LINKING HOUSEHOLD ENERGY TO LOCAL AND GLOBAL ENVIRONMENTAL CHANGE: UNDERSTANDING IMPACTS OF CLEAN COOKING INTERVENTIONS IN RURAL INDIA

by

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Abstract

Almost 40% of the global population relies on fuelwood to meet their daily cooking energy needs, accounting for over 50% of all wood extracted in many developing countries. This dependency can have negative impacts on forest stocks and climate change, and is not expected to decline without a major change in current polices. Consequently, there is a need for improved understanding of fuelwood dependency to both inform the transition to cleaner cooking solutions and for sustainable management of local forest resources to ensure supply for dependent communities in the interim. This requires a careful analysis of the long-term management of local forest and agroforestry resources, the particular fuel collection habits of local populations, and the impact of new cooking technologies and fuels on fuelwood consumption. However, understanding biomass extraction and its impacts on forest resources remains under-developed in comparison to demand-side issues of fuelwood consumption. I fill these gaps by first tracking household fuelwood collection behavior in two regions of India. The patterns indicate that fuelwood collection is a function of both socio-economic drivers and the resource base, and collection is not evenly spread out among villages. Next, I demonstrate the need to develop local level estimates of biomass renewability to isolate household fuelwood collection impacts on local forest resources. Then, I estimate the impact of cooking solutions on fuelwood consumption behavior and the circumstances under which households move away from forest fuelwood sources. Finally, I examine a national level transition to clean cooking in India over ten years, and conclude that it reduced pressure on forests and achieved modest climate change mitigation benefits with some uncertainty due to the extent of biomass renewability and inclusion of differing climate-forcing emissions. Overall, the dissertation elucidates the need for local level estimates to isolate household fuelwood extraction impacts on forests and climate

change, and the need to carefully consider spatial scale and included emissions in future analyses and policy-making.

Lay summary

In many developing countries, over 50% of all wood extracted is used as fuelwood by almost 40% of the global population to meet daily cooking energy needs. Without a major change in policy, this dependence on fuelwood is not expected to decline much. Such large amounts of extraction raises serious concerns of the long-term sustainability of forest resources and the impacts on dependent communities. In my work, I used unique approaches to estimate household fuelwood collection patterns in India to understand how fuelwood extraction and consumption impacts forest resources and climate change. To understand household extraction impacts on forest resources, biomass estimates need to be at local scales, where socio-economics and topography dictate the change in household fuelwood consumption behavior. My results have important implications for international policy and local forest resources management.

Preface

This dissertation is an original intellectual product of author Devyani Singh. University of British Columbia Ethics Certificate number H14-01210 and H14–00648 covered the fieldwork reported in Chapters 2-4.

A version of Chapter 2 has been published [Singh, D., Aung, T., Zerriffi, H. 2018. Resource Collection Polygons: A spatial analysis of woodfuel collection patterns. Energy for Sustainable Development. 45 (C), 150-158]. Dr. Ther Aung provided GPS tracks for one location out of five used in the Chapter. I was responsible for data collection for the other four sites, as well as all analysis and manuscript composition. Dr. Hisham Zerriffi was the research supervisor and provided valuable inputs throughout the process from concept formulation to manuscript composition.

A version of Chapter 5 has been published [Singh, D., Pachauri, S., Zerriffi, H. 2017. Environmental payoffs of LPG cooking in India. Environmental Research Letters]. Dr. Shonali Pachauri was involved throughout the process in concept formation, inputs on data analysis, and manuscript edits. However, I was the lead investigator and responsible for all data collection, analysis, and manuscript composition. Dr. Hisham Zerriffi was the research supervisor and provided valuable inputs throughout the analysis and manuscript edits.

I was the lead investigator for the projects in Chapters 3 and 4. Dr. Valerie LeMay and Dr. Hisham Zerriffi provided valuable inputs throughout the process from concept formation to manuscript edits. However, I was solely responsible for all data collection and analysis, as well

as the manuscript composition. Jerry Maedel provided valuable inputs for spatial analysis using ArcGIS, and also provided the Landsat images.

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List of abbreviations

BC	Black Carbon
BSC	Biomass Stock Change
CCS	Clean Cook-stoves
CO_2	Carbon Dioxide
FSI	Forest Survey of India
GHG	Greenhouse gas emissions
ICS	Improved Cook-stoves
KPT	Kitchen Performance Test
LPG	Liquefied Petroleum Gas
MCP	Minimum Convex Polygon
$MtCO_2e$	Million tonne of Carbon Dioxide equivalent
NRB	Non-renewable Biomass (or unsustainable harvest)
NSS	National Sample Survey
RCP	Resource Collection Polygon
TCS	Traditional Cooking Systems

Key definitions

Biomass	Used for cooking and heating needs primarily in TCS, including charcoal, fuelwood, crop residue, and dung etc.
CCS	Clean cookstoves using modern fuels such as LPG or electricity.
Fuelwood	Unprocessed woody biomass (mainly deadwood, branches, and small trees), used directly for energy in TCS.
Hotspot	Regions where extraction exceeds regrowth of forest biomass in the year.
ICS	A variety of improved biomass cookstoves ranging from relatively simple rocket stoves to sophisticated forced-draft stoves.
Modern Fuels	Non-solid fuels such as Liquefied Petroleum Gas (LPG), biogas, and electricity.
NRB	unsustainably extracted wood, i.e., extraction is more than the yearly regrowth in the forest.
Solid fuels	Various solid materials (e.g., woodfuels, coal, and biomass, etc.) used for energy to meet daily cooking and heating needs, primarily in TCS.
TCS	Traditional Cooking Systems which include 3-stone fires or basic mudstoves used to meet daily cooking energy needs.
Traditional Woodfuels	Mainly fuelwood and charcoal that is used in TCS.
Woodfuels	All sources of woody biomass for energy generation, including direct use of wood (fuelwood) as well as processed wood (e.g., wood pellets and charcoal).

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Dedication

This thesis is dedicated to:

The inclusion of science in policy-making.

"*Science without policy is science, but policy without science is gambling*" – Dr. David Grey

Chapter 1: Introduction

Approximately 2.6 billion people, mostly in developing countries, rely on burning biomass (fuelwood, crop residues, charcoal, and dung) to meet their daily household cooking energy requirements. Of this, almost 800 million individuals live in India alone (Arnold et al., 2003; International Energy Agency (IEA), 2016; World Bank & IEA, 2017), and the estimated annual fuelwood consumption is 385.25 million cubic meters per year, or 85% of annual wood production (Shrivastava & Saxena, 2017). The use of traditional woodfuels represents almost 8% of the global total final energy consumption (REN21, 2018) but in many developing countries, woodfuels can constitute 50 to 90% of all household energy (FAO, 2016). While woodfuels include any source of woody biomass (including wood pellets and industrial fuelwood), traditional woodfuels[1] include both fuelwood and charcoal when burned in traditional cooking technologies (TCS) such as three-stone fires or basic mudstoves (Bonjour et al., 2013). This extraction of woodfuels is not equally distributed globally, and can vary substantially between regions, ranging from over 60% of all wood extractions in Asia-Pacific to over 90% in Sub-Saharan Africa (FAO, 2016). Africa and Asia-Pacific are the global leaders contributing to more than 2/3rd of total woodfuel production (FAO, 2017). Of this estimated 1,890 million cubic meters of global production, India alone contributes to 16%, primarily because it harbors almost a quarter of the world's traditional woodfuel using population (FAOSTAT, 2018).

[1] Going forward woodfuel refers to traditional woodfuels unless stated explicitly.

In coming years, without a major change in policy and markets, the total number of households using TCS is expected to stay relatively stable at over 2 billion out to 2030 (IEA, 2017). The inefficient combustion of woodfuels in TCS emits pollutants such as black carbon, contributing about 1.9% to 2.3% of net global emissions (Bailis et al., 2017). In addition, black carbon has been blamed for disruptions in the South Asian monsoon (Kar et al., 2012; Ramanathan & Carmichael, 2008); this in turn can have negative impacts on the livelihood of the farmers, as almost 60% of cultivable land in India is dependent on rain-fed agriculture (FarmGuide, 2018). The emissions also have a negative effect on air quality with approximately 25-30% of ambient fine particulate pollution ($PM_{2.5}$) in South Asia being attributable to household solid fuel combustion (a broader category that includes woodfuels, coal, and dung etc.) (Balakrishnan et al., 2014; Chafe et al., 2014; Rehman at al., 2011; Smith et al., 2014). The World Health Organization (WHO) estimates that household air pollution from TCS is one of the top environmental health risks, contributing to 5% of the global human burden of disease, which translates to approximately 2.6 million deaths per year (IHME, 2017; WHO, 2016). Finally, the use of biomass for cooking in TCS also has a number of social implications given the time spent collecting fuelwood, differential gender and age impacts of health outcomes and time spent, and the socio-economics of transitioning from traditional to improved and clean cookstoves (Agarwal, 2009; Das, Jagger, & Yeatts, 2016; Thakur et al., 2018; Wan et al., 2011).

Estimates of and literature on the use of TCS in the developing world often combines fuelwood and charcoal under the single term, “woodfuels”. Statistics on global production and consumptions, such as from the Food and Agriculture Organization (FAO), are also often available only for woodfuels. However, the focus of my research in this dissertation is on fuelwood, including wood from forest land, agricultural trimmings, and other sources of fuelwood; and thus, I have referred to fuelwood, where possible, rather than woodfuels, unless charcoal was explicitly being considered.

In theory, a transition to improved and clean cookstoves can positively influence forest resource health, global climate, local air quality, and human health and well-being. Improved biomass stoves (ICS) have both higher thermal efficiency, which results in reduced fuel consumption (Adler, 2010), and combustion efficiency, which reduces emissions of incomplete combustion (Anenberg et al., 2013). Clean cookstoves (CCS) use modern (i.e., non-solid) cooking fuels such as Liquefied Petroleum Gas (LPG), natural gas, and electricity. Some ICS and CCS have been shown to substantially improve household air quality and human health (Dutta, Shields, Edwards, & Smith, 2007; Singh, Gupta, Kumar, & Kulshrestha, 2014; WHO, 2016), and have indirect social benefits, such as reduced fuelwood collection time (which can be utilized for income generating activities, such as agriculture) (Brooks et al., 2016; Hutton & Rehfuess, 2006). CCS using modern fuels such as LPG are viewed as being ‘cleaner’ based on emissions at point of use, but not including those from manufacturing or transportation processes. They are highly beneficial from the perspective of human health, as they considerably reduce emissions of household air pollutants (e.g., daily $PM_{2.5}$ intake: 0.5 mg/day for LPG versus 81.3 mg/day for TCS) (Grieshop et al., 2011; WHO, 2014). However, a concern raised is that LPG is a fossil fuel that is replacing an ostensibly renewable fuel, namely, biomass. In spite of this, the literature suggests that a switch to LPG is still beneficial due to its substantially higher thermal and combustion efficiency, and reductions in the emissions of both gases and aerosols relevant for local air pollution and climate change (e.g., $PM_{2.5}$ emissions: 0.5 g/kg for LPG versus 8.5 g/kg for TCS) (Bruce, Aunan & Rehfuess, 2017; Grieshop et al., 2011).

Fuelwood is a natural, renewable resource, but only under sustainable management. Unsustainable harvesting, especially in densely populated areas of developing countries, can lead to: a) deforestation (Arnold et al., 2003; Foley et al., 2007; Hosier, 1993; McGranahan, 1991); b) accelerated degradation (DeFries & Pandey, 2010; Ghilardi, Guerrero, & Masera, 2007, 2009; Heltberg, Arndt, & Sekhar, 2000); and c) depletion of local resources (Masera, Ghilardi, Drigo, & Trossero, 2006). In coming decades, continued pressure on forest resources from household and commercial extraction is likely to occur, along with uncertain future growing conditions and land stability because of climate change, raising concerns about forest resources sustainability. What is largely absent in existing literature is an understanding of the connection between household fuelwood consumption (demand) and collection behavior (forest supply), and a methodology to identify the impact on forest resources, particularly as consumption changes due to the introduction of cleaner cooking (ICS/CCS) options. This requires an assessment of household consumption (i.e., what and how much is consumed) and collection (i.e., what and where fuelwood is obtained) patterns, and the development of methodologies to estimate the relationship between consumption, collection and impacts on forests. This needs to be done with an explicit consideration of spatial scale given the very local collection and consumption of fuelwood. Yet, very limited research has been undertaken assessing all these factors (but see exceptions including Bailis et al., 2015 and Masera et al., 2006).

There is an established and still-growing literature on factors affecting fuelwood demand (e.g., site conditions including elevation, income, physical access, etc.) at national (e.g., Ghilardi 2007) and local levels (e.g., Bhatt, Negi, & Todaria, 1994; Ghilardi, Guerrero, & Masera, 2007; Kumar & Sharma, 2009; Singh, Rawat, & Verma, 2010). Research is more limited on the supply-side factors impacting biomass extraction for household use – few researchers have examined the spatial aspects of fuelwood collection and consumption, but these studies were limited in geographical scale and/or used large radii buffers around the study sites (such as Bailis et al., 2015; Top et al., 2004, 2006). Other researchers have highlighted the need for multi-scale spatially explicit estimates of fuelwood collection to identify its impact on forest resources (Johnson et al., 2009; Masera et al., 2006).

Therefore, the main objective of my research in this dissertation was to assess household fuelwood collection and consumption behavior, and the potential implications for both forest resources and climate change, of a move away from traditional biomass cooking. My dissertation helps to fill the conceptual and methodological gap on identifying household fuelwood collection behavior on a local scale, and estimating its impacts on forest resources. First, I mapped household fuelwood collection patterns to prove that current methods of using simple radii buffers around village centers are poor approximations of actual extraction areas. Second, I demonstrated the need for local level estimates of biomass renewability to isolate household fuelwood collection impacts on forest resources. Third, I estimated the change in household consumption behavior and the circumstances under which they can move away from forest fuelwood sources. Fourth and finally, I estimated the impact of transitioning to ICS/CCS on fuelwood consumption, and showed how biomass renewability estimates could dictate the amount of national emissions accounting.

The following sections cover a brief history of fuelwood use and clean cooking interventions, followed by the gap in existing research and dissertation objectives. Next, I describe the research methods (including the research site and data collection), and end with a dissertation overview.

1.1 Brief history of fuelwood research

The early 1970's and 1980's saw substantial human encroachment into forest-lands as a result of population growth and expansion of agricultural lands, particularly throughout the tropics (Hiemstra-van der Horst & Hovorka, 2009). This led to a rise in interest on the issue of fuelwood sustainability, through publications such as Eckholm et al. (1984) and Agarwal (1986), suggesting a major fuelwood crisis in the coming decades. In 1981, the Food and Agriculture Organization (FAO) of the United Nations estimated that 2.4 billion people could suffer acute fuelwood deficits by the year 2000 (FAO, 1981), due to a major supply/demand gap. In light of this crisis, improved (ICS) and clean cookstoves (CCS) were seen as a potential solution, and various governments (e.g., China and India) started large-scale intervention programs. ICS/CCS interventions gained popularity, both as a strategy to combat future shortages of fuelwood, and to promote environmental conservation (Agarwal, 1983; Arnold et al., 2003; Manibog, 1984; Kammen, 1995), but these early programs focused more on the thermal efficiency of stoves and viewed reduced emissions as a secondary benefit (Sinton et al., 2004).

By the mid 1990's the fuelwood shortage did not seem to be as intense as earlier suggested (Arnold et al., 2003; Cecelski, 1984). Research indicated that clearing of land for increasing area under agriculture, to ameliorate low agriculture productivity and increasing human populations, was the greatest driver of permanent removal of tree cover (World Bank, 2013, p. 6), and questions were raised about the assumption that foraging of fuelwood by the rural poor was the main cause of shortage (Agarwal, 1986; Arnold et al., 2003; McGranahan, 1991). Moreover, rural supply of fuelwood was rarely found to be an environmental threat since a large proportion of the rural supply came from dead trees, trees outside forests (e.g., farms), and by cutting branches, not from cutting live trees (Abbot & Homewood, 1999; Fairhead & Leach, 1996; Morton & Morton, 2007). While there were areas of concern or so-called fuelwood hot-spots, where extraction exceeded growth of local biomass resources, it was not considered to be a widespread global issue (Egeru et al., 2010). However, there were, and still are, concerns that a concentrated urban and industrial demand, in absence of strong regulations, could contribute to degradation and deforestation (WHO, 2013). Current average global estimates of unsustainable extraction of fuelwood and charcoal range from 10% (IEA, 2012; IPCC, 2007) to 30% (Bailis et al., 2015), with the exception of a few hotspots (>50%) mainly in Sub-Saharan Africa and parts of south Asia (Figure 1.1). Such extraction would directly affect local communities, as forest ecosystems are their main source of income and livelihood (Byron & Arnold, 1999; Salafsky, 1994; Smith & Scherr, 2003).

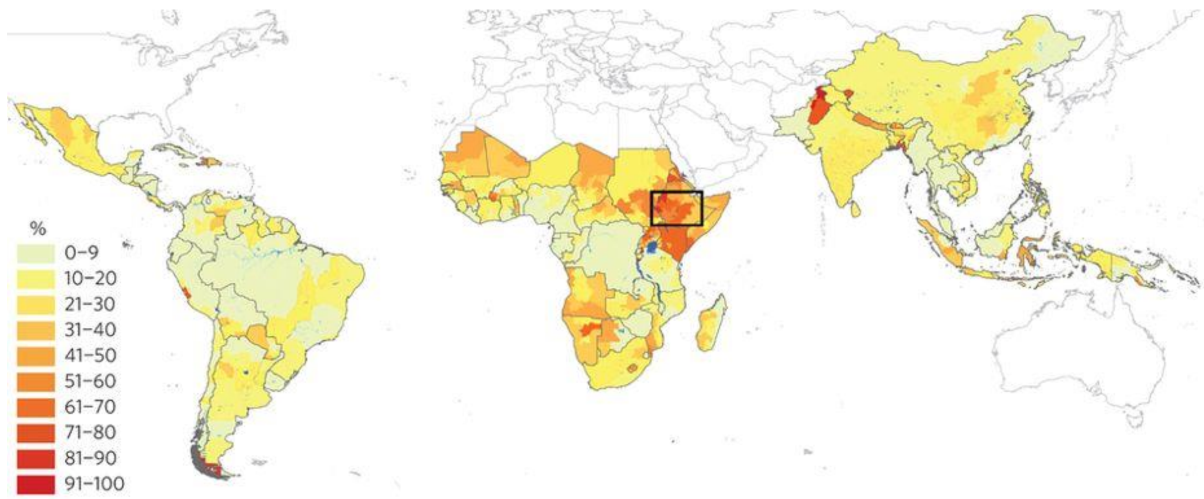

Figure 1.1: Percentage of unsustainably harvested fuelwood and charcoal [reprinted with the permission of 'nature climate change' and Bailis et al., 2015].

Subsequent research linking household air pollution to multiple health effects (de Koning et al., 1985; Smith, 1993; Zhang & Smith, 1996) fostered concern about the use of traditional cooking technologies (TCS). This led to a renewed interest in ICS/CCS, due to their ability to reduce negative impacts of household air pollution and on climate change from the reduction in emissions, most importantly emissions of incomplete combustion (Jamison et al., 2006; Sinton et al., 2004; Smith, 1993; Von Schirnding 2002). This focus on fuelwood consumption for over three decades (since the 1980's) helped create a vast literature base on the socio-economics of fuelwood demand, variables affecting the quantity of fuelwood consumed, and the variation in global fuelwood consumption patterns.

Considerable research on fuelwood demand has been carried out on a variety of spatial scales, from estimating fuelwood demand at national levels (e.g., Ghilardi et al., 2007), to determining local fuelwood collection patterns (e.g., Bhatt et al., 1994; Kumar & Sharma, 2009; Singh et al., 2010). There is growing empirical research on fuelwood demand linking socio-economic and demographic factors to fuelwood consumption (Berrueta, Edwards, & Masera, 2008; Bhatt, Negi, & Todaria, 1994; Granderson, Sandhu, Vasquez, & Ramirez, 2009; Kituyi, Marufu, Huber, & Wandiga, 2001; Kumar & Sharma, 2009; Singh, Rawat, & Verma, 2010), and on determining local consumption differences based on geographical region, altitude, and local cooking habits (Bhatt et al., 1994; Kumar & Sharma, 2009; Pattanayak, Sills, & Kramer, 2004).

At the household level, research suggests that labor energy expenditure is highest in temperate regions for fuelwood collection but the consumption is highest in tropical regions, with considerable oscillation in the consumption rate across seasons (Kumar & Sharma, 2009). At a commercial scale, fuelwood and charcoal consumption depends largely on availability of the alternate fuels, and differs between catering enterprises and public institutions (e.g., schools, colleges), and also between urban and rural regions (Kituyi et al., 2001). In light of fuelwood scarcity, dependence on local forests could be reduced through increasing forest access costs, promoting trees on farms, ICS/CCS, and through overall development and generation of wealth promoting the use of alternative fuels (Pattanayak et al., 2004). However, the environmental implications of fuelwood demand (i.e., interaction between fuelwood collection and forest degradation) remain highly variable and context dependent (Heltberg et al., 2000). Demand for fuelwood can lead to forest degradation (de Montalembert & Clément, 1983; Geist & Lambin, 2002), or there is evidence of resilient forests, and fuelwood users switching fuels or augmenting fuelwood supplies through agroforestry and trees outside forests (e.g., Leach & Mearns, 1988; Dewees, 1995; Bhattarai, 2001).

Thus, while an established and still-growing literature exists on the demand-side factors and the role of fuelwood in households, research is more limited on the supply-side to understand fuelwood collection patterns (Bailis et al., 2007; Masera et al., 2015). A few researchers have examined the spatial aspects of fuelwood collection and consumption, but they were limited in geographical scale and/or used large zones around the study sites (i.e., uniform circular buffers of given radii). For example, Top et al. (2004, 2006) studied fuelwood consumption patterns in Cambodia at three different scales (1, 3 and 5 km radii) and found that high population density was linked to lower forest stocks. Similarly, in Malawi, it was found that degraded forest resources often led to fuelwood consumption supported by other means, such as purchasing of fuelwood or charcoal from other areas, thus increasing fuel expenditures (Jagger & Perez-Heydrich, 2016). In Uganda, however, biomass reduction due to degraded forests increased the use of low quality fuels, such as dung and crop residues, by households (Jagger & Kittner, 2017).

As a mechanism for understanding relationships between fuelwood (and charcoal) demand and supply, models such as WISDOM and MoFuSS have been developed. WISDOM (Woodfuel Integrated Supply/Demand Overview Mapping), a GIS based spatially explicit model, uses administrative or regional scale data, from satellite images and national forest inventory datasets, to identify fuelwood priority areas, or global hot-spots indicating regions where fuelwood is unsustainably / non-renewably sourced (Figure 1.1) (Ghilardi et al., 2007; Masera et al., 2006). It has been applied to multiple countries and regions, including Mexico, Nepal, Slovenia, Senegal, and East Africa (Drigo, 2004a, 2004b, 2005, 2017). WISDOM estimates fuelwood supply and demand by defining the accessible areas to fuelwood collectors based on the International Union for Conservation of Nature guidelines and access from road networks (Ghilardi et al., 2009; Masera et al., 2006). However, the spatial scale of these analyses generally has been limited by the availability of production and other data provided by mid-level administrative units (e.g., counties or districts) at best. Higher resolution satellite data that have been used in these models have had to be aggregated up to the same administrative unit. Thus, while useful at the regional scale within countries, these models lack information at lower community level geographical scales.

MoFuSS (Modeling Fuelwood Savings Scenarios), another GIS based tool developed to quantify non-renewable fuelwood (and charcoal) extraction, builds upon the WISDOM model (Ghilardi et al., 2016). It simulates future forest cover and is capable of incorporating uncertainties for data-poor landscapes, savings from reduced fuelwood consumption, and projects scenarios for the future (Ghilardi, Tarter, & Bailis, 2018). However, even though it includes socio-economic inputs and allows site-specific processes to be integrated into the model, it does not look at specific local heterogeneity. MoFuSS uses data similar to WISDOM - existing satellite imagery and estimates of fuelwood harvest from FAO. Thus, while both models promote understanding of the dynamics of global fuelwood supply and demand, they do so at a larger aggregated spatial extent. Moreover, both models, exclude branches and deadwood from biomass analyses, whereas fuelwood demand is often met by cutting branches, and collecting snags and deadwood, not by felling live trees (Abbot & Homewood, 1999; Fairhead & Leach, 1996; Morton & Morton, 2007)

Thus, on the one hand is literature that attempts to measure forest impacts extensively but at a non-local spatial scale (Masera et al., 2006). On the other hand is literature that covers a local spatial extent but has simplified fuelwood collection to be in a uniform radius around population centers (e.g., Top et al., 2004, 2006; Jagger & Perez-Heydrich, 2016). What is missing are models and/or methods to extensively understand local spatial patterns of fuelwood collection and their impacts on forest resources.

1.2 Brief history of a transition to improved and clean cookstoves

Given the large number of people dependent globally on fuelwood for daily cooking needs, coupled with potential local fuelwood shortages and negative impacts on health, a transition to ICS and CCS has been a policy priority globally on and off since the 1980's, as noted earlier. ICS include higher efficiency biomass cookstoves, ranging from rocket stoves up to forced draft gasifiers. ICS have higher thermal and combustion efficiency, and better heat transfer from stove to device, resulting in reduced fuel consumption and lower emissions, specifically emissions of incomplete combustion (Adler, 2010; Anenberg et al., 2013). CCS use modern cooking fuels (i.e., non-solid) such as Liquefied Petroleum Gas (LPG), biogas, and electricity. Clean cooking interventions - programs aimed to transition people to ICS and CCS - have been implemented in over 50 countries, ranging from small, local initiatives, to large government-funded programs (Barnes et al., 1994). These interventions span from the installation of chimneys to vent smoke (Smith, 2002; Smith et al., 2009) and the use of simple more efficient biomass stoves called rocket stoves (Bruce et al., 2006, Naeher et al., 2007), to alternate modern or 'clean' fuels such as LPG (Ballard-Tremeer & Mathee, 2000; Bruce et al., 2006; Naeher, 2000). CCS using modern fuels such as LPG are viewed as being ‘cleaner’ as they considerably reduce emissions of household air pollutants contributing to improved human health (Grieshop et al., 2011; WHO, 2014).

Research has shown that using ICS/CCS can: a) substantially improve household air quality from reduced smoke (Dutta et al., 2007; Singh et al., 2014; WHO, 2016); b) reduce negative impacts on human health (Rosenthal et al., 2018; Thakur et al., 2018); c) positively impact forest resources through reduced dependence on forest biomass, where increase in forest stocks over time can help mitigate impacts of flood events, and provide a variety of other ecosystem services, including wildlife habitat, reduction in air pollution, and improved water quality; d) mitigate climate change from the reduced use of fuelwood and its resulting emissions (Serrano-Medrano et al., 2018); and e) provide social benefits such as time saved from reduced fuelwood collection (Brooks et al., 2016; Hutton & Rehfuess, 2006). However, not all ICS/CCS are the same, and range from basic more efficient biomass stoves to those using modern fuels such as LPG. The positive impacts of ICS/CCS on health and climate change mitigation vary widely in terms of options regarding the use of biomass, or by using liquid or gaseous fuels (Table 1.1).

While the LPG stoves rank high on both positive health and climate benefits, most other ICS/CCS do not necessarily rank similarly on both. For example, while a charcoal unvented stove (Char-U) provides more positive health benefits, from a lower individual $PM_{2.5}$ intake fraction, compared to a traditional unvented wood stove (W-Tr-U), it ranks worse in terms of climate change mitigation benefits due to its overall emissions, which includes black carbon. Moreover, in terms of forest impacts, unsustainable charcoal production can have larger negative impacts during its production (Chidumayo & Gumbo, 2013), where it could contribute to degradation and destruction of already disturbed forests (Hofstad, Kohlin, & Namaalwa, 2009), compared to traditional fuelwood extraction which is often met by cutting branches and collecting deadwood, not by cutting live trees.

Table 1.1: Various ICS/CCS ranked on health and climatic performance for Kyoto gases and total global warming potential (GWP) [reprinted with permission from Freeman and Zerriffi, 2012].

Health Benefits (Individual $PM_{2.5}$ Intake Fraction)		Climate Benefits (Kyoto Gases)	Climate Benefits (Total GWP)
<1 mg/day $PM_{2.5}$	**LPG-U**	**LPG-U**	**LPG-U**
	Ker-U	**W-Fan-U/ Ker-U** (~1mg/day)	**Ker-U**
1-10 mg/day $PM_{2.5}$	**W-Fan-U**		**W-Fan-U**
	Char-U	**W-Gas-U**	**W-Gas-U**
	W-Pat-V	**W-Pat-V**	**W-Pat-V**
	Coal-V	**W-Im-V**	**W-Im-U**
	W-Im-V	**W-Im-U**	**W-Im-V**
	W-Gas-U	**W-Tr-U**	**Coal-V**
10-100 mg/day $PM_{2.5}$	**W-Im-U**	**Coal-V**	**W-Tr-U**
	Coal-U	**Coal-U**	**Coal-U**
	W-Tr-U	**Char-U**	**Char-U**

*****Stoves: W-Tr-U = traditional unvented wood stove; W-lm-U = improved, Indian, unvented, metal, wood stove; W-lm-V = improved, Chinese, unvented, brick, wood stove; W-Pat-V = improved, Mexican, 'Patsari', vented, mason, wood stove; W-Gas-U = gasifer, Indian, unvented, metal, wood stove; W-Fan-U = 'Philips Fan', unvented, metal, wood stove; Char-U = Indian, unvented, metal/mud, charcoal stove (climate emissions include both use and production); Coal-U = Chinese, unvented, metal, coal stove; Coal-V = Chinese, vented, metal, coal stove; Ker-U = Indian, unvented, metal, kerosene wick stove; LPG-U = Indian, unvented, metal, LPG stove.

Clean cooking interventions have gained popularity due to their potential to alleviate the negative impacts of cooking with fuelwood on health, environment, forest resources, and climate change. While the early programs focused on the thermal efficiency of stoves (Sinton et al., 2004), the later programs aimed at improving human health through reduced emissions from traditional cooking systems (TCS) (Ezzati et al., 2004; Smith et al., 2004). In late 1990's, the Kyoto protocol paved the road for ICS/CCS to also be used as climate mitigation tools, due to their ability to reduce greenhouse gas (GHG) emissions and emissions of incomplete combustion, from the reduced use of fuelwood in more efficient cooking systems (Bond et al., 2004; Venkataraman et al., 2005). This potential for emissions reductions was recognized by the international carbon markets in 2008, when emission reductions certification methodologies for ICS/CCS were approved in both the compliance (i.e., Clean Development Mechanism) and voluntary markets (e.g., Gold Standard). By the end of 2014, there were over 286 wood-based (i.e., fuelwood and charcoal) offset projects, at various stages of development, in these markets (Bailis et al., 2018).

An evaluation of monetary costs of clean cooking programs shows that most ICS/CCS have considerably positive benefit-cost ratios (e.g., Hutton et al., 2006; Hutton & Rehfuess, 2006; Habermehl 2007, etc.); yet, over 2 billion individuals globally do not use any form of clean cooking device. Corresponding research has been concentrated on stove efficiency, emissions and pollution exposures (Berrueta et al., 2008; Ezzati et al., 2004; Smith & Haigler, 2008), or the various components of fuelwood demand and savings from ICS/CCS (e.g., Bhatt et al., 1994; Berrueta et al., 2008; Granderson et al., 2009; Kituyi et al., 2001; Kumar & Sharma, 2009; Singh et al., 2010). However, there is a lack of rigorous research on the changes in fuelwood consumption and collection behavior, especially following an ICS/CCS intervention (Bailis et al., 2007), or on the determinants of fuelwood collection in relation to forest degradation (Heltberg et al., 2000; Mekonnen & Köhlin, 2009) relating to spatial and geographical measures (Bailis et al., 2007).

India has been committed to promoting ICS/CCS for many decades, starting as early as the 1970's, when the Government of India instituted ICS, biogas, and fuelwood cultivation programs (Barnes et al., 2012). In the 1980's, the government mobilized the National Program on Improved Cook-stoves (NPIC), partnering with non-governmental organizations (NGOs) and local technical institutes to reduce inefficient energy use, achieve fuel conservation, and emissions reductions. The NPIC also aimed at reducing deforestation (Agarwal, 1983; Mehta, 1988), drudgery for women, cooking time, and improving employment opportunities for the rural poor. More than 34 million ICS were produced and distributed (Barnes et al., 2012; Kishore & Ramana, 2002). In 2002, the government of India decentralized the program, hoping to fix identified faults in the program and achieve wide dissemination through the National Biomass Cook-stove Initiative (NCI) (Venkataraman et al., 2010). Despite these efforts, only 5% of the rural households had, or were using ICS in 2006 (Zhang et al., 2006). Most recently, in 2016, the Indian government implemented a large social intervention scheme, called the Prime Ministers Ujjwala Yojana (PMUY). This new ambitious program, currently underway, aims at disseminating LPG to over 60 million poor rural women by the end of 2019, and has been praised due to its potential positive impacts on health and climate change mitigation (Kar et al., 2019). However, research is lacking on post-ICS/CCS household fuelwood consumption behavior changes, as well as on the environmental impacts of a large-scale transitions to LPG, such as the PMUY.

1.3 Problem statement and research objectives

In most developing countries, over 60% of all wood extracted is consumed to meet daily cooking energy needs, and the total number of dependent households is estimated to stay relatively stable, without any major change in policy or markets, out to 2030 (IEA, 2017). Such extensive extraction of biomass raises the question about sustainability of forest resources, current and future, to meet the primary energy needs of dependent communities. Unsustainable extraction of biomass can have negative impacts on the environment and accelerate climate change through forest degradation, and its associated impacts on ecosystem services (Bhatt & Sachan, 2004; Foley et al., 2007; Heltberg, 2005; Hosier, 1993; Rajwar & Kumar, 2011). Consequently, it is important to understand the drivers of biomass use to estimate the impacts of fuelwood use on local forest resources and ICS/CCS interventions. At the same time, it is also important to ensure sustainable supply for the dependent communities to meet their daily cooking needs. Sustainable management of forest resources requires a deeper understanding of the local resource, the particular fuel collection habits of local populations, and the amount of unsustainable extraction commonly termed non-renewable biomass (NRB).

While existing research is informative, multi-scale spatially explicit estimates (such as collection area, distance from village, and inaccessibility) are required to fully understand fuelwood extraction patterns and their impacts on forest resources. At the local scale, biomass stocks are largely impacted by the particular fuelwood collection habits of the local population and the level of demand, both functions of the particular stove technology used (TCS vs. ICS/CCS). Additionally, sustainable supply requires the assessment of the impact of fuelwood extraction on biomass stocks to identify potential hotspots - where extraction exceeds growth of local resources - to prioritize management of these locations. This requires the knowledge of where households travel to collect fuelwood, the spatial area under consideration when estimating extraction impacts, what and how much is being consumed, and the tools to model these impacts on forests. Yet such research is lacking, especially at the local spatial scale. Consequently, in order to address the overall objective introduced in Section 1.1 of this chapter and to help fill this gap in literature on the impacts of fuelwood extraction on forest sustainability and climate change, the main objective for each of the chapters to follow are:

- Chapter 2 - Identify household fuelwood collection patterns;
- Chapter 3 - Estimate the role of spatial extent (i.e., area under consideration) on isolating the impact of fuelwood collection on forests;
- Chapter 4 - Identify impact of household fuelwood consumption behavior on forest resources due to a transition to ICS/CCS; and
- Chapter 5 - Estimate the impact on fuelwood consumption, and resulting emissions, due to a large-scale transition to LPG in India.

