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Indoor Air Pollution Associated with Household Fuel Use in India

An exposure assessment and modeling exercise in rural districts of Andhra Pradesh, India

Kalpana Balakrishnan, Sumi Mehta, Priti Kumar, Padmavathi Ramaswamy,
Sankar Sambandam, Kannappa Satish Kumar, Kirk R. Smith

THE WORLD BANK

ESMAP

June 2004

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Cover photos: Sri Ramachandra Medical College and Research Institute

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List of Abbreviations

ACGIH	American Conference of Governmental Industrial Hygienists
ANOVA	Analysis of variance
AP	Andhra Pradesh
ARI	Acute respiratory infection
Cd	Cadmium
CO	Carbon monoxide
CO_2	Carbon dioxide
ESMAP	Energy Sector Management Assistance Program (of the joint UNDP/World Bank)
GM	Geometric mean
HCHO	Formaldehyde
HDS	Human Development Survey
IHS	Institute of Health Systems
ICMR	Indian Council for Medical Research
IQR	Inter-quartile range
LPG	Liquefied petroleum gas
Lpm	Liters per minute
Mn	Manganese
MPHS	Multi Purpose Household Survey
NFHS	National Family Health Survey
NH_3	Ammonia
NIOSH	National Institute for Occupational Safety and Health
NO_x	Nitrogen oxides
NSS	National Sample Survey
O_3	Ozone
PAH	Polycyclic aromatic hydrocarbon
PDRAM	Personal datalogging real time aerosol monitor
Pb	Lead
PM_{10}	Particulate matter with an aerodynamic diameter of less than 10 μm
$PM_{2.5}$	Particulate matter with an aerodynamic diameter of less than 2.5 μm
PVC	Polyvinyl chloride
RCT	Randomised control trial
RIT	Randomised intervention trial

REDB	Rural energy database
RSPM	Respirable suspended particulate matter
SO_2	Sulfur dioxide
SPM	Suspended particulate matter
SRMC & RI	Sri Ramachandra Medical College and Research Institute
TERI	The Energy and Resources Institute
TSP	Total suspended particulates
UCB	University of California, Berkeley
UNEP	United Nations Environment Programme
UNDP	United Nations Development Programme
USEPA	United States Environmental Protection Agency
VOC	Volatile organic compounds
WHO	World Health Organization

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Acknowledgements

The investigators would like to express their gratitude to the many individuals and organizations whose cooperation was crucial for the successful completion of this study.

This study was undertaken as part of a broader program, *Household Energy, Indoor Air Pollution and Health in India*, developed and managed by the South Asia Environment and Social Development Unit of the World Bank. Financial assistance from the Government of the Netherlands through the joint World Bank-UNDP Energy Sector Management Assistance Programme (ESMAP) and the Government of Norway is gratefully acknowledged. The World Bank team included Sameer Akbar, Sadaf Alam, Uma Balasubramanian, Douglas F. Barnes, Masami Kojima, Priti Kumar, and Kseniya Lvovsky (Task Team Leader). The team provided support in the design and implementation of the exercise and in the review and preparation of this report. Peer reviewers were Rachel B. Kaufmann (U.S. Centers for Disease Control on secondment to the World Bank) and Gordon Hughes (NERA). Editorial assistance was provided by Deborah Davis.

Sri Ramachandra Medical College and Research Institute, Chennai; the University of California, Berkeley; and the Institute of Health Systems, Hyderabad, provided an enormous amount of support, during both the field exercises and data analysis, for which we are deeply grateful. We also would like to thank the administration of SRMC&RI, including Mr. V. R. Venkatachalam (Chancellor), Dr. T. K. Partha Sarathy (Pro-Chancellor), Dr. S. Thanikachalam (Vice-Chancellor), Dr. K. V. Somasundaram (Dean of Faculties), Mrs. Radha Venkatachalam (Registrar) and Dr. D. Gnanaprakasam (Director-Academic Administration), whose support throughout the study was invaluable. They mobilized staff from various departments and facilitated administrative matters for the execution of the project. We owe them all a debt of gratitude.

Finally, we wish to thank Dr. Timothy Buckley of the Johns Hopkins University School of Hygiene and Public Health (Division of Environmental Health Sciences), and Dr. Sumeet Saksena, TERI, New Delhi, for loaning us the programmable pumps used in monitoring the households.

The authors of this report are Kalpana Balakrishnan, Sumi Mehta, Priti Kumar, Padmavathi Ramaswamy Sankar Sambandam, Satish Kumar K. and Kirk R. Smith.

Executive Summary

Indoor air pollutants associated with combustion of solid fuels in households of developing countries are now recognized as a major source of health risks to the exposed populations. Use of open fires with simple solid fuels, biomass, or coal for cooking and heating exposes an estimated 2 billion people worldwide to concentrations of particulate matter and gases that are 10 to 20 times higher than health guidelines for typical urban outdoor concentrations. Although biomass makes up only 10 to 15 percent of total human fuel use, since nearly half the world's population cooks and heats their homes with biomass fuels on a daily basis, indoor exposures are likely to exceed outdoor exposures to some major pollutants on a global scale. Use of traditional biomass fuels—wood, dung, and crop residues is widespread in rural India. According to the 55th round of the National Sample Survey conducted in 1999–2000, which covered 120,000 households, 86 percent of rural households and 24 percent of urban households rely on biomass as their primary cooking fuel.

Burning biomass in traditional stoves, open-fire three-stone stoves, or other stoves of low efficiency, and often with little ventilation, emits smoke containing large quantities of harmful pollutants, with serious health consequences for those exposed, particularly women involved in cooking and young children spending time around their mothers. Several recent studies have shown strong associations between biomass fuel combustion and increased incidence of chronic bronchitis in women and acute respiratory infections in children. In addition, evidence is now emerging of links with a number of other conditions, including asthma, tuberculosis, low birth weight, cataracts, and cancer of upper airways. Assessments of the burden of disease attributable to use of solid fuel use in India have put the figure at 4 to 6 percent of the national burden of disease. These estimates, derived from household fuel-use statistics in India and epidemiological studies of the risk of indoor air pollution from a number of developing countries, indicate that some 440,000 premature deaths in children under 5 years, 34,000 deaths from chronic respiratory disease in women, and 800 cases of lung cancer may be attributable to solid fuel use every year in the early 1990s. More recent and thorough analysis carried out as part of the large World Health Organization (WHO)-managed Global Comparative Risk Assessment (CRA) studies, determined only slightly smaller burdens in India for 2000.

Although, it has been known that as per capita incomes increase, households generally switch to cleaner, more efficient energy systems for their domestic energy needs (i.e., move up the "energy ladder"[2]), the picture is often complex in localized

[2] The energy ladder (Reddy and Reddy 1994) is made up of several rungs, with traditional fuels such as wood, dung, and crop residues occupying the lowest rung. Charcoal, coal, kerosene, gas, and electricity represent the next higher steps sequentially. As one moves up the energy ladder, energy efficiency and costs increase while pollutant emissions typically decline. While several factors influence the choice of household energy, household income has been shown to be the one of the most important determinants. The use of traditional fuels and poverty thus remain closely interlinked

situations. In many rural areas, households often simultaneously employ multiple types of stoves and fuels, in which they essentially stretch across two or more steps of the energy ladder and fuel substitution is often not complete or unidirectional. Given the wide spread prevalence of solid fuel use, the slow pace and unreliability of natural conversion to cleaner fuels in many areas, and the emerging scientific evidence of health impacts associated with exposures to emissions from solid fuel, indoor air pollution issues in rural households of developing countries are of tremendous significance from the standpoint of finding ways to improve population health.

From a policy standpoint, although it is health effects that drive concern, it is too late by the time they occur to use disease rates as an indicator of the need for action in particular places. In addition, because these diseases have other causes as well, it is difficult, lengthy, and costly to conduct careful epidemiological studies to quantify the disease burden in any one place due to indoor air pollution, and to distinguish it from the burden due to other common risk factors, including malnutrition and smoking. As a result, it is necessary to develop ways of determining pollution exposure, a measure combining the number of people, the level of pollution, and the amount of time spent breathing it, as an indicator of where the health effects are likely to be. Improved knowledge of exposures then becomes a useful tool for determining effective intervention options.

In India over the last two decades, although a few dozen studies concerning indoor air pollution levels/exposures associated with biomass combustion have been carried out, they have had small sample sizes and were not statistically representative of the population. Some qualitative data on exposures such as primary fuel type are routinely collected in national surveys such as the Census and National Family Health Survey, and serve as readily available low-cost exposure indicators, but they often lack precision for estimating household-level exposures. The influence of multiple household-level variables such as the type of fuel, type and location of kitchen and type of stove, on actual exposures is poorly understood. Thus, although these efforts have convincingly shown that indoor pollution levels can be quite high compared to health-based standards and guidelines, they do not allow us to estimate exposure distributions over wide areas. Further, compared to the north and west, relatively few studies have been carried out in southern and eastern India, which contain a significant proportion of the national population. In particular, there are substantial climatic and socio-cultural differences between the northern and southern regions, including different food habits and the use of these biomass fuels for heating, which could have an important bearing on household exposures.

Based on this background, the present study[3] was designed with three major objectives:

- To monitor household pollution concentrations in a statistically representative rural sample in southern India;
- To model household indoor air pollution levels based on information on household-level parameters collected through questionnaires, in order to determine how well such survey information could be used to estimate air pollution levels without monitoring;
- To record time/activity and other information at the household-level, in order to estimate the exposures of different household members.

The state of Andhra Pradesh (AP) in southern India was chosen as the study region. AP's use of solid fuels for household cooking is representative of India as a whole; around 85 percent rural households in AP used solid fuels for cooking in 1991, as

[3] The exposure assessment and modeling results presented in this report are the outcome of one of four principal components examined in a larger study, "India: Household Energy, Air Pollution and Health" conducted by the South Asia Environment and Social Development Unit of the World Bank under the Joint UNDP/World Bank Energy Sector Management Assistance Programme (ESMAP). The other three components are a review of best-performing improved stove programs in six states, to identify the necessary elements for successful implementation and long-term sustainability; an evaluation of the capital subsidy for LPG in Andhra Pradesh, to assess its effectiveness in encouraging switching from biomass to commercial fuels by the rural poor; and dissemination of information and awareness building; to foster improved knowledge and awareness about mitigation options and policies among the target population (World Bank 2002).

compared to a national average of 86 percent. Its average household annual income (Rs. 24,800) is also similar to India's household annual income (Rs. 25,700). In addition, the consistency, quality, and quantity of existing sources of information on household characteristics and health outcomes in AP is generally considered to be better than in other states.

The study employed a tiered exposure assessment approach, to collect detailed primary data on several household-level exposure indicators (for fuel type, housing type, kitchen type, ventilation, stove type, etc.) in approximately 1030 households; and, in a subset of households, to perform quantitative air quality monitoring of respirable particulate matter, probably the best single indicator pollutant for ill-health in the complicated mixture contained in biomass smoke. Approximately 420 households in 15 villages of three districts in AP were monitored for respirable particulate levels. Combining the results of both these exercises, a model to predict indoor air pollution concentrations based on household characteristics was developed to identify a key set of household-level concentration determinants that could be used to classify populations into major air quality sub-categories. In addition, exposure estimates were derived for each major category of household members.

Measurements of respirable particulate matter (RSPM <4 mm) show that 24-hour average concentrations ranged from 73μg/m^3 to 730μg/m^3 in the kitchen and 75 μg/m^3 to 360μg/m^3 in the living area, in gas (LPG) and solid fuel (wood/dung) using households, respectively.[4] The 24-hr average outdoor levels of RSPM ranged from 66 to 110μg/m^3. Kitchen and living area concentrations were significantly different across fuel types. Use of dung resulted in the highest concentrations, followed by wood, and then gas. Concentrations in kerosene-using houses, although lower than solid fuel-using households, were more than twice the average levels found in gas-using households. However, these households while reporting kerosene as their primary fuel also frequently switch to cooking with wood, thus sometimes resulting in high concentrations.

Kitchen configuration was also an important determinant of concentrations in solid-fuel but not gas-using households. Kitchen area concentrations were significantly higher in enclosed kitchens as compared to outdoor kitchens. Among solid fuel users, both kitchen and living area concentrations were significantly correlated with fuel quantity, while only living area concentrations were correlated with the number of rooms and windows. Neither kitchen nor living room concentrations was significantly correlated with kitchen volume, cooking duration, or the number of people being cooked for.

Household-level variables significantly associated with kitchen and living areas concentrations were included in the modeling process to explore whether and how certain household characteristics can be used to predict household concentrations. Predicting household concentrations of particulate matter in India is not an easy task, given the wide variability of household designs and fuel-use patterns. As households with low concentrations due to use of clean fuels are relatively easy to identify, the objective of the modeling exercise was to attempt to minimize a misclassification of low-concentration solid-fuel using households. Linear regression models that were used to predict continuous outcome variables for kitchen and living-area concentrations did not yield sufficient information to explain great variability in the kitchen and living area concentrations. Subsequently, modeling was conducted for binary concentration categories (high and low exposure households), using logistic regression and classification and regression trees (CART) techniques.

Three variables—fuel type, kitchen type, and kitchen ventilation[5]—were found to be good predictors of kitchen and living-area concentrations. Fuel type was the best predictor of high concentrations in the kitchen area, but not a very good predictor of low concentrations. This was presumably due to the wide range of concentrations within fuel

[4] All figures reported in this summary have been rounded to reflect their degree of certainty.
[5] Ventilation was assessed qualitatively by the fieldworker's perception to be poor, moderate or good.

categories. Kitchen type was also an important predictor; indoor kitchens were much more likely to have high concentrations than outdoor kitchens. Households with good kitchen ventilation were much less likely to have high kitchen area concentrations than households with moderate or poor ventilation. Fuel type was also the best predictor of high living area concentrations. This was true in both the presence and absence of information on Kitchen area concentration. Information on kitchen area concentrations improved the accuracy of living area predictions substantially, however. For living area concentrations, knowing the specific type of kitchen was less important than knowing whether or not the kitchen was separate from the living area. Information on kitchen ventilation was consistent with the results of the Kitchen area concentration models; solid fuel-using households with good kitchen ventilation are likely to have lower living area concentrations. This suggests that improvements in kitchen ventilation are likely to result in better air quality in the living areas.

Finally, exposures were reconstructed for household members subdivided as cooks and non-cooks, and then classified into 8 subgroups on the basis of sex and age. Mean 24-hour average exposure concentrations ranged from $80\mu g/m^3$ to $570\mu g/m^3$ in gas and solid fuel-using households, respectively. Among solid fuel users, mean 24-hour average exposure concentrations were the highest for women cooks ($440\mu g/m^3$), and were significantly different from exposures for men ($200\mu g/m^3$) and children ($290\mu g/m^3$). Among solid fuel users, cooks (90 percent of the cooks in the sample were women between ages of 16–60) experience the highest exposures, and these exposures are significantly different than for all other categories of non-cooks. Among non-cooks, women in the age group of 61–80 experience the highest exposure, followed by women in the age group of 16–60, while men in the age group of 16–60 experience the lowest exposure. This is presumably because older women in the category of non-cooks are most likely to remain indoors, and younger women (16–60) in this category are most likely to be involved in assisting the cooks, while men in the age group of 16–60 are most likely to have outdoor jobs that may lower their exposure. Men in the age group of 60–80 experience higher exposures as compared to men in the age group of 16–60, perhaps also owing to their greater likelihood of remaining indoors. Some female children in the age group of 6–15 reported involvement in cooking, and their exposures were as expected, i.e., much higher than for other children.

The study has provided measurements for 24-hour concentrations and exposure estimates for a wide cross-section of rural homes using a variety of household fuels under a variety of exposure conditions in Andhra Pradesh. Although the study design did not permit addressing temporal variations in each household, given the large sample size and the limited variability in weather conditions in this study zone, inter-household differences are likely to contribute the most to the concentration and exposure profiles, and the results of this study are likely to be useful as representing the indoor air pollution profile for the rural households of the study districts in the state.

Through quantitative estimates, the study has confirmed and expanded what only a few other studies have measured; i.e., that women cooks are exposed to far higher concentrations than most other household members, and adult men experience the least exposure. In addition, exposure potentials are high for the old or the infirm, who are likely to be indoors during cooking periods, and for children, who are likely to remain close to their mothers. Further, even for households that cook outdoors, the 24-hour concentrations and exposures could be significant both in the cooking place and indoors, and well above levels considered acceptable by air quality health guidelines. This challenges the conventional wisdom and a frequent excuse to ignore the problem, that cooking outdoors—as many poor households do in India—prevents the health risks from fuel smoke.

Given that health benefits from interventions would take a much longer time (often several years) to establish, region-specific quantitative exposure information from this study could be useful for developing metrics to assess the potential of the available interventions for exposure reduction. The results of the quantitative assessment have, for example, provided additional evidence of the benefits of looking at interventions other than fuel switching. Ventilation and behavioral initiatives may offer a potential for substantial exposure reduction, and given that these are likely to be the short-term alternatives for a great majority of rural populations, the results could be used to aid the design of such efforts.

One of the criteria for choosing this area of AP was that biomass stoves had been promoted in the past thus potentially allowing for including stoves with chimneys or flues and other improvements in the analyses. Unfortunately, however, only one currently operating improved stove was found in all the study households, although some households reported using them previously. Thus it was not possible to characterize the potential concentration/exposure improvements that might accompany such devices and to see how concentrations/exposures vary in relation to other important parameters, such as fuel and kitchen types.

Although exploratory in nature, the effort at modeling indoor air pollution concentrations has provided valuable insights into the key determinants of exposure—fuel type, kitchen type, and/or kitchen ventilation. Although the predictive power of models developed in the study needs to be improved, the finding is that only two easily determined factors (primary fuel type and kitchen ventilation conditions) turn out to be significant in the modeling exercise, and are attractive for use in the design of a simple and reliable environmental health indicator for indoor air quality. Since improved stoves seem to offer one of the best near-term options for reducing the human health impacts of household solid-fuel use, it would be important to focus future studies in India on this issue as well as discovering the reasons why such programs have not worked well in so many areas in the past.

Today, there is only one set of widely accepted household environmental health exposure indicators—*access to clean water and access to sanitation.* These are reported annually and separately for rural and urban areas by nearly every country, and are commonly cited as measures of ill-health risk and indicators of poverty. These indicators of water pollution-related hygiene at the household level are strikingly parallel to those emerging from this study for household air quality-related hygiene; i.e. *access to clean fuel and access to ventilation.* In both cases, although not ideal measures of true exposure and risk, they have the extremely important benefit of being easily and cheaply determined by rapid surveys requiring no measurements. In both cases, they do not claim to specify what is actually done on a daily basis by households, but rather the potential represented by what is physically present, as indicated by the term "access." The models developed in the study, with some additional refinements, could influence the design of such indicators in large-scale survey instruments such as the Census or National Sample Survey, with a view to facilitating classification of population subgroups into exposure sub-categories. Validation of these models across other states and regions in India would then eventually allow the generation of exposure atlases based on information collected routinely through large-scale population surveys, and aid in establishing regional priorities for interventions. Such priority setting could greatly improve the cost effectiveness and the rate of health improvements from interventions, by directing resources to the most affected households first.

The issue of indoor air pollution associated with household fuels in developing countries is deeply embedded in a matrix of environment, energy, health, and economic considerations. The disease burden has been shown to consistently fall as regions develop and incomes grow, reflecting the need to mainstream indoor air pollution reduction in poverty alleviation initiatives. The high burden for children under 5 (through its contribution to acute respiratory infections) also indicates the need to mainstream this issue in children's health initiatives. Finally, women who are at the center of care giving at the family level, bear a significant disease burden that can have implications beyond their own health (most importantly, children's health). Health risks from indoor air pollution in household settings thus have complex inter-linkages, and a holistic understanding of these linkages is crucial for the design of strategies to minimize negative impacts. An in-depth understanding of the potential for health risks as reflected in exposure potentials is especially crucial for ensuring that the poorest and most vulnerable communities do not endure years of suffering before development can catch up with them. Addressing critical public health risks in a framework of intervention and risk reduction is key for human development, and represents an important mechanism for ensuring equity in quality of life among populations. It is hoped that the information presented here represents a small, incremental step toward better understanding the issue of indoor air pollution exposure in homes of rural India, and has improved the evidence base for implementing and integrating environmental management initiatives in the household, energy, and health sectors.

Chapter 1

Background

1.1 Introduction

Indoor air pollution is recognized as a significant source of potential health risks to exposed populations throughout the world. The major sources of indoor air pollution worldwide include combustion of fuels, tobacco, and coal; ventilation systems; furnishings; and construction materials (Table 1). These sources vary considerably between developing and developed nations.

The most significant issue that concerns indoor air quality in household environments of developing countries is that of exposure to pollutants released during combustion of solid fuels, including biomass (wood, dung, and crop residues) or coal used for cooking and heating. A majority of rural households burn these simple solid fuels in inefficient earthen or metal stoves, or use open pits in poorly ventilated kitchens, resulting in very high concentrations of indoor air pollutants.[6] It is estimated that use of open fires with these fuels exposes nearly 2 billion people in the world to enhanced concentrations of particulate matter and gases, up to 10–20 times higher than health-based guideline values available for typical urban outdoor concentrations (Barnes et al 1994; Reddy et al 1996; World Health Organization [WHO] 1999). Although biomass makes up only 10–15 percent of total human fuel use, since nearly half the world's population cooks and heats their homes with biomass fuels on a daily basis, indoor exposures[7] likely exceed outdoor exposures to some major pollutants on a global scale (Smith 1988). Fuel use patterns across world regions are shown in Figure 1.

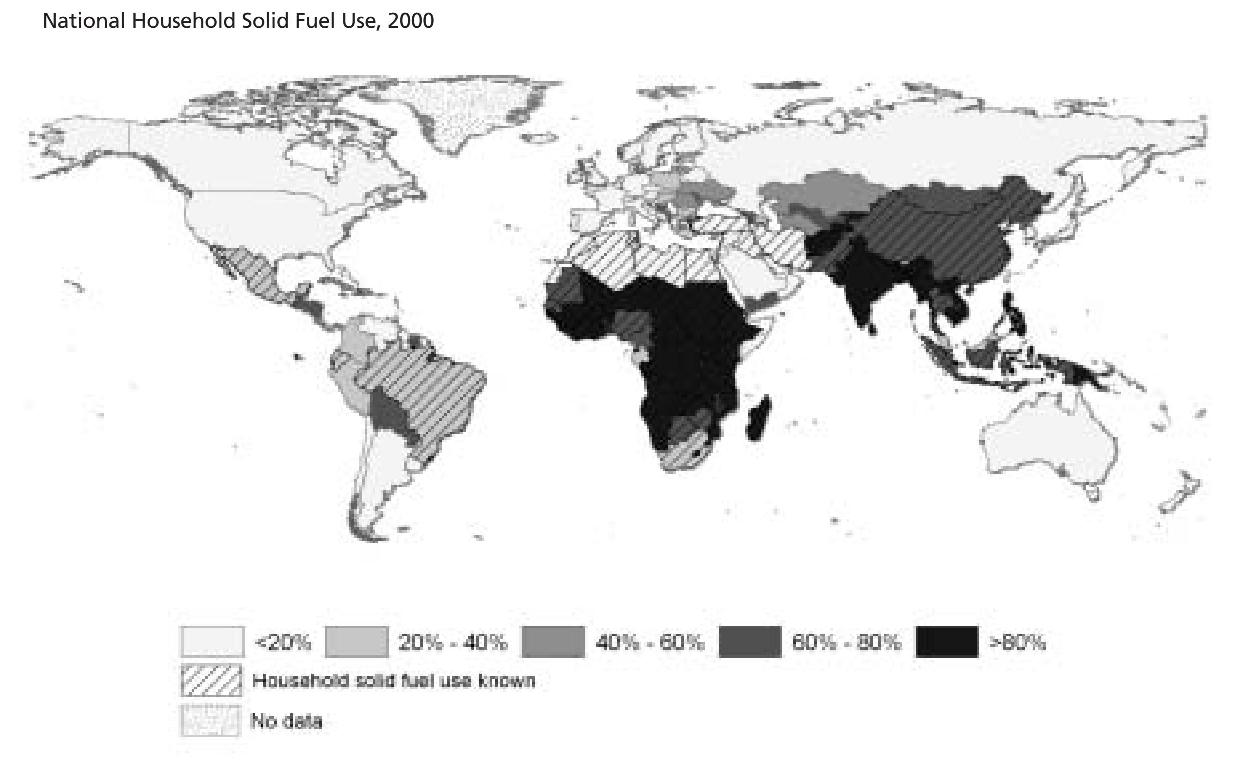
Such exposures have serious health consequences for household members, particularly for the women involved in cooking and young children spending time around their mothers. Several recent studies have shown strong associations between biomass fuel combustion and increased incidence of chronic bronchitis in women and acute respiratory infections in children in developing countries. In addition, evidence is now emerging of links with a number of other conditions, including low birth weight, asthma, tuberculosis, cataracts and cancer of the upper airways (reviewed in Bruce et al 2000). The recently concluded comparative risk assessment (CRA) exercise conducted by WHO estimates that exposure to indoor smoke from solid fuels may be annually responsible for about 1.6 million premature deaths in developing countries and 2.6 percent of the global burden of disease (WHO 2002).

Use of traditional biomass fuels—fuelwood,

[6] In many rural households of developing countries, it is common to find kitchens with limited ventilation being used for cooking and other household activities. Even when separated from the adjacent living areas, most offer considerable potential for smoke to diffuse across the house. Use of biomass for space heating creates additional potential for smoke exposure in living areas.

