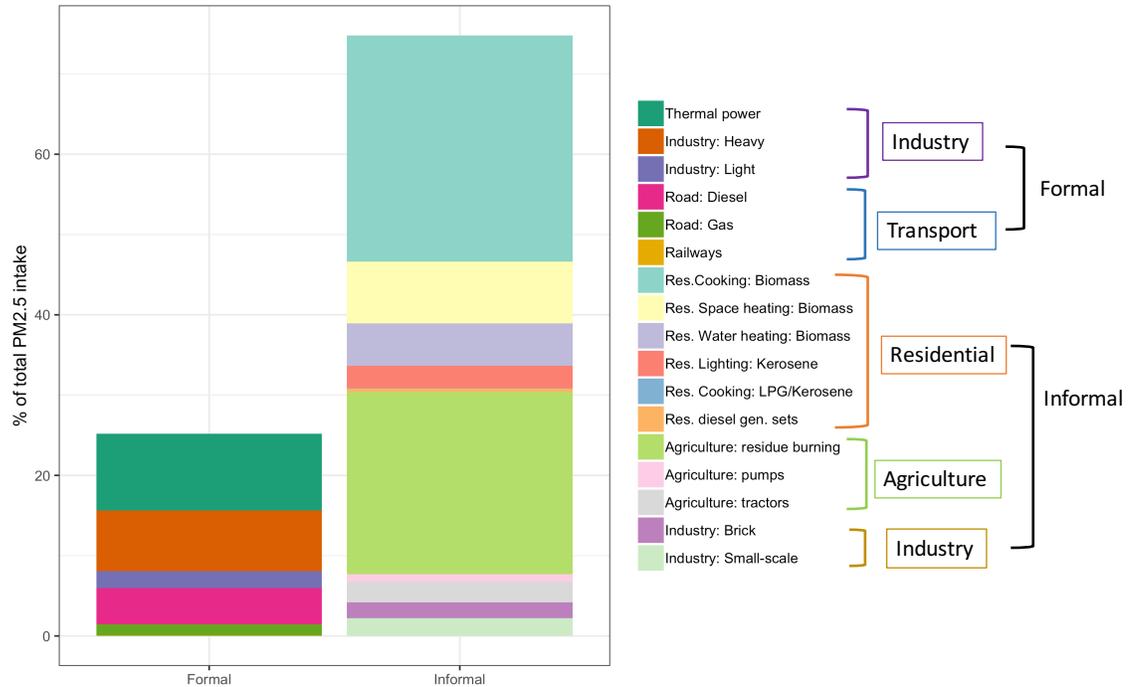
Indoor exposure to household fuels is far greater than outdoor exposure to air pollution.

Household fuels contribute about 95% to total (indoor and ambient) PM<sub>2.5</sub> inhaled, across all seasons (from Chapter 4, indoor intake fractions (1420-1565 ppm in rural and urban India) are a

few orders of magnitude greater than outdoor intake fractions (mean of 51 ppm and 14 ppm in urban and rural India, respectively). Of this, about 60-80% is biomass use for cooking, with the remainder being biomass for heating and kerosene lighting, and heating accounting for a greater share in winter and autumn (See Appendix D Figure D.1 for the distribution of per household indoor PM<sub>2.5</sub> intake due to residential fuels across India). The remainder of this chapter focusses on ambient PM<sub>2.5</sub> exposure.

#### **5.4.2 Exposure to ambient air pollution**

Model results show that informal sources account for 75% of annual ambient PM<sub>2.5</sub> inhaled – of this, the leading contributor is residential biomass burning (55%), followed by agricultural residue burning (30%) (see Figure 5.1). In the formal sector, which accounts for 25% of total annual ambient PM<sub>2.5</sub> intake, the most significant sources are thermal power (38%) and heavy industries (30%), followed by diesel transport (17%). Ground-level sources such as residential and agricultural emissions, have higher intake fractions associated with them leading to higher estimated intake of ambient PM<sub>2.5</sub>, compared to high stack emission sources such as heavy industries and thermal power plants. The informal sector is still responsible for the majority of PM<sub>2.5</sub> intake (58%) if the effect of emission stack height is discounted, assuming that all emissions are released at the same height.



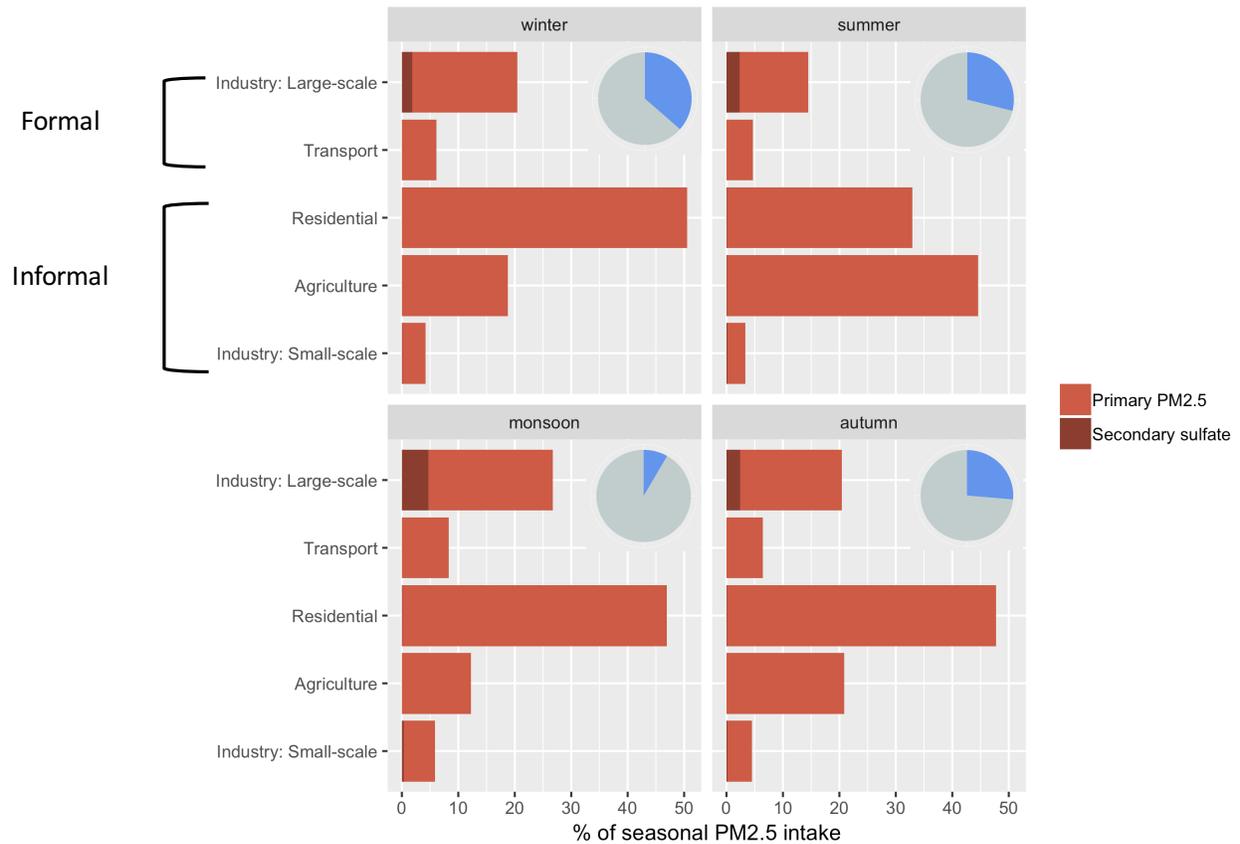
**Figure 5.1** Contribution (%) of formal and informal sources to annual ambient PM<sub>2.5</sub> intake (mg) in India

### 5.4.3 Seasonal and regional characteristics of PM<sub>2.5</sub> emission sources

Model results for source-contribution to ambient PM<sub>2.5</sub> intake by season and region are presented in Figure 5.2 and Figure 5.3 respectively. Nationally averaged intake levels (mg/day) are highest in the winter (Dec-Feb) (37% of total annual intake occurs during winter months) and lowest in the monsoon season (Jun-Aug) (8% of total annual intake). The largest share of ambient PM<sub>2.5</sub> is inhaled during winter, primarily driven by high intake fraction values due to low atmospheric mixing height. Overall, biomass use for cooking is the largest contributor to ambient PM<sub>2.5</sub> intake in all seasons except in the summer (28-37% of intake during monsoon, autumn and winter). In addition, residential space and water heating in the winter contribute to 19% of seasonal intake. High levels of PM<sub>2.5</sub> exposure during the Indian summer (Mar-May) result from two factors. First, levels of rainfall are low in May across the entire region, and

particularly in the densely populated Indo-Gangetic Plain where the agricultural sector is significant. Second, there are high levels of agricultural residue burning in summer as farmers prepare for the monsoon cropping season. Agricultural residue burning contributes to about 41% of ambient PM<sub>2.5</sub> intake in summer.

Emissions from the formal sector are calculated only on an annual basis in the inventory used for this analysis, thus modelled intake of primary PM<sub>2.5</sub> emissions from the formal sector shows little seasonal variation. However, sulfate formation in the model depends on cloud conditions and temperature, with resultant seasonal variation. Sulfur dioxide emissions, precursors to sulfates, are substantial for the formal industry sector - the shares of sulfate in the total intake contribution of coal use in thermal power, heavy industry and light industry are 12%, 9% and 26% respectively. Sulfate formation is the highest in the monsoon due to greater cloud cover (19% of PM<sub>2.5</sub> intake from formal industry sector during the monsoon), however due to greater washout through heavy rainfall during the period, the monsoon season accounts for only about 8% of total annual PM<sub>2.5</sub> intake.



**Figure 5.2** Seasonal and sector contribution (%) to ambient PM<sub>2.5</sub> intake (mg/day).  
*Pie charts represent the seasonal contribution to annual ambient PM<sub>2.5</sub> intake - Winter(Dec-Feb): 37%; Summer (Mar-May): 28%; Monsoon (Jun-Aug): 8%; Autumn (Sep-Nov):26%*

#### 5.4.4 Spatial distribution of PM<sub>2.5</sub> emission sources

The spatial distribution of PM<sub>2.5</sub> sources provides insights into appropriate policies for sectoral mitigation in each region. India's 640 districts are divided into 5 broad geographic regions – Far North/North- East (6% of total population); Indo-Gangetic Plain (40% of total population); North-Central (9% of total population); South-Central (33% of total population); South (12% of total population). (See Figure 5.3 and Appendix D for a map of geographic regions). Districts are further classified into urban and regional categories. Districts with a population density of more

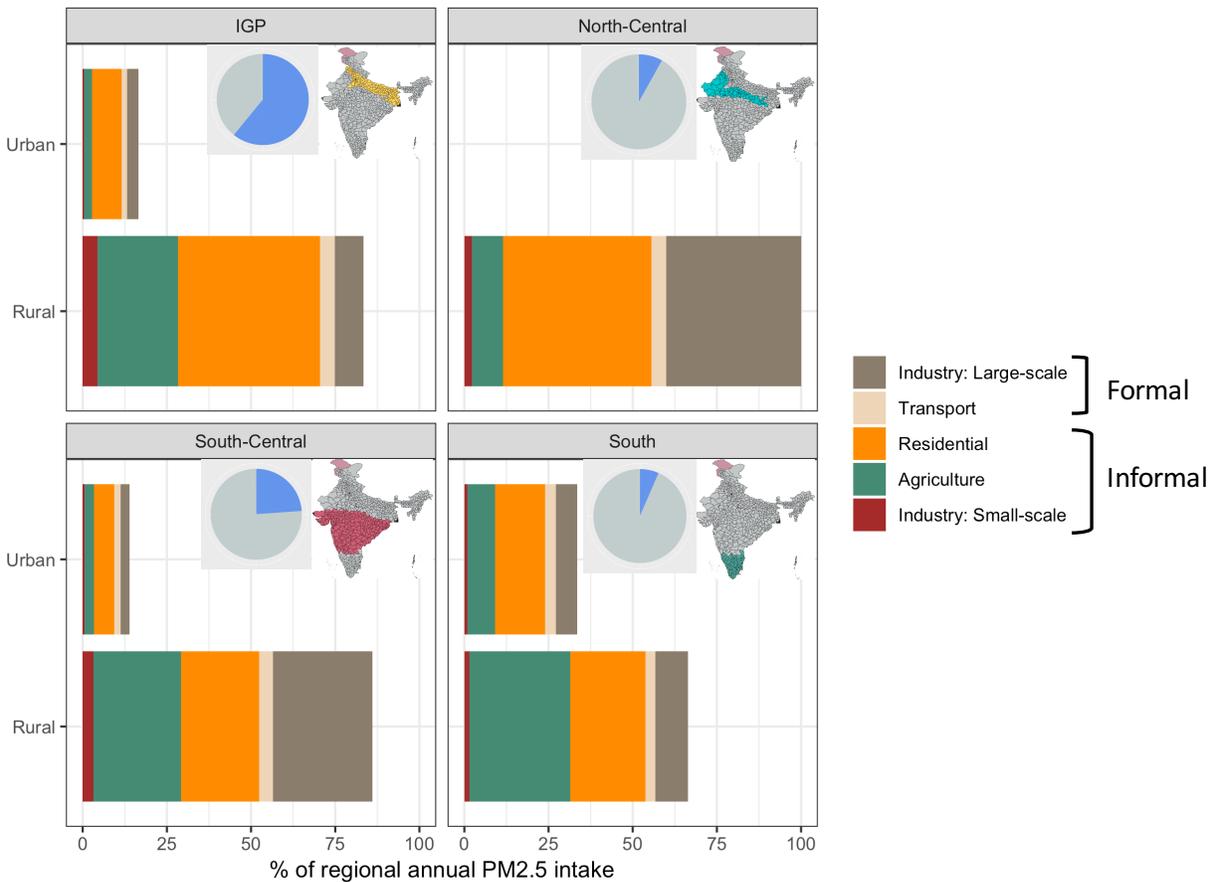
than 400 people/km<sup>2</sup> and 75% of the working population involved in non-agricultural activities are classified as ‘urban’ (India 2011)<sup>26</sup>. Emissions from the Far North/North-East region are excluded since they account for only 1% of nation-wide PM2.5 intake.

Overall, there are clear regional differences. Sources in the densely populated IGP account for more than half of annual PM2.5 inhaled in India (61%). In the IGP informal sources dominate, with 51% of regional intake contribution attributable to residential fuel use - of this 61% is due to biomass for cooking, 31% due to biomass use for space and water heating, and 6% due to kerosene lighting. Agricultural sources contribute about 26% of ambient intake from IGP sources (of this 85% is due to residue burning). Formal sources in the IGP i.e., large-scale industry and transportation, account for about 18% of intake, two-thirds of which is due to industry including power, and one-third due to transport. The picture is similar in the South, with informal sources accounting for 78% of total intake contribution, with agricultural burning as the dominant source (38%), followed by biomass for cooking (27%), and an additional 10% from biomass use for heating and kerosene lighting. Large point sources (industry and thermal power) play a more significant role in North-Central and South-Central India with the majority of these emission sources located in less densely populated rural districts. In the North-Central region, formal

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<sup>26</sup> In Chapter 4 districts are classified as urban or rural solely based on population density (threshold value= 400 persons/sq.km.), as the exposure metric used in intake fraction calculations is a function of population density. In this chapter, an additional criterion based on agricultural activity is used to better understand the locational distribution of sources.

sources account for 44% of regional intake contribution, and in South Central region formal sources contribute 36%.



**Figure 5.3** Regional contribution (%) to annual ambient PM2.5 intake (mg). Total intake contribution (urban+rural) for each region shown aggregates to 100%. Pie charts show % regional contribution to total PM2.5 inhaled across India – IGP: 61%; North-Central:8%; South-Central: 24%; South: 6%.

### 5.4.5 City-specific emission sources and air pollution

Urban districts, i.e., non-agricultural districts with >400 persons/sq.km., account for 18% of India’s population, and sources in these districts constitute a less than proportional share of total PM2.5 intake in India (15.5%). However, major urban centers in India are air pollution hotspots

with high levels of ambient PM<sub>2.5</sub> concentrations, and so are a key focus of regulation. A number of policy levers have been attempted to tackle air pollution sources in cities, particularly in the capital New Delhi. These include requiring all public transit to operate on compressed natural gas (Reynolds & Kandlikar 2008; Reynolds, Kandlikar, et al. 2011) and controlling the number of cars on the road by rationing of vehicles access to city roads based on odd-even of license plate numbers (P. Kumar et al. 2017).

Here, model results for pollution sources in 24 most populous cities in India (12 in the IGP and 12 in the rest of the country) and their contribution to ambient PM<sub>2.5</sub> exposures are presented. These cities are represented in the model as densely populated urban districts. Urban districts include high density urban zones of the inner city and lower density peri-urban zones. In some cases, a city is represented by more than one district. For example, New Delhi is an urban agglomeration of 5 districts. Average annual PM<sub>2.5</sub> concentrations in cities in the IGP (75-165  $\mu\text{g}/\text{m}^3$ ) are distinctly higher than cities elsewhere (25-75  $\mu\text{g}/\text{m}^3$ ) (See Appendix D Figure D.2 for annual average airborne concentrations of PM<sub>2.5</sub> in the 24 urban districts).

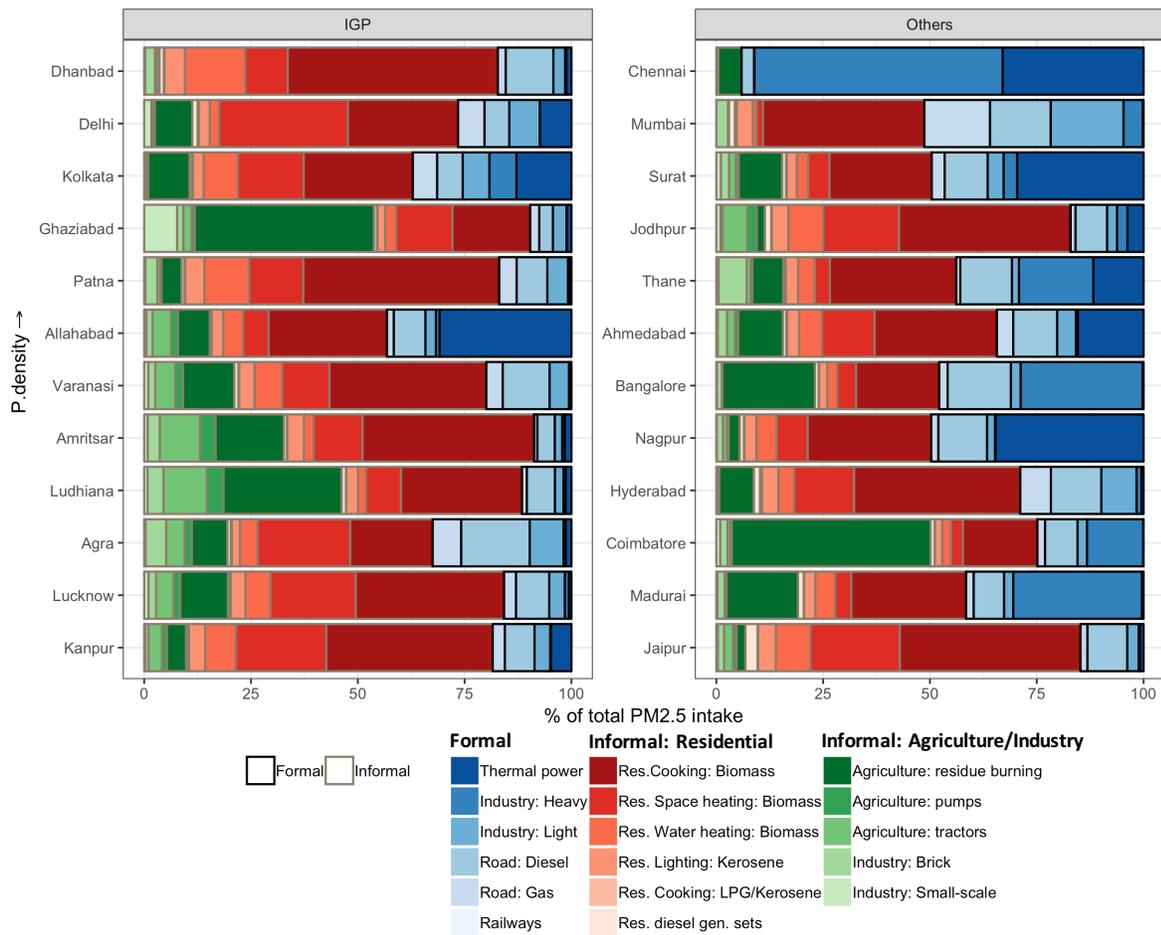
Informal sources in 21 of the 24 cities remain the major contributors to ambient PM<sub>2.5</sub> intake (see Figure 5.4). On average, informal sources are responsible for 78.5% of PM<sub>2.5</sub> exposure contribution (total PM<sub>2.5</sub> inhaled in mg/day) from sources in IGP cities, and 58.5% in other major cities. Residential biomass use accounts for more than 75% of informal sources across this sample, and is a dominant urban source of ambient exposure in the IGP; overall, it contributes to 25-80% of ambient PM<sub>2.5</sub> intake from city sources, with the least in southern cities such as Chennai, Bangalore and Madurai (1-25%), and the highest in Jaipur and IGP cities of Patna,

Kanpur and Dhanbad (75-80%). Biomass for cooking contributes about 60-75% of intake contribution from residential biomass in most cities except Delhi and Agra where the contribution of biomass for space heating is also equally important.

The agricultural sector in a number of cities is a significant contributor to ambient PM<sub>2.5</sub> exposure, with an average 18% of source contribution in cities of the IGP and 13% in other cities. The agricultural sector's contribution to ambient PM<sub>2.5</sub> exposure is the highest (29-47%) in Ghaziabad, Amritsar and Ludhiana in the IGP, and Coimbatore in the South; and the lowest (less than 5%) in Mumbai, Nagpur and Dhanbad. In most locations, exposure due to agricultural residue burning is highest during summer (Mar-May) (47-56% of total annual intake due to residue burning occurs during these three months), followed by autumn and winter months (Sep-Feb) (40-45% of total annual intake over six months). Small-scale industry sector constitutes 5% or more of exposure contribution in only a few cities.

The contribution of the formal sector (thermal power, heavy and light formal industries, road and rail transport) to PM<sub>2.5</sub> intake from city sources shows great variation. Though high in some cities such as Chennai (94%) and a few other non-IGP cities (42-50% in Mumbai, Nagpur, Surat, Thane, Madurai), formal sector contributions to ambient intake tend to be low relative to those in the informal sector. Overall, the formal sector on average contributes to only 10% of ambient PM<sub>2.5</sub> intake from city sources in the IGP and 28% in all other cities. There is also great variation in exposure contributions across source categories in the industrial sector. For example, in non-IGP cities (such as Bengaluru, Nagpur and Surat), heavy industry and power contribute to a third of the PM<sub>2.5</sub> intake (30-36%), with a high of 91% for Chennai, and lows of <5%

elsewhere. The transport sector in the megacities of Mumbai, Bangalore and Hyderabad contributes 17-30% to PM2.5 intake due to city sources. In Chennai, the formal industry sector overshadows the transport sector's contribution (3%), and the transport sector's contribution is 7% or less in Amritsar, Ghaziabad and Ludhiana. Overall, there is a high level of heterogeneity in contributions to PM2.5 intake across cities from formal sources of pollution.