Specific research questions used to address these objectives are provided in Section 1.5, along with an overview of each chapter.

1.4 Research methods:

Addressing the objectives of this dissertation required multiple sources of both qualitative and quantitative data, and included both primary and secondary data collection. This is a mixed-methods dissertation involving multiple sources of data and statistical methodologies for meeting the objectives described above. The detailed methods and analysis are explained in each chapter, respectively. Table 1.2 shows the basic research objectives, data used, and methods for each chapter of the dissertation to follow.

Table 1.2: Basic research objectives, data utilized, and method by chapter

Chapter Objective	Data Used	Methods
Estimate household fuelwood collection patterns in rural India.	GPS tracks, household socio-economic survey.	Minimum Convex Polygon, basic statistical summary.
Assess the role of spatial scale on isolating fuelwood collection impacts on forest resources.	FSI forest sample plot data, Landsat satellite images, GIS layers from Google earth and OpenDEM, and RCPs.	ArcGIS spatial mapping, R statistical model.
Identify household fuelwood consumption change because of an ICS/CCS intervention in India.	Kitchen performance test (KPT), household socio-economic survey, semi-structured interviews.	Difference in differences regression, consumption scenario predictions.
Estimate the change in fuelwood consumption, and resulting emissions, due to a large-scale transition to LPG cooking in India.	Indian National Census 2001 and 2011; and National Sample Survey rounds 55 and 68.	Statistical Matching, Tobit model, Emissions reductions.

The next sections describe the particular geographic context for this work (rural India) and the data collection methods.

1.4.1 Field sites

Research was conducted in India, given the large population dependent on fuelwood, as well as the long history of ICS/CCS intervention programs. Two districts across two states in India were selected: Kullu district in the northern state of Himachal Pradesh, and Koppal district in the southern state of Karnataka (Figure 1.2).

Figure 1.2: Map of India showing the two field site locations[2]

These two locations were selected as specific cases to study the pre- and post-ICS/CCS intervention characteristics of fuelwood demand and collection. Examining cook-stove technologies across two locations and sampling from eight different villages helped capture variation in the behavior of individuals, and the magnitude of change due to the clean cooking intervention. This allowed inferences to be drawn about the impacts of individual behavior, site

[2] The representation of this map does not imply the expression of any opinion whatsoever on the part of the authors concerning the legal status of any territory, or concerning the delimitation of its frontiers or boundaries.

specific characteristics, and ICS/CCS on local forest resources under varying forest types, climate, cooking styles, and geographic regions.

1.4.1.1 Kullu district, Himachal Pradesh

Kullu is a district in the hilly region of the North-West Himalayan state of Himachal Pradesh, spatially extended between 31º20' - 32º26' north and 76º59' - 77º50' east. The district covers approximately 5,503 km^2 and has a largely rural population of 438,000 spread across 172 villages (FSI, 2015; HP Forest Department, 2014). Forest cover is approximately 1,958 km^2 or about 35.58% of the geographical area in the state (FSI, 2011). The altitude varies from 1089m to over 6500m, with most forests occurring between 2800m to 4100m. The climate ranges from subtropical to alpine, resulting in extensive conifers and temperate broad leaved forests in the upper slopes to subtropical vegetation in the valleys (Sah & Mazari, 2007). Some of the dominant species are *Cedrus deodara, Abies pindrow, Picea smithiana*, *Robinia pseudoacacia, Populus ciliate*, and *Quercus leucotrichophora* (HP Forest Department, 2014). The district faces mild-hot summers (25^0 - 30^0 C) to cold winters (as low as -2^0 C), with heavy rainfall in the summer monsoon (July-September) (Sah & Mazari, 2007; Vishwa et al., 2013). Households in the region use fuelwood, not only for cooking purposes, but also for heating in winter. Orchard crops such as apple, pear and peach are cultivated on agricultural land, whose post-harvest trimmed branches supplement fuelwood from forests for household cooking and heating needs.

1.4.1.2 Koppal district, Karnataka

Koppal is a district in the south Indian state of Karnataka. It covers approximately 7,190 km^2 and has a population of ~1.2 million, 85% of which reside in rural areas. However, the forested area of the district is very small, covering only 14 km^2 or 0.19% of the total geographical area (FSI, 2011). The district is situated in the Rayalseema region, which is typically interspersed with plains and mainly barren hills with large rocks (Premchander et al., 2003). There is no dense forest, and most area in the district is classified as open forest or scrub, with major tree species being *Azadirachta indica*, *Tamarindus indica*, *Acacia arculiforms*, and *Casium*. Koppal has a semi-arid climate, with an average annual rainfall of 572 mm spread over 40–50 days. It consists mainly of plateau, with elevations of 600m to 900m above mean sea level, broken up by mountains and ravines (Ramachandra et al., 2004). The region does not experience major variation in temperatures between summer and winter (GOI, 2008). The harvest residue consists mainly of farm crop (e.g., maize, bajra) resulting in cobs and husk, while roadside and trees on farms constitute species such as *Dalbergia sissoo* and Eucalyptus species.

1.4.2 Data collection

At each of the two sites, local partner NGOs have been working on socio-economic issues and disseminating ICS/CCS under various programs. Data were collected in four villages per site annually over three years (2015 to 2017): in Kullu during April-May and in Koppal during August-September. Field staff helped in the collection of primary data through household surveys, in-home weighing of fuelwood, and GPS tracking of household fuelwood collection. Secondary data were obtained from the Indian National Census, Indian National Sample Survey Organization, USGS Landsat, and from the Forest Survey of India.

Primary data were collected for analyses in Chapters 2 and 4. The primary data from surveys and Kitchen Performance Tests (KPT) of fuelwood consumption were collected as part of a parallel project to conduct a randomized control trial (RCT) in these eight villages (please refer to Menghwani et al., 2018 for details on the RCT project). The selected villages within a site were similar in size, socio-demographics, and economic activity to minimize variation within sites, but also to maximize variation between sites. In all, data were collected for 480 households across eight villages (60 households at each village). At each location, households were randomly assigned as control (10 households with no provision of ICS/CCS) and treatment (50 households given ICS/CCS during intervention) households. The treatment households were given an ICS/CCS of their choice, ranging from improved biomass stoves to LPG and induction, while the control households were not given such an option and continued their use of the traditional mudstove until after completion of the trial. In-depth, full-length, socio-economic surveys were conducted (please refer to Appendix D for sample survey questionnaire). The treatment households were given an ICS/CCS of their choice, ranging from improved biomass stoves to LPG and induction, while the control households were not given such an option and continued their use of the mudstove until after completion of the trial. The survey asked households about fuel use, demographics, fuelwood collection distance, and social networks, and other socio-economic indicators.

A subset of 12-14 households from each village, consisting of both control and treatment, were selected for in-home KPT measurements, as explained in detail in Chapter 4. The socio-economic surveys and KPT were conducted in three phases: Phase I) baseline - where data were collected before stove distribution; Phase II) 1 year post-intervention after households received the ICS/CCS; and Phase III) post-intervention - 2 years after households received the ICS/CCS. This dissertation investigates only Phase I (baseline) and Phase III (2 years post-intervention) of data collection. Data were collected in the same months each year to remove any effects of seasonality. The KPT households were also selected for GPS tracking while gathering fuelwood to estimate the fuelwood collection area, termed Resource Collection Polygons (RCPs).

Secondary data informed analysis in Chapters 3 and 5. To create a biomass stock map for Kullu in Chapter 3, I used Landsat satellite images for 2002 and 2016, and the national forest inventory sample plot data from the Forest Survey of India (FSI). The process of integrating Landsat images and the sample plots is explained in detail in Chapter 3. To estimate the environmental payoffs of liquefied petroleum gas (LPG) in Chapter 5, I used the Indian national census data for 2001 and 2011, and the Indian National Sample Survey (NSS) household consumer expenditure round 55 (1999-2000) and round 68 (2011-12). The clean processed NSS datasets were acquired from the International Institute of Applied Systems analysis (IIASA) in Vienna, Austria.

1.5 Dissertation overview

The broad research objective (Section 1.1) and chapter-specific objectives (Section 1.3) are addressed in four chapters, each with its own specific questions and methodologies. The following is an outline of the dissertation to follow.

In **Chapter 2** *(Resource Collection Polygons: A spatial analysis of fuelwood collection patterns),* I used GPS loggers to track household fuelwood collection trips in India. Using a novel application of Home Range Analysis, a method for understanding the movement patterns of wildlife, I created resource collection polygons (RCPs). The specific research questions addressed in this chapter are:

- What are the geographical and spatial patterns to household fuelwood collection in rural India?
- How do the fuelwood collection patterns (i.e., location and distance) differ between and within regions?
- What key variables drive the differences in fuelwood collection patterns?

In **Chapter 3** *(Local Collection – Regional Measurement: the impact of spatial scale on assessing biomass stock changes relevant to fuelwood interventions),* I used national forest inventory ground plot data and Landsat satellite images to create a map of aboveground and fuelwood biomass stock changes. Using three spatial extents, I built a case for project level estimates of biomass stock to isolate impacts of fuelwood extraction on local forest resources. Specifically I answered:

- What is the impact of spatial extent on estimates of biomass renewability?

In **Chapter 4** *(Forest, Farms and Fuelwood: Measuring changes in fuelwood collection and consumption behavior from a clean cooking intervention)*, I identified household behavior changes and the factors which play an important role in consumption because of a clean cooking intervention in India. I used a difference in differences regression approach and predicted fuelwood consumption changes under various household scenarios. The specific research questions addressed in this chapter are:

- Was there a change in total fuelwood consumption due to the clean cooking intervention?
- Was there a change in fuelwood composition because of the intervention?
- What factors affect the magnitude of household fuelwood consumption change?

In **Chapter 5** *(Environmental payoffs of LPG cooking in India)*, I assessed the aggregate change in fuelwood consumption and resulting changes in emissions that occurred as a result of both the suite of policies put in place as well as the supply-side and demand-side decisions that were made by companies and households over the decade from 2001–2011. The analysis included the estimation of net impacts considering a suite of various climate-active emissions (Kyoto gases and other short-lived climate pollutants) and biomass renewability scenarios (a fully renewable and a 0.3 fraction of non-renewable biomass case). Specifically, I answered:

- What is the amount of fuelwood displaced (i.e., not consumed) by households in 2011 as a result of gaining access to LPG?

- What is the climate effect (i.e., the change in emissions) of the switch from fuelwood to LPG cooking in India over 2001-2011?

In **Chapter 6**, I synthesized the main empirical findings of the dissertation, and integrate the results from the dissertation. I discussed the contributions, limitations, and strengths. Finally, I provided future research directions, applications, and policy relevance.

Chapter 2: Resource collection polygons: a spatial analysis of fuelwood collection patterns

2.1 Introduction

As noted in Chapter 1, while an established and still-growing literature exists on the demand-side factors and the role of fuelwood in households, research is more limited on the supply-side to understand fuelwood collection patterns (Bailis et al., 2007; Masera et al., 2015). Understanding fuelwood collection is important for both sustainable management of forest resources, as well as for understanding any household energy transition (including clean cooking interventions). In coming years, without a major change in policy, demand for fuelwood to meet household energy is likely to remain static out to 2030 (IEA, 2017). Thus, it is becoming increasingly important to manage our natural resources sustainably to alleviate the negative climatic, social, and economic impacts that might arise. Household energy options are influenced, in part, by the particular ways in which those households are dependent on the local resource base. This can be understood through their current fuelwood collection behavior. Moreover, knowledge of their current collection behavior can help in understanding the potential impacts of a clean cooking transition on forest resources (which I cover in Chapter 3). A deeper understanding of fuelwood supply requires knowledge of what is extracted, how much is extracted, and where it is extracted from. Consequently, this chapter helps fill the gap by demonstrating a method to understand local spatial patterns of fuelwood collection.

A few researchers have examined the spatial aspects of fuelwood collection and consumption, but these studies were limited to large geographical scale in comparison to fuelwood collection and/or used uniform zones around the study sites (i.e., circular buffers of given radii). Thus, on the one hand is literature that attempts to measure forest impacts extensively but at a non-local spatial scale (Masera et al., 2006). On the other hand is literature that covers a local spatial extent but simplifies fuelwood collection to be a uniform radius around population centers (e.g., Top et al., 2004, 2006; Jagger & Perez-Heydrich, 2016).

There is growing empirical research on fuelwood demand linking socio-economic and demographic factors to fuelwood consumption (Berrueta ey al., 2008; Bhatt et al., 1994; Granderson et al., 2009; Kituyi et al., 2001; Kumar & Sharma, 2009; Singh et al., 2010), and on determining local consumption differences based on geographical region, altitude, and local cooking habits (Bhatt et al., 1994; Kumar & Sharma, 2009; Pattanayak, Sills, & Kramer, 2004). However, research on fuelwood collection behavior is limited, specially relating to spatial and geographical measures (Bailis et al., 2007). Those who have studied fuelwood collection have set the research in household frameworks that rely on self-reported data (Top et al., 2004), or large-scale analysis to map regional and national patterns (Bailis et al., 2015; Jagger & Perez-Heydrich, 2016). While these can each be informative, to fully understand fuelwood extraction patterns, there is a need for multi-scale spatially explicit estimates (such as collection area, distance from village, and accessibility). At the local level, it is necessary to go beyond simple circular buffers around villages and understand heterogeneity in local fuelwood collection locations (Masera et al., 2006). It is also imperative to understand the factors that drive these spatial patterns such as socio-demographics, local laws, and culture. Therefore, to fill this gap in understanding fuelwood collection behavior, I answer the following research questions:

1. What are the geographical and spatial patterns to household fuelwood collection in rural India?

2. How do the fuelwood collection patterns (i.e., location and distance) differ between and within regions?
3. What key variables drive the differences in fuelwood collection patterns?

To answer these questions, I pilot a novel application of Home Range Analysis, a method for understanding the movement patterns of wildlife. Applying this method, I construct what I term as Resource Collection Polygons (RCPs) to evaluate household fuelwood (or woodfuel) collection patterns. To the best of my knowledge, this is the first time that home range analysis has been applied to analyze human behavior, such as fuelwood collection patterns and boundaries. The further development and application of this method could have significant implications for resource management in this region and other parts of the developing world that rely heavily on fuelwood. It can serve as a base to build upon for further, more detailed analysis, such as using kernel density method to understand frequency and intensity of fuelwood extraction. It can also be applied to understand other human spatial patterns, such as water collection or food foraging around villages.

2.1.1 Home range

The concept of a "home range" first arose when Darwin (1861) noticed that animals restricted their movements to certain territories. Later Burt (1943) refined the definition to be the area traversed by an individual in its normal activities of food gathering, mating, and caring for young. Thus, a home range is the area in which an animal lives and moves (Worton, 1987). Home ranges have been widely used as ecological tools for wildlife management and decision support for conservation policies. Various tools, such as the minimum convex polygon (MCP) or kernel density, assess an animal's home range. The MCP is a relatively simple non-parametric method for estimating home ranges. It was the first method created for this purpose and also the most widely used, especially until the 1990's (Carey, Reid, & Horton, 1990; Simcharoen, Savini, Gale, & Simcharoen, 2014). The MCP became an internationally accepted standard for estimating home range, especially for presence-only spatially explicit data (Burgman & Fox, 2003). The International Union for Conservation of Nature red list categories (1994) specified MCP as the method of choice to evaluate trends in occupied habitat to assess the conservation status of a species. The MCP is defined by connecting the outermost locations of the data to create the smallest possible convex polygon with no internal angles greater than 180 degrees (Hayne, 1949), thus encompassing the entire region that an animal covers. MCP is easily computed from coordinate data and its estimates can be used to evaluate thresholds for extent of occurrence and to infer trends in home range over time of a species (Burgman & Fox, 2003).

However, MCP suffers from certain limitations such as its sensitivity to sample size. Larger sample sizes tend to be biased and could include outliers thus extending home ranges beyond a usually traversed route (Burgman & Fox, 2003; Seaman et al., 1999). However, Walter, Onorato, and Fischer (2015), compared MCP to other methods (e.g., kernel density) and found that even though there were no systematic differences between the two methods under various scenarios, Kernel density was better for larger sample sizes to reduce the disproportionate influence of outliers. Nonetheless, MCP is still the tool of choice for most research published in peer-reviewed journals; 75% of home range studies published between 2004 and 2006 and over 50% between 2010 and 2015 used MCP (Fauvelle, Diepstraten, & Jessen, 2017; Laver & Kelly, 2008). Thus, given my small sample size, simplicity of use, and its wide application, MCP was used for estimation of fuelwood collection area in this chapter. In what follows, I name these MCPs as Resource Collection Polygons (RCPs). The RCP for each village shows the area where households from that particular village frequent for fuelwood collection and it creates definite boundaries of an area traversed by the households. Furthermore, MCP is sufficient to act as a proof-of principle for using home range analyses on human spatial behavior patterns as it is still the most widely used tool in wildlife biology, and adds rich information to fuelwood collection behavior and patterns.

2.2 Methods

Data for developing the RCPs were collected in India, which has the largest fuelwood using population - of all the wood removals in India, over 85% is consumed as fuelwood by more than 70% of rural households and 20% of urban households (FAO, 2016b; MOSPI, 2011; World Bank & IEA, 2017). Five villages across two states were selected, Himachal Pradesh in the north and Karnataka in the south. In Himachal Pradesh, two villages (HP1[3] and HP2) from Kullu district were chosen. In Karnataka, two villages (KA1 and KA2) from Koppal district and one village (KA3) from Raichur district were chosen. Figure 2.1 shows the location of the study sites in each of the districts i.e., Kullu, Koppal, and Raichur.

[3] I don't use village names and instead use the district name and a number to ensure confidentiality given the highly sensitive nature of data.

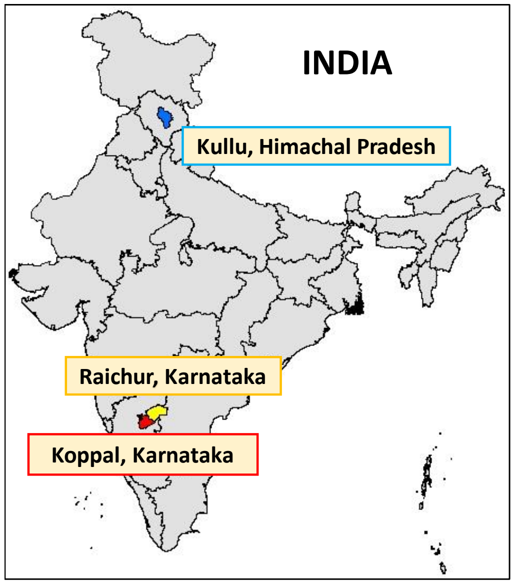

Figure 2.1: Study site locations in three districts in India[4]

Koppal and Raichur have a semi-arid climate resulting in a landscape dominated by barren hills with large rocks and open forest and scrubs (Premchander et al., 2003). By contrast the climate in Kullu ranges from subtropical to alpine, resulting in extensive conifers and temperate broad leaved forests in the upper slopes, to subtropical vegetation in the valleys (Sah & Mazari, 2007). Koppal and Raichur have limited forest cover[5] of only 0.19% (14 km^2) and 0.34% (23 km^2) respectively of their geographical area, while Kullu has a forest cover of approximately 35.60% (1958 km^2) of its geographical area (Forest Research Institute, 2011; FSI, 2015). For more details about Kullu and Koppal, please refer to research site description (Chapter 1, sub-section 1.4.1).

[4] The representation of this map does not imply the expression of any opinion whatsoever on the part of the author concerning the legal status of any territory, or concerning the delimitation of its frontiers or boundaries.

[5] Forest cover as defined by Forest Survey of India (FSI) and as accounted for by them in state of forest report 2015, 2017.

The study was conducted in Kullu from October to November 2014, and in Koppal from May to June 2015 as part of a larger project analyzing improved cookstove (ICS) adoption impacts on household air pollution and climate change (please refer to Chapter 1, sub section 1.4.2 for details on study design). In Raichur District, the study took place from May – July 2014 as part of a separate research on subjective and objective estimates of fuelwood collection time. Thus, the data used for estimating RCPs might be limited in scope as they were not deliberately collected with this particular analysis in mind. However, the variation in local characteristics, such as socio-economics, demographics, topography, and biomass cover allow for comparisons between regions heavily dependent on biomass fuel for household energy. As mentioned earlier, when referring to woodfuel collection within the research sites, I include only fuelwood, as there is no charcoal production in this region. Having said that, this method can be applied to any woodfuel collection patterns.

2.2.1 Household recruitment, survey, and characteristics

A total of 95 households were recruited for the study for global positioning system (GPS) monitoring of fuelwood collection. Households for Kullu and Koppal were recruited from villages where local partner non-governmental organizations (NGOs) have been disseminating ICS/CCS under various programs, as well as working on other socio-economic issues in the villages. The 60 households selected (33 in Kullu, 27 in Koppal) were a subset of the 480 households originally selected for the larger clean cooking, air pollution and climate change project (full description in Menghwani et al., 2019). In Raichur, households were recruited from a village where the same NGO from Koppal was implementing a cookstove intervention program financed under the Clean Development Mechanism (CDM). A subset of 35 households from the households that were eligible under the CDM program were randomly selected for fuelwood collection monitoring. At all five study communities, extensive household surveys were administered to collect socio-demographic information, including family size, caste, occupation, assets (chairs, fans, television, etc.), and amount of land owned. Households were recruited upon obtaining oral informed consent.

Socio-economic characteristics are more similar within a region than between regions (Table 2.1). All households in Koppal and Raichur belong to scheduled caste (SC), scheduled tribe (ST), and other backwards castes (OBC), but only a third of households in Kullu belonged to SC/ST and OBC groups. The SC, ST, and OBC are official caste classifications by the Indian government for those individuals deemed to be the socially and educationally disadvantaged (Government of India, 2015).

Table 2.1: Selected socio-economic characteristics of the study communities

	Himachal Pradesh	Karnataka	
	Kullu	**Koppal**	**Raichur**
Sample size (HH)	**33**	**27**	**35**
Caste (%)			
SC/ST	36	59	52
OBC	3	41	48
General	**61**	**0**	**0**
# HH members			
Mean (SD)	**5.2 (1.9)**	**6.3 (3.3)**	**6.3 (2.2)**
Range	2 to 9	2 to 15	2 to 11
Assets (%)			
Chair	57.6	66.7	70
Radio	9.1	7.4	4
Fan	15.2	55.6	80
TV	90.9	33.3	50
Computer	6.1	0	0
Car	15.2	0	0
HH with land ownership (%)	**100**	**89**	**86**

Koppal and Raichur also have larger household sizes (mean (SD): 6.3 (3.3) and 6.3 (2.2), respectively) compared to Kullu (5.2 (1.9)). In Koppal and Raichur, land ownership ranges from 86 to 89% of households with mean (SD) of 4.9 (4.6) acre and 3.3 (3.1) acre, respectively. In Kullu, all households own land with a smaller average size (SD) of 0.18 (0.16) acre, but gain all their agricultural income by working solely on this land. This is likely because land in Kullu is more fertile than in Koppal. Furthermore, Kullu farmers have orchard crops (i.e., fruit trees such as pear, peach, and apple) that are of much higher value and yield large quantities from small land-holdings. By contrast, land in Koppal is less fertile due to its semi-arid climate and the crops (i.e., paddy, wheat, maize etc.) require large tracts of land to yield substantial quantities for sale and/or profit. Households in Kullu seem to be wealthier owning higher end goods, such as a TV, computer and car, compared to those in Koppal and Raichur.

2.2.2 Collection of GPS data points

The GPS data for the study were obtained by providing M-241 Holux loggers to each of the selected households. Households in Kullu and Koppal were instructed to carry the GPS logger for all fuelwood collection trips during a seven-day period for two rounds (i.e., total of 14 days per household) in the same season, with a gap of ten days between each round. In Kullu, the tracking was done post-harvest representing their major fuelwood collection season and non-farming season, while in Koppal the data were collected in the summer, also representing a non-farming season. The field team downloaded data every three days and verbally enquired about the number of trips taken, average time spent, and average distance traveled on each trip. In Raichur, the GPS trackers were given to all participating households over a seven-day period, again, representing a non-farming season in the community. Here, the field team downloaded the GPS data points daily if participants went for fuelwood collection, and overlaid the data points on a map obtained from Quickbird images from Google Earth. These data were then shown to each participant on the map to verify actual fuelwood collection activity.

I compiled a total of 322 GPS tracks that were usable, including 57 tracks in Koppal, 100 tracks in Kullu, and 165 tracks in Raichur (Table 2.2). Data collection issues such as temporary or permanent loss of satellite signal (for 36 tracks) were a result of mountainous terrain, cloud cover, dense forest cover, and rare instances where the battery ran out before switch-out or where the individual turned off the GPS logger by mistake. Data signal loss due to mountainous terrain and dense forest cover was more for Kullu than in Koppal, but there weren’t any households where data loss was more than from other hosueholds. Out of these 36 tracks, I was not able to recover 25 tracks as there was no usable data, however I was able to reconstruct 11 tracks from temporary loss of signal. While I understand that such loss could result in a bias in assessing where household's traversed, I feel this bias does not have a major impact on my results for multiple reasons: a) each household had multiple days of track information, thus loss of one track for a household need not impact the overall pattern of fuelwood collection substantially; b) the lost signals at specific points align with non-lost signals for a given household; c) there was no spatial correlation in the regions of lost signals, and there were other tracks from other households which caught signal in those regions; and d) where partial track data was available I checked trajectories to confirm that the basic traverse route was similar to other household tracks.

Table 2.2: Number of GPS tracks analyzed and fuelwood collection activities by district

Location	# HH	# of GPS tracks (usable)	GPS monitoring season
Himachal Pradesh			
Kullu	33	100	Post-harvest non-farming (October-November)
Karnataka			
Koppal	27	57	Non-farming (May - June)
Raichur	35	165	Non-farming (June - July)

Despite the same number of participants, there are fewer tracks in Koppal than in Kullu. This is likely because fuelwood collection is done year round in Koppal and households may go only every few days. By contrast, in Kullu fuelwood is collected daily in the post-harvest month to build stocks for winter. As GPS monitoring was conducted in the non-farming season, the GPS tracks indicate trips made primarily for fuelwood collection purpose.

2.2.3 Construction of resource collection polygins (RCPs)

The GPS track data collected was used to create RCPs using Convex Hull within the Minimum Bounding Geometry tool in ArcMap10.4 for spatial representation (ESRI, 2011). The RCP is the smallest polygon in which no internal angle exceeds 180 degrees and contains all sites where the selected households of a village travel for fuelwood collection. Only the outermost boundary of RCPs created for each individual GPS track has been taken as the combined RCP for each village (Figure 2.2), which matches techniques used in wildlife home range estimation (e.g., Leo et al., 2016 for feral cats). Thus, my RCPs might appear to have angles greater than 180 degrees due to accounting for only the boundary, but this is not true for each individual GPS track MCP.

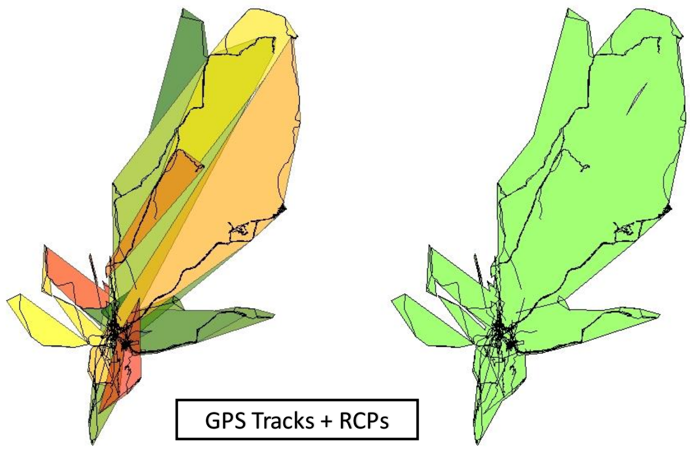

Figure 2.2: Creation of resource collection polygons (RCP) from GPS track data (the outer shaded region is the RCP, while the black lines are the actual GPS tracks)

Future work could look at creating RCPs from combined GPS tracks depending on what questions they are being used to answer. The RCP excludes all those regions not accessed by the households, for a multitude of reasons, ranging from legal (e.g., protected areas), to physical (e.g., steep terrain, water bodies, dense forest), or societal (e.g., private land, non-legal village boundaries). These are discussed further in the Results section. The RCP is simple to interpret and visualize, and can be used to describe the extent of distribution of fuelwood collection locations of households. Once the RCPs were constructed, I identified the locations within the polygon boundaries where fuelwood collection was taking place. To identify these locations, I used the GPS track time data where the speed was zero kilometers per hour, indicating a hault in trips. While I identify location of collection within the RCP, I cannot ascertain whether certain areas were used more than others (i.e., intensity of use), and would need more detailed data for such analyses.

2.3 Results

Resource Collection Polygons (RCPs) for each of the five villages are displayed in Fig. 2.3. The RCPs indicate that fuelwood collection is not evenly spread out among villages, and there are unique patterns for each community. The RCPs are not homogenous but are directional (i.e., preference towards one direction over another), and the distance traveled varies between villages. On average, the collection distance in Himachal Pradesh was shorter at around a kilometer from the village center as compared to 2 to 2.5 km in Karnataka.

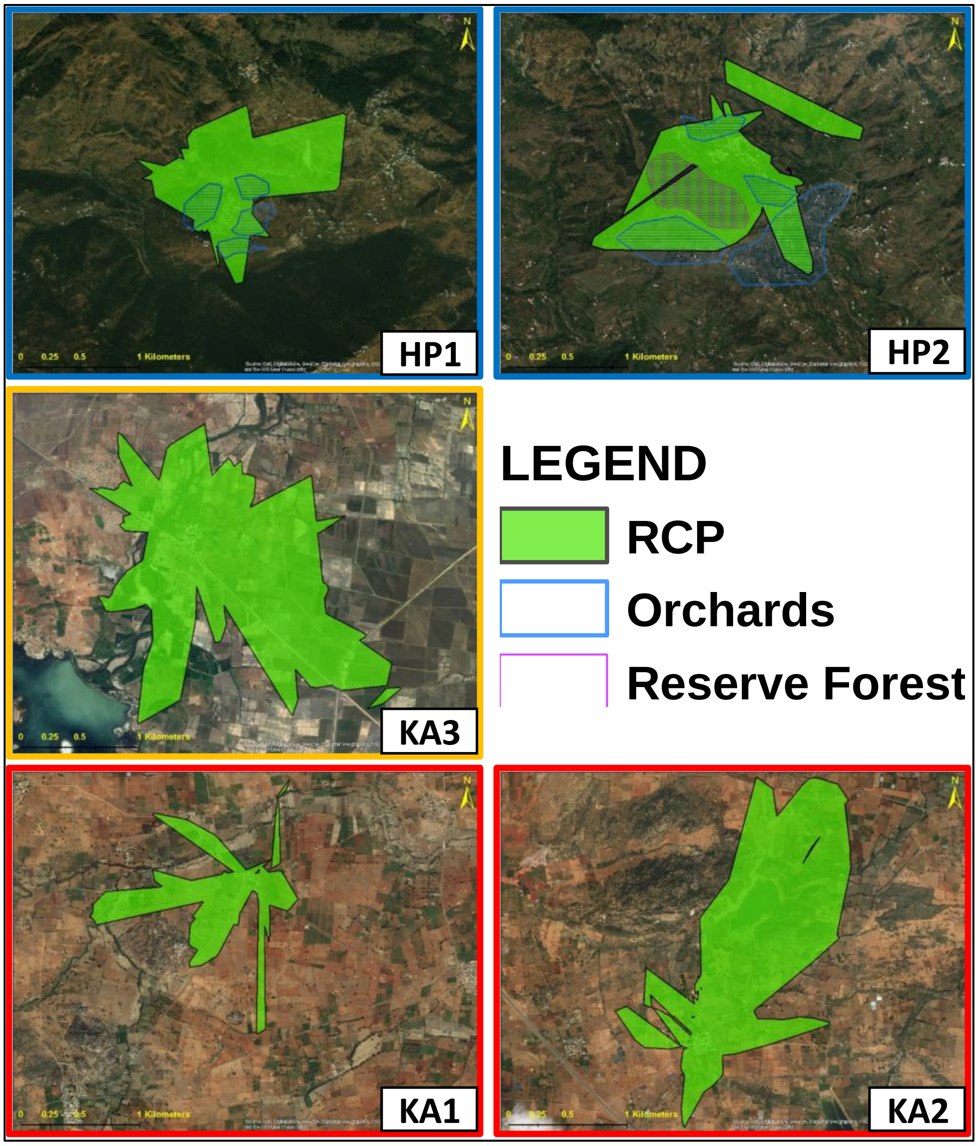

Figure 2.3: Resource collection polygons (RCPs) for each of the five villages (overlaid on Google Earth)[6]

Results indicate that for households in HP1, fuelwood was mainly sourced from private orchards (such as apple, pear, and peach), along with *Pinus roxbughii* from the forest just north of the

[6] The RCP to the north in HP2 belongs to a household which sits slightly removed from the rest of the village, and thus is an outlier in terms of fuelwood collection location and pattern.

village, covering just over 1 km^2. In HP2, the households sourced most of their fuelwood from private orchards and from the reserve forest adjoining the village to the South West resulting in a coverage of approximately 1.35 km^2 (Table 2.3).

Table 2.3: Fuelwood collection locations & distance traveled

Location	Frequented RCP sites	RCP (Sq. km) Area	Max distance traveld
Himachal Pradesh			
HP1	Forest, private orchards	1.01	0.9
HP2	Forest, private orchards	1.35	1.2
Karnataka			
KA1	Forest, along road, private farms	0.76	1.8
KA2	Forest, along road, private farms	2.29	2.5
KA3	Stream, private farms	2.88	2.2

Households in KA1 traveled shorter distances on average (furthest being 1.8 km from village center) than KA3 households and followed a narrower, more concentrated path (which is likely the reason for RCP spanning only around 0.76 km^2). In contrast, KA2 traveled distances similar to those in KA3, for a maximum distance of 2.5 km from the village center, mostly towards the north spanning approximately 2.29 km^2. Households in KA3 concentrated their collection mostly to the south and south east, traveling for a maximum distance of 2.2 km from the village center for an area spanning approximately 2.88 km^2. Here, collection was frequently along the stream and private farms.

Within the RCPs, fuelwood collection was concentrated not only along the polygon boundaries, but also along the route taken (within the polygons) as can be seen in Figure 2.4 - which shows exact locations where fuelwood was collected in red.