[7] Exposure to air pollutants refers to the concentration of pollutants in the breathing zone during specific periods of time, and are a function of pollution levels in places where people spend the majority of their time. Thus, although air pollutant emissions are dominated by outdoor sources, human exposure to air pollutants is dominated by the indoor environment.

Figure 1 : Household fuel use across world regions



(*Source:* Mehta 2002)

Table 1 : Major health-damaging pollutants generated from indoor sources

Pollutant	Major indoor sources
Fine particles	Fuel/tobacco combustion, cleaning operations, cooking
Carbon monoxide	Fuel/tobacco combustion
Polycyclic aromatic hydrocarbons	Fuel/tobacco combustion, cooking
Nitrogen oxides	Fuel combustion
Sulfur oxides	Coal combustion
Arsenic and fluorine	Coal combustion
Volatile and semi-volatile organic compounds	Fuel/tobacco combustion, consumer products, furnishings, construction materials, cooking
Aldehydes	Furnishing, construction materials, cooking
Pesticides	Consumer products, dust from outside
Asbestos	Remodeling/demolition of construction materials
Lead	Remodeling/demolition of painted surfaces
Biological pollutants	Moist areas, ventilation systems, furnishings
Radon	Soil under building, construction materials
Free radicals and other short-lived, highly reactive compounds	Indoor chemistry

Source: Zhang and Smith 2003.

dung, and crop residues—is widespread in rural India. According to the 55th round of the National Sample Survey conducted in 1999–2000 (NSS 2000) covering 120,000 households, 86 percent of rural households and 24 percent of urban households rely on biomass as their primary cooking fuel. Assessments of the burden of disease attributable to use of solid fuel use in India have put the figure at 3–5 percent of the national burden of disease (Smith 2000, Smith and Mehta, 2003).

Although, it has been known that as per capita incomes increase, households generally switch to cleaner, more efficient energy systems for their domestic energy needs (i.e., move up the "energy ladder") due to increased affordability, demand for greater convenience, and energy efficiency, the picture is often more complex in localized situations. In many rural areas, households often simultaneously employ multiple types of stoves and fuels, in which they essentially stretch across two or more steps of the energy ladder and fuel substitution is often not complete or unidirectional. In some areas, despite the availability of cleaner fuels, households continue to use a combination of fuels as a result of socio-cultural preferences or as a risk reduction mechanism against an unreliable supply of cleaner fuels (Omar and Masera 2000). There is even evidence of increasing dependence on biomass in some countries especially among the poorer households (WHO 1997).

Given the prevalence of solid fuel use, the slow pace and unreliability of natural conversion to cleaner fuels in many areas, and the emerging scientific evidence of health impacts associated with exposure to emissions from solid fuel use, indoor air pollution issues in rural households of developing countries are of tremendous significance from the standpoint of finding ways to improve population health.

1.2 Characteristics of biomass smoke

The amount and characteristics of pollutants produced during the burning of biomass fuels depend on several factors, including composition of fuel, combustion conditions (temperature and air flow), mode of burning, and shape of the combustion chamber (Smith 1987). Hundreds of harmful chemical substances are emitted during the burning of biomass fuels in the form of gases, aerosols (suspended liquids and solids) and suspended droplets. Smoke from wood-burning stoves has been shown to contain 17 pollutants designated as priority pollutants by the United States Environmental Protection Agency (USEPA 1997) because of their toxicity in animal studies (Cooper 1980; Smith and Liu 1993). These pollutants include carbon monoxide, small amounts of nitrogen dioxide, aerosols (called particulates in the air pollution literature) in the respirable range (0.1–10 μm in aerodynamic diameter), and other organic matter including polycyclic aromatic hydrocarbons such as benzo [a] pyrene, and other volatile organic compounds such as benzene and formaldehyde (Table 2).

An explanation of terms listed in the table is provided in the glossary.

1.3 Indoor air pollutant levels in biomass using households—concentrations and exposures

Some of the earliest studies to determine levels of indoor air pollutants associated with biomass combustion and their effects on health were carried out in the early 1980s (Smith et al 1983). Initial studies determined levels of total suspended particulates and exposures[8] for cooks during cooking periods. Subsequently, several studies have been carried out to determine concentrations of other particulate fractions as well as other pollutants, including CO, sulfur dioxide, formaldehyde, and nitrogen dioxide. Many studies indicate that particulate matter (especially respirable particulate matter) may be the single best available indicator of overall indoor air pollution levels associated with biomass combustion. Table 3 provides a list of some

[8] Exposure to air pollutants is usually determined by attaching personal air samplers to individuals or by measuring area concentrations in various household micro-environments, together with detailed time budget assessments, to reconstruct a time-weighted average concentration.

recent studies carried out in developing countries that compares the levels of particulate matter across households using various fuels averaged over varying periods of a day(s).

Concentrations of total suspended particulates (TSP) in the range of 200–30,000μg/m^3, and carbon monoxide concentrations between 10–500 ppm during the cooking period have been reported in some of the earlier studies (Reid et al 1986, Pandey et al 1990, Ellegard 1996). Average 24-hour concentrations of respirable particulate concentrations are in the range of 300 –3000 μg/m^3 (Smith et al 1994, McCracken and Smith 1998). In the absence of specific indoor air quality standards and associated requirements for accredited protocols, measurements have largely been conducted on an accessible cross-section of households using available technical and instrumentation resources ("convenience sample"). Logistic and financial constraints make it difficult to conduct large-scale measurements, thus resulting in small sample sizes. More recently, however, systematic, large-scale 24-hour measurements of respirable particulates have been reported from studies conducted in Kenya (Ezzati et al 2000), Guatemala (Albalak et al 2001), and India (Parikh et al 2001, Balakrishnan et al 2002), which—in addition to measurements—have also identified several household-level determinants of concentrations and exposures.

The available studies clearly show a great deal of variation in levels across households in different geographical settings and across seasons in the same region, in addition to spatial and temporal variations within households, resulting in widely different exposure potentials for household subgroups. The reported levels are also somewhat influenced by the measurement protocols. Several household-level determinants, including fuel type, kitchen type, duration of cooking, stove type, ventilation parameters, and behavioral factors are now known to influence pollution levels and individual exposures. Despite the complexity and inter-linkages among various factors, nearly all the studies point out that use of biomass results in high pollutant levels (much higher than health-based guideline values available for the outdoor setting), and that women and children face the biggest risk of high exposure because of their proximity to the fire during cooking periods. The available information also points to the need for collecting this information on a regional basis to expand the evidence base for potential health risks and assess opportunities for exposure reduction.

Table 2: Toxic pollutants from biomass combustion and their toxicological characterstics

	Pollutant	Known toxicological characteristics
1	Particulates (PM 10, PM 2.5)	Bronchial irritation, inflammation increased reactivity, reduced muco-ciliary clearance, reduced macrophage response
2	Carbon monoxide	Reduced oxygen delivery to tissues due to formation of carboxy hemoglobin
3	Nitrogen dioxide (relatively small amounts from low temperature combustion)	Bronchial reactivity, increase susceptibility to bacterial and viral lung infections
4	Sulphur dioxide (relatively small amount from most biofuels)	Bronchial reactivity (other toxic end points common to particulate fractions)
5	Organic air pollutants	
	Formaldehyde	
	1,3 butadiene	
	Benzene	Carcinogenicity/mutagenecity
	Acetaldehyde	Co-carcinogenicity
	Phenols	Cilia toxicity, leukemia
	Pyrene Benzopyrene	Increased allergic sensitization
	Benzo(a)pyrene	Increased airway reactivity
	Dibenzopyrenes	
	Dibenzocarbazoles	
	Cresols	

Sources: Cooper 1980, Smith 1987, Smith and Liu 1993, Bruce 2000.

Table 3: Comparison of particulate levels as determined in a selection of recent studies in developing countries

Location and References	Fuel Type	Average sampling duration	Time of measurement	Types of measurement (area or personal)	Areas of measurement (kitchen, living or outdoors)	Size fractions (TSP, PM10 or PM2.5)	Exposure for adult women (μg/m³)	Concentrations (μg/m³)	
								AM	GM
Nepal (Davidson et al 1986)	Wood	1–2 hrs	Cooking period	Area	Kitchen	TSP RSPM-<4_m			8800 4700
Garhwal, India (Saksena et al 1992)	Wood/Shrubs		Cooking period			TSP			4500
Pune, India (Smith et al 1994)	Wood	12–24 hrs		Area personal		PM10 PM10	 1100	2000	
Mozambique (Ellegard 1996)	Wood	1.5 hrs	Cooking period	Personal		PM 10	1200		
Bolivia (Albalak et al 1999)	Dung	6 hrs	Total duration that the fire was on, including one cooking period	Area	-Indoor kitchens -Outdoor kitchens	PM 10 PM 10		3690 430	1830 430
Kenya (Ezzati et al 2000)	Wood	24-hours	Cooking period & time-activity recall	Area	Kitchen	PM10	4898		
Guatemala (Albalak et al 2001)	Wood	24 hr	24 hrs	Area	Kitchen	RSPM-3.5		1930	1560
Tamil Nadu, India (Balakrishnan et al 2002)	Wood		Cooking period			RSPM-<4_*m*	1307		
	Agricultural wastes	1–2 hrs		Personal	Kitchen		1535		
	Wood	Daily average	Cooking period & time-activity recall	Personal and area	Kitchen, living and outdoor		226		
	Agricultural wastes						262		
	Wood		Cooking	Area	Living			847	498
	Agricultural wastes							1327	913

TSP-Total suspended particulates; PM-particulate matter; RSPM-respirable suspended particulate matter; AM-arithmetic mean; GM-geometric mean; μg/m³-microgram per meter cube.

1.4 Health effects of exposure to biomass smoke

Supporting evidence for health effects associated with exposure to smoke from biomass combustion is provided by studies on outdoor air pollution, as well as by studies dealing with exposure to environmental tobacco smoke. Criteria documents for outdoor air pollutants published by the USEPA detail the health effects of many pollutants such as particulate matter, carbon monoxide, oxides of sulfur and nitrogen, and polycyclic aromatic hydrocarbons (PAHs) (USEPA 1997).

Respirable particulate matter is now considered the single best indicator pollutant for assessing the overall health-damaging potential of most kinds of combustion, including that of biomass. Considerable scientific understanding now exists on the aerodynamic properties of these particles that govern their penetration and deposition in the respiratory system. The health effects of particles deposited in the airways depend on the defense mechanisms of the lung, such as aerodynamic filtration, mucociliary clearance, and in situ detoxification. Since most particulate matter in biomass fuel smoke is less than 2μm in diameter, it is possible that such particulate matter may reach the deepest portions of the respiratory tract and alter defense mechanisms. Several biomass fuel combustion products may also impair mucociliary activity and reduce the clearance capacity of the lung, resulting in increased residence time of inhaled particles, including microorganisms. In situ detoxification, the main mechanism of defense in the deepest non-ciliated portions of the lung, may also be compromised by exposure to components of biomass fuel smoke (Demarest et al, 1979).

Carbon monoxide binds to hemoglobin in preference to oxygen and thus reduces oxygen delivery to key organs, which may have important implications for pregnant women, with developing fetuses being particularly vulnerable. Although emissions of sulfur dioxide and nitrogen dioxide are of lesser concern in biomass combustion (high levels of sulfur dioxide may be reached with other solid fuels such as coal), they are known to increase bronchial reactivity. PAHs such as benzo[a]pyrene are known carcinogens. Volatile organic compounds in biomass smoke, such as formaldehyde, benzene, 1–3 butadiene, styrene, and xylene, are known or suspected carcinogens (Table 2).

Some of the earliest human evidence linking indoor air pollution from biomass combustion with respiratory health came from studies carried out in Nepal and India in the mid-1980s (Smith et al 1983, Pandey 1984, Ramakrishna et al 1989). Since then, there has been a steady stream of studies, especially on women who cook with these fuels and young children (recent reviews may be found in Bruce et al. 2000, Smith et. al. 2000). Associations between exposure to indoor air pollution and increased incidence of chronic bronchitis in women and acute respiratory infections (ARI) in children have been documented (Armstrong and Campbell 1991, Robin et al 1996, Bruce et al 1998, Ezzati and Kammen 2001). Many recent studies have also been conducted in rural Indian villages (Behera et al 1991, Smith 1993, Awasthi et al 1996, Smith 1996, Mishra and Retherford 1997). A recent study has also characterized the exposure–response relationship between biomass smoke exposure and acute respiratory infection in children of rural Kenyan households (Ezzati et al 2000). Odds ratios[9] in the range of 2–5 for incidence of acute respiratory infections in children exposed to biomass smoke have been reported (Smith et al., 2003). The incidence of chronic obstructive pulmonary disease (COPD) in non-smoking women using biomass for cooking has also been shown to be dependent on the number of years cooking with biomass and often to be comparable to that of men (who usually have high smoking rates).

Although most studies on the health effects of biomass combustion have been observational in nature and have relied on proxy measures of exposure (such as reported hours spent near the stove, years of cooking experience, or child being carried by mother while cooking), the consistency of evi-

[9] Odds ratios represents the ratio of the probability of occurrence of an event to non-occurrence; e.g., an elevated odds ratio in biomass-using households reflects the incremental risks for people in this set of households as compared to clean fuel-using households. An odds ratio of 2 for ARI in children for biomass using households for e.g. would imply a two fold higher risk of ARI for these children as compared to the reference group of children in clean fuel (gas) using households.

dence from studies exclusively carried out in developing countries, together with supportive evidence provided by outdoor air pollution and environmental tobacco smoke studies, indicates that there is likely to be a strong association between indoor smoke exposure and acute respiratory infections in children and chronic bronchitis in women.[10] The evidence for other health outcomes including asthma, tuberculosis, and cataracts is in need of additional strengthening from studies that have better indicators for exposure and control for confounders. Associations with adverse pregnancy outcomes (including low birth weight and stillbirth) and ischemic heart disease are biologically plausible, as they have been associated with outdoor air pollution and smoking (passive and active), but have not yet been adequately explored for exposures from use of solid household fuels. Table 4 shows relative risk[11] estimates for health outcomes that are associated with exposure to smoke from solid fuel use (Smith 2000).

Based on this evidence, it has been estimated that the indoor air pollution contributes to 3–5 per cent of the national burden of disease in India (Smith 2000, Smith et al 2003). More specifically, some 440,000 premature deaths in children under 5 years, 34,000 cases of chronic respiratory disease in women under 45 years, and 800 cases of lung cancer may be attributable to solid fuel use every year. A recent WHO analysis for the year 2000 done as part of the global CRA exercise has determined slightly smaller risks, but they lie in the same range; i.e., about 400,000 premature deaths annually in India (WHO 2002).

1.5 Rationale and purpose of the study

From the preceding account, it is clear that indoor air pollution associated with household fuel use in India is a significant public health concern. From a policy standpoint, although it is health effects that drive concern, it is too late by the time they occur to use disease rates as an indicator of the need for action. In addition, because these diseases have other causes as well, it is difficult, lengthy, and costly to conduct careful epidemiological studies to

Table 4: Health effects of exposure to smoke from solid fuel use: plausible ranges of relative risk in solid fuel-using households

Health Outcome	Population affected	Relative Risk Low	Relative Risk High	Strength of evidence
Acute lower respiratory infections (ALRI)	<5 years	2.0	3.0	Strong
Asthma	Females ≥15 years	1.4	2.5	Intermediate/ moderate
Blindness (cataracts)	Females ≥15 years	1.3	1.6	Intermediate/ moderate
Chronic obstructive pulmonary disease (COPD)	Females ≥15 years	2.0	4.0	Strong
Lung cancer (coal only)	Females ≥15 years	3.0	5.0	Strong
Tuberculosis	Females ≥15 years	1.5	3.0	Intermediate/ moderate

Source: Adapted from Smith 2000.

[10]The best way to prove causality is to apply the "gold standard" of epidemiology, the randomised control trial (RCT) in which the improvement being tested is given at random to a portion of population such that all other possible risk factors and confounders are equal between the control and intervention groups. Any differences in disease observed afterwards in these groups can be more confidently attributed to the improvement and not to other difference in the populations than in examinations of existing populations. Such randomised intervention trials (RITs) are commonly required for convincing authorities to invest limited health resources in interventions such as vaccines, clean water, and nutrition supplements. At present, the first RIT in air pollution history is ongoing in wood-burning household of highland Guatemala and should provide more concrete evidence of the risk of ARI and other major diseases from biomass smoke (http://ehs.sph.berkeley.edu/guat/default.htm).

[11]Relative risk refers to the magnitude of association between exposure and disease, and indicates the likelihood of developing a disease among the exposed group relative to the unexposed. A relative risk of 1 indicates that the risk is the same in the exposed and unexposed groups; i.e. there is no increased risk associated with exposure. For example, in Table 4, children exposed to indoor air pollution from solid fuel use have two to three times greater risk of developing lower respiratory infections compared to unexposed children.

quantify the disease burden in any one place due to indoor air pollution and or to distinguish it from the burden due to other common risk factors, including malnutrition and smoking. As a result, it is necessary to develop ways of determining pollution exposure—a measure combining the number of people, the level of pollution, and the amount of time spent breathing it—as an indicator of where the health effects are likely to be. Improved knowledge of exposures also then becomes a useful tool for deciding or determining effective intervention options.

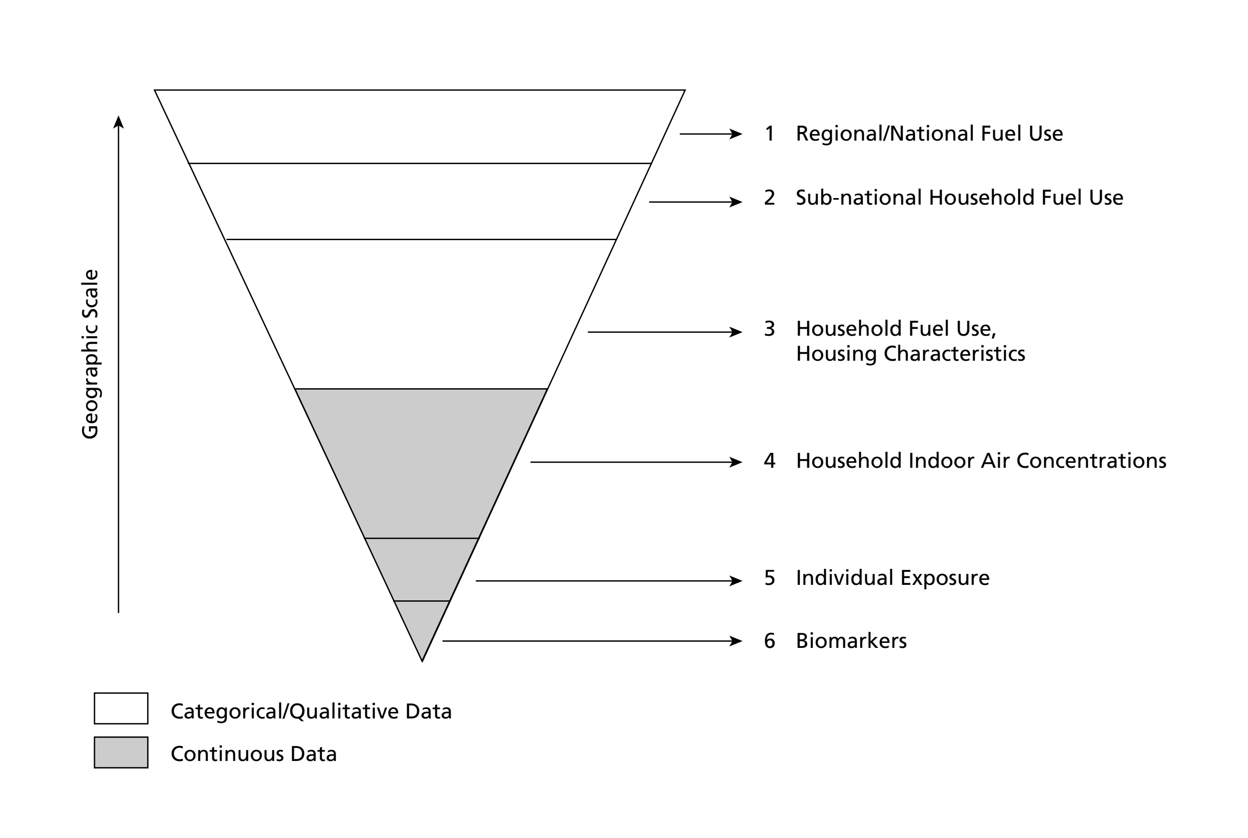
In India over the last two decades, although a few dozen studies concerning indoor air pollution (IAP) levels/exposures associated with biomass combustion have been carried out, they have had small sample sizes and were not done in a way to be statistically representative of the population. Some qualitative data on exposures, such as by primary fuel type, are routinely collected in national surveys such as the Census and National Family Health Survey, and serve as readily available low-cost exposure indicators, but they often lack precision for estimating household-level exposures. The influence of multiple household-level variables such as the type of fuel, type and location of kitchen, and type of stove, on actual exposures is poorly understood. Thus, although these efforts have convincingly shown that indoor pollution levels can be quite high compared to health-based standards and guidelines, they do not allow us to estimate exposure distributions over wide areas.

The task of conducting measurement studies of respirable particulate matter in 160 million Indian households using solid fuels to estimate exposure is prohibitively expensive and time consuming for practical use in policymaking. However, as a compromise between cost and accuracy, it is possible to assess exposure with lower and varying degrees of accuracy using either secondary data or primary data collection in smaller samples of households. As shown in Figure 2, secondary data sources, such as national fuel use data, give some measure of potential exposure (tier #1). However, they do not provide information on the ways that different exposure indicators are linked, i.e., to what extent fuel-use patterns in the community or households predict actual household air pollution concentrations. More accurate but more expensive ways to measure exposure, are actual household surveys of fuel use (tier #2). Indeed, this measure has been often used as the indicator of exposure in many epidemiological studies. Even better, but more expensive, would be surveys not only of fuel use, but also of household characteristics such as type of construction material, stove type, number of rooms and windows, etc., as might be part of a census or national housing survey (tier #3). Following this, higher in cost but affording more accuracy, come air pollution studies but with devices set in stationary positions in the house (tier #4). Finally, there could be studies where people actually wear devices to measure their pollution (personal) exposures, or where biological fluids or tissues (biomarkers) are examined to determine how much pollution they have been exposed to (tier's #5 and #6). In general, as the geographic scale decreases, specificity increases, the availability of pre-existing or routinely collected data decreases, and the cost of original data collection increases.

The exposure assessment methodology in this study straddles tiers #3 and #4. Primary data on parameters such as household fuel use, available through the Census or other national surveys, are used together with primary data collection on certain household-level characteristics and indoor air pollution measurements. This allows the generation of surrogate exposure indices that can be scaled up to cover whole regions with similar socio-economic and cultural profiles. It could also assist in designing better exposure indicators by elucidating, for example, which questions might be asked in a national census survey to best predict actual household pollution levels. Better estimates of exposure would, in turn, assist in targeting interventions to the population subgroups with the highest potential health risks due to IAP. Finally, if robust models to predict indoor pollution levels using household survey parameters are developed and established, they could help estimate the impact and, ultimately, the cost effectiveness of interventions that alter the determinants of exposure.

Finally, compared to the north and west, relatively few studies have been carried out in southern

Figure 2: Tiered exposure assessment: indoor air pollution from solid fuel use



Source: Mehta 2002.

and eastern India, which contain a significant proportion of the national population. There are substantial climatic and socio-cultural differences between the northern and southern regions, including different food habits and the use of biomass fuels for heating, which could have an important bearing on household exposures.

Based on this background, the present study was designed with three major objectives:

- To monitor household pollution concentrations in a statistically representative rural sample in southern India;
- To model household indoor air pollution levels based on information on household-level parameters collected through questionnaires, to determine how well such survey information could be used to estimate indoor air pollution levels without monitoring; and
- To record time/activity and other information at the household level to estimate the exposure of different household members.

The state of Andhra Pradesh (AP) in southern India was chosen as the study region. AP's use of solid fuels for household cooking is representative of India as a whole; around 85 percent of rural households in AP used solid fuels for cooking in 1991, as compared to a national average of 86 percent. Its average household annual income (Rs. 24,800) is also similar to India's household annual income (Rs. 25,700) (National Family Health Survey [NFHS] 1995). In addition, the consistency, quality, and quantity of existing sources of information on household characteristics and health outcomes in AP is generally considered to be better than in other states. The study tested a methodology for predicting exposure indicators that could be applied to a larger spatial context.

1.6 Study team

The exercise was designed by the Environmental Health Sciences Division of the School of Public Health, University of California, Berkeley (UCB), and undertaken in partnership with the Institute for Health Systems (IHS), Hyderabad, and Sri Ramachandra Medical College (SRMC), Chennai. The Environment and Social Development Unit of the World Bank provided coordination and support in the design and implementation of the exercise.

IHS administered the questionnaire for the household-level survey, with support from the local administration, health functionaries, and self-help groups. SRMC conducted the household air pollution measurements and time-activity surveys, and developed exposure estimates using the data. Data sets from the two components were used in models developed at UCB to predict quantitative categories of indoor air quality, based on housing and fuel characteristics.

Chapter 2

Study Design and Methodology

The study employed a tiered exposure assessment approach, collecting detailed primary data on several household-level exposure indicators (for fuel type, housing type, kitchen type, ventilation, stove type, etc.) through the administration of a questionnaire in 1,032 households, together with quantitative air quality monitoring of respirable particulate matter—probably the best single indicator pollutant for ill-health in the complicated mixture contained in biomass smoke—in a subset of households. Approximately 420 households in 15 villages of three districts in AP were monitored for respirable particulate levels. Combining the results of both these exercises, a model to predict indoor air pollution concentrations based on household characteristics was developed, with a view to identifying a key set of household-level concentration determinants that would provide sufficient resolution to classify populations into major air quality sub-categories. In addition, exposure estimates were derived for each major category of household members. The detailed methodology for each of these components is described in the following sections.