**Figure 5.4** Cities: Heterogeneity in source contribution (%) to annual ambient PM2.5 intake (mg)

The regional nature of air pollution suggests that effective intra-city pollution management is difficult to achieve, since a substantial portion of PM<sub>2.5</sub> exposure in cities may be attributable to sources in the region outside city district boundaries. Here the regional contribution to intra-city pollution in India's six most populous 'mega-cities' - Mumbai, Kolkata, Delhi, Chennai, Bangalore and Hyderabad – is analyzed. I use a 'leave one out' modelling strategy, i.e., I run the national scale model that includes all emission sources, and then for each consequent model run I a) omit all emissions from each city and then b) omit all emissions except those from the region contiguous to each city. The ratio between modelled ambient PM<sub>2.5</sub> concentrations in each city from the initial and consequent run a) gives the proportional contribution of regional pollution sources in each city, while the ratio between results from the initial run and run b) gives the proportional contribution of the region contiguous to each city. The analysis of the six most populous cities shows that city sources contribute only 20-45% of PM<sub>2.5</sub> concentrations in these cities, with sources in the immediately surrounding region contributing about 29-50% and sources farther away contributing about 10-30%, indicating the significant role for sources outside city boundaries. This is in general agreement with a study by TERI and ARAI in Delhi (TERI & ARAI 2018) which concludes that sources within Delhi are only responsible for 26-36% of concentrations within the city. Three source categories – residential biomass use, agricultural residue burning and formal industry – form the largest shares of emissions from regions contiguous to mega-cities (see Table 5.1).

City	Residential biomass burning	Agricultural residue burning	Formal industry	Other sectors
Delhi	34%	17%	29%	20%
Kolkata	45%	17%	23%	15%
Mumbai	31%	18%	28%	23%
Chennai	26%	22%	44%	8%
Hyderabad	32%	11%	42%	15%
Bangalore	33%	37%	19%	11%

**Table 5.1** Source-contribution (%) to annual emissions from regions contiguous to mega-cities

### **5.5 Mortality burden due to ambient air pollution**

This study estimates that diseases due to ambient air pollution were responsible for about 605,000 deaths in India, of which 517,000 were due to COPD, 45,000 to IHD, 41,000 to stroke and 2000 to lung cancer. The IGP accounted for 67% of total deaths and 50-70% of deaths due to each disease (Table 5.2). The health impact of certain sectors, such as trash burning and anthropogenic dust, that were excluded from the emissions inventory used in this analysis, is not estimated. The additional mortality burden due to indoor air pollution is also excluded.

	Deaths (all-India)	IGP (%) <sup>1</sup>	North- Central (%) <sup>1</sup>	South- Central (%) <sup>1</sup>	South (%) <sup>1</sup>	Far- North/North- East (%) <sup>1</sup>
COPD	517,200	69.2	8.4	14.7	5.2	2.5
Lung Cancer	2,200	56.1	8.9	22.9	9.6	2.5
IHD	45,200	57.2	11.8	13.1	11.4	6.6
Stroke	40,700	53.1	11.6	18.7	12.1	4.5
Total	605,280	67.1	8.9	14.9	6.1	3.0

**Table 5.2** Regional distribution of health impacts of ambient air pollution by disease

<sup>1</sup> % of mortality burden attributable to each disease

*Note: Estimated mortality due to lung cancer is low relative to its proportional contribution in the GBD-MAPS study (2018). One reason is nation-wide baseline mortality estimates, which yield lower estimates relative to state-specific values (Chowdhury & Dey 2016), are used for lung cancer as state-specific values were not available.*

Deaths attributable to ambient air pollution are primarily due to due to informal sources (73%), and this pattern is observed in all regions except South-Central India where about half the deaths (56%) can be attributed to formal sources.

Table 5.3 shows the mortality burden due to each source. In the formal sector (161,080 deaths), 46.9% of deaths can be attributed to thermal power and 48.7% to formal industry, with only 4.4% of deaths to road and rail transport. Regionally, the IGP accounts for 49.5% of deaths attributable to the formal sector, while South-Central India accounts for 31.5%.

In the informal sector (444,200 deaths), 88.5% can be attributed to the ambient impact of residential biomass use (87.2%) and kerosene lighting (1.3%), while the seasonal agricultural

sector accounts for 8%, brick industry 2.5% and other small-scale industries 1.3%. Regionally, the IGP accounts for 73% of all deaths from the informal sector, particularly 75% of deaths due to residential biomass use.

	Deaths all-India	% of formal/informal sector
<b>Formal</b>	161,080	
Thermal Power + Heavy + light industry	154,050	95.6
Transport: diesel (Road + Rail) + gas (Road)	7,030	4.4
<b>Informal</b>	444,200	
Residential	392,900	88.5
Agricultural residue burning + diesel (tractors + pumps)	34,600	7.8
Small-scale industries (including Brick)	16,700	3.8
<b>Total</b>	<b>605,300</b>	

**Table 5.3** Source-contribution to total mortality burden due to ambient air pollution

Table 5.4 shows a comparison of mortality burden by emission sector as estimated by this study against the Global Burden of Diseases assessment (GBD MAPS Working Group 2018) and

Upadhyay et al. (2018)<sup>27</sup>. This study overestimates deaths from ambient exposure to residential biomass, and substantially underestimates the mortality burden due to some other emission sectors relative to the GBD study. There are key differences in data and methodology between this analysis and the GBD study that help explain these differences. First, this model excludes secondary PM<sub>2.5</sub> (except sulfates), i.e., nitrates, ammonium and secondary organic aerosols (SOA). Precursor gases to secondary PM<sub>2.5</sub> are significant from transport and industry sectors (oxides of nitrogen), the agricultural sector (non-methane volatile organic compounds or NMVOCs which are ozone precursors that in turn aid in nitrate and SOA formation, and ammonia) as well as the residential biomass sector (NMVOCs) (GBD MAPS Working Group 2018). Although modelled estimates for the residential and industrial coal use sectors are close to that of the GBD study, they might still be an underestimate because secondary PM<sub>2.5</sub> are excluded. Second, the GBD study uses nation-wide baseline mortality rates that might itself result in an underestimation of mortality levels compared to using state-specific baseline mortality rates, as inferred by Chowdhury and Dey (2016). Third, the GBD study includes deaths due to Lower Respiratory Tract Infection (LRI) that this study does not include. In the GBD

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<sup>27</sup> Upadhyay et al.(2018) use a different emissions inventory than this study – my mortality estimate for coal use in power and industry (Upadhyay et al. do not include light industries in their emissions inventory) are higher, and those for transport (Upadhyay et al. include inland waterway, pipeline, mobile machinery and NO<sub>x</sub> emissions) are lower. Overall, Upadhyay et al., underestimate total mortality burden due to ambient air pollution relative to the GBD study by about 30%.

study, LRI is responsible for almost 20% of total deaths attributable to ambient air pollution. Fourth, the GBD study uses an assimilated PM<sub>2.5</sub> emissions dataset, incorporating the emissions inventory used in this work (Sadavarte & Venkataraman 2014; Pandey et al. 2014), with additional satellite and surface measurements, as well as simulations from the chemical transport model GEOS-CHEM. As noted in Chapter 4 this model tends, on average, to underestimate the PM<sub>2.5</sub> concentrations.

Emission sector	Our estimates	(GBD MAPS Working Group 2018)	(Upadhyay et al. 2018)
Residential <sup>1</sup>	392,900	267,700 <sup>2</sup>	378,295
Coal use in thermal power and formal industry	154,050	169,300	64,000
Agricultural residue burning	30,600	66,200	-
Transport <sup>3</sup>	7,000	23,100	28,000
Distributed diesel <sup>4</sup>	4,000	20,400	-
Brick industry	10,900	24,100	-
Others	5830 <sup>5</sup>	412,500 <sup>6</sup>	-
Total	605,300	983,300	470,300

**Table 5.4** Comparison of mortality burden by emission sector with (GBD MAPS Working Group 2018) and (Upadhyay et al. 2018) <sup>1</sup> Residential biomass: 387200 deaths; Kerosene lighting: 5700 deaths

<sup>2</sup> Only biomass use; excludes kerosene lighting

<sup>3</sup> Modelled estimates, in contrast to Upadhyay et al.'s, only include on-road gasoline and diesel and railways (diesel), and exclude secondary PM<sub>2.5</sub> from NO<sub>x</sub> emissions

<sup>4</sup> Diesel use in agricultural pumps and tractors; the GBD study also includes residential diesel generator sets in this category

<sup>5</sup> Other small-scale informal industries; <sup>6</sup> Total dust

## 5.6 Limitations

The analysis in this chapter is limited by the structure of the emissions inventory and PM<sub>2.5</sub> modelling framework used – for example, trash burning and dust are not included among emission sources; and air pollution exposure analysis is limited to primary PM<sub>2.5</sub> and secondary sulfates, with other secondary PM<sub>2.5</sub> such as nitrates, ammonium and organic aerosols excluded. Additionally, the analysis is limited by the spatial scale of the emissions inventory and there is some uncertainty regarding the accurate grouping of emission points, and corresponding sources, in the inventory (0.25° x 0.25° scale) within districts. Restricting this analysis to PM<sub>2.5</sub> also meant discounting the role of PM<sub>10</sub>, significant in the transport sector (Suleiman et al. 2016), in ambient air pollution. This analysis of health impacts of air pollution is restricted to mortality burden; disability-adjusted life-years (DALYs) are not estimated due to data limitations. DALYs, calculated as the sum of years of life lost due to death and years lived with disability, is often considered a more comprehensive measure of health impact as it addresses the age at which a disease occurs, instead of simply estimating the number of deaths (GBD MAPS Working Group 2018). Additionally, there are uncertainties associated with the dose-response function used to estimate mortality burden due to the absence of epidemiological evidence on the effect of ambient air pollution levels observed in developing countries. The dose-response function used to estimate relative risk to diseases is based on estimating the fractional impact of ambient air

pollution, using epidemiological studies on ambient air pollution, smoking and household air pollution (Burnett et al. 2014).

## **5.7 Conclusion**

Informal sources, defined here as sources considered difficult to monitor and regulate such as household, agriculture and small-scale industry sectors, account for about three-quarters of ambient PM<sub>2.5</sub> inhaled by the population. Any national approach to improving air quality in India will need to address the role of informal sources. Of these, household-level biomass burning has the most significant impact in terms of PM<sub>2.5</sub> exposure, not only for biomass users (as shown in Chapter 3), but also in terms of its ambient impact. Ambient air pollution from residential biomass lead to about 390,000 deaths in 2015 and constituted 65% of all deaths related to ambient air pollution. The ambient impact of residential fuels is particularly significant in the Indo-Gangetic Plain (IGP), which accounts for 75% of deaths from ambient PM<sub>2.5</sub> attributed to residential fuel use in India. High exposures during summer are due to low rainfall in addition to high levels of residue burning in the IGP and in the South, while high exposures during winter are due to biomass use for heating and low mixing heights, particularly in northern India. In the formal sector, I estimate that coal use in thermal power and industry resulted in more than 150,000 deaths across India in 2015, mostly split between the IGP (50%) and south-central India (32%). Large point sources are primarily rural by location, and are significant urban pollution sources only in a small number of cities.

The analysis of ambient PM<sub>2.5</sub> intake from sources in 24 most populous cities shows that there is significant heterogeneity across key sources. Informal sources dominate in cities as well, implying

that effective local air pollution management is challenging in most cities – on average 78.5% of exposure contribution of sources in IGP-cities and 58.5% in cities elsewhere are due to informal sources. Residential biomass is the dominant contributor across this sample (75% of PM<sub>2.5</sub> intake), while agriculture makes a significant exposure contribution in some IGP cities, and is especially high in certain seasons (41% in the summer and 15% in the winter). Further, about 55-80% of PM<sub>2.5</sub> concentrations in the six largest megacities in India could be attributed to regions outside city boundaries, primarily sources in regions bordering cities. Emissions from regions contiguous to these cities are predominantly from residential biomass use (26-45%), agricultural burning (11-37%) and formal industry (23-44%). Regional air pollution management thus needs to play a significant role in PM<sub>2.5</sub> exposure reduction strategies in cities.

## Chapter 6: Conclusion

### 6.1 Introduction

India faces three major challenges in the energy sector – providing universal access to modern cooking and lighting energy, reducing ambient air pollution levels and forging a low carbon development pathway. In this thesis, I inter-linked the role of improved energy access with ambient air pollution and climate, demonstrating that better access to modern household fuels reduces both indoor and ambient air pollution substantially, and may have lower climate impact compared to traditional fuel use.

In chapters 2 and 3, I analyzed developmental, health and climate aspects of the household energy transition- a shift from biomass for cooking to LPG and kerosene for lighting to electrification. Access to modern cooking and lighting services plays a key role in development - it improves indoor air quality, reduces the time and effort spent in collecting and cooking with biomass, and improves general quality of life. Government policy emphasizes *inclusive development* highlighting the need for economic growth that benefits everyone (Planning Commission 2012), and the urgent need for universal access to modern energy services. In light of this, I quantified energy equity in terms of the burden on women due to cooking activities, urban-rural disparity in access to modern energy services, and affordability in low-income households. First, my analysis shows that a complete transition from solid fuels to exclusively using LPG for cooking offers significant benefits in terms of improved health and time savings. The benefits of exclusively using LPG are particularly noteworthy for women who are primarily responsible for collecting fuels and cooking. Partial transition or ‘fuel stacking’ provides

minimal benefits. Thus a complete household energy transition plays a significant role in realizing gender equity in households.

Second, adoption and use of LPG rise with income in both urban and rural households, albeit at a slower rate in rural households. Current trends in modern fuel adoption, when extrapolated to 2030, lead to widespread LPG adoption in urban households, but firewood usage is projected to prevail in rural households by 2030 due to a lack of affordability and supply constraints.

Modelling multiple transition scenarios for 2030 shows that improving LPG availability in rural India, without addressing affordability, leads to LPG adoption in high-income rural households, but low and middle income rural households remain dependent on biomass (assuming LPG adoption follows income patterns). Substantial reduction in indoor air pollution across all income classes is achieved when LPG is used exclusively for cooking by all. This involves addressing the supply disparity between rural and urban India as well as affordability of fuel such that the quantities of modern fuel used make a significant difference in indoor air quality. On the climate front, a transition to universal LPG and electricity leads to 20% greater Kyoto emissions in 2030 compared to a business-as-usual (BAU) scenario in which current trends of LPG adoption persist; however, it leads to 21% lower net GHG (Kyoto + non-Kyoto) emissions relative to BAU scenario in 2030, if the climate impact of non-Kyoto emissions (pollutants such as black carbon) of firewood and kerosene are considered<sup>28</sup>. The message from chapters 2 and 3 is clear – a complete transition to LPG and electricity provides greater health and developmental benefits compared to a partial transition. It improves indoor air quality substantially across

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<sup>28</sup> Assuming that biomass is 70% renewable.

households, provides health and time savings benefits, particularly for women, and may have a lower climate impact than traditional fuels, if non-Kyoto emissions are considered.

In chapters 4 and 5, I expanded the focus from energy use and indoor air pollution in households to energy use in the broader economy and its relationship with ambient air pollution. Air pollution is the leading risk factor for mortality in India (Lim et al. 2012), with particularly high levels of pollution in cities and densely populated areas such as the Indo Gangetic Plain (IGP) (Brauer et al. 2012; Guttikunda, Goel & Pant 2014). To address the role of ambient air pollution, I conducted a spatially and seasonally disaggregated analysis of source-specific contribution to PM<sub>2.5</sub> exposure and consequent mortality burden across India. Chapter 4 presents an atmospheric transport model designed to conduct the disaggregated exposure analysis; in chapter 5, I used the model to estimate source, location and season-specific ambient PM<sub>2.5</sub> exposure, as well as associated human mortality. Intake fractions, i.e. the fraction of a unit emission inhaled by the exposed population, are the highest in the northern IGP and in winter. Traditional fuel use in households - biomass burning and kerosene lighting – is not only responsible for high levels of indoor exposure, but is also the most significant contributor to ambient PM<sub>2.5</sub> exposure and consequent mortality (estimated in Chapter 5 at about 393,000 deaths in 2015). 75% of deaths that can be attributed to household fuel use occur in the Indo-Gangetic Plain (IGP). Other informal sectors, i.e., sectors that are not under the direct ambit of regulation such as agricultural burning and small-scale industries, are significant sources of PM<sub>2.5</sub> exposure. In the formal sector, thermal power plants and industry caused about 150,000 deaths in 2015. PM<sub>2.5</sub> exposure due to sources in large cities can also be primarily attributed to residential and other informal sources, with large industrial point sources significant only in a few cities, predominantly in

southern India. Importantly, a substantial portion of urban air pollution can be attributed to sources outside city limits, indicating that the challenge in regulating pollution in urban India is a regional one.

In this dissertation, I have focused on the themes of household access to modern fuels and ambient air pollution, which constitute two critical energy challenges facing India today. This concluding chapter addresses the role that ambient air quality improvement could play in climate mitigation, India's third major energy challenge.

## **6.2 Joining the dots: household energy transition, ambient air pollution and climate mitigation**

The following sections focus on linkages/co-benefits between ambient air pollution reduction and climate mitigation. The term co-benefit has been used in two senses. In the first (and more commonly used) sense, reducing carbon emissions is the primary policy aim and air pollution benefits are secondary. In the second approach, improving air quality would be the primary policy aim, and carbon emission reduction would be seen as the co-benefit.

Air pollution control can provide important co-benefits in terms of climate mitigation for two reasons: first, greenhouse gas (particularly CO<sub>2</sub>) as well as PM<sub>2.5</sub> emissions in India originate from the combustion of fossil fuels - major sources include thermal power plants, transport, and heavy industry (MOEF 2010; Dholakia et al. 2013; Guttikunda & Kopakka 2014); second, short-lived climate pollutants (SLCPs), such as Black Carbon (BC) which is a constituent of PM<sub>2.5</sub>, have significant impact on radiative forcing of the global climate (Bond 2007; Lam,

Chen, et al. 2012). Air pollution policies can have significant climate impact if the radiative forcing effects of SLCPs is considered (Shindell et al. 2012; Rypdal et al. 2009; McCollum et al. 2013; Tollefsen et al. 2009). For example, biomass sources are often considered low-carbon or even carbon-neutral, but the emission of SLCPs shifts the focus of climate policy target sectors to household biomass use, if non-Kyoto pollutants are considered.

India is the third highest emitter of CO<sub>2</sub> among all nations, and India's Intended Nationally Determined Contributions (INDCs) developed in response to the Paris Agreement in 2015 include the following: reducing GDP emission intensity by 33-35% by 2030 compared to 2005 levels; increasing installed renewable energy capacity to 175GW<sup>29</sup> by 2022 and nuclear capacity to 63 GW by 2032 so that 40% of total installed capacity is non fossil-fuel based; improving energy efficiency in buildings, transport and industry; and improvement in infrastructure such as railways and power grid (Government of India 2015).

Air pollution thus provides a 'double barrelled' climate mitigation opportunity. Policies aimed at reducing air pollution can (i) directly reduce radiative forcing by lowering emissions of BC and (ii) as a co-benefit, reduce carbon emissions by shifting the economy away from more carbon-intensive fossil fuels (e.g. by substituting coal for gas or renewables in electricity generation). Air pollution also tends to be more local by nature, as its health impacts are experienced on a local scale. Regulatory oversight such as those related to transport planning, land use decisions

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<sup>29</sup> With the latest revised target at 227GW by 2020 (<https://economictimes.indiatimes.com/industry/energy/power/india-will-add-225-gw-renewable-energy-project-capacity-by-2022-r-k-singh/articleshow/64461995.cms>).

and local air quality management are often under the purview of municipal or state governments. Air pollution control policies tend to be politically easier to implement, both because of the proximate nature of air pollution, and greater incentives for sub-national or local governments to improve air quality. On the other hand, climate change is a long-term concern, and a collective action problem that requires cooperation among multiple nations. This makes it difficult to frame effective international strategies to combat it, and to gain public support for these strategies. Thus, reframing climate mitigation as a co-benefit of air quality improvement may be a way of achieving both goals in India.

In what follows I analyze the opportunities for PM<sub>2.5</sub> exposure reduction and concomitant greenhouse gas mitigation in India. A brief overview of the co-benefits of climate mitigation policy for improving local air quality and vice-versa is followed by a simple analysis of co-benefits/trade-offs for climate mitigation from improvements to ambient air quality. I conclude with broader lessons for a joint solution to questions of air quality, climate change and energy equity, the limitations of this research and proposals for future work.

### **6.3 Air pollution and Climate change: Co-benefits**

Consideration of potential air quality benefits of CO<sub>2</sub> abatement through reduction in particulate matter, SO<sub>2</sub> or NO<sub>x</sub> emissions, dates back to late 1990's (Ekins 1996; Syri et al. 2001). Co-benefits analyses have focused on sector-specific air pollution benefits of carbon policy, for example, coal abatement in China (Aunan et al. 2004) and US (Burtraw et al. 2003). Other studies include those on economy-wide co-benefits analysis of climate mitigation in Europe (van Vuuren et al. 2006), Thailand (Shrestha & Pradhan 2010) and the US (Garcia-Menendez et al.

2015). While most focus on the co-benefits of climate policy, a few studies have discussed the potential trade-offs with air quality on switching from petrol to diesel transport in the UK (Mazzi & Dowlatabadi 2007) and the cooling effect of pollutants such as sulfate aerosols (Ramanathan & Feng 2009). Studies on climate co-benefits of air pollution policy at the national or continental scale are mostly focused on Europe (Tollefsen et al. 2009; Bollen & Brink 2014; Bollen et al. 2009), with a few studies on China and the US (He et al. 2010; Nam et al. 2014).

In the Indian context, co-benefits analyses have focused on: cooking technology-specific synergies between indoor air pollution exposure and climate (Grieshop et al. 2011); fuel switching in transport (Reynolds, Grieshop, et al. 2011) and more broadly emissions from the transport sector (Pathak & Shukla 2016; CSTEP 2016); scenario analysis for future Kyoto and particulate matter emissions (Garg et al. 2003). While there has been some work addressing the co-benefits question for India at a national scale (Venkataraman et al. 2016), analyses that address co-benefits in terms of (i) health, ambient air quality and climate outcome trade-offs at (ii) the sub-national scales are missing.

#### **6.4 PM<sub>2.5</sub>-related mortality vs. Climate impact**

Household and ambient air pollution rank first and sixth in risk factors for mortality in South-Asia (Lim et al. 2012), with household burning of solid fuels contributing an estimated 26% to ambient PM<sub>2.5</sub> concentrations (Chafe et al. 2014). The contribution of household solid fuel use to ambient air pollution, and consequent mortality burden, is the highest in South Asia compared to the rest of the world (Chafe et al. 2014). While I do not estimate mortality due to household air pollution in this work, household air pollution is estimated to be responsible for almost

482,000 premature deaths in India annually (Health Effects Institute 2019); additionally, according to my estimates, ambient air pollution is responsible for more than 600,000 deaths in the country.