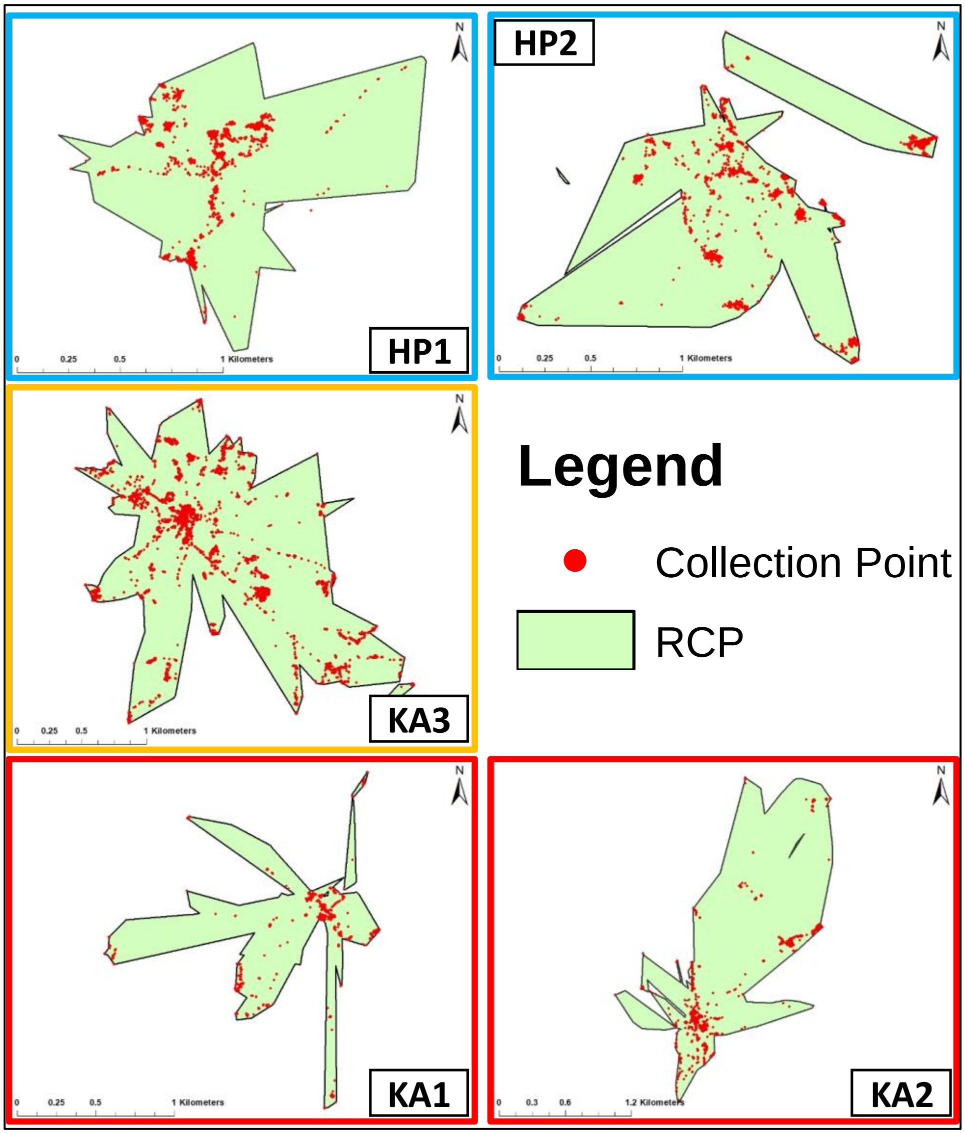

Figure 2.4: RCPs showing fuelwood collection locations (red dots)

2.4 Discussion and conclusion

The International Energy Agency (IEA) estimates that, without a major change in policies, there will still be about 2.3 billion individuals in 2030 who are dependent upon woodfuels and other biomass to meet their basic cooking and heating energy needs (IEA, 2017; World Bank, 2013). Most of this woodfuel consumption (making up to 60 to 80% of total wood consumption) takes place outside the formal economy through self-collection for the use of the household. There is also a formal market which can account for almost 35% of forest income contributing up to 8% of total household income (Angelsen et al., 2014; FAO, 2016). However, regulations or management of resource supply, especially in informal woodfuel collection for self-use is lacking, leading to areas of over harvest and/or unsustainable practices (EUEI PDF, 2009). Instead, if woodfuel resources were to be managed efficiently and sustainably, they could reliably provide resources to households over the long-term and provide a constant source of income for some urban and rural poor. For example, in Rwanda, the value of firewood and charcoal was worth US $122 million (about 5% of the gross domestic product) and traded charcoal is worth US $55 million a year, more than the electricity sector (EUEI PDF, 2009). Thus, it is essential to understand woodfuel extraction behavior to ensure long-term sustainable management of its supply.

However, research on specific distances, locations, or times required for collection is limited, particularly spatially explicit measures of collection. Previous research has often assumed a few kilometer radius around a village as a measure of woodfuel/fuelwood collection area to be used for analysis as the collection boundary, or to aggregate data at an administrative or regional scale (e.g., Top et al., 2006, Bailis et al., 2015). Filling in this knowledge gap requires additional tools to understand spatial collection patterns and this study demonstrates one such potential tool. Using modern GPS technology and methodologies from the study of animal movement patterns, I was able to better understand where households travel for fuelwood collection. With the application of my technique (i.e., RCP), it is possible to identify specific polygons within which the collection is occurring. The RCP includes all areas where a member of the household traveled to collect fuelwood. It gives equal weight to all fuel collection trips within the polygon, such that even if one household went in a particular direction, it is included in the RCP. In addition, using the GPS track data the exact collection points can be identified. Such data can help identify specific regions within the RCP where the extraction impact may be greatest.

The RCP results show specific patterns in distance traveled and location unique to each village, within and between regions. In general, these variations in RCP shape (direction, location, & distance) could be a result of various factors, such as: a) proximity of the village to forest and orchards; b) quality of crop residue; and c) socio-demographics (such as caste, land ownership etc.). In my study sites, I find a number of factors within these three categories that could explain differences in RCPs.

Proximity of village to forests might be a reason for Karnataka households covering larger distances, on average, than those in Himachal Pradesh. Forests in Koppal were about a kilometer away from KA1 and KA2, there was no forest in proximity of KA3, and in Kullu the forests were adjoining the two villages. Another reason affecting distance and time required for fuelwood collection could be the nature and quality of forest resources. Households in Karnataka might have to travel farther and longer, given poorly stocked forests, to collect similar quantities of fuelwood as in Kullu, which has dense alpine forests. Thus, proximity and quality of forest cover could be guiding factors in the distance traveled by households, while location of the forest could explain the preferred direction of travel for fuelwood collection.

The quality and quantity of farm residue, used along with/or in place of fuelwood, to meet daily cooking requirements also impacts RCP shape and size. Farmlands are often a major source of fuelwood (accounting for almost 78% in one study) (Kituyi et al., 2001), and households are more likely to collect from trees on their farms (Pattanayak et al., 2004). Farm residue in Karnataka consists mainly of low quality crop by-products (e.g., maize cobs, rice husk) which require large quantities to meet cooking energy demands, while farm residue in Himachal Pradesh is of higher quality consisting of orchard tree trimmings (e.g., apple, pear, peach). Households in Kullu indicated that the trimmings from orchards after harvest were usually sufficient to meet most of the household winter heating and cooking needs, with minimal supplementation of fuelwood from local forests. However, I also observe that while RCP in Koppal was directed towards the nearby forests, private farms seemed to provide sufficient fuel for the households in Raichur. I lack farm location data for Koppal and Raichur, thus, interpretation of the results might differ if I were to obtain such data.

In addition to the local bio-geography, various socio-economic and demographic factors might also explain the chosen RCP patterns at the various villages. Since all households in Kullu own tree-based agricultural land and almost all these households work solely on their own piece of land, they tend to supplement most of their fuelwood from private orchard trimmings. In Koppal, the agricultural activities are not tree based as with the fruit orchards in Kullu. The fuel available from such farms is largely from shrubs and trees bordering the fields or along the roads. In addition, many households work on other tracts of land as laborers, and might not be allowed to cut fuelwood from another owner's land. Thus, it is likely they rely more on forest collection in addition to roadsides and small amounts from farms. Research by Kohlin, Parks, Barbier, and Burgess (2001) suggests that, in Koppal, the lower social standing (i.e., wealth and social caste) of the households might affect their access to cleaner cooking fuels, and thus impact collection distance, where they travel longer and farther to collect more fuelwood to meet daily needs.

While the RCP methodology described in this paper provides useful information on collection patterns, it does have some limitations. First, the RCPs do not identify which route is dominant over others (i.e., density), as it is beyond its scope. The purpose of the RCPs is to estimate the area of extraction, and to demonstrate the utility and advantage of a new tool in identification of the specific region of extraction. The fact that one household traversed the route for collection means it is also accessible by other households and needs to be included within the local resource collection boundary. As stated before, the RCP identify all possible locations of collection rather than the density of collection, for which other methods such as Kernel density are more suited. This has been partially mitigated by looking at specific collection points to partially determine if the shape of the RCP is driven by small numbers of collection points at the edge of the RCP. Moreover, as seen in Figure 2.4, collection was not concentrated along the edges of the RCPs, but also within it along the route taken (within the polygons). However, this detail is not enough to identify the intensity of extraction, but rather points only to locations within the RCPs where extraction takes place.

Second, collection of GPS data for constructing RCPs entails financial costs and some additional effort for data collection. However, while household surveys are cheaper and can be implemented with larger sample sizes, GPS monitoring of fuelwood collection behavior is preferable for capturing actual location, distance, and time information compared to self-reported measures. The surveys are useful however in providing a means to compare some of the potential determinants of fuelwood collection behavior and of the RCP. The RCP also provides definite boundaries of fuelwood collection that could be integrated into existing models such as WISDOM or MoFuSS to obtain more precise data on sustainability of extraction. This improved understanding of collection patterns could identify local fuelwood hotspots, where extraction exceeds growth of local resources, and help to prioritize interventions and forest management plans. It could also inform future intervention programs in communities where collection distances are increasing. Collection of GPS track data and use of the RCPs should be considered for contexts where spatial distribution of fuelwood and woodfuel collection may be particularly important (e.g., near reserve forests).

Third, there is the possibility of a self-selection bias. It is possible that participants in the study were those who only collect from farms and/or legal areas, whereas those collecting from illegal areas (i.e., protected forests) may choose not to participate in the study. Therefore, the RCPs presented may not be representative of the communities' entire fuel collection behavior. While this is not a major concern since the purpose of my study is to show feasibility of applying home range analysis to human fuelwood collection behavior, future studies should be aware of any potential self-selection bias during study design and participant recruitment. It should also be noted that the GPS data collection was restricted to one season only. For example, GPS monitoring of fuelwood collection was conducted during a non-farming season, but collection behavior may be different during farming season where households may combine fuelwood collection with farm work. Future studies should consider these seasonal or temporal variations that may influence RCP patterns.

Overall, despite these limitations, my study makes an important contribution to a limited body of knowledge on fuelwood collection practices. Through this unique application of wildlife home range techniques for understanding fuelwood collection area, I was able to identify local patterns and preferences by households for fuelwood collection. This information in itself is a rich addition and an advancement in the understanding of fuelwood extraction impacts and concentration. My research provides a base to build upon for further, more detailed analysis (for example, using kernel density to estimate frequency of use).

While my study identified household fuelwood collection patterns across five geographically different communities in rural India, the tool is not limited to this region. Application of RCPs to other regions dependent on solid fuels, especially in Sub-Saharan Africa, would be helpful to study similarities and differences between regions. It can help in better identification and understanding of fuelwood collection and charcoal production patterns, and identify specific factors that impact these differences or similarities. By isolating preferred clusters of extraction, we can better manage local resources to ensure long-term sustainable supply for the dependent communities. For areas of significant forest pressure as exists where charcoal production is high in Sub-Saharan Africa, tools such as RCPs could prove quite useful in creating management plans. Future work could involve showing the RCPs to households and asking for their assessment of whether they are a more accurate representation of the fuelwood supply shed for their village than a circular buffer.

Better GPS data collected for the intended purpose of home range analysis, could help researchers understand the impact of a transition to cleaner cooking technology. It would be possible to identify frequency of use and stratify household fuelwood collection preferences on the basis of traditional versus improved and cleaner stoves to identify post intervention behavior change in fuelwood collection. RCPs can also help with improved understanding of local forest impacts and answer the questions around sustainable extraction and renewability of fuelwood consumption. Finally, as the first attempt to map out household fuelwood collection areas, it serves as an example of how such tools can be applied in the future to various fields of human consumption patterns. It can also be applied to other fields to better understand resource dependencies such as water collection behavior or food foraging patterns. Such information would be useful especially in the light of climate change and the risk of increased droughts and water shortages, such as in Sub-Saharan Africa.

Chapter 3: Local collection – regional measurement: the impact of spatial scale on assessing biomass stock changes relevant to fuelwood interventions

3.1 Introduction

As noted in Chapters 1 and 2, the use of biomass for cooking is widespread and can have a number of potentially negative social and environmental consequences. This chapter focuses on one of those consequences - the possibility of the biomass being harvested unsustainably. Unsustainable extraction of biomass near communities can often lead to forest degradation resulting in negative impacts on the environment and reduced ability to mitigate climate change, as well as associated impacts on ecosystem services (Bhatt & Sachan, 2004; Foley et al., 2007; Heltberg, 2005; Hosier, 1993; Rajwar & Kumar, 2011).

Sustainability of fuelwood consumption is dependent on local fuelwood demand and the supply (or growth) of local forest resources. Harvesting is sustainable if the annual amount of fuelwood extracted from a given area is below the annual growth rate of biomass resources. Fuelwood extraction in excess of the growth rate has been termed "non-renewable biomass" (NRB), and areas under non-sustainable extraction have been termed "fuelwood hotspots" (Bailis et al., 2015; Clean Development Mechanism (CDM), 2015, 2018). Understanding the level at which fuelwood extraction is unsustainable requires analyses of the spatial and behavioral dynamics of fuelwood supply and demand (Masera et al., 2006; Rehfuess etal., 2010). In particular, the assessment includes determining where fuelwood is extracted, what and how much is consumed, and how biomass supply stocks change over time in the area under consideration. While there is considerable research on fuelwood demand at national (e.g., Ghilardi 2007) and local levels

(Bhatt, Negi, & Todaria, 1994; Kumar & Sharma, 2009; Singh, Rawat, & Verma, 2010), research is limited on the supply of biomass for household use (exceptions include Bailis et al., 2015; Masera et al., 2006). Consequently, in this chapter, I examined the role of spatial extents of forest resources on average annual changes in biomass stocks over a 14 year period (i.e., 2002-2016), as well as changes in fuelwood stocks. First, I examined aboveground biomass stock changes (BSC) including both boles (i.e., main stems) and branches of trees. More important, since fuelwood collection was commonly based on collection of branches alone in the areas studied, I also examined fuelwood biomass stock changes based on branch biomass only, but not deadwood as this data was unavailable to me. It is important to keep in mind that I am more interested to show the impact of spatial scale on biomass estimates rather than focusing on the absolute numbers itself from the analysis.

Biomass stock changes are impacted by various factors, including natural disturbances (e.g., floods, landslides, fires, and insects, etc.), fuelwood collection habits of the local community, Landuse/Landcover (LULC) changes, and non-fuelwood related drivers of change (e.g., commercial timber extraction). At larger aggregated scales, aboveground biomass stock changes average out impacts of local household extraction behavior with these other sources of change. At the local scale, aboveground BSC largely excludes major impacts of LULC, and industrial or commercial extraction, although it might still be impacted by natural disturbances. As a result, aboveground BSC estimates at larger scales would not be expected to provide accurate estimates of fuelwood extraction impacts or NRB, as they would include other drivers of BSC. Alternately, fuelwood BSC is largely impacted by household fuelwood extraction especially at the local scale. Thus, a negative fuelwood BSC at the local scale likely indicates the level of

NRB due to household fuelwood consumption behavior. Yet, current methodologies and guidelines to estimate fuelwood extraction impacts or for estimating NRB are unclear about the biomass components included and about the spatial extent, often suggesting the use of large spatial scales (regional or even national level values) (CDM 2015, 2018).

Calculation of NRB requires estimates of harvest (fuelwood and other extraction) and growth of biomass resources in the region. Current methodologies (CDM 2015, 2018) and models (Ghilardi et al., 2016; Masera et al., 2006) to estimate NRB use mean annual increment (MAI) as a measure of biomass growth in the region. For many jurisdictions, MAI has been calculated as the cumulative biomass stocks up to the time when the forest area is measured, divided by the time (years or months) since the forest was established (Bailis et al., 2015). However, for a given stand of trees, MAI increases from stand establishment reaching a peak growth rate at maturity, and then declines (Kershaw, Ducey, Beers, & Husch, 2016, p. 459). The rate of increase and the time at which the peak occurs varies with species composition and age of stands due to differential growth rates. As a result, MAI changes depending on the year of measurement given the growth trends of each stand, as well as with natural and human disturbance factors causing re-establishment of stands (e.g., fire, harvests, floods, etc.). An accurate assessment of forest sustainability over a foreseeable time horizon and under biomass extraction requires using a complex forest management decision support system (FMDSS) to simulate growth of each stand under natural and/or human disturbances. These complex FMDSS models couple accurate forest inventory data with growth and yield models, essential for assessing forest biomass extraction sustainability under different management scenarios (e.g., timber cutting methods including selection or clearcutting, extraction of branches for fuelwood, replanting to single or multiple species, reforestation programs, permanent harvest exclusion zones, etc.) (Segura, Ray & Maroto, 2014). However, accurate forest inventory, and required growth and yield models, along with the skilled professionals required to build and run these FMDSS models, are lacking for many areas of the global south. Unfortunately, those are precisely the areas with high populations and high fuelwood extraction rates and the need for data and models to guide decision-making.

Instead of using an FMDSS model, commonly, a single MAI for a forest area is often calculated and used to estimate NRB. This single MAI has been used in modelling fuelwood supply and demand in models such as WISDOM (Woodfuel Integrated Supply / Demand Overview Mapping) (Masera et al., 2006; Ghilardi et al., 2009). MoFuSS (Modeling Fuelwood Savings Scenarios) builds upon WISDOM to simulate future forest cover and incorporates uncertainties for data-poor landscapes, and savings from reduced fuelwood consumption (Ghilardi et al., 2016). Further, site-specific processes can be integrated into MoFuSS. However, both models exclude branches and deadwood from analyses, whereas fuelwood demand is often met by cutting branches, and collecting snags and deadwood, not by felling live trees (Abbot & Homewood, 1999; Fairhead & Leach, 1996; Morton & Morton, 2007). Also, these models are unable to incorporate the variable fuelwood consumption between communities and estimate it at a more aggregate level (Ghilardi et al., 2009; Johnson et al., 2010). MAI is based on a large spatial extent using low resolution satellite imagery data coupled with national forest inventories (where possible) and national level data from the United Nations Food and Agricultural Organization (FAO). This information is insufficient for identifying differences at the community level.

However, even calculating a single MAI for a forest area for use in these supply and demand models is problematic. While estimating aboveground biomass stocks for an area at a given time can be done using remotely sensed imagery coupled with ground measured plots for the numerator of this MAI, there is ambiguity on the number of years (or months) to be used as the denominator. The time since establishment will vary for each stand within the forest area. As another alternative growth measure, periodic annual increment (PAI), defined as average annual growth of the forest stand during a specific time period, could be used. For this, estimates of biomass stocks at two points of time are required to estimate stock change, which is then divided by the measurement period to obtain PAI. While MAI is always positive, PAI can also be negative since biomass stocks will decline over time if reductions in biomass stocks from human and/or natural disturbances exceed growth of remaining stands (Kershaw et al., 2016, p. 459).

Using simple MAI for a region, extraction is assumed to be sustainable with zero NRB, when it does not exceed the MAI for the region (Bailis et al., 2015). Similarly, a zero or positive PAI indicates that forest stocks have not declined over the measurement period, demonstrating sustainability. Further, using fuelwood BSC, a non-negative PAI points towards sustainable fuelwood harvest. However, as noted, temporal (i.e., time period) and spatial (i.e., area under consideration) extents impact both MAI and PAI, as they affect stand growth rates and natural/human disturbances, including the frequency and intensity of fuelwood extraction (Franklin, Moskal, Lavigne, & Pugh, 2000; Pinzón, Ewel, & Putz, 2003).

Beyond the need for more accurate assessment of changes in biomass stock in order to evaluate local forest impacts, the degree of sustainability of biomass harvesting has taken on additional importance due to its link to global climate change. To reduce negative impacts of fuelwood extraction on forest resources and greenhouse gases from incomplete combustion in inefficient traditional cooking systems, a transition to improved (ICS) and clean cookstoves (CCS)[7] has been promoted for decades (Armendáriz-Arnez et al., 2010; Barnes, 1994; Johnson et al., 2007; Singh et al., 2017). However, the rates of adoption have consistently stayed low, often due to high costs of dissemination and the inability of consumers to finance the improved technology and fuels (Pattanayak & Pfaff, 2009; Wallmo & Jacobson, 2002). Consequently, in the last decade, carbon revenue has become an important tool in realizing ICS/CCS projects (Johnson et al., 2015) by enabling low consumer costs and providing access to long-term financing for adoption of stoves (Adler, 2010; Bumpus & Liverman, 2008; Jeuland & Pattanayak, 2012; Liverman, 2010). The emission reductions for ICS/CCS are based on switching from non-renewable (i.e., unsustainably extracted) to renewable biomass (i.e., sustainably extracted) and/or modern fuels (e.g., LPG), and this value of NRB is an important factor in determining the feasibility of the carbon project (i.e., the number of credits granted) (Freeman & Zerriffi, 2014). The difference in carbon dioxide (CO_2) emissions from renewable vs. non-renewable biomass far outweigh the differences in emissions from using various stove types (Edwards, Smith, Zhang, & Ma, 2004; Freeman & Zerriffi, 2012). However, there is a lack of tools that can consistently estimate the NRB in a region (Johnson, 2009).

[7] Please see Section 1.2 for information on improved and clean cookstoves.

Community-level NRB assessment is essential, as harvesting varies among regions and carbon finance projects are not distributed equally across all communities (Ghilardi et al., 2009; Johnson et al., 2009; Top et al., 2006). However, guidelines and approaches for NRB estimation are based on highly aggregated national values and poor-quality data (CDM, 2015) incorporating high levels of uncertainty (Johnson et al., 2009, 2010; Masera et al., 2006). They do not include specific local heterogeneity, nor account for the impact of local fuelwood harvesting, non-accessible areas, land ownership, and regional diversity of climatic and geographic conditions. As a result, NRB can be over- or under-estimated as it is highly dependent on site-specific variables, such as biomass supply, land cover change, local topography, and fuelwood consumption patterns (Arnold et al., 2006; Johnson et al., 2007; Mahapatra & Mitchell, 1999; Top et al., 2004). While the potential differences between local impacts and larger scale assessments used in the literature have been discussed, there has not been an attempt to date, that I am aware of, to quantify that difference. Therefore, in this chapter, I demonstrate the impacts of spatial extent on biomass stock change estimates, particularly on fuelwood stock changes, for study areas in India to emphasize the need for local values to reflect project-specific behavior (i.e., impact of fuelwood extraction on local forest resources). Specifically, I answered the question: What is the impact of spatial extent on estimates of biomass renewability?

For this purpose, I used PAI over fourteen years from 2002 to 2016, and assumed that this would be implemented in existing supply and demand models such as WISDOM and MoFuSS. In doing so, this research adds to the academic literature, on conducting informative analyses for impacts of fuelwood extraction and ICS/CCS interventions on local forest resources. Such information could maximize benefits by allowing organizations to focus forest management and prioritize ICS/CCS projects in regions where NRB values are highest (i.e., where unsustainable extraction is largest).

3.2 Methods

I conducted the research in two valleys of Kullu district[8] in the northwestern Indian state of Himachal Pradesh. The district has a largely rural population of 438,000 individuals spread across 172 villages with 35% forest cover (Forest Survey of India (FSI), 2015). Fuelwood is the main source of primary cooking energy in the region, and dissemination programs for ICS/CCS have been active for decades. Fuelwood used in traditional cooking technologies consists of mostly snags, lopped branches, and deadwood (Abbot & Homewood, 1999; Fairhead & Leach, 1996; Morton & Morton, 2007).

The district has seen a population growth of 14.76% from 2001 to 2011 with density increasing from 69 individuals/km^2 to 80 individuals/km^2 (MOSPI 2016), adding pressure on surrounding forest resources. The climate ranges from subtropical to alpine, and the altitude varies from 1089m to over 6500m, with most forests occurring between 2800m to 4100m. Valley 1 has an average elevation of 2796m ranging between 1275m to 4525m, with the study villages located at 1600m (Village 1) and 1750m (Village 2) (Figure 3.1). Valley 2 has an average elevation of

[8] For detailed information please refer back to Chapter 1.4.1 Field Site, sub-section 1.4.1.1. Kullu.

3146m ranging between 1050m to 5025m, with the study villages located at 1775m (Village 3) and 1575m (Village 4).

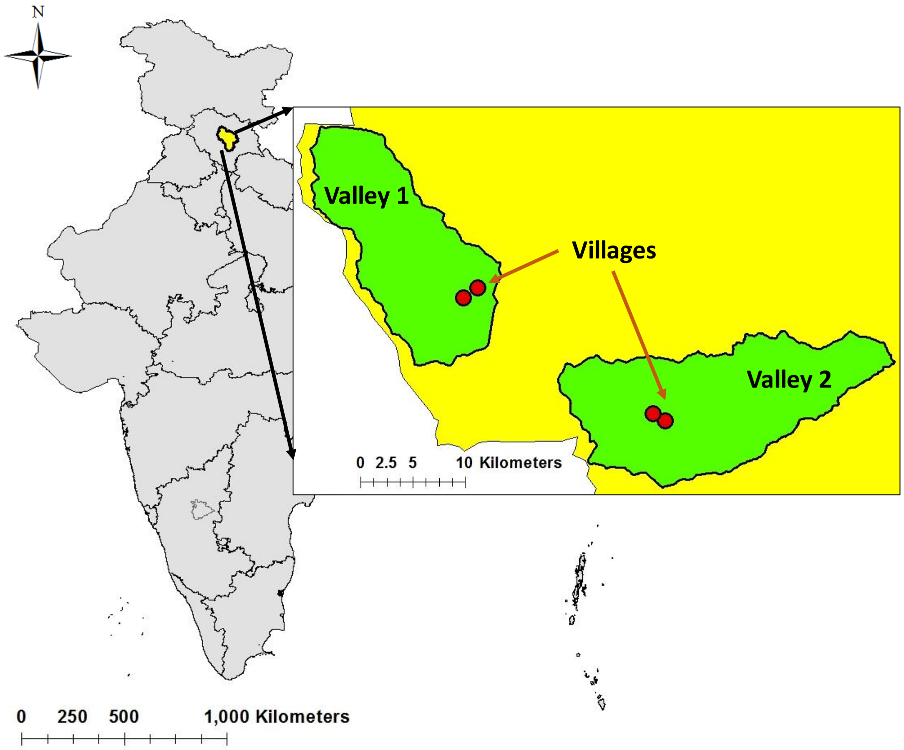

Figure 3.1: Field site location showing the two valleys (green) and villages (red dots).

I calculated ‘aboveground’ (i.e., branches + bole of tree) and ‘fuelwood’ (i.e., branches) biomass stock change (BSC) in tonnes per hectare per year. To show variation in BSC, I used three spatial extents:

1. Valley extent – This is a broad spatial extent that uses valley boundaries as demarcated by the Forest Survey of India (FSI). Valley 1 covers 18,636 hectares (ha) and Valley 2 covers 23,709 ha.

2. Village buffer extent – This spatial extent is bounded by a buffer of 1.5 km radius around each of the four village centers. This buffer was chosen to reflect current methods for estimation of local extraction region (e.g., Top et al., 2004, 2006).
3. Village RCP extent – This spatial extent is defined by the Resource Collection Polygons (RCP) from Chapter 2 (Singh et al., 2018) for two villages covering 101 ha (RCP1) and 135 ha (RCP2).

In all, the study included two Valleys, four village buffers, but only two RCPs (one in each Valley – for Village 1 and Village 3). As an example, Figure 3.2 shows the overlapping 1.5km buffers of Village 1 and Village 2 as well as the RCP for Village 1 (see Chapter 2).

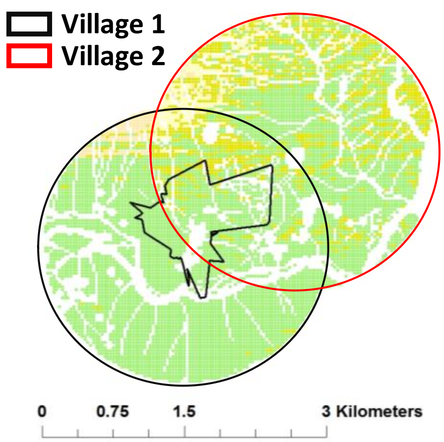

Figure 3.2: Village 1 RCP (black polygon) and Village 1 buffer (black circle), and Village 2 buffer (red circle) in Valley 1.

In this chapter, I used the following data sources:

1. National Forest Inventory (NFI) data, including biomass per plot, from Forest Survey of India (FSI) for 107 square plots covering approximately 0.1 ha each (i.e., 31.62m X 31.62m) (FSI, 2002). None of these NFI plots lay within my Village buffers or RCPs;
2. Elevation contours: 25m resolution elevation contours data from OpenDEM (OpenDEM, n.d.);
3. Landsat-7 (2002) and Landsat-8 (2016) images, courtesy of the U.S. Geological Survey, covering the entire study area at a scale of 1:250,000 with a spatial resolution of 30m pixels. Both images were surface reflectance corrected and thus comparable across time and satellites;
4. Geographic layers of roads, villages, and rivers from Google Earth V9.2 and ESRI World Imagery (DigitalGlobe, 2014); and
5. Landuse/Landcover (LULC) from NASA Earth Explorer: MODIS LULC Type 5 classification, 2013, for 1995 and 2011 (NASA Earth Explorer, 2013).

Data were analyzed using ArcMap 10.4 (ESRI, 2011) and R version 3.5.1 (R Core Team, 2018). Each NFI ground plot collected in 2002 was spatially matched to the 2002 Landsat data. Specifically, I used the ArcMAP 10.4 Intersect tool (ESRI, 2011) and a 20m buffer around each ground plot center. For each plot, I calculated the average values for pixels within the range of this radius, specifically:

1. Landsat reflectance bands for 2002 and 2016. Table 3.1 shows the various bands used from each image, and their wavelengths (in micrometers);

Table 3.1: Landsat 7 (2002) and Landsat 8 (2016): bands and wavelength (in micrometers)

Bands & Wavelength	Landsat 7	Landsat 8
Blue	0.45-0.52	0.452-0.512
Green	0.52-0.60	0.533-0.590
Red	0.63-0.69	0.636-0.673
Near Infrared (NIR)	0.77-0.90	0.851-0.879
SWIR 1	1.55-1.75	1.566-1.651
SWIR 2	2.09-2.35	2.107-2.294
Panchromatic	0.52-0.90	0.503-0.676
TIRS 1	10.40-12.50	10.60-11.19

2. Normalized Difference Moisture Index (Xue & Su, 2017) using Landsat bands:

   NDMI = (Red - NIR) / (Red + NIR)

3. Difference Vegetation Index using Landsat bands:

   DVI = NIR - Red

4. Normalized Difference Vegetation Index (Tucker, 1979) using Landsat bands:

   NDVI = (NIR - Red) / (NIR + Red)

5. Enhanced Vegetation Index using Landsat bands, MODIS-EVI algorithm coefficients:

   EVI = 2.5* (NIR - Red) / (NIR + 6*Red – 7.5*Blue + 1)

Other geographic layers, including elevation, roads, rivers, and villages, were also spatially matched to the NFI ground plots. Next, I fitted alternative lognormal linear models using the R package ‘lme4’ (Douglas et al., 2015; Frank et al., 2018) to estimate aboveground biomass using the matched NFI ground plot-Landsat image-geographic layers data. To select from these alternative models, I used Akaike’s Information Criterion (AIC) as a measure of model accuracy, and selected a model with the lowest AIC (Appendix A). I also considered model parsimony in the selection, where other models did not improve the AIC and/or did not meet the criteria of model parsimony and no lack of fit. Using these criteria, the selected model was:

Estimated Aboveground biomass stock (in tonnes per ha) =

exp {1.3026 + 0.0007 Elevation + 2.1926 NDVI – 0.2065 DVI + 1.4723 NDMI – 0.1314 Blue + 0.1781 NIR}

Where, Elevation is in metres; NDVI, DVI, and NDMI are indices from Landsat data (as defined above); and Blue and NIR are reflectances for these Landsat bands.

Using the selected lognormal aboveground biomass model, I then estimated fuelwood biomass stock as a proportion of aboveground biomass stock using a logistic model within R Package 'lme4' (Douglas et al., 2015). This was estimated as a proportion to reflect current methods used in forest resource assessment where branch biomass is a function of aboveground biomass, which varies across tree species. Moreover, Alternative models were tested (Appendix A), and the selected model, based on lowest AIC was:

Estimated Fuelwood biomass stock proportion =

$$\frac{\exp\left(-4.535 - 0.0001\,\boldsymbol{Elevation} - 0.0051\,\boldsymbol{NDMI} - 0.0001\,\boldsymbol{EVI}\right)}{1 + \exp\left(-4.535 - 0.0001\,\boldsymbol{Elevation} - 0.0051\,\boldsymbol{NDMI} - 0.0001\,\boldsymbol{EVI}\right)}$$

Finally, I multiplied the fuelwood biomass stock proportion with estimated aboveground biomass stock to get fuelwood biomass stock in tonnes using:

Estimated Fuelwood biomass stock = Estimated aboveground biomass stock * estimated fuelwood biomass stock proportion

Resulting estimates were checked for validity by comparing to the range of values in the FSI data.

The selected aboveground biomass model and fuelwood proportions were then applied to each pixel of the 2002 and 2016 Landsat images, to calculate the estimated aboveground and fuelwood biomass (tonnes per ha) for each pixel. Once each pixel was populated with a biomass value from the model, I excluded pixels over 4200m elevation as these locations were above the permanent snowline (Allen et al., 2016). I then conducted spatial imputation using nearest neighbor (using Euclidean distance) for variable space (i.e., using elevation in metres) to replace outliers where estimated aboveground biomass > 2000tonnes/ha, resulting in 52 replacements out of over 6 million pixels.

To calculate the estimated aboveground and fuelwood BSCs, for each spatial extent, first, the biomass in tonnes/ha was converted to tonnes per pixel (i.e., 30 m X 30 m = 0.09 ha). The estimated aboveground BSC was then calculated as:

$$\textbf{BSC (tonnes/ha/yr)} = \frac{\boldsymbol{\Sigma}(\textbf{2016 biomass tonnes per pixel}) - \boldsymbol{\Sigma}(\textbf{2002 biomass tonnes per pixel})}{(\boldsymbol{No.\ hectares}) * (\textbf{14}\ \boldsymbol{years})}$$

Where, the summation and number of hectares were for all pixels within the particular spatial extent. This was repeated for estimated fuelwood biomass, as well as for all spatial extents defined for this study.

3.3 Results

Using the selected models, results indicate that biomass stock change (BSC) varies between Valleys, and within each Valley at the Village level (Table 3.2).