2.1 Development of questionnaires for collection of primary data on household-level exposure determinants

An inventory of national and state-level surveys was first prepared to understand the nature of information relevant to indoor air pollution that may already be available. Compilation of such an inventory allowed the identification of variables that were not well characterized in previous surveys, and formed the basis for designing the household survey instrument used in the present study.

A review of the various population-level survey questionnaires, such as the Census of India 1991 and 2001, AP Multi-Purpose Household Survey (MPHS), Human Development Survey (HDS), and the sampled survey data sets—viz., the National Family Health Survey 1 and 2 (NFHS 1995, 2000), the National Sample Survey (NSS 50th Round 1993-94), and the Rural Energy Database (REDB), a secondary compilation of studies, undertaken by the Tata Energy Research Institute (TERI) found that data were available only for a few variables, such as house type and fuel type. These sources do not provide data on the larger inventory of variables that are likely to affect air pollution levels in households, such as kitchen type and household ventilation. An overview of key variables present in the above-mentioned national and state surveys is given in Annex 1. Based on this review, primary data collection was undertaken for two categories of information:

- Information from households that parallels the information already collected by demographic surveys, including the Census and the National Family Health Survey; and
- Information on household characteristics that are currently not well captured in demographic and health surveys, but could be incorporated into future surveys if found to be predictive of indoor

air pollution (such as kitchen type, household ventilation, presence/absence of chimneys, number of windows/doorways, fuel quantity, etc.). This survey also provides an opportunity to test whether or not this information can be effectively ascertained by questionnaires .

A few examples of household-level variables chosen for the survey are shown in Table 5. The complete household survey instrument[12] is given in Annex 2.

2.2 Selection of study households

2.2.1 IAP monitoring (sample 1)

The households were selected in three districts: Nizamabad, Warangal, and Rangareddy of the Telangana region of AP. The sampling scheme was devised keeping in mind the primary household characteristics (different fuel use patterns, including clean fuels and different kitchen types) that affect exposure to indoor air pollution. Household selection was done purposively, using a cluster sampling method that would ensure that a combination of kitchen types and fuel types are selected within each cluster of households. Clustering was necessary to efficiently use the field team's available time and pollution monitoring equipment. The sampling scheme for the three districts is given in Annex 3. The three-stage cluster-sampling scheme, aimed at obtaining approximately 150 households in each district, proceeded as follows:

- Selection of *mandals*[13] as the first-stage sampling unit *(5 from each district)*
- Selection of *habitations* as the second-stage sampling unit *(1 from each mandal)*
- Selection of *households* as the third-stage sampling unit *(up to 30 from each habitation).*

Selection of mandals as the first-stage sampling unit

Data on patterns of fuel use were available at the mandal level from the 1991 Census. In each of the selected districts, mandals were ranked in descending order according to percentage of use of clean fuels. It was found that the percentage of clean fuel use was very low (< 5 percent) in almost all mandals from each of the districts. The sampling scheme required that some households using clean fuels be included in the sample from each cluster. To ensure this requirement was met, all mandals in which the percentage of clean fuel use was below 2 percent were excluded from the sampling frame. From the remaining mandals, five were selected as survey mandals, using probability proportionate to size criteria.[14] Roughly 10 percent of the study households used clean fuels.

Selection of habitations as the second-stage sampling unit

Within each of the selected mandals, habitations were listed in descending order of population size. It was assumed that habitations having populations of more than 2,000 were likely to yield sufficient households that would meet each of the categories

Table 5: Household characteristics related to exposure

Category	Variable
Emissions	Fuel use categories Stove characteristics
Housing	Housing materials Kitchen type
Ventilation	Roof type Separate kitchen for cooking Number of windows/openings in kitchen Size of kitchen and living areas Chimney venting smoke outdoors
Crowding	Number of people / Number of rooms

[12] The survey instrument was a bilingual questionnaire (Telugu and English). To avoid data entry errors and facilitate data validation, all possible answers in each question were pre-coded, and open-ended questions were minimized. A pilot survey was conducted in the Ravirayal habitation (Maheswaram mandal, Rangareddy district) to validate the survey instrument (12 households). In addition, about 45 households (from sample 2) were selected for validation of the survey instrument by repeat administration. Response rates were greater than 90 percent, as considerable groundwork with the local administration was completed prior to visiting the habitation.

[13]A mandal is an administrative unit below the district level but above the gram panchayat. A mandal usually comprises 15 gram panchayats/villages and is further subdivided into habitations.

[14]PPS probability proportional to population size; this ensures that each household within the district has an equal chance of being selected regardless of mandal size. If a constant number of households is selected within each cluster, then the sampling will be self-weighting; i.e. each household in the population will have an equal probability of being in the sample at this stage.

of kitchen site and fuel type, as listed in the definition of clusters. Therefore, habitations having fewer than 2,000 people were excluded from the sampling frame. From this sampling frame, one habitation was randomly selected (using a random number-generating tool in Excel) in each of the survey mandals to serve as the survey habitation. The number of eligible habitations in each district included in the sampling frame, and the final list of habitations included in the survey, are listed in Annex 4.

Selection of households as the third-stage sampling unit

Past experience had shown that kitchen type was an important determinant of household exposures in solid fuel users but not for clean fuel (gas) users (Balakrishnan et al 2002). Therefore, it was decided that each selected cluster of households should include households using solid fuels in each of the typical kitchen types of the region, as well as households using clean fuels.

Kitchen configuration commonly found in these villages can be classified into one of the following types: enclosed indoor kitchen with partition, enclosed indoor kitchen without partition, separate enclosed kitchen outside the house, and outdoor kitchen (i.e., open air cooking).[15] A schematic diagram of these kitchen types is given in Figure 3. Each cluster of households, therefore included households using biomass fuels in each of the kitchen types described above, as well as households using clean fuels, as listed below, for a total of 30 households per cluster:

Solid fuel users:

- Enclosed indoor kitchen with partition (n=6)
- Enclosed indoor kitchen without partition (n=6)
- Separate enclosed kitchen outside the house (n=6)
- Outdoor kitchen (i.e., open air cooking) (n=6)

Clean fuel users:

- Houses using clean fuels (n=6)

The sampling protocol for selecting 30 households that satisfied the desired criteria involved visiting every fourth household, starting from the center of a habitation. However, technical constraints in the field resulted in only 420 households being selected for pollution monitoring, as against a planned target of 450. Both pollution monitoring and household survey exercises were completed in the selected houses.

2.2.2 *For household survey (sample 2)*

In addition to the 420 households selected for IAP monitoring, the household survey was administered to a larger random sample of 1,032 households in order to develop a larger energy use and socio-economic profile for the households in the region under consideration. The selection of these households was done by targeting every fourth household, after the cluster of 30 households filling the desired criteria for IAP monitoring was achieved in each habitation (for a total of 70 households per habitation). The household survey was carried out with support from the local administration, health functionaries, and self-help groups.

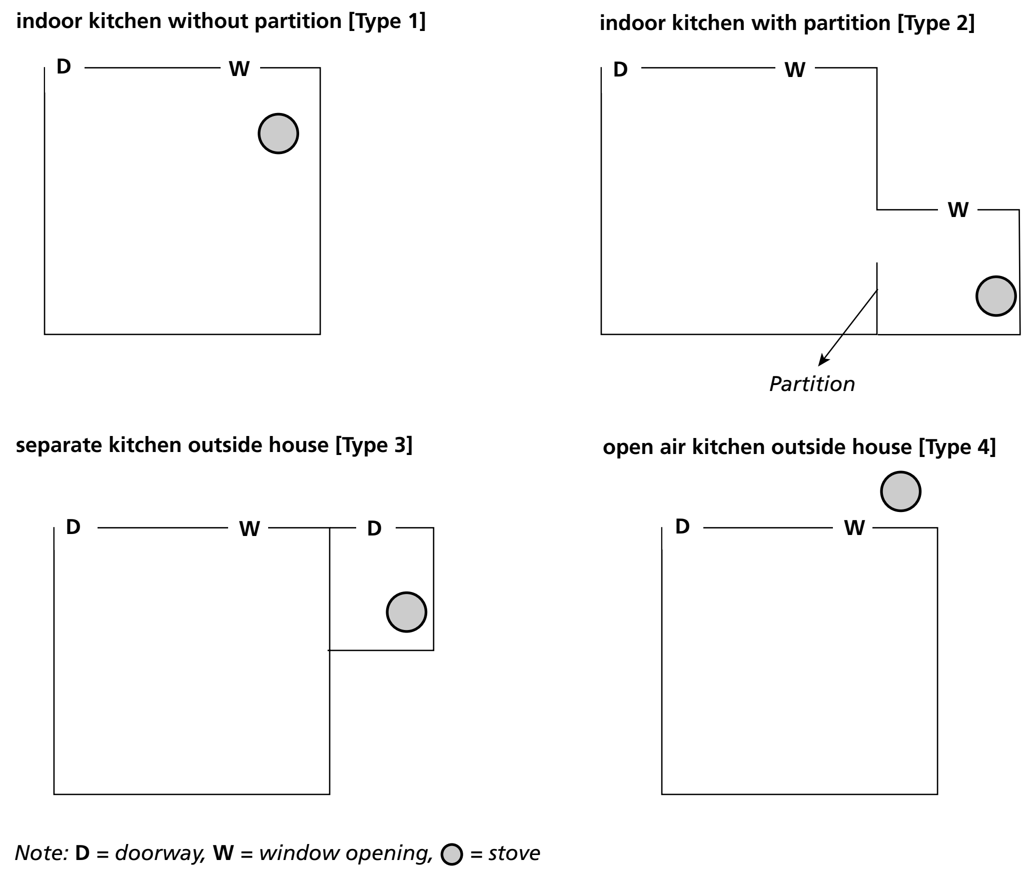
2.3 Measuring IAP concentrations

Indoor air pollution levels were monitored using respirable particulate matter (RSPM) as an indicator pollutant.[16] Respirable particulate levels as defined by the American Conference of Governmental Industrial Hygienists (d50=4μm) are used in setting workplace standards for protecting workers' health. The size-selection device (cyclone) used to measure RSPM is designed to mimic the size selection of the

[15] Enclosed indoor kitchens with partition (Type 1) typically were well separated from the living areas and also usually well ventilated. Enclosed indoor kitchens without partitions (Type 2) typically had very little separation between the cooking area and the adjacent living area. Most importantly, because these households had only one indoor area that was used for cooking and all other indoor activities including sleeping, the potential for exposures was maximal in this configuration. Separate enclosed kitchens outside the house (Type 3) were somewhat difficult to define. This is because few households had definite walled kitchens outside the main living areas; many were semi-enclosed and some were connected through corridors to the rest of the house and therefore not truly outside the house. Outdoor kitchens (Type 4) typically had stoves kept in the open without enclosures, or occasionally with a thatched roof on top to protect from it from rain, but were open on all other sides.

[16] Respirable suspended particulate matter (RSPM) includes the fraction of inhaled aerosols that is capable of penetrating the alveolar (gas exchange) regions of the adult lung. Since previous studies (Smith 1987) have shown that RSPM includes particles in the size range produced during the combustion of biomass fuels (i.e. <3μm), the concentration of RSPM was taken to be an appropriate surrogate for the concentration of biomass smoke.

Figure 3: Sketches of types of kitchen



human respiratory system; i.e., to reject essentially all particles above 10 μm and to accept essentially all smaller than 2 μm. The 50 percent cut-off for particles measured according to this criterion occurs at about 4 μm (Vincent 1999), as opposed to sampling with a sharp cut-off at either 10 (PM10) or 2.5 (PM 2.5) μm.[17] This gradual cut-off is useful when assessing exposures to human respiratory health hazards, since the pre-collector excludes particles from the sample in a way that parallels how the respiratory system functions, to prevent larger particles from reaching the deeper (alveolar) region of the lung.

2.3.1 Monitoring households within a habitation

About 8-10 households were monitored in a day, resulting in each habitation being monitored within 3-4 days. Consent to monitor was usually obtained from an adult household member the previous day. Cooking times were determined at the beginning of the day so as to facilitate scheduling of monitoring. A village volunteer accompanied the team to most households. These volunteers were instrumental in obtaining cooperation from household members for the placement of samplers.

[17] Given that a large number of observations and exposure-response relationships in outdoor air pollution studies are based on PM10 (particulate matter less than 10 micron in diameter), it is useful to know a typical ratio of RSPM to PM10. In this study, the ratio of RSPM to PM 10 ranged from 0 .57 to 0 .73 with a mean of 0.61. Although differences in measurement protocols should be kept in mind, this ratio is consistent with some other available measurements.

2.3.2 Monitoring within a household

Low-volume samplers were placed at the kitchen and living locations of all households. Samplers were placed at kitchen locations usually at a height of 1 to1.5 m, within 1 m from the stove. Samplers for living area locations were usually placed in rooms/areas adjacent to the kitchen, and for outdoor locations, in the porch at the same height as in kitchen locations. In households where there was no separation between the kitchen and adjacent living areas, living area samples were taken at distances of 2-3 m from the stove at the same height. Whenever continuous data-logging monitors were used, they were placed adjacent to the low-volume sampler at either the kitchen or living room locations.

2.3.3 Methodology for measuring concentrations of respirable particulates

Sampling for respirable dusts was done according to the National Institute for Occupational Safety and Health (NIOSH) USA protocol 0600, which is designed to capture particles with a median aerodynamic diameter of 4 mm. Samples were collected using a 10-mm nylon cyclone equipped with a 37 mm diameter polyvinyl-chloride (PVC) (pore size 5μm) filter, at a flow rate of 1.7liters/minute. Air was drawn through the cyclone pre-selectors using battery-operated constant flow pumps (PCXR8 supplied by SKC Inc., PA USA). All pumps were calibrated prior to and after each sampling exercise using a field soap bubble meter. Pumps were also calibrated in the laboratory after each field exercise using a Mini Buck soap bubble meter in the laboratory. In order to conserve battery power, the pumps were programmed to cover the 22–24-hour window through intermittent sampling (one minute out of every 4–6 minutes). Ten percent of all samples were subjected to analysis as field blanks. Continuous data-logging measurements were carried out in 10 percent of households using the Personal Data logging Real time Aerosol Monitor (PDRAM) monitor (MIE Inc., Bedford, MA, USA). The PDRAM monitor uses a nephelometric (photometric) technology and is based on passive sampling. The response range for the monitor is from 0.1–10μm and therefore is likely to capture a greater fraction of particles emitted, as opposed to the cyclones with a 50 percent cut-off of 4μm.

2.3.4 Recording time-activity patterns

A short exposure questionnaire was administered to each household the day after monitoring, to gather additional information on exposure determinants and record time-activity schedules. Household-level parameters collected included fuel type, fuel quantity, household ventilation, cooking duration, and other potential sources of particulates inside homes, such as cigarettes, incense, and mosquito coils. Household members were asked to put out an amount of biomass fuel approximating the quantity used during the preceding day (while monitoring was going on in the same household), which was weighed on a pan balance. Kerosene was measured using a graduated cylinder, and gas use was recorded as cylinders used per month. Time-activity records were obtained from household members on the basis of a 24-hour recall that detailed the type, location, and duration of each activity. In about 10 percent of the households, independent field assistants assessed the bias in time-activity recalls by repeat administration twice during the project period.

Gravimetric analyses were conducted at SRMC & RI laboratory using a Metlar 10 μg Microbalance (Mettler Toledo AG 245), calibrated against standards provided by the National Physical Laboratory in New Delhi, India. All filters were conditioned for 24-hours before weighing. Respirable dust concentrations expressed in terms of mg/m^3 or μg/m^3 were calculated by dividing the blank-corrected filter mass increase by the total air volume sampled.

2.3.5 Validation protocols

The exposure questionnaire was written in English but administered in the local language by the study team. It was validated by independent repeat administration on consecutive days in approximately 10 percent of the households. Also in 10 percent of households, duplicate measurements were taken on consecutive days to validate the measurements of particulates. The same validation methods were used for the time-activity recalls. The field supervisor cross-checked all field forms after each day of monitoring activity to ensure that the forms were completely filled out by the field assistants. Two independent data entry operators in the laboratory verified the computer data entry prior to analysis using the SPSS (10.0) package.

The data forms and household-level exposure questionnaire used by the monitoring teams are furnished in Annex 5.

2.4 Modeling concentrations

Household survey data collected from households were used together with measurements in the same households to develop models to predict quantitative exposures based on fuel use and housing characteristics (i.e., modeling was based on data collected from households of sample 1). Variables significantly associated with kitchen and living areas concentrations were included in the modeling process to explore whether and how certain household characteristics can be used to predict household exposure levels. The following methods were used for the modeling exercise.

2.4.1 Linear regression

Initially, a linear regression model was used. Linear regression is a modeling technique used to describe the relationship between a continuous dependent (outcome) variable and a set of independent (predictor or explanatory) variables. Since the distributions of both kitchen and living concentrations were skewed with a larger proportion of households having concentrations higher than average concentrations (i.e. lognormally distributed), loglinear regression models were used.

2.4.2 Modeling with categories of concentration

Under the hypothesis that it might be easier and more practical to predict higher and lower categories of concentration than actual concentration values, modeling was also conducted using binary categories of concentration. Two modeling techniques, logistic regression and Classification and Regression Trees (CART), were utilized.

Logistic regression

Like linear regression, logistic regression is a modeling technique used to describe the relationship between a dependent (outcome) variable and a set of independent (predictor or explanatory) variables. Logistic regression differs from linear regression models, however, in that the outcome variable is binary, or dichotomous. Logistic regression is commonly used in public health research to ascertain the risk factors for disease or mortality, since the outcome variable is often binary (for example, diseased or not diseased, in this case high or low pollution levels).

Classification and regression trees (CART)

Classification and regression trees (CART), a decision-tree procedure, was used to examine how fuel use and housing characteristics can be used to predict air concentration categories. CART is a nonparametric procedure, which has the benefit of not requiring a functional (i.e., linear, logistic, etc.) form (Brieman et al 1984). "Nonparametric" refers to methods that do not make assumptions about the functional form, or shape, of the distribution that the data come from. They thus differ from classical methods, such as regression, that assume that data come from a normal distribution. CART searches for relationships through a series of yes/no questions related to the data. CART produces several different classification trees, and then determines the optimal tree; i.e., the tree that classifies most accurately with a minimal amount of complexity. For example, in one of its first applications, CART was used to predict which heart attack patients were most likely to survive at least 30 days based on data measured during the first 24-hours of hospitalization (Brieman et al 1984). CART is increasingly used in environmental research as well as epidemiology (Avila et al 2000). All models are described in detail in Annex 6.

2.5 Methodology for exposure reconstruction

Continuous particulate monitoring data (PDRAM records) were used to determine relative ratios of 24-hour concentrations (determined gravimetrically) to concentrations during cooking and non-cooking windows. Although the size fractions monitored by the PDRAM (<10μm) and the cyclones (50 percent cutoff—4 μm) are somewhat different, as are the analytical techniques, it was assumed that the ratios would be stable over time in the households. Thus, 24-hour average concentrations for each location were split into concentrations during cooking and non-cooking windows for each of the three locations; viz., kitchen, indoors, and outdoors. Time-activity records had information not only about where an individual was present but also when, and thus it was also possible to split the total times at each location into times spent at the location during cooking/non-cooking windows. Exposures were thus reconstructed on a case-by-case basis, taking into account individual time budgets in various microenvironments. Exposure modeling is described in greater detail in Annex 7.

Chapter 3

Results

3.1 Profile of sampled households

A profile of the sampled households is assessed separately for the two categories of households (see Table 6):

- Sample 1 with 420 households, in which both household surveys and pollution monitoring were undertaken. These households were selected following the three-stage purposive cluster sampling method, as described in the previous section, and their characteristics were used for linking to the results of monitoring and exploring the determinants of pollution levels.
- Sample 2 with 1,032 households in which only household surveys were done. This sample was more representative of a typical household profile in the Telangana region, and based on the analysis of exposure determinants, provides a broader picture of prevalent exposure patterns in rural AP.

3.1.1 Socioeconomic characteristics

The socioeconomic characteristics in both samples of households are similar. The majority of the villagers are either small or marginal farmers and up to 20 percent are landless. Prevalence of education is low in both samples. In approximately 23 percent of the households in both samples, household members had not even completed one year of schooling, while 49 and 44 percent of the households in samples 1 and 2, respectively, had five years of schooling as the highest education level. About 23 and 31 percent of sample 1 households and 26 and 36 percent of the sample 2 households owned a radio and TV, respectively. In terms of smoking habit, an important compounding factor in the health impacts of fuel smoke, 43 and 44 percent of households in samples 1 and 2, had at least one member who smoked bidis (tobacco wrapped in leaves), and the prevalence of cigarette smoking was less at 6 percent in both cases. Smoking among women was virtually non-existent.

3.1.2 Housing and kitchen characteristics

The housing characteristics in the two samples were remarkably similar, as shown in Table 6. About 48 percent of the households in both samples had roofs made of tiles, slate, or shingles; leaves, while 30 percent had roofs made of thatch or bamboo. Concrete roofs, a sign of a wealthier household, were generally uncommon (7 percent in sample 1 and 11 percent in sample 2). Most households had walls made of mud or dirt (70 percent in sample 1 and 77 percent in sample 2).

Not surprisingly, given the sampling design, sample 1 and 2 households had distinct kitchen characteristics. In sample 2, which is more representative of the prevalence of kitchen types, a much larger proportion of households cooked their food in the open air compared to sample 1 (50 percent

Table 6: Overview of household, fuel, and kitchen characteristics of the sampled households

Housing Characteristic	Percentage of households in each sample	
	Sample 1 (420 households)	Sample 2 (1,032 households)
Roof material		
Grass/leaves/reeds/hatched/wood/mud/		
bamboo/unfired bricks	30.2	27.7
Tiles, slates, shingle	48.1	47.6
Metal sheets	4.0	2.3
Asbestos, cement sheets	10	9.8
Brick stone/lime/stone	0.2	0.7
Concrete	7.4	11.7
Other material	–	0.2
Wall Material		
Grass/leaves/reeds/bamboo/thatch	2.1	1
Mud/dirt	76.7	70.8
Unfired bricks	0.5	1.6
Wood	0.2	0.4
Fired brick	19	23.9
Metal sheets	0.2	0.1
Stone	0.5	0.5
Cement/concrete	0.7	1.6
Other material	–	0.1
Kitchen type		
Indoor kitchen with partition	29	27.5
Indoor kitchen without partition	25.2	6.4
Separate indoor kitchen outside house	23.6	15.7
Open-air kitchen	22.1	50.4
Fuel type		
Biogas	1.7	0.4
Kerosene	2.6	1.6
LPG	7.1	9.9
Dung/Mixed	8.8	6.6
Wood	79.8	81.5
Stove type		
Traditional stove made of three stones	18.6	21.5
Traditional stove made of three stones, plastered with mud	55.5	74.7
Traditional stove made of three stones, plastered with mud and ridges	30	27.7
Traditional stove made of three stones, plastered with mud, with chimney	10.5	8.5
Improved stove with chimney (n = 1)	0.2	0.1
Kerosene stove	31.9	25.5
LPG stove	12.4	15.2
Biogas stove	1.7	0.5

versus 22 percent). In contrast, the number of households with indoor kitchens without partitions was smaller (6 percent in sample 2 versus 25 percent in sample 1). There were indoor kitchens with partitions in 29 percent and 27 percent of the households in samples 1 and 2, respectively.

3.1.3 Fuel-use pattern

Biomass fuel use was prevalent in all the rural households of the three study districts in Andhra Pradesh (as has been repeatedly observed in many previous studies carried out in other states). Although this was a purposive sample not designed to establish prevalence of fuel types, clean fuel-using households were rare in the villages, as were households with improved stoves (only 1 out of the 1032 surveyed reported using an improved stove). Questions on fuel-use pattern revealed that majority of the households used wood for cooking (80 percent in sample 1 versus 82 percent in sample 2), whereas prevalence of clean fuel usage (biogas, LPG, or kerosene) was 11 percent and 12 percent, respectively, in the samples. Kerosene, which is supplied through the public distribution system and is mostly restricted to a quota of 3 liters per household, is mainly used for lighting and ignition of firewood.

3.1.4 Stove type

The majority of households were found to be traditional stove users, cooking on three stones plastered together with mud (56 percent in sample 1 and 75 percent in sample 2). The usage of traditional stoves with chimneys is 11 percent in sample 1 against 9 percent in sample 2. In both samples, usage of improved stoves was negligible. Kerosene stoves were used in 32 percent of households in sample 1 and 26 percent of households in sample 2, while only 3 percent and 2 percent, respectively, indicated that kerosene was their main cooking fuel. This implies, as evident from other studies in India and elsewhere (Masera et al 2000) that many households seem to be using more than one type of stove and fuel. This was usually the case with households with access to clean fuels, particularly kerosene, which reported switching frequently to biomass fuel use. On many occasions, the study team would initiate the monitoring in a household that cited kerosene as their main cooking fuel, only to find wood having been used the subsequent morning. This reduced the number of samples taken in households that used kerosene exclusively.

3.1.5 Cooking habits

Women's cooking habits were assessed in the sample of 420 households. Typically, women who had outdoor jobs cooked two small meals over half-hour periods in the morning and evening. Women who stayed at home cooked one large meal over a period of 1.5–2 hours. Men who stayed indoors without jobs were old or suffering from minor ailments. There were many variations in the kitchen configurations of the sampled households, and many households reported switching the location of the stove depending on the weather and their convenience. The village residents were, however, able to relate to four categories of kitchen types selected in the study, and confirmed that this template would be inclusive of most kitchen configurations found in village households.