This dissertation also shows that transition to clean cooking and lighting services may lead to lower GHG (Kyoto and non-Kyoto) emissions relative to traditional fuel use while mitigating household air pollution. Chapter 3 shows that greater and more affordable access to clean cooking fuel for all is needed to reduce indoor air pollution to levels that provide substantial and equitable health benefits. Improved access to clean cooking fuel and electrification might lead to higher emissions of Kyoto GHGs compared to a business-as-usual scenario in 2030 in which current trends of traditional fuel use are extrapolated, as predicted by other studies (Cameron et al. 2016; van Ruijven et al. 2011). However, if the radiative forcing of non-Kyoto pollutants is considered, particularly black carbon emitted from biomass burning and kerosene lamps, improved access to modern fossil-fuel based household energy services will have a lower climate impact compared to traditional household fuels. A transition to modern energy for all, accompanied by cleaner electricity and a more efficient power grid, may result in *lower* household GHG emissions in 2030 compared to 2009 levels<sup>30</sup>. In addition, ambient air pollution mitigation through a transition away from thermal power may have considerable climate benefits (World Bank 2011; McKinsey & Company 2009).

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<sup>30</sup> Assuming that biomass is 70% renewable (Singh et al. 2017).

*Informal Sources:* The informal sector, including residential fuel use, accounts for 33% of GHG emissions, if non-Kyoto pollutants are included, and 73% of deaths attributable to ambient air pollution nation-wide (Figure 6.1). Household fuels - biomass for cooking and heating and kerosene for lighting – have the most significant impact on PM<sub>2.5</sub> exposure, not only for biomass/kerosene lamp users but also in terms of their overall health impact through ambient exposure. These two sources alone contribute about 44% of total intake from ambient sources in 2015, and 65% of total deaths due to diseases caused by ambient air pollution. Household fuel use also accounts for about 15-26% of total national GHG emissions, depending on whether biomass is considered to be renewable (15% of GHG emissions) or not (26% of GHG emissions), and if non-Kyoto pollutants are considered. Non-Kyoto emissions from biomass and kerosene lighting constitute 11% and 4.5% of *nation-wide* GHG emissions respectively, suggesting an important missed opportunity for targeting climate mitigation.

Agricultural residue burning contributes about 22% to PM<sub>2.5</sub> intake but is seasonal. It is highest in summer and in the Indo-Gangetic Plain (IGP); it is responsible for only 3% of total GHG (Kyoto + non-Kyoto) emissions and an estimated 30,600 deaths in 2015. Additionally, there are myriad informal sources (small-scale industry such as brick kilns and agricultural tractors and pumps) that constitute India's 'long tail' air pollution problem wherein numerous small sources have a combined adverse impact on local air quality (for example, Amritsar and Ludhiana in the IGP where brick kiln and agricultural diesel use are significant contributors to ambient PM<sub>2.5</sub> exposures). Such sources account for 10% of GHG (Kyoto + non-Kyoto) emissions and 8.5% of total mortality burden due to ambient air pollution. Brick kilns alone constitute about 5% of

GHG emissions and caused 16,700 deaths in 2015, and along with other such informal economic activities represent a major co-benefits opportunity (Croitoru & Sarraf 2012).

*Formal Sources:* Chapter 5 shows that coal combustion in power plants and industry is the second biggest contributor to mortality due to ambient PM<sub>2.5</sub> exposures. Thermal power and industry are two key sectors responsible for CO<sub>2</sub> emissions and a transition away from coal can significantly reduce GHG (Kyoto) emissions. (McKinsey & Company 2009; MOEF 2010). Formal sources (thermal power, industry & transport) account for 25% of total annual PM<sub>2.5</sub> inhaled by India's population and 26.5% of deaths attributable to ambient air pollution. Formal sources also account for 67% of GHG emissions in 2015. Almost half of all GHG (Kyoto and non-Kyoto) emissions can be attributed to coal use in thermal power plants (30.2%) and industry (21.5%). Mitigating carbon emissions from coal, either by reducing energy intensity or increasing the role of renewable electricity, is a significant part of India's INDC commitments. While a systematic analysis of carbon mitigation from coal use is beyond the scope of this thesis, two policies described in chapter 3 – improving power grid efficiency by 10% and displacing coal by increasing renewables' share to 25% (from 16% in 2009) can reduce household-level GHG (Kyoto + non-Kyoto) emissions by 15% relative to a business-as-usual scenario by 2030. These same approaches applied to the power sector in 2015 can reduce the numbers of deaths from ambient air pollution by 10%.

Road transport (gasoline and diesel use) accounted for 13.8% of total GHG emissions (of which 4.7% are non-Kyoto emissions), and is expected to grow at a rapid pace (with a predicted increase in transport energy demand by 3 times between 2012 and 2030 (CSTEP 2016)).

Modelled estimates for the mortality burden due to pollution from transport sector are unusually low (1% of total) compared to other studies (GBD MAPS Working Group 2018; Upadhyay et al. 2018) for reasons cited in chapter 5<sup>31</sup>. However, diesel use in transport is a significant pollutant source in large cities as inferred from the analysis in chapter 5, and a move away from diesel emissions in particular has substantial co-benefits with the inclusion of BC in accounting for mitigation (Reynolds, Grieshop, et al. 2011).

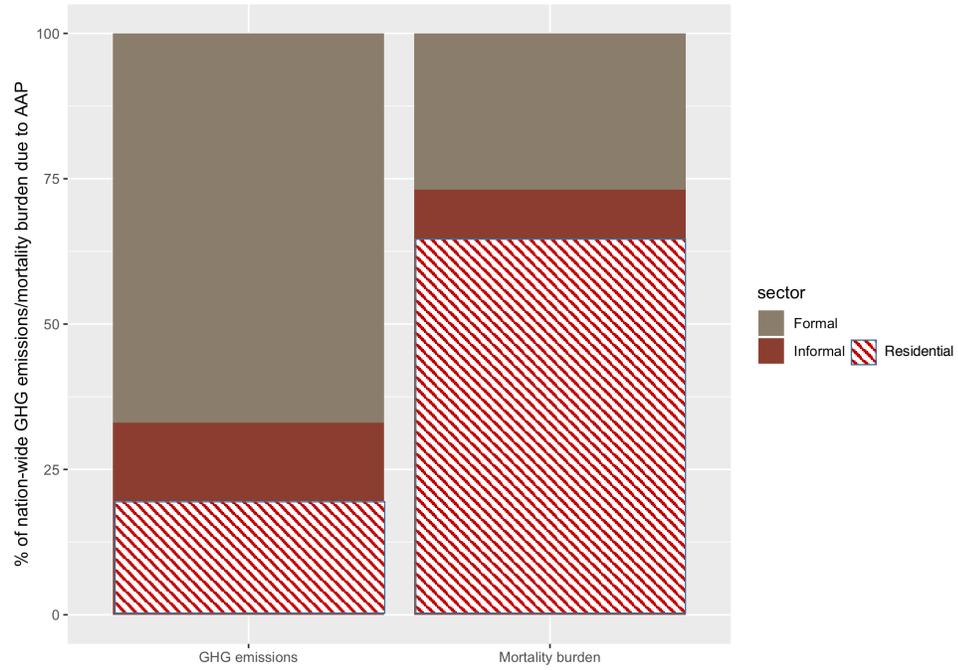
*Spatial Distribution:* While the the impact of reductions in CO<sub>2</sub> equivalents is not location-sensitive, the spatial distribution of emissions reduction matters from an air pollution co-benefits perspective. Chapter 5 shows that informal sources have the greatest health impact in the IGP while formal industrial sources dominate in central India. The IGP accounts for about 30% of total GHG (Kyoto+non-Kyoto) emissions – emissions are primarily split between formal industry (thermal power and large-scale industry account for 38% of regional GHG emissions) and residential sectors (biomass and kerosene lighting, assuming biomass is 70% renewable, account for 26% of regional GHG emissions). The IGP also accounts for 67% of total deaths attributable to ambient air pollution nationwide, and specifically, 75% of deaths attributable to ambient effects of household biomass burning (Figure 6.2). GHG emissions from South-Central India (43% of nation-wide GHG emissions; see Figure 5.3 for a map of regions) are dominated

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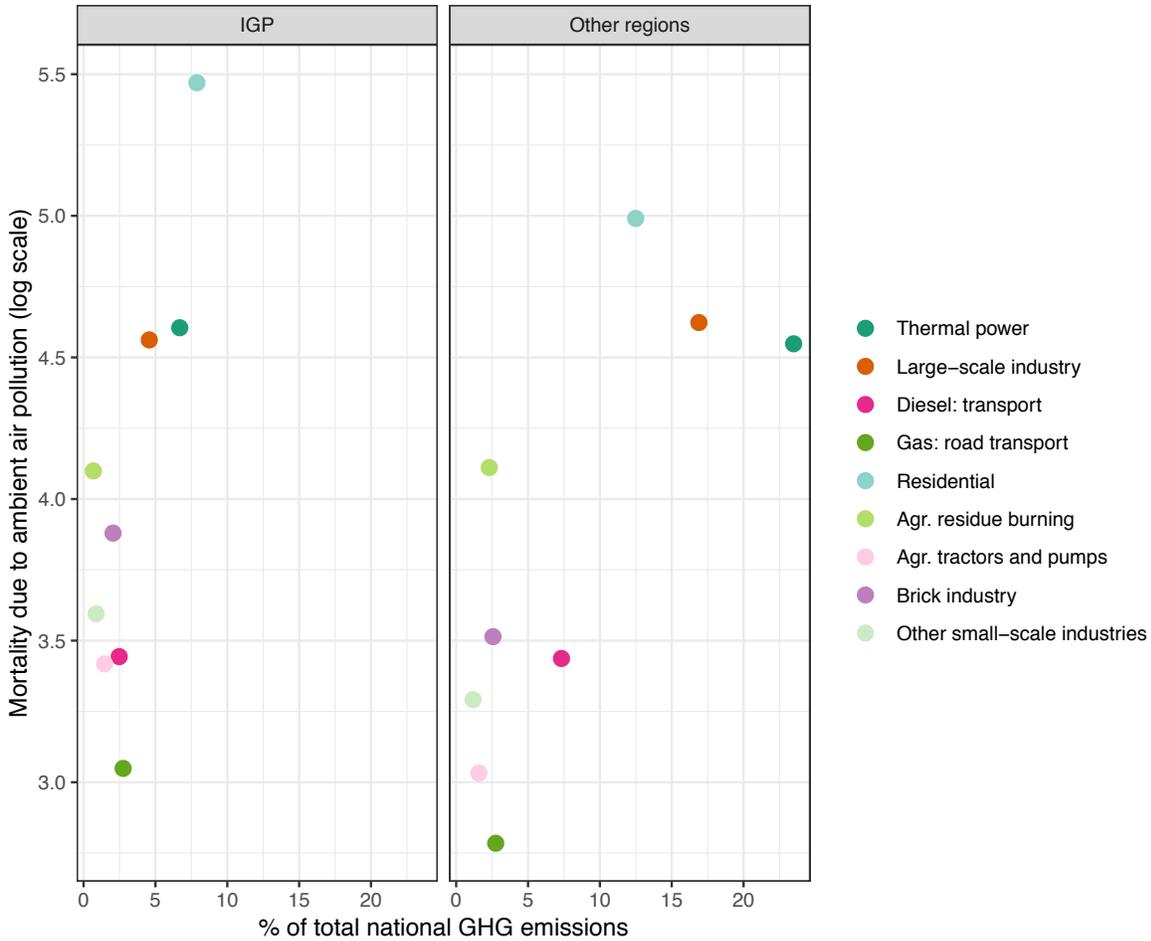
<sup>31</sup> Transport sector estimates used here exclude sources such as shipping, waterways, mobile machinery, and in particular all NO<sub>x</sub> emissions, a key precursor to secondary PM<sub>2.5</sub> in the form of nitrates.

by formal industry including thermal power plants (61% of regional GHG emissions) and 31% of deaths attributed to large-scale industrial sources occur in this region. Thus, climate policies aimed at reducing carbon dioxide from formal sources would provide greater health co-benefits in South-Central India relative to the IGP.

Significant climate co-benefits can be realized from air pollution control policies in both formal and informal sectors. Yet, the focus of climate and ambient air pollution policies in India has to date been the formal sector. India's INDCs emphasize renewable power and energy efficiency in industry and transport sectors (Government of India 2015). Regulatory action on air pollution in India has also been generally limited to industry and transport sectors, through the enforcement of vehicle emission standards and emission limits for industries (e.g. SO<sub>2</sub>, NO<sub>x</sub> and suspended particulate matter emission standards in thermal power plants and large industries). The informal sector, including household fuel use, agricultural burning and small-scale industries, offers substantial potential for policy action that could provide both health and climate benefits.



**Figure 6.1** Sectoral contribution to GHG emissions (Kyoto+ non-Kyoto) and mortality burden due to ambient air pollution (AAP)  
*(Note: GHG calculations for residential biomass assume 70% renewability)*



**Figure 6.2** Regional mortality due to ambient air pollution and contribution to nation-wide GHG (Kyoto+non-Kyoto) emissions  
*(Thermal power: 30.2%; Large-scale industry: 21.5%, Diesel transport: 9.8%; Gasoline road transport: 5.5%; Residential sources: 20.4%; Brick industry: 4.6%; Other small-scale industries and agriculture: 8%). Note: y-axis scales represent logarithm (base 10) of annual mortality in regions); assumed biomass renewability=70%*

## 6.5 Concluding thoughts, limitations and future directions

The household energy transition from biomass for cooking to LPG and from kerosene for lighting to electricity, has wide-ranging impacts – it is an essential component of development and plays a significant role in bringing about gender equity, reduced exposure to indoor air pollution and greater well-being in households that transition from traditional to modern fuels.

While the impact of residential fuels on indoor air quality is well known, a key finding of this dissertation is the considerable role they play in contributing to *ambient air pollution* and consequent mortality burden across India. This dissertation shows that informal sources of air pollution are responsible for higher mortality due to ambient air pollution compared to formal sources. Such sources are small, numerous, spatially distributed, and thus difficult to track and regulate. Accurate data on the level of activity, fuel type and emission factors, are hard to collect for informal sources. The significance of the informal sector implies that air quality improvement will be difficult to monitor and implement. Consequently, policies aimed at air quality and climate mitigation tend to focus on formal sources. The focus on the formal sector alone, however, implies continued high levels of mortality from air pollution and associated emissions of greenhouse gases, both Kyoto and non-Kyoto.

*Limitations:* This dissertation has several limitations highlighted below. The statistical analyses and exposure modelling conducted is based on nation-wide secondary data, viz., the two survey datasets in chapters 2 and 3; modelled meteorological data, a national emissions inventory and census data on districts in chapters 4, 5 and 6. A significant characteristic of nation-wide datasets is that the breadth and national representativeness of the dataset is such that it would not have been feasible to collect such primary data. Certain metrics or variables that would have been useful for my purposes, were simply unavailable in these datasets. Missing data include, for example: the year of adoption of clean fuels/technologies, such as improved cookstoves in the IHDS dataset (chapter 2) that might have helped understand whether the observed benefits of switching to ICS were simply short term impacts; the reliability of electricity supply in the NSS (chapter 3) that would have helped differentiate income and availability-related consumption

patterns; emissions from shipping or anthropogenic dust in the emissions inventory or waste burning in cities (chapters 4 and 5) to provide a more comprehensive estimation of PM<sub>2.5</sub> concentrations.

A second limitation results from the choice of the simplified exposure modelling framework. While the use of such models avoids computationally expensive model runs in alternate chemical transport models and can be used to better understand what is driving the results, they are necessary simplifications of atmospheric transport and chemistry. For example, (i) the model excludes the formation of secondary organic aerosols, nitrates and ammonium and their role in ambient PM<sub>2.5</sub> exposure, and (ii) modelling at the spatial scale of districts or groups of districts might obscure local effects which might result in biased outcomes, such as excluding the impact of a high-density urban zone within a rural district.

Third, the discussion of ambient air pollution mitigation, does not consider the costs and benefits of potential policy options in each emission sector, and the economy at large. Accounting the potential costs and benefits of a given policy option would help in understanding the feasibility (economic and regulatory) as well as effectiveness of policies. While there are estimates of the costs of mitigation of carbon emissions in India (McKinsey & Company 2009; Shukla 1995), costs of reducing air pollution, especially of informal sources have not yet been well characterized.

Finally, the global warming potential of non-Kyoto pollutants such as black carbon and NMVOCs, along with organic carbon and sulfur dioxide which have a cooling impact, has been

considered in this dissertation. However, uncertainty analysis on the non-Kyoto emissions from biomass burning and kerosene lamps, and their warming impact has not been conducted. This would provide valuable information on the expected range of their contribution to climate.

*Future directions:* Much of the recent energy sector modelling work in India, such as that by McKinsey & Company, TERI, World Bank, Government of India and CSTEP<sup>32</sup>, focusses on future climate impacts of energy consumption. While some include developmental aspects such as household access to modern energy or PM2.5 emissions alongside climate impacts, an integrated approach to analyzing benefits and trade-offs between the multiple energy sector goals of equitable energy access, reducing indoor and ambient particulate matter exposure and mitigating climate impacts, is missing from current modeling frameworks. This dissertation highlights a number of striking energy systems characteristics in India - biomass usage and associated non-Kyoto GHG emissions, unmet electricity needs of the population, the spatial differences in air pollution, and the significance of informal sector activity. Future work could include creating a more holistic and realistic energy systems model for India, that could be used to construct a comprehensive view of policy impacts and aid in better informed decision-making.

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<sup>32</sup> (McKinsey & Company 2009; World Bank 2011; WWF-India & TERI 2013; Planning Commission 2014; CSTEP 2016)

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## Appendices

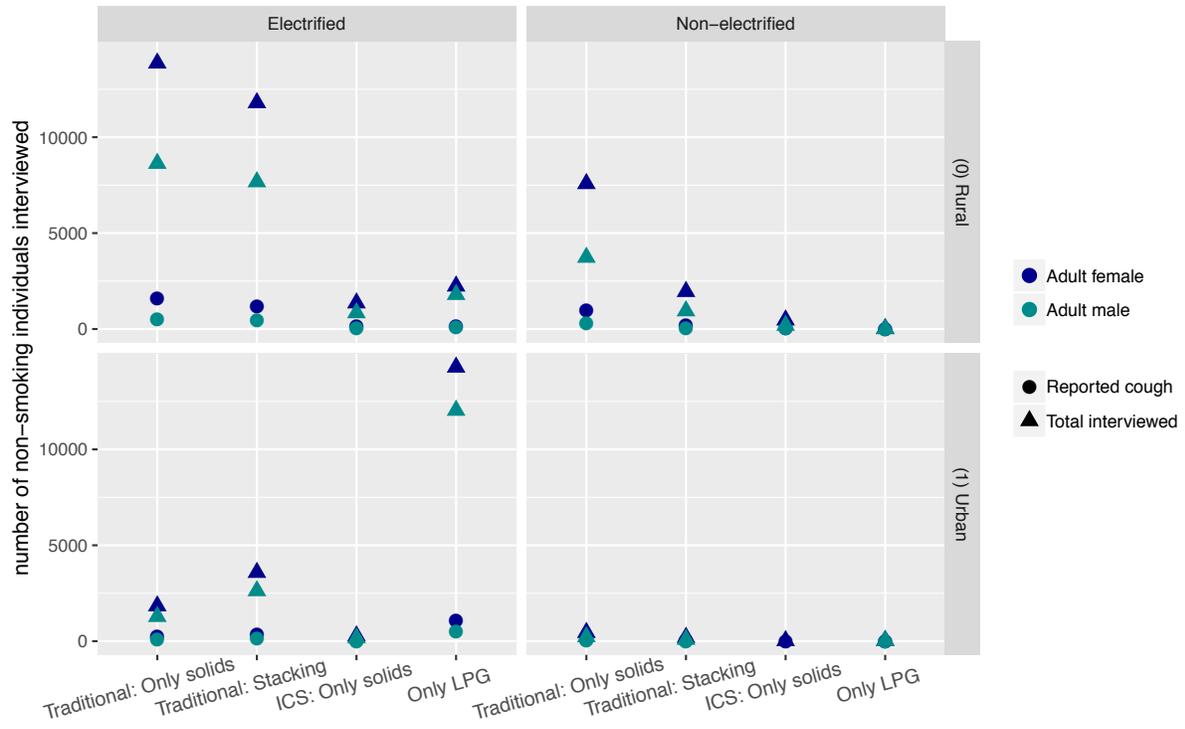
### Appendix A Chapter 2

#### A.1 Descriptive summary of outcome variables

1. Occurrence of cough in non-smoking adult men and women in the IHDS datasets for 2005 and 2011

Figure A.1 shows the number of adults interviewed in each of the categories of interest in this study. The largest groups are solid fuel-users in rural India and only-LPG users in electrified urban India. The following groups comprise of less than 15 adult male or female household members interviewed - non-electrified households using only LPG in both rural and urban subsets; and non-electrified urban households using ICS. The number of people who report having a cough in each of these categories is less than 6. I exclude these categories in the discussion of the impacts of household energy transition in Section 4.1.

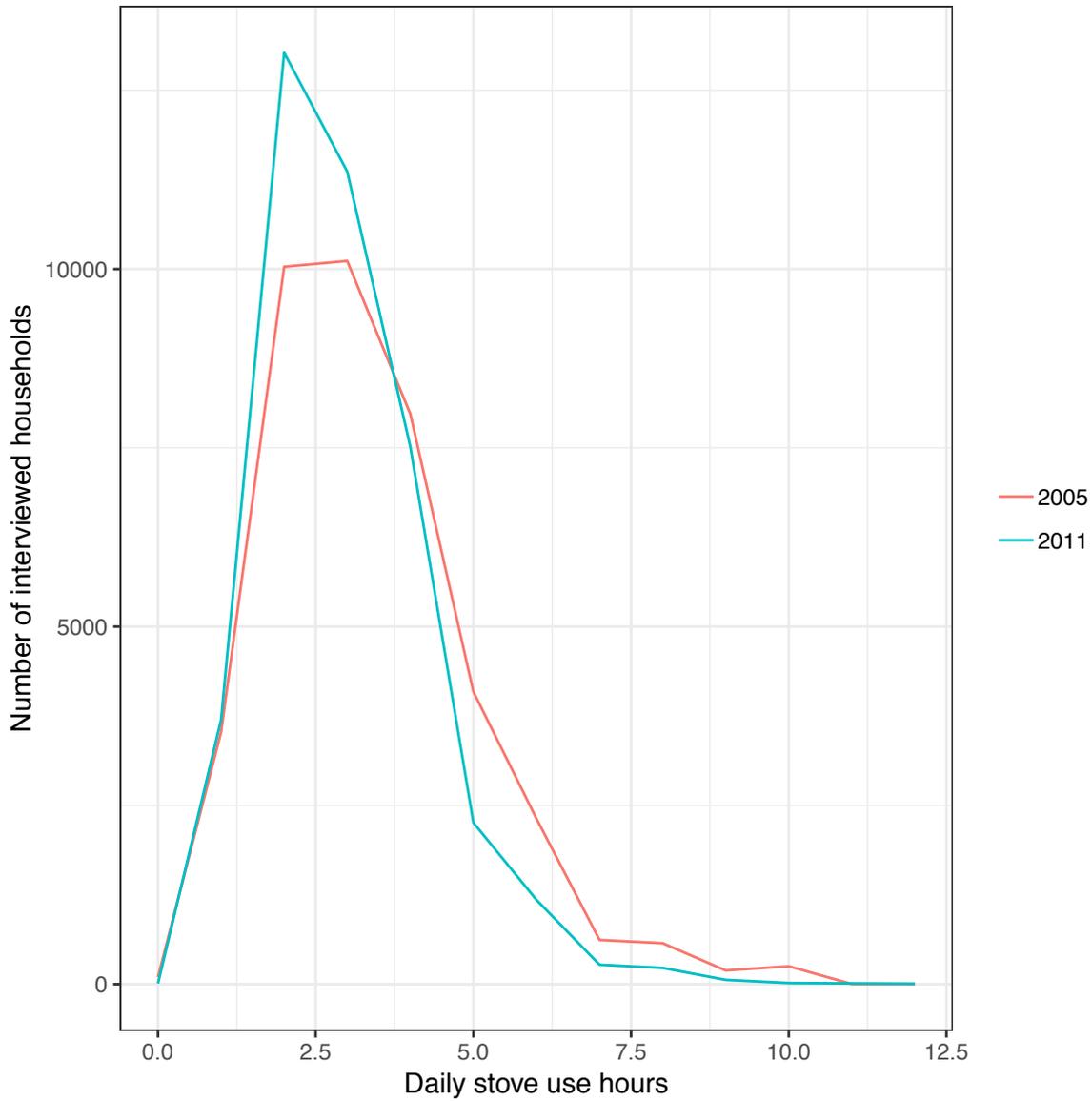
A higher proportion of adult men and women reported a cough in non-electrified households compared to households using electricity and in solid-fuel using households compared to LPG-using households. The proportion of women reporting a cough is higher than men across household groups.