Table 3.2: Aboveground and fuelwood biomass stock change (BSC) in tonnes/ha/yr at various spatial extents over the 14-year period

BSC (tonnes/ha/yr)		Aboveground	Fuelwood
	Valley 1	-9.70	-0.10
Village 1	Buffer	-2.01	-0.02
	RCP	-1.94	-0.02
Village 2	Buffer	-2.83	-0.03
	Valley 2	-9.13	-0.09
Village 3	Buffer	-6.16	-0.06
	RCP	-6.37	-0.06
Village 4	Buffer	-6.42	-0.06

The negative fuelwood BSC at all spatial extents points towards over-extraction in the region, while the magnitude shows the severity of over-extraction. Fuelwood BSC obtained reflects extraction impacts mainly by the households, while aboveground BSC includes all human (e.g., timber harvest, fuelwood extraction, conversion to roads, conversions to agriculture, etc.) and natural (e.g., landslides, fires, etc.) disturbances occurring between 2002 and 2016.

At the larger Valley spatial extent, aboveground and fuelwood BSC are more similar between the two valleys, than at the local Village extent. Aboveground and fuelwood BSC declined in Valley 1 by 9.7 tonnes/ha/yr and 0.1 tonnes/ha/ yr, respectively, while they declined in Valley 2 by 9.13 tonnes/ha/yr and 0.09 tonnes/ha/yr, respectively. Moreover, while Valley 1 had a larger decline in both aboveground and fuelwood BSC, the villages of Valley 2 observed larger declines in BSC. Thus, the greater decline in biomass resources at the Village buffer scale in Valley 2 likely indicated averaging out of biomass changes at the broader spatial extent.

At the local Village buffer spatial extent, both aboveground and fuelwood BSCs varied substantially between the two Valleys over the 14-year period. The decline in aboveground BSC for Village 1 (2.01 tonnes/ha/yr) and Village 2 (2.83 tonnes/ha/yr) was less than the declines for Village 3 (6.16 tonnes/ha/yr) and Village 4 (6.42 tonnes/ha/yr). Similarly, decline in fuelwood BSC for Village 1 (0.02 tonnes/ha/yr) and Village 2 (0.03 tonnes/ha/yr) was less than the declines for Village 3 (0.06 tonnes/ha/yr) and Village 4 (0.06 tonnes/ha/yr). Moreover, while decline in fuelwood BSC for Villages 3 and 4 was the same, there were differences in decline of aboveground BSC for the two.

There was also a variation in the aboveground BSC between the 1.5km buffer of a Village and its respective resource collection polygon (RCP). The decline in aboveground BSC for Village 1 buffer (2.01 tonnes/ha/yr) differed from its RCP (1.94 tonnes/ha/yr), and, also, for Village 3 buffer (6.16 tonnes/ha/yr) and its RCP (6.37 tonnes/ha/yr). However, fuelwood BSC was the same between Village 1 buffer and its RCP, and for Village 3 buffer and its RCP.

3.4 Discussion and conclusion

Sustainability of fuelwood consumption is dependent on local fuelwood demand and the supply (or growth) of local forest resources. An increase in population density, especially rural population dependent on fuelwood, puts increased pressure on surrounding biomass resources (Top et al., 2006). Moreover, when extraction exceeds the growth of local forest resources, it can lead to the use of unsustainably extracted fuelwood, called non-renewable biomass (NRB). Research suggests that households tend to respond to fuelwood scarcity by increasing collection efforts rather than by reducing consumption or substituting between fuels (Damte et al., 2011; Heltberg et al., 2000). Increased collection efforts include either a higher intensity of extraction from local forest resources, and/or the expansion of extraction area.

Increased extraction intensity to meet growing population and fuelwood demands could lead to higher NRB values and a negative fuelwood BSC. Conversely, expansion of the extraction area could have more variable impacts on these estimates, in particular: a) the larger region might include areas with forest cover away from human settlement and thus a lower or zero fuelwood NRB value; or b) it could include more non-productive regions resulting in a higher NRB. In Kullu, population density in the past decade has risen without a substantial decrease in the proportion of households dependent on fuelwood (MOSPI 2016). Consequently, there has been an increased fuelwood demand in the region. This demand is likely to have been met through increasing resource extraction intensity, rather than an increase in extraction area, because unofficial village collection boundaries are respected by households and they usually do not collect outside of these areas.

Results showed that at all spatial extents there was a decline in overall biomass stocks between 2002 and 2016, with differences in the magnitude of decline in BSC between the various spatial extents. The decline in BSC for the Village buffers and RCPs was much smaller than the decline in BSC for the Valleys. Moreover, while Valley 1 had a larger decline in both aboveground and fuelwood BSC, the Villages of Valley 2 observed larger declines in BSC. Thus, local village impacts seemed to be averaged out at the larger spatial extent due to LULC changes (i.e., conversion of forests), and due to increased population and urbanization in Kullu (SEDAC, 2017). At the Village extent, the impact on forest resources was mainly a result of household fuelwood extraction activities, which does not necessarily result in high degradation or deforestation, as fuelwood extraction largely consists of branches and deadwood, not whole trees (Abbot & Homewood, 1999; Fairhead & Leach, 1996; Morton & Morton, 2007). However, at the Valley extent, major LULC changes over time have included dense forests converted to open forests or grasslands (NASA Earth Explorer, 2013). Thus, there was a greater decline in aboveground and fuelwood BSC at this larger extent, than at the smaller Village extent. Consequently, using larger spatial extents could wrongly allocate negative impacts to local populations when the decline in stocks could likely be a result of LULC change and other commercial extraction. These results highlight the importance of using local Village estimates to isolate fuelwood extraction impacts, as these estimates vary considerably between Valleys.

At the Village extent, there was a substantial variation in BSC for Villages between the two Valleys, while there was lesser variation in BSC of Villages within a Valley. Impact on biomass stocks from fuelwood extraction differed between Villages due to various physical (e.g., elevation, weather) and socio-economic factors (e.g., wealth, accessibility, etc.). In Valley 1, there was a reforestation program as part of the Joint Forest Management program with the Indian Forest Service in the early 90s (Van ’t Veld et al., 2006). The resulting increase in biomass from the program is reflected in Village 1, which had the lowest decline in aboveground and fuelwood BSC (both for the buffer and RCP), as it includes parts of this reforested area. The positive biomass impact of reforestation could also be seen in Village 2, given its proximity and overlap in collection area with Village 1. In contrast, there was no such initiative in Valley 2, that I am aware of, and notice a greater decline in biomass stocks for

Villages 3 and 4 compared to the Villages of Valley 1. Moreover, areas around the Villages in Valley 2 have seen a decline in forest cover over the years, given conversion to cropland and orchards (NASA Earth Explorer, 2013). This could explain the much higher aboveground biomass stock changes relative to fuelwood stock changes in the local assessments for Valley 2 as compared to Valley 1.

At the Village level, there were differences in aboveground BSC using the 1.5km buffers for Villages versus the RCPs, but little to no difference in fuelwood BSCs. RCPs encompass all those areas where households of the village gather fuelwood (Chapter 2), but the difference in the aboveground BSCs points towards the possible inclusion of external factors (e.g., natural disturbances, expansion of agricultural land, etc.) encompassed in the larger area using the 1.5km buffer around the village center. As households are selective on the location for collection based on various physical and socio-economic characteristics (Chapter 2), taking a simple radius around the village center to represent true extraction area, which is often used (e.g., Top et al., 2004; 2006), might not accurately reflect all local impacts, positive or negative, on surrounding forest resources. However, given the similarity in fuelwood BSC for the two, when it comes to fuelwood extraction, buffers could be initially used to determine the eligibility of villages for interventions. Once available, the RCPs could be utilized in a more targeted fashion to determine actual impacts on forest resources due to household collection behavior. Furthermore, differences between the two might arise in locations that are not surrounded by dense forests as in Kullu, such as in semi-arid regions of southern India which is scattered with sparse vegetation and barely any forest cover.

My analysis does suffer from some limitations. I was not able to account for natural disturbances, nor was I able to confirm the results at such a local scale from publicly available records for the area. Access to better forest inventory data and other GIS layers could make my estimates more reflective of the biomass stock in the region. Additionally, the decision to avoid the use of complex forest resources management decision support (FMDSS) models to obtain estimates of BSC under different management scenarios was based upon two factors. First, there was a lack of access to reliable inventory data for the region and lack of growth and yield models needed to forecast alternative scenarios. Second, FMDSS models have not been used to evaluate sustainability of biomass extraction required for carbon crediting methodologies following clean cooking interventions in many areas of the global south due to a lack of required expertise. Unfortunately, those are precisely the areas with high populations and high fuelwood extraction rates, highlighting the needs for accurate data and models to guide decision-making. However, I used estimated biomass stock changes, here PAI, which have been used in demand and supply models such as WISDOM and MoFuSS applied to a number of countries.

At larger aggregated scales, aboveground BSC estimates do not provide accurate estimates of fuelwood extraction impacts or NRB, as they include other drivers of BSC (i.e., all natural and human disturbances over time). Alternately, fuelwood BSC is largely impacted by household fuelwood extraction especially at the local scale. Thus, at the Village extent, negative fuelwood BSC largely indicates the amount of NRB or over-extraction due to household consumption behavior, but zero or positive fuelwood BSC could indicate sustainable extraction practices. However, not only are current biomass estimates for carbon crediting methodologies based on a one-time MAI, they are also estimated at a larger aggregated scales which do not reflect the actual extraction area. National estimates (for NRB) or aggregated extents do not accurately capture the isolated effect of fuelwood harvesting as they can incorporate other significant drivers of biomass stock change, and are unable to incorporate local/regional differences in household consumption and collection behavior. Biomass stocks vary considerably depending on differences in elevation, precipitation, location of rivers, roads and villages, and natural disturbances such as wildfires, landslides and ice storms. Aggregated scales fail to capture these variations that occur at the Village level as seen by the differences in aboveground BSC for the Valleys, and the 1.5km Village buffers and their RCPs. Even though I did not look at national numbers and only compared Valleys or Villages, my analysis does show large variations between these two extents, and variations are likely to be of a larger magnitude at national levels due to higher variability in resources when areas range greatly such as from tropical forests to barren desserts.

My analyses act as a proof of principal for more spatially explicit measures to estimate project-specific NRB to avoid averaging out impacts using the landscape level, and they also build a case for using the fuelwood biomass proportion to isolate impacts of household collection behavior. Existing woodfuel models such as WISDOM and MoFuSS estimate biomass stock changes at larger spatial extents, as does current national forest inventory data which aggregates forest biomass stocks to district or regional extents (e.g., annual State of Forests report by the Forest Survey of India) (FSI, 2015).

Larger extents can lead to substantial inaccuracies in calculation of fuelwood supply (Johnson et al., 2009) by failing to account for non-accessible areas, topography, LULC, and localized biomass extraction (Masera et al., 2006; Johnson et al., 2007; Top et al., 2006). A local extent for calculating NRB is essential to reflect extraction impacts on biomass stocks for the region where carbon credits and clean cooking interventions are undertaken. Spatially explicit analyses can help focus and prioritize projects in regions where the NRB values are highest since changes can be more justifiably attributed to fuelwood extraction as opposed to other drivers, and especially when only fuelwood biomass is included. These analyses could help maximize local benefits (e.g., income from carbon sales) of clean cooking interventions by allowing organizations to estimate NRB at a project level. Results could indicate the extent of carbon neutrality of communities, as well as the impacts of fuelwood collection on forest resources.

Nonetheless, while local estimates are valued, there are many issues associated with obtaining the data and other information required. In regions where the impact of fuelwood extraction on forests may be the greatest (e.g., rural areas of developing countries), forest inventory data may be extremely hard to get given bureaucratic barriers and lack of digitization of data. Even if such digitized data exists, growth and yield models to forecast this forest inventory under different scenarios is very often not available. This highlights the need more broadly for improved field data collection, including repeated measures permanent sample plots needed for developing growth and yield models in these regions, along with associated technical support. Along with these difficulties, estimating RCPs is extremely time consuming and expensive, requiring field staff and GPS loggers. Moreover, many organizations that apply for carbon credits are small NGO's that lack the highly skilled and experienced field staff to collect field data, let alone to develop and then run complex FMDSS models to estimate biomass stock changes under different forest management and climate scenarios.

The case for smaller-scale and, ideally, village localized biomass assessments is, therefore, counter-balanced by the difficulties in obtaining forest inventory data and growth and yield models, fuelwood collection behavior data, and having skilled practitioners to build and run complex models. Future research will seek to bridge that gap and seek methods for reducing the data load and model complexity to capture at least part of the impact of smaller scale assessments. Research could focus on estimating biomass stocks before and after a clean cooking intervention using longitudinal data to identify direct impacts of the intervention on forest resources. Incorporating some of the insights gained from my analysis and from Chapter 2 (Singh et al., 2018) into the larger scale fuelwood supply and demand modeling exercises (e.g., MoFuSS) is underway as one avenue for using the data to improve existing models. At the same time, the degree to which the increased accuracy of biomass stock change at the local level is required is as much a policy decision as it is a technical decision. This should be a topic of discussion among the research, policy-making and implementation communities across both the clean cooking and carbon credit domains as trade-offs will need to be made between accuracy and data acquisition and processing.

Chapter 4: Forest, farms and fuelwood: measuring changes in fuelwood collection and consumption behavior from a clean cooking intervention

4.1 Introduction

In Chapter 2, I provided a method to determine where households collect fuelwood. In Chapter 3, I showed the importance of scale in understanding the impact of fuelwood extraction on the biomass resource base. In this chapter, I examine the impact of a clean cooking intervention[9] (i.e., improved and clean cookstoves) on fuelwood use.

A transition to improved (ICS) and clean cookstoves (CCS) is desirable not only from an environmental perspective, due to their potential positive impacts on forest resources from the reduced use of fuelwood and climate change from reduced emissions, but also for improved human health due to reduced smoke inhalation and reduced collection time. Further, ICS/CCS can impact climate change mitigation in two ways: a) through reduced cookstove emissions; and b) through conservation of forest stocks. Moreover, increased forest cover can mitigate impacts of flood events, and provide a variety of other ecosystem services, including wildlife habitats, reductions in air pollution, and improved water quality.

ICS can contribute to a minimum fuelwood saving of 20-35% of fuelwood (Rai & McDonald, 2009), which could suggest positive impacts on forest and society from reduced consumption. Full adoption of a CCS, like one using LPG, would result in an elimination of biomass use in the

[9] Please refer to Chapter 1, sub-section 1.2 for more detailed information on ICS and CCS.

household, again suggesting positive impacts. However, the impact of clean cooking interventions on forest biomass is made more complicated by the fact that households engage in "fuel stacking" (Cheng & Urpelainen, 2014; Ruiz-Mercado & Masera, 2015). This refers to the fact that even when households gain access to ICS/CCS, they often continue the use of fuelwood in traditional cooking technologies. This stacking of fuels reduces the full range of positive impacts on environment and society from ICS/CCS, as the transition does not necessarily mean a substantial reduction in the use of fuelwood.

While knowing the total mass of fuelwood reduced via a clean cooking intervention is useful, it is insufficient on its own for assessing the impact of such interventions on forest biomass stocks, since forests may not be the only source of fuelwood for households. Households can also collect fuelwood from agricultural lands or from other trees and shrubs growing outside forests (e.g., along roadways). As a result, in addition to the fuelwood quantity consumed there is a need for information on the change in fuelwood composition (i.e., fuelwood gathered from forest vs non-forests) that results from the ICS/CCS intervention.

Identifying species composition of fuelwood used can help identify the fuelwood source. In the remainder of this chapter, two fuelwood sources were identified: a) "forest", where species were identified as coming from forestlands; versus b) "farm", where species are primarily found in farms and orchards, but also along roadsides. Information on fuelwood source can isolate the impacts of ICS/CCS interventions on forest stocks and further elucidate the degree of climatic positive impacts from reduced emissions. Identifying the source of reduction in consumption (i.e., farm vs forest) due to a clean cooking intervention is essential for assessing the true impact of the intervention on forest biomass stocks, and goes beyond just climate impacts. For example, reduced consumption of forest fuelwood due to the ICS/CCS intervention would retain or increase forest stocks as carbon sinks, whereas reduced consumption of farm fuelwood might not impact forest stocks even though it might have positive climatic impacts from reduced emissions and retention of carbon sinks. Prior measurements and research of changes in fuel consumption due to clean cooking interventions only measured total mass change in fuelwood and do not differentiate between farms and forests by species. Moreover, literature often assumes that a reduction in consumption (from either source) leads to positive forest impacts, whereas not all wood collected is necessarily from forest sources.

Consequently, to work towards filling this gap in knowledge, I studied household fuelwood consumption behavior changes, if any, due to a clean cooking intervention in India. In particular, I asked the following:

1. Was there a change in total fuelwood consumption due to the clean cooking intervention?
2. Was there a change in fuelwood composition (farm vs. forest) because of the clean cooking intervention?
3. What factors (socio-economic and physical) affect the magnitude of household fuelwood consumption change?

4.1.1 Fuelwood collection and consumption

While fuelwood is an integral part of rural life, and will likely continue to be into the foreseeable future, its collection is labor intensive and demands high levels of human time and energy. As a result, women and children, who are often tasked with its collection, have less time for education and/or other income earning activities, such as agriculture (Agarwal, 2009; Anoko, 2008; Wan et al., 2011). Beyond the enormous human time and energy requirements, fuelwood collection can expose women and children to many dangers, such as attacks by wild animals and/or humans (BAM 2018; UNHCR & FAO, 2017). Collecting fuelwood also imposes emotional stress and physical discomfort on those responsible for its collection (Laxmi et al., 2003; Parikh & Laxmi, 2000; Parikh, 2011). Moreover, as local forest resources become scarce near communities, the energy and time required for collection can increase (Agarwal, 2001; Gbetnkom, 2007; Laxmi et al., 2003; Parikh & Laxmi, 2000; Parikh, 2011), further reducing the time available to women and children for education and/or income pursuits (Cooke, 1998). Fuelwood is a renewable resource, but unsustainable harvesting, especially in densely populated areas of developing countries, can lead to accelerated degradation and depletion of local resources (DeFries & Pandey, 2010; Ghilardi et al., 2007, 2009; Masera et al., 2006).

Researchers have estimated the contribution of unsustainable fuelwood harvesting to forest degradation, deforestation, and climate change for several regions in India (Bhatt & Sachan, 2004; Heltberg, 2005; Rajwar & Kumar, 2011; Samant, Dhar, & Rawal, 2000; Singh, Rawat, & Verma, 2010). Globally, Bailis et al. (2015) presented a spatially-explicit assessment of pan-tropical fuelwood supply and demand to estimate the degree to which demand exceeds growth. Top et al. (2006; 2004) estimated fuelwood consumption patterns in Cambodia at three different distances from the village centers (1, 3 and 5 km radii) and found that high population density was linked to lower forest resource availability. Silori (2004) looked at fuelwood collection and consumption across seasons and altitudes in northern India, and found that easy accessibility to fuelwood in the surrounding forests, cold climatic conditions and the lack of alternatives resources led to higher consumption rates, especially at higher altitudes.

However, research on household responses to fuelwood scarcity is quite variable, and shows different behaviors in different locations and conditions. On one hand, research has shown that households respond to fuelwood scarcity by increasing collection efforts, rather than by reducing its consumption or substituting between fuels (Amacher et al., 1993; Heltberg et al., 2000; Kumar & Hotchkiss, 1988). On the other hand, research suggests that forest dependence can be reduced by increasing forest access costs, use of ICS/CCS and alternate fuels (Pattanayak et al., 2004). For example, locally degraded forest resources led to fuelwood consumption supported by purchasing of fuelwood or charcoal from other sources in Malawi (Jagger & Perez-Heydrich, 2016), increased use of low quality fuels and crop residues in Uganda (Jagger & Kittner, 2017), or consumption from private forests or trees on farms in Nepal (Webb & Dhakal, 2011).

A limited, but growing literature has looked at fuelwood species and their characteristics. For example, Singh et al. (2010) examined 54 trees and 34 shrubs consumed as fuelwood and the impact of tourist season on increased consumption. Madhubansi et al. (2007) assessed the change in fuelwood use following electrification in South Africa, while Arnold et al. (2006) looked at consumption and livelihood changes, and found that fuelwood was the main source of cooking energy, and main source of income from forests for rural Africa and south Asia. Webb and Dhakal (2011) examined collection patterns and drivers of fuelwood consumption, the contribution of public and private sources, as well as the number of species used by households in Nepal. Research has also looked specifically at the consumption and usage patterns of particular species (e.g., *Rhododendron arboretum* by Ranjitkar et al., 2014). Furthermore, the Fuel Value Index (FVI) has been used to screen desirable wood species and their fuelwood properties based on calorific value, density, moisture and ash content of wood (Goel & Behl, 1996). Specific to India, fuelwood properties of indigenous trees and shrubs, based on FVI, have been estimated for the Aravalli mountains (Kumar et al., 2011), Central India (Jain & Singh, 1999), Indian Himalayas (e.g., Bhatt et al., 1994; Bhatt & Tomar, 2002; Bhatt & Sachan, 2004), and Northeast India (e.g., Kataki & Konwer, 2002).

Prior literature has added substantially to our knowledge about fuelwood collection in the face of resource scarcity, fuelwood consumption before and after interventions, and fuelwood species composition. What is largely absent is the connection between fuelwood composition and change in household collection behavior (i.e., fuelwood species preferences and collection locations) due to a transition to cleaner cooking solutions.

4.2 Methods

I measured the quantity of fuelwood consumed by each household through a kitchen performance test (KPT). Specifically, I measured fuelwood consumption in 2015 for all households, termed baseline data. Then, a few households were selected for ICS/CCS (termed ‘treatment’ households), while the others did not receive any ICS/CCS (termed ‘control’ households). Measures were then taken for all households in 2016 and 2017, regardless of whether or not they received the ICS/CCS. For this chapter however, I used measures from 2015 and 2017 only. I then developed models to examine impacts on household fuelwood consumption, with and without ICS/CCS. Specifically, I developed a difference in differences (DiD) regression model. I further examined socio-economic factors that might affect these impacts on household fuelwood consumption. I also examined changes in fuelwood consumption with regards to farm versus forest species compositions. For this chapter, farm sources were from orchards in Kullu but from agricultural land used for crops and agroforestry in Koppal.

4.2.1 Study area and data collection

I focused my research in India as it has the largest fuelwood using population globally (Ki-Moon, 2011; World Bank & IEA, 2017), where over 85% of all wood removals is consumed by 70% of rural and 20% urban households to meet daily cooking requirements (FAO, 2016; MOSPI 2011). I selected two districts across two states in India: Kullu district in the northern state of Himachal Pradesh and Koppal district in the southern state of Karnataka. These sites were selected to allow comparison based on varying fuelwood consumption patterns (i.e., quantity and species), forest resources, agricultural activities, and socio-economic characteristics.

Kullu has a climate ranging from sub-tropical to alpine and a forest cover of 35.60% of its geographical area (FRI 2011; FSI 2015). The altitude varies from 1089m to over 6500m above sea level, resulting in cold winters (with an average low of -2^{0} C) and moderate to hot summers (average high between 25^0 - 30^0 C) (Sah & Mazari, 2007). Households in the region use fuelwood, not only for cooking purposes, but also for heating in winter. Orchard crops such as apple, pear and peach are cultivated on agricultural lands, and branches trimmed following fruit harvests are used to supplement fuelwood from forests for household cooking and heating needs. In contrast, the climate in Koppal is semi-arid with negligible forest cover of 0.34% of its geographical area (FRI 2011; FSI 2015), resulting in a landscape dominated by barren hills, large rocks, open forests and scrubs (Premchander et al., 2003). The region has an average elevation of 500m above sea level, and does not experience major variation in temperatures between summer and winter (GOI 2008). The harvest residue is of lower quality coming from farm crop (e.g., maize, bajra) resulting in cobs and husks, or from trees on farms, and along roads, such as *Dalbergia sissoo*, *Azadiractha indica*, and Eucalyptus species. The past two decades have seen a major depletion of forest and agro-forest resources in the region, resulting in low crop yields and reducing the number of tree species available for fuelwood use (Premchander et al., 2003).

At each of the two sites, four villages were selected, where local partner NGOs had been working on socio-economic issues and disseminating ICS/CCS under various programs (please refer to Chapter 1, sub section 1.4.2 for details on household recruitment). Data in Kullu were collected in April-May and in Koppal in August-September for each of the three years from 2015 to 2017. At each of these eight villages, 12-14 households were recruited, for a total of 53 households each in Kullu and in Koppal.

Data for socioeconomics and demographics were collected through extensive in-home surveys, which were conducted as part of a larger project analyzing ICS/CCS adoption impacts on stove emissions, as well as on climate change (please refer to Menghwani et al., 2019 for details about the larger project). Survey data included the perceived change in forest fuelwood collection distance, education of the main cook, main cook as decision maker for all major household purchases, main cook as the household head, main cook engages in non-agricultural activities, and social caste of the household. These variables were chosen from literature and expert knowledge as influencing fuelwood consumption and collection. I used a wealth index derived from asset ownership data collected for this project using the household surveys (described in Menghwani et al., 2019).

4.2.2 Kitchen performance test (KPT)

The Kitchen Performance Test (KPT) is a field–based longitudinal evaluation of energy consumption by households (HH) through in-home measurements of fuel consumption. I followed a three-day KPT protocol (Bailis et al., 2018)[10], which was modified to include information about fuelwood species. The KPT data were collected for 2015 (baseline) and again two years post-intervention (2 years after the households received ICS/CCS). In each household, for each day, field staff measured the total wet fuelwood weight (kg) consumed by species, moisture content for three random logs per species, the number of meals prepared, and the number of household members present.

[10] Originally prepared by Bailis et al., (2003) for the Household Energy & Health Programme; revised Bailis et al., (2018).

Total dry weight of fuelwood consumed was obtained based on moisture content readings. To obtain fuelwood consumption per household and per capita, the number of household members was converted to average adult equivalents by converting the fractional food requirement by age and gender to that of an adult man. Along with identifying the species of each fuelwood piece, field staff also indicated whether these were from farm or forest sources. Species that could not be identified by field staff as from farm or forest sources were assigned based on household survey results regarding fuelwood collection sources. For example, if a household collected only from farm, then its unknown fuelwood was allocated to farm; however, if a household collected from both farm and forest, it was allocated as 50% from farm and 50% from forest (for more details, please refer to Appendix B).

4.2.3 Difference in differences (DiD) regression

I ran a difference in differences (DiD) regression to estimate the impact of the clean cooking intervention on average fuelwood consumption in Kullu and Koppal. The DiD is a statistical technique mainly used in social sciences and econometrics to estimate the effect of a specific intervention by using longitudinal data from treatment and control groups (Ashenfelter & Card, 1985). DiD isolates the intervention effect by removing the general trends or biases between treatment and control groups over time, called counterfactual effects, which could be a result of permanent differences between the groups (illustrated in Figure 4.1).

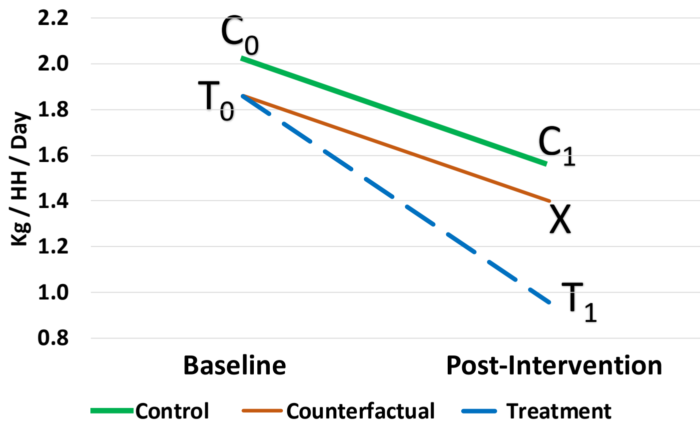

Figure 4.1: Theoretical impact of ICS/CCS on fuelwood consumption: counterfactual line (T_0,X), control (C_0, C_1), and treatment (T_0, T_1) at baseline and post-intervention

The counterfactual line (T_0,X) in Figure 4.1 is the observed impact on treatment households due to external factors impacting all households in a similar manner. Without the DiD, the difference T_1-C_1 could be wrongly attributed to the ICS/CCS intervention. However, given the DiD assumption of parallel trends, X-C_1 would be expected to occur even without the ICS/CCS. Since, the interaction term (i.e., treatment * time) in DiD regression accounts for any difference in starting conditions between households (T_0-C_0) plus any changes that affect both treatment and control households in a similar manner, the pure treatment effect is T_1-X.

Factors that could be expected to influence fuelwood dependence over the time period of the study would include changes in: forest stock, agricultural productivity, fuelwood demand and macro-economic conditions. I expect that the parallel trends assumption for DiD to hold in this case as each village included both treatment and controls, and the villages within a study site were selected to be similar. Both control and treatment households within a village would be impacted by change in forest stocks surrounding the community that could impact their forest resource dependence, extreme weather events which could impact forest resources as well as farm resources, or functions which could lead to increased cooking on certain days of the year (e.g., religious festivals). Moreover, both control and treatment groups included a mix of both upper and lower caste households which would be affected by a change in consumption behavior due to changes in macro-economic conditions. However, it is hard to be certain whether the households were actually impacted or changed their behavior similarly over time.

Consequently, my DiD model was developed to isolate the pure effect of the ICS/CCS intervention on household fuelwood consumption. To account for time correlation (i.e., multiple measures over time for each household), I used 'Maximum Likelihood' or 'Restricted Information Maximum Likelihood' (ML or REML; Pinheiro & Bates, 2000) function within the 'Linear and Nonlinear Mixed Effects Models' (nlme) package in R (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2018). The mixed effects model was selected to account for both the fixed and random effect in our data. Finally, generalized least squares helped estimate the parameters of the DiD while accounting for inequality of variance within the observations. In all, three DiD models were developed: one each for total fuelwood, farm fuelwood, and forest fuelwood consumption. Construction residue[11] was removed from regression analysis for farm and forest DiD, but was included for total wood DiD. The DiD model used was:

Estimated Daily Wood Use (total/farm/forest) in KG

$$= \beta_0 + \beta_1 D_{tr} + \beta_2 D_{post} + \beta_3 (D_{tr} * D_{post})$$

Where, D_{tr} is a dummy variable for treatment (control = 0, treatment = 1) group;

[11] Construction residue consists of construction waste, sawdust, and timber.

D_{post} is a dummy variable for of 0 for pre- and 1 for post - treatment period;

and $\beta_0, \beta_1, \beta_2, \beta_3$ are parameters to be estimated. Of note, the β_3 parameter in these models is the DiD treatment effect, in that this interaction term isolates the impact of the intervention.

Next, I expanded the DiD model to include covariates. This model moves beyond the pure treatment effect by adding several socio-economic factors that might explain the variability in fuelwood use with or without the ICS/CCS treatment. The specific factors considered were:

a) Main cook as decision maker for all major household purchases (MC_decision);

b) Perceived forest fuelwood collection distance increase (wood_collection);

c) Non-solid fuel stove use in baseline (nsfB);

d) Non-solid fuel stove use post-intervention (nsfT);

e) Household head as main cook (HHH_MC);

f) Main cook has a minimum of high school education (MC_education);

g) Average number of adults in the household; and

h) Wealth index of the household (WI).

For all of the above, expect for the number of adults and wealth index, "yes" was numerically represented as 1, whereas "no" was represented as 0. These factors were selected since they have been shown in literature as having an impact on fuelwood and stove decision-making (Menghwani et al., 2019; Puzzolo et al., 2016; Rehfuess et al., 2014; Stanistreet et al., 2014).

The selection of these socio-economic factors to include in a model was based on the Akaike information criterion (AIC), where a lower AIC indicates greater support for the model

(Sakamoto, Ishiguro, & Kitagawa, 1986). Once again, separate models were developed for total fuelwood, farm fuelwood, and forest fuelwood consumption. These models enabled me to examine how socio-economic factors related to household fuelwood consumption behaviors with/without ICS/CCS treatment.

4.2.4 Prediction scenarios

While knowing the total mass of fuelwood reduced due to ICS/CCS through DiD is useful, it is insufficient on its own for assessing the impact of the intervention on forest biomass stocks. As noted earlier, households collect fuelwood not only from forests, but also from agricultural lands and from trees along roadways. Consequently, in addition to the fuelwood quantity consumed, information on the change in fuelwood composition (i.e., fuelwood gathered from forests vs non-forests) resulting from the use of ICS/CCS is needed in order to isolate impacts on forest resources and climate change mitigation. Further, examining various socio-economic and biophysical factors that affect the magnitude of any household fuelwood consumption changes also improves the interpretation of intervention impacts. Thus, the expanded DiD models were used to predict changes in fuelwood consumption for treatment households under various scenarios, based on differing household socio-economic factors.

For this purpose, changes in household consumption were predicted for total, farm, and forest fuelwood under different socio-economic and biophysical factors by specifying particular inputs to the expanded DiD model. Predicted values for each set of inputs (hereafter termed "scenario" in this chapter) were obtained using the 'predictSE.gls' function in the 'AICcmodavg' package in R (Mazerolle, 2017). The choices of values of each socio-economic factor of the expanded

DiD model under various scenarios was based on common characteristics of majority (i.e., more than 2/3rd) households to reflect a 'typical' household (Table 4.1).

Table 4.1: Socio-economic factors and their values used for 'typical' households (HH) in Kullu and Koppal under the various scenarios

Characteristics for a 'typical' HH	Kullu		Koppal	
	Upper Caste	Lower Caste	MC_decision = 0	MC_decision = 1
Average Adults	4.46	3.80	4.29	3.69
Wealth Index	0.42	-0.67	-0.16	-0.15
MC_decision	Yes	Yes	-	-
Wood_collection	No	Yes	No	No
nsfB	Yes	No	No	No
nsfT	-	-	Yes	Yes
HHH_MC	No	No	No	No
MC_education	No	No	No	No

*MC_decision = main cook as decision maker for all major household purchases, Wood_collection = perceived forest wood collection distance increase, nsfB = non-solid stove in baseline, nsfT = non-solid stove post-intervention, HHH_MC = household head as main cook, MC_education = main cook has high school education.

Prediction for fuelwood consumption in Kullu was based on two scenarios: a 'typical' upper caste and a 'typical' lower caste household. The lower castes consist of scheduled caste (SC), scheduled tribe (ST), and other backwards castes (OBC), which are the official caste classifications by the Indian government for those individuals deemed to be the socially and educationally disadvantaged (Government of India, 2015). Prediction for Koppal was also based on two scenarios: main cook as decision maker for all major household purchases (MC_decision = 1) or not (MC_decision = 0).

4.3 Results

4.3.1 Kitchen performance test (KPT)

Survey results at baseline indicated that almost a quarter of the households in Kullu collected only from forests, while in Koppal almost a quarter collected solely from farm sources (Table 4.2). In all, more than half the households at both locations collected from a combination of farms and forests.

Table 4.2: Source of fuelwood collection in baseline as identified by field staff

% of households (HH) collecting from:	Kullu			Koppal		
	All HH	Control	Treatment	All HH	Control	Treatment
Farm	4%	8%	3%	38%	18%	43%
Forest	26%	23%	28%	2%	0%	2%
Both	70%	62%	73%	57%	73%	52%

The KPT results post-intervention indicated that fuelwood consumption decreased across all households, with declines larger in Kullu than in Koppal, and with differences between fuelwood from farms and forest sources (Table 4.3). Even though control households observed some decline in consumption post-intervention, the magnitude of decline in consumption for treatment households was larger indicating the intervention had the intended impact (please refer to Appendix B for DiD graphs with counterfactual lines). In both, Kullu and Koppal, treatment households reduced more in percentage overall and from farm sources, compared to control households.