3.2. Results of particulate monitoring exercises

3.2.1 Across fuel types

A total of 97 dung, 270 wood, 11 kerosene and 34 gas (LPG/Biogas) households were monitored. Table 7 and Figure 4 present the distribution of 24-hour average respirable particulate matter (RSPM) concentrations in the kitchen and living outdoor areas for households using various fuels.

The use of dung resulted in the highest concentrations, followed, in order, by wood, kerosene, and gas. The 24-hour average RSPM concentrations ranged from 73 $\mu g/m^3$ to 732 $\mu g/m^3$ in the kitchen and g/m^3 to 362 $\mu g/m^3$ in the living area, in gas and solid fuel-using households, respectively. One-way ANOVA analysis (shown in Table 7) of kitchen and living area concentrations across fuel categories shows that the levels at both locations are significantly different across fuel types ($p<0.01$). The concentrations in kerosene households

Figure 4: 24-hr average respirable particulate concentrations in kitchen and living areas across households using various fuels

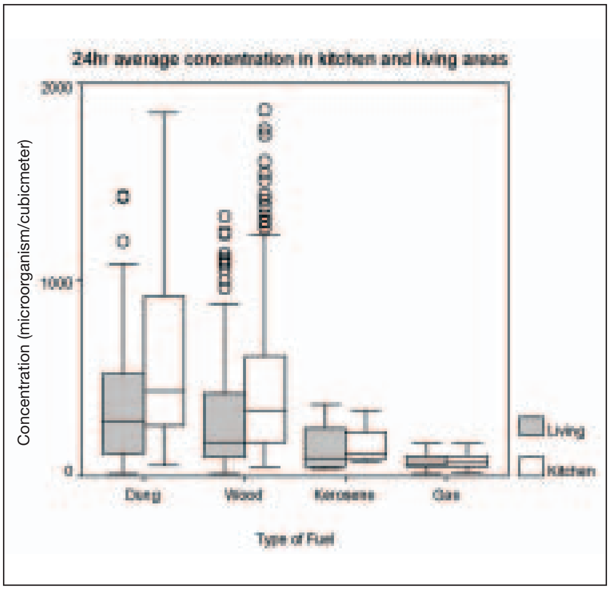


Table 7: Description and results of ANOVA analysis for 24-hr average concentrations in kitchen and living areas across fuel types

Type of fuels		24-hr kitchen Conc. (µg/m³)	24-hr living-area Conc. (µg/m³)
DUNG	Mean	732*	362*
	N	83	87
	GM	470	235
	SEM	88	37
WOOD	Mean	500	345
	N	259	251
	GM	340	204
	SEM	30	26
KEROSENE	Mean	203	289
	N	11	9
	GM	156	140
	SEM	59	150
GAS	Mean	73	75
	N	32	28
	GM	61	64
	SEM	7	7

*F-statistic significant at p<0.01 compared to other fuel types,
GM-Geometric mean; SEM-standard error of mean; NM-not monitored.

(GM= 156 μg/m³), although much lower than in solid-fuel households (GM Dung =470 μg/m³; Wood = 340 μg/m³), were more than twice the level found in gas-using households (GM= 61μg/m³). The 24- hr average outdoor concentrations (not shown) ranged from 66 to 113 μg/m.³

3.2.2 Across kitchen types

Kitchen configuration was an important determinant of kitchen and living area concentrations in solid-fuel but not kerosene/gas-using households. Among solid fuel users, kitchen area concentrations were significantly higher in enclosed kitchens as compared to outdoor kitchens ($p<0.01$), but not significantly different among enclosed kitchen types (Figure 5a and Table 8). This is not surprising, as kitchen dimensions were similar across enclosed kitchens; and since kitchen measurements were always taken close to the stove, dispersion of emissions played very little role in influencing kitchen area concentrations. Since, in general, dispersion is much higher outdoors, outdoor kitchens resulted in lower concentrations close to the stove.

Living area concentrations followed a similar trend, with levels in enclosed kitchens being significantly higher than in outdoor kitchens (Figure 5b & Table 8). In addition, indoor kitchens without partitions had higher concentrations as compared to separate indoor and outdoor kitchens partitioned from the living area, owing to greater contributions from dispersion to living area concentrations. Interestingly, living area concentrations were comparable between households cooking outdoors and separate enclosed kitchens outside the house. This presumably is the result of putting the stoves right in front of the house. The resulting outdoor dispersion may lower kitchen area concentrations, but also increase adjacent living area concentrations. This may have important implications for exposure, as the reduction in exposure may not be substantial for household subgroups who spend time indoors even though cooking outdoors.

3.2.3 Correlation between kitchen/living area concentrations and other exposure determinants (kitchen volume/fuel quantity/cooking duration/windows)

Upon completion of monitoring, a short exposure questionnaire was administered to each household by the monitoring team, which collected information on fuel quantities (by weighing) in solid fuel-using households, and on the duration of cooking and presence of other potential sources of particulate emissions (e.g., incense/mosquito coils, smoking). Fuel quantity records of clean fuel users could not be obtained, as the exact amount used per meal could not be measured; thus, the analysis of the impact of fuel quantity was limited to solid fuel users only. The household survey team also collected information on kitchen volume and number of windows.

Living area concentrations were significantly correlated with kitchen area concentrations for all kitchen types among solid fuel users, although the correlation was stronger for indoor kitchens ($r= 0.5$ and 0.24; $p<0.05$ for indoor and outdoor kitchens, respectively).

Correlation analysis showed that both kitchen and living area concentrations were significantly correlated (Pearson's correlation significant at $p< 0.05$) with fuel quantity among solid fuel users. In addition, the living area but not the kitchen area concentrations were significantly negatively correlated with the number of windows and the number of rooms. This could be explained by living area concentrations being influenced more by dispersion through windows or to other rooms as opposed to kitchen area concentrations, as most of the windows in the house were outside the kitchen. Neither kitchen nor living area concentrations were correlated with kitchen volume. This may be due to inaccuracies in measuring kitchen volume, homogeneity in kitchen dimensions in our sample, and/or the much greater importance of other parameters. Concentrations were also not correlated with the number of people being cooked for; total cooking duration; use of kerosene lamps, incense, or mosquito coils; or tobacco smoking in the house.

3.3 Results of modeling

3.3.1 Analyses of variance to determine choice of variables for modeling

The results of the measurements were used together with information collected through household surveys to develop models to predict household levels of indoor air pollutants. The first step in developing these models was to identify variables significantly correlated with both kitchen and living area concen-

Figures 5a and 5b: 24-hour average respirable particulate concentrations in kitchen and living areas across households using various fuels in different kitchen configurations

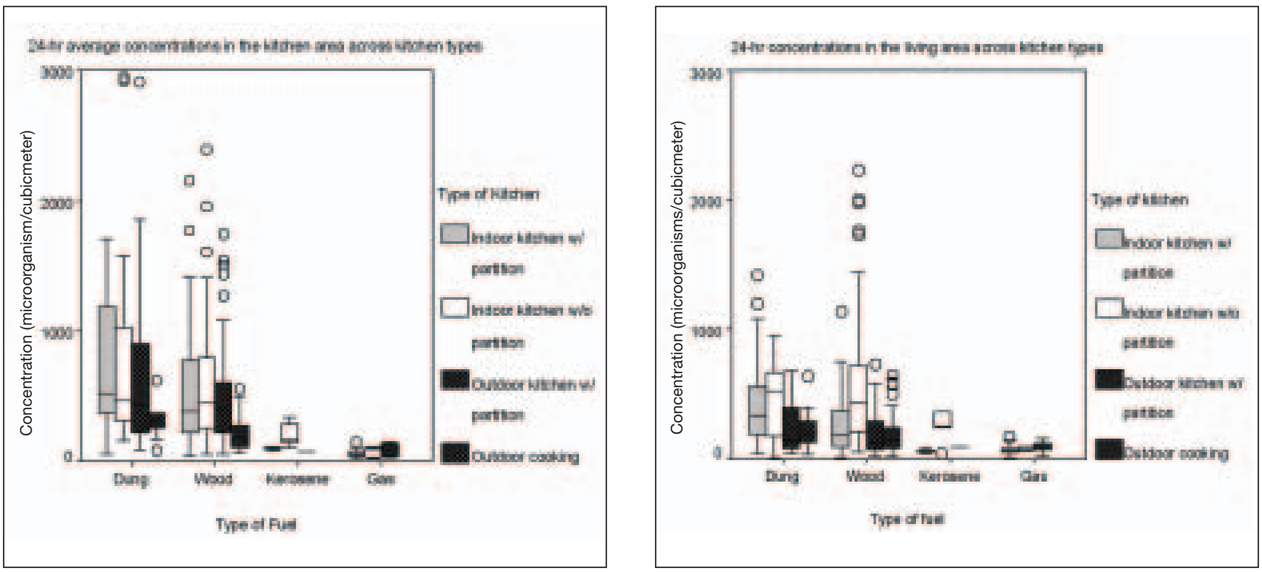


Table 8: Description and results of ANOVA analysis for 24-hour average concentrations in the kitchen and living areas among solid-fuel users across kitchen configurations

Type of kitchen		24-hr kitchen area conc. (μg/m³)	24-hr living-area Cconc. (μg/m³)
Enclosed indoor kitchen with partitions	Mean	666	357
	N	86	84
	SEM	75	41
	GM	428	219
Enclosed indoor kitchen without partitions	Mean	652	559[a]
	N	92	82
	SEM	61	55.
	GM	465	377
Separate enclosed kitchen outside the house	Mean	575	280
	N	87	83
	SEM	65	44
	GM	389	157
Outdoor cooking	Mean	297*	215*
	N	77	89
	SEM	35	19
	GM	220	158

*F-statistic significant at p<0.05 compared to other kitchen types
[a] Significantly different from other enclosed kitchens
GM-Geometric mean; SEM-standard error of mean

trations. This analysis of variance resulted in the following variables being identified (see a detailed description in Annex 6):

- Type of cooking fuel (solid, mixed, kerosene, gas)
- Type of kitchen (4 types, as described above)
- Separate kitchen (outside the living area or not)
- Kitchen ventilation (poor, moderate, good)
- Wall type (pucca, semi-pucca, kachha)[18]
- Floor type (pucca, semi-pucca, kachha)
- Housing type (pucca, semi-pucca, kachha)
- Stove type (traditional, improved, kerosene, gas)

Fuel quantity was omitted from this analysis, as it was not possible to estimate accurate quantities across all types of fuel users. Overall, living area concentrations differed across various fuel and housing characteristics in a manner similar to those across kitchen area concentrations. There were two major differences observed, however. Households with semi-pucca, an intermediate quality floor, seemed to have the lowest living area concentrations, followed by households with pucca and kaccha floors, respectively. In addition, although living concentrations varied with kitchen type, they also varied depending on whether or not households had separate kitchens.

3.3.2 Summary of results from all models

Household-level variables significantly associated with kitchen and living areas concentrations were included in the modeling process to explore whether and how certain household characteristics can be used to predict household concentrations. Predicting household concentrations of particulate matter in India is not an easy task, given the wide variability within household designs and fuel use patterns. As households with the potential for highest concentrations are relatively easy to identify, the objective of the modeling exercise was really to attempt to minimize the misclassification of low-concentration households. For e.g there is a great deal of variability in concentrations among households using biomass fuels with certain household configurations experiencing low concentrations while at the same time some clean fuel using households experiencing high concentrations due to mixed fuel use. Linear regression models that were used to predict continuous outcome variables for kitchen and living area concentrations did not yield sufficient information to explain the great variability in kitchen and living area concentrations. Subsequently, modeling was conducted for binary concentration categories (high and low-exposure households), using logistic regression and CART techniques.

As a result of all modeling approaches and specifications, three variables—fuel type, kitchen type, and kitchen ventilation (as perceived by households to be poor, moderate, or good)—were

[18] *Pucca* refers to more durable higher quality materials and construction techniques; e.g., a brick house with a tile roof. *Kachha* refers to more temporary and lower-quality materials and techniques; e.g., a mud house with a thatched roof.

found to be good predictors of kitchen and living area concentrations. Fuel type was the best predictor of high concentrations in the kitchen area, but not a very good predictor of low concentrations. This was presumably due to the wide range of concentrations within fuel categories. Kitchen type was also an important predictor; indoor kitchens were much more likely to have high concentrations than outdoor kitchens. Households with good kitchen ventilation were much less likely to have high concentrations than households with moderate or poor ventilation. Fuel type was also the best predictor of high living area concentrations. This was true in both in the presence and absence of information on kitchen area concentrations. Information on kitchen area concentrations improved the accuracy of living area predictions substantially, however. For living area concentrations, knowing the specific type of kitchen was less important than knowing whether or not the kitchen is separate from the living area. Information on kitchen ventilation was consistent with the results of the Kitchen area concentration models; solid fuel-using households with good kitchen ventilation are likely to have lower living area concentrations. This suggests that improvements in kitchen ventilation do not occur at the expense of air quality in the living area.

Households with good kitchen ventilation are less likely to have high concentrations in both kitchen and living areas than are households with moderate or poor ventilation. CART trees that utilized both kitchen type and kitchen ventilation were not better predictors than those that used only one of these parameters. This suggests that it may not be necessary to collect information on both kitchen type and kitchen ventilation. In future work, the decision whether to collect information on kitchen type or ventilation will be dependent on the study location. Kitchen types vary from region to region; thus the classifications used here may not be applicable to other locations. Likewise, depending on the amount of variation in kitchen and housing types, differences in kitchen ventilation may or may not be easily assessed by surveyors. In future studies, observations made during the initial site visit should make it relatively easy to decide which parameter to use.

Results were consistent across linear regression, logistic regression, and CART models. In other words, the same variables were found to be important in all models. Although this does not guarantee the validity of the model, it does provide some reassurance about the robustness of the parameters used in the modeling exercise.

3.4 Results of exposure assessment exercises

3.4.1 Time-activity data

The mean time spent by various subgroups of household members at each of the micro-environments during cooking and non-cooking windows is summarized in Table 9. Women cooks spend the largest amount of time in the kitchen while cooking, and therefore kitchen area concentrations while cooking are an important contributor to cooks' exposures. Among non-cooks, women between 15 and 60 years of age spend the largest amount of time in the kitchen cooking windows, which indicates the potential for high exposure for this subgroup. Other subgroups spend a part or major portion of the cooking window in the living areas. Living area concentrations are therefore a very important determinant of exposures for non-cooks.

3.4.2 Daily average exposures

3.4.2a 24-hour average exposure concentrations of respirable particulates for cooks and non-cooks across households using various fuels (Figure 6 and Table 10)

Exposures of members across households using various fuels shows that exposures are significantly different across fuel categories. This parallels the trends in concentrations wherein both kitchen and living concentrations were significantly different across fuel types. Dung produced the highest concentrations and exposures followed by wood, kerosene and gas in that order. This suggests that average household exposures are reflected well by average concentrations. Exposure distributions across fuel types are shown in Figure 6.

Table 9: Mean duration (hours) spent by household subgroups in the kitchen/living/outdoor micro-environments

		Cooking period		Non-cooking period		
COOKS		**Kitchen**	**Living**	**Kitchen**	**Living**	**Outdoor**
Female (6–15)	Mean	2.0	0.4	5.3	9.6	6.5
	N	12	12	12	12	12
	Std. deviation	1.1	0.9	7.5	5.9	6.5
Female (16–60)	Mean	2.4	0.08	2.6	15.1	3.6
	N	299	299	299	299	299
	Std. deviation	1.1	0.3	4.2	5.8	4.3
Female (61–80)	Mean	1.7	0.09	6.5	12.2	3.3
	N	22	22	22	22	22
	Std. deviation	0.9	0.4	7.8	8.0	3.1
NON-COOKS						
Female (2–5)	Mean	0.1	1.2	1.2	11.0	10.2
	N	26	26	26	26	26
	Std. deviation	0.4	1.0	3.3	5.0	3.3
Female (6–15)	Mean	0.1	1.3	1.0	11.9	9.4
	N	172	172	172	172	172
	Std. deviation	0.4	0.9	2.6	4.6	3.7
Female (16–60)	Mean	0.5	1.5	1.6	14.8	5.4
	N	117	117	117	117	117
	Std. deviation	1.1	1.2	2.9	5.2	5.3
Female (61–80)	Mean	0.2	1.9	.4	17.9	3.3
	N	28	28	28	28	28
	Std. deviation	0.8	1.4	1.0	4.7	4.5
Male (2–5)	Mean	0.06	1.1	1.5	11.3	9.8
	N	44	44	44	44	44
	Std. deviation	0.2	0.8	3.7	4.7	2.6
Male (6–15)	Mean	.09	1.2	1.1	11.2	10.2
	N	175	175	175	175	175
	Std. deviation	0.3	0.9	3.1	4.8	3.0
Male (16–60)	Mean	0.08	1.2	1.0	11.4	10.0
	N	317	317	317	317	317
	Std. deviation	0.3	0.9	2.9	4.8	4.3
Male (61–80)	Mean	0.1	1.5	2.3	13.5	6.3
	N	70	70	70	70	70
	Std. deviation	0.5	1.3	4.9	6.8	5.6

3.4.2b Exposures for cooks and non-cooks across kitchen types from households using solid fuels

The exposures of cooks were not significantly different across enclosed kitchen types (in agreement with the results of kitchen area concentrations that show little variation across enclosed kitchens but are higher than for outdoor kitchens). Since living area concentrations differ considerably across kitchen types among solid fuel users, it could be expected that exposures for non cooks may also be different across kitchen types. Non- cooks had the highest exposures in enclosed indoor kitchens without partitions (in agreement with concentrations in the living area being the highest with these kitchens). Distributions of exposures for cooks and non cooks of solid fuel using households across kitchen types are shown Figure 7 and Table 11.

3.4.2c Exposures across subcategories of household members

Household members were subdivided as cooks and non-cooks and then classified into 8 subgroups on

Figure 6: 24-hour average exposure concentrations of respirable particulates for cooks and non-cooks across households using various fuels

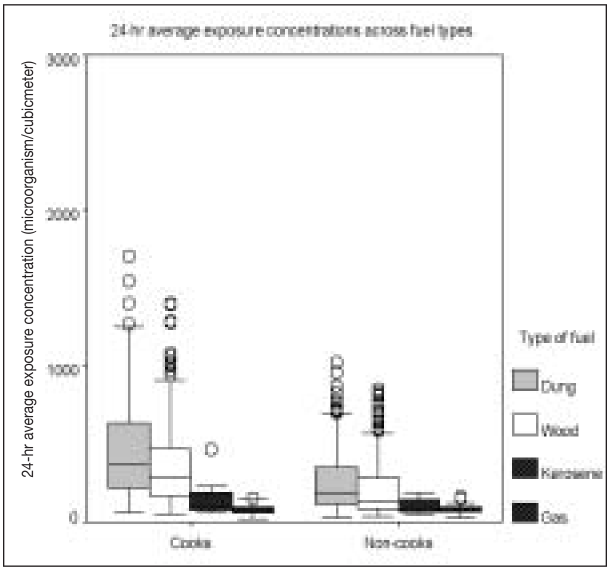


Figure 7: Exposures for cooks and non- cooks across kitchen types in households using solid fuels

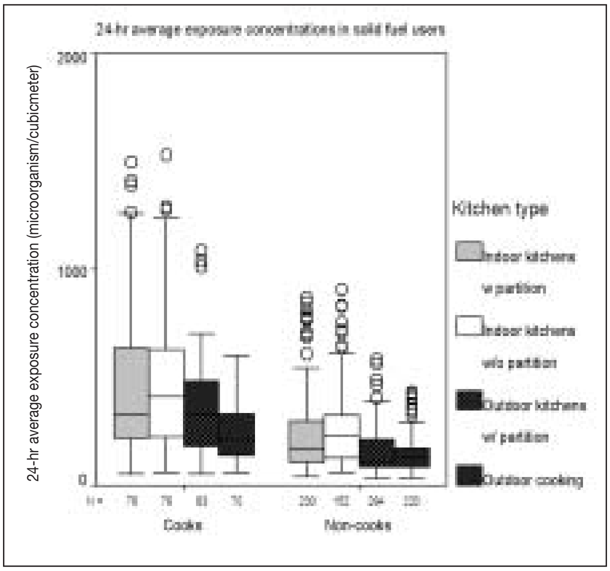


Table 10: Description and results of ANOVA analysis for 24-hour average exposure concentrations for cooks and non-cooks across fuel types

Type of fuel	Mean	N	SEM	GM
Cooks				
Dung	573*	70	65	402
Wood	403	232	25	293
Kerosene	156	8	48	121
Gas	81	28	6	72
Non-cooks				
Dung	264*	231	16	195
Wood	202	640	7	149
Kerosene	104	18	11	94
Gas	79	78	2	75

* denotes F statistic significant at $p<0.05$ as compared to other fuel types
N-number; SEM-standard error of mean;
GM-geometric mean

Table 11: Description for 24-hour exposure concentrations for household sub-groups in solid fuel using households across kitchen types

Exposure concentration in solid fuel users	Mean	SEM
Enclosed Kitchens		
Enclosed indoor kitchen with partitions	520	56
Enclosed indoor kitchen without partitions	540	50
Separate enclosed kitchen outside the house	439	52
Outdoor kitchen		
Outdoor cooking	259*	23
NON-COOKS		
Enclosed kitchens		
Enclosed indoor kitchen with partitions	264	17
Enclosed indoor kitchen without partitions	280[a]	17
Separate enclosed kitchen outside the house	178	11
Outdoor kitchen		
Outdoor cooking	175*	10

SEM-standard error of mean
*F –statistic significant at $p<0.05$ as compared to other kitchens
[a] Significantly different as compared to non-cooks in other types of enclosed kitchens.

the basis of sex and age. Mean 24-hour average exposure concentrations ranged from 79μg/m^3 (GM= 75μg/m^3) to 573 μg/m^3 (GM= 402μg/m^3) in gas and solid fuel-using households, respectively (Table 10). Among solid fuel users, mean 24-hour average exposure concentrations were the highest for women cooks (Mean= 442μg/m^3; GM = 318μg/m^3), and were significantly different from exposures for men (Mean =204μg/m^3; GM= 146μg/m^3) and children (Mean=291μg/m^3;

GM= 170$\mu g/m^3$)[19]. Figure 8 and Table 12 show the distribution of exposures across household subgroups in solid fuel-using households. Exposures of subcategories are not significantly different from each other among clean fuel users (Figure 9 and Table 13).

This is not surprising since differences in subcategories of household members are likely to arise when cooking and non-cooking concentrations vary a great deal and clean fuels do not show such differences. Among solid fuel users, cooks (90 percent of the cooks in the sample were women between ages of 16–60) experience the highest exposures and are significantly different from all other categories of non-cooks. Among non-cooks, women in the age groups of 61–80 experience the

Figure 8: 24-hour average exposure concentrations for household subgroups in solid fuel using households

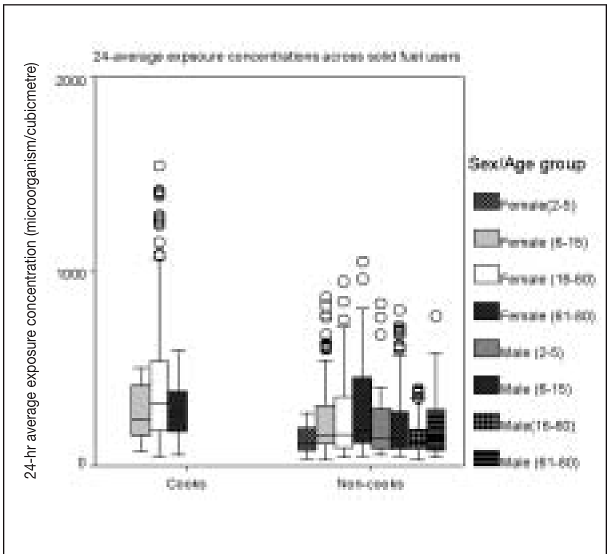


Table 12: 24-hour average exposure concentrations for household subgroups in solid fuel using households

COOKS*	Mean	N	SEM	GM
Female (6–15)	467	11	159	293
Female (16–60)	442	267	26	318
Female (61–80)	431	19	117	282
NON-COOKS				
Female (2–5)	254	23	67	151
Female (6–15)	237	162	14	185
Female (16–60)	276	106	27	191
Female (61–80)	337	26	57	232
Male (2–5)	268	33	47	178
Male (6–15)	227	163	15	167
Male (16–60)	148	278	5	128
Male (61–80)	260	62	40	165

N-Number; SEM-standard error of mean;GM-Geometric mean
*F-statistic <0.05 as compared to all categories of non-cooks

Figure 9: 24-hour average exposure concentrations for household subgroups in clean fuel-using households

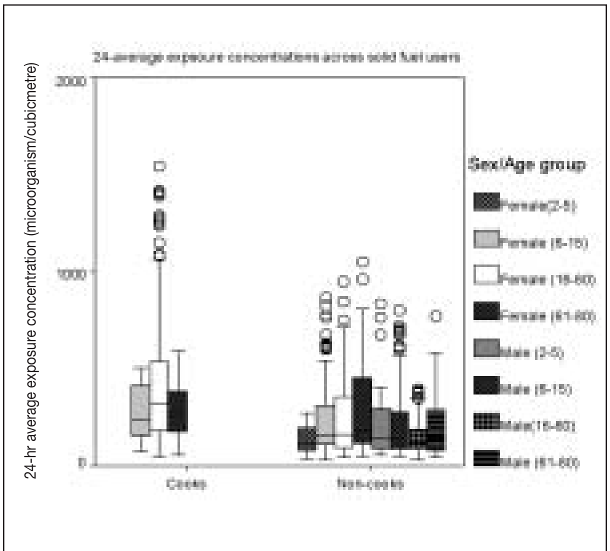


Table 13: 24-hour average exposure concentrations for household subgroups in clean fuel-using households

COOKS	Mean	N	SEM	GM
Female (6–15)	79	1	8	79
Female (16–60)	79	25	7	70
Female (61–80)	103	2	42	93
NON-COOKS				
Female (2–5)	69	1	.	69
Female (6–15)	77	9	7	74
Female (16–60)	72	10	8	66
Male (2–5)	77	9	7	73
Male (6–15)	82	10	6	79
Male (16–60)	79	32	3	76
Male (61–80)	88	7	18	77

N-Number; SEM-standard error of mean; GM-Geometric mean

The means listed here are averages for all subgroups of men, children respectively while Table 12 lists means of individual sub-groups.

highest exposures followed by women in the age –group of 16–60, while men in the age groups of 16–60 experience the lowest exposures. This is presumably because older women are most likely to remain indoors and women between the age group 16–60 are most likely to be involved in assisting the cooks, while men in the age group of 16–60 are most likely to have outdoor jobs that may lower their exposures. Men in the age group of 60–80 also experience higher exposures as compared to men between 16–60 perhaps also owing to a greater likelihood of remaining indoors. Some female children in the age group of 6-15 reported involvement in cooking and their exposures were as expected much higher than other children. Exposures for children not involved in cooking were still higher than men and there were no significant differences between the sexes.