**Figure A.1** Occurrence of cough in non-smoking individuals interviewed in the IHDS  
 \*'Traditional' = traditional cookstove without chimney; 'ICS'=improved cookstove with chimney

## 2. Distribution of reported daily stove use hours

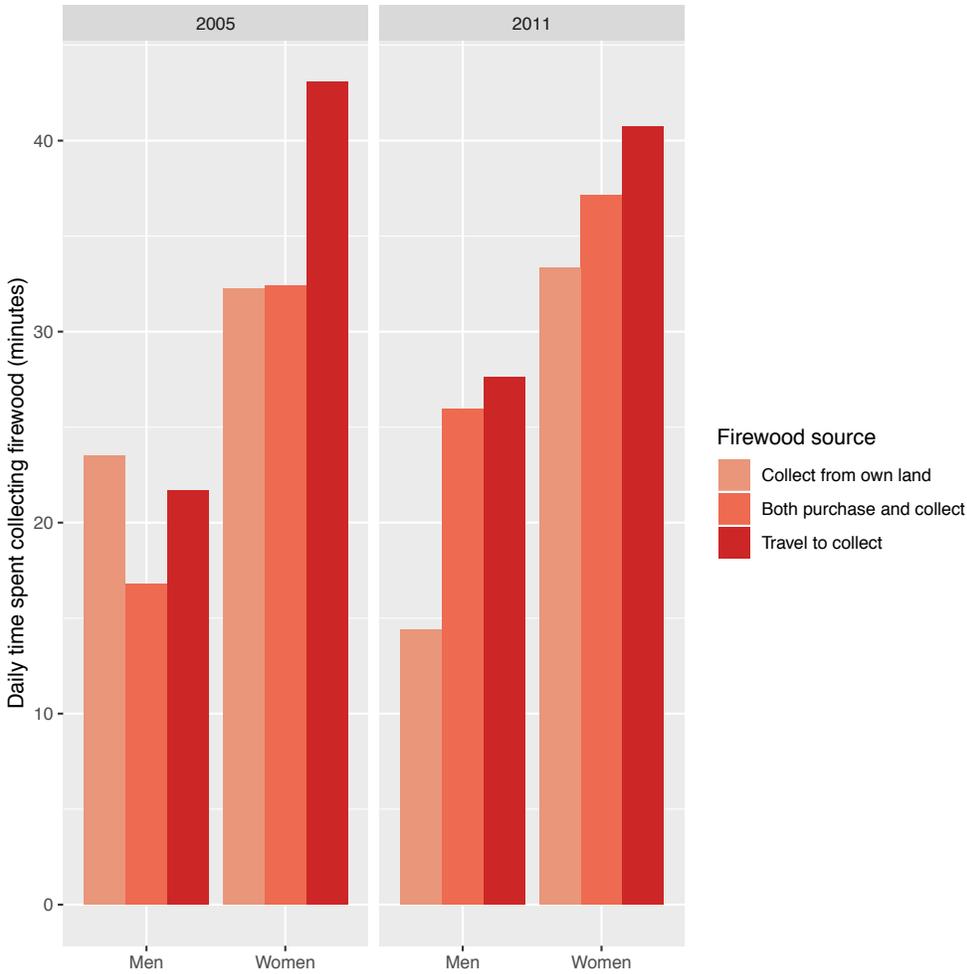
Figure A.2 shows the distribution of reported daily stove use hours in the IHDS surveys conducted in 2005 and 2011 – the average is about 3 hours in both years.



**Figure A.2** Daily stove use hours as reported in the IHDS surveys 2005 and 2011

### 3. Source of firewood in rural and urban households

Figure A.3 shows the average time spent by men and women collecting fuel – in general women spend more time than men on daily fuel collection, and households that travel to collect fuel spend more time (excluding the travel time).



**Figure A.3** Daily time spent collecting firewood in rural households in the IHDS surveys

## A.2 Occurrence of cough in adults in rural and urban households

1. The Stata equation for mixed effects logistic equation used for this analysis is as follows:

```

melogit cough_30days i.cooking#i.rural#i.age_gender i.electricity#i.rural i.quarter stovehours
log_incomepc i.passive || State: || id:

```

where cough\_30days={0=no cough reported within the previous month, 1=cough reported}

cooking= {0= No solid fuels, 1=Solid fuels with LPG for cooking in traditional cookstoves without chimney, 2= Only solid fuels in traditional cookstoves without chimney, 3= Only solid fuels in improved cookstoves with chimney}

electricity = {0 = No electricity used, only kerosene, 1= Electricity used with/without kerosene}

rural= {1= Rural, 0=Urban}

age\_gender = { >15 female, >15 male}

quarter = {1= Dec-Feb (winter), 2= Mar-May (spring/summer), 3= Jun-Aug (monsoon), 4= Sep-Nov (post-monsoon/pre-winter)}

passive= {0=no exposure to passive tobacco smoke from other household members, 1= exposed to passive smoke}

## 2. Mixed model suitability: Intra-class correlation

As part of post-estimation model diagnostics, the intra-class correlation (ICC) indicates if a mixed effects model, where the data is clustered by households and States, is suitable. Intra-class correlation is the ratio of the inter-cluster variance to the total model variance. It denotes how much of the model variance is explained by clustering at a given level. It also signifies the correlation between observations in the same cluster or group in the mixed model - high values of ICC indicate lower variability within clusters and imply higher variability across clusters hence justifying the use of the clustering variable as a random effect in the model (Seltman 2010; STATA n.d.). Observations within households show a correlation of 32% (i.e. grouping observations by

households explains 32% of the model variance), while State-level grouping show 5.7% correlation.

Level	ICC	Std. Err.	[95% Conf.	Interval]
State	0.056	0.0142	0.034	0.092
Households>State	0.321	0.012	0.300	0.345

**Table A.1** Occurrence of cough in individuals: Intra-class correlation (ICC) for mixed effects logistic regression

### 3. Post-hoc tests for statistical significance of differences between categories of interest

After running the model, I conduct pairwise comparisons across different levels of explanatory factor variables to test if groups with overlapping confidence intervals are statistically significant (at 95% confidence level) in terms of their difference – ‘pwcompare’ command in Stata reports the differences of marginal means along with the p-value and confidence interval of the difference.

I find that differences in predicted probability of developing a cough between the following groups are not statistically significant at 95% confidence level: only using solid fuels vs. stacking them with LPG; and men vs. women in LPG-using rural households.

Group	Comparison	Contrast	std.error	z	p-value	Confidence interval (95%)	
Non- Electrified rural male	Only solids vs. stacking with LPG in TCS using households	-0.16	0.06	-2.62	0.06	-0.33	0.00
Non- Electrified urban male	Only solids vs. stacking with LPG in TCS using households	-0.12	0.13	-0.91	1.00	-0.47	0.23
Non- Electrified urban female	Only solids vs. stacking with LPG in TCS using households	-0.03	0.09	-0.32	1.00	-0.27	0.21
Urban solid fuel use non-electrified: males	ICS vs. TCS	0.04	0.20	0.18	1.00	-0.49	0.56
Urban solid fuel use non-electrified: females	ICS vs. TCS	0.09	0.14	0.63	1.00	-0.27	0.45

Group	Comparison	Contrast	std.error	z	p-value	Confidence interval (95%)	
Urban solid fuel use electrified: males	ICS vs. TCS	0.04	0.20	0.18	1.00	-0.49	0.56
LPG using rural households: non-electrified	Men vs Women	-0.44	0.17	-2.63	0.05	-0.89	0.00
LPG using rural households: electrified	Men vs Women	-0.44	0.17	-2.63	0.05	-0.89	0.00

**Table A.2** Results from post-hoc pairwise statistical testing of differences  
*\*TCS: traditional biomass cookstove without chimney; ICS: Improved biomass cookstove with chimney*

4. Predictive performance of mixed effects logistic regression model

I test the predictive performance of the mixed effects regression model employed in Chapter 2 Section 2.4.1 using the method described by Foulkes et al. (2010). I first employ the following predictive classification rule for individuals (based on the predicted probability of cough in women in solid fuel using households = 0.18 – 0.27):

$$\begin{aligned} \text{Predicted occurrence of cough} &= 1 \text{ if } p \geq 0.2 \\ &= 0 \text{ if } p < 0.2 \end{aligned}$$

where p = predicted probability of occurrence of cough

Predicted occurrence of cough	Reported occurrence of cough in the dataset		
	0	1	Total
0	65020	4286	69306
1	6772	7874	14646
Total	71792	12160	83952

**Table A.3** Contingency table: comparing predicted and observed occurrence of cough in non-smoking adult household members

I then calculate the sensitivity (true positive rate or observed individuals with a cough who are correctly classified as such by applying the classification rule to results from the regression model) and specificity (true negative rate or observed individuals without a cough who are correctly classified as such by applying the classification rule to results from the regression model).

$$\text{Sensitivity} = 7874/12160 = 65\%$$

$$\text{Specificity} = 65020/71792 = 91\%$$

Thus the model can correctly identify 65% of occurrences of cough and 91% of non-occurrences of cough.

The area under the ROC or Receiver Operating Characteristic Curve curve (a plot of sensitivity vs. 1- specificity of a model) is often used as a measure of the diagnostic accuracy of the model (Mandrekar 2010) and ranges between 0 and 1 – the higher the area under the curve, the better the predictive power of the model. The area under the ROC curve in Stata is calculated as 0.89.

### A.3 Stove use

1. The regression model used in Stata is as follows:

```
mixed hours i.cooking#i.rural mealsperday hhsz i.quarter || id: , vce(robust)
```

hours = daily stove use hours

*cooking*= {0= No solid fuels, 1=Solid fuels with LPG for cooking in traditional cookstoves

without chimney, 2= Only solid fuels in traditional cookstoves without chimney, 3= Only solid fuels in improved cookstoves with chimney}

*rural*= {1= Rural, 0=Urban}

*quarter* = {1= Dec-Feb (winter), 2= Mar-May (spring/summer), 3= Jun-Aug (monsoon), 4= Sep-Nov (post-monsoon/pre-winter)}

2. Mixed model suitability:

Stata results show that the household-level standard deviation (standard deviation on the intercept or random effect) is close to zero, in which case the household-level panel effect (or households as grouping variable) is not significant (as further indicated by the Likelihood Ratio test output comparing the pooled estimator with the panel estimator) and the model can be treated as a pooled dataset.

Stata results for standard deviation of intercept (or the random effect) and likelihood ratio test:

	Estimate	Std.error	Confidence interval (95%)	
Std. deviation of intercept (sigma_u)	.008	0.001	0.0008	0.0084
Likelihood-ratio test of sigma_u=0: chibar2(01)= 0.72 Pr>=chibar2=0.1981				

**Table A.4** STATA results for standard deviation of random effect parameter (households)

Intra-class correlation is low at 0.04% which further implies that the the household-level grouping variable is not significant.

3. Post-hoc tests for statistical significance of differences between categories of interest

I conduct post-hoc pairwise tests for statistical significance of differences for observation groups with overlapping confidence intervals. Results are presented in Table A.5. Differences in stove use hours between improved cookstove use and traditional cookstove use in urban households are not statistically significant (at 95% CI).

Rural	Contrast	std.error	z	p-value	Confidence interval (95%)	
Only solid vs. Only LPG	0.62	0.03	20.36	0.00	0.51	0.72
Only solids vs. stacking in traditional cookstoves	0.02	0.02	1.29	0.20	-0.01	0.06
Only solids in ICS vs. traditional cookstoves	0.02	0.03	0.80	1.00	-0.07	0.11
Urban	Contrast	std.error	z	p-value	Confidence interval (95%)	
Only solid vs. Only LPG	0.41	0.03	13.76	0.00	0.31	0.51
Only solids vs stacking in traditional cookstoves	0.10	0.03	3.31	0.00	0.00	0.20
Only solids in ICS vs. traditional cookstoves	-0.15	0.10	-1.61	0.11	-0.34	0.03

**Table A.5** Results from posthoc pairwise testing of differences

#### A.4 Firewood collection time

1. The regression model used in Stata is as follows:

```
mixed log_collection i.source i.cooking#i.age_gender hhsize hours log_incomepc gender ||  
district: || id:
```

Collection=Annual time (minutes) spent collecting solid fuels in rural households

Source = {Collect from own land, Collect from other places, Both purchase and collect}

*cooking*= {1=Solid fuels with LPG for cooking in traditional cookstoves without chimney, 2= Only solid fuels in traditional cookstoves without chimney, 3= Only solid fuels in improved cookstoves with chimney}

Age\_Gender = { >15 female, >15 male }

Hours= daily stove use hours

Hhsize = number of household members

District and id represent the State-level and household-level random effects respectively

2. Model suitability: Intra-class correlation

Observations within the same household shows 57% correlation while the intra-district observations show about 16% correlation. I consider a mixed model with district and household grouping variables suitable for this analysis.

Level	ICC	Std. Err.	[95% Conf.	Interval]
District	0.1598295	0.0128894	0.1361518	0.1867348
Id>District	0.5859858	0.007113	0.5719793	0.5998546

**Table A.6** Fuel collection time in households: Intra-class correlation (ICC) for mixed effects linear regression

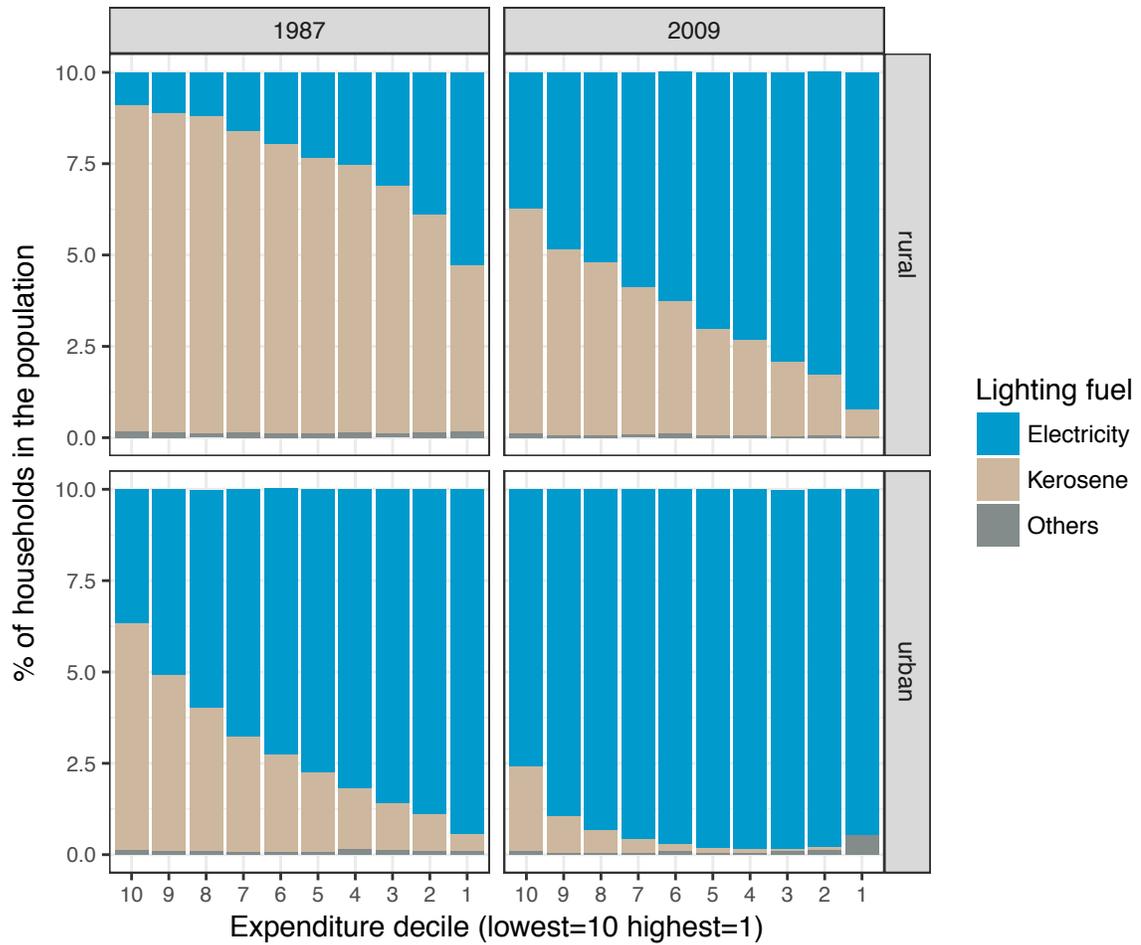
3. Duan’s smearing factor

Duan’s smearing estimator is used to back-transform logarithmic predicted values into non-logarithmic form (Duan 1983). It is calculated as the mean exponentiated residual from the regression model. The value for this regression model (with predicted variable as logarithm of fuel collection time) is calculated as 1.3. Duan’s smearing estimator is then multiplied with the exponentiated predicted value to get estimates of fuel collection time. The model is checked to ensure homoscedasticity.

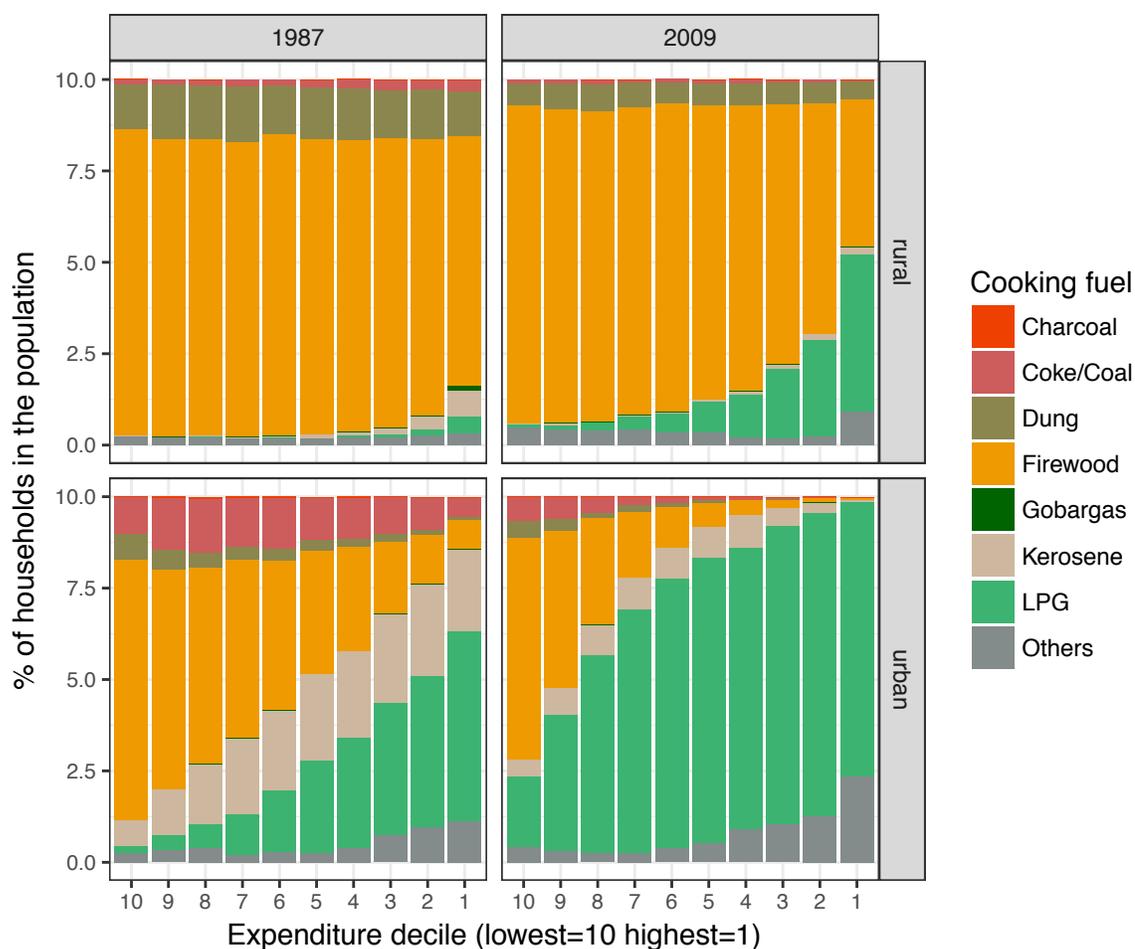
## Appendix B Chapter 3

### B.1 Transition in primary cooking and lighting fuel (1987-2009)

Figures B.1 and B.2 show the household fuel transition between 1987 and 2009 discussed in Section 3.3.1.