Table 4.3: Average daily household fuelwood consumption by location of collection

Avg. Fuelwood Consumption	Kullu (kg/HH/day)				Koppal (kg/HH/day)			
			Treatment				Treatment	
	Control	Treatment	Upper Caste	Lower Caste	Control	Treatment	MC_decision = 0	MC_decision = 1
Total fuelwood								
Baseline	6.31	6.14	5.41	6.96	4.34	4.39	4.41	4.36
Post-intervention	4.60	2.85	2.69	2.97	3.73	2.96	3.18	2.57
Farm fuelwood								
Baseline	1.86	2.02	2.16	1.78	2.94	3.37	3.46	3.24
Post-intervention	1.56	0.96	1.05	0.75	2.93	2.05	2.56	1.11
Forest fuelwood								
Baseline	4.45	3.94	3.02	5.08	1.40	1.02	0.95	1.13
Post-intervention	2.92	1.89	1.64	2.23	0.80	0.92	0.62	1.46

In Kullu, the average fuelwood consumption in control households declined by 1.71 kg (27%) post-intervention. This decline in consumption for treatment households was met by reducing similar percentages from both sources (~53% farm and ~52% forest); however the actual quantity reduced from forests (2.05 kg/HH/day) was larger and almost twice the amount from farms (1.06 kg/HH/day) given the initially higher dependence on forests. Moreover, the variation in consumption among treatment households was larger than those for control households (Figure 4.2), and some households increased rather than decreased consumption. Within the treatment households in Kullu, the upper castes consumed less quantity of forest fuelwood post-intervention (1.64 kg/HH/day), compared to lower castes (2.23 kg/HH/day), while consuming more from farms post-intervention (1.05 kg/HH/day), compared to lower castes (0.75 kg/HH/day).

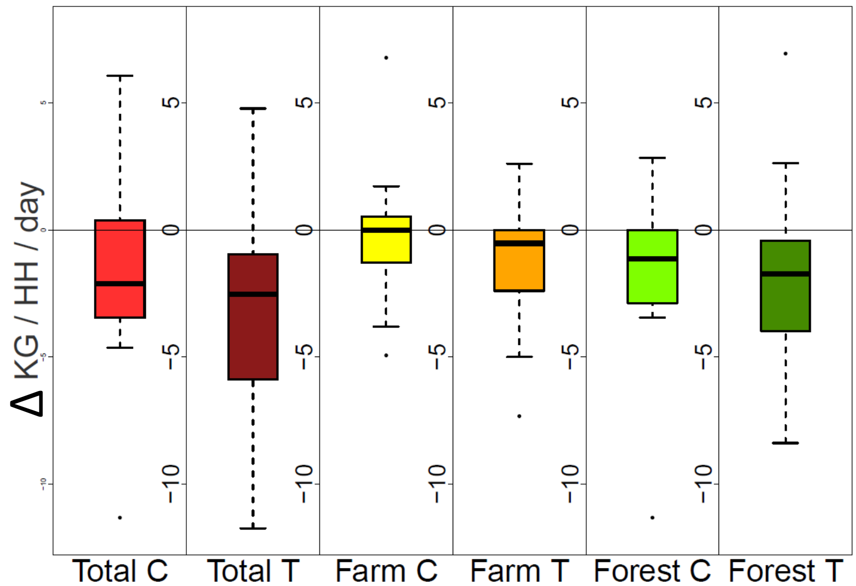

Figure 4.2: Kullu: change in daily household fuelwood consumption for Control (C) and Treatment (T) by fuelwood source.[12]

In Koppal, control households reduced their forest species consumption by 43%, while treatment households reduced it by only 10%, post-intervention. Alternately, while control households did not reduce their farm fuelwood consumption, treatment households reduced farm species consumption by 39%. When added together, the aggregate decline in overall fuelwood consumption for control households was 14% as compared to 33% for treatment households. However, the actual quantity consumed post-intervention from farms (2.05 kg/HH/day) for treatment households was more than twice the amount consumed from forests (0.92 kg/HH/day). Moreover, control households had a much larger variation for farm fuelwood consumption, while treatment households had a larger variation for forest fuelwood consumption (Figure 4.3). Once again, some households increased rather than decreased consumption.

[12] The box spans the interquartile range of the data, the whiskers extend to the highest and lowest observations.

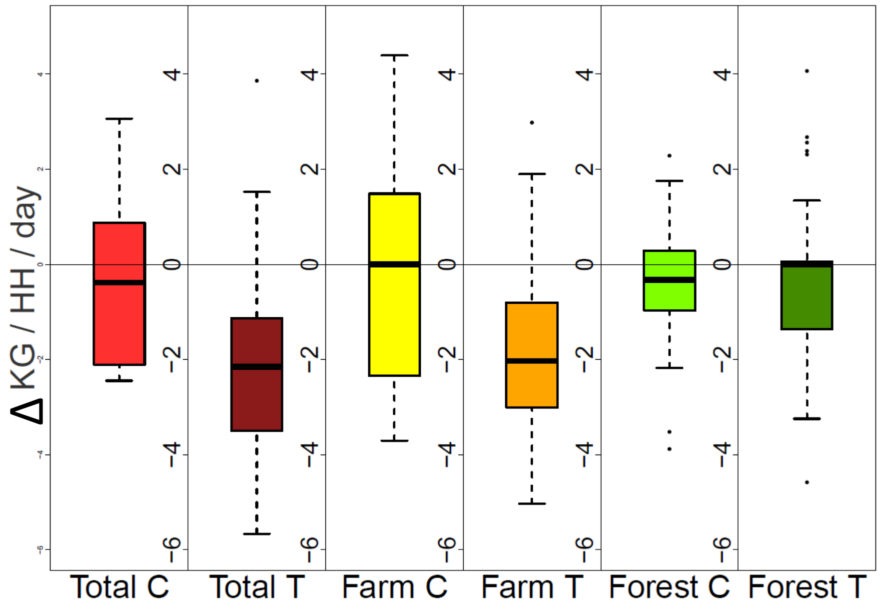

Figure 4.3: Koppal: change in daily household fuelwood consumption for Control (C) and Treatment (T) by fuelwood source[13]

Within the treatment households in Koppal, when the main cook was involved in decision making (MC_decision = 1), there was a larger decline in overall fuelwood (41%) and from farms (66%) but an increase from forests (30%). Conversely, households where main cook was not involved in decision making reduced more from forests (35%) but not as much overall (28%) and from farms (26%).

4.3.2 DiD model

The DiD model was used to remove the common trends between control and treatment households and to isolate the impact of the ICS/CCS intervention. Although a decline in fuelwood consumption from all sources is observed over time, the DiD model (Table 4.4)

[13] The box spans the interquartile range of the data, the whiskers extend to the highest and lowest observations.

indicates that the only statistically significant effect (i.e., $\beta_3 \neq 0$; $p<0.05$) occurred for farm species in Koppal, showing a decline by 1.32 kg/HH/day. In this case, the clean cooking intervention had a direct impact in the reduction of farm species consumption.

Table 4.4: Coefficients of the difference in differences (DiD) regression

DiD Coefficients	Intercept (β_0)	Dtr (β_1)	Dpost (β_2)	Dtr*Dpost (β_3)
Kullu				
Total Fuelwood	6.52	-0.48	-1.82 .	-1.44
Farm Fuelwood	-2.02	0.39	-0.26	-0.81
Forest Fuelwood	9.57	-0.59	-1.68 *	-0.33
Koppal				
Total Fuelwood	3.53	0.18	-0.77	-0.69
Farm Fuelwood	3.00	0.90	-0.01	-1.32 *
Forest Fuelwood	1.62	-1.17	-1.42	1.18

* Dtr - control = 0, treatment = 1; Dpost - pre-treatment = 0, post-treatment = 1; Dtr*Dpost - interaction isolating intervention impact.
p-value significance codes: '***' .001, '**' 0.01, '*' 0.05, '.' 0.1.

Other declines were observed across Kullu and Koppal, but the cross term (Dtr*Dpost) isolating the treatment effect was not statistically significantly different from 0. However, any effects may have been masked by the large variability amongst households, as evidenced in Fig 4.2 and 4.3. To account for this variation, as well as to examine the impacts of socio-economic factors, the extended DiD models with covariates were developed (please refer to Appendix B, for fitted extended models).

Based on the extended DiD models, in Kullu, total fuelwood consumption was impacted by the wealth index, number of adults, social caste, and main cook participating in purchasing decisions. In addition to these socio-economic factors, farm and forest consumptions were also impacted by the perceived increase in forest wood collection distance and by non-solid fuel stove in baseline (nsfB). In Koppal, total fuelwood consumption was impacted by wealth index, number of adults, main cook participating in purchasing decisions, and non-solid fuel stove in baseline (nsfB). Additionally, farm consumption was impacted by main cook as household head, while forest consumption was impacted by a perceived increase in forest wood collection distance.

4.3.3 Prediction scenarios

Using the extended DiD models, I predicted various consumption scenarios for a 'typical' household in Kullu and in Koppal. Variables for the scenarios were based on the socio-economics factors of households at the two locations, and using the extended DiD models. Social caste of the household was found to be a key differentiating factor between households in Kullu, but it played no role in Koppal (as all households were of lower caste). In Koppal, the key differentiating factor between households was found to be whether or not the main cook of the household was involved in major purchasing decisions (MC_decision). The key differentiating factors were based on corresponding statistical significance of a class variable, and its interaction with other variables.

For a 'typical' household in Kullu, overall quantity consumed post-intervention was less for upper caste households and from forest sources (Figure 4.4), compared to lower caste households. However, upper castes consumed more from forest sources post-intervention, and less from farm sources, as compared to lower castes.

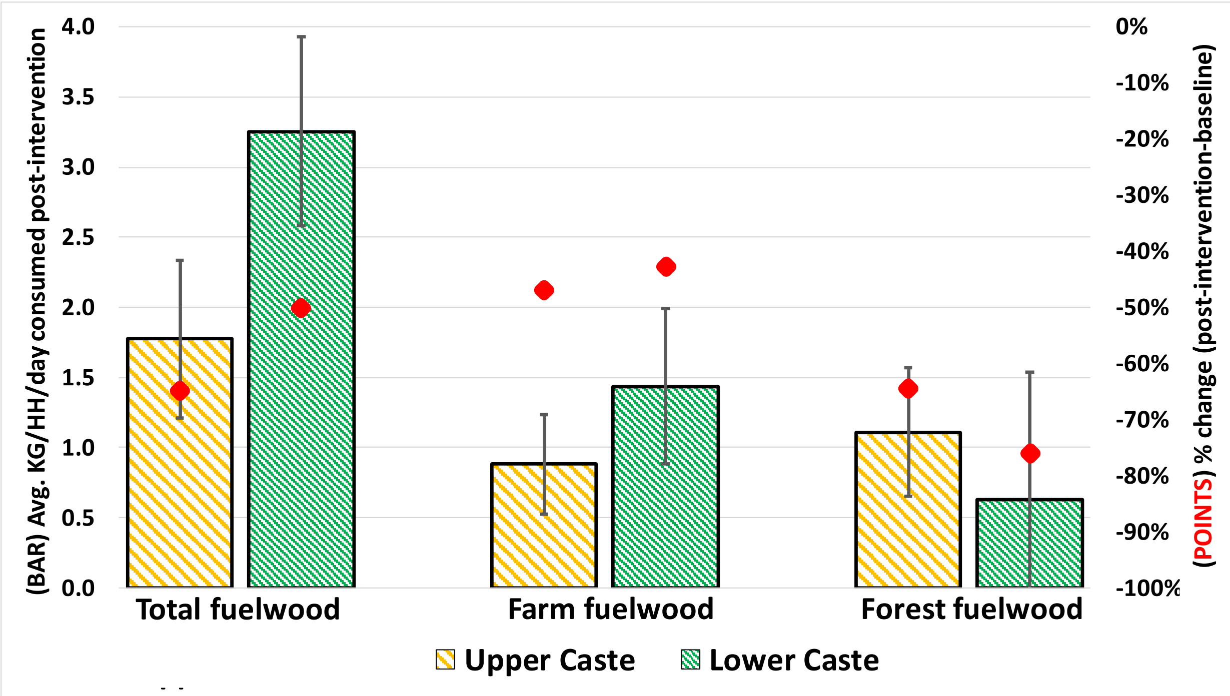

Figure 4.4: Fuelwood consumption scenarios for 'typical' Kullu households: quantity consumed post-intervention (bars), percentage change in consumption (red diamonds)

*'Typical" Upper Caste: WI = 0.42, adults = 4.46, wood_collection = 0, nsfB = 1, nsfT =0, MC_decision = 1, MC_education = 0, and HHH_MC = 0.
'Typical' Lower caste household is: WI = -0.67, adults = 3.8, wood_collection = 1, nsfB = 0, MC_decision = 1, MC_education = 0, and HHH_MC = 0.

I also predicted forest fuelwood consumption only for various scenarios to isolate how varying household socio-economic factors influence the forest impacts of the intervention (please refer to Appendix B for forest scenario outputs). When forest fuelwood collection distance was perceived to increase, both castes reduced consumption substantially from forest sources. Moreover, lower caste households reduced more from forests post-intervention whether or not they gained access to a non-solid fuel stove post-intervention (nsfT). Non-solid fuel stove post-intervention (nsfT) was not included in the selected extended DiD model for forest consumption using the AIC criterion for selection of socio-economic factors.

In Koppal, there was a larger decline in consumption overall and from farm sources post-intervention for a ‘typical’ household where the main cook was involved in household purchasing decisions (Figure 4.5). However, when the main cook is the decision maker, the reductions from forests were lower than other households and the amount from forests was higher.

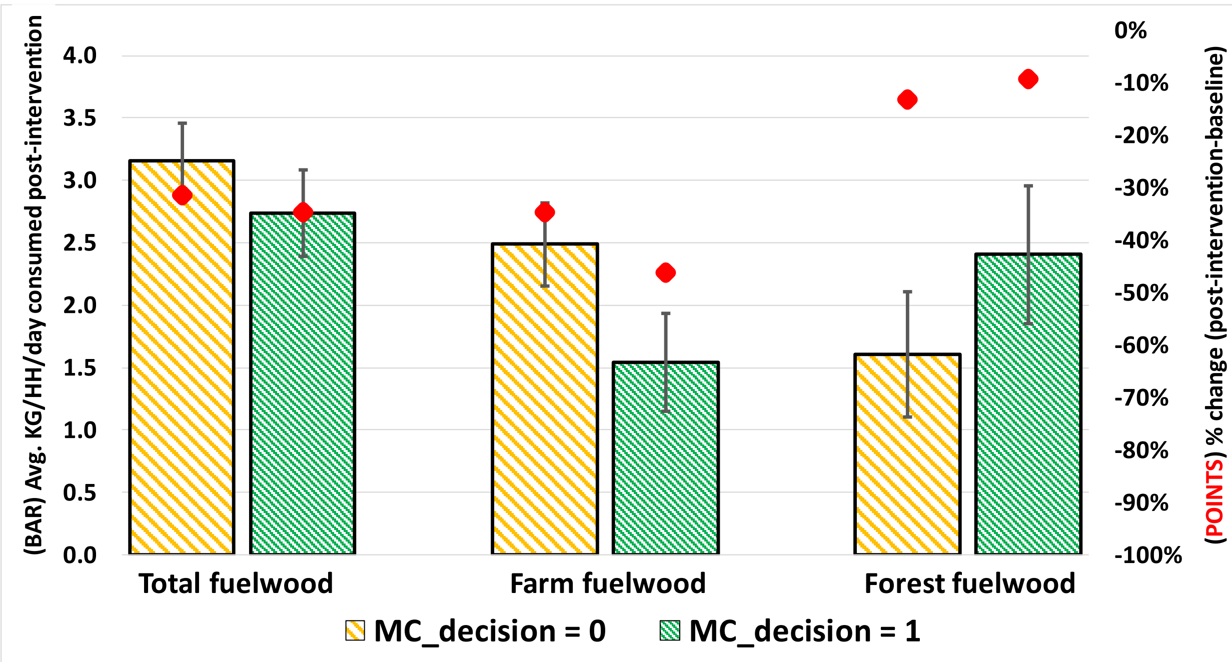

Figure 4.5: Fuelwood consumption scenarios for 'typical' Koppal households: quantity consumed post-intervention (bars), percentage change in consumption (red diamonds)

*‘Typical’ MC_decision = 0 is: WI = -0.16, adults = 4.29, wood_collection = 0, nsfB = 0, nsfT = 1, MC_education = 0, and HHH_MC = 0.
‘Typical’ MC_decision = 1 is: WI = -0.15, adults = 3.69, wood_collection = 0, nsfB = 0, and HHH_MC = 0.

Once again, I predicted forest fuelwood consumption only for various scenarios to isolate how varying household socio-economic factors influence the forest impacts of the intervention (please refer to Appendix B). Under these scenarios, when main cook was not involved in decision-making, the decline in consumption from forest sources was higher. The decline from forest sources was largest when forest fuelwood collection distance increased and/or when households already had access to a non-solid fuel stove in baseline (nsfB). Here too, non-solid fuel stove post-intervention (nsfT) was not included in the selected extended DiD model for forest consumption using the AIC criterion for selection of socio-economic factors.

4.4 Discussion and conclusion

Kitchen Performance Test (KPT) results indicated that there was an overall decline in consumption in Kullu by almost half for treatment households, with the percentage reduction from forests and farms being roughly equal. However, the absolute decline in forest fuelwood was almost twice that from farms. This is likely due to the fact that orchard tree products (e.g., apple, apricot, almond, pear, plum, peach, and walnut, etc.) are the major agricultural crops in the area. The regular pruning of fruit and nut trees provides a steady supply of fuelwood to households in Kullu, as it is a residual from agricultural processes not related to cooking requirements. Besides, wood collected from pruning fruit trees is free - not just in terms of money but also in labor: the labor to trim branches post-harvest would be required regardless of fuelwood use and thus the opportunity cost of not cutting branches for fuelwood does not exist. Additionally, this wood would have to be transported away from the fields to use as fuelwood or to sell. Thus, it is likely that households reduced consumption more in quantity from forests rather than from farms to meet the reduced overall wood requirements post-intervention, as the use of wood pruned from agricultural crop trees requires no extra effort in terms of money or labor.

Within treatment households in Kullu, upper castes consumed more pre- and post-intervention in actual quantity from farms and less from forests, compared to lower castes. Upper castes also had a higher percentage of farm fuelwood in the composition mix, as compared to lower castes who had a higher percentage of forest fuelwood in total consumption. This is likely because the higher castes own more land on average (0.31 acres versus 0.15 acres for lower caste) and thus might have access to more pruned farm wood, allowing them to reduce their additional forest trips in light of reduced fuelwood requirements. However, regardless of caste or the use of non-solid fuels in baseline (nsfB) or post-intervention (nsfT), when forest wood collection distance was perceived to increase, all households substantially reduced consumption from forest sources.

In Koppal, the lower fuelwood requirements due to the ICS/CCS intervention were met by reducing consumption more from farms than from forest sources. While the relative proportion of farm fuelwood declined, the actual quantity consumed from farms remained higher than for forests, as with the pre-intervention period. The relative decrease in importance of farm fuelwood and increase of forest fuelwood could have been driven by the specific requirements of the new stove (e.g., better quality or longer burning wood) and/or by the relative quality of farm resources in Koppal. Land productivity in Koppal is low being a semi-arid plateau region, as compared to the fertile soils of the lower Himalayas in Kullu. The harvest residue is of lower quality, coming from either farm crop (e.g., maize, *bajra*) resulting in cobs and husk, or from shrubs and trees on farms and along the roads. The trees growing on farms and along roads in Koppal are often not a good source of energy, consisting of *Dalbergia sissoo* (19.46 MJ/kg), *Azadiractha indica* (18.73 MJ/kg), and Eucalyptus species (17.75 MJ/kg), compared to forest species such as *Acacia nilotica* (25.65MJ/kg) and *Bosvelia serrata* (26.6MJ/kg) (Chakradhari & Patel, 2016; Puri, Singh, & Bhushan, 1994). Agricultural activities in Koppal are not tree based, unlike the fruit orchards in Kullu, meaning that cutting from the pruning of trees is an additional effort required beyond regular farm activities. Moreover, many households work on other tracts of land as laborers, and might not be allowed to cut fuelwood from another owner's land. Thus, when farm sources are unable to provide for all household cooking needs, even at the reduced consumption levels, the households supplement with forest fuelwood, in addition to collection from roadsides. Forested areas are also somewhat further from the village (more than a kilometer) as compared to Kullu (adjoining the village). As a result, when an individual makes a trip to collect fuelwood from the forest, they might still collect the same quantity (for constant effort), instead of spending additional energy (both in time and labor) to collect from farm or roadside. Additionally, households might prefer to collect better quality fuelwood from forests compared to the possible lower quality wood from farms and along roads, resulting in more forest species used in the final composition mix.

Within treatment households in Koppal, consumption patterns varied based on whether or not the main cook was involved in major household purchasing decisions. Households where the main cook was involved in decision making reduced more overall and particularly from farms, both in quantity and percentage, compared to households where the main cook was not involved in decision-making. Households where the main cook was a decision-maker also reduced their relative consumption of farm fuelwood and increased the forest species in the mix, while households where the main cook was not involved in decision-making increased their relative proportion of farm fuelwood in the composition mix. This is mainly because, when the main cook is involved in purchasing decisions, they are more likely to buy ICS/CCS and use them. In many cases, as the literature has pointed out (Lewis & Pattanayak, 2012), women are more likely to invest in better cooking technologies as they understand the effort (physical and time) required to use traditional cooking technologies. However, the reason for an increase in forest composition for households where main cook was not involved in purchasing decision could be the constant effort of collection from forests, as mentioned earlier. Additionally, these households might not be motivated to substantially reduce forest collection efforts as most of these households (~85%) indicated that they did not perceive forest wood collection distance to be increasing over time. Whereas, results also show that when forest wood collection distance is perceived to increase, regardless of decision making power, there is a larger decline in forest consumption.

Difference in differences (DiD) results indicated that fuelwood consumption by households at both research sites declined, but the interaction parameter was not statistically significant from zero, except for farm species in Koppal. Such results are also observed in other similar interventions where there is high variability across households masking impacts of the intervention, coupled with the limited number of households measured during the KPT (Granderson, Sandhu, Vasquez, & Ramirez, 2009). Second, a majority of households in Kullu, and a few in Koppal, already had access to a non-solid fuel stove in the baseline (nsfB). Third, not all households opted for a non-solid fuel stove post-intervention (nsfT): just over a third of the households in Kullu and just over half in Koppal. All other households picked some version of an improved biomass cookstove, which uses fuelwood even if at reduced amounts. Last, even if households opted for a non-solid fuel stove post-intervention (nsfT), they likely continue to stack cooking devices and used traditional stoves for preparation of certain dishes (e.g., roti) and/or for heating purposes (such as in Kullu). Thus, it is likely that I was unable to detect a statistically significant effect of the intervention due to a low sample size (i.e., study design), coupled with other effects of the intervention (such as access to non-solid fuel stove in baseline, opting for biomass stove during the intervention, and stacking of fuels) such that a limited decrease in fuelwood consumption over time is observed.

The one statistically significant result was for farm consumption in Koppal, as noted earlier. In this case, there was a reduction in farm fuelwood consumption by 1.32 kg/HH/day ($p<0.05$) directly correlated to the intervention. The majority of the households in Koppal opted for a non-solid fuel treatment (both LPG and electric induction, neither of which require the use of fuelwood), and almost no households had access to such stoves in the baseline case. These likely contributed to larger changes in the magnitudes of consumption, and/or a switch in sources such that even with a small sample size and large within-treatment variability, the DiD effect showed up as statistically significant. Conversely, in Kullu, no statistically significant changes were noted, likely since the majority of the households already had a non-solid fuel stove in the baseline (primarily LPG). As a result, only one third opted for a non-solid fuel stove for their treatment (nsfT) with the rest opting for some kind of improved biomass stove. The chosen biomass treatment stove was mostly a “tandoor,” used in the region for heating homes in the winter. This heat load, due to the colder climatic conditions in Kullu compared to Koppal, and easier accessibility to fuelwood from the surrounding forests, likely explains the higher overall fuelwood consumption in Kullu, regardless of type of stove (Silori, 2004). Thus, any impacts might be too small to be detected using the small sample size and high within-treatment variability.

I realize that my study could have been affected by certain limitations. First among them is the ability of field staff to correctly identify species from branches. This limitation was mitigated by the fact that field staff were recruited from their own local villages and have extensive personal experience collecting and using different tree species. A second potential limitation arose from allocation of species into farm versus forest sources in the small number of cases where field staff could not identify the species. However, this limitation does not apply to estimates of total fuelwood consumption changes; it only impacts estimates for farm vs. forest fuelwood consumption. Even then, the percentage of total kilograms allocated was too low to create a cause for concern. Moreover, a simple sensitivity analysis determined that it did not change the outcomes substantially (i.e., there was no change in sign or changes in relative importance of the factors). Third, there could be other factors that I was unable to control for, such as crop failure in one year, such that farm consumption might be substantially less and households may have needed to supplement from forests, or an extremely cold year where overall consumption in the mountains might be more. However, data were collected in the same months each year and thus, there was likely not much variation in average temperature during the collection months. Fourth, as data were collected during one season each year, I was unable to capture seasonal variation where results might differ if data were collected in winter or during the fall harvest season. In future studies, information could be collected across seasons in multiple years to further extend my results by examining how consumption changes seasonally and annually.

My results have a number of implications for forest management and policy. For example, if overall fuelwood consumption declines and the reduced quantity is met from local farm sources, this would result in lower reliance on forest resources as well as reduced fuelwood collection time. This was partially the case in Kullu where households reduced consumption overall and from both sources. While the percentage decline was the same, the higher collection from forests pre-intervention meant that the absolute quantity reduced from forests was higher than for farms. The differences in magnitude were also guided by individual socio-economic factors such as caste and perceived change in fuelwood collection distance. Conversely, in Koppal there was reduced consumption overall and from farms but not from forests. Again the differences in magnitude were guided by individual socio-economic factors, such as the main cook participating in purchasing decisions or perceived change in forest wood collection distance. Thus, one could potentially conclude that there was a positive impact on forest stocks in Kullu as consumption and dependence on forests reduced because of the intervention. This would then have a positive impact on climate change mitigation due to reduced emissions as well as increased forest stocks acting as carbon sinks. By contrast, in Koppal the intervention resulted in a decline in overall consumption, but forest consumption stayed steady. This indicates that the intervention did not necessarily have any positive forest impacts. However, it still had an overall positive climatic impact from reduced emissions of burning fuelwood. Furthermore, the reduced consumption from forest sources in Kullu can also indicate positive societal impacts, whereby reducing fuelwood collection time could result in more time for women and girls to pursue education and income generating activities. Moreover, regardless of location or household characteristics, when forest fuelwood collection distance was perceived to be increasing over time, all households at both locations reduced forest consumption. Thus, my results explain under what physical and socio-economic factors a household truly reduces its dependence on forest resources, potentially resulting in positive social, climatic, and forest impacts.

While multiple studies have looked at consumption changes due to an ICS/CCS intervention, to the best of my knowledge, this is the first time a study has looked at species preferences and composition change as a result of the intervention. Thus, my research contributes towards filling the gap in evaluating post-intervention household behavior and species preference. The results help explain whether a household truly reduced its dependence on forest resources, and if it did, then what factors guided this magnitude of change. Identification of these changes helps isolate impacts of ICS/CCS on forests, climate, and society. I showed that results vary across regions with a combination of demand and the substitutability of fuelwood from other sources, such as farms. There was a difference between sites and within each site, as well as between collection sources. The reduction in consumption from forest sources was dependent on the quality of farm residue and forest resources, and the structure of non-economic activities of the household. Lower quality farm residue required more substitution for cooking from forest sources, while social caste and wealth impacted the consumption and collection decisions for households. I also noticed that, regardless of fuelwood requirements, certain regions would not experience a full transition to ICS/CCS for cooking due to climatic (heating requirements) or other processes (orchard harvest).

My results also have important implications for climate change mitigation via ICS/CCS carbon credits through reduced extraction from forests, and for promotion of social welfare from reduced collection efforts for women. For example, as shown earlier, if overall fuelwood collection reduced and the reduced quantity was met from local farm sources, it could indicate positive climate change mitigation benefits from reduced emissions and reduced reliance on forest resources. Integration of my results with resource collection polygons, as estimated in Chapter 2 (Singh et al., 2018), could identify fuelwood hotspots, where extraction exceeds growth of local biomass resources, for focused forest management in those regions. Such information would be important for future ICS/CCS interventions and forest resource policy decisions for the region. While I predicted fuelwood use for a ‘typical’ household, the model could be also used to estimate fuelwood consumption changes for a variety of households. More data, when available, could be added and the models developed again, such that future interventions can be prioritized, not only to those locations where negative extraction impact on forest resources is greatest, but also where the households are more likely to move away from forest sources. It would also be interesting to study the impacts of agroforestry on fuelwood collection behavior, with and without an ICS/CCS intervention. Future research could also connect forest cover change with longitudinal data on species preferences, to isolate forest resource impacts, and to track a change in degradation of local resources.

Chapter 5: Environmental payoffs of LPG cooking in India

5.1 Introduction

Almost 40% of the world's population (World Bank & IEA, 2017) depends on solid fuels (including traditional biomass such as wood, crop residue, and dung) to meet their daily household cooking energy requirements (Arnold et al., 2003; International Energy Agency (IEA), 2016; World Bank & IEA, 2017). About a quarter of the global population dependent on traditional biomass, or about 800 million individuals, live in India alone, and this burning of biomass contributes to about 31% of total emissions in India (Sharma et al., 2011; World Bank & IEA, 2017). Inefficient combustion of biomass in traditional stoves has both local as well as global environmental impacts. Unsustainable harvesting of fuelwood, especially in densely populated areas, leads to deforestation (Arnold et al., 2003; Foley et al., 2007; Hosier, 1993; McGranahan, 1991), accelerated degradation (DeFries & Pandey, 2010; Ghilardi et al., 2007, 2009; Heltberg et al., 2000), and depletion of local resources (Masera et al., 2006). How biomass is harvested (sustainably or not) can also have an impact on the contribution to climate change from the carbon dioxide (CO_2) released (Edwards et al., 2004; Hutton & Rehfuess, 2006; Smith et al., 2000). Additionally, burning of biomass contributes to the emissions of products of incomplete combustion such as black carbon (Kar et al., 2012; Ramanathan & Carmichael, 2008). The resultant household air pollution from inefficient use of solid fuels is one of the top environmental health risks in developing countries, contributing to over 2.6 million deaths per year (IHME, 2017; WHO, 2016). Furthermore, about 25-30% of ambient fine particulate pollution ($PM_{2.5}$) in South Asia is attributable to household solid fuel combustion (Chafe et al., 2014), making it a leading contributor to the burden of disease in the region (Balakrishnan, Cohen, & Smith, 2014; Rehman, Ahmed, Praveen, Kar, & Ramanathan, 2011; Smith et al., 2014). Research has shown that the use of improved (ICS) and clean (CCS) cookstoves[14] can considerably improve household air quality and human health from reduced smoke (Dutta, Shields, Edwards, & Smith, 2007; Singh, Gupta, Kumar, & Kulshrestha, 2014; WHO 2016), as well as have other social benefits such as time saved from reduced fuelwood collection (Brooks et al., 2016; Hutton & Rehfuess, 2006).

Due to the multiple benefits of ICS/CCS, numerous programs in India to encourage their use have been implemented since the 1970's. These programs include LPG interventions, price subsidies, public awareness campaigns, and improved distribution/delivery mechanisms. The Indian government in recent years has accelerated efforts through an ambitious new program to increase LPG access to another 60 million poor rural women by 2019 (Ministry of Petroleum & Natural Gas, 2016). However, to what extent past and current policies have enabled a transition away from fuelwood to cleaner-burning fuels like LPG, and what the net emissions impacts of this has been has not been adequately studied.

Transitioning to ICS and CCS (such as those using LPG) can, in theory, positively influence forest resources, global climate, local air quality, and human health and well-being. CCS using modern fuels, such as LPG, natural gas and electricity, are viewed as being the most beneficial from the perspective of human health as they substantially reduce emissions of household air pollutants (WHO, 2014). However, households might be transitioning from a renewable fuel

[14] Please refer to Chapter 1, Sub-section 1.2 for ICS and CCS details.

(biomass) to a fossil fuel. This raises the question of the net climate change impact of such a switch. There has been limited work assessing this potential trade-off to date. Existing studies include calculations based on hypothetical stove switch-outs or modeling of future emissions based on projected stove adoption (Cameron et al., 2016; Freeman & Zerriffi, 2012; Ghilardi et al., 2009; Pachauri et al., 2013). A 2017 KfW report provides an overview of the evidence base on the impact of LPG use on the climate and forests (Bruce, Aunan & Rehfuess, 2017). One gap in the existing knowledge base, highlighted by this and other studies, is the lack of estimations of net climate relevant emissions impacts from historic data on household fuel switching that reflect actual conditions of stove use and stacking (Ruiz-Mercado & Masera, 2015). This chapter addresses this gap specifically by examining the climate effect of the switch from fuelwood to LPG cooking in India over the decade from 2000 to 2011. My analysis includes the estimation of net impacts considering a suite of various climate-active emissions (Kyoto gases and other short-lived climate pollutants) and biomass renewability scenarios (a fully renewable and a 0.3 fraction of non-renewable biomass case). I assess the aggregate change in fuel consumption and resulting changes in emissions that occurred as a result of both the suite of policies put in place as well as the supply-side and demand-side decisions that were made by companies and households over this period. However, I am unable to estimate the effect of specific policies in place between 2001 and 2011 in transitioning people to the use of LPG as policy-specific data is unavailable to me.

5.2 Materials and methods

I assess the net impact on emissions from increased access to LPG for cooking in Indian households over the decade from 2000 to 2011. In what follows, I describe my main data sources and methods. A more complete description of the methods, including data tables, is presented in Appendix C. I define fuelwood displaced as the amount of fuelwood not used (i.e., saved) due to the use of liquefied petroleum gas (LPG). I focus the research on India, as it has the largest solid fuel using population globally, and over two-thirds of the Indian households still depend on these fuels (GOI, 2016; Ki-Moon, 2011; World Bank & IEA, 2017). In addition, the country has seen a huge governmental push towards transitioning people to the use of ICS/CCS for over three decades.

Two key national sources of data on LPG and fuelwood access and consumption were utilized in this analysis:

- Bottom-up estimates of household LPG and fuelwood consumption are derived from the large nationally representative socio-economic surveys conducted by the National Sample Survey (NSS) organization (MOSPI 1999, 2011).
- Data on the total number of households using fuelwood vs. LPG as their primary fuel are taken from the Indian national censuses and are used to scale the bottom-up survey estimates to national aggregates.