3.4.2d Correlation between personal exposures and area concentrations in kitchen and living areas

24-hour average exposure concentrations for cooks were significantly correlated with 24-hour average kitchen area concentrations (R^2= 0.77; $p<0.05$). 24-hour average exposure concentrations for non-cooks were significantly correlated with 24-hour average living area concentrations (R^2= 0.69; $p<0.05$). Results are shown in figures 10 and 11.

Figure 10: Correlation between kitchen and living area 24-hour average concentrations and 24-hour exposure concentrations for cooks

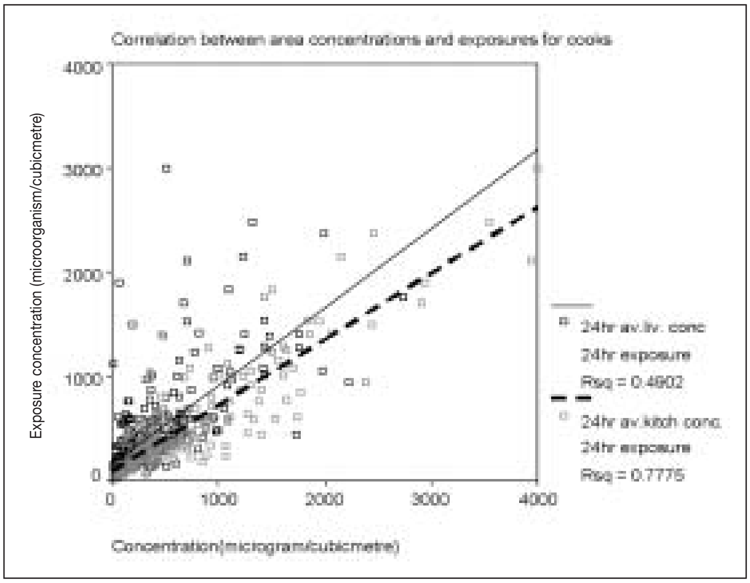
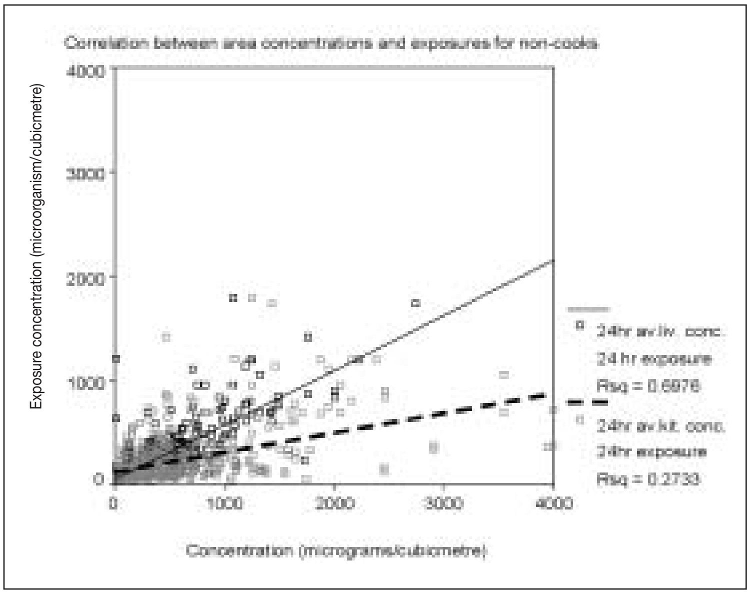


Figure 11: Correlation between kitchen and living area 24-hour average concentrations and 24-hour exposure concentrations for non-cooks



Chapter 4

Conclusions

The study involved two sets of field measurements:

- Based on a stratified randomized design in three districts of Andhra Pradesh, a detailed household questionnaire was administered to 1,032 households covering demographic, economic, architectural, fuel use, and other parameters potentially relevant to indoor air pollution.
- A stratified and randomized subset of 417 households were monitored for respirable particulates for approximately 24-hour period in kitchens and living areas. At the end of each monitoring period, a time-activity questionnaire was administered covering 1,300 household members.

Using these field data, two modeling exercises were undertaken:

- Based on the measured indoor air pollution levels and time-activity data, personal exposures were estimated using a time-weighted exposure model for each major category of household member.
- Several statistical models were applied to determine which could best estimate indoor air pollution levels using the survey data as inputs.

This concluding section covers the implications of the study results for further research and policy.

4.1 Research issues and needs

This study provides measurements of 24-hour concentrations and estimated exposures to respirable particulate matter for a wide cross-section of rural homes in southern India, using a variety of household fuels and under typical exposure conditions. Although the study design did not permit addressing temporal (intra-household) variations in each household, given the large sample size and the limited variability in weather conditions in this study zone, inter-household differences are likely to contribute the most to the concentration and exposure profiles, and the results of this study are likely to be useful as representing the indoor air pollution profile for the rural households of Andhra Pradesh. It is prudent, however, to exercise caution in extrapolations made from this study, since its findings are based on a sample from only three districts of a single agro-climatic zone of one state in southern India, while socio-cultural, housing, and climatic conditions are known to be quite different across different parts of the country. Further, the monitoring was carried out only in the summer months, which may not be reflective of the time-activity pattern of household members or of the nature of biomass fuel used during other seasons.

The study confirms and expands upon what is available from studies in other parts of the world; i.e., that traditional use of biomass fuels exposes all members of the family on a daily basis to levels of air pollution that well exceed available health guidelines for outdoor air quality. More importantly, the study shows that this holds true even in a warm climate such as that of southern India, where no space heating is required and these fuels are used only for cooking. Even when cooking is done outside the house—in a separate kitchen or in the open air, a common practice of poor rural households—the resulting indoor levels of RSPM and estimated exposure of all family members greatly exceed health guidelines for ambient air.

Through a combination of monitoring and exposure-reconstruction techniques, this study highlights the important gender and age dimensions of the IAP problem. Women, in their traditional capacity as cooks, suffer from much greater average daily exposures than other family members, and adult men experience the least exposure. Among non-cooks, those who are most vulnerable to the health risks of IAP, such as young children, tend to experience higher levels of exposure because they spend more time indoors. This finding lends support to the results of other studies in India and elsewhere that link household fuel use with higher infant and child mortality rates. Therefore, IAP punishes young children twice—by making them ill and making their mothers ill, which reduces the mother's ability to take care of children.

The results of the quantitative assessment have also provided additional evidence of the importance of interventions other than fuel switching. Ventilation and behavioral initiatives may offer a potential for substantial exposure reduction, and given that these are likely to be the short-term alternatives for a great majority of the rural population, the results could be used to aid the design of such efforts. Unfortunately, in the area of AP where this study took place, there were few improved stoves with chimneys still in use, although apparently some households reported having used them in the past. Thus it was not possible to characterize the potential concentration/exposure improvements that might accompany such devices and to see how concentrations/exposures vary in relation to other important parameters, such as fuel and kitchen types. Since improved stoves seem to offer one of the best near-term options for reducing the human health impacts of household solid fuel use, it would be important to focus on this issue in future studies in India as well as learn why improved-stove programs have not succeeded in many areas

Although exploratory in nature, the effort at modeling indoor air pollution concentrations provides valuable insights into the key determinants of exposure: fuel type, kitchen type, and/or kitchen ventilation. The models developed in this study offer results that can provide definite improvement for epidemiological and intervention studies. Although the predictive power of models developed in the study needs to be improved further, the finding that only two easily determined factors (primary fuel type and kitchen ventilation condition) turn out to be significant in the modeling exercise make it attractive for use in the design of a simple and reliable environmental health indicator for indoor air quality.[20] Significant improvement in the performance of the models would be achieved with measurement periods substantially greater than the 24 hours used in this study. This would reduce intra-household variability in human daily activities (especially for behavioral factors such as the way a stove is operated), and would be unrelated to the long-term household characteristics used in the model (kitchen location, etc.).

4.2 Policy implications

Biomass will remain the principal cooking fuel for a large majority of rural households for many years to come. Hence, an effective IAP mitigation strategy should employ a variety of options, from improvements in fuels and cooking technologies to housing improvements, such as kitchen configuration and ventilation conditions, to facilitating behavioral

[20] Although the impact of improved stoves was not addressed in our study because only one was found still in use, undoubtedly existence of a working chimney or flue would also be an important predictor.

changes among women, children, and other household members (e.g., keeping children away from smoke).

Health benefits from interventions take a much longer timeframe (often several years) to establish, and region-specific quantitative exposure information is thus useful for developing metrics to assess the potential of various interventions to reduce exposure to indoor air pollution. The findings of the study provide a strong basis for formulating effective interventions by, for example, strengthening the evidence that cooking with cleaner fuels (kerosene and LPG) reduces exposure substantially, and makes it equally low for all household members, including women cooks. At the same time, a study finding that indoor concentrations are well correlated with the quantity of solid fuel used indicates that the adoption of cleaner fuels will lead to a tangible reduction in exposure only if these fuels are used for a substantial portion of cooking needs and biomass consumption is reduced considerably. In the reality of rural life, however, complete or substantial switching to cleaner fuels is rare, and people continue to rely on biomass fuels. Improving awareness coupled with improved access could move this segment of population with partial access into the low exposure category by increasing the use of available clean fuels. Although the study could not ascertain through measurements, the levels in improved stove-using households, the same rationale can be extended for better use of improved stoves; i.e., target households with opportunities for improved ventilation and find a means of sustaining such low-exposure conditions.

The study also confirms that IAP exposures are widespread among the rural poor, and that women and children face maximal potentials for high exposures. Local health agencies therefore should play a greater role in integrating indoor air pollution into existing women (maternal) and child health programs, and also IAP in other home-related health programs (e.g., hygiene, water and sanitation). Various methods—from including IAP issues in basic hygiene education by primary schools and health centers to mass media—could be utilized. Improving knowledge of the IAP problem and possible solutions among all major stakeholders, including the medical community, is also important. Awareness raising may thus be an important mechanism for initiating behavioral interventions that provide opportunities for exposure reduction.

Currently, only two widely recognized exposure indicators for household environmental health exist, both of which are related to water quality and hygiene: *levels of access to clean water and to sanitation.* These are reported annually and separately for rural and urban areas by nearly every country, and are commonly cited as measures of ill-health risk and indicators of poverty. These indicators are strikingly parallel to two possible new indicators for household air-quality-related hygiene: *levels of access to clean fuel and to ventilation* (Smith 2002). Both indicators, although not ideal measures of true exposure and risk, have the extremely important benefit of being easily and cheaply determined by rapid surveys requiring no measurements. The models developed in the study, if validated with other data and further refined, could influence the design of such indicators in large-scale survey instruments, such as the Census or National Sample Survey, with a view to facilitating classification of population subgroups into exposure sub-categories. Validation of these models across other states and other regions in India would then eventually allow the generation of exposure atlases based on information collected routinely through large-scale population surveys, and aid in establishing regional priorities for interventions. Such priority setting could greatly improve the cost-effectiveness and the rate of health improvements of interventions by directing resources to the worst affected households first.

The exposure and the health studies on IAP have largely remained separate from each other. While financial constraints may be responsible for some studies not being able to address them simultaneously, it is also in some measure a reflection of lack of capacity to perform quantitative environmental health assessments in developing country settings. Even in instances where health-based environmental standards are available (criteria for outdoor air pollutants for example), they are based on underlying exposure-response relationships that are largely derived from developed country studies. Risk perception and risk communication mechanisms within research/policy communities are therefore significantly handicapped, due either to the lack of locally derived relationships that reduce acceptability, or to lack of understanding of methodologies that limit transferability across settings. With indoor air pollution being a largely developing country issue with strong regional differences, it is anticipated that health-based standards will have to rely on studies largely executed in individual countries. The strengthening of local technical capacities through academic and interagency partnerships is thus crucial to enhance not only the cost-effectiveness of research initiatives, but also to ensure sustainability of subsequent environmental management initiatives and supporting policies.

Indoor air pollution associated with household fuels in developing countries is deeply embedded in a matrix of environmental, energy, health, and economic/developmental considerations. An in-depth understanding of the potential for health risks in terms of exposure potentials is especially crucial for ensuring that the most vulnerable poor communities among us are not required to endure years of suffering, before development can catch up with them. As is already well established with clean water and sanitation, the public and policy-makers should be made encouraged to understand that it is neither necessary nor acceptable to wait until people become wealthy before they have the benefits of clean fuels and ventilation. Indeed, addressing such health risks is an essential element for ensuring equity in quality of life among populations, and it is hoped that the information presented here represents a small, incremental step toward achieving that goal.

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Annex 1

Overview of IAP related questions in state and national surveys

List of key variables available from current national and state level surveys

Source	Year of Administration	How often	Questions on fuel used for cooking/ lighting	Codes	Questions on Housing Characteristics	Codes
Census 1991 House-list Schedule	1991	Every 10 years	Q.19 Type of fuel used for cooking.	1. Cow dung cakes 2. Electricity 3. Coal/coke/lignite 4. Charcoal 5. Cooking gas 6. Wood 7.Biogas 8. Kerosene 9. Others	Predominant construction material of the census house Q.4. Wall Q.5. Roof Q.6. Floor	Wall (Q.4) 1. Grass / leaves /etc 2. Mud 3. Unburnt brick 4. Wood 5. Burnt-brick 6. GI Sheets/Metal sheet, 7. Stone 8. Cement concrete 9. Ekra 10. Other Roof (Q.5) 1.Grass/leaves/reeds/ Unburnt brick / bamboo 2.Tiles / slate 3.Corrugated iron, zinc or other metal sheets 4. Asbestos sheets 5. Brick / sand and lime 6. Stone 7. RCC/RBC 8.Others Floor (Q.6) 1.Mud 2. Wood/planks 3. Bamboo/logs 4. Brick, stone & lime 5. Cement 6. Mosaic / tiles 7. Others
Census 2001 House-list Schedule	2001	Every 10 years	Q. 22 Source of light. Q. 27 Fuels used for cooking	Q. 22. 1. Electricity 2.Kerosene 3. Solar 4. Other oil 5. Any other, 6. No light Q .27. 1. Firewood 2. Crop residues 3. Cow dung cake 4. Coal/lignite/charcoal 5. Kerosene 6. LPG 7. Electricity 8.Biogas 9. Any other 10. No cooking	Predominant construction material of the floor, wall, and roof of the census house. Q.4 Floor Q.5 Wall Q 6. Roof Q.26. Kitchen within the house Q.17. Number of dwelling rooms within the house holds (Record 0.1.2.3..)	Floor (Q. 4) 1. Mud 2. Wood / bamboo 3. Brick 4. Stone 5. Cement 6.Mosaic floor / tiles 7.Any other Wall (Q.5) 1. Grass/ thatch Bamboo etc 2. Plastic / polythene 3. Mud / Unburnt brick 4. Wood 5. GI Metal / asbestos sheets 6. Burnt brick 7 .Stone, 8. Concrete 9. Any other. Roof (Q.6) 1. Grass/thatch/ bamboo/wood/mud 2. Plastic/ polythene 3. Tiles 4. Slate 5. GI / metal / asbestos sheets 6. Brick 7. Stone 8. Concrete 9. Any other Q.26. 1. Yes 2. No 3. Cooking in open 4. No cooking

Source	Year of Administration	How often	Questions on fuel used for cooking/ lighting	Codes	Questions on Housing Characteristics	Codes
NFHS 1 (National Family Health Survey)	1992–1993	—	Q.30.What type of fuel does your household mainly use for cooking? Q.27.What is the main source of lighting for your household.?	Q.30 . 01.Wood 02. Cow dung cakes 03. Coal/coke/ lignite 04. Charcoal 05. Kerosene 06. Electricity 07.Liquid Petroleum gas 08.Biogas 09. Other specify Q.27. 1. Electricity 2. Kerosene 3. Gas 4. Oil 5. Others	Q.28. How many rooms are there in your household. Q.29 Do you have a separate room which is used as a kitchen? Q.31. Type of house Roof_Wall_Floor __	Q.28. No of rooms ____ Q.29. Yes..1, No...2 Q.30. 1. Pucca 2. Kacha 3. Semi-pucca
NFHS 2 (National Family Health Survey)	1998–1999	—	Q.37.What type of fuel does your household commonly use for cooking? Q.38.What other types of fuel does your household commonly use for cooking or heating ? Q.34.What is the main source of lighting for your household ?	Q.37. 01.Wood 02. Crop residues 03. Dung cakes 04. Coal/coke/lignite 05. Charcoal 06. Kerosene 07. Electricity 08. Liquid petroleum gas 09. Biogas 96. Other specify Q.38. A.Wood B. Crop residues C.Dung cakes D. Coal/coke/lignite E.Charcoal F. Kerosene G.Electricity H. Liquid petroleum gas I. Biogas X. Other specify Y. No other types. Q.34. 1. Electricity 2. Kerosene 3. Gas 4. Oil 6. Other	Q.35. How many rooms are there in your household. Q.36. Do you have a separate room which is used as a kitchen? Q.49. Type of house. Roof_Wall_ Floor	Q.35. No. of rooms Q.36. Yes. 1 No. 2 Q.49. 1. Pucca 2. Semi-pucca 3. Kacha
NSS (Household Energy Survey)	50th round 1993–1994	5 years (Quinquennially)	Block 3, Item 11. Primary source of energy for cooking. Block3, Item 12. Primary source of energy for lighting 5.1(460-479) Cash and purchase of fuels & lights during the last 30 days.	Item 11, 01. Coke, coal 02. Firewood and chips 03. LPG 04.Gas 05. Dung cake 06. Charcoal 07. Kerosene 08. Electricity 09. Others 10. No cooking arrangements Item 12, 1. Kerosene 2. Other oil 3. Gas 4. Candle 5. Electricity 6. No lighting arrangement 9. Others		
Multi Purpose Household Survey (MPHS)*	1995	—	—	—	Q 4. Type of shelter	Q 4. Pucca-Kacha

Source	Year of Administration	How often	Questions on fuel used for cooking/ lighting	Codes	Questions on Housing Characteristics	Codes
Human Development Survey (HDS)**	2000 January (Janmabhoomi Program)	— -	Q. 45. Main source of cooking	Q.45. 1. LPG 2. Kerosene 3. Coal 4. Electricity 5.Biogas 6. Fuel wood 7. Other	Q.9. Type of house	Q.9. 1. RCC 2. Tiles 3. Asbestos sheets

*Multi Purpose Household Survey (MPHS), Andhra Pradesh, 1995. Chief Commissioner of Land Adminstration (CCLA). Government of Andhra Pradesh.

** Human Development Survey (HDS), Andhra Pradesh, 2000. Chief Commissioner of Land Adminstration (CCLA). Government of Andhra Pradesh.

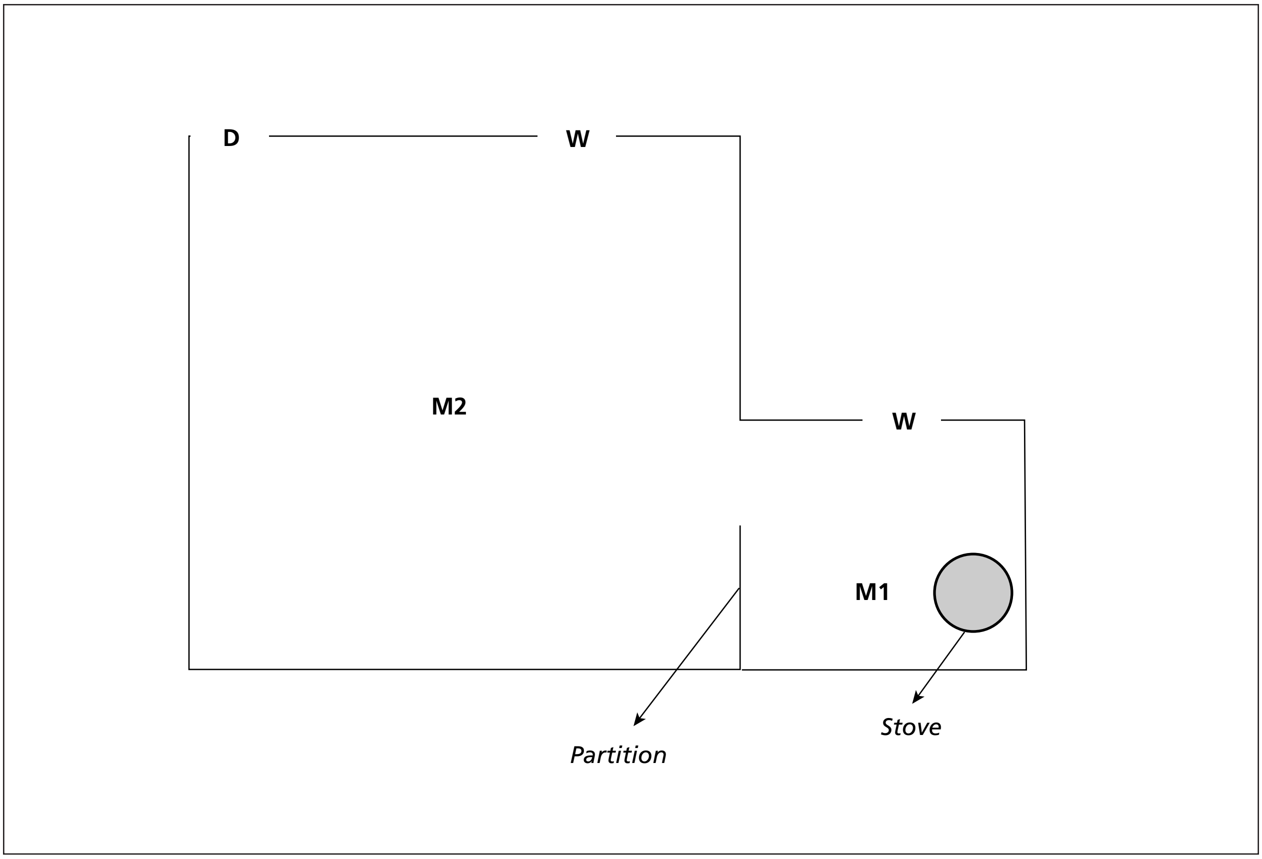
Annex 2

Exposure atlas: Survey instrument

District	NIZAMABAD . . . . .1 RANGAREDDY . . . . .2 WARANGAL 3
Mandal	
Habitation	
Household Number	
Name of Respondent	______________________________
Address / Location of Household	______________________________ ______________________________
Pincode	
Date	M M / D D
Interviewers	#1 #2
Result	AGREES TO INTERVIEW . . . . .1 DECLINES INTERVIEW 2
Monitoring Visit:	Yes No
Date	M M / D D
Time for Monitoring Visit	Morning . . . . .1 Afternoon . . . . .2 Evening 3
Monitoring Team Names:	#1 #2

Household sketch

Sample sketch given below:



Please include the following: *(check off as completed)*

______ Location of kitchen(s)

______ Location of stove(s)

______ Partition of kitchen (*if applicable*)

______ Location of all doorways, windows, and major openings

(please distinguish between doorways and windows/openings)

Monitor labeling to be completed by the monitoring team.

M1 = Location of kitchen sampler

M2 = Location of living area sampler

PLEASE MAKE SKETCHES AS LARGE AS POSSIBLE.