**Figure B.1** Use of kerosene and electricity as primary lighting fuel.  
NSS (1987-88 and 2009-10)

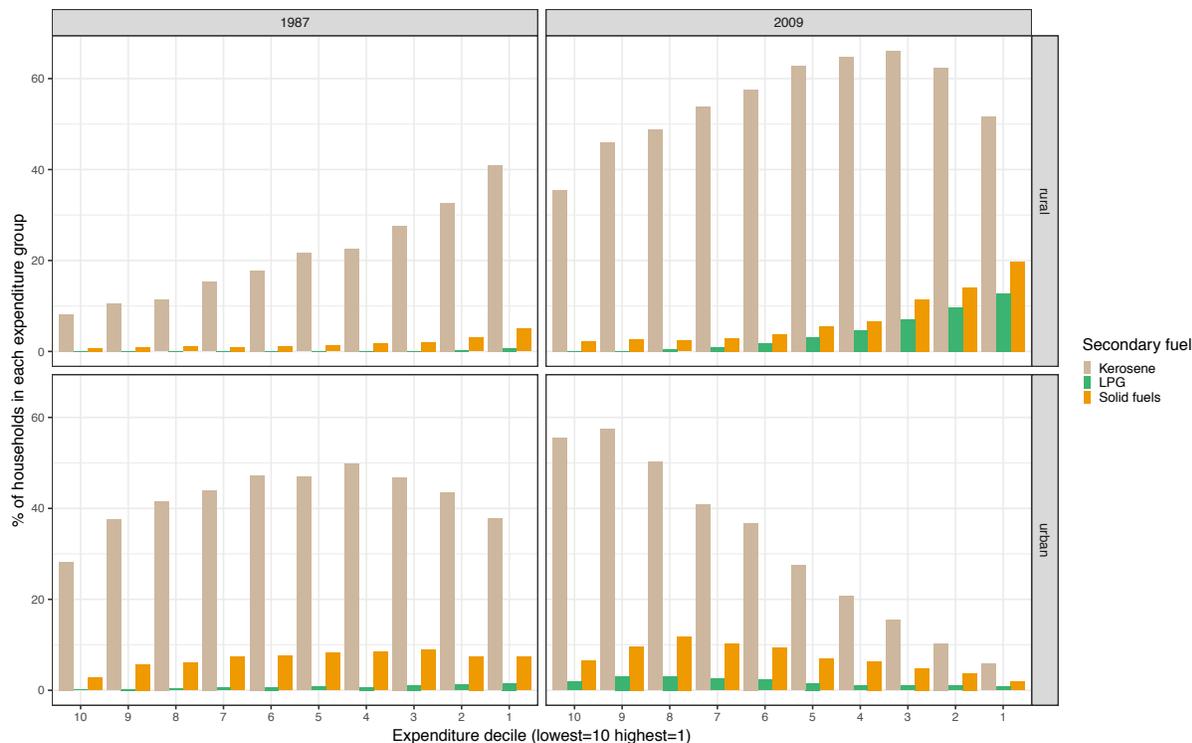


**Figure B.2** Use of primary cooking fuel by source.  
*NSS (1987-88 and 2009-10)*

The primary lighting fuel category of ‘Others’ includes candles, oil (diesel generators), non-specified sources and reported instances of no lighting arrangement, while the primary cooking fuel category of ‘Others’ includes electricity, non-specified fuel and reported instances of no cooking arrangements.

Figure B.3 shows the share of households, disaggregated by urban-rural location and income groups, who use kerosene, LPG and firewood as secondary fuels or ‘stack’ them with other fuels. Fuel stacking, particularly using kerosene as a secondary fuel, is common in rural India and in fact

increased in prevalence between 1987 and 2009, while in urban India it was restricted to low-income households by 2009.



**Figure B.3** Share of households (%) who use kerosene, LPG and solid fuels as secondary fuels NSS (1987-88 and 2009-10)

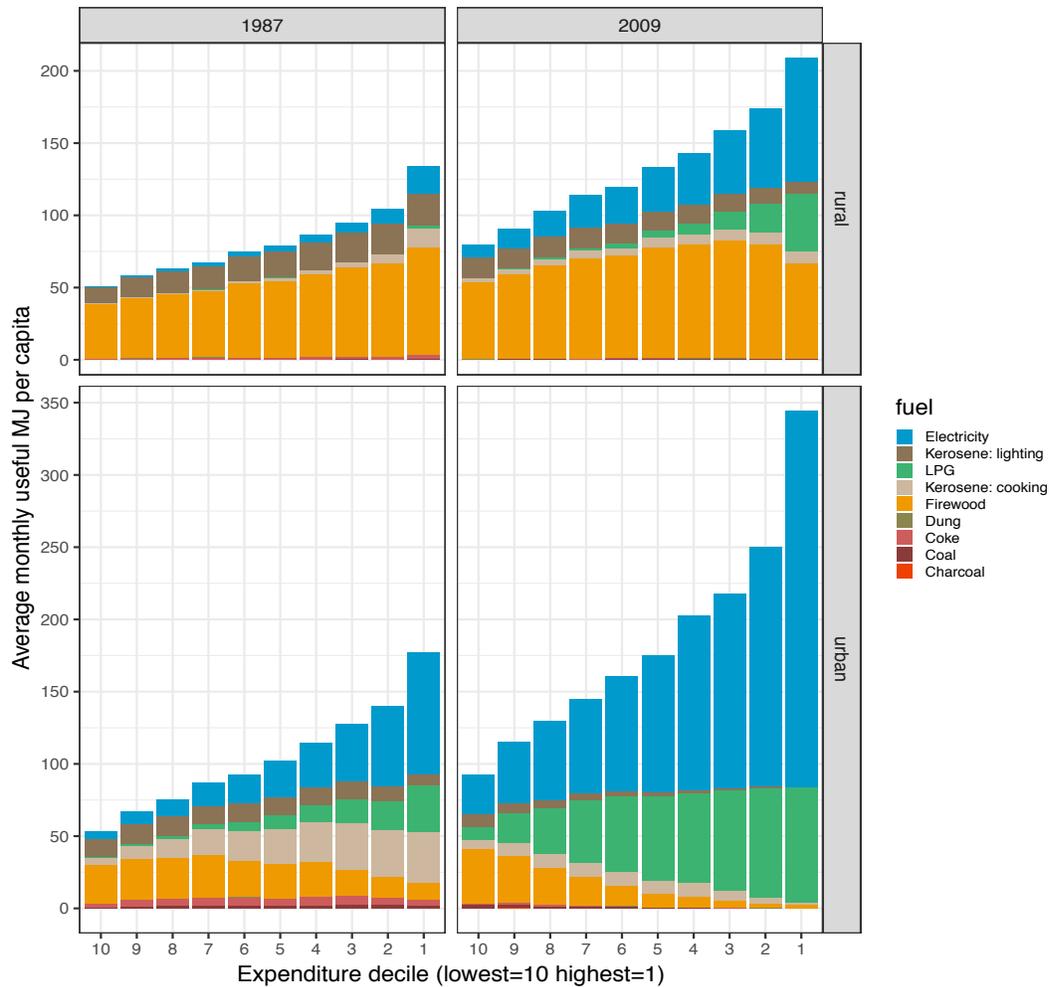
## B.2 Transition in energy consumption and GHG emissions

Table B1 presents the cooking fuel energy density and stove efficiency used to calculate household energy use discussed in Section 3.3.1 and presented in Figure B4. Tables B2 – B4 present the GWPs of pollutants and the emission factors for cooking and lighting fuel used to calculate GHG emissions and PM2.5 exposure as discussed in Section 3.3.2.

### B.2.1. Cooking fuel: Energy density and stove efficiency

	Fuel content (MJ/kg)	Stove efficiency (%)
LPG	46	54
Kerosene	34*	50
Firewood	16	18
Firewood (Improved cookstove)	16	23
Coke	26 <sup>1</sup>	17 (assumed same as coal)
Coal	20	17
Charcoal	26	18
Dung <sup>2</sup>	11.8	11
PNG	51 <sup>1</sup>	54 (assumed same as LPG)

**Table B.1:** Cooking fuels: energy density and stove efficiency  
 (Source: (Grieshop et al. 2011) \*MJ/litre <sup>1</sup>Planning Commission  
<http://planningcommission.nic.in/sectors/index.php?sectors=energy>) <sup>2</sup>



**Figure B.4** Average monthly per capita useful energy consumption in urban and rural India by fuel type (Kerosene for lighting is represented as total energy of kerosene used per capita)

Since the NSS dataset does not provide the end-use for kerosene consumption, I split reported household kerosene consumption into cooking and lighting uses as follows: if it is used as a primary fuel for cooking *or* lighting, I assume that all kerosene is used for the stated purpose; if it is used as a primary fuel for cooking *and* lighting, I assume that all kerosene greater than 4 litres is used for cooking (N. D. Rao 2012) and if consumption is < 4 litres/month, I equally split it into cooking and lighting uses; if kerosene is used as secondary fuel, I assume that consumption for cooking and lighting is split in the ratio in which it is used in an average

kerosene-using household in the dataset. The end-use specific consumption ratios are derived by dividing average kerosene consumption in households that use kerosene as a primary cooking fuel and kerosene use in households where kerosene is the primary lighting fuel, and correspond to 5.25:1 and 3.27:1 for 1987 and 2009 respectively.

#### B.2.2. Emission factors (g/kg fuel or g/litre for kerosene) for cooking fuels and kerosene lamps

	CO2	CH4	N2O	CO	BC	NMV OC	OC	SO2	PM2.5
Firewood	1533 <sup>1</sup>	6.4 <sup>1</sup>	0.14 <sup>3</sup>	82 <sup>1</sup>	1.5 <sup>1</sup>	6.9 <sup>2</sup>	4 <sup>1</sup>	0.06 <sup>1</sup>	8.5 <sup>1</sup>
ICS	1533 <sup>1</sup>	3.9 <sup>1</sup>	0.07 <sup>3</sup>	68 <sup>1</sup>	1.2 <sup>1</sup>	8.5 <sup>1</sup>	1 <sup>1</sup>	0.01 <sup>1</sup>	2.5 <sup>1</sup>
Kerosene	2360 <sup>1</sup>	0.207 <sup>1</sup>	0.063 <sup>3</sup>	14 <sup>1</sup>	0.39 <sup>1</sup>	13.3 <sup>2</sup>	0.08 <sup>1</sup>	0.03 <sup>1</sup>	0.39 <sup>1</sup>
LPG	3084 <sup>1</sup>	0 <sup>1</sup>	0.15 <sup>3</sup>	18 <sup>1</sup>	0.2 <sup>1</sup>	19 <sup>2</sup>	1 <sup>1</sup>	0 <sup>1</sup>	0.5 <sup>1</sup>
Coke	2512 <sup>4</sup>	10.3 <sup>4</sup>	0.036 <sup>4</sup>	78 <sup>4</sup>	2.08 <sup>4</sup>	2.6 <sup>4</sup>	0 <sup>4</sup>	0.37 <sup>4</sup>	1.17 <sup>4</sup>
Coal	2512 <sup>1</sup>	10.3 <sup>1</sup>	0.024 <sup>4</sup>	71 <sup>1</sup>	4.4 <sup>1</sup>	10.5 <sup>2</sup>	3.1 <sup>1</sup>	0.15 <sup>1</sup>	8.7 <sup>1</sup>
Charcoal	4081 <sup>1</sup>	62 <sup>1</sup>	0 <sup>4</sup>	480 <sup>1</sup>	2.3 <sup>1</sup>	63.5 <sup>1</sup>	8 <sup>1</sup>	0.01 <sup>1</sup>	0.4 <sup>1</sup>
Dung	1046 <sup>2</sup>	4.5 <sup>2</sup>	0.3 <sup>2</sup>	40 <sup>2</sup>	0.4 <sup>2</sup>	24.1 <sup>2</sup>	3.1 <sup>2</sup>	0.9 <sup>2</sup>	9.8 <sup>2</sup>
PNG	2846 <sup>4</sup>	10.2 <sup>4</sup>	0 <sup>4</sup>	1.53 <sup>4</sup>	0.0663 <sup>4</sup>	2.1 <sup>4</sup>	0.0765 <sup>4</sup>	0.05 <sup>4</sup>	0.102 <sup>4</sup>
Kerosene-lamp (wick)	2185 <sup>2</sup>	0.136 <sup>4</sup>	0.078 <sup>2</sup>	8.68 <sup>2</sup>	70.2 <sup>2</sup>	0 <sup>2</sup>	0.312 <sup>2</sup>	0.016 <sup>2</sup>	72.54 <sup>2</sup>

**Table B.2** GHG and PM2.5 emission factors of cooking fuels

\*ICS=Improved biomass cookstove <sup>1</sup>(Grieshop et al. 2011) <sup>2</sup>(Pandey et al. 2014) <sup>3</sup>(Smith et al. 2000)

<sup>4</sup> GAINS database for South Asia ([http://gains.iiasa.ac.at/models/gains\\_models3.html](http://gains.iiasa.ac.at/models/gains_models3.html))

Table B.2 shows CO2 emission factors for firewood assuming 0% renewability.

B.2.3. Emission factors for electricity in 2009 and 1987 (g/kWh)

Fuel	% generation 2009 <sup>1</sup>	% generation 1987 <sup>1</sup>	CO2 (2009) <sup>1</sup>	CO2 (1987) <sup>1</sup>	CH4 <sup>2</sup>	N2O <sup>2</sup>
Hydro	16%	22%	0	0	0	0
Nuclear	2%	2%	0	0	0	0
Thermal: Coal	65%	71%	1058.3	1138.7	0.015	0.1314
Thermal: Gas	12%	2%	440	540.6	0.0294	0.0098
Thermal: Lignite	3%	3%	1409.6	1646.8	0.015	0.1314
Thermal: Naphtha	2%	-	1062	-	0.036	0.02
Thermal: Oil	1%	0%	1062	1062.5	0.036	0.02

**Table B.3** GHG (Kyoto) emission factors for electricity

<sup>1</sup>(CEA 2011) <sup>2</sup>(Sadavarte & Venkataraman 2014)

*Non-CO2 GHG emission factors for lignite and naphtha power plants are assumed to be the average values for coal and oil power plants respectively.*

Fuel	% generation 2009 <sup>1</sup>	% generation 1987 <sup>1</sup>	CO <sup>2</sup>	NMVOC <sup>2</sup>	BC <sup>2</sup>	OC <sup>2</sup>	SO <sub>2</sub> <sup>3</sup>
Hydro	16%	22%	0	0	0	0	0
Nuclear	2%	2%	0	0	0	0	0
Thermal: Coal	65%	71%	1.1023	0.0219	0.00876	0.0292	8.2
Thermal: Gas	12%	2%	0.1176	0.0065	0	0	0
Thermal: Lignite	3%	3%	1.1023	0.0219	0.00876	0.0292	8.2
Thermal: Naphtha	2%	-	0.376	0.368	0.002	0.0002	2.6
Thermal: Oil	1%	0%	0.376	0.368	0.002	0.0002	2.6

**Table B.4** GHG (non-Kyoto) emission factors for electricity

<sup>1</sup> (CEA 2011) <sup>2</sup> (Sadavarte & Venkataraman 2014) <sup>3</sup> GAINS database for South Asia

([http://gains.iiasa.ac.at/models/gains\\_models3.html](http://gains.iiasa.ac.at/models/gains_models3.html)). Non-CO<sub>2</sub> GHG emission factors for lignite and naphtha power plants are assumed to be the average values for coal and oil power plants respectively.

#### B.2.4. Global Warming Potential (GWP or CO<sub>2</sub> equivalent)

Greenhouse pollutant	GWP or CO <sub>2</sub> eq
CO <sub>2</sub>	1
CH <sub>4</sub>	24
N <sub>2</sub> O	300
CO	2.69
NM VOC	7.32
EC	533
OC	-83
SO <sub>2</sub>	-64

**Table B.5** Global warming potential (GWP) of GHGs.  
*Source: (Venkataraman et al. 2016)*

### B.3 Modelling energy scenarios for 2030

#### B.3.1. Income growth projection for 2030

OECD analysis for GDP per capita for India project Compounded Annual Growth Rate (CAGR) for 2010-2020 =5.8% and CAGR for 2020-2030 =5.6%. I assume that the income distribution remains constant and consumption increases across individuals in income groups uniformly. I project Monthly Per Capita Expenditure (MPCE) in 2030 for rural and urban households in each income decile *i* as follows:

$$MPCE_i = MPCE_{i,2009} \left(1 + \frac{r}{100}\right)^T$$

Where  $r$  = CAGR and  $T$  = time period between 2030 and 2009 in years

### B.3.2. Household size projection for 2030

	Urban	Rural
NSS 2009	4.1	4.7
World Bank projection for 2030	4.2	3.7

**Table B.6:** Household size projection for 2030  
*Source: (World Bank 2008b)*

For rural and urban households:

Household size ratio is the mean household size in 2030 (World Bank projected) divided by the mean household size in 2009 (NSS).

Projected household size in 2030 in income decile  $i$  is set equal to the mean household size in income decile  $i$  in 2009 (NSS) multiplied by the household size ratio.

### B.3.3. Population projections for 2030

Urban population in 2030 = 583,038,000

Rural population in 2030 = 893,339,000

*Source: World Urbanisation Prospects 2018, UN (<https://esa.un.org/unpd/wup/DataQuery/>)*

Estimated households in each urban decile in 2030 = 15,753,905

Estimated households in each rural decile in 2030 = 21,205,703

Each NSS household interviewed in 2009 is assigned a new projected weight (weight in NSS 2009 multiplied by the ratio of households in each decile in 2030 and 2009) to represent households in 2030.

#### B.3.4. Projection of electrification rate

I use the Gompertz function to model access to electricity as a function of MPCE in 2030. The Gompertz function is a 3-parameter logistic function, often used to represent technological diffusion (Meade & Islam 1998; Braimllari Spaho & Sala 2017; K. U. Rao & Kishore 2010), including electrification (World Bank 2008b). In a sigmoid growth curve, growth is slow at the beginning when only a few users adopt a technology, then rises rapidly as the technology diffuses and after an inflexion point, adoption slows down till the saturation point, or maximum number of adopters, is reached. While a logistic curve is symmetrical about the point of inflexion (point where rate of growth starts decreasing), the Gompertz model allows asymmetry about the point of inflexion, providing some flexibility in the form of the growth curve.

I use the ‘grofit’ package in R to fit forms of the logistic growth curve to electrification rate and average MPCE in each decile and select the Gompertz function since it provides the best fit. The Gompertz function as used in the grofit package in R (Kahm et al. 2010):

$$y(t) = A \exp \left( - \exp \left( \mu \left( \frac{\lambda - t}{A} \right) + 1 \right) \right)$$

where A= saturation level or maximum level of adoption

$\mu$ = slope of curve or rate of adoption of a technology

$\lambda$ = lag phase or displacement on the x-axis

	Urban	Rural
A	100	100
$\mu$	0.72	0.41
$\lambda$	-2.1	-11.3

**Table B.7** Gompertz curve parameters for 2030 electrification rate projection

For 2030 projections, saturation level of electrification is assumed to be 100% for both rural and urban households.

#### B.3.4.a. Projection of per capita electricity consumption:

I select the best fitting sigmoid growth curve for mean per capita electricity consumption (in electrified households) against mean MPCE in each decile. I model increase in per capita electricity consumption with MPCE using a generalized logistic function or Richards function. The Richards function allows flexibility in the position of point of inflexion through a shape parameter (Höök et al. 2011; Teleken et al. 2017), unlike the logistic (inflexion point=0.5) and Gompertz function (inflexion point~0.37). The generalized logistic function has been used to model biological growth (Teleken et al. 2017) and forecast electricity consumption (Mohamed & Bodger 2005).

	Urban	Rural
A	102	26/52/102
$\mu$	0.08	0.06
$\lambda$	3.97	-28.8
Shape parameter	-0.8972	-0.1000

**Table B.8** Growth curve parameters for projection of per capita electricity consumption

For 2030 projections, the per capita electricity consumption in the highest income group in rural households scenarios are modelled as follows:

- 1) BAU: 26 kWh/capita/month – no additional government effort in improving electricity supply and an individual in the highest rural decile does not increase consumption relative to 2009 as income rises.
- 2) Medium effort: 52 kWh/capita/month – moderate improvement in rural electricity supply such that those in highest income decile are allowed to double their per capita electricity use (leading to a 30% increase in total rural electricity supply)
- 3) Strong push: 102 kWh/capita/month – no physical barriers to electricity supply and high-income rural deciles increase their electricity consumption as income changes, i.e. per capita electricity consumption in the highest income group is determined by income. Rural household mimic urban households in this scenario.

**B.3.4.b: Projection of total electricity consumption:**

Total electricity consumption for 2030 is estimated using projected electrification rate in each decile and projected mean per capita electricity consumption in electrified households. Here we

present the estimated values for electricity consumption in 2030 for Scenario 3 in which electricity consumption in urban as well as rural households follows income patterns (Strong effort in rural LPG and electricity) (All MPCE are presented in 2009 values):

Rural households:

Decile	Mean MPCE (2009)	Mean MPCE (2030)	Mean hhsiz (2009)	Household size (2030)	% electrified (2009)	% electrified (2030)	Mean monthly electricity/capita (2009)	Mean monthly electricity/capita (2030)
10	83	253	5.8	5.2	38.37	86.4	6.80	17.77
9	109	331	5.5	4.9	49.73	94.1	7.76	21.76
8	127	385	5.2	4.7	53.62	96.7	9.42	24.62
7	143	433	4.9	4.4	60.28	98.0	10.56	27.32
6	160	484	4.8	4.3	64.87	98.9	10.92	30.22
5	179	541	4.5	4.1	71.94	99.4	12.15	33.53
4	202	612	4.5	4.0	75.22	99.7	13.17	37.70
3	235	711	4.2	3.8	80.74	99.9	15.23	43.47
2	290	880	3.9	3.5	84.53	100.0	18.42	53.05
1	568	1722	3.4	3.0	93.53	100.0	25.91	85.90

**Table B.9** Rural households: per capita expenditure, size and electricity consumption in 2009 and 2030 (projection: Scenario 3)

Urban households:

Decile	Mean MPCE (2009)	Mean MPCE (2030)	Mean hh-size (2009)	House- hold size (2030)	% electrified (2009)	% electrified (2030)	Mean monthly electricity/ capita (2009)	Mean monthly electricity/ capita (2030)
10	119	361	5.7	5.1	76.8	99.8	10.11	28.46
9	167	506	5.2	4.7	90.3	100.0	13.30	38.27
8	206	623	4.9	4.3	93.7	100.0	16.39	45.34
7	247	747	4.5	4.0	96.0	100.0	19.10	52.03
6	293	887	4.3	3.8	97.6	100.0	23.02	58.71
5	348	1055	4.0	3.6	98.4	100.0	27.01	65.62
4	415	1259	3.6	3.2	98.50	100.0	34.53	72.59
3	511	1548	3.5	3.1	98.5	100.0	38.44	80.35
2	677	2053	3.2	2.9	99.0	100.0	47.58	89.41
1	1444	4374	2.6	2.3	99.0	100.0	77.89	101.42

**Table B.10** Urban households: per capita expenditure, size and electricity consumption in 2009 and 2030

(projection)

Model projections for total household electricity consumption for 2030 is 9% higher than that from the World Bank study (World Bank 2008a), in which projections for residential electricity consumption in 2030 are based on appliance adoption trends.

Kerosene use for lighting in 2030:

Assumed monthly quantity for lighting = 4 litres per household (N. D. Rao 2012)

Monthly kerosene quantity needed for lighting in each decile (litres) = 4 \* the number of households without electricity access in each decile.

B.3.5. Projections for cooking fuel mix in 2030:

The share of different fuels in the cooking energy mix and useful cooking energy requirements per capita are considered specific to income groups. As household's MPCE rises from 2009 to 2030, the fuel mix curve is assumed to shift to the right. LPG adoption (share of LPG in per capita cooking energy use) is modelled using Gompertz and Richards functions in rural and urban households respectively (selected using the 'grofit' package in R). Firewood's share in useful cooking energy mix is adjusted according to LPG adoption projection in each decile. Given the widespread availability of firewood in rural areas, I keep a constraint of 90% of rural households' energy requirements being met with LPG.

	Urban	Rural
A	0.95	0.38/0.6/0.9
$\mu$	0.004386	0.00155
$\lambda$	76.7	137.9
Shape parameter	-0.670075	-

**Table B.11** Growth curve parameters for urban and rural LPG adoption rate

For 2030 projections, saturation level in the share of LPG in cooking energy requirements in rural households takes 3 values for 3 scenarios –

- 1) BAU: 38% - highest income rural decile does not increase LPG consumption relative to 2009 as income rises; fuel stacking persists.
- 2) Medium effort: 60% - moderate improvement in LPG supply such that highest income decile is allowed to satisfy 60% of their cooking energy requirements with LPG (leading to a 38% increase in total rural LPG supply)
- 3) Strong push: 90% - no physical barriers to rural LPG supply. High income rural deciles can increase their LPG consumption as income changes, and satisfy up to 90% of their cooking energy requirements using LPG. I keep a limit of 90% as firewood is readily available in rural areas and I assume that rural households prefer to use some firewood for cooking.