Using the data from the two representative national surveys, NSS rounds 55 (year 1999-2000) and 68 (year 2011-2012), I identified primary users of LPG and fuelwood (those households who identified it is their main cooking fuel), and secondary users of LPG and fuelwood (those households who did not identify it as their main cooking fuel yet consumed some amount of fuelwood or LPG). In 2011, there were about 70 million primary users of LPG, and 29 million secondary users of the fuel. Both primary and secondary users are accounted for in my analysis so that the emissions impact of stove stacking is included.

My methodology in this chapter consists of three key steps. First, I applied statistical matching techniques to create a synthetic dataset of matched households considering the subset of households that gained access to LPG between 2000 and 2011. In a second step, I used this synthetic dataset to estimate the amount of fuelwood displaced due to increased LPG access in 2011. Finally, I used my estimates of fuelwood displaced and LPG use in 2011 to estimate the net emissions impacts of this cooking fuel transition considering a suite of climate-active emissions and biomass renewability assumptions.

For the statistical matching, I utilized a mixed method based on D'Orazio (2006, 2016), which was implemented using the R StatMatch package (R Core Team, 2018). The method was applied to create a synthetic dataset of over 100,000 matched households to examine changes in household fuel consumption over the decade in the absence of longitudinal panel data by matching similar households from the two NSS rounds 55 and 68 based on State, sector (urban/rural), and caste. Further details regarding the statistical matching techniques applied are also presented in Appendix C.

This synthetic dataset was then used in the analysis that followed. A filter was applied such that only those households having no access to LPG in 2000 were included in the analysis, regardless of access to or level of LPG consumption in 2011. To estimate the amount of fuelwood displaced due to LPG access in 2011, I used a three step Tobit model, based on the technique in

Greene (2003). My R-code for this analysis was based on the gamma hurdle biological model by Anderson (2014), which is the same as the Tobit model used in econometrics. I tested the model using a range of explanatory variables (urban/rural, LPG quantity, household size, income, caste, employment, and religion), and the best model was selected based on the Akaike information criterion (AIC) and log likelihood (logLik). AIC estimates the quality of a model relative to other models, while logLik compares the fit of different coefficients to maximize optimal values. By these criteria, the model I selected to predict firewood use in 2011 included the quantity of LPG consumed, household size and urban/rural as independent variables.

Coefficients of the estimated Tobit model were then used to predict the amount of annual fuelwood displaced by an average sized household that gained access to LPG in 2011. Estimates were made for average sized urban households and rural households separately. Using the census enumeration of number of households that gained access to LPG between 2000 and 2011, I then estimated the total fuelwood displaced in 2011. These estimates on household LPG consumption and fuelwood displaced were then ultimately utilized to calculate the net emissions impact (in million metric tonnes of carbon dioxide equivalent or $MtCO_2e$) from increased LPG access. Net emissions were calculated utilizing the emissions factors and hundred year global warming potentials (GWP_{100}) from Freeman and Zerriffi (2014) for a traditional open fire and an LPG stove. This includes the uncertainty associated with estimates of the emission factor based on reported stove testing results.

If fuelwood is sustainably procured (i.e., 100% renewable), the CO_2 emission from wood is zero, as it is presumed to be reabsorbed into the ecosystem cycle during tree growth. However, it is known from literature that not all fuelwood harvested is renewable (Bailis et al., 2015), and in fact, the fraction of non-renewable biomass (fNRB) extracted can vary by huge margins (0-90%) globally. A higher fNRB would ascribe correspondingly higher emissions to biomass fuels and a greater benefit to a switch to LPG. In this chapter, I consider two cases of fuelwood renewability: an unrealistic case of fully renewable biomass (fNRB = 0), and a more realistic but globally conservative case where we use an estimate of 0.3 as the fNRB. Cookstove carbon markets tend to use high values hovering at 80% or more, however, Bailis et al. (2015) estimated the national fNRB for India to be around 24 percent. Thus, I assume a conservative 30% as the fNRB to illustrate the impact of fNRB on emissions accounting.

The difference between emissions from fuelwood displaced and increased LPG use determined my estimates of the net emissions impact from the transition to LPG cooking in 2011. Net emissions were estimated under the alternate assumptions of renewability of biomass extraction as mentioned above, for a restricted case considering only Kyoto gases (Carbon Dioxide and Methane), and a more complete case including also emissions of other important climate-active emissions (Carbon Monoxide, Non-Methane Hydrocarbons, Organic Carbon, Black Carbon, and Sulphur Dioxide).

5.3 Results

Basic statistical analysis indicates that the proportion of Indian households primarily using fuelwood for cooking decreased by 3.5% even though the total number of households using fuelwood increased by almost 20 million over the decade 2000 to 2011 (Table 5.1). This was due to the rapid growth of the Indian population from approximately 1.02 billion in 2001 to 1.22 billion in 2011 (Government of India, 2016).

Table 5.1: Descriptive statistics of NSS and census datasets for 2001 and 2011

Descriptive Statistics	2001		2011		Source
	# of HH	Percent (%)	# of HH	Percent (%)	
# of HH	191,963,935		246,740,228		Census
# Urban HH	138,271,559	72.03%	167,874,291	68.04%	Census
# Rural HH	53,692,376	27.97%	78,865,937	31.96%	Census
Primary LPG HH	33,596,798	17.50%	70,425,518	28.54%	Census
Secondary LPG HH	5,050,475	2.63%	29,071,487	11.78%	NSS
Primary fuelwood HH	100,842,651	52.53%	120,878,598	48.99%	Census
Secondary fuelwood HH	5,050,475	2.63%	29,071,487	11.78%	NSS

At the same time, households using LPG increased both in number and in percentage over this decade indicating a national trend towards increased use of LPG as a primary household fuel. However, the proportion of secondary users of fuelwood also increased (by 9%) suggesting that households tend to initially stack fuels before moving primarily to the use of LPG. As I do not have yearly numbers for LPG access and use over the decade, I cannot estimate the population moving from fuelwood and obtaining LPG as a primary fuel, or using it as a secondary fuel at any point during the decade.

Results of the Tobit model indicate that the total fuelwood displaced per year, assuming average sized households, due to increased LPG access in 2011 was 6.19 million tonnes in urban regions, and 0.99 million tonnes in rural regions (Table 5.2). At a national level, this amounted to a displacement of 7.2 million tonnes of fuelwood in 2011. At the same time, the LPG consumption increase due to household gaining access amounted to approximately 0.028 million tonnes and 0.189 million tonnes in rural and urban households respectively.

Table 5.2: Average LPG consumption and fuelwood displaced by households in 2011

	Rural	Urban	Source
Average HH size in 2011	5.11	4.34	Matched data
KG fuelwood displaced / HH / yr	-88.32	-242.52	Calculated
# HH gaining access to LPG 2000-2011	11,294,825	25,533,895	Census
Fuelwood (metric tons) displaced / yr	**-997,524**	**-6,192,501**	Calculated
LPG (metric tons) used in 2011	**27,691**	**189,315**	Matched data

In estimating the emissions of Kyoto gases alone due to the displacement of fuelwood between 2000 and 2011, the assumption regarding fNRB extraction, makes a substantial difference. When all fuelwood used is assumed to be renewably sourced (fNRB = 0), I estimate a slight net emissions decrease in rural regions of 0.01 $MtCO_2e$, and in urban regions of 0.02 $MtCO_2e$ in 2011. However, if I conservatively assume a positive fNRB of 0.3, I estimate a net emissions reduction of 0.43 $MtCO_2e$ in rural, and of 2.62 $MtCO_2e$ in urban regions (Figure 5.1). The larger net emissions decrease estimated for urban households is due to the more rapid gain in access to LPG and the higher per household consumption of it in urban regions. Furthermore, the higher net emissions reductions estimated when assuming a positive fNRB is because the increase in emissions from LPG use is offset by the reduction in positive CO_2 emissions from avoided burning of non-renewable biomass. The uncertainty in net emissions ranges are due to emission factors utilized from Freeman & Zerriffi (2014).

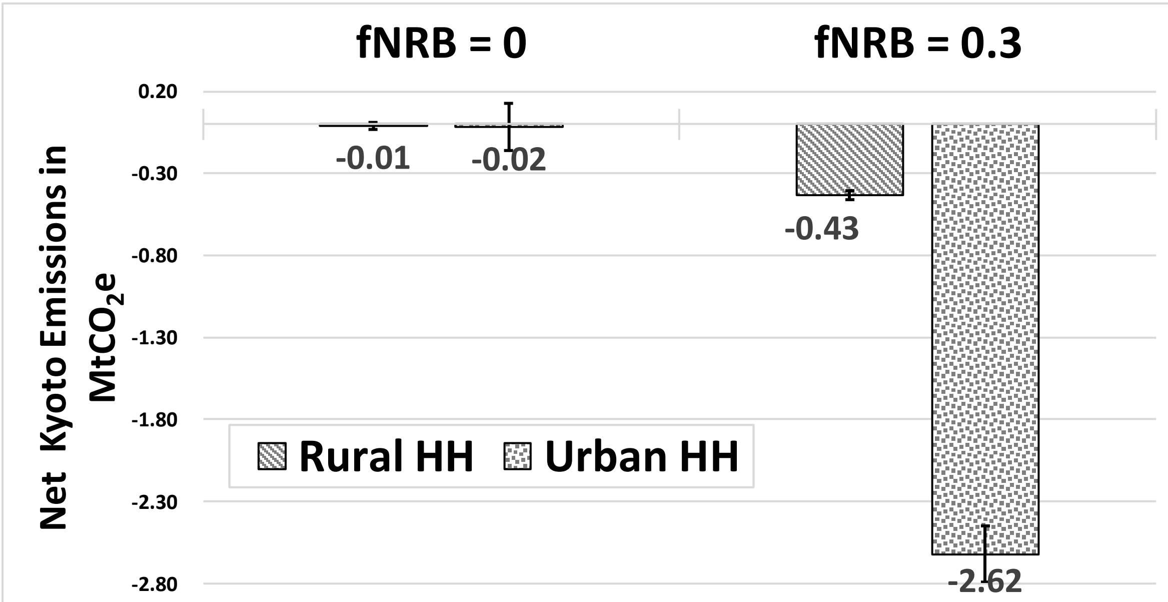

Figure 5.1: Change in net emissions of Kyoto gases under differing assumption regarding the fNRB[15]

When I also consider a suite of non-Kyoto climate pollutants, in addition to a positive fNRB, my estimate of net emissions reductions is even higher at 0.94 $MtCO_2e$ in rural and 5.79 $MtCO_2e$ in urban regions (Figure 5.2). This is due to the much higher non-Kyoto climate forcing emissions associated with the use of traditional biomass stoves as compared to LPG stoves. Given that there is no well-accepted protocol for calculating fNRB globally or agreement on the suite of emissions to account for, there can be large variances in the net emissions calculated for the same quantity of fuel consumed. Regardless of these associated uncertainties, however, I still estimate a large reduction in climate forcing emissions due to the observed transition from traditional biomass stoves to LPG stoves in India between 2001 and 2011.

[15] Error bars depict uncertainty in emissions ranges due to emission factors utilized

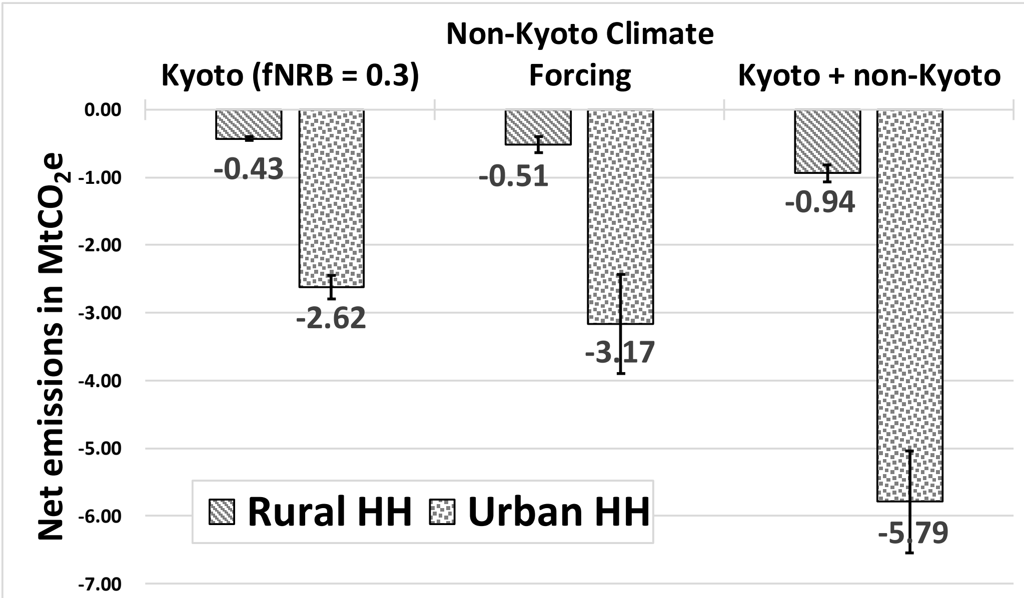

Figure 5.2: Change in net emissions considering (a) only Kyoto gases at fNRB = 0.3, (b) other short-lived climate pollutants, and (c) combined Kyoto and non-Kyoto climate forcers[16]

5.4 Discussion and conclusion

In recent years, there has been a strong revival in global policy circles to promote a transition to cleaner cooking given the increasing evidence of the huge environmental, social and health externalities of solid fuel use. India has a long history of providing subsidies for cleaner-burning fuels, specially LPG. The LPG subsidy burden for the Indian government has been estimated at about US$6 billion per year (Shenoy, 2010). Government initiatives in recent years, such as PAHAL, Give it UP and Ujjwala, could further accelerate the rate of LPG access. Ujjwala in

[16] Error bars depict uncertainty in emissions ranges due to emission factors utilized

particular is targeting an additional 60 million poor rural women by 2019, with an allocated budget of US$300 million in 2016-17 (Ministry of Petroleum & Natural Gas, 2016). The Indian government plans to meet this estimated growth in LPG demand by appointing approximately 10,000 new LPG distributors (40% of the current base) in 2016-17. Several analyses of the household energy transition in India exist, but the emissions consequences of this remain uncertain. My analysis provides an estimate of the net emissions impacts of the observed transition from traditional biomass cooking to LPG stoves over the decade 2001-2011 as a consequence of both policies and socio-economic developments over this period. While my analysis is unable to attribute the net emissions impact to specific policies, it provides a first historical estimate at the national level of emissions impacts of the household cooking energy transition that accounts for actual conditions and fuel stacking.

Between 2001 and 2011, I observe a sharp increase in LPG access in urban India (by 17%), compared to rural India (by 5%). Two factors contributed to this: a) enhanced access and stable supply of LPG in urban regions; and b) rapid urbanization of India whereby rural regions are being converted to urban and rural populations are moving to urban areas (Kumar & Rai, 2014). Both primary and secondary users of fuelwood were accounted for in my analysis to include the emissions impact of the continued use of fuelwood along with LPG. Thus, my net emissions impact is likely to be more conservative when compared to analyses that account for only primary users of LPG. As access to LPG improved, assuming all households were of average size, urban India displaced 6.19 million tonnes of fuelwood in 2011, while in rural India only 0.99 million tonnes were displaced. The variation between urban and rural regions is due to the differences in the LPG distribution networks, average incomes and price of fuelwood across these regions. Urban households tend to generally buy fuelwood (if available) and have access to better LPG distribution and after sales networks. Urban households, thus tend to make a more rapid and complete transition to ICS/CCS and are less likely to use fuelwood as a secondary fuel. Conversely, as fuelwood is easily accessible in rural regions and the LPG distribution networks are not reliable, stacking of fuels is more common among rural households. In addition to fuelwood, households also use crop and animal residues like dung as cooking fuels, especially in rural India, and the emissions from these fuels also have substantial negative health and climatic impacts. However, a lack of reliable data on crop and animal residue use in the NSS surveys limits my ability to include it in my net emissions impact estimations. Thus, I have only included emissions from fuelwood and LPG use in the analysis.

A key finding of this chapter is that even when biomass harvesting is assumed to be fully renewable (resulting in no CO_2 impact) there is no net emissions from the switch to LPG when considering Kyoto gases only (with some uncertainty around zero, see Appendix C). This is because of the considerably higher efficiency of LPG stoves compared to traditional fuelwood stoves and the fact that traditional stoves emit methane while LPG stoves do not (coupled with the higher GWP_{100} for methane than CO_2) (Freeman & Zerriffi, 2012; Grieshop et al., 2011; Shen et al., 2017). Accounting for black carbon and other non-Kyoto climate forcings results in a net reduction in emissions from a switch to LPG even at fNRB = 0 (see Appendix C for the full range of uncertainties). Considering a more realistic, but still conservative assumption of 0.3 as the fNRB results, according to my estimates, in a larger net decrease of Kyoto emissions of 3.05 $MtCO_2e$. Accounting for non-Kyoto climate-active emissions increases my estimate of net emissions reductions even further to 6.73 $MtCO_2e$ at the national level.

The estimates I provide on reduction in fuelwood consumption (and thus on reductions in emissions) are conservative for a number of reasons. First, the fraction of biomass that is non-renewably harvested is conservatively assumed to be 0.3. Some have estimated a higher fraction at the national level for India while others have estimated a slightly lower fraction (Bailis et al., 2015; Cashman, Rodgers, Huff, & Feraldi, 2016). However, all estimates are highly uncertain and I consider a fraction towards the lower end of the uncertainty range to ensure avoiding over-estimation. Second, the estimates of fuelwood displaced per kg of LPG consumed were made using NSS data that included both primary and secondary users of LPG. However, in scaling these to the aggregate national level, Census data on the total number of households with access was used, which only includes primary users of the fuel. I would expect that primary users would have a higher consumption of LPG than secondary users or a mix of primary and secondary users (as is observed in the NSSO data). Thus, the estimate at the national level is likely to be a lower bound on what each primary user of LPG is consuming. Third, again due to the fact that the Census only captures primary stove use, my estimate of households gaining access over the decade is likely a lower bound as it only captures households switching from no LPG to primary use of LPG and does not include households gaining access to LPG but using it as a secondary fuel. Fourth, the GWP_{100} used for black carbon is a global value of 455, whereas reported values in the literature vary regionally and some estimates for India put the GWP_{100} for black carbon at 1110 (Freeman & Zerriffi, 2014). Finally, I acknowledge that my estimates of net emissions from increased LPG access and use do not account for upstream emissions from the supply and manufacture of LPG. However, estimates of the emissions in the production and transport stage of LPG suggest that these are less than 10% of total emissions from LPG

(Cashman et al., 2016). It should also be noted that this analysis only captures changes at the extensive margin. That is, I only account for the reduction in fuelwood consumption and increase in LPG consumption associated with households moving from no access to having LPG access. I do not account for changes at the intensive margin (i.e., increases in LPG consumption from 2001 to 2011 by households that already had LPG in 2001). This is left to future work.

Despite these limitations, my analysis can be used to inform the design of public policies and investments to support clean cooking transitions in developing countries. The calculation of net emissions impact and fuelwood displaced due to increased LPG access and use can also be estimated using other methods. However, this is a first attempt to do so for India using the statistical matching techniques as far as I know. Better data availability in the future could allow the application of alternative methods and to other national contexts as well. Availability of longitudinal data could also make possible more research on trends in fuel stacking and LPG use over time. Little work has been done on determining the extent of public benefits from reduced emissions even though there is increasing interest in quantifying the environmental and welfare benefits for public policy and to generate more funding to promote cleaner fuel/stove use. This work could also inform future analysis of the net emissions impact from increased household LPG access as a consequence of the new set of policies being implemented by the Indian government.

Even though the transition of households from fuelwood to LPG for cooking have substantial impacts on health and fuelwood quantity used, the net climate impacts continue to remain uncertain, and have major implications for household emissions accounting. The choices regarding the fNRB use and climate-active emissions accounted for are important for the results and household emissions accounting. These should be considered carefully in any analysis and policy-making. This also has an important impact on potential revenue generation through utilization of carbon crediting methodologies to fund future clean cooking interventions. The fNRB assumed is crucial in determining the feasibility of a carbon credit based interventions, as carbon credits are based on the premise that improved stove efficiency and fuel substitution reduce the use of non-renewable biomass and its associated emissions. However, no matter what the assumption regarding fNRB, my results emphasize the importance of including non-Kyoto climate-active emissions in estimating the net climate impacts of transitioning from biomass to LPG cooking.

Chapter 6: Conclusion

6.1 Overview

In many developing countries, the use of traditional woodfuels (i.e., fuelwood and charcoal) can contribute 50–90% of all household energy, primarily to meet daily household cooking energy needs. Incomplete combustion of fuelwood in traditional inefficient cooking systems (TCS) can have negative impacts on human health, environment, climate change, and society. Without major policy changes and sustained effort, the total number of households dependent on fuelwood is expected to stay relatively constant out to 2030. Consequently, in recent years, there has been a strong revival in global policy circles to promote a transition to cleaner cooking solutions, such as improved cookstoves (ICS) and clean cookstoves (CCS), in light of their ability to reduce the negative environmental and health externalities from fuelwood use. However, a transition to ICS/CCS has been slow, and there is a likelihood to see increased pressure on forest resources from household and commercial extraction, and climate change in coming decades. Consequently, identification of the drivers of local use of fuelwood is essential to assess the impacts on forest resources of ICS/CCS interventions. At the same time, it is also important to ensure sustainable supply for dependent communities to meet their daily cooking needs. This requires a deeper understanding of the local resource and the particular fuel collection habits of local populations.

While decades of interventions, and corresponding research, has covered demand-side issues of fuelwood consumption in detail, the supply-side understanding of biomass extraction and its impacts on forest resources remains under-developed. Consequently, for the purpose of this dissertation, I focused primarily on the issue of fuelwood collection and the sustainability of its use, and not on the health or societal impacts. As a result, the main goal of this dissertation was to develop the tools and techniques useful for understanding fuelwood collection and its relationship to forest sustainability, and to apply those tools to household energy transitions (i.e., ICS/CCS interventions) in India at multiple spatial scales. This was accomplished by using mixed-methods approaches that included GPS tracking, remote-sensing data, household socio-economic surveys, and in-home measurements (kitchen performance test).

In Chapter 2, I mapped fuelwood extraction locations across three districts in India. Through the unique application of wildlife home range techniques, I identified local patterns and household preferences for fuelwood collection. In Chapter 3, I assessed the role of spatial extent in analyzing estimates of forest renewability, and built a case for local level estimates using RCPs from Chapter 2. In Chapter 4, I found that various socio-economic and demographic variables played a substantial role in changing fuelwood consumption due to an ICS/CCS intervention. Finally, in Chapter 5, I estimated the impact of a large-scale ICS/CCS intervention on household fuelwood use, and showed that forest renewability estimates and the suite of emissions included can substantially impact national carbon accounting.

To the best of my knowledge, this represents the first time that fuelwood extraction areas have been tracked and mapped at a local scale. This is also the first time I am aware of, that fuelwood consumption changes due to an ICS/CCS intervention have been estimated, taking into account species preferences and the source of fuelwood (farm vs. forest). Lastly, this is also the first time that the climatic impacts have been estimated at a national scale using national level historic data that reflects actual conditions of stove use and fuel stacking. Consequently, the dissertation makes a substantial contribution to a limited body of knowledge, and is an advancement in understanding the impact of fuelwood collection practices on forest resources and climate change. This research also contributes to literature in that it presents a conceptual and methodological structure within which future research on fuelwood collection behavior and on clean cooking interventions can occur.

6.2 Empirical findings

Empirical findings and conclusions are presented below by chapter theme.

6.2.1 Resource collection polygons (RCPs)

By using modern GPS technology and methodologies and by applying a unique technique from the study of animal movement patterns (i.e., RCP), I was able to better understand where households travel for fuelwood collection. The RCP results show specific patterns in distance traveled and on the location of collection, unique to each village, within and between regions. I identified the regions within the RCP where actual collection occurs - useful to identify extraction hotspots (locations of greatest impact) for long-term forest management. In general, the variations in RCP shape (direction, location, & distance) were a result of various factors, such as: a) proximity of the village to forest and orchards, b) quality of crop residue, and c) socio-demographics (such as caste, land ownership etc.). For example, households in Karnataka traveled longer and further, on average, as their forests were more than a kilometer away, compared to Kullu where the forests were adjacent to the villages.

6.2.2 Local collection – regional measurement: the impact of spatial scale on assessing biomass stock changes relevant to fuelwood interventions

Sustainability of fuelwood consumption is dependent on local fuelwood demand and the supply (or growth) of local forest resources. Biomass stocks vary considerably based on non-accessible areas, topography, LULC, and localized biomass extraction patterns. Consequently, my results showed variations in biomass stock changes between Valleys and between the Villages in those Valleys. This variation between the three spatial extents (Valley, Village buffer, and RCP) explains the need for local estimates, as impact of fuelwood harvesting is ignored at the larger aggregated extents. Failure to incorporate these local differences in household consumption and collection behavior can lead to substantial inaccuracies in calculation of fuelwood supply, as large scale estimates of biomass growth do not capture the regional differences. For example, fuelwood BSCs for the Villages declined between 0.02 to 0.06 tonnes/ha/year while the fuelwood BSCs for the Valleys declined by 0.9 to 0.10 tonnes /ha/year. Moreover, these variations are likely to be of a larger magnitude at national extents due to higher variability in biomass resources - ranging from tropical forests to barren desserts.

6.2.3 Forest, farms and fuelwood: measuring changes in fuelwood collection and consumption behavior from a clean cooking intervention

While multiple studies have looked at overall biomass consumption changes due to a clean cooking intervention, to the best of my knowledge, this was the first investigation of species preferences and composition changes as a result of the intervention. Results explained under what physical and socio-economic factors a household truly reduced its dependence on forest resources, potentially resulting in positive social, climatic, and forest impacts. Identification of these changes helped isolate impacts of clean cooking technologies on forests and society. Results varied across regions with a combination of demand and the substitutability of fuelwood from other sources, such as farms. There was a difference between sites and within each site, as well as between collection sources. In Kullu, households reduced overall fuelwood consumption and from forest and farms by about 50%, while households in Koppal reduced overall consumption by about 1/3rd, where forest consumption reduced by almost 40% and farm reduced by only 10%. The amount of reduction in consumption from forest sources was dependent on the quality of farm residue and forest resources, and the structure of non-economic activities of the household. Lower quality farm residue requires more substitution for cooking from forest sources, while social caste and wealth could impact the consumption and collection decisions for households. Moreover, regardless of fuelwood requirements, certain regions will not experience a full transition to ICS/CCS due to climatic conditions (biomass is used extensively for heating), or other processes (availability of orchard harvest wood that must be pruned regardless). However, regardless of location or household characteristics, when forest fuelwood collection distance was perceived to be increasing over time, all households at both locations reduced forest consumption.

6.2.4 Environmental payoffs of LPG cooking in India

My analysis provides an estimate of the net emissions impacts of the observed transition from fuelwood cooking to LPG stoves in India over the decade 2001−2011, as a consequence of both policies and socio-economic developments over this period. A key finding was that even when biomass harvesting was assumed to be fully renewable (resulting in no CO_2 impact) there were no net emissions from the switch to LPG, when considering Kyoto gases only. This is because of the considerably higher efficiency of LPG stoves compared to traditional fuelwood stoves and the fact that traditional stoves emit methane while LPG stoves do not (coupled with the higher GWP_{100} for methane than CO_2). Accounting for black carbon and other non-Kyoto climate forcings resulted in a net reduction in emissions from a switch to LPG, even at fNRB = 0. Considering a more realistic, but still conservative assumption of 0.3 as the fNRB, resulted in a larger net decrease of Kyoto emissions of 3.05 $MtCO_2e$. Accounting for non-Kyoto climate active emissions increased my estimate of net emissions reductions even further to 6.73 $MtCO_2e$ at the national level.

6.2.5 Overall conclusions

This dissertation helps fill the gap in literature and adds to the knowledge base of fuelwood extraction impacts on forest sustainability by tracking household fuelwood collection patterns, and identifying changes in fuelwood consumption behavior due to a clean cooking intervention. The combined analysis of the research findings presented in this dissertation reveals the need for greater understanding of local fuelwood extraction behavior to isolate its impacts on forest resources. ICS/CCS interventions are carried out locally but fuelwood renewability for these projects is often estimated at larger scales, thereby not being representative of the region where the intervention occurs. The theme that local estimates are needed in order to understand forest impacts from fuelwood use is apparent throughout the dissertation: in the RCPs showing actual household collection behavior rather than simple radii buffers; in estimating forest renewability which varies considerably at different spatial extents; in estimating household consumption behavior changes due to a switch to ICS/CCS; and finally in national emissions accounting where biomass renewability estimates can have substantial impacts in estimating emissions from various policies and interventions. Consequently, there needs to be increased discussion on the choice of this spatial extent among the research, policy-making and implementation communities across both the cookstove and carbon credit domains.

6.3 Limitations

As with all research, this dissertation also has its limitations. The RCPs in Chapter 2 identified locations of collection. A further step would be to measure the density of collection (i.e., which routes were dominant over others using methods such as Kernel Density. However, this was beyond the scope of the data originally collected. The RCPs were also potentially limited by a self-selection bias. It is possible that participants in the study were those who only collect from farms and/or legal areas, whereas those collecting from illegal areas (i.e., protected forests) may have chosen not to participate in the study. It is also possible that some households might have changed behavior knowing that their movements were being tracked. Therefore, the RCPs presented may not be fully representative of the communities' entire fuel collection behavior. However, the main purpose of the chapter was to show feasibility of applying home range analysis to human fuelwood collection behavior. It can be improved upon in future work, and studies should be aware of any potential self-selection bias during study design and participant recruitment.

Limitations for Chapter 3 on estimation of biomass renewability at varying spatial extents was due to inherent restrictions of using secondary data, including remotely sensed data. The data used was not able to provide information on natural disturbances, nor was I able to confirm disturbances from publicly available records for the area. I also lacked longitudinal sample plot data (repeated measures over time) and detailed GIS layers for boundaries of villages, orchards, towns, roads and streams. Access to such information could result in very different estimates of biomass stock. Improvements to the method can be made with better data in future work, and the most valuable contribution of this chapter was in demonstrating the importance of spatial scale in estimation of biomass stocks, and the need to estimate fuelwood biomass stocks rather than just total biomass stock in order to isolate ICS/CCS impacts on forest resources.

Data collected for Chapter 4 also has its limitations. First among them is the legitimacy of species identification by field staff, where I relied on their local knowledge and ability to identify species from branches. However, field staff was recruited from local villages where they grew up using these species and know what they look like from personal experience. A second limitation arises from my allocation of species into farm or forests based on the survey data rather than field data. However, the allocation had no impact on total fuelwood estimates, and only impacted farm vs. forest estimates: allocation using the survey data in location of collection was only applied to a small percentage of total kilograms. Third, there could be other factors that I was unable to control for, such as crop failure in one year such that farm consumption might be considerably less or an extremely cold year where overall consumption in the mountains might be more. However, data were collected in the same months each year and there was likely not much variation in average temperature during the collection months to create any cause for concern. Fourth, I was unable to capture seasonal variation where results might differ if data were collected in winter or during agriculture season.

Finally, in Chapter 5, the estimates provided on net emissions from increased LPG access and use did not account for upstream emissions from the supply and manufacture of LPG. However, estimates of the emissions in the production and transport stage of LPG suggest that these are less than 10% of total emissions from LPG (Cashman et al., 2016). Lastly, I only captured changes at the extensive margin – the reduction in fuelwood consumption and increase in LPG consumption associated with households moving from no access to having LPG access. Changes at the intensive margin (i.e., increases in LPG consumption from 2001 to 2011 by households that already had LPG in 2001) were left to future work.

6.4 Future research and practice

6.4.1 Future research

While there is increasing interest in quantifying the environmental and welfare benefits of a clean cooking transition for developing more effective public policies and to generate more funding to promote ICS/CCS use, more work needs to be done to determine the extent of benefits on forests and climate from this transition. Better GPS data collected for the intended purpose of RCP analysis could help researchers understand the impact of a transition to ICS/CCS. More extensive GPS datasets would make it possible to identify frequency of use and stratify household fuelwood collection preferences on the basis of traditional stoves versus ICS/CCS. Such data could better indicate post-intervention behavior change in fuelwood collection. The RCPs also provide boundaries of fuelwood collection that can be integrated into existing models such as WISDOM and MoFuSS to obtain more precise data on sustainability of fuelwood extraction. This improved understanding of collection patterns can help detect potential fuelwood hotspots, where extraction exceeds growth of local resources, and prioritize interventions and forest management in those regions. Incorporating some of the insights gained from the dissertation, and from Singh et al. (2018), into the larger scale fuelwood supply and demand modeling exercises (e.g., MoFuSS) is underway as one avenue for using the data to improve existing models.

Household fuelwood consumption data collected across various seasons can indicate the change in household behavior, and identify the variables that affect fuelwood species composition under different situations. For example, immediately post-harvest it might be that all households reduce fuelwood consumption as there is a flow of cash and they are able to buy LPG. However, during non-agricultural season, when cash flows are limited, it might be the wealthier household and / or higher caste households still reduce fuelwood consumption by using LPG, while others are unable to do so. Such information would be useful in roll out of large scale clean cooking interventions and to understand under which circumstances a complete transition to ICS/CCS is possible. Additionally, future research could identify the impact of agroforestry on household collection behavior and consequently on forest resources. Moreover, longitudinal data on species preference could also be combined with remote sensing data to track any degradation of local resources over time. Lastly, while I predicted fuelwood use for a ‘typical’ household, the model could also be used to estimate fuelwood consumption changes for a variety of households. More data could be added and the models developed again, such that future interventions can be prioritized, not only to those locations where negative extraction impact on forest resources is greatest, but also where the households are more likely to move away from forest sources.

For large national interventions, such as for LPG in India, it would be valuable to calculate the climatic impact of those households who already have access to LPG and have increased consumption over time (i.e., intensive margin). Such data could isolate the impact of fuel stacking and, in light of my results, how much it contributes to the national carbon accounting. Moreover, the intensive and extensive (Chapter 5) margins together could help isolate policy impacts on national carbon accounting, such as for the Ujjwala program, and its contribution to meeting India's Paris commitments. Application of this research to other regions such as in Sub-Saharan Africa, would also be extremely valuable for future policy and ICS/CCS interventions.

6.4.2 Policy and other applications

The research covered in this dissertation has multiple implications for energy and climate policy, forest management, and future clean cooking interventions. The identification of local fuelwood hotspots can help prioritize interventions and help in the creation of forest management plans. It could also inform future ICS/CCS programs in communities where fuelwood collection distances are increasing and local forest resources are being depleted.

More specifically, there are a number of applications of the methods and data developed for this dissertation. First, collection of GPS track data and use of the RCPs should be considered for contexts where spatial distribution of fuelwood collection may be particularly important (e.g., near reserve forests). Such information would also be important for future ICS/CCS interventions in terms of understanding the baseline conditions of forest and farm biomass dependence and the impact of any interventions. RCPs could also be applied in the future to various fields of human consumption patterns to better understand resource dependencies such as water collection behavior or food foraging patterns. Such information would be useful especially in the light of climate change and the risk of increased droughts and water shortages, such as in Sub-Saharan Africa. RCPs could also be used to identify hotspots for targeted resource management in those regions.