Household characteristics

(eligibility criteria)

Roof Materials	Grass Leaves,Reeds,Thatch,Wood,Mud,Unburnt Bricks or Bamboo . . . . .1 Tiles, Slate, Shingle . . . . .2 Corrugated Iron, Zinc or Other Metal Sheets . . . . .3 Asbestos Cement Sheets . . . . .4 Brick Stone and Lime . . . . .5 Stone . . . . .6 Concrete RBC/RCC . . . . .7 All other Materials not stated 8
Wall Materials	**CHECK ALL THAT APPLY:** Grass, Leaves, Reeds, Bamboo or Thatch . . . . .01 Mud / Dirt . . . . .02 Unburnt Bricks . . . . .03 Wood . . . . .04 Burnt Bricks . . . . .05 GI Sheets or Other Metal Sheets . . . . .06 Stone . . . . .07 Cement Concrete . . . . .08 Ekra . . . . .09 Other Materials Not Stated 10
Floor	**CHECK ALL THAT APPLY:** Mud / Dirt . . . . .1 Wood/Planks . . . . .2 Bamboo or Logs . . . . .3 Brick, Stone & Lime . . . . .4 Cement . . . . .5 Mosaic/Tiles . . . . .6 Other Materials Not Stated 7
Do you have a separate room that is used as a kitchen?	Yes No
Characteristics of the kitchen:	Indoor Kitchen With Partition . . . . .1 Indoor Kitchen Without Partition . . . . .2 Separate Indoor Kitchen Outside The House . . . . .3 Open Air Kitchen Outside The House 4
What type of fuel does your household mainly use for cooking? **(check only one)**	Wood (logs) . . . . .1 Crop Residues . . . . .3 Dung Cakes . . . . .4 Coal/Coke/Lignite . . . . .5 Charcoal . . . . .6 Kerosene . . . . .7 Electricity . . . . .8 Liquid Petroleum Gas (LPG) . . . . .9 Bio-Gas . . . . .10 Other . . . . .11 (Specify)________________________

Consent for interview

My name is ____and I am working at the Institute of Health Systems. We are conducting a survey about household energy and indoor air pollution in Andhra Pradesh. We would very much appreciate your participation in this survey. I would like to ask you some questions about your household. This information will help people plan programs to decrease indoor air pollution in homes. It will take about 20 minutes. Participation in this survey is voluntary. You can choose not to answer any question. If you decide to participate, you may stop answering questions at anytime.
All information will be kept strictly confidential and will not be shown to other persons. Do you want to ask me anything about this survey at this time?

Signature of interviewer

____

Date__________________	M M / D D
Response:	Respondent agrees for interview . . . . .1 Respondent declines interview 2
Start time	____:____ am/pm

Demographic information

Now I would like some information about the people who usually live in your household or are staying with you know.
Please give me the names of the persons who usually live in your household, starting with the head of the household.

Name	Relationship to Head of Household* HEAD	Sex	Age <1 year give age in months	Involved in cooking?	Usually present in kitchen during cooking?	What kind of work does (head) do most of the time
NAME1	Head of Household 0 1	Male ......1 Female....2		Yes No	Yes No	
NAME2		Male ......1 Female....2		Yes No	Yes No	
NAME3		Male.......1 Female....2		Yes No	Yes No	
NAME4		Male.......1 Female....2		Yes No	Yes No	
NAME5		Male.......1 Female....2		Yes No	Yes No	
NAME6		Male.......1 Female....2		Yes No	Yes No	
NAME7		Male.......1 Female....2		Yes No	Yes No	
NAME8		Male.......1 Female....2		Yes No	Yes No	
NAME9		Male.......1 Female....2		Yes No	Yes No	
NAME10		Male ......1 Female....2		Yes No	Yes No	

01=HEAD, 02=WIFE OR HUSBAND, 03=SON OR DAUGHTER, 04=SON-IN-LAW OR DAUGHTER-IN-LAW, 05=GRANDCHILD, 06=PARENT, 07=PARENT-IN-LAW, 08=BROTHER OR SISTER, 09=BROTHER-IN-LAW OR SISTER-IN-LAW, 10=NIECE OR NEPHEW, 11=OTHER RELATIVE, 12=ADOPTED/FOSTERCHILD, 13=NOT RELATED

Assets

Does the household own any of the following:		
Livestock?	Yes	No
A cot/bed?	Yes	No
A clock/watch?	Yes	No
An electric fan?	Yes	No
A bicycle?	Yes	No
A moped/scooter/motorcycle	Yes	No
A radio/transistor?	Yes	No
A television?	Yes	No
A bullock cart?	Yes	No
Does the household have access to electricity?	Yes	No
What is the highest grade completed by any member of the household? (00 if LESS THAN 1 YEAR COMPLETED)		
Does any member of the household smoke more than 1 cigarette every day at home?	Yes	No
Does any member of the household smoke more than 1 bidi every day at home?	Yes	No

		Now	Winter	Summer	Monsoon
What type of fuel does your household mainly use for cooking? **(check only one)**	Wood (logs) 1	1	1	1	1
	Wood (twigs / branches) 2	2	2	2	2
	Crop Residues 3	3	3	3	3
	Dung Cakes 4	4	4	4	4
	Coal/Coke/Lignite 5	5	5	5	5
	Charcoal 6	6	6	6	6
	Kerosene 7	7	7	7	7
	Electricity 8	8	8	8	8
	Liquid Petroleum Gas (LPG). . . 9	9	9	9	9
	Bio-Gas 10	10	10	10	10
	Other 11	11	11	11	11
	(Specify)____________________				
What type of fuel does your household mainly use for boiling / heating water?	Wood (logs) 1	1	1	1	1
	Wood (twigs / branches) 2	2	2	2	2
	Crop Residues 3	3	3	3	3
	Dung Cakes 4	4	4	4	4
	Coal/Coke/Lignite 5	5	5	5	5
	Charcoal 6	6	6	6	6
	Kerosene 7	7	7	7	7
	Electricity 8	8	8	8	8
	Liquid Petroleum Gas (LPG). . . 9	9	9	9	9
	Bio-Gas 10	10	10	10	10
	Other 11	11	11	11	11
	(Specify)__________________				
	Not used 12	12	12	12	12
What type of fuel does your household commonly use for space heating indoors?	Wood (logs) 1	1	1	1	1
	Wood (twigs / branches) 2	2	2	2	2
	Crop Residues 3	3	3	3	3
	Dung Cakes 4	4	4	4	4
	Coal/Coke/Lignite 5	5	5	5	5
	Charcoal 6	6	6	6	6
	Kerosene 7	7	7	7	7
	Electricity 8	8	8	8	8
	Liquid Petroleum Gas (LPG). . . 9	9	9	9	9
	Bio-Gas 10	10	10	10	10
	Other 11	11	11	11	11
	(Specify)__________________				
	Not used 12	12	12	12	12
What is the main source of lighting for your household?	RECORD ALL MENTIONED: Electricity . . . . 1 Kerosene . . . . 2 Gas . . . . 3 Oil . . . . 4 Other . . . . 5 (Specify) ______________________________				

Questions for the cook

		Fuel	How much (fueltype) do you use (per household) per day?		About what percent of your total fuel use is (fueltype)?	Is (fueltype) collected or purchased?	If collected, approximately how much time you spend collecting (fueltype) per unit of time? (ex: 20 min per day)	If purchased, approximately how much do you spend on (fueltype) per unit of time?
For (fuel) mainly used for cooking:	FUEL1			kg liters	%	Collected ....1 Purchased 2	Time per	Rs per
What other types of fuel does your	FUEL2			kg liters	%	Collected ....1 Purchased 2	Time per	Rs per
household commonly use for cooking?	FUEL3			kg liters	%	Collected ....1 Purchased 2	Time per	Rs per
RECORD ALL	FUEL4			kg liters	%	Collected ....1 Purchased 2	Time per	Rs per
MENTIONED	FUEL5			kg liters	%	Collected ....1 Purchased 2	Time per	Rs per

Does the household's cooking pattern change seasonally? If yes, describe changes and reasons for change.	Yes No
Has your household ever changed its fuel use pattern? If yes, describe changes, when they occurred, and reasons for change.	Yes No
Has your household ever changed its cooking area? If yes, describe changes, when they occurred, and reasons for change.	Yes No

	COOK #1 **Name:**	COOK #2 **Name:**
When do you usually cook? FILL IN THE FOLLOWING FOR ALL MENTIONED		
MORNING *Before Noon*	Yes No	Yes No
If yes, how long do you cook for in the morning?	minutes	minutes
AFTERNOON *Noon to 5 pm*	Yes No	Yes No
If yes, how long do you cook for in the afternoon?	minutes	minutes
EVENING *After 5 pm*	Yes No	Yes No
If yes, how long do you cook for in the evening?	minutes	minutes
OTHER TIMES		
Specify Other Times and Activities (making tea, etc.)	Yes No	Yes No
If yes, how long do you cook for at other times?	minutes	minutes
What kind of work do you (cook) do most of the time?		
Do you (cook) earn cash for this work?	Yes No	Yes No
Do you (cook) smoke more than 1 cigarette every day?	Yes No	Yes No
If yes, about how many cigarettes do you smoke every day?		
If yes, for how long have you smoked cigarettes?		
Do you (cook) smoke more than 1 bidi every day?	Yes No	Yes No
If yes, about how many bidis do you smoke every day?		
If yes, for how long have you smoked bidis?		
How long have you (the cook) lived here?		
What was the fuel mainly used for cooking in the place you lived before this?		
How long did you live there?		
Do you (cook) suffer from tuberculosis?	Yes No	Yes No
Have you (cook) ever received medical treatment for tuberculosis?	Yes No	Yes No
Does anyone in the household suffer from blindness?	Yes No	
If yes, who?		
Has anyone in the household ever been diagnosed with or had surgery for cataracts?		
Diagnosed with cataracts	Yes No	
If yes, who?		
Had surgery for cataracts	Yes No	
If yes, who?		
If there is more than one cook, who is the main cook?	Cook #1 1 Cook #2 2	

Household Characteristics

How many rooms are there in your household?	
Roof height (in meters)	Highest point:________ Lowest point: ________ Average height: ________
Wall height (in meters)	Highest point: ________ Lowest point: ________ Average height: ________
Is there a gap between the wall and roof?	Yes No
If yes, record the size of the gap in centimeters	cm
Number of doorways	
Number of windows / major openings	

Kitchen characteristics

Length in meters	Longest wall:________ Shortest wall: ________ Average length: ________
Width in meters	Longest wall:________ Shortest wall: ________ Average width:________
Height in meters	Highest point:________ Lowest point: Average height:
Number of windows / openings in kitchen	
For each window / opening in kitchen, rate size: Small: less than half of survey page (A4 sheet) Medium: half to full size of survey page (A4 sheet) Large: larger than survey page (A4 sheet)	Window #1 Small Medium Large Window #2 Small Medium Large Window #3 Small Medium Large Window #4 Small Medium Large Window #4 Small Medium Large
Please rate the ventilation of the kitchen:	Poor ________ 1 Moderate ________ 2 Good ________ 3

Kitchen characteristics, continued

For households with kitchen partition: Does partition extend to the ceiling?	Yes No
If no, record height of partition in centimeters	cm
For households with open air kitchen outside the house: Is the stove located under any shed roof or canopy?	Yes No
If yes, what is this shed roof or canopy made of? (check all that apply)	Grass, Leaves, Reeds, Thatch, Wood, Mud, Unburnt Bricks or Bamboo . . . . 1 Tiles, Slate, Shingle . . . . 2 Corrugated Iron, Zinc or other Metal Sheets . . . . 3 Asbestos Cement Sheets . . . . 4 Brick Stone and Lime. . . . . Stone . . . . 6 Concrete RBC/RCC . . . . 7 All other Materials not stated. 8
If yes, record height of shed roof/canopy in cms	Highest point: Lowest point: Average height:
How many sides of the outdoor kitchen are enclosed? (i.e. by walls, make-shift partitions, etc.)	

Biomass stove characteristics

NOTE: A stove is defined by the presence of a fire / combustion chamber. Count two fires as two stoves, even if they look alike and are side by side.

Traditional Biomass Stoves (No Chimney)

	Traditional Stove #1	Traditional Stove #2
	Fixed . . . . 1 Portable 2	Fixed. . . . . 1 Portable 2
Type of stove	3 Stone or Brick . . . . 1 Simple Chula . . . . 2 Modified Chulha (ridges at pot hole 3	3 Stone or Brick. . . . . 1 Simple Chula. . . . . 2 Modified Chulha (ridges at pot hole 3
If stove is a modified chulha (#3 above), was this stove constructed as an improved chulha?	Yes No	Yes No
Number of pot holes		
Height of the stove in centimeters	cm	cm

Biomass Stove characteristics, continued

Traditional Biomass Stoves (No Chimney), continued

Stove material (develop codes after the pilot)	Mud . . . . 1 Brick . . . . 2 Other. . . . . 3 (Specify)____________________	Mud . . . . 1 Brick . . . . 2 Other . . . . 3 (Specify)___________________
Does the stove have a hood?	Yes No	Yes No
If yes, describe the hood:		
Is the stove ever used for space heating indoors?	Yes No	Yes No
Is the stove ever used for cooking cattle feed?	Yes No	Yes No

Improved biomass stoves

Improved biomass stoves are characterized by the presence of a chimney or flue.	Improved Stove #1	Improved Stove #2
	Fixed . . . . 1 Portable 2	Fixed . . . . 1 Portable 2
Does the stove have a chimney (flue)?	Yes No	Yes No
If no, this is not an improved stove—please record stove details in traditional stove section		
If improved, what type?	___________________________	__________________________
If improved, for how long have you had this stove?	months / years	months / years
Number of pot holes		
Describe chimney material:		
Height of chimney in centimeters:	cm cm	
Please rate the overall condition of the chimney:	Poorly maintained / inefficient. 1	Poorly maintained / inefficient 1
	Moderately well maintained. 2	Moderately well maintained 2
	Well maintained / efficient 3	Well maintained / efficient 3
Describe the maintenance of the chimney		
Does the stove have a controllable damper?	Yes No	Yes No
Height of the stove in centimeters	cm	cm
Does the stove have a hood?	Yes No	Yes No
If yes, describe the hood:		
Please rate the overall condition of the stove:	Poorly maintained. 1	Poorly maintained 1
	Moderately well maintained . 2	Moderately well maintained . 2
	Well maintained 3	Well maintained 3
Is the stove ever used for space heating indoors?	Yes No	Yes No
Is the stove ever used for cooking cattle feed?	Yes No	Yes No

Kerosene stove characteristics

Do you have a kerosene stove?	Yes No
Type of stove	Wick-fed Stove . . . . 1 Pump Stove 2
When is the stove used?	CHECK ALL THAT APPLY For Cooking . . . . 1 When making tea . . . . 2 When heating/boiling water . . . . 3 Rainy days . . . . 4 Monsoon . . . . 5 During shortage of other fuel . . . . 6 Other . . . . 7 Specify ______________________

LPG stove characteristics

Do you have an LPG cylinder?	Yes No
Do you have an LPG stove?	Yes No
Number of burners	
Is the stove certified?	Yes No
Volume of cylinder	______kg
How often do you refill your cylinder?	
For how long have you had this stove?	months / years
How did you acquire this stove? (describe)	Deepam Scheme . . . . 1 Purchased independently . . . . 2 Other. . . . . 3 Specify ______________________
When is the stove used?	CHECK ALL THAT APPLY For Cooking . . . . 1 When making tea. . . . . 2 When heating/boiling water . . . . 3 Rainy days . . . . 4 Monsoon . . . . 5 During shortage of other fuels . . . . 6 Other. . . . . 7 Specify ______________________

Biogas stove characteristics

Do you have a biogas stove?	Yes No
Number of burners	
Describe the maintenance of the stove	
If the household has more than one stove, which stove is mainly used for cooking? **(check only one)**	Traditional Stove #1 . . . . . . 1 Traditional Stove #2 . . . . . . 2 Improved Stove #1 . . . . . . 3 Improved Stove #2 . . . . . . 4 Kerosene Stove . . . . . . 5 LPG Stove . . . . . . 6 Biogas Stove 7

Consent for monitoring

Tomorrow, some other people from our team will be measuring the air quality in several homes in (name place). This will take one full day (about 24 hours, including 1 hour for set-up time and collection of samplers). Measuring will involve the placement of samplers inside and outside the houses while cooking and also while cooking is not going on. Participation is voluntary. The monitors are run by batteries and are very safe. They do not cause electrical shocks or fires and will have no effect on children or others in the house, although they do make a small amount of noise. You can choose to have the monitor removed at any time. We would very much appreciate your participation in this survey.

Do you want to ask me anything about the monitoring at this time?

Signature of interviewer

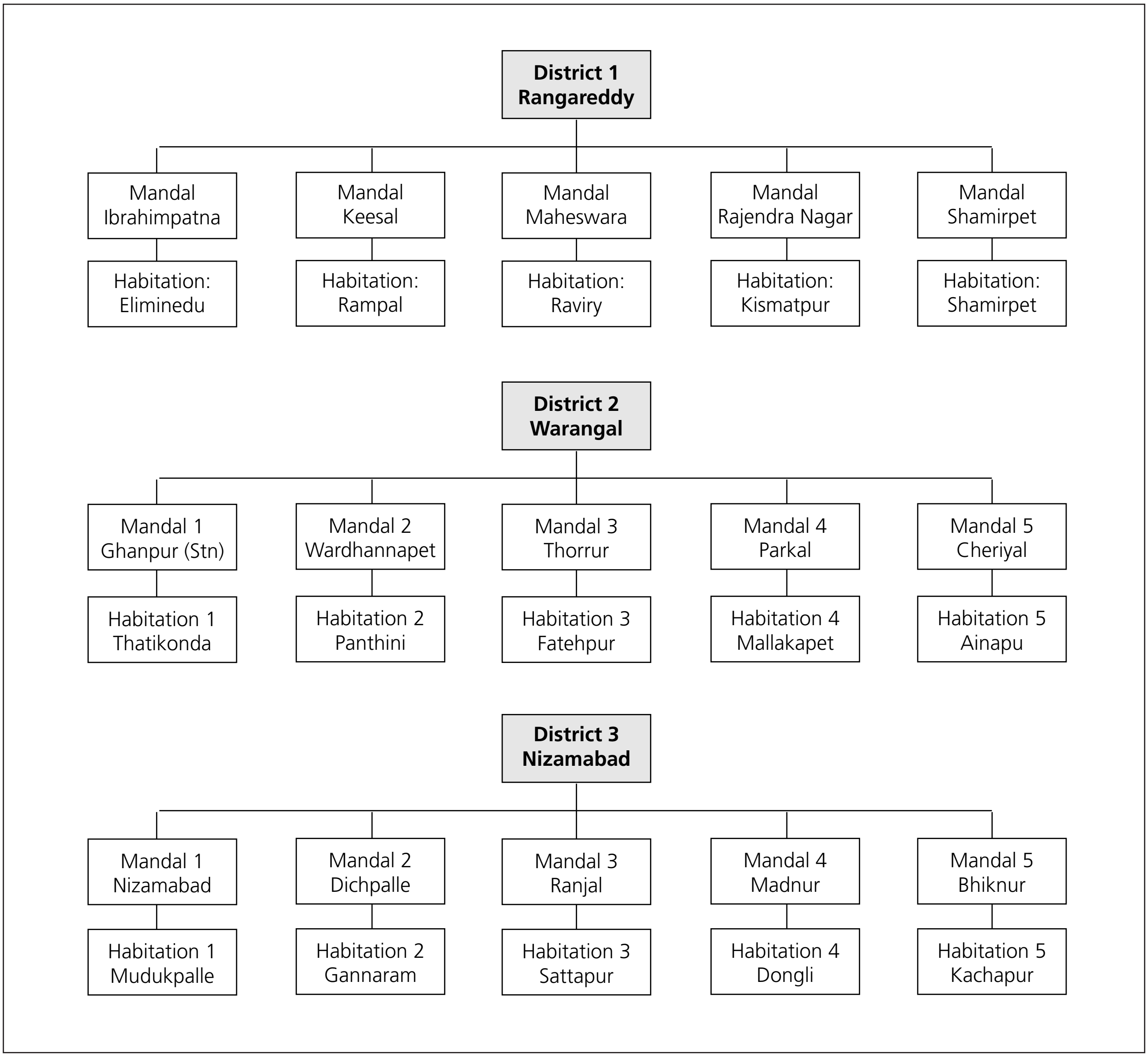
____

Date__________________	M M / D D
Response:	Respondent agrees to all monitoring . . . . .1 Respondent declines monitoring 2
Record the End Time	____:____ am/pm

Survey field notes:

Annex 3

Sampling scheme for Rangareddy, Warrangal and Nizambad districts



Annex 4

Habitations in each district and list of habitations included in the survey

Sampling scheme for the study

Number of eligible habitations in each district included in the sampling frame

District	Mandal	No of habitations with pop > 2000
Rangareddy	Maheswaram	7
	Ibrahimpatam	6
	Shamirpet	10
	Keesara	3
	Rajendranagar	8
Nizamabad	Nizamabad	9
	Ranjal	6
	Dich Palle	9
	Bhiknur	8
	Madnur	4
Warangal	Parkal	12
	Thorrur	13
	Cheriyal	11
	Ghanpur(Stn)	16
	Wardhannapet	13

Final list of habitations included in the survey

District	Mandal	Habitation Id	Habitation	Population
Ranga Reddy	Maheswaram	AP153301801	Raviryal	2921
	Ibrahimpatnam	AP153402301	Yeliminedu	2947
	Shamirpet	AP150902301	Shameerpet	3025
	Keesara	AP151101501	Rampally	2375
	Rajendranagar	AP151602701	Kismatpur	4196
Nizamabad	Nizamabad	AP181203601	Mudakpalle	2146
	Ranjal	AP180100201	Satapur	2803
	Dich Palle	AP182101901	Gannaram	3940
	Bhiknur	AP183501001	Kachapur	3342
	Madnur	AP181601701	Dongli	2166
Warangal	Parkal	AP213900701	Malakpet	2017
	Thorrur	AP211801601	Fathepur	2103
	Cheriyal	AP210101301	Ainapur	2620
	Ghanpur(stn)	AP210800901	Thatikonda	4097
	Wardhannapet	AP211200401	Panthini	3056

(Census of India 1991)

Annex 5

Sri Ramachandra Medical College & Research Institute
Environmental Health Engineering Cell

Field monitoring data forms

Monitoring for respirable particulates

Household Name and Location: ____________________ Date of Monitoring: ____________

Monitoring Conducted By: ____________________

Air Temperature: ____________˚C Air Pressure: __________mm Hg Relative Humidity: ________%

Sample ID	Location of Sampler* (Record location on sketch and height from floor)	Pump No	Battery No	Cyclone No	Filter Cassette ID	Pre-Sample Calibration Flow Rate	Post-Sample Calibration Flow Rate	Sample Time (Include programming instruction)	Sample Stop Time

FieldNotes: ____________________

____

____

____

____

____

Environmental Health Engineering Cell, Sri Ramachandra Medical College & Research Institute

Respirable dust sampling data

General information			
Sample ID			
Date Collected			
Collected by			
Location (Note from sketch)	❏ Kitchen	❏ Living	❏ Outdoor
Height from floor			
Pump			
Model			
Serial No.			
Battery			
Serial No			
Cyclone			
Serial No			
Filter			
Manufacturer/Type			
Lot No.			
Post-weight (mg)			
Pre-weight (mg)			
Weight of dust on filter (mg)			
Sampling parameters			
Flow rate # 1 (l/min)			
Flow rate # 2 (l/min)			
Average flow rate(l/min)			
Start time			
Stop time			
Elapsed time (min)			
Programme settings			
Total Pump time			
Volume of air sampled (l)			
Result			
Concentration (mg/m^3)*			

NOTE

$$\text{*Concentration C } (mg/m^3) = \frac{\text{Weight of dust on filter (mg)}}{\text{Volume of air sample (l)}} \times 10^3$$

Volume of air sampled = Flowrate (lpm) *Total pump Time(Min)

Additional exposure questions

(To accompany SRMC field monitoring forms)

Household ID:

Initials of Interviewer: Date:

Location / Address:

1.Were the activities in your household over the last day typical? Yes No

2. If no, what was unusual for the day?

3.What type of fuel did you use over the last 24 hours since the monitor was put in? (check all that apply)

Fuel type	Used	How much fuel did you use in last 24 hours (Include units e.g. Kg or L)	Record weight /volume (If approximate amounts of fuel used are produced)
Wood			
Crop Residues			
Dunk Cakes			
Coal/Coke/Lignite			
Charcoal			
Kerosene			
Electricity			
LPG			
Bio-Gas			
Other (specify)			

4. Cooking Pattern

Please specify time and duration of cooking activities and number of people being cooked for

	Who cooked?	Number of people being cooked for	Duration
Morning			
Afternoon			
Evening			
Others (chai, boiling etc)			

5. Total time that the fire was on (hours)

6. Did you light any lamps within the household?

7. If yes a. How long was the lamp burning

b. What did you use to keep it burning?

8. Were any cigarettes or bidis smoked indoors?

Yes No

9. If yes, how many of each?

Smoker #1	Cigarettes
	Bidis
Smoker #2	Cigarettes
	Bidis
Smoker #3	Cigarettes
	Bidis

10. Did anyone burn incense?

Yes No

11. If yes, how many? Sticks / Cones / Leaves / Other (specify label appropriately)

12. Did any one burn mosquito coils?

Yes No

13. If yes, how many or for how long? (record appropriate)

14. Were there any disturbances to the monitoring equipment while it was kept in your home?

Yes No

If yes, describe:

Time activity record form

(To accompany SRMC field monitoring forms)

For the following time of the day, please specify the room or are where you spend most of the time, and what you do during these times.

Householder	Morning			Afternoon			Evening			Night		
	Activity	**Duration**	**Loc**	**Activity**	**Duration**	**Loc**	**Activity**	**Duration**	**Loc**	**Activity**	**Duration**	**Loc**
NAME1												
NAME2												
NAME3												
NAME4												
NAME5												
NAME6												
NAME7												
NAME8												
NAME9												
NAME10												

Locations:
1 = IN THE KITCHEN, CLOSE TO STOVE
2 = IN KITCHEN, NOT NEAR STOVE
3 = INDOORS AT HOME, BUT NOT IN KITCHEN
4 = INDOORS NOT AT HOME
5 = OUTDOORS

Annex 6

Development of a methodology for predicting concentrations & results of modeling for household concentrations

As funds for public health research are often limited by the need to address immediate public health concerns, it would be ideal to have a low-cost exposure assessment approach that allows for maximum utilization of these existing sources of data. In other words, if the exposure proxies using routinely collected information can be refined (optimized) to better predict exposures, more refined exposure profiles could be created at national levels with a minimal amount of costly air sampling. This Annex summarizes the outcomes of an extensive modeling exercise to predict kitchen and living areas concentrations in rural households based on information that is relatively easy to obtain through household surveys.