Useful cooking energy requirements are calculated from projected fuel mix in each scenario, household size and per capita cooking energy requirements in each decile, and assumed stove efficiencies.

#### **B.4 Kyoto, non-Kyoto and net GHG emissions for energy transition pathways to 2030**

Figure B.7 shows the projected change in emissions per household between 2009 and 2030 for the BAU scenario, while Figure B.8 shows total change in emissions across India. In figure B.7, emissions from electricity are split into Kyoto (positive) and non-Kyoto (negative primarily due to SO<sub>2</sub> emissions). LPG consumption per household in middle and high-income urban households is projected to reduce due to lower household sizes. Firewood and kerosene consumption is expected to reduce across all household groups. In figure B.8, total rural emissions are projected to reduce by 2030 due to a transition away from firewood and kerosene lighting, and consequent reduction in non-Kyoto emissions, while rising urban emissions are primarily driven by electricity consumption.

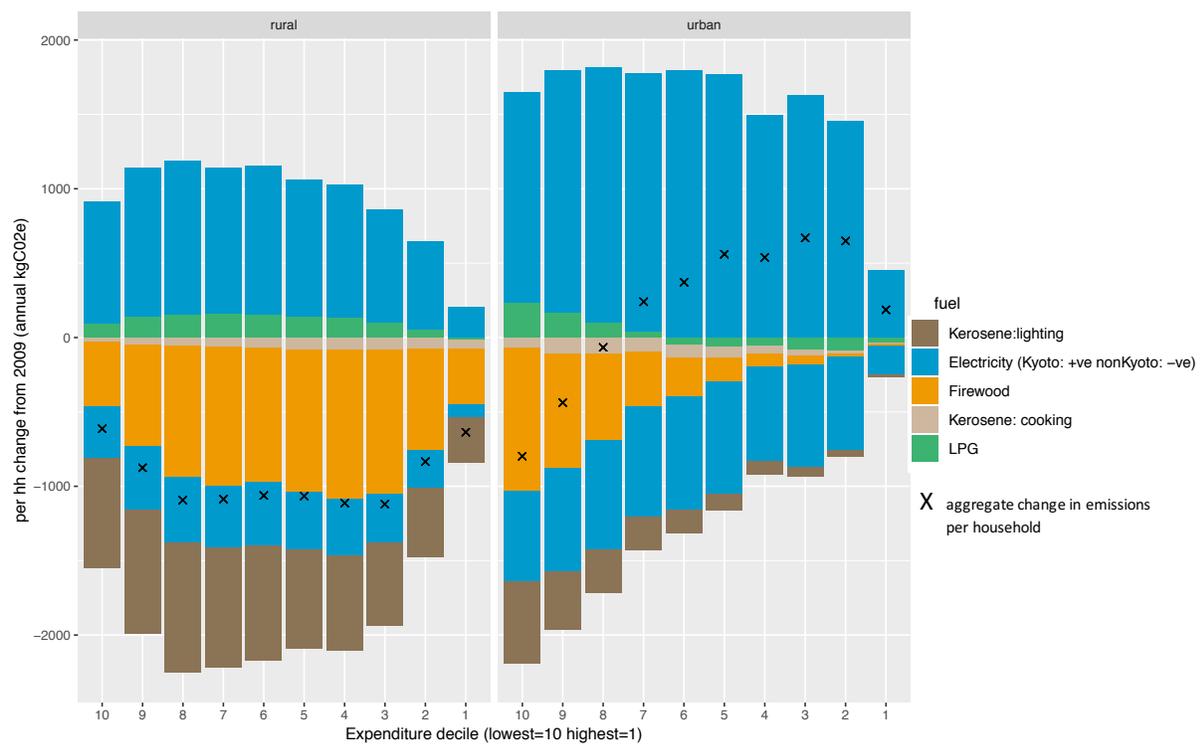
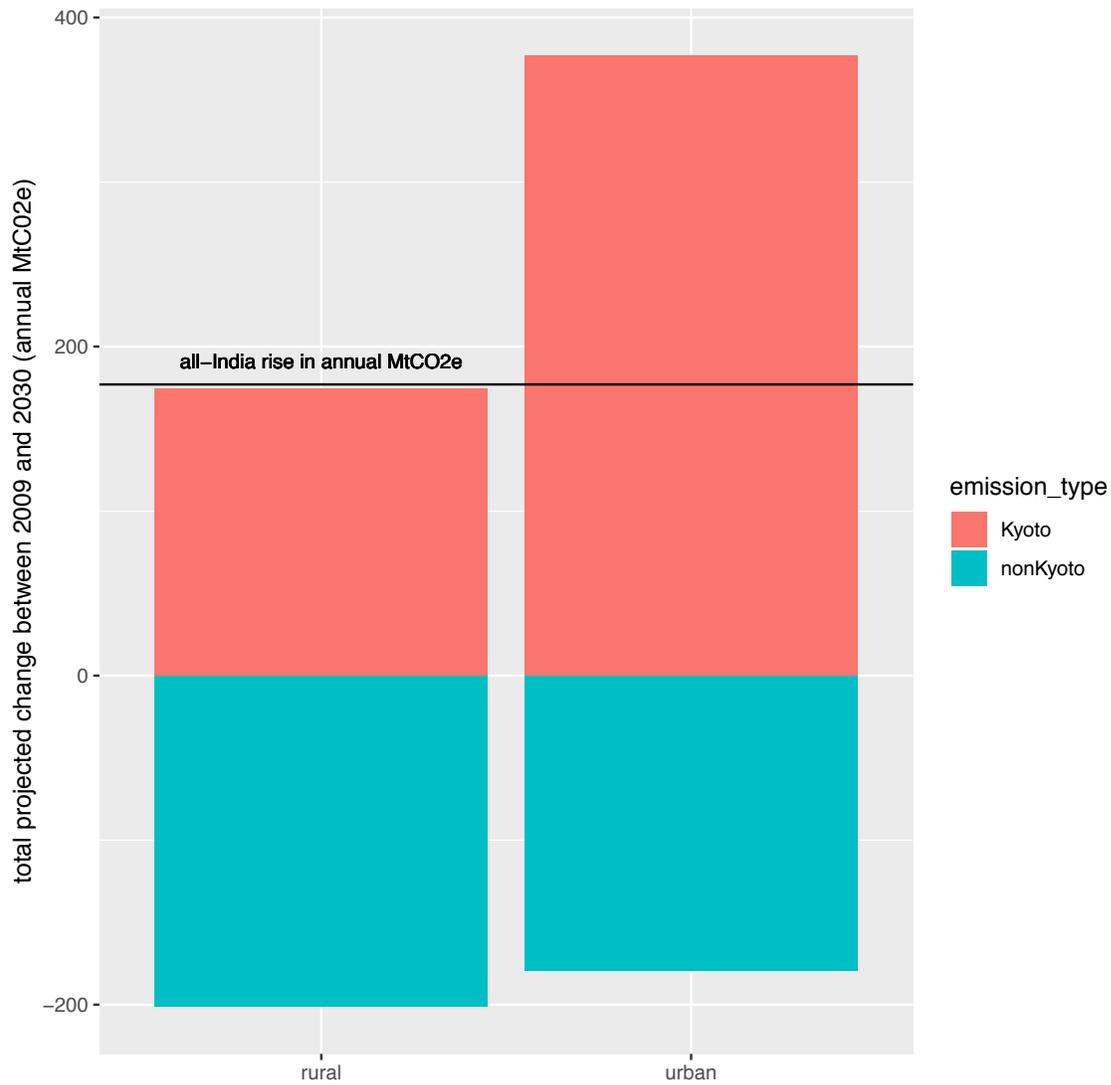


Figure B.5 Business-As-Usual scenario: Per household (hh) change in emissions between 2009 and 2030



**Figure B.6** Business-As-Usual Scenario: Total projected change in emissions between 2009 and 2030

The following graph shows the change in GHG emissions, both using only Kyoto as well as total emissions that include non-Kyoto pollutants for different transition pathways considered in this analysis for 2030.

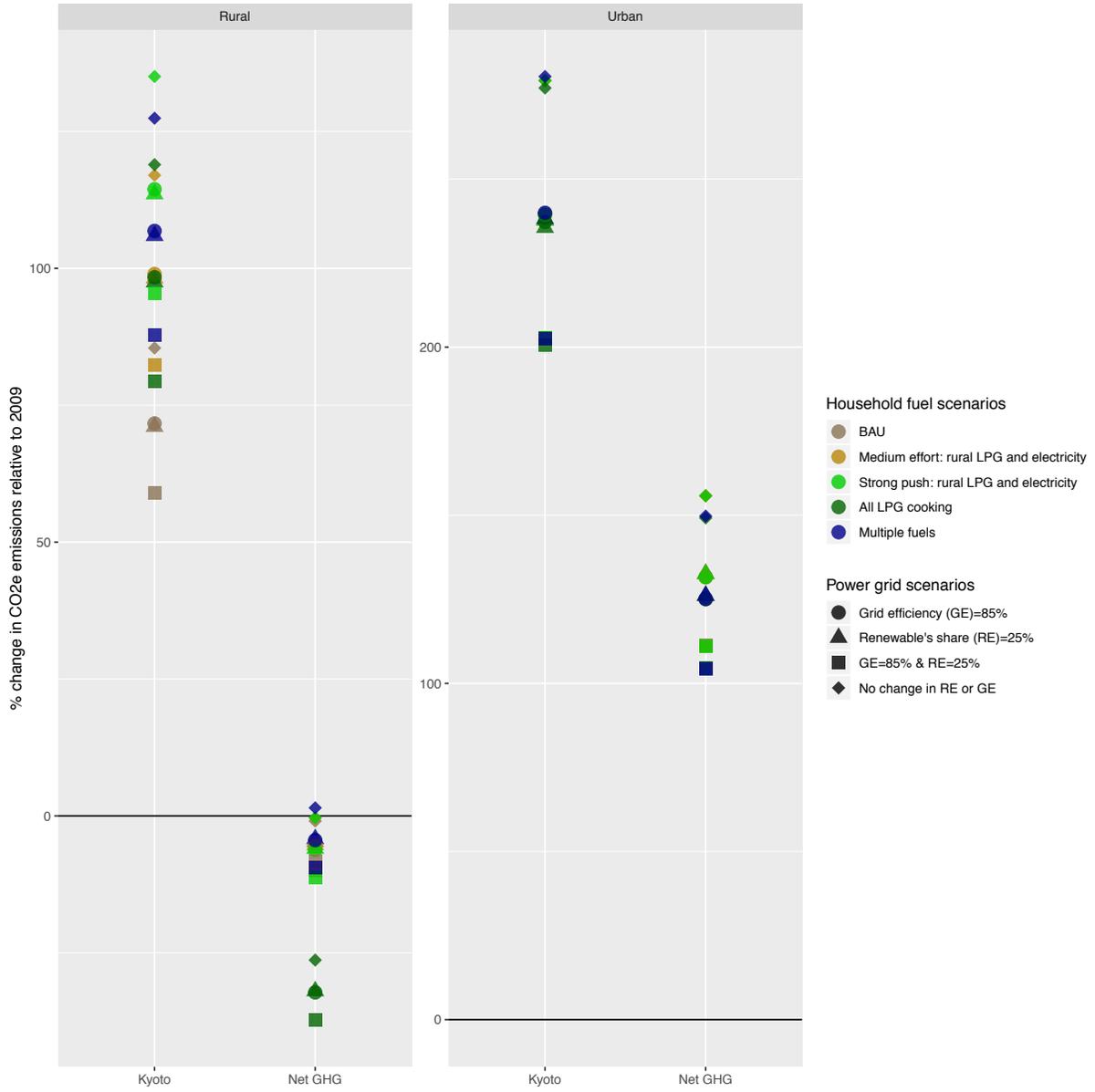


Figure B.7 Kyoto and net GHG emissions for transition pathways to 2030

## Appendix C Chapter 4

### C.1 Classification of districts into compartments

I first group districts into 4 population density classes for modelling purposes (see Section 4.4.1 Table 4.2 in the paper), and then use mixing height followed by wind speed to group districts into compartments. For modelling simplicity, I do not differentiate between population classes I (400-1200 p/km<sup>2</sup>) and II (1200-4000 p/km<sup>2</sup>) in South India (a nearest neighbor analysis of districts in population density class II in South India reveals that they are within 25% of upper limit of class I). Figure C.1 shows the grouping of districts into population density, mixing height and wind speed classes.

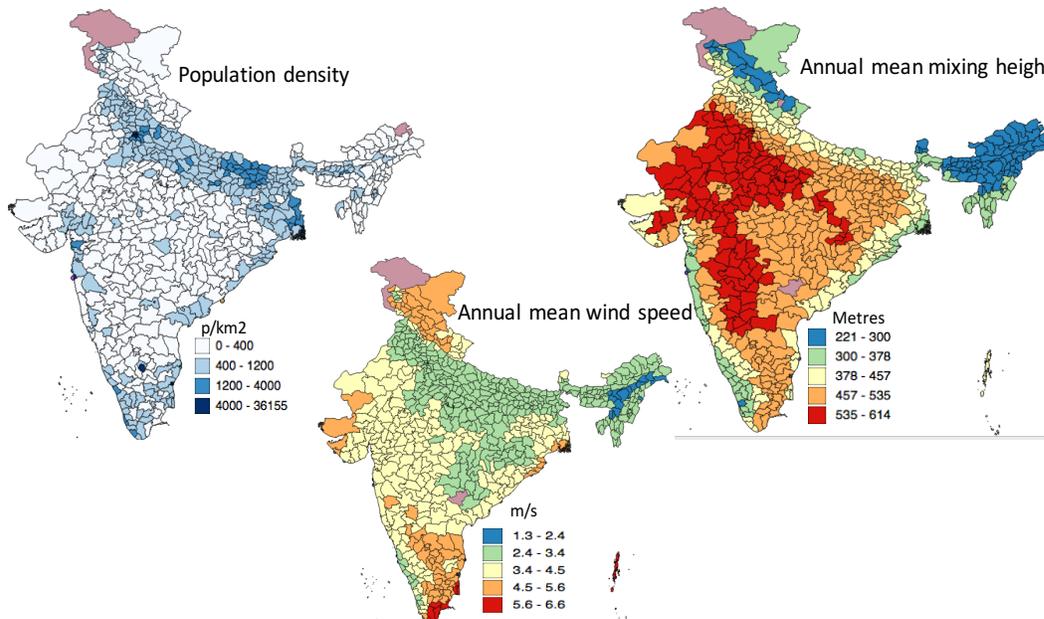
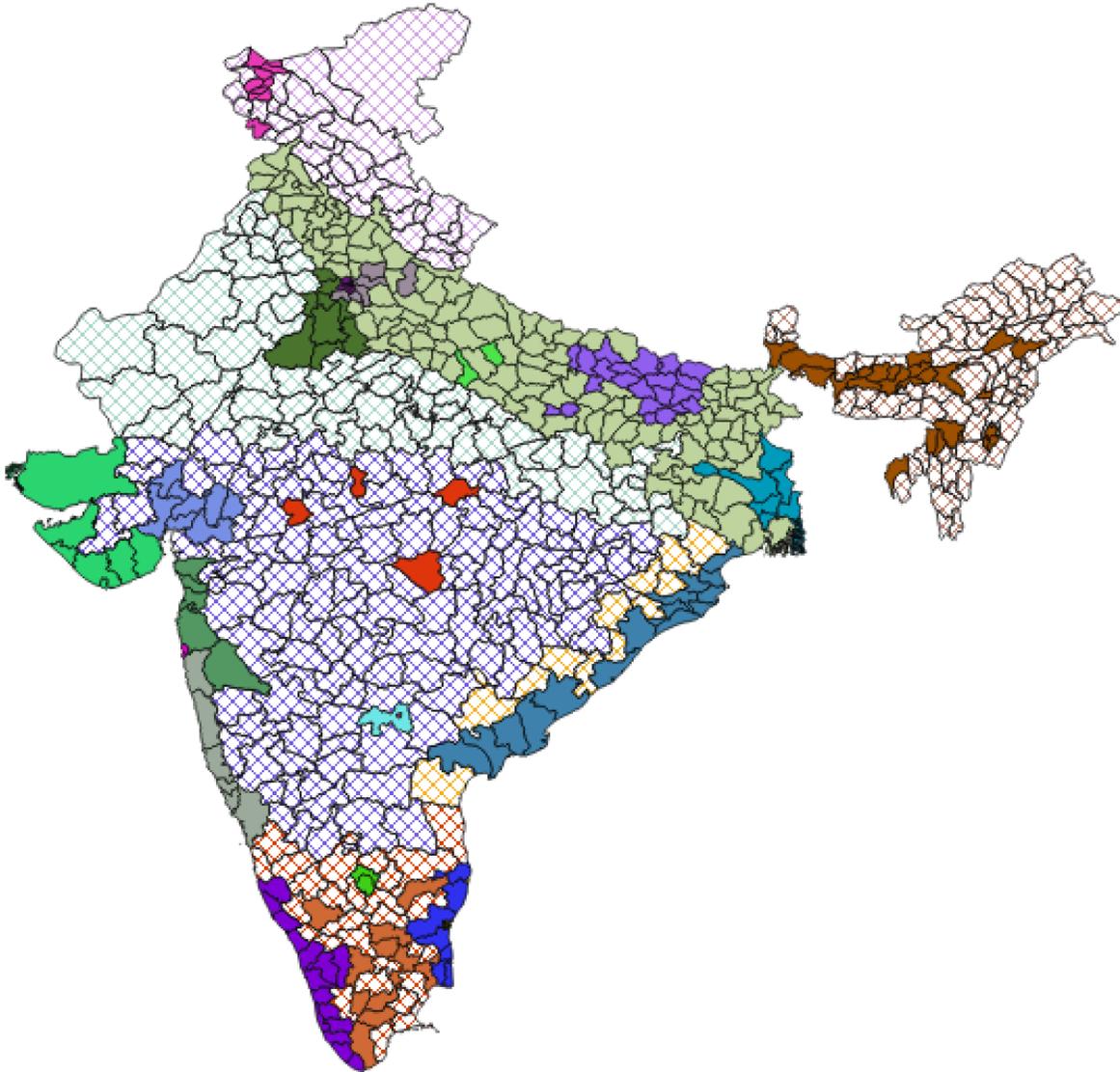


Figure C.1 Population density, mixing height and wind speed classes by district

Figure C.2 shows the districts in India grouped into model compartments based on criteria outlined in Section 4.4.1. There is a total of 5 high-density urban, 19 urban/coastal and 6 rural compartments, which are enclosed by 2 sub-continental compartments.



**Figure C.2** Map of districts classified into compartments in the model  
(each colour represents a distinct compartment; hatched fill represents a regional rural compartment; solid fill represents high-density urban/urban/coastal compartments)

## C.2 Constants used in the analysis

Following are the constant terms used in model equations to estimate intake fraction and concentrations of primary PM<sub>2.5</sub> and sulfates:

- 1) Correction factor for residence time in compartments,  $C_f = 0.75$  (Humbert et al. 2011)
- 2) Inhalation rate of individuals,  $BR = 16 \text{ m}^3/\text{day}$  (Fantke et al. 2017)
- 3) Dry deposition velocity of primary PM<sub>2.5</sub> outdoors,  $v_{\text{dep\_dry}} = 0.001 \text{ m/s}$  (Bijster et al. 2017)
- 4) Wet deposition constants (Jolliet & Hauschild 2005):
  - a) The volume of air scavenged by rain of aerosol content per unit volume of rain or Aerosol collection efficiency,  $CE = 200,000$
  - b) Average time period between rain events,  $t_{\text{rain event}} = 80 \text{ hours}$
  - c) Rainfall intensity during a rain event,  $R_{\text{intensity}} = 0.0013 \text{ m/h}$
- 5) Indoor constants (Fantke et al. 2017):
  - a) Surface to volume ratio of houses,  $S = 3 \text{ m}^{-1}$  (Volume to surface ratio  $V\_to\_S = 1/S$ )
  - b) Deposition velocity indoors,  $v_{\text{dep\_indoors}} = 1 \text{ m/day}$
  - c) Indoor height = 3 m

d) Air exchange rate of indoor air with outdoors, assuming high air exchange rate typical to India (Rosenbaum et al. 2015):

$$k_{\text{indoor\_outdoor}} = 14 \text{ hr}^{-1}$$

e) Indoor volume per person assuming high occupancy conditions,  $V_{\text{individual}} = 30 \text{ m}^3$  (National Sample Survey 64<sup>th</sup> round data shows that average household area is 103 and 117 sq. ft. per person for rural and urban India respectively, and volume per person, assuming average indoor height is 3m, is 29-33  $\text{m}^3/\text{person}$ )

f) Fraction of time spent indoors,  $f_{\text{indoors}} = 0.9$

6)  $\text{SO}_2$  to  $\text{SO}_4^{2-}$  pathway:

a) Dry deposition velocity of  $\text{SO}_2$  outdoors,  $v_{\text{dep\_dry\_SO}_2} = 0.006 \text{ m/s}$  (Xu & Carmichael 1998; Venkataraman et al. 1999)

b) Indoor deposition velocity of  $\text{SO}_2$ ,  $v_{\text{dep\_indoors\_SO}_2} = 105 \text{ m/s}$  (Grøntoft & Raychaudhuri 2004)

c) Cloud volume fraction by month:

Average cloud area fraction over India (from MODIS data) (Dey et al. 2015) is converted to cloud volume fraction (b) using the relationship formulated by Brooks et al. (2005):

$$\text{Cloud area fraction} = \frac{1}{1 + e^{(-0.1635 * H^{0.6694} * L^{-0.1882})} * \left(\frac{1}{b} - 1\right)}$$

where H= vertical box dimensions or mean mixing height = 700m for India,

and  $L$  = horizontal box dimensions given by square root of the area of the Indian sub-continent ( $4.6E+06 \text{ km}^2$  (Humbert et al. 2011))

The values of cloud volume fraction obtained match reasonably well with the range of 0.06-0.29 used by Venkataraman et al. (1999)

Month	b
Jan	0.054
Feb	0.036
Mar	0.035
Apr	0.052
May	0.122
Jun	0.257
Jul	0.300
Aug	0.215
Sep	0.157
Oct	0.092
Nov	0.075
Dec	0.074

**Table C.1** Cloud volume fraction by month

- d) Time period between cloud encounters,  $\tau_{nc} = 34$  hours (12-56 hours from (Venkataraman et al. 1999))

- e) Residence time of SO<sub>2</sub> in clouds,  $\tau_{\text{SO}_2_c} = 40$  minutes (Venkataraman et al. 2001). I use the residence time for Cumulus, Stratocumulus and Stratus clouds since cloud type over India is primarily dominated by stratocumulus, alto and cirro-stratus clouds, followed by cumulus and deep convection clouds (Gupta & Kapoor 2011).
- f) Hydroxyl radical concentration in the atmosphere,  $[\text{OH}] = 1 \cdot 10^5$  molecules/cm<sup>3</sup> (Venkataraman et al. 2001; Meng & Seinfeld 1994). Although I assume a constant value of atmospheric hydroxyl radical concentration here, it is dependent on UV radiation and shows diurnal and seasonal variation (Rohrer & Berresheim 2006).
- g) Rate constant for SO<sub>2</sub> reaction with OH,  $K_{11} = 1.2 \cdot 10^{-12}$  cm<sup>3</sup>/molecules/second (Meng & Seinfeld 1994)
- h) pH of clouds = 5 (Venkataraman et al. 2001; Meng & Seinfeld 1994)
- i) Fe concentration in atmosphere,  $[\text{Fe}]^{+3} = 3 \cdot 10^{-7}$  M (Venkataraman et al. 1999; Meng & Seinfeld 1994; Seinfeld & Pandis 2006a)
- j) Mn concentration in atmosphere,  $[\text{Mn}]^{+3} = 3 \cdot 10^{-7}$  M (Venkataraman et al. 1999; Ibusuki & Takeuchi 1987)

- k) O<sub>3</sub> concentration in atmosphere, [O<sub>3</sub>] = 50 ppb (Meng & Seinfeld 1994; Lelieveld 1993; Saxena & Seigneur 1987)
  
- l) H<sub>2</sub>O<sub>2</sub> concentration in atmosphere, [H<sub>2</sub>O<sub>2</sub>] = 1000 ppt (Venkataraman et al. 2001; Meng & Seinfeld 1994)
  
- m) Gas constant, R = 0.082057 L atm/mol/K
  
- n) Dry deposition velocity of SO<sub>4</sub><sup>2-</sup>, v<sub>dep\_dry\_so4</sub> = 0.002m/s (Venkataraman et al. 1999; Wesely et al. 1985)

### **C.3 Model equations for primary and secondary PM2.5**

All equations below are based on the outdoor model structure of the USEtox model (Bijster et al. 2017) and indoor model of Fantke et al. (Fantke et al. 2017), with wet deposition equations from Jolliett and Hauschild (2005) and sulfur dioxide-to-sulfate pathway equations from Venkataraman et al. (2001). In this section, I first summarize and then describe model equations as follows: indoor and outdoor airflow equations in Section C.3.1, deposition equations in Section C.3.2, sulfate formation pathway in Section C.3.3, with Section C.3.4 detailing the equations of sulfate formation in clouds, and SIA contribution to PM2.5 from literature in Section C.3.5.