Second, spatially explicit data could help focus and prioritize projects in regions where the non-renewable biomass (NRB) values are highest and can be more justifiably attributed to fuelwood extraction as opposed to other drivers. Carbon markets for ICS/CCS are centered on avoided emissions from the use of non-renewably sourced fuelwood, where one tonne of CO_2 equivalent offsets a tonne emitted elsewhere (i.e., for the buyer). These credits are often used to generate finance for clean cooking interventions and can impact the support for such programs by further demonstrating the potentially positive climate benefits of ICS/CCS. Consequently, allowing organizations to estimate NRB at a project level could help maximize global and local (largest income from carbon sales) benefits from clean cooking interventions. Results could indicate the extent of carbon neutrality of using ICS/CCS, as well as the impacts of fuelwood collection on forest resources. However, the limitations of obtaining spatially explicit data, as explained in Chapters 2 and 3, highlights the need more broadly for improved field data collection, digitization of data, and technical support for record-keeping in these regions. At the same time, the degree to which the increased accuracy of biomass stock change at the local level is required is as much a policy decision as it is a technical decision and should be a topic of discussion among the research, policy-making and implementation communities. Both the cookstove and carbon credit domains need to be aware of these tradeoffs which might need to be made between accuracy, and data acquisition and processing, for estimating climate impacts of ICS/CCS, such as for using easily available but less precise data versus using stringent methodologies to obtain spatially explicit data.

Third, information gained on the change in fuelwood consumption behavior has important implications for climate change mitigation via ICS/CCS carbon credits through reduced extraction from forests, and for promotion of social welfare from reduced collection efforts for women. For example, as shown in Chapter 4, if overall fuelwood collection reduces due to an ICS/CCS intervention and the reduced quantity is met from local farm sources, it could indicate positive climate change mitigation benefits from reduced emissions and a reduced reliance on forest resources. Such information can be incorporated into future carbon crediting methodologies. This information is also important for future ICS/CCS interventions and forest resource policy decisions for the region such that interventions can be prioritized, not only to those locations where negative extraction impact on forest resources is greatest, but also where the households are more likely to move away from forest sources.

Finally, even though the transition of households from fuelwood to LPG for cooking has major impacts on human health and fuelwood quantity used, the net climate impacts continue to remain uncertain, and can have important implications for household emissions accounting. The choices regarding the NRB and climate-relevant emissions accounted for are important for household emissions accounting and should be considered carefully in any analysis and policymaking. However, no matter what the assumption regarding NRB, my results emphasize the importance of including non-Kyoto climate forcings in estimating the net climate impacts of transitioning from fuelwood to LPG cooking.

More broadly, my analysis can also be used to inform the design of public policies and investments to support ICS/CCS transitions in developing countries. With 2.6 billion people globally and 800 million people in India relying on solid fuels to meet their basic cooking requirements, there is an urgent need for evidence-based policies to minimize the impacts and aid in the transition of these households to cleaner cooking solutions. Developing these evidence-based policies requires complementing the existing knowledge base around fuelwood demand with better tools, methods, and data around fuelwood collections patterns and biomass supply. Integration of the tools developed in this dissertation into existing and future policies and programs should be considered, recognizing the need to balance the cost and complexity of data collection and modeling with the improved information that can be derived from these methods. This task would be made easier with better processes to develop the underlying data at the national and sub-national level and making that data more readily available and accessible in digital form. For example, forest measurement data from national forest agencies as well as household energy consumption data from national statistical offices are often either missing, inadequate, poorly defined or inaccessible in many regions. Better data collection and analytical methods, as demonstrated in this dissertation, will aid both governments and civil society organizations in this domain to better understand forest dependency, the relationship between household energy demand and climate change, and the specific implications of any clean cooking intervention.

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Appendices

Appendix A : **Chapter 3 - Biomass estimates at varying spatial extents**

A.1 Biomass model R-code

```
# data is not normally distributed, so run lognormal
M <- lm(log(total_bm_t) ~ Altitude + NDVI + DVI + NDMI + band1 + band4, data = df)
summary(M)
df$woody_bm_t <- kullu$woody_bm_t
# get diagnostic plots
df$yhat <- fitted (M) # the estimated y values
df$yhat.M <- exp(df$yhat)
df$resid.M <- resid (M)  # the errors

#####   Small wood ############### Step 2 #################
df$wood_percent <- df$woody_bm_t / df$total_bm_t
df1 <- data.frame(df,
        #change percent into number of successes out of 100.
        #Remove the decimal place on percent small wood by rounding it to the nearest
percent
        RESPONSE=round (df$wood_percent, digits=0),
        NOBS=100)
logistic.GLM <- glm(cbind(RESPONSE, NOBS-RESPONSE) ~ Altitude + NDMI + EVI,
        family=binomial (link = "logit"), data=df1)
df$yhat.GLM <- fitted (logistic.GLM)  # the estimated y values for the LME model
df$resid.GLM <- resid (logistic.GLM)  # the errors for the LME model


### get woody biomass value #########
df$predlogit <- predict (logistic.GLM)
df$predprop <- exp(df$predlogit) / (1 + exp(df$predlogit))
range (df$predprop)
df$pred_small_wood <- df$predprop * df$yhat.M
range(df$pred_small_wood)
range(df$woody_bm_t)

#NOW take the biomass model and use it to predict the biomass values for each pixel
pixel$total_biomass <- predict (M, pixel, interval="none")
pixel [is.na(pixel)] <- 0
range(pixel$total_biomass)
#Back transform
pixel$predlogit<- predict (logistic.GLM, pixel, interval="none")
pixel$predprop<- exp(pixel$predlogit) / (1+exp(pixel$predlogit))
# All values should range from 0 to 1.
```

```
#Then, take the estimated biomass and multiply by the predicted proportion of total biomass that is small wood.
pixel$pred_small_wood <- pixel$predprop * pixel$total_biomass
pixel [is.na(pixel)] <- 0
range(pixel$predprop)
range(pixel$pred_small_wood)
```

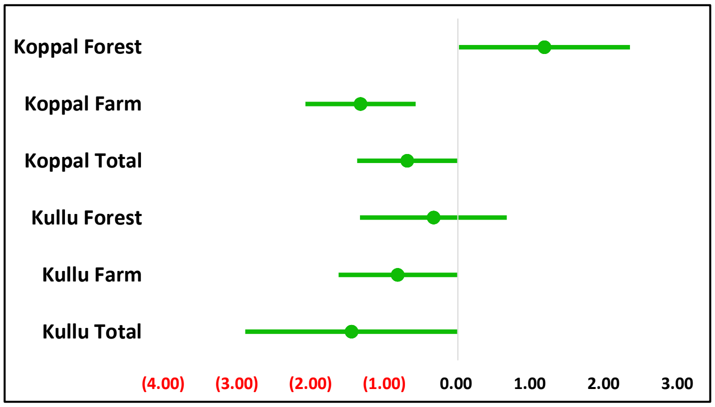
A.2 X-variable selection using AIC for log-normal and logistic models

	Aboveground X-Variable combinations (Log-Normal)	AIC	logLIK
0	Null	216.67	-106.33
1	Elevation	190.12	-92.06
2	Elevation + Blue + Green + Red + NIR	186.35	-86.18
3	Elevation + EVI + ARVI + SAVI	183.45	-85.73
4	**Elevation + NDVI + NDMI + Blue + NIR**	**180.70**	**-82.35**

	Fuelwood X-Variable combinations (Logistic)	AIC	logLIK
0	Null	13339	-6670
1	Elevation + Blue + Green + Red + NIR	216.95	-102.48
2	Elevation + EVI + ARVI + SAVI + NDMI + NDVI	218.95	-102.48
3	Elevation + NDVI + DVI + NDMI + Blue + NIR	216.94	-102.47
4	**Elevation + NDMI + EVI**	**212.96**	**-102.48**

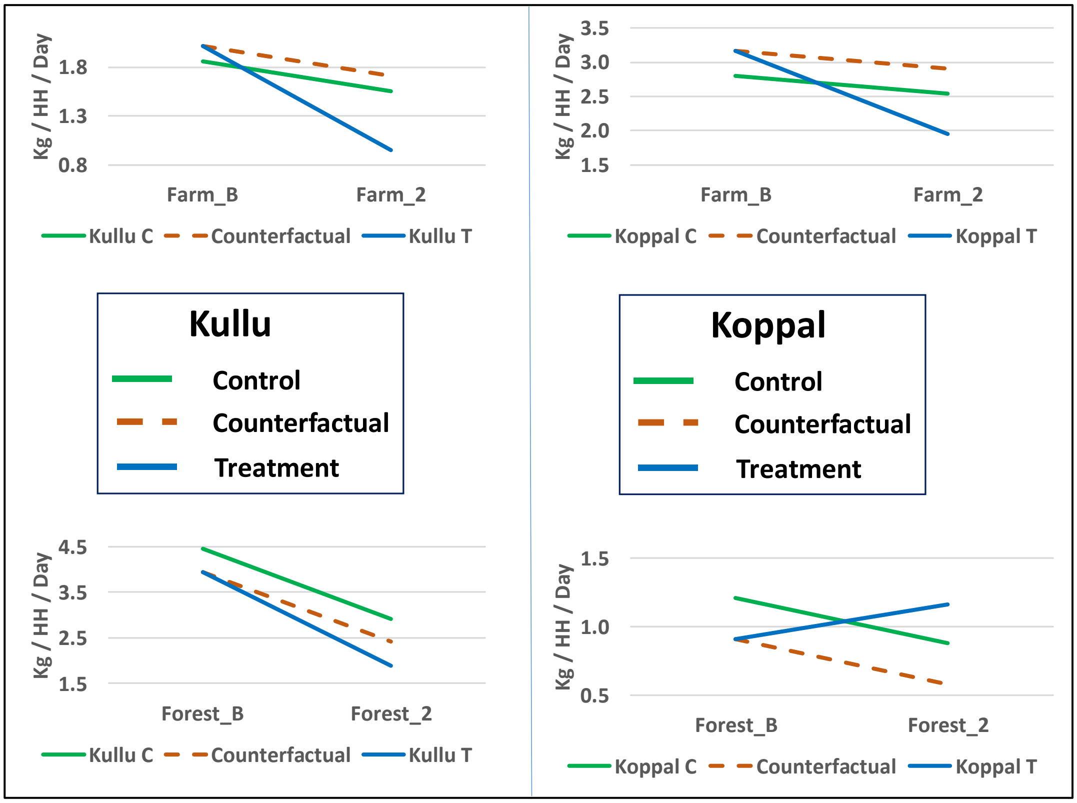
Appendix B **: Chapter 4 - Change in fuelwood consumption behavior**

B.1 DiD plot and full model estimates



DiD Coefficients	KULLU Total	KULLU Farm	KULLU Forest	KOPPAL Total	KOPPAL Farm	KOPPAL Forest
Intercept	6.52	-2.02	9.57	3.53	3.00	1.62
Dtr	-0.48	0.39	-0.59	0.18	0.90	-1.17
Dpost	-1.82 .	-0.26	-1.68 *	-0.77	-0.00	-1.42
Dtr*Dpost	-1.44	-0.81	-0.33	-0.69	-1.32 *	1.18
Wealth Index (WI)	-0.35	2.23 **	-2.81 ***	0.03	0.55 .	-0.89 **
Adults	0.27	0.40	0.00	0.21 *		0.29 *
Caste	-2.43	-0.49	-2.75			
MC_decision	-1.96 .	0.84	-3.69 ***	-0.30	-0.91 *	0.99 *
Wood_Collection	3.64	1.01 *	-3.68 ***			-1.01 *
Non-Solid B (nsfB)		3.28 .	-2.14 *	0.16	0.27	-0.94
HHH_MC					-0.07	
WI*Caste		-1.54 .				
WI*MC_decision	-0.26	-1.43 *	2.69 ***		0.31	
WI*HHH_MC					-0.95	
WI*Wood_Collection		-1.18 *				
WI*nsfB				-0.63	-1.22	1.60
Adults*Wood_Collection	-1.08 .					
Adults*Caste	1.03 *		0.97 *			
Adults *nsfB		-0.59				
Wood_Collection*nsfB			3.11 *			2.64
Residual Std. err.	2.57	1.60	2.07	1.44	1.58	2.25
Significant codes:	'***' 0.001	'**' 0.01	'*' 0.05	'.' 0.1		

B.2 Counterfactual graphs for both sites by wood source



B.3 Kilogram allocation tables

Table B.3.1: KG unidentified, and composition for species for source for each season

KULLU	Total KG	Removed	% Rem.	Allocate Orchard	% Allocate	Total Orchard	% Orchard	Allocate Forest	% Allocate	Total Forest	% Forest
Baseline	328	1.6	0.5%	31	10%	105	32%	28	8%	216	66%
season 1	214	4.1	1.9%	13	6%	46	21%	5	3%	168	79%
season 2	174	2.9	1.7%	9	5%	58	34%	11	6%	114	65%

Koppal	Total KG	Removed	% Rem.	Allocate Farm	% Allocate	Total Farm	% Farm	Allocate Forest	% Allocate	Total Forest	% Forest
Baseline	215	12.7	5.6%	7	3%	164	72%	7	3%	52	23%
season 1	177	0.4	0.3%	7	4%	124	70%	7	4%	52	29%
season 2	171	3.0	1.7%	18	10%	110	64%	18	10%	58	34%

Table B.3.2: Percent of total kgs allocated to each source based on self-reported survey

Allocated based on Survey	Kullu		Koppal	
	Baseline	Season 2	Baseline	Season 2
Kullu	10%	5%	3%	10%
Koppal	8%	6%	3%	10%

Table B.3.3: Change in kilograms consumed by various groups

	Kullu						Koppal					
	Upper			Lower			MC = 0			MC = 1		
	Base	Post-Int.	diff (kg)	Base	Post-Int.	diff (kg)	Base	Post-Int.	diff (kg)	Base	Post-Int.	diff (kg)
Total Wood / day	5.43	2.87	-2.56	7.17	3.80	-3.37	4.36	3.46	-0.90	4.41	2.54	-1.86
Farm / day	2.32	1.23	-1.09	1.54	0.94	-0.60	3.25	2.86	-0.39	3.33	1.07	-2.26
Forest / day	2.93	1.64	-1.29	5.55	2.79	-2.76	1.12	0.60	-0.52	1.08	1.48	0.40

B.4 Forest species consumption scenarios

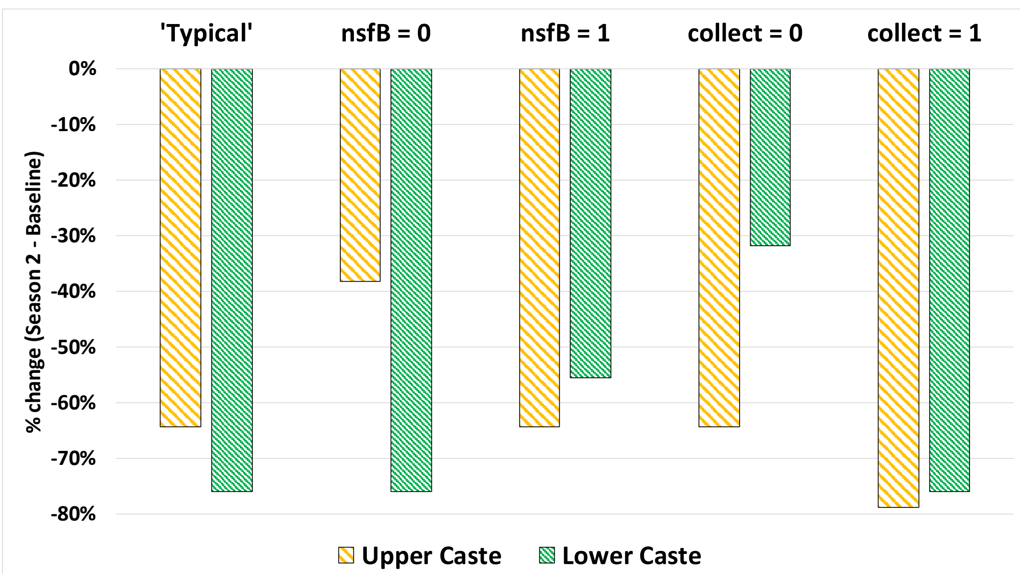


Figure B.4.1: % change in forest consumption in Kullu, where 1=yes, and 0=no: a 'typical' HH, nsfB, and increase in forest wood collection distance (collect)

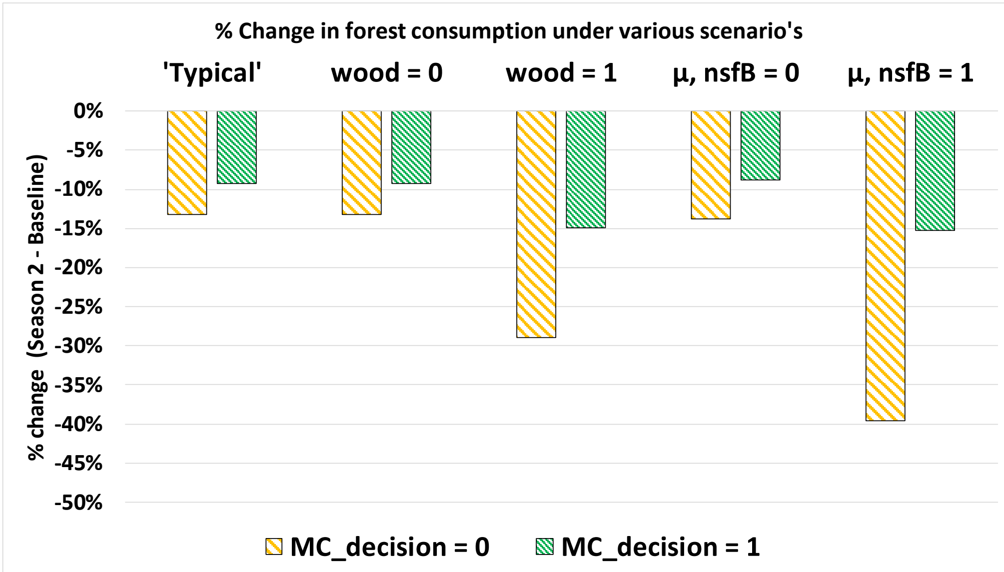


Figure B.4.2: % change in Forest consumption in Koppal, where 1=yes and 0=no: a 'typical' HH, nsfB, and nsfT for Main cook as decision maker (MC_decision).

Appendix C : Chapter 5 - Environmental payoffs of LPG cooking in India

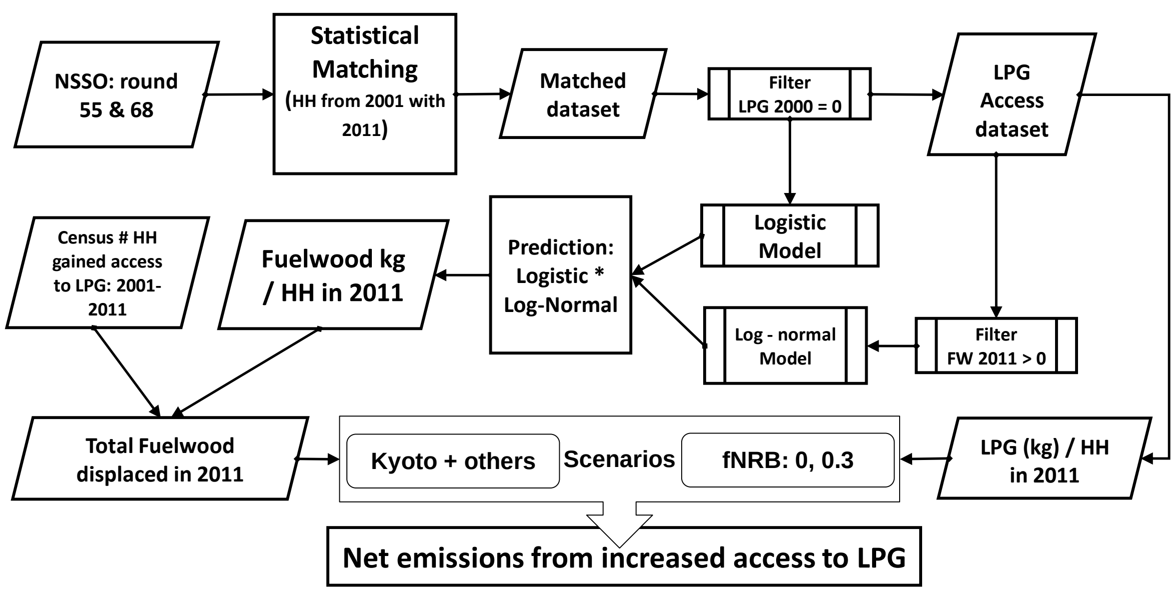
The appendix includes information that was included in the supplementary information for the manuscript published in Environmental Research Letters. Each of the figures and tables below can be found in the Supplementary Information section for: Singh, D., Pachauri, S., & Zerriffi, H. (2017). Environmental payoffs of LPG cooking in India. Environmental Research Letters, 12(11), 115003. https://doi.org/10.1088/1748-9326/aa909d.

C.1 Data information

I use the Indian national censuses (2001 and 2011) and the Indian National Sample Survey (NSS) Organization socio-economic surveys (round 55 and round 68) to estimate the amount of fuelwood displaced due to an increase in liquefied petroleum gas (LPG) access. The Indian national census is a complete enumeration of all Indian households and is a publicly available primary data source at the village and town level (Census of India, 2016). The NSS is India's largest organization conducting regular nationwide sample surveys relating to various socio-economic topics since 1950 (MOSPI, 2011). Both datasets contain socio-cultural and demographic data including population characteristics, economic activity, education, household size, and type of cooking fuels. While the census provides information for all households in India on the primary fuel used for various household activities (e.g. cooking, heating etc.), it ignores the actual quantities of fuel used. Conversely, the NSS does contain information on the quantities and expenditures of various household fuels, but is limited in that it does not cover the entire population (it is a sampled population that is representative of the total). Thus, to obtain the best possible estimate for fuelwood and LPG use in India, I utilized both sources.

To calculate the net emissions impact I utilized the emissions factors as reported in Table S1 of Freeman & Zerriffi (2014) for various climate forcing emissions. Averages reported for W-Tr-U were taken as the emissions factors for a traditional open fire and those for LPG-U were taken for estimates of LPG stoves. Table S2 of Freeman & Zerriffi (2014) provided the 100-year global warming potential (GWP_{100}) values used in my analysis. The conservative value of 0.3 for fraction of non-renewable biomass (fNRB) was based on the estimates from Bailis et al 2015.

C.2 Method flowchart for arriving at net emissions impact



C.3 Statistical matching

I applied statistical matching techniques to assess the number of households that gained access to LPG between 2000 and 2011. Households from the NSS rounds 55 and 68 were ‘matched’ on the basis of State, urban/rural, and caste for a total of 109,507 observations in the synthetic dataset. The mixed procedure was utilized in the R StatMatch package to match 2011 households with those in 2000. The R-code with explanations for statistical matching is given below:

```
# Load the NSS rounds 55 and 68 combined file.
survey <- read.csv ("C:\\Users\\Devyani\\NSS.SurveysCombined.csv",
                    header=T)
# split the NSS survey data by years 2000 and 2011
survey2000 <- subset (survey, year==2000)
survey2011 <- subset (survey, year==2011)
# now rename LPG quantities for each year
colnames (survey2000) [16] <- "lpg_q2000"
colnames (survey2011) [16] <- "lpg_q2011"
# make modely = year 2011 and modelz = year 2000 variables
lm.modely <- lm (lpg_q2000 ~ firewood_q * income * employment_type
                 * HHsize * caste * kerosene_q, data=survey2000)
summary (lm.modely)
lm.modelz <- lm (lpg_q2011 ~ firewood_q * income * employment_type
                 * HHsize * caste * kerosene_q, data=survey2011)
summary (lm.modelz)
# Now calculate predicted values znew and ynew
# ynew is the predicted value of lpg2000 based on 2011 model
ynew <- predict (lm.modely, survey2011, interval="none")
length (ynew)
# znew is the predicted value of lpg2011 based on 2000 model
znew <- predict (lm.modelz, survey2000, interval="none")
length (znew)
# rename lpg_q variables to match one another
# this is required to run StatMatch code
survey2000$lpg_q2011p <- znew
survey2011$lpg_q2000p <- ynew
survey2000$lpg_q2000p <- survey2000$lpg_q2000
survey2011$lpg_q2011p <- survey2011$lpg_q2011
survey2000yz <- subset (survey2000, select = c (lpg_q2000p, lpg_q2011p))
survey2011yz <- subset (survey2011, select = c (lpg_q2000p, lpg_q2011p))
# create the group of matching variables
group.v <- c ("state2000", "urban", "caste")
# used states in 2000 for consistency between datasets
# as some of the states were split up in India between 2000-2011
X.mtc <- c ("lpg_q2000p","lpg_q2011p")
out.nnd <- NND.hotdeck (data.rec = survey2000, data.don = survey2011,
            match.vars = X.mtc, don.class = group.v)
summary (out.nnd$dist.rd)
summary (out.nnd$noad)
# Create a fused dataset with 2011 variables in the matched file
# this matched file uses HH from 2000 as base
```

```
fused.nnd <- create.fused (data.rec = survey2000, data.don = survey2011,
                           mtc.ids=out.nnd$mtc.ids,
                           z.vars = c(8, 9, 11:14, 16, 18:20))
# add 2011 variables to fused dataset: HHsize, weights, employment_type,
                caste, income, firewood_q, kerosene_q, charcoal_q, and coal_q
summary (fused.nnd)
matched <- fused.nnd # rename file to matched to be used in tobit model
```

C.4 Tobit model

The statistically matched synthetic dataset was utilized to estimate the amount of fuelwood displaced due to LPG access in 2011. I used a three step Tobit model, based on the technique used by Green (2003):

1. Logit transformation (i.e., a logistic model): this model estimated the probability of a household using fuelwood in 2011 as a function of household size, urbanization and LPG use in 2011.

$$Prob\ (fuelwood\_q2011 > 0) = \beta_0 + \beta_1 * lpg2011 + \beta_2 * HHsize2011 + \beta_3 * Urban2011$$

2. Log-normal transformation: this model predicted the quantity of fuelwood consumed by a household using fuelwood in 2011.

$$fuelwood\_q2011 = \beta_0 + \beta_1 * lpg2011 + \beta_2 * HHsize2011 + \beta_3 * Urban2011$$

3. Step 3 = logit transformation * log-normal transformation: this final step predicted the quantity of fuelwood used by all households considering the probability of them using fuelwood in 2011.

I used the Tobit model by Greene (2003) because the existence of zeros for fuelwood use in the synthetic dataset was more than one would expect from a binomial distribution, however, it is expected to be the case for households gaining access to LPG. A Tobit model models the zero's and the non-zero as separate processes (Greene 2003). Thus, I first determined whether a household uses fuelwood in 2011 ('participation' equation to model probabilities), and if so, then how much is being used on average (conditional consumption equation). The R-code for analysis was based on the gamma hurdle biological model by Anderson (2014) and is given below:

```
##### Read in data – the matched dataset.
matched <- read.csv ("C:\\Users\\Devyani\\Matched.csv", header = T)
# Filter the data where only those HH with no access in 2000 are included
lpg_access <- matched %>%
   filter(lpg_q2000 == 0)
# Add in urban2011.f to be recognized as factor.
lpg_access$urban2011.f <- as.factor (lpg_access$urban2011)
# get the non zero file for lognormal model to be used in step 2
lpg_access_nozeros <- lpg_access %>%
  filter (firewood_q2011 > 0)


            ### Step 1:  Logistic model
#Logit transformation this model estimates the probability of a household using fuelwood in 2011 as a re
sult of the x-variables
##  Set up the binomial y variable.
lpg_access$firewood_q_2011yes <-
                                    ifelse (lpg_access$firewood_q2011 <=0.0, 0,1)
# fit the null model with no x variables.
logistic.null <- glm (lpg_access$firewood_q_2011yes ~1,
                                    family=binomial(link = "logit"),data=lpg_access,
                                    weights=Weight2011)
summary(logistic.null)
# now fit the best model (details given later in SI)
logistic.M1 <- glm (lpg_access$firewood_q_2011yes  ~ lpg_q2011
                                    + urban2011.f + HHsize2011
                                    + lpg_q2011 * urban2011.f
                                    + HHsize2011 * urban2011.f,
                        data = lpg_access, weights = Weight2011)
summary (logistic.M1)
AIC(logistic.null); AIC(logistic.M1)
logLik(logistic.null);logLik(logistic.M1)
pred.logit.M1 <- fitted (logistic.M1)
pred.prob.M1 <- (exp(pred.logit.M1)) / (1+(exp(pred.logit.M1)))


         # Step 2: Log-normal distribution for non-zero firewood.
#Log-normal transformation: this model predicts the quantity of fuelwood
```

```
#consumed by a household using fuelwood in 2011.
normal.null <- glm (firewood_q2011 ~ 1,
                data = lpg_access_nozeros,
                family = gaussian (link = log), weights=Weight2011)
normal.M1 <- glm (firewood_q2011 ~ lpg_q2011 + urban2011.f
                          + HHsize2011 + lpg_q2011 * urban2011.f
                                      + HHsize2011 * urban2011.f,
                                      data = lpg_access_nozeros,
                                      family = gaussian (link = log), weights=Weight2011)
summary (normal.M1)
AIC(normal.null); AIC(normal.M1)
logLik(normal.null);logLik(normal.M1)
# predicted values for the normal model.
# get the Beta and the X matrix and use that to get predicted y values
n <- length (lpg_access$firewood_q2011)
# coefficients as a matrix.
Beta.M1 <- normal.M1$coefficients
Betamat.M1 <- as.matrix (Beta.M1) # convert to a matrix.
dim (Betamat.M1)
# X matrix for the model for data without zeros
Xmat.M1.no0 <- model.matrix ( ~ lpg_q2011 + urban2011.f
                         + HHsize2011 + lpg_q2011 * urban2011.f
                         + HHsize2011 * urban2011.f,
                                                  lpg_access_nozeros)
# head (Xmat.M1.no0)
dim (Xmat.M1.no0)
yhat.M1.no0 <- exp (Xmat.M1.no0%*% Betamat.M1)
head (yhat.M1.no0)
length (yhat.M1.no0)  # yhats using > 0 data.
resid_b_nM1.no0 <- lnfirewood_q2011 - lnyhat.M1.no0
## Predicted values using both models on all data.
##     yhat given firewood>0  times Prob (firewood>0)
n <- length (lpg_access$firewood_q2011)
# coefficients as a matrix.
Beta.M1 <- normal.M1$coefficients
Betamat.M1 <- as.matrix (Beta.M1) # convert to a matrix.
dim (Betamat.M1)
# X matrix for the model.
Xmat.M1 <- model.matrix ( ~ lpg_q2011 + urban2011.f
                     + HHsize2011 + lpg_q2011 * urban2011.f
                     + HHsize2011 * urban2011.f, data = lpg_access)
head (Xmat.M1)
dim (Xmat.M1)
yhat.M1 <- exp (Xmat.M1%*% Betamat.M1) # same as predict prob. in step 1
                                          but here multiply matrix
head (yhat.M1)
length (yhat.M1)  # yhats for all data using model built > 0 data.
```

 # MAIN STEP – Step 3

```
#Step 3 = logit transformation * log-normal transformation:
#predicts the quantity of fuelwood used by all households considering the
#probability of them using fuelwood in 2011.
#This part of model was based on p. 821 of Greene, Econometric Analysis.
lpg_access$pred_b_nM1 <- yhat.M1 * pred.prob.M1
head (lpg_access$pred_b_nM1)
```

I tested a combination of x-variables (urban/rural, LPG quantity, household size, income, caste, employment, and religion) and selected the 'best model' based on AIC and logLIK to predict firewood use in 2011 (Table C.4.1). The AIC and LogLik for the various combinations of x-variables is given below (for both the logistic and log-normal models). To avoid complexity in the model for the sake of minor gains in model fit, I chose LPG quantity consumed (lpg_q2011), urban/rural (urban2011.f), and household size (HHsize) as the variables to use in the tobit model (Model 3).

Table C.4.1: X-variable selection using AIC and LogLIK for the logistic and log-normal models

	X-variable combinations	**AIC (logistic)**	**logLik (logistic)**	**AIC (log-normal)**	**logLik (log-normal)**
0	Null	40386121	-20193059	79660	-39828
1	lpg_q2011	30752	-15373	79012	-39503
2	lpg_q2011 + urban2011.f + lpg_q2011 * urban2011.f	27468	-13729	78862	-39426
3	**lpg_q2011 + urban2011.f + HHsize2011 + lpg_q2011 * urban2011.f + HHsize2011 * urban2011.f**	**25676**	**-12831**	**77978**	**-38982**
4	lpg_q2011 + urban2011.f + HHsize2011 + caste2011 + lpg_q2011 * urban2011.f + HHsize2011 * urban2011.f + lpg_q2011 * caste2011 + HHsize2011 * caste2011	24995	-12841	77883	-38925
5	lpg_q2011 + urban2011.f + HHsize2011 + caste2011 + income2011 + lpg_q2011 * urban2011.f + HHsize2011 * urban2011.f + lpg_q2011 * caste2011 + HHsize2011 * caste2012 + income2011 * caste2011 + income2011 * urban2011.f	24837	-12397	77759	-38858
6	lpg_q2011 + urban2011.f + HHsize2011 + caste2011 + income2011 + employment_type2011 + lpg_q2011 * urban2011.f + HHsize2011 * urban2011.f + lpg_q2011 * caste2011 + HHsize2011 * caste2012 + income2011 * caste2011 + income2011 * urban2011.f + lpg_q2011 * employment_type2011 + Hhsize2011 * employment_type2011 + income2011 * employment_type2011	23593	-11747	77347	-38624

Selection of these variables also makes sense from an economic viewpoint. Urban regions tend to use more LPG due to better access and distribution facilities. Additionally larger households require more energy for cooking thus consuming more quantity, on average, of fuelwood. Regression results below confirm this, where less fuelwood is consumed with an increase in LPG use, and urban regions tend to use less fuelwood, while a larger household size shows an increase in fuelwood consumed.