In doing so, the following questions are addressed:

- How can household characteristics be used to predict which households are likely to have the highest concentrations of indoor air pollution from solid fuel use?
- How can concentrations and, ideally, individual exposures be characterized at the household level?

The qualitative information on fuel use and housing characteristics in the household survey parallels the information collected in larger secondary sources of data, namely the Census of India and the National Family Health Survey (NFHS). The utility of parameters currently included in Indian household surveys, such as the presence or absence of a separate kitchen, is evaluated. In addition, rather than simply relying on the types of information relevant to indoor air pollution already routinely collected by government and public health organizations, other housing or ventilation related parameters are evaluated. Additional parameters found to be significant in the model could be added to future surveys. It is necessary, however, to ensure that these parameters can be collected by minimally trained surveyors with reasonable accuracy. Thus, once the model has been created, the following issues are explored:

- How can the results of this model be applied to secondary sources of data, such as the National Family Health Survey (NFHS) to obtain a more refined exposure profile of a larger subset of the Indian population?
- Are there any housing or energy-related parameters not currently assessed in national surveys that considerably improve our ability to predict household concentrations? If so, the addition of questions in future surveys can be recommended.

MODELING

Linear regression

Initially, Linear regression models were used to predict quantitative concentrations based on fuel use and housing characteristics. Linear regression is a modeling technique used to describe the relationship between a dependent (outcome) variable and a set of independent (predictor or explanatory) variables. These models were created using continuous outcome variables for kitchen and living-area concentrations. Since both kitchen and living concentrations are approximately log normally distributed (Figures A6.1 and A6.2), log linear regression models were used.

Modeling with categories of concentration

Under the hypothesis that it might be easier and more practical to predict higher and lower categories of concentration than actual concentration values, modeling was also conducted using binary categories of concentration. Two modeling techniques, logistic regression and Classification and Regression Trees (CART), were utilized.

MODEL INPUTS

Continuous dependent variables

Kitchen area concentrations

Table A6.1: Summary of kitchen area concentrations

	Kitchen area concentration RSPM (μg/m³)	ln (kitchen area concentration) RSPM (μg/m³)
N	385	385
Geometric Mean	310	5.64
Mean	506	5.74
Minimum	17.9	2.89
Maximum	4000	8.29
Std. Error of Mean	29.5	.005

Figure A6.1: Kitchen area concentration in μg/m³

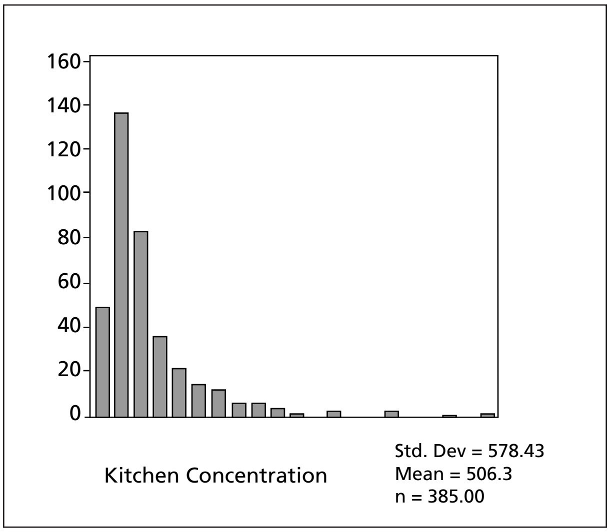
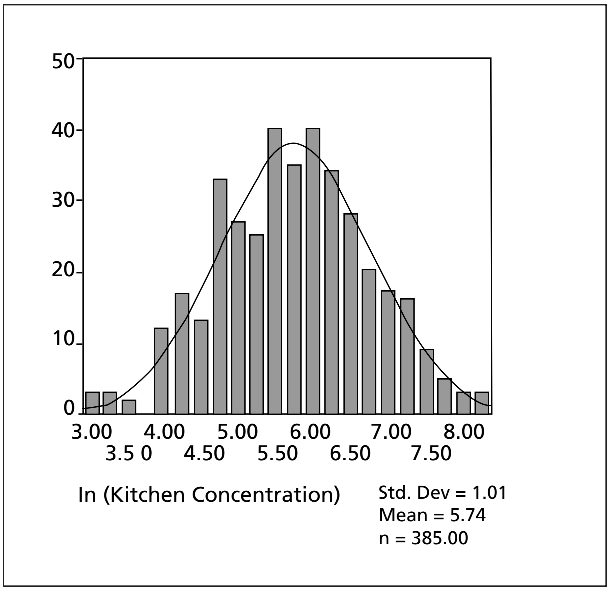


Figure A6.2: ln (Kitchen area concentration) in μg/m³



Living-area concentrations

Table A6.2 summarizes living-area concentrations. As with kitchen area concentrations, living are concentrations are approximately log normally distributed. See Figures A6.3 and A6.4.

Table A6.2: Summary of living-area concentrations

	Living-area concentration (μg/m³)	ln (living-area concentration) (μg/m³)
N	375	375
Geometric Mean	191.8703	5.1517
Mean	328.371	5.2568
Minimum	12.2	2.5
Maximum	2739.09	7.92
Std. Error of Mean	20.4128	5.36E-02

Figure A6.3: Living area concentration in μg/m³

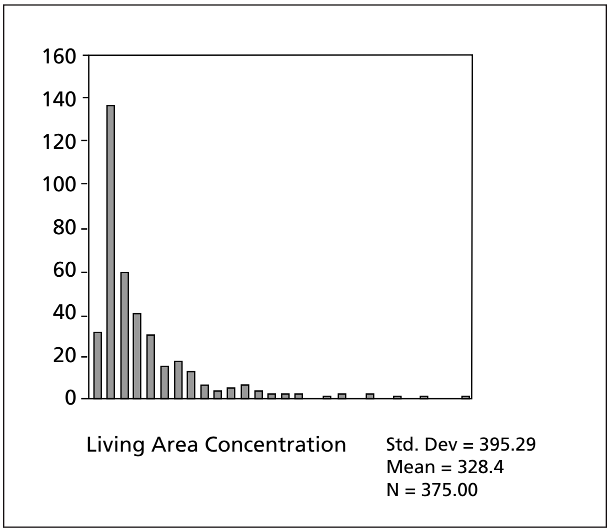
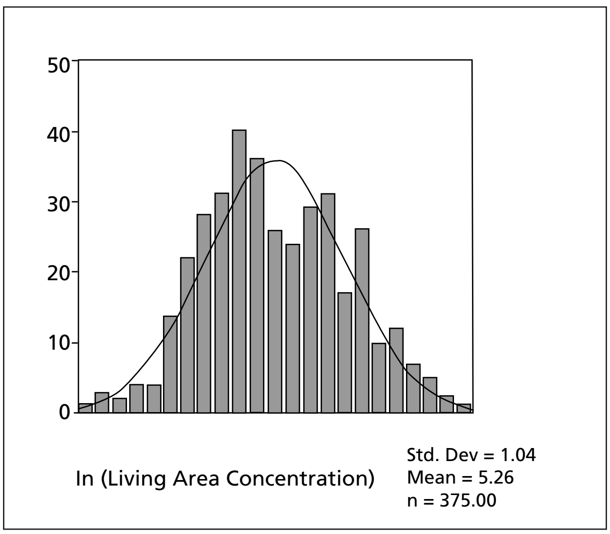


Figure A6.4: ln (Living-area concentration) in μg/m³



Binary dependent variables

Although using binary concentration categories results in a loss of statistical power, it increases the practical application and interpretation of the models created. In order to create binary concentration categories, we had to define a cut-off between high and low concentrations. There is no universal or completely objective way to determine what constitute a 'high' concentration under these circumstances. There is no epidemiological evidence to suggest a cut-off point, for example, since the epidemiological literature is based on qualitative categories of exposure, such as the type of fuel used for cooking, whether or not children are indoors during cooking, or whether or not children are carried on the backs while cooking is taking place. At the same time, because there may be a flattening of the exposure/response curve at higher concentration levels, it is not possible to extrapolate from studies conducted in developed countries with much lower concentrations. Indeed, the most recent WHO air quality guidelines specify that the health impacts slope for PM_{10} (RSPM is a significant proportion of PM_{10}, which includes all particles less than 10 mm in diameter) should not be extrapolated beyond 150 $\mu g/m^3$ (WHO, 1999). Even under the conservative assumption that RSPM is 50% of PM_{10}, only 30 households in this study would have average kitchen area concentrations below 150 $\mu g/m^3$.

In the absence of a clear approach, we had to make a judgment as to where the cut-off should be made. We decided to start with a value close to the geometric mean of the kitchen and living-area concentrations and thus 300 $\mu g/m^3$ was used as the cut-off point for kitchen area concentrations, and 200 $\mu g/m^3$ was used as the cut-off point for living-area concentrations. All households at or above these cut-offs were considered 'high' concentration households. This allowed us to have relatively even numbers of high and low concentration households, thus improving the statistical stability of the model. We also conducted a sensitivity analysis to evaluate changes if other cut-off points were chosen.

Table A6.3: Analysis of variance: ln (kitchen area concentration)

			ln (Kitchen area Concentration)	
		n	Mean	Std. Dev.
Fuel Category**	Wood	259	-1.08	0.88
	Dung	83	-0.75	0.94
	Kerosene	11	-1.86	0.69
	Gas	32	-2.78	0.63
Kitchen Type**	Indoor with partition	110	-1.26	1.19
	Indoor without partition	104	-0.92	0.95
	Separate indoor kitchen outside the house	94	-1.07	0.98
	Open air kitchen outside the house	77	-1.51	0.72
Separate Kitchen	No	177	-1.18	0.91
	Yes	208	-1.17	1.09
Roof Type	Pucca[1]	264	-1.23	1.05
	Kaccha[2]	121	-1.04	0.91
Wall Type**	Pucca[1]	81	-1.42	0.95
	Semi-pucca	69	-1.39	1.08
	Kaccha[2]	235	-1.02	0.99
Floor Type**	Pucca[1]	143	-1.43	1.08
	Semi-pucca	16	-1.66	1.20
	Kaccha[2]	226	-0.97	0.91
Housing Type**	Pucca[1]	38	-1.63	1.00
	Semi-pucca	276	-1.20	1.02
	Kaccha[2]	71	-0.82	0.88
Main Stove**	Traditional #1	319	-0.99	0.88
	Traditional #2	4	-1.68	1.40
	Improved	21	-1.13	1.15
	Kerosene	9	-1.73	0.79
	LPG	26	-2.73	0.62
	Biogas	6	-3.03	0.63
Kitchen Ventilation**	Poor	102	-0.75	0.90
	Moderate	151	-1.16	1.05
	Good	55	-1.51	1.14

*F-statistic for one-way Anova significant at p<0.05 level

**F-statistic for one-way Anova significant at p<0.001 level

[1]*Pucca* refers to more durable higher quality materials and construction techniques, e.g., a brick house with a tile roof.

[2]*Kachha* refers to more temporary and lower quality materials and techniques, e.g., a mud house with a thatched roof.

Table A6.4: Analysis of variance: ln (living-area concentration)

			ln (Kitchen area Concentration)	
		n	**Mean**	**Std. Dev.**
Fuel Category**.	wood	251	-1.59	1.02
	dung	87	-1.45	0.98
	kerosene	9	-1.96	1.19
	gas	28	-2.74	0.62
Kitchen Type**	indoor with partition	108	-1.81	1.09
	indoor without partition	89	-1.03	1.00
	separate indoor kitchen outside house	89	-1.89	1.00
	open air kitchen outside the house	89	-1.84	0.79
Separate Kitchen**	no	175	-1.44	1.00
	yes	200	-1.84	1.04
Roof Type	pucca	254	-1.67	1.07
	kachha	121	-1.62	0.97
Wall Type*	pucca	76	-1.99	1.06
	semi-pucca	66	-1.66	0.95
	kachha	233	-1.54	1.03
Floor Type*	pucca	131	-1.81	1.07
	semi-pucca	17	-2.20	1.20
	kachha	227	-1.52	0.99
Housing Type*	pucca	36	-2.12	1.17
	semi-pucca	266	-1.61	1.02
	kachha	73	-1.56	1.00
Main Stove**	traditional #1	318	-1.53	0.98
	traditional #2	3	-1.50	1.17
	improved	20	-2.01	1.27
	kerosene	6	-2.09	1.47
	LPG	22	-2.66	0.65
	biogas	6	-3.05	0.38
Kitchen Ventilation**	poor	94	-1.22	1.01
	moderate	136	-1.65	1.04
	good	55	-2.04	1.18

*F-statistic for one-way Anova significant at $p<0.05$ level
**F-statistic for one-way Anova significant at $p<0.001$ level

Independent variables

Table A6.5 below shows the variables included in the modeling process. Note that only variables shown to be significantly associated with higher concentrations were selected. Kitchen volume and roof type were not associated with kitchen or living-area concentrations. In addition, the following continuous variables were found to be associated with kitchen and living-area concentrations in univariate regression analyses, and were included in the modeling process: 1) time the main cook spends cooking and 2) number of kitchen openings. Although analysis of variance indicated that there is a significant difference in concentrations within the different stove types, stove type is highly correlated with fuel type, and was therefore dropped from the analysis.

Table A6.5: Variables included in the modeling process

Variable name	Description	Values
Kitch	Kitchen area concentration	Continuous variable
Lnkitch	Kitchen area concentration	Continuous variable
Living	Living-area concentration	Continuous variable
Lnliving	Living-area concentration	Continuous variable
K300	Kitchen area concentration (categorical)	0 = low 1 = high
L200	Living-area concentration (categorical)	0 = low 1 = high
fuel type	Cooking fuel	1 = wood 2 = dung 3 = kerosene or gas*
kitch2	Kitchen type	1 = indoor with partition 2 = indoor without partition 3 = separate indoor kitchen outside the house 4 = open air kitchen outside the house*
kitsep	Separate kitchen	0 = no separate kitchen 1 = separate kitchen*
kitvent3	Kitchen ventilation	1 = poor 2 = moderate 3 = good*
maintime	Time main cook spends cooking	Continuous variable
wallb	Wall type	0 = kachha 1 = pucca
floorb	Floor type	0 = kachha 1 = pucca
kitopenc	Number of kitchen openings	0 = 0 1 = 1 2 = >1

*Reference category

RESULTS

Linear regression

Linear regression models were used to assess which household characteristics are associated with high concentrations of respirable particulate matter. All models use log-transformed values for kitchen and living-area concentrations. Univariate linear regression with an exclusion criterion of $p>0.25$ was used to select independent variables eligible for inclusion in the model. Stepwise selection was used to arrive at the most parsimonious model.

An interaction occurs when the impact of one risk factor on the outcome variable of interest varies according to the value of another variable. For example, in this study, there was a possibility that kitchen types could impact kitchen area concentrations differently depending on the type of fuel being used. Two-way analysis of variance was used to screen for the possibility of interactions between the predictor variables. In addition, all possible two-way interactions between the predictor variables were assessed. No evidence of interaction was found.

Kitchen area Concentrations

Table A6.6 shows the final model for kitchen area concentrations. This model includes 3 parameters: fuel type, kitchen type, and kitchen ventilation. This model has an R2 of 0.323, suggesting that around 32% of the variation on kitchen area concentration is explained by the model.Part of the task of this modeling exercise was to evaluate not only the best fitting model, but also to assess the capability of the best fitting model compared to simpler models. In other words, how much better does the best model, that includes information on fuel type, kitchen type, and ventilation, perform compared to models that only include information on fuel type? Table A6.7 shows the R2 for regression models with fewer parameters. Including information on kitchen type and kitchen ventilation clearly improves the explanatory power of the model. Including information on both kitchen type and kitchen ventilation, however, does not result in much improvement compared to adding only one of these parameters.

Table A6.6: Final linear regression model for kitchen area concentrations

Final model adjusted $R^2 = 0.323$

Household characteristic	Coefficient	Standard error of coefficient	P>|t|
Fuel type			
Wood	1.54	0.147	0.000
Dung	1.86	0.165	0.000
Kerosene or Gas*			
Kitchen Type			
Indoor kitchen with partition	0.430	0.165	0.010
Indoor kitchen without partition	0.596	0.174	0.001
Separate indoor kitchen outside the house	0.424	0.158	0.008
Outdoor kitchen*			
Ventilation			
Poor	0.323	0.147	0.027
Moderate	0.132	0.132	0.322
Good*			
Constant	***-3.13***	***0.172***	***0.000***

*reference category

Table A6.7: Kitchen area concentration models with different parameters

Parameters included in the model	Adjusted R^2
fuel type	0.245
fuel type + kitchen type	0.313
fuel type + kitchen ventilation	0.307
fuel type + kitchen type + kitchen ventilation	0.323

Living-area concentration

Table A6.8 shows the final model for living-area concentrations. This model includes the same 3 parameters as the kitchen area concentration model: fuel type, kitchen type, and kitchen ventilation. This model has a lower R^2 of 0.198, however. In other words, less variation in living area is explained by the model compared to kitchen area concentration. This is not surprising, since living-area concentrations are generally more distally related to solid fuel use in the kitchen. Even in cases where the kitchen and living area are in the same room (type 1 kitchen), measurements for living-area concentration were taken in the main living space, i.e. away from the hearth. It is interesting to note that the same parameters that influence kitchen area concentrations influence living-area concentrations. In particular, poor kitchen ventilation not only affects kitchen area concentrations, but affects living-area concentrations in the same manner. In other words, improvements in kitchen ventilation do not occur at the expense of living room concentrations.

Table A6.9 shows the R^2 for the living-area concentration models using different parameters. Adding information on kitchen type and kitchen ventilation more than doubles the prediction capability of the model. If only one parameter is to be added to fuel type, however, kitchen type adds more to the model that kitchen ventilation.

Table A6.8: Final linear regression model for living-area concentrations

Final model: Adjusted R^2 = 0.198

Household characteristic	Coefficient	Standard error of coefficient	P>|t|
Fuel type			
Wood	0.893	0.179	0.000
Dung	1.100	0.196	0.000
Kerosene or Gas*			
Kitchen Type			
Indoor kitchen with partition	0.041	0.186	0.826
Indoor kitchen without partition	0.648	0.197	0.001
Separate indoor kitchen outside the house	-0.140	0.175	0.425
Outdoor kitchen*			
Ventilation			
Poor	0.385	0.170	0.024
Moderate	0.183	0.153	0.230
Good*			
Constant	*-2.80*	*0.202*	*0.000*

*reference category

Table A6.9: Living-area concentration models with different parameters

Parameters included in the model	Adjusted R^2
fuel type	0.081
fuel type + kitchen type	0.192
fuel type + kitchen ventilation	0.134
fuel type + kitchen type + kitchen ventilation	0.198

In summary, three variables were found to predict kitchen and living-area concentrations: fuel type, kitchen type, and kitchen ventilation. Linear regression techniques had little predictive power, however. The best model for kitchen area concentration could only explain around 32% of the variance in concentrations. This is partially due to the fact that the data consist of continuous outcome variables and mostly categorical or qualitative predictor variables.

Logistic regression

The coefficients in a logistic regression model are not easy to interpret, as the outcome is binary. Therefore, results are discussed in the form of odds ratios, which are simply the antilogs of the coefficients in a logistic regression model. Odds ratios represent the ratio of the odds of having the characteristic of interest among high-concentration households to that among low-concentration households. Each variable has a reference category, which is the baseline with respect to which the odds ratios for all other categories are defined. An odds ratio of 1 indicates that households with the characteristic of interest have no greater or lower risk of having a high concentration compared to those in the reference category. Odds ratios above 1 indicate an increased risk, and odds ratios below one indicate a decreased risk.

Univariate logistic regression with an exclusion criterion of $p>0.25$ was used to select independent variables eligible for inclusion in the model. Stepwise selection was used to arrive at the most parsimonious model.

Kitchen area concentrations

Three variables were found to be significantly associated with high kitchen area concentrations: fuel type, kitchen type, and kitchen ventilation. The model predicts about 88% of high concentration households and nearly 53% of low concentration households correctly, for an overall prediction accuracy of around 71%.

FUEL TYPE

Kerosene and LPG using households were used as the reference category for fuel type Compared to these households, dung using households were at a 68 times greater risk of having high kitchen area concentrations. Wood-using households had a risk of high kitchen area concentration that is 28 times that of kerosene and LPG using households.

KITCHEN TYPE

Outdoor open-air kitchens were used as the reference category for kitchen type. Indoor kitchens without partitions had the highest risk of having high kitchen area concentrations, followed by households with separate indoor kitchens outside the house, and then households with indoor kitchens with partitions.

KITCHEN VENTILATION

Households assessed to have poor ventilation had more than a two-fold risk of having high kitchen area concentrations compared to households with good ventilation. Households with moderate ventilation had a slightly elevated risk, but this risk was not statistically significant. See Table A6.10.

Living-area concentrations

A subtle difference between predicting kitchen and living-area concentrations is the way in which kitchen type affects concentrations. Testing using kitchen type and separate kitchen indicated that information on whether or not a household has a separate kitchen is more meaningful and more informing when predicting living-area concentrations. The modeling for living-area concentration was conducted in two ways:

1. Modeling under the assumption that kitchen area concentrations are known. Here, information on kitchen area concentrations is included in the model.
2. Modeling under the assumption that kitchen area concentrations are unknown. Here, no information on kitchen area concentrations is included in the model.

The first model would also give information as to the additional value of doing more than just one pollution measurement per household. If kitchen area concentrations, combined with survey results, predict living-area concentrations sufficiently well, much time and money could potentially be saved in field surveys.

Modeling when kitchen area concentrations are known

In the model that included information on kitchen area concentration, four variables were significantly associated with high living-area concentrations: kitchen area concentration, fuel type, kitchen type, and ventilation. This model was able to identify 73% of high concentration and 63% of low concentration households, for an overall prediction accuracy of 67%. See Table A6.11.

Table A6.10: Predictors of high kitchen area concentrations: Logistic regression analysis

Household Characteristic	Odds Ratio (OR)	95% CI†
Fuel Type		
Wood	28.2	(6.5, 121.6)
Dung	62.8	(13.6, 289.8)
Kerosene or LPG	1.0 *	—
Kitchen Type		
Indoor kitchen with partition	3.4	(1.4, 8.2)
Indoor kitchen without partition	4.6	(1.8, 11.6)
Separate indoor kitchen outside the house	4.1	(1.8, 9.6)
Outdoor kitchen	1.0 *	—
Ventilation		
Poor	2.3	(1.0, 5.0)
Moderate	1.1	(0.5, 2.3)
Good	1.0 *	—

*Reference Category

† 95% Confidence Interval (CI) for the Odds Ratio. CI refers to the computed interval with a 95% probability that the true value of the OR lies within. For example, the point estimate for the OR for wood fuel is 28.2, but this is the estimate within a range of uncertainty ranging from 6.5 to 121.6.

Table A6.11: Predictors of high living-area concentrations

Logistic regression analysis when kitchen area concentration is known

Household Characteristic	Odds Ratio (OR)	95% CI†
Kitchen area concentration		
Low	1.0 *	—
High	3.1	(1.9, 5.2)
Fuel type		
Wood	3.5	(1.1, 11.4)
Dung	5.0	(1.4, 17.7)
Kerosene or LPG	1.0 *	—
Kitchen Type		
No Separate Kitchen	1.0 *	—
Separate Kitchen	0.33	(0.20, 0.57)
Ventilation		
Poor	3.5	(1.8, 6.7)
Moderate	2.5	(1.3, 4.6)
Good	1.0 *	—

*Reference Category

† 95% Confidence Interval for the Odds Ratio

KITCHEN AREA CONCENTRATION

Households with low kitchen area concentrations (< 300 mg/m^3) were used as the reference category. Households with high kitchen area concentrations have over a three-fold greater risk of having high living-area concentrations.

FUEL TYPE

The reference category consisted of all households using kerosene or LPG for cooking. Households cooking with dung fuels were at greatest risk of having living-area concentrations, with over five times the risk compared to kerosene or LPG using households. Households using wood had a risk three and a half times greater than their kerosene or LPG using counterparts.

KITCHEN TYPE

Households without a separate kitchen were used as the reference category here. Households with a separate kitchen have, on average, lower living-area concentrations. Households with separate kitchens have a 33% lower risk of high living-area concentrations compared to households without separate kitchens. In other words, households without separate kitchens have a three fold higher risk of high living-area concentrations.

VENTILATION

Compared to households with good kitchen ventilation, households with moderate kitchen ventilation have more than double the risk of high living-area concentrations. Households with poor kitchen ventilation have over three and a half times the risk of high living-area concentrations. This finding is notable, in that it suggests that good kitchen ventilation is not achieved at the expense of air quality in the rest of the household. Since households with separate kitchens are at lower risk of high living concentrations, the direction of the effect of kitchen ventilation on living-area concentrations was not certain. If kitchen ventilation were achieved by shifting air pollution to the living area of households, then decreasing kitchen area concentrations through improved ventilation might not affect average household exposures at all. That better kitchen ventilation is associated with decreased kitchen and living-area concentrations suggests that improved kitchen ventilation could actually be associated with a decrease in the overall exposure of household members.

Modeling when kitchen area concentrations are unknown

When information on kitchen area concentrations was not included in the model, the predictive value of the model decreased somewhat. Around 61% and 67% of high and low living-area concentration households were classified correctly, with nearly 64% of households classified accurately overall. In the absence of information on kitchen area concentrations, the influence of the other variables (fuel type, kitchen type, and ventilation) increased, but the overall model remained the same. See Table A6.12.

FUEL TYPE

Households cooking with dung have nearly ten times the risk of high living-area concentrations of kerosene or LPG using households. Households using wood have more than a five and a half fold greater risk of high living concentrations.