C.3.1 PM2.5 airflow equations (Fantke et al. 2017; Bijster et al. 2017):

Summary of indoor and outdoor compartment airflow:

Indoor mass balances:

Variable	Equation	Input variables
Rate constant for indoor deposition	$k_{\text{dep\_indoors}} = v_{\text{dep\_indoors}}/V_{\text{to\_S}}$	$v_{\text{dep\_indoors}}$ =deposition velocity of PM2.5 indoors* $V_{\text{to\_S}}$ = volume to surface ratio of the living space*
Air exchange rate from outdoor to indoor	$k_{\text{outdoor-indoor}} = k_{\text{indoor\_outdoor}} * V_{\text{indoor}}/V_{\text{outdoor}}$	$k_{\text{indoor-outdoor}}$ = exchange rate constant between indoor and outdoor air* $V_{\text{indoor}}$ = total volume of indoor compartment ( $V_{\text{individual}} * \text{Population of compartment}$ ) $V_{\text{outdoor}}$ = volume of the outdoor compartment surrounding the indoor compartment.
Total loss rate coefficient for indoor air	$k_{\text{indoors}} = k_{\text{dep\_indoors}} + k_{\text{indoor-outdoor}}$	

**Table C.2** Indoor-outdoor air exchange: Rate coefficients  
\*constants; see Section C.2

Outdoor box mass balance:

Variable	Equation
Rate of total airflow out of any box or airflow from innermost urban box to surrounding/rural box ( $k_{\text{urban}>\text{rural}}$ )	$k_{\text{airflow\_out}}$ or $k_{\text{urban}>\text{rural}} = 1/\tau$
Rate of airflow from the surrounding rural (or urban) compartment into an urban (or high density urban) compartment	$k_{\text{rural} > \text{urban}} = k_{\text{urban} > \text{rural}} * V_{\text{urban}}/V_{\text{rural}}$

Variable	Equation
Rate of airflow from rural compartment to the surrounding sub-continental compartment	$k_{rural > sub-continental} = k_{rural} - \Sigma k_{rural > urban}$
Rate of airflow from sub-continental to rural box	$k_{sub-continental > rural} = (k_{rural} * V_{rural} - \Sigma k_{urban > rural} * V_{urban}) / V_{sub-continental}$
Rates of airflow between 2 sub-continental compartments	$k_{sub-continental 1 > sub-continental 2} = k_{sub-continental 1} - \Sigma k_{sub-continental 1 > rural}$ $k_{sub-continental 2 > sub-continental 1} = (k_{sub-continental 1} * V_{sub-continental 1} - \Sigma k_{rural > sub-continental 1} * V_{rural}) / V_{sub-continental 2}$

**Table C.3** Airflow in outdoor compartments: Rate coefficients

\* $V_{compartment}$  is the volume of air in the compartment and  $\tau$  is the residence time in the box

a) The residence of PM2.5 in any compartment is given by :  $\tau = cf * \sqrt{Area}/U$

Where cf = correction factor of residence time in compartments (see Section C.2.1)

Area = area of the compartment,

U = Wind speed in the compartment

The rate constant for total airflow out of any box is given by  $k_{airflow out} = 1/\tau$

I calculate advection rate coefficients using 2 airflow volume balance conditions: 1) Total volume of air flowing out of a compartment per unit time is the sum of airflow to compartments within

and outside, and 2) Volume of air flowing out per unit time from any compartment is equal to the volume of air flowing in.

Using condition 1) I get:

- b) For the innermost outdoor compartment (urban or high-density urban), airflow into the surrounding rural/urban box is given by the total airflow out of the compartment.

$$k_{urban > rural} = 1/\tau$$

- c) Air from each rural compartment flows into the urban compartments within and out to the surrounding sub-continental compartment.

$$k_{rural > sub-continental} = k_{rural} - \Sigma k_{rural > urban}$$

$k_{rural > urban}$  is derived from part vi) below

- d) Airflow from sub-continent 1 to 2 is given by :

$$k_{sub-continental 1 > sub-continental 2} = k_{sub-continental 1} - \Sigma k_{sub-continental 1 > rural}$$

$k_{sub-cont > rural}$  is derived from part vii) below

Using condition 2) stated above:

- e) For an indoor compartment, the volume of air flowing out per unit time is equal to the volume of air flowing in:

$$k_{outdoor > indoor} * V_{outdoor} = k_{indoor > outdoor} * V_{indoor}$$

Or,

$$k_{outdoor > indoor} = k_{indoor > outdoor} * V_{indoor}/V_{outdoor}$$

(see Section C.2 for  $k_{indoor > outdoor}$  and  $V_{indoor}$ )

- f) Similarly, for the innermost outdoor urban box, rate of inflow of air is equal to the rate of outflow of air:

$$k_{rural > urban} * V_{rural} = k_{urban > rural} * V_{urban}$$

Or,

$$k_{rural > urban} = k_{urban > rural} * V_{urban} / V_{rural}$$

- g) Solving for the inflow-outflow volume balance condition for each rural box:

$$k_{sub-cont > rural} * V_{sub-cont} + \Sigma k_{urban > rural} * V_{urban} = k_{rural} * V_{rural}$$

Or,

$$k_{sub-cont > rural} = (k_{rural} * V_{rural} - \Sigma k_{urban > rural} * V_{urban}) / V_{sub-cont}$$

- h) And solving for the balance of airflow in and out of sub-continent 1,

$$\begin{aligned} k_{sub-cont 2 > sub-cont 1} * V_{sub-cont 2} + \Sigma k_{rural > sub-cont 1} * V_{rural} \\ = k_{sub-cont 1} * V_{sub-cont 1} \end{aligned}$$

Or,

$$\begin{aligned} k_{sub-cont 2 > sub-cont 1} \\ = (k_{sub-cont 1} * V_{sub-cont 1} - \Sigma k_{rural > sub-cont 1} * V_{rural}) / V_{sub-cont 2} \end{aligned}$$

C.3.2 PM2.5 dry and wet deposition (Jolliet & Hauschild 2005):

Summary of deposition rate coefficients:

Variable	Equation	Input variables
Dry deposition rate constant	$k_{dry} = v_{dep\_dry}/h$ (Bijster et al. 2017)	$v_{dep\_dry}$ = dry deposition velocity* $h$ = mixing height of the compartment
Wet deposition rate constant	$k_{wet} = (v_{rainfall} * \frac{CE}{h}) / (\frac{t_{wet}}{t_{wet}+t_{dry}})$	CE = aerosol collection efficiency* $h$ = mixing height $v_{rainfall}$ = rainfall rate for the compartment. $t_{wet}$ and $t_{dry}$ are the average durations of wet and dry periods respectively *
Mean rate of removal of PM2.5 through dry and wet deposition	$k_{mean\ deposition} =$ $\left( \left( \frac{1}{k_{dry}} \right) * \frac{t_{dry}}{t_{wet}+t_{dry}} + \left( \frac{1}{k_{wet}} \right) * \frac{t_{wet}}{t_{wet}+t_{dry}} - \frac{\left( \frac{1}{k_{wet}} - \frac{1}{k_{dry}} \right)^2}{t_{wet}+t_{dry}} * \frac{(1-e^{-k_{dry}*t_{dry}})*(1-e^{-k_{wet}*t_{wet}})}{(1-e^{-k_{dry}*t_{dry}-k_{wet}*t_{wet}})} \right)^{-1}$	
Rate constant for total loss in an outdoor compartment:	$k_{tot} = k_{airflow\ out} + k_{mean\ deposition}$	

**Table C.4** Dry, wet and mean deposition: Rate coefficients

\*constants; see Section C.2

a) Wet deposition rate coefficient:

Wet deposition rate constant for each compartment is given by :

$$k_{wet} = (v_{rainfall} * \frac{CE}{h}) / (\frac{t_{wet}}{t_{wet} + t_{dry}})$$

where CE = aerosol collection efficiency (see section C.2.4)),  $v_{rainfall}$  =rainfall rate and h= mixing height in the compartment, and  $t_{wet}$  and  $t_{dry}$  are the average duration of wet and dry time periods calculated as below.

b) Average duration of wet and dry time periods:

$$t_{wet}(days) = \left( \frac{t_{rain\ interval}}{24} \right) * v_{rainfall} / \left( \frac{R_{intensity}}{3600} \right)$$

$$t_{dry}(days) = t_{rain\ event} - t_{wet}$$

where  $t_{rain\ interval}$  is the average period between rainfall events in hours and  $R_{intensity}$  is the rainfall intensity during a rain period (see Section C.2.4) for values)

c) Mean atmospheric deposition rate

The mean rate of removal of PM2.5 through dry and deposition,  $k_{mean}$  is calculated by

$$\left( \left( \frac{1}{k_{dry}} \right) * \frac{t_{dry}}{t_{wet}+t_{dry}} + \left( \frac{1}{k_{wet}} \right) * \frac{t_{wet}}{t_{wet}+t_{dry}} - \frac{\left( \frac{1}{k_{wet}} - \frac{1}{k_{dry}} \right)^2}{t_{wet}+t_{dry}} * (1-e^{-k_{dry}*t_{dry}}) * (1-e^{-k_{wet}*t_{wet}}) \right)^{-1}$$

C.3.3 SO<sub>2</sub> to SO<sub>4</sub><sup>2-</sup> ion pathway (Venkataraman et al. 1999; Venkataraman et al. 2001):

Summary of sulfate formation pathway:

Variable	Equation	Input variable
Total rate of removal of SO <sub>2</sub> from a compartment	$k_{tot\_outdoor} = k_{dry} + k_{airflow} + K_{OH} + (F_{cc} * k_{cloud})$ $k_{tot\_indoor} = k_{dry\_indoor} + k_{indoor>outdoor}$	
Rate constant for gaseous phase reaction of SO <sub>2</sub> with hydroxyl ions	$K_{OH} = K_{11} * [OH^-]$	$K_{11}$ = reaction rate with OH <sup>-</sup> *
Rate of SO <sub>2</sub> delivery to clouds	$k_{cloud} = \frac{1}{(1 - b) * \tau_{nc}}$	b = cloud volume fraction by month* $\tau_{nc}$ = time period between cloud encounters*
Fraction of SO <sub>2</sub> reaching the clouds that is converted to sulfate ions	$F_{cc} =$ $b * H_{SO2}$ $* \frac{K_{O2} + K_{O3} + K_{H2O2}}{b * H_{SO2} * (K_{O2} + K_{O3} + K_{H2O2}) + \frac{1}{\tau_{cloud} * R * T}}$	b = cloud volume fraction* $\tau_{cloud}$ = in-cloud residence time of SO <sub>2</sub> * R = gas law constant* T = compartment and month-specific temperature in Kelvin H <sub>SO2</sub> = Henry's constant for SO <sub>2</sub> dissolution K <sub>O2</sub> , K <sub>O3</sub> and K <sub>H2O2</sub> are the temperature-dependent rate constants

Variable	Equation	Input variable
		for reactions of SO <sub>2</sub> with O <sub>2</sub> , O <sub>3</sub> and H <sub>2</sub> O <sub>2</sub> respectively (see Section C.4 for equations)

**Table C.5** Removal of SO<sub>2</sub> from a compartment: Rate coefficients  
\*constants; see Section C.2

Variable	Equation	Input variables
Sulfate yield: gaseous phase reaction of SO <sub>2</sub> with OH <sup>-</sup>	$S(VI)_{OH} = K_{OH} * m_{SO_2}$	m <sub>SO<sub>2</sub></sub> =equilibrium mass of SO <sub>2</sub> in each compartment K <sub>OH</sub> , F <sub>cc</sub> , k <sub>cloud</sub> =see Table C.5
Sulfate yield: in-cloud oxidation of SO <sub>2</sub>	$S(VI)_c = F_{cc} * k_{cloud} * m_{SO_2}$	
Total sulfate formed through gaseous and aqueous phase reactions	$(S(VI)_{OH} + S(VI)_c) * 96/64$	Molar weight of sulfate/molar weight of SO <sub>2</sub> = 96/64

**Table C.6** Sulfate formation through oxidation of SO<sub>2</sub>

Formation of secondary PM<sub>2.5</sub> in the form of sulfate ions is modeled in three steps based on the work by Venkataraman et al. (1999; 2001):

- a) Estimating the equilibrium concentration of SO<sub>2</sub> in each compartment:

I assume SO<sub>2</sub> is removed from an outdoor compartment through advection, dry deposition, gaseous stage conversion to SO<sub>4</sub><sup>2-</sup> ion through reaction with hydroxyl ions and through delivery to clouds and consequent conversion to SO<sub>4</sub><sup>2-</sup> ion (Venkataraman et al. 1999; Venkataraman et al. 2001;

Seinfeld & Pandis 2006b). I ignore wet deposition of SO<sub>2</sub> since it accounts for less than 10% of removal (Venkataraman et al. 1999). For indoor SO<sub>2</sub> emissions, I only consider advection and deposition as removal mechanisms.

Rate coefficients for dry deposition and advection ( $k_{\text{dry}}$  and  $k_{\text{airflow}}$ ) are calculated as outlined for primary PM<sub>2.5</sub> in Chapter 4 Section 4.3 (dry deposition velocity of SO<sub>2</sub> provided in Section C.2). From the rate coefficients matrix, I calculate the fate factor matrix, and the equilibrium concentration of SO<sub>2</sub> in each compartment using the methodology outlined in Chapter 4 Section 4.3.

b) Estimating sulfate ion formation:

SO<sub>2</sub> oxidizes to form sulfate ions in the gaseous phase, through its reaction with hydroxyl radicals, and in the aqueous phase primarily through reactions with O<sub>2</sub>, O<sub>3</sub> and H<sub>2</sub>O<sub>2</sub> (see point (d) below for reaction rate constants) for sulfate formation in clouds, when an air parcel containing SO<sub>2</sub> reaches clouds. I only consider sulfate ion formation through the chemical transformation of the equilibrium mass of SO<sub>2</sub> in outdoor compartments.

c) Equilibrium concentration of sulfate ions:

I assume that SO<sub>4</sub><sup>2-</sup> formed from gaseous and aqueous phase reactions of SO<sub>2</sub> undergoes similar removal processes as primary PM<sub>2.5</sub> through advection and dry and wet deposition. I construct a rate coefficients matrix (dry deposition velocity of sulfate in Section C.2) and calculate FF and iF matrices and equilibrium concentration of SO<sub>4</sub><sup>2-</sup> using the method described in Chapter 4 Section 4.3.

d) SO<sub>2</sub> to SO<sub>4</sub><sup>2-</sup> formation in clouds (Venkataraman et al. 2001):

i) Reaction rate of SO<sub>2</sub> with O<sub>2</sub> :

$$K_{O_2} = (k_{22} * [Fe^{+3}] * [Mn^{3+}] * [H^+]^{0.67}) [SO_2(gas)] * H_{SO_2}$$

assuming pH in clouds > 4.2 and k<sub>22</sub> is calculated as:

$$k_{22} = 5.47 * 10^{25} * e^{-8432/T} M^{-1}s^{-1}$$

where T is the temperature in Kelvin

See (iv) below for H<sub>SO2</sub> calculation and Section C.2 for values of Fe and Mn concentrations and pH used.

ii) Reaction rate of SO<sub>2</sub> with O<sub>3</sub>:

$$K_{O_3} = (k_{31} * [SO_2 \cdot H_2O] + k_{32} * [HSO_3^-] + k_{33} * [SO_3^{2-}]) * [O_3(gas)] * H_{O_3}$$

Where H<sub>O3</sub> is the Henry's law constant for O3 and rate constants are given by,

$$k_{31} = 2.4 * 10^4 M^{-1}s^{-1}$$

$$k_{32} = 3.7 * 10^5 * e^{-5530/T} M^{-1}s^{-1}$$

$$k_{33} = 1.5 * 10^9 * e^{-5280/T} M^{-1}s^{-1}$$

Substituting the equilibrium constant of dissolution of SO<sub>2</sub> in water and rate constants for dissociation of dissolved SO<sub>2</sub> into HSO<sub>3</sub><sup>-</sup> and SO<sub>3</sub><sup>2-</sup> (provided in Table 1 (Venkataraman et al. 2001)), K<sub>O3</sub> can be calculated as:

$$K_{O_3} = \left( k_{31} + \left( k_{32} * \frac{K_1}{[H^+]} \right) + \left( k_{33} * K_2 * \frac{K_1}{[H^+]^2} \right) \right) * [H_{SO_2}] * [SO_2(gas)] * H_{O_3} * [O_3(gas)]$$

where H<sub>SO2</sub> is the Henry's law constant for SO<sub>2</sub> and equilibrium constants are given by,

$$K_1 = 1.23 * 10^{-2} * e^{-1960/T} M$$

$$K_2 = 6.61 * 10^{-8} * e^{-1500/T} \text{ M}$$

See (iv) below for  $H_{SO_2}$  and  $H_{O_3}$  calculation and Section C.2 for values of ozone concentrations and pH used.

iii) Reaction of  $SO_2$  with  $H_2O_2$ :

$$K_{H_2O_2} = \frac{(k_{41} * [H^+] * [H_{H_2O_2}] * [H_2O_2(gas)] * [HSO_3^-])}{1 + K_4 * [H^+]}$$

Where  $H_{H_2O_2}$  is the Henry's law constant for  $H_2O_2$  and rate constants are given by,

$$k_{41} = 7.5 * 10^7 * e^{-\frac{4430}{T}} \text{ M}^{-1}\text{s}^{-1}$$

$$K_4 = 13 \text{ M}^{-1}$$

Substituting the the equilibrium constant of dissolution of  $SO_2$  in water and rate constant for dissociation of dissolved  $SO_2$  into  $HSO_3^-$  (provided in Table 1 (Venkataraman et al. 2001)),  $K_{H_2O_2}$  can be calculated as :

$$K_{H_2O_2} = \frac{(k_{41} * K_1 * [H^+] * [H_{H_2O_2}] * [H_2O_2(gas)] * [H_{SO_2}] * [SO_2(gas)])}{1 + K_4 * [H^+]}$$

where  $K_1$  is given above. See (iv) below for  $H_{SO_2}$  and  $H_{H_2O_2}$  calculation and Section C.2 for values of  $H_2O_2$  concentrations and pH used.

iv) Temperature-dependent Henry's law constants for  $SO_2$ ,  $O_3$  and  $H_2O_2$  are given by:

$$H_{SO_2} = 1.23 * e^{3020 * (\frac{1}{T}) - (\frac{1}{298})}$$

$$H_{O_3} = 1.1 * 10^{-2} * e^{2300 * (\frac{1}{T}) - (\frac{1}{298})}$$

$$H_{H_2O_2} = 7.1 * 10^4 * e^{6621 * (\frac{1}{T}) - (\frac{1}{298})}$$

### C.3.5 Secondary inorganic aerosols (SIA):

I estimate the contribution of nitrates and ammonium to total PM2.5 concentrations by reviewing literature on SIA measurements across India. I assume an average of 8.4% (3.6% from nitrates and 4.6% from ammonium) for the contribution of nitrates and ammonium to total PM2.5.

NO <sub>3</sub> <sup>-</sup> (%)	NH <sub>4</sub> <sup>+</sup> (%)	SO <sub>4</sub> <sup>2-</sup> (%)	Location	Study	Month
2.2	6.3	8.4	Delhi	(M. Z. Chowdhury 2004)	March
3.1	4.0	10.4			June
2.3	2.8	6.3			October
7.3	5.3	8.1			December
1.9	3.3	15.5	Mumbai	(M. Z. Chowdhury 2004)	March
4.4	1.9	14.9			June
2.9	3.6	12.4			October
3.2	4.7	12.3			December
2.0	4.0	15.9	Kolkata	(M. Z. Chowdhury 2004)	March
3.2	2.0	11.4			June

NO <sub>3</sub> <sup>-</sup> (%)	NH <sub>4</sub> <sup>+</sup> (%)	SO <sub>4</sub> <sup>2-</sup> (%)	Location	Study	Month
1.1	3.0	8.9			October
3.0	3.4	4.3			December
2.5	6.7	16.2	Chandigarh	(M. Z. Chowdhury 2004)	June
9.1	8.8	15.9	Kanpur	(Behera & M. Sharma 2010)	Apr-June
11.2	8.0	12.8			Dec-Jan
2.1	5.7	17.5	Ahmedabad	(Rengarajan et al. 2011)	December
1.4-4.8	3.0-3.8	7.0-10.0	Kanpur	(Ram & Sarin 2011)	October
1.44	6.25	16.5	Mumbai	(R. Kumar et al. 2006)	Year-round
7.1	1.4	5.3	Kolkata	(Chatterjee et al. 2012)	Mar-May
6.0	2.4	5.9			Jun-Sep
3.5	2.9	3.5			Oct-Nov
4.8	4.8	4.3			Dec - Feb
1.6	4.8	19.3	Mount Abu (rural)	(A. Kumar & Sarin 2010)	Mar-Jun
2.0	10.8	29.5			Oct-Feb
3.8	4.6	11.9		<i>Average value from literature</i>	

**Table C.7** Secondary inorganic aerosols as % of total measured PM<sub>2.5</sub> concentrations from previous studies in

India

#### C.4 Intake fraction estimation by stack height

Emission sources from the inventory developed by Sadavarte and Venkataraman and Pandey et al. (Sadavarte & Venkataraman 2014; Pandey et al. 2014) are grouped into stack height categories (Table C.8). I then calculate stack height specific iF values from the modeled iF (see Section 4.3 and 4.5.1 in Chapter 4), using equations in Section C.4.2.

##### C.4.1 Emission sources: Stack height and location (indoor vs. outdoor)

Sector	Source	Location	Stack height
Agriculture	Pumps	Outdoor	Ground
	Residue burning		Ground
	Tractors		Ground
Industry	Thermal power plants	Outdoor	High
	Heavy		High
	Light		High
	Brick		Low
	Informal		Low
Residential	Cooking: biomass	Indoor	-
	Cooking: LPG & kerosene		-
	Diesel generators		-
	Lighting: kerosene		-
	Space heating		-

Sector	Source	Location	Stack height
	Water heating		-
Transport	Road: Diesel	Outdoor	Ground
	Road: Gas		Ground
	Rail		Low

**Table C.8** Emission sources: location and stack height

#### C.4.2 Stack-height specific $iF$ :

$iF$  values specific to stack height (ground, low stack and high stack) are calculated using Humbert et al.'s (2011) methodology.

$$iF_{high} = \frac{iF_{mean}}{high + (low * Y) + (ground * X * Y)}$$

$$iF_{low} = \frac{Y * iF_{mean}}{high + (low * Y) + (ground * X * Y)}$$

$$iF_{ground} = \frac{X * Y * iF_{mean}}{high + (low * Y) + (ground * X * Y)}$$

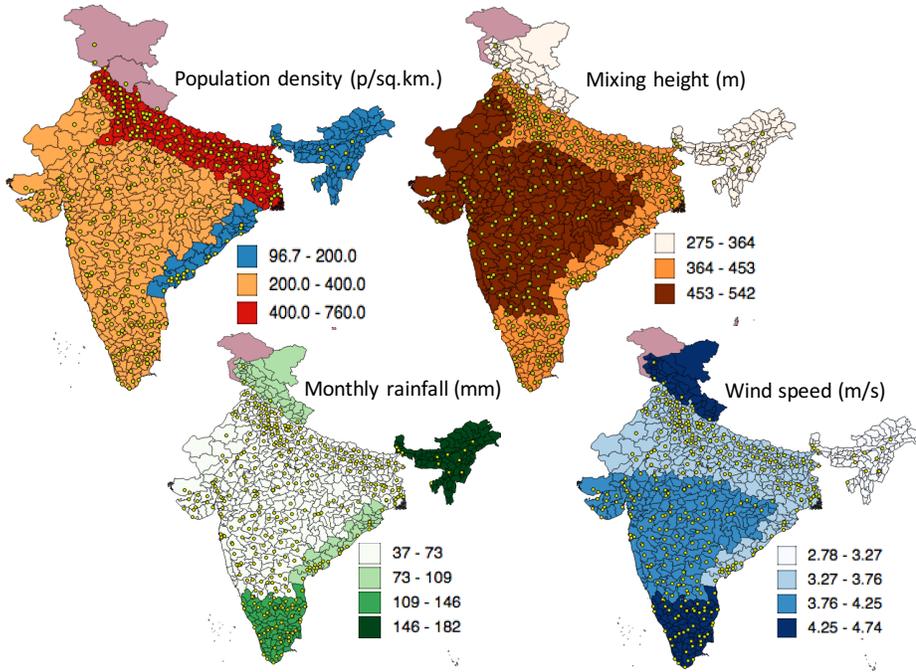
where 'high', 'low' and 'ground' represent the stack height shares in emissions in each compartment,  $X = iF_{ground}/iF_{low}$  (2.9 for urban and 1.9 for rural compartments) and  $Y = iF_{low}/iF_{high}$  (1.3 for urban and 1.2 for rural) (Humbert et al. 2011). X and Y represent the ratio of intake

fractions from stack height categories and are specific to regional archetypes defined by population density.

## **C.5 Model validation and Sensitivity analysis**

### **C.5.1 Variation in regional population density and meteorology across India.**

Modelled iF values differ from those in the Fantke et al. study (Fantke et al. 2017) primarily due to spatially disaggregated model framework adopted in which regional population density and meteorology are taken into account (see Chapter 4 Section 4.6 for details). Figure C.3 shows the variation in regional population density and meteorology across the country (average values for rural compartments in the model and the Indo-Gangetic Plain represented) – the green dots represent the 337 cities in the study by Fantke et al. The Indo-Gangetic Plain shows high population density, low rainfall and low wind speed than most other parts of the country, leading to high intake fraction values in the model.



**Figure C.3** Mean population density and meteorological parameters for regional compartments in the model

### C.5.2 Mean bias relative to Fantke et al.'s study (2017)

I calculate the regional Normalized Mean Bias of modelled  $iF$  values relative to  $iF$  from Fantke et al.'s study. I divide the country into 4 geographical quarters - Far North/North East, Indo-Gangetic Plain, Central and South (see Figure C.4). The Normalized Mean Bias (NMB) relative to  $iF$  values for 337 cities in the Fantke et al. study are calculated as follows:

$$NMB = \frac{\sum (M_i - F_i)}{\sum F_i}$$

where  $M_i$  is the modelled ground-level  $iF$  value from this study for each city and  $F_i$  is the ground-level  $iF$  value from the study by Fantke et al.

Geographical quarter	NMB
Central	0.3726
Far North/North East	-0.3524
Indo-Gangetic Plain	2.8490
South	0.0670

**Table C.9** Regional Normalized Mean Bias of modelled ground-level iF for 337 cities in India relative to Fantke et al. (2017)

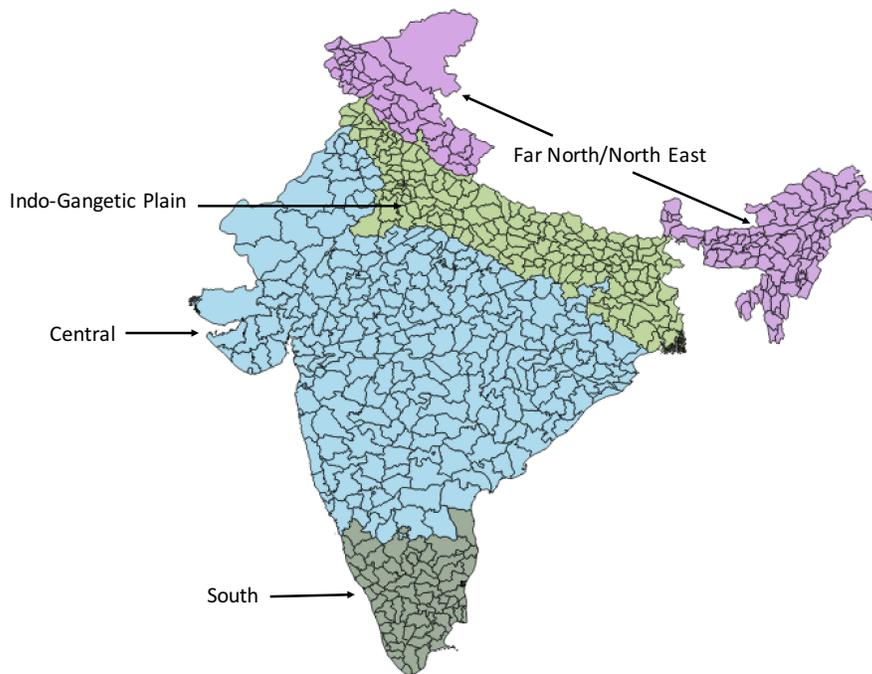
### C.5.3 Mean bias relative to GBD study (GBD MAPS Working Group 2018)

I calculate the Normalized Mean Bias (NMB) of modelled mean annual PM<sub>2.5</sub> concentrations (primary plus sulfate) relative to total PM<sub>2.5</sub> concentrations from the GBD study, aggregated to model compartment level, for 4 geographical quarters (see Figure C.2) and 4 population classes (1 = < 400, 2 = 400- 1200, 3 = 1200- 4000, and 4 = >4000 p/km<sup>2</sup>). NMB is lowest in densely populated regions - population class 4 of IGP (4%), followed by population classes 3 and 4 of Central India and class 4 of South India (13-14%) - while it ranges from -27% to -17% for the rest of the country except the Far North/North East compartment, where NMB is -65% to -60%.

Geographical quarter	Population class	NMB
Central	1	-0.21
Central	2	-0.17
Central	3	0.13
Central	4	0.13
Far North/ North East	1	-0.64

Geographical quarter	Population class	NMB
Far North/ North East	2	-0.65
Far North/ North East	3	-0.60
Indo-Gangetic Plain	1	-0.24
Indo-Gangetic Plain	2	-0.23
Indo-Gangetic Plain	3	-0.27
Indo-Gangetic Plain	4	0.04
South	1	-0.24
South	2	-0.19
South	3	-0.17
South	4	-0.14

**Table C.10** Regional Normalized Mean Bias of modelled PM<sub>2.5</sub> concentration (primary PM<sub>2.5</sub> + sulfate) values relative to GBD study (GBD MAPS Working Group 2018)



**Figure C.4** Geographical quarters for Normalized Mean Bias calculations

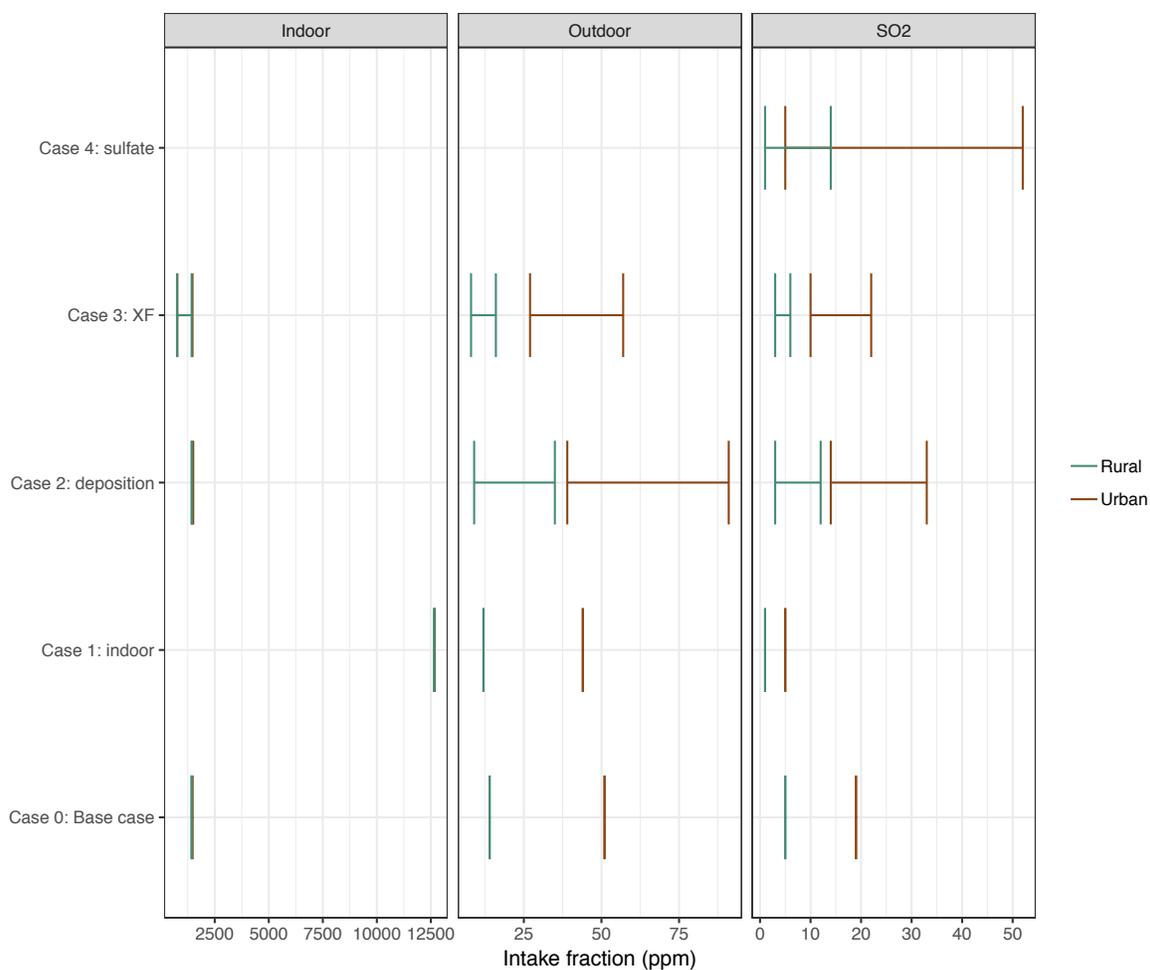
#### C.5.4 Sensitivity of modelled sulfate concentrations to cloud characteristics

I examine the sensitivity of modelled sulfate concentrations to three cloud characteristics: cloud pH, residence time of sulfate in clouds and time period between cloud encounters (see Chapter 4 Section 4.6.3). Table C.11 below shows the results of the sensitivity analysis conducted.

			Mean modelled sulfate concentrations ( $\mu\text{g}/\text{m}^3$ )	
cloud pH	Residence time (minutes)	Period between cloud encounter (hours)	Urban	Rural
5	40	34	17.3	10.2
6.5	40	34	10.6	6.2
5	12	12	26.0	15.0
7	12	12	10.0	5.8
5	40	12	29.6	17.1
7	40	12	17.1	9.9
5	12	56	10.3	6.1
7	12	56	3.4	2.0
5	40	56	12.5	7.4
7	40	56	6.2	3.6
5	12	34	14.4	8.5

**Table C.11** Sensitivity of modelled sulfate concentrations to assumed cloud characteristics

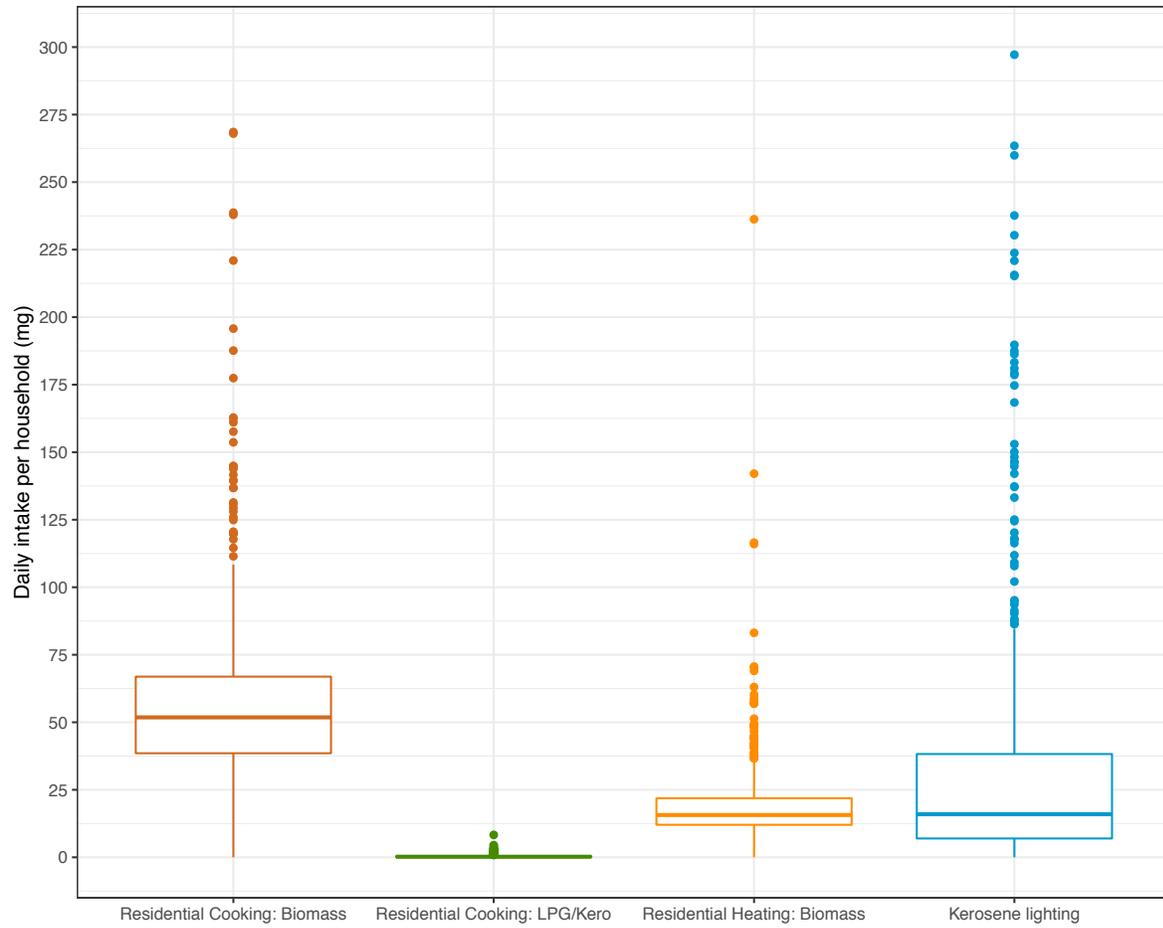
Figure C.5 presents the results of the sensitivity analysis conducted for indoor box characteristics (Case 1: occupancy and air exchange with outdoors), deposition (Case 2: dry deposition velocities and aerosol washout ratio), exposure (Case 3: period of exposure indoors/outdoors and breathing rates of individuals) and cloud parameters (Case 4: cloud pH, residence time of aerosols in clouds and time period between cloud encounters).



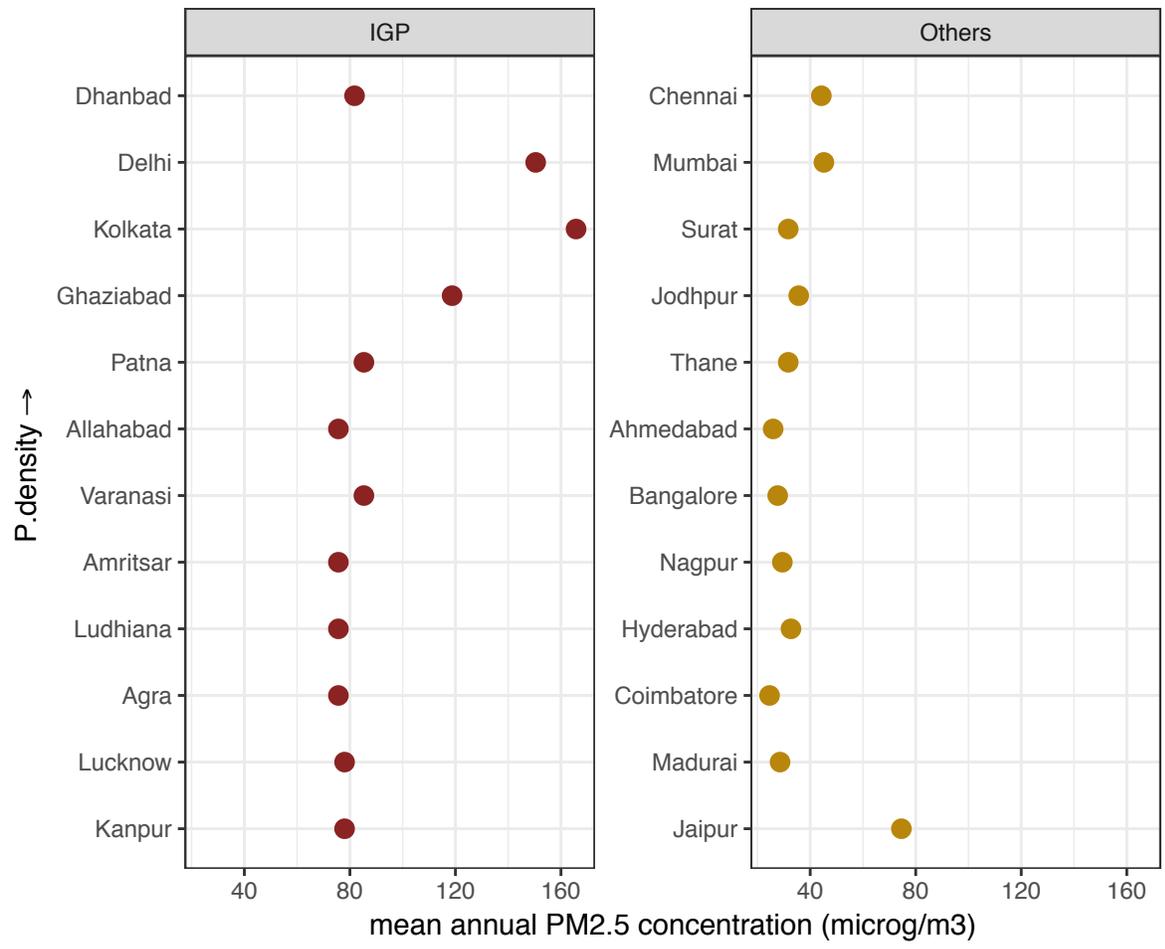
**Figure C.5** Sensitivity of iF (indoor and outdoor primary PM2.5 and SO2 emissions) to model parameters  
*Case 1: indoor - occupancy and air exchange with outdoors; Case 2: deposition - dry deposition velocities and aerosol washout ratio; Case 3: XF - period of exposure indoors/outdoors and breathing rates of individuals; Case 4: sulfate - cloud pH, residence time of aerosols in clouds and time period between cloud encounters*

## **Appendix D Chapter 5**

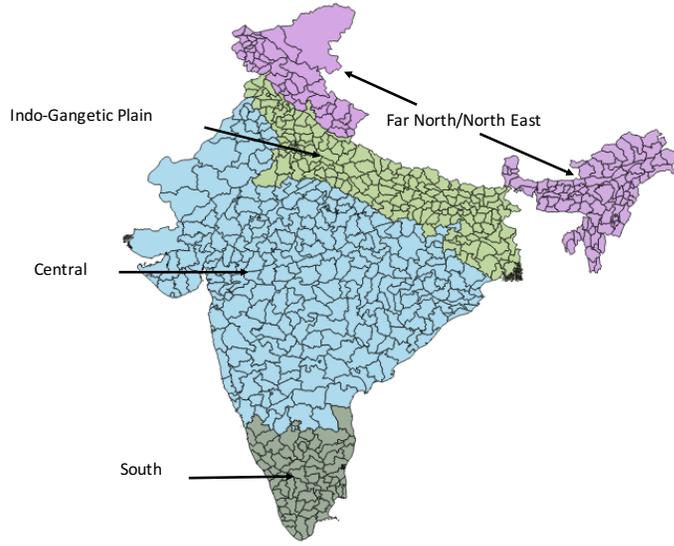
I use district-level data on the number of households using each type of fuel from Census 2011 to estimate the indoor PM<sub>2.5</sub> intake per household due to residential sources. Figure D.1 shows the distribution of daily indoor intake of PM<sub>2.5</sub> in each household using solid fuels for cooking or heating, LPG/kerosene for cooking and kerosene lighting. Indoor exposure to PM<sub>2.5</sub> is the highest in households using solid fuels for cooking (median=52 mg/day), and the least in households using modern cooking fuels (LPG or kerosene). PM<sub>2.5</sub> exposure due to kerosene lighting is highly variable across households, indicating that kerosene is used in varying quantities for supplemental and primary lighting.



**Figure D.1** Estimated indoor PM2.5 intake per household from residential sources



**Figure D.2** Average annual PM2.5 concentrations in 20 most populous cities in India in 2015



**Figure D.3** Map of regions used in the analysis