R code and output for the logistic and log-normal model using the selected variables is:

Step 1: Logistic Model

```
> logistic.M1 <- glm (lpg_access$firewood_q_2011yes  ~ lpg_q2011 + urban2011.f +
                + HHsize2011 + lpg_q2011 * urban2011.f
                + HHsize2011 * urban2011.f,
                data = lpg_access, weights = Weight2011)
> summary (logistic.M1)

Call:
glm(formula = lpg_access$firewood_q_2011yes ~ lpg_q2011 + urban2011.f +
    HHsize2011 + lpg_q2011 * urban2011.f + HHsize2011 * urban2011.f,
    data = lpg_access, weights = Weight2011)

Deviance Residuals:
    Min        1Q     Median      3Q       Max
-162.810    1.270    6.104     11.719   80.479
```

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.7738594	0.0031141	248.50	<2e-16 ***
lpg_q2011	-0.0250164	0.0007478	-33.45	<2e-16 ***
urban2011.f1	-0.3772846	0.0079502	-47.46	<2e-16 ***
HHsize2011	0.0155226	0.0005660	27.43	<2e-16 ***
lpg_q2011:urban2011.f1	-0.0246765	0.0010491	-23.52	<2e-16 ***
urban2011.f1:HHsize2011	0.0568233	0.0016386	34.68	<2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 561.2585)

Null deviance: 54488717 on 84494 degrees of freedom

Residual deviance: 47420169 on 84489 degrees of freedom

AIC: 138580

Number of Fisher Scoring iterations: 2

> Anova (logistic.M1, type='III')

Analysis of Deviance Table (Type III tests)

Response: lpg_access$firewood_q_2011yes

	LRChisq	Df	Pr(>Chisq)
lpg_q2011	1119.22	1	< 2.2e-16 ***
urban2011.f	2252.09	1	< 2.2e-16 ***
HHsize2011	752.12	1	< 2.2e-16 ***
lpg_q2011:urban2011.f	553.29	1	< 2.2e-16 ***

```
urban2011.f:HHsize2011          1202.60          1         < 2.2e-16 ***
---
Signif. codes:  0 '***'  0.001 '**'  0.01 '*'  0.05 '.'  0.1 ' '  1
```

 # Step 2: Log-normal distribution for non-zero firewood.

```
> normal.M1 <- glm (firewood_q2011 ~ lpg_q2011 + urban2011.f +
                + HHsize2011 + lpg_q2011 * urban2011.f
                + HHsize2011 * urban2011.f,
                 data = lpg_access_nozeros, family = gaussian (link = log),
                 weights=Weight2011)
> summary (normal.M1)

Call:
glm(formula = firewood_q2011 ~ lpg_q2011 + urban2011.f + HHsize2011 +
    lpg_q2011 * urban2011.f + HHsize2011 * urban2011.f,
    family = gaussian(link = log),
    data = lpg_access_nozeros, weights = Weight2011)

Deviance Residuals:
   Min       1Q    Median     3Q       Max
-21740   -1922      -348    1416     99651

Coefficients:
                              Estimate        Std. Error        t value          Pr(>|t|)
```

(Intercept)	4.2548902	0.0066301	641.752	< 2e-16 ***
lpg_q2011	-0.0368756	0.0025980	-14.194	< 2e-16 ***
urban2011.f1	-0.4667261	0.0337133	-13.844	< 2e-16 ***
HHsize2011	0.0715726	0.0009737	73.505	< 2e-16 ***
lpg_q2011:urban2011.f1	-0.0197092	0.0074869	-2.632	0.00848 **
urban2011.f1:HHsize2011	0.0365373	0.0046711	7.822	5.28e-15 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 26169678)

Null deviance: 1.8412e+12 on 64970 degrees of freedom

Residual deviance: 1.7001e+12 on 64965 degrees of freedom

AIC: 797883

Number of Fisher Scoring iterations: 6

C.5 Fuelwood displacement

Coefficients of the tobit model helped predict the amount of fuelwood displaced in a year by for three household sizes (small, average, medium) that gained access to LPG in 2011 (Table C.5.1). The household sizes were selected by quartiles (0.25, 0.5, and 0.75) from the matched LPG access dataset. Average LPG quantity consumed was also calculated from the LPG access matched dataset. Using the census number of households who gained access to LPG between 2000 and 2011, I estimated the total fuelwood displaced in 2011 by the various household sizes. Figure C.5.1 shows the amount of fuelwood displaced by various households at varying levels of LPG consumption.

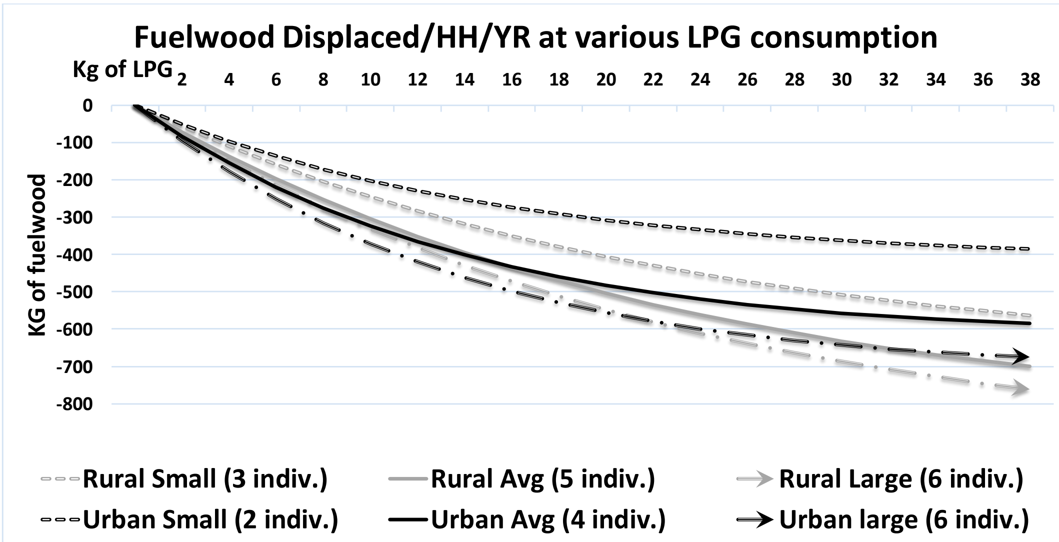


Figure C.5.1. Fuelwood displaced by the households at varying levels of LPG consumption.

Table C.5.1. Fuelwood displacement calculation using estimates from logistic, lognormal models for various household sizes.

		Rural, small house		Urban, small house		Rural, Avg. house		Urban, Avg. house		Rural, large house		Urban, large house	
Logistic Model (all HH)	**Estimate**	**No Access**	**Access**	**No Access**	**Access**	**No Access**	**Access**	**No Access**	**Access**	**No Access**	**Access**	**No Access**	**Access**
(Intercept)	0.7739	1	1	1	1	1	1	1	1	1	1	1	1
lpg_q2011	-0.0250	0	2.452	0	7.414	0	2.452	0	7.414	0	2.452	0	7.414
urban2011.f1	-0.3773	0	0	1	1	0	0	1	1	0	0	1	1
HHsize2011	0.0155	3	3	2	2	5.105	5.105	4.340	4.340	6	6	6	6
lpg_q2011:urban2011.f1	-0.0247	0	0	0	7.414	0	0	0	7.41	0	0	0	7.414
urban2011.f1:HHsize2011	0.0568	0	0	2	2	0	0	4.340	4.340	0	0	6	6
Pred.logit		0.820	0.759	0.541	0.173	0.853	0.792	0.711	0.342	0.867	0.806	0.831	0.462
Probability of a HH using fuelwood		0.694	0.681	0.632	0.543	0.701	0.688	0.671	0.585	0.704	0.691	0.696	0.614
Lognormal Model (non 0 fw HH)	**Estimate**	**No Access**	**Access**	**No Access**	**Access**	**No Access**	**Access**	**No Access**	**Access**	**No Access**	**Access**	**No Access**	**Access**
(Intercept)	4.2549	1	1	1	1	1	1	1	1	1	1	1	1
lpg_q2011	-0.0369	0	2.452	0	7.414	0	2.452	0	7.414	0	2.452	0	7.414
urban2011.f1	-0.4667	0	0	1	1	0	0	1	1	0	0	1	1
HHsize2011	0.0716	3	3	2	2	5.105	5.105	4.340	4.340	6	6	6	6
lpg_q2011:urban2011.f1	-0.0197	0	0	0	7.41428	0	0	0	7.414	0	0	0	7.414
urban2011.f1:HHsize2011	0.0365	0	0	2	2	0	0	4.340	4.340	0	0	6	6
Pred.lnfirewood		4.470	4.379	4.004	3.585	4.620	4.530	4.257	3.838	4.684	4.594	4.437	4.017
Pred.firewood (how much wood non0 FW HH use)		87.322	79.774	54.838	36.048	101.521	92.746	70.623	46.424	108.237	98.881	84.506	55.550
Predicted firewood (All HH)		**60.630**	**54.339**	**34.664**	**19.578**	**71.188**	**63.829**	**47.355**	**27.145**	**76.212**	**68.345**	**58.858**	**34.082**
		Rural, small house		**Urban, small house**		**Rural, Avg. house**		**Urban, Avg. house**		**Rural, large house**		**Urban, large house**	
Difference (FW kg/HH/mth)		**-6.29**		**-15.09**		**-7.36**		**-20.21**		**-7.87**		**-24.78**	
Fuelwood Displaced	**in KG / HH / yr**	**-75.50**		**-181.03**		**-88.32**		**-242.52**		**-94.40**		**-297.31**	
# HH Gained LPG access (FROM Census)													
Urban	25,533,895												
Rural	11,294,825	**Rural, small house**		**Urban, small house**		**Rural, Avg. house**		**Urban, Avg. house**		**Rural, large house**		**Urban, large house**	
TOTAL Fuelwood displaced (kg/yr) in 2011		**-852,729,197**		**-4,622,417,567**		**-997,523,945**		**-6,192,501,148**		**-1,066,246,892**		**-7,591,409,912**	

No access households were described as lpg_q2011 = 0 and the average quantity for LPG access households was the average from the matched synthetic dataset. The difference in predicted firewood use between the access and no access households gave me the amount of fuelwood displaced for the year by each household. Then using the number of households that gained access to LPG from the census of India (which states only primary users of LPG, and thus a conservative estimate of households), I estimated the total fuelwood displaced in by an average household in urban regions to be 6,192,501,148 kg.

C.6 Net emissions

The net impact on emissions in 2011 was calculated using the estimates of fuelwood displaced due to increased LPG access in 2011. I calculated the net emissions reduction (in million metric tonnes of carbon dioxide equivalent or $MtCO_2e$) utilizing the emissions factors and hundred year global warming potentials (GWP_{100}) from Freeman & Zerriffi (2014) for a traditional open fire and an LPG stove. Freeman and Zerriffi (2014) include the uncertainty associated with estimates of the emission factor based on reported stove testing results. For the fuelwood renewability assumptions, the case of fully renewable biomass, and a conservative estimate of 0.3 for non-renewable biomass, based on research by Bailis et al., 2015 was applied.

Table C.6.1. Emissions factors (with uncertainty expressed as one standard deviation) from Table S1 of Freeman & Zerriffi (2014) for a traditional wood stove and LPG stove.

Stove	CO2	CO	CH4	NMHC	OC	BC	SO_2 (g/kg)	$PM_{2.5}$ (g/kg)	Production+
W-Tr-U	382.28 ± 13.77	20.67 ± 1.67	2.92 ± 0.68	3.65 ± 0.44	2.15 ± 0.59	1.10 ± 0.25	0.27 ± 0.30	2.78 ± 0.60	N/A
LPG-U	842.06 ± 22.28	3.69 ± 0.85	0.22 ± 0.35	7.35 ± 2.04	0.07 ± 0.06	0.07 ± 0.06	N/A	0.52 ± 0.45	96.78

*** in gC/kg unless otherwise noted.**

Table C.6.2: Table S2 of Freeman & Zerriffi (2014) for GWP_{100} values for species included

Species	CO_2	CO	CH_4	NMHC	OC	BC	SO_2
GWP_{100}	1	1.9	25	3.4	-35	455	-76

Fuelwood displaced under each model was multiplied by the emissions factors and GWP_{100} for a traditional wood stove to get the $MtCO_2e$ reduction in 2011. The climate forcers considered were carbon dioxide (CO_2), carbon monoxide (CO), methane (CH_4), non-methane hydrocarbons (NMHC), organic carbon (OC), black carbon (BC), and sulphur dioxide (SO_2). $MtCO_2e$ from increased access to LPG was then calculated for each of these. The net emission impact is the difference between the $MtCO_2e$ from LPG stoves and the $MtCO_2e$ of fuelwood displaced for each model.

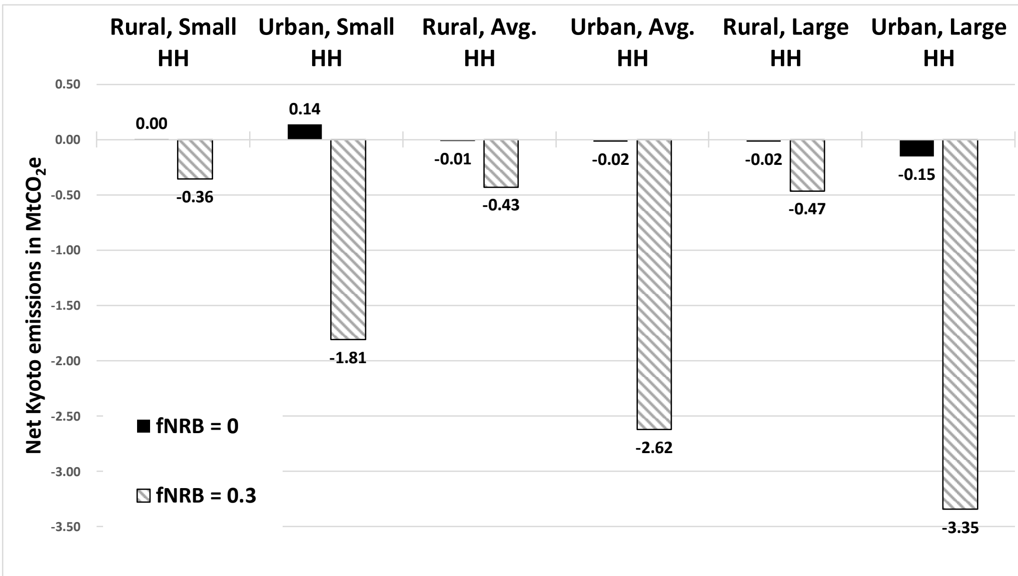


Figure C.6.1. Changes in net Kyoto emissions due to changes in fNRB for average sized households.

Emissions reductions were calculated in the case of fNRB = 0 and fNRB = 0.3. When fNRB = 0 is assumed, the CO_2 emissions from wood are zero as it is presumed to be reabsorbed into the ecosystem cycle during tree growth. However, when fNRB > 0, a fraction of the CO_2 emissions from wood gets accounted for, such as in the case of fNRB=0.3 where 30% of the CO_2 emissions are included in total emissions. However, other emissions do not change with the fNRB, as they would be emitted from burning of wood whether or not the wood is sustainably extracted.

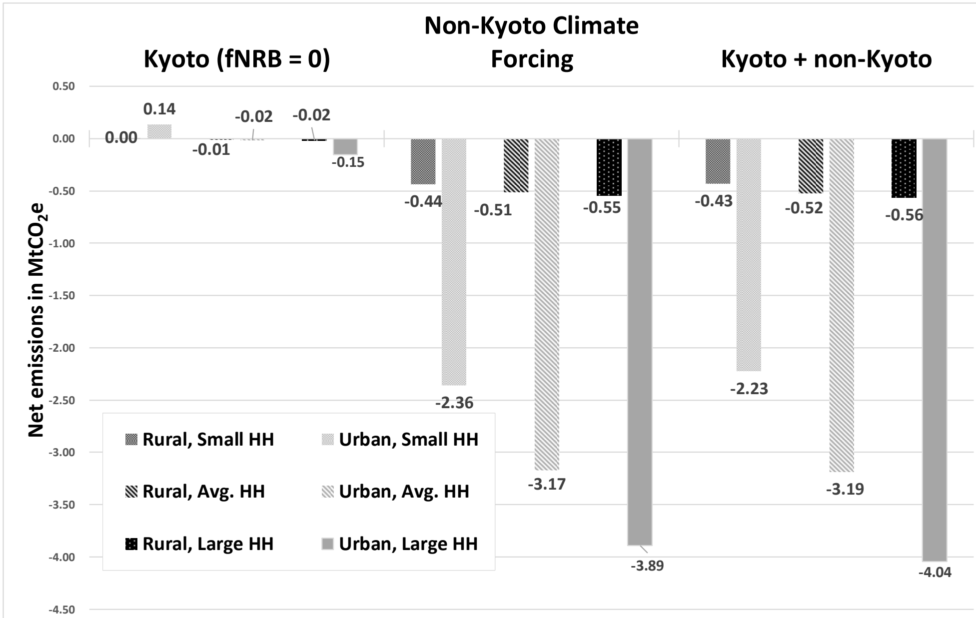


Figure C.6.2. Net emissions from increased LPG access at fNRB = 0.

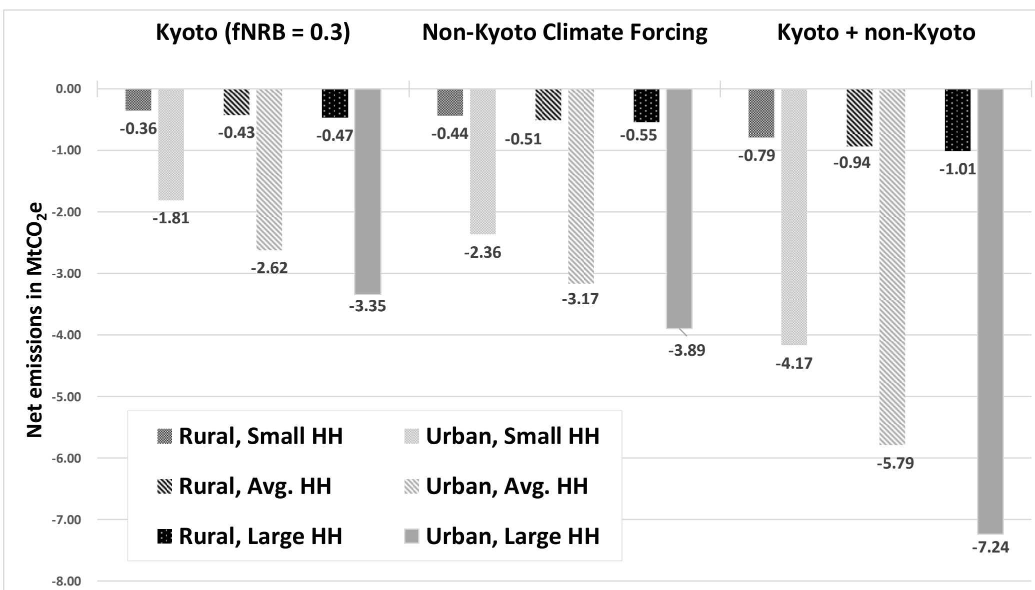


Figure C.6.3. Net emissions from increased LPG access at fNRB = 0.3.

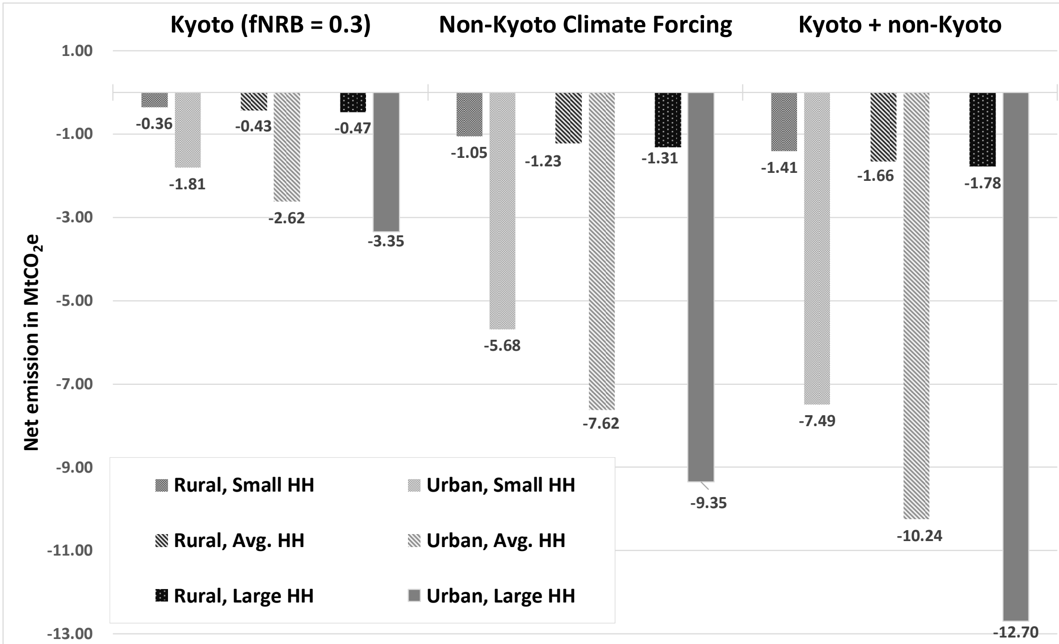


Figure C.6.4. Net emissions from increased LPG access at black carbon GWP_{100} = 1110, for varying household sizes.

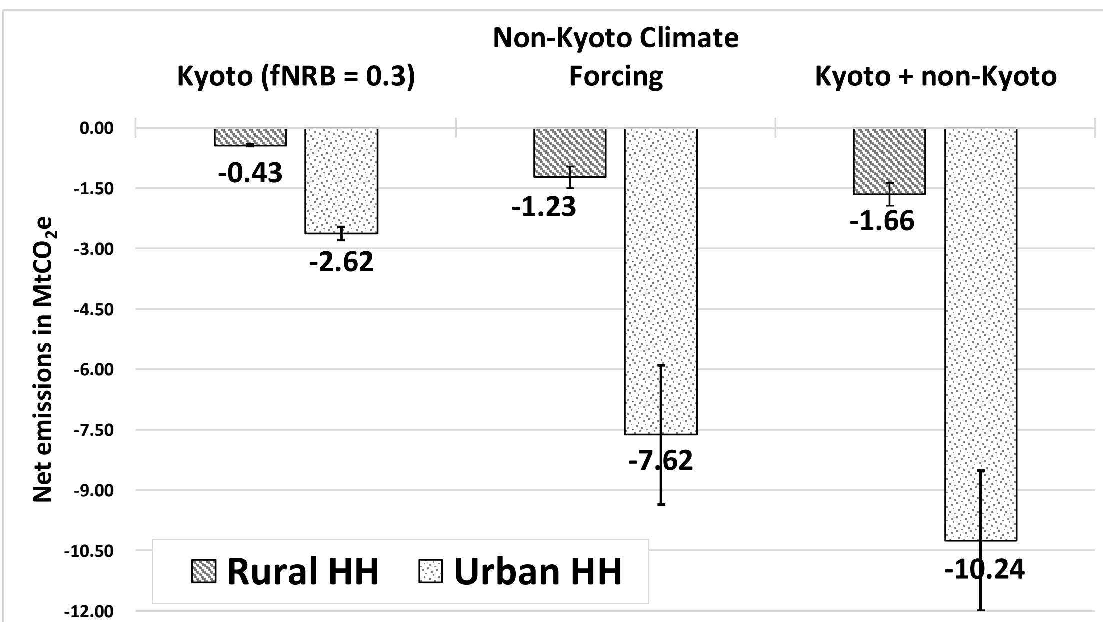


Figure C.6.5. Net emissions (& associated uncertainties) from increased LPG access at black carbon GWP_{100} = 1110 for average sized households.

Appendix D **: Sample socio-economic survey questionnaire**

SOCIO-ECONOMIC SURVEY
Sample
Last update: May 02, 2017

Hello, you have been participating in a study on improved stove adoption, cooking, and indoor smoke. The study is being conducted by a consortium of universities from the US and Canada funded by the US Environmental Protection Agency working in partnership with JAGRITI (now TIDE), an NGO that has been active in this area for many years.

We have collected information about your household, asset ownership, sources of income, energy use, fuelwood collection, and knowledge of improved cooking devices. Now, we would like to update our information to see how things have changed since we last visited. As before, your participation in this survey is voluntary. You may choose not to answer any question we ask and you may ask us to stop at any time. If you decide not to participate, your choice will not affect your relationship with JAGRITI/TIDE in any way. You responses will be fully confidential. The survey will take about 45 minutes to complete. Are you willing to participate?

1. Household identifying information:

a.	Respondent Code (try to speak to the same respondent as in the baseline survey, and note if that is not possible and you speak to a different person)	
b.	Household ID	
c.	Enumerator ID	
d.	GPS coordinates	
e.	What is your Religion, and Caste or Tribe?	Religion (Specify) ____________________ Caste (Specify) ____________________ Tribe (Specify) ____________________ No Caste/Tribe (circle if applicable) Don't Know
f.	Do you belong to a scheduled caste, a scheduled tribe, other backward class, or none of these?	□ Scheduled Caste □ Scheduled Tribe □ OBC □ None

2. Household demographics:

NOTE: A household is defined as people living within the same physical unit and sharing living space. In other words, two families having separate ration cards but living in the same housing unit would be considered one household.

Last year you told us the HH consisted of X (HHH), Y(MC), Z, etc…have there been any changes (additions, removals, etc)?

No…[go to next question]

Yes…[record stats as in table]

a. Household details

ID	Individual	Sex (circle)	Age	Relation to HH head	Highest education level attained	
01	Respondent - check appropriate box below: □ Respondent is head of household □ Respondent is main cook □ Respondent is secondary cook	M F		□ Spouse □ Child □ Parent □ Sibling □ Other ________	□ Did not attend □ Primary school (<=4th standard) □ Middle school (>4th AND <= 7th standard) □ High school (> 7th AND <=10)	□ 10th standard pass □ 12th standard pass/Junior college □ College □ Post graduate degree
02	Head of Household (if not respondent) □ Individual 02 is main cook □ Individual 02 is secondary cook	M F			□ Did not attend □ Primary school (<=4th standard) □ Middle school (>4th AND <= 7th standard) □ High school (> 7th AND <=10)	□ 10th standard pass □ 12th standard pass/Junior college □ College □ Post graduate degree

03	Check appropriate box below: □ Individual 03 is main cook □ Individual 03 is secondary cook	M F		□ Spouse □ Child □ Parent □ Sibling □ Other ________	□ Did not attend □ Primary school (<=4th standard) □ Middle school (>4th AND <= 7th standard) □ High school (> 7th AND <=10)	□ 10th standard pass □ 12th standard pass/Junior college □ College □ Post graduate degree
04	Check appropriate box below: □ Individual 04 is main cook □ Individual 04 is secondary cook	M F		□ Spouse □ Child □ Parent □ Sibling □ Other ________	□ Did not attend □ Primary school (<=4th standard) □ Middle school (>4th AND <= 7th standard) □ High school (> 7th AND <=10)	□ 10th standard pass □ 12th standard pass/Junior college □ College □ Post graduate degree
05	Check appropriate box below: □ Individual 05 is main cook □ Individual 05 is secondary cook	M F		□ Spouse □ Child □ Parent □ Sibling □ Other ________	□ Did not attend □ Primary school (<=4th standard) □ Middle school (>4th AND <= 7th standard) □ High school (> 7th AND <=10)	□ 10th standard pass □ 12th standard pass/Junior college □ College □ Post graduate degree
06	Check appropriate box below: □ Individual 06 is main cook □ Individual 06 is secondary cook	M F		□ Spouse □ Child □ Parent □ Sibling □ Other ________	□ Did not attend □ Primary school (<=4th standard) □ Middle school (>4th AND <= 7th standard) □ High school (> 7th AND <=10)	□ 10th standard pass □ 12th standard pass/Junior college □ College □ Post graduate degree
07	Check appropriate box below:	M F		□ Spouse □ Child	□ Did not attend =	□ 10th standard pass

	□ Individual 07 is main cook □ Individual 07 is secondary cook			□ Parent □ Sibling □ Other ________	□ Primary school (<=4th standard) □ Middle school (>4th AND <= 7th standard) □ High school (> 7th AND <=10)	□ 12th standard pass/Junior college □ College □ Post graduate degree
08	Check appropriate box below: □ Individual 08 is main cook □ Individual 08 is secondary cook	M F		□ Spouse □ Child □ Parent □ Sibling □ Other ________	□ Did not attend □ Primary school (<=4th standard) □ Middle school (>4th AND <= 7th standard) □ High school (> 7th AND <=10)	□ 10th standard pass □ 12th standard pass/Junior college □ College □ Post graduate degree

b. Who is the Head of HH? (List by individual ID)

c. Who is the primary cook? (List by individual ID)

d. Who is the primary caretaker of children less than 3 years of age?

List by individual's ID from section 2.a ________

e. Does house have a chimney (separate from Tandoor pipe)?

Yes

No

f. Changes in land ownership since last year

01	Have you bought/sold any agricultural land in the last year? If Yes, go to **Error! Reference source not found.**; if No, go to h	Yes No
02	Did you buy land, sell land, or do both?	Bought Sold Both

03	How much agricultural land did you buy in the last year? ?	Acres _________ bought (if not in acres, specify size and unit)
04	How much of this land is/was irrigated?	Acres _________ bought (if not in acres, specify size and unit)
05	How much agricultural land did you sell in the last year?	Acres _________ sold (if not in acres, specify size and unit)
06	How much of this land is/was irrigated?	Acres _________ sold (if not in acres, specify size and unit)

g. Did you make any major purchases in the past year (prompt with some of the more costly items below and record any new assets)

ELECTRICITY	□	B & W TELEVISION	□	BICYCLE	□
MATTRESS	□	COLOUR TELEVISION	□	MOTORCYCLE/SCOOTER	□
PRESSURE COOKER	□	SEWING MACHINE	□	ANIMAL-DRAWN CART	□
CHAIR	□	MOBILE TELEPHONE	□	CAR	□
COT/BED	□	ANY OTHER TELEPHONE	□	WATER PUMP	□
TABLE	□	COMPUTER	□	THRESHER	□
ELECTRIC FAN	□	REFRIGERATOR	□	TRACTOR	□
RADIO/TRANSISTOR	□	WATCH/CLOCK	□		

h. Have you shifted to a new house or made major renovations to your current house since last year? (if Yes, redo housing questions below; if no, then go to 2.i)

1) Main type of windows in the house
   - No windows ☐
   - Windows with no covering (always open) ☐
   - Windows with glass, screens, or shutters ☐

2) Main type of flooring in the house
   - Natural (e.g. mud/clay/earth; sand, or dung) ☐
   - Rudimentary (e.g. rough wood planks, palm, bamboo, brick or stone) ☐
   - Finished (e. g. polished wood, vinyl, ceramic, cement, carpet, or polished stone) ☐

3) Primary material of exterior walls
   - No walls ☐
   - Natural (e.g. cane, palm, bamboo, mud, grass, thatch, plastic sheets) ☐
   - Rudimentary (e.g. bamboo w/mud, stone w/mud, plywood, cardboard, unfired brick, rough/reused wood) ☐
   - Finished (e. g. cement/concrete, stone w/lime or cement, fired bricks, wood planks, shingles, metal/ asbestos sheets) ☐

4) Primary roofing material
   - No roof ☐
   - Natural (e.g. thatch/palm leaf/reed/grass, mud, plastic sheeting) ☐
   - Rudimentary (e.g. woven mats; palm; bamboo, rough planks, unfired bricks, loose stones) ☐
   - Finished (e. g. metal sheets, finished wood, cement, asbestos sheets, tiles, slate) ☐

5) What is the main source of drinking water for members of your household?
   - Surface (includes river, dam, lake, pond, stream, or irrigation channel) ☐
   - Spring (protected or unprotected) ☐
   - Dug well (protected or unprotected) ☐
   - Tubewell or borehole ☐
   - Public tap or standpipe ☐
   - Piped water into home or compound ☐
   - Other (__________) ☐

6) What kind of toilet facility do members of your household usually use?
   - No facility (uses open space or field) ☐
   - Pit latrine (includes open pit, pit with or w/o slab, ventilated pit, or biogas latrine) ☐
   - Flush toilet (includes piped or pour toilets) ☐

	Other (__________)	☐
7)	Does any member of this household own this house or any other house?	
	No	☐
	Yes	☐
8)	How many rooms in this household are used for sleeping?	________

i. Labour and income for main cook

Last year we asked about income for HHH and MC. Have there been any changes in the past year in the following areas?

1)	MC - Agricultural work?	□ Yes □ No - go to h.3
2)	Describe change in ag work (type of land, cash or in kind payment)	
3)	MC - Non-agricultural work in the last year?	□ Yes □ No – go to h.5)
4)	Describe change in non-ag work (type of land, cash or in kind payment)	
5)	HHH - Agricultural work?	□ Yes □ No - go to h.7
6)	Describe change (type of land, cash or in kind payment)	
7)	HHH - Non-agricultural work in the last year?	□ Yes □ No – go to 3
8)	Describe change (type of land, cash or in kind payment)	

3. Fuel use

Energy Use *The following questions concern the fuels you use*		
a.	Does HH have LPG (with or without project)? **a.1 How many cylinders have they refilled in the past year?** a.2 If possible, ask to see LPG card and record no. & date of cylinder purchases in the past year	□ Yes □ No (go to b) Cyl 01/Date Cyl 02/Date Cyl 03/Date etc…

b.	**Does HH have electricity?** **b.1 Does HH have Ind stove** (with or without project)? **b.2** Ask to see elec bills (if possible) and record monthly consumption as far back as available.	□ Yes □ No (go to c) □ Yes □ No Month – kWh Month – kWh Month – kWh etc…
c.	How has your cooking fuel consumption changed: • (treatment) since receiving your new stove • (control) in the past year (Check ALL THAT APPLY)?	□ Wood □ More □ Same □ Less □ Crop residue / coconut husk □ More □ Same □ Less □ Dung cakes □ More □ Same □ Less □ Coal/coke/lignite □ More □ Same □ Less □ Wood-charcoal □ More □ Same □ Less □ Kerosene □ More □ Same □ Less □ Liquid Petroleum Gas (LPG) □ More □ Same □ Less □ Electricity □ More □ Same □ Less □ Other □ More □ Same □ Less (Specify)___________________
d.	(If the household cooks with more than one fuel) What is currently the main type of cooking fuel used on most days or for most meals (Check one)?	□ Wood □ Crop residue / coconut husk □ Dung cakes □ Coal/coke/lignite □ Wood-charcoal □ Kerosene □ Liquid Petroleum Gas (LPG) □ Electricity □ Other (Specify)_________________
e.	Does the household have heating needs?	□ Yes □ No Go to 0
f.	How has your use of heating fuel changed since last year (or since before receiving your new stove)(Check ALL THAT APPLY)?	□ Wood □ More □ Same □ Less □ Crop residue / coconut husk □ More □ Same □ Less □ Dung cakes □ More □ Same □ Less □ Coal/coke/lignite □ More □ Same □ Less □ Wood-charcoal □ More □ Same □ Less □ Kerosene □ More □ Same □ Less □ Liquid Petroleum Gas (LPG) □ More □ Same □ Less □ Electricity □ More □ Same □ Less □ Other □ More □ Same □ Less (Specify)___________________
g.	(If the household heats with more than one fuel) What is the main type of heating fuel used on most days (Check one)?	□ Wood □ Crop residue / coconut husk □ Dung cakes □ Coal/coke/lignite □ Wood-charcoal □ Kerosene □ Liquid Petroleum Gas (LPG) □ Electricity □ Other (Specify)_________________

New stoves impacts (skip for controls)

h.	For one-time communities: Which stove did you select? Can you show us? (please check)	□ Chulika □ Envirofit Double-pot □ Envirofit PCS-1 □ Himanshu Tandoor □ Induction □ LPG □ Prakti □ TERI Forced-Draft □ TIDE Pyro Mini
i.	For switchout communities only: Did you change your stove the at the last opportunity?	Yes No
j.	For one-time communities only: If you had to choose again would you select the same stove?	
k.	Why did you select this model? (leave this open ended – we can categorize responses after)	
l.	Are you happy with your choice – why/why not (leave this open ended – we can categorize responses after)	Happy Unhappy Neutral
m.	Who uses the new stove? (Note all Individual IDs) Is there anyone among these who began cooking only as a result of the new stove? (Note individual IDs) Who uses the new stove?	
n.	Name two things you like about this stove	MAKE THIS MULTI-CHOICE BASED ON LIST (ALLOW ONLY TWO RESPONSES): Faster Cleanliness Less smoke Uses less fuel Space heating