KITCHEN TYPE

Here too, households with a separate kitchen have, on average, lower living-area concentrations. Households with separate kitchens have around a 34% lower risk of high living-area concentrations compared to households without separate kitchens. This translates into households without separate kitchens having a three fold higher risk of high living-area concentrations.

VENTILATION

Better kitchen ventilation is associated with decreased living-area concentrations. Households with moderate kitchen ventilation have nearly three times the risk of households with good ventilation, and households with poor ventilation have over four and a half times the risk.

Classification and regression trees (CART)

After allowing CART to select what it determined to be the 'optimal' tree, several different trees were produced, using different combinations of the predictor variables, in order to determine which tree(s) had the best ability to predict high and low concentration households.

Table A6.12: Predictors of high living-area concentrations

Logistic regression analysis when kitchen area concentration is unknown

Household Characteristic	Odds Ratio (OR)	95% CI†
Fuel Type		
Wood	5.7	(1.9, 17.6)
Dung	9.9	(3.0, 32.4)
Kerosene or LPG	1.0 *	—
Kitchen Type		
No Separate Kitchen	1.0 *	—
Separate Kitchen	0.34	(0.20, 0.56)
Ventilation		
Poor	4.6	(2.5, 8.5)
Moderate	2.9	(1.6, 5.1)
Good	1.0 *	—

*Reference Category

† 95% Confidence Interval for the Odds Ratio

Kitchen area concentrations

CART produces several different classification trees, and then determines the 'optimal' tree, i.e. the tree that classifies most accurately with a minimal amount of complexity. After allowing CART to select what it determined to be the 'optimal' tree, several different trees were produced, using different combinations of the predictor variables, in order to determine which tree(s) had the best ability to predict high and low concentration households.

The optimum tree generated by CART included two parameters: fuel type and kitchen type. In this model, households were first split on the basis of fuel type; all households using kerosene or LPG were classified as low concentration households. Next, households using wood or dung are further split by kitchen type; all households with outdoor kitchens are classified as low concentration households.

Fuel type predicted high concentration households well, but did very poorly in predicting low concentration households. Using fuel type alone, with no further splitting (see FIGURE A6.5 above), nearly all high concentration households were identified, but only 20% of low concentration households were identified accurately. Using fuel type alone would thus be useful in a context where all households using wood or dung had high kitchen area concentrations. In reality, however, there are a wide range of household concentrations within wood and dung fuel types. Hence, a model that only takes fuel type into account will identify the clean fuel using households, but does not tell us why some solid fuel using households are able to sustain low kitchen area concentrations. Splitting the wood and dung using households by kitchen type resulted in a small loss of prediction accuracy in high concentration households, but a significant improvement in the prediction of low concentration households, with 89% and 53% of high and low concentration households identified accurately.

This suggests that there are important household characteristics other than fuel type influencing kitchen area concentration. In fact, kitchen type was not the only parameter found to greatly improve the ability to identify low concentration households. Although the optimal tree as determined by the CART program used fuel type and kitchen type, an examination of the other trees generated by CART indicated that kitchen ventilation minimizes misclassification of low concentration households as well as kitchen type. After splitting by fuel type, splitting by either kitchen type or kitchen ventilation results in nearly the same improvement in classification. Table A6.13 shows how the number of parameters utilized in the different trees generated

Figure A6.5: Optimal tree for kitchen area concentrations

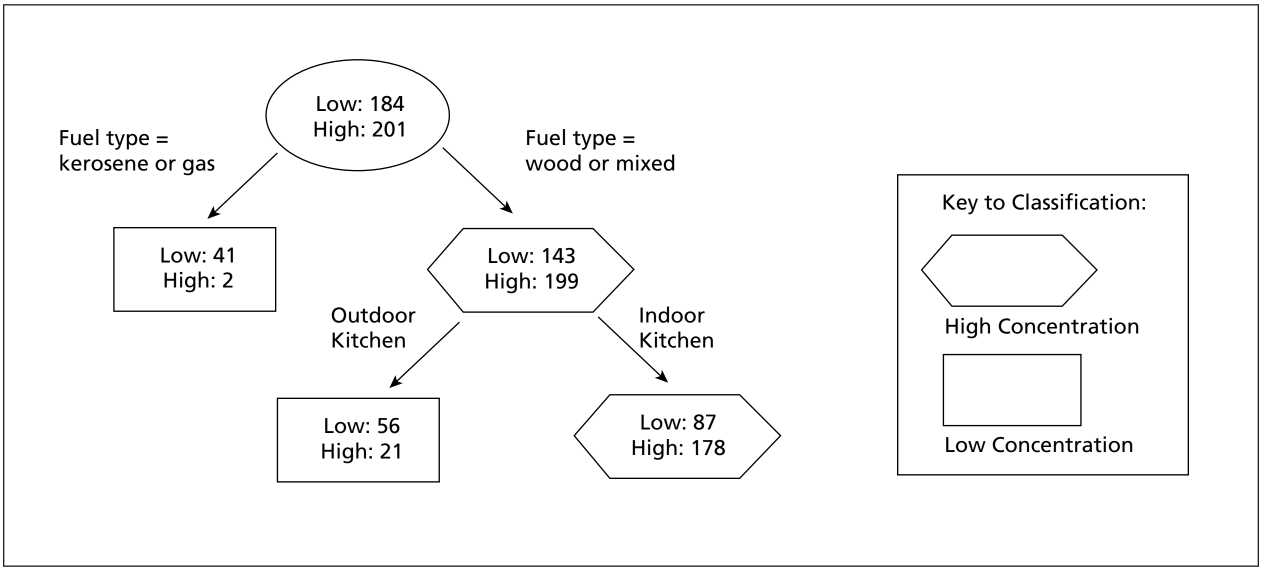


Table A6.13: Prediction accuracy of CART models predicting kitchen area concentration

	% Predicted accurately	
Parameters utilized by CART	**Low concentration**	**High concentration**
Fuel type	22%	99%
Kitchen type	30%	90%
Kitchen ventilation	46%	78%
fuel type + kitchen type	53%	89%
fuel type + kitchen ventilation	55%	86%
fuel type + kitchen type + kitchen ventilation	52%	93%

by CART affects the prediction accuracy for low and high concentration households.

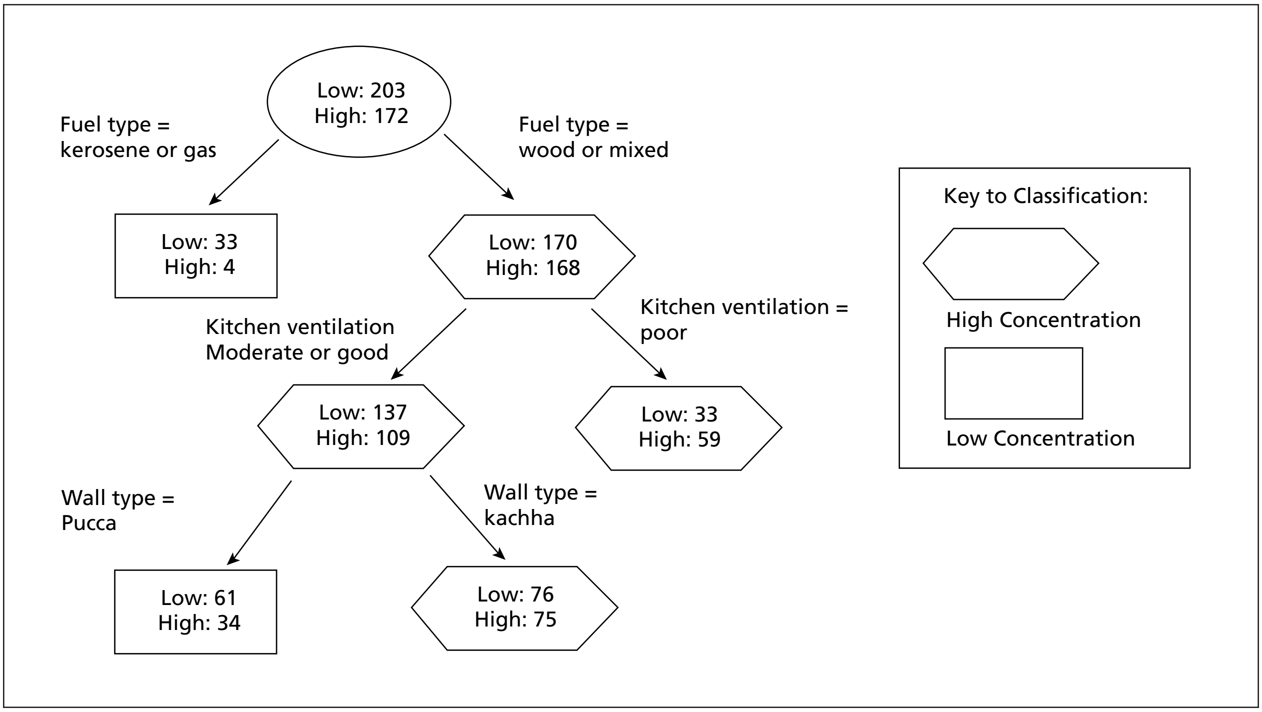
The tree that utilized both kitchen type and kitchen ventilation did not predict much better than the trees that used only one of these parameters. This suggests that it is not necessary to collect information on both kitchen type and kitchen ventilation. In future work, the decision whether to collect information on kitchen type or ventilation will be dependent on the study location. Kitchen types vary from region to region, thus the classifications used here may not be applicable to other locations. Likewise, depending on the amount of variation in kitchen and housing types, differences in kitchen ventilation may or may not be easily assessed by surveyors. In future studies, observations made during the initial site visit should make it relatively easy to decide which parameter to use.

Living-Area Concentrations

The optimum tree generated by CART included three parameters: fuel type, kitchen ventilation, and wall type. In this model, as with the model for kitchen area concentrations, households were first split on the basis of fuel type; all households using kerosene or LPG were classified as low concentration households. Next, households using wood or dung were further split by kitchen ventilation; households with poor kitchen area concentration were classified as high concentration households. Households with moderate or good kitchen ventilation were split by wall type; households with pucca walls were classified as low concentration households, and households with kachha walls were classified as high concentration households.

Another tree generated by CART, that utilized information on fuel type, kitchen ventilation, wall

Figure A6.6: Optimal tree for living-area concentrations



type, and roof type, was better at predicting low concentrations, but slightly worse at predicting high concentrations.

Once again, after allowing CART to select what it determined to be the 'optimal' tree, other trees were produced, using different combinations of the predictor variables, in order to determine which tree(s) had the best ability to predict high and low concentration households. Here, the parameters found to be significant in the logistic regression models for living-area concentration were used. Results were similar to the results of the kitchen models, although prediction accuracy was much less overall. Fuel type alone was a very good predictor of high concentrations, but very poor at predicting low concentrations. Once fuel type was included in the model, adding information on either kitchen type (separate or not) and kitchen ventilation had nearly the same effect, although using kitchen ventilation predicted a few more high concentration and a few less low concentration households accurately. When information on both kitchen type and kitchen ventilation was included, the model predicted low concentration households much better, but prediction accuracy of high concentration households declined. Once again, collecting information on both kitchen type and kitchen ventilation seems to be unnecessary. See Table A6.14.

SUMMARY

Kitchen area concentrations

Fuel type is the best predictor of high concentrations, but not a very good predictor of low concentrations. This is due to the wide range of concentrations within fuel categories. Kitchen type is also an important predictor; indoor kitchens are much more likely to have high concentrations than outdoor kitchens. Households with good kitchen ventilation are much less likely to have high concentrations than households with moderate or poor ventilation.

Living-area concentrations

Fuel type is the best predictor of high living-area concentrations. This is true both in the presence and absence of information on kitchen area concentration. For living-area concentrations, knowing the specific type of kitchen is less important than knowing whether or not the kitchen is separate from the living area. Information on kitchen ventilation is consistent with the results of the kitchen area concentration models; wood or dung using households with good kitchen ventilation are likely to have lower living-area concentrations. This suggests that improvements in kitchen ventilation do not occur at the expense of air quality in the living area.

How does changing the cut-off point affect prediction?

We conducted a sensitivity analysis to evaluate how changing the cut-off affects prediction accuracy. The optimum tree was used to identify high and low concentration households using different cut-off points, from 300 $\mu g/m^3$ to 850 $\mu g/m^3$ (approximately one standard deviation above the geometric mean). The sensitivity analysis was only done in one direction, i.e. we did not assess cut-off points below 300 $\mu g/m^3$, as a lowering of the cut-off point below 300 $\mu g/m^3$ would put a majority of the households into the high concentration category. In other words, since the model has been developed to predict high-concentration households, classifying most of the households as 'high concentration' would defeat the purpose of the exercise. Changing the cut-off did not seem to affect the prediction accuracy of high-concentration households. Prediction accuracy of low concentration households increased as the cut-off decreased. For example, 53% of low concentration households were identified correctly using a 300 $\mu g/m^3$ cut-off, compared with only 37% of households using a cut-off of 700 $\mu g/m^3$. See Table A6.15.

Consistency and stability

Results were consistent across linear regression, logistic regression, and CART models. In other words, the same variables were found to be important in all models. Although this does not guarantee the validity of the model, it does provide some reassurance about the robustness of the parameters used in the modeling exercise.

In the CART model, bootstrap aggregation (bagging) was used to determine how much the results

Table A6.14: Prediction accuracy of CART models predicting living-area concentration

	% Predicted accurately	
Parameters utilized by CART	**Low Concentration**	**High Concentration**
Fuel type + kitchen ventilation + wall type	46%	78%
Fuel type + kitchen ventilation + wall type + roof type	58%	70%
Fuel type	16%	98%
Separate kitchen	62%	57%
kitchen ventilation	83%	35%
fuel type + separate kitchen	51%	72%
fuel type + kitchen ventilation	46%	79%
fuel type + separate kitchen + kitchen ventilation	71%	58%

Table A6.15: Effect of concentration cut-off on prediction accuracy

	% Predicted accurately	
Concentration cut-off	**Class 0**	**Class 1**
kitchen RSPM = 300 $\mu g/m^3$	53%	89%
kitchen RSPM = 400 $\mu g/m^3$	47%	91%
kitchen RSPM = 500 $\mu g/m^3$	41%	92%
kitchen RSPM = 600 $\mu g/m^3$	39%	92%
kitchen RSPM = 700 $\mu g/m^3$	37%	92%
kitchen RSPM = 850 $\mu g/m^3$	36%	92%

might have changed if another random sample had been used. The results of 50 re-samplings of the data were averaged. If the results of the different samplings were different, suggesting instability, then the averaging would yield more accurate predictions. If the separate analyses are very similar to each other, the trees exhibit would stability and the averaging will not harm or improve the predictions. Averaging the results of the re sampled data did not improve prediction accuracy, suggesting that the model is quite stable.

Assessing the ability to collect model parameters

A key component of this exercise was to evaluate which parameters could be collected by minimally trained surveyors with reasonable accuracy. This section will discuss the relative difficulties of collecting information on the parameters found to be significant in the modeling process.

Fuel type

At the beginning of the study, because different fuel types and fuel combinations result in different emissions, the surveyors attempted to obtain information on fuel mixtures and quantities. It was found, however, that such information was often difficult to assess. In fact, as mentioned in the section on predictor variables, the greatest amount of discrepancy was found within households reporting kerosene fuels. Many of the households that reported using kerosene or gas as their main source of cooking fuel were found to be using a mixture of fuels. Indeed, the dung category was created as a result of the observation that many households reporting the use of kerosene as their main fuel were actually using kerosene for lighting, but wood or dung as their main cooking energy source. In general, however, information on the main fuel used for cooking is relatively easy to assess.

Kitchen type

Information on kitchen type was relatively straightforward. While there was some concern that there could be difficulty in differentiating between some of the kitchen types (for example, indoor kitchen with partition vs. separate kitchen outside the house), a comparison of the kitchen types identified by the household surveying team vs. the monitoring team suggests that there was actually little discrepancy in the classification of kitchen types. See Table A6.16 below.

Kitchen ventilation

Kitchen ventilation was also reasonably straightforward to assess. There were no reports from the surveying team about difficulties with this question (there was acknowledged difficulty in determining other parameters, such as proportions of dung use). In addition, most of the missing values that were entered into the database were for open-air kitchens, which were assumed to be outdoors and thus have good ventilation by definition.

Summary

Predicting household concentrations of particulate matter in India is not an easy task, given the wide variability within household designs and fuel use patterns. As the highest concentrations can be identified relatively accurately, the important issue is

Table A6.16: Cross-tabulation of kitchen classifications by survey and monitoring teams

KITCHEN CLASSIFICATION BY SURVEY TEAM	Kitchen classification by monitoring team: Indoor kitchen without partition	Indoor kitchen with partition	Separate kitchen outside the house	Open air kitchen outside the house
Indoor kitchen without partition	113	2	3	1
Indoor kitchen with partition	0	103	1	1
Separate kitchen outside the house	0	2	92	1
Open air kitchen outside the house	0	1	0	92

really minimizing a misclassification of low concentration households. Three variables, fuel type, kitchen type, and kitchen ventilation, were found to be good predictors of kitchen and living-area concentrations. In addition, the results of this study suggest that reliable information on all three variables can be collected by minimally trained surveyors.

Annex 7

Exposure assessment methodology

Exposure reconstruction models

Exposures to indoor air pollution are reconstructed using two sets of measurements: (1) 24-hour area concentrations and (2) relative ratios of the 24-hour averages to the cooking and non-cooking window concentrations, respectively, calculated using real time (PDRAM) monitoring instruments in a few households. Accordingly two models of exposure were constructed. The first (Model 1) used average 24-hr concentrations at the kitchen/living/outdoor locations, applied it to the total time spent by each individual member at these locations during the preceding 24-hrs (obtained from time activity records) and calculated the average 24-hr exposure.

$$\text{Average 24-hr exposure (Model 1)} = \frac{K1*T1+L1*T2+O1*T3}{T1+T2+T3}$$

Where
K1= 24-hr average concentration in kitchen (Loc.1)
T1= Total time spent in kitchen
L1= 24-hr average concentration in living area (Loc.2)
T2= Total time spent in living area
O1= 24-hr average concentration outdoors (Loc.3)
T3= Total time spent outdoors
and T1+T2+T3= 24

Since the 24-hr average concentrations determined gravimetrically does not yield information on relative concentrations during cooking and non-cooking windows this model did not address the contributions originating from differences between cooking and non-cooking window concentrations. For e.g. a cook may spend 3 hrs in kitchen while cooking (and thereby experience much higher concentrations) while another member may spend

3 hrs at the same location during a non-cooking window but yet the contributions to 24 exposures from this location will remain the same for the two individuals, in this model.

In order to refine this calculation, PDRAM records were used to determine relative ratios of 24- hr concentrations to concentrations during cooking and non-cooking windows (see Table A4). Although the size fractions monitored by the PDRAM (<10μm) and the gravimetric cyclones (50% cut off of 4 μm) are somewhat different and so is the analytical technique, it was assumed that the ratios would be comparable. 24- hr average concentrations for each location were thus split into concentrations while cooking and non-cooking windows. Since detailed time activity records had information not only where an individual was present but also when, it was possible to split the total times at each location (from Model 1) into times spent at the location during cooking / non- cooking windows. Thus Model 2 was constructed using the following formula

$$\text{Average 24-hr exposure (Model 2)} = \frac{K1a*T1a+K1b*T1b+L1a*T2a+L1b*T2b+O1*T3}{T1a+T1b+T2a+T2b+T3}$$

Where K1a= Average concentration in kitchen (location1) during cooking periods
T1a= Total time spent in kitchen during cooking periods
K1b= Average concentration in kitchen (location1) during non-cooking periods
T1b= Total time spent in kitchen during non-cooking periods
L1a= Average concentration in living area (location 2) during cooking periods
T2a= Total time spent in living area during cooking periods
L1b= Average concentration in living area (location 2) during non-cooking periods
T2b= Total time spent in living area during non-cooking periods
O1= 24-hr average concentration outdoors (location 3)
T3= Total time spent outdoors
and T1a+T1b+T2a+T2b+T3= 24

Outdoor concentrations were not adjusted in Model 2 as PDRAM measurements were not taken outdoors and also because the differences in outdoor concentrations between cooking and non-cooking windows is not significant. The exposure calculations have been thus performed on a case-by-case basis, using individual time- activity records together with the particular micro-environmental concentration information collected in the concerned household.

Table A7.1: Relative ratios of 24-hr average concentrations at the kitchen and living areas to concentrations in these areas during cooking/non-cooking windows

Type of Fuel	Type of kitchen	Cooking periods		Non-cooking periods	
		Kitchen area	Living area	Kitchen area	Living area
Solid fuels	Indoor kitchens w/ partitions	3.87	1.42	0.57	0.89
	Indoor kitchens w/o partitions	5.24	2.96	0.28	0.60
	Outdoor kitchens w/ partitions	3.87	1.34	0.52	0.81
	Outdoor cooking	4.22	3.40	0.75	0.74
Clean fuels	Indoor kitchens w/ partitions	1.37	1.35	0.94	0.93
(Gas users only)	Indoor kitchens w/o partitions	1.64	2.12	0.90	0.74
	Outdoor kitchens w/ partitions	1.99	1.79	0.83	0.82

Methodology for recording time-activity

Time- activity records were obtained from members of the households, which included women cooks, women not involved in cooking, children and men. Time- activity records were not collected from infants below the age of 2. Records were obtained on the basis of a 24-hr recall that detailed the type, location and duration (including start and stop times) of each activity carried out. In about 10% of the households, independent field assistants were used to assess the bias in time activity recalls. The monitoring data (obtained from the gravimetric analyses) provided 24-hr average area concentrations for three microenvironments viz. kitchen, living area and outdoors. These concentrations were used with real time measurements (described above) to compute the ratio of 24-hr averages to average concentrations during cooking and non-cooking windows. Using area concentrations at each microenvironment together with the total duration spent at each location during cooking/non-cooking windows gave the 24-hr exposures.

Model 1 predicts lower exposures than Model 2 for both cooks and non-cooks amongst solid fuel users. The difference is most pronounced for cooks as their exposures are underestimated by not addressing cooking window concentrations. Although Models 1 and 2 are different in absolute values, the trends amongst sub-categories of household members are similar as determined after analyses using both model values. Hence, results of comparisons across fuel and kitchen types are presented in the main text using only Model 2.

Glossary

Allergic sensitization—Increase in the body's response to a certain stimulus.

ANOVA—Analysis of Variance is a method of testing the null hypothesis that several group means are equal in the population, by comparing the sample variance estimated from the group means to that estimated within the groups.

ARI—Acute (short duration) respiratory tract infection.

Box plot—A graphical method of presenting the distribution of a variable measured on a numerical scale. Summary plot based on the median, quartiles, and extreme values. The box represents the inter quartile range which contains the 50% of values. The whiskers are lines that extend from the box to the highest and lowest values, excluding outliers. A line across the box indicates the median.

Bronchus—Large passage conveying air to the lungs.

Cancer of upper airways—Malignant growth in the upper respiratory passage.

Carcinogenic—Substances or agents that produce or predispose to cancer.

Cataracts—Opacity of the lens of the eye causing partial or complete blindness.

Chronic bronchitis—Inflammation of the bronchi of long duration.

Classification and regression trees (CART) techniques—refer Annexe 6.

Cluster sampling—Sampling method in which each unit selected is a group of persons (all persons in a city block or a family etc) rather than an individual.

Co-carcinogenicity—Substance that requires another agent to get activated and cause cancer.

COHb—Hemoglobin bound to Carbonmonoxide which has higher affinity to hemoglobin.

Comparative Risk Assessment—Qualitative or quantitative estimation of the likelihood of adverse effects that may result from exposure to specified health hazards.

Confounder—A variable that can cause or prevent the outcome of interest and is associated with the factor under investigation.

COPD—Chronic obstructive pulmonary disease—Inflammatory disease of lung tissue of long duration.

Correlation—Measure how variables or rank orders are related. The degree to which the variables change together.

Energy ladder—The energy ladder is made up of several rungs with traditional fuels such as wood, dung and crop residues occupying the lowest rung. Charcoal, coal, kerosene, gas and electricity represent the next higher steps sequentially. As one moves up the energy ladder, energy efficiency and costs increase while typically the pollutant emissions decline. While several factors influence the choice of household energy, household income has been shown to be the one of the most important determinants. The use of traditional fuels and poverty thus remain closely interlinked.

Epidemiology—study of the distribution and determinants of health related states or events in specified populations and application of this study to control of health problems.

Hemoglobin—protein present inside the Red blood cell which carries oxygen.

In situ detoxification—process of neutralizing toxic substances.

Inflammation—localized response by the blood and tissue to an injury.

Ischemic heart disease—deficiency of blood supply to the heart muscles.

Logistic regression—is useful for situations in which you want to be able to predict the presence or absence of a characteristic or outcome based on values of a set of predictor variables.

Macrophage—a large cell which has the power to ingest cell debris and bacteria.

Median aerodynamic diameter—applies to the behavioral size of particles of aerosols.

Muco-ciliary clearance—mucus secretions from the mucus membrane of respiratory tract and microscopic filaments projecting from epithelial cells of bronchi, which clears the inhaled particles.

Multiple regression—estimates the coefficients of the linear equation, involving one or more independent variables, that best predict the value of the dependent variable.

Odds ratio—the ratio of the probability of occurrence of an event to that of non occurance.

Relative risk—The ratio of the risk of disease or death among the exposed to the risk among the unexposed.

Still birth—a birth in which the baby is born dead (after 24th week of pregnancy).

Tuberculosis—an infectious, notifiable disease produced by Mycobacterium tuberculosis, affects the lung tissue commonly and can also affect other parts of the body like intestine, bones etc..

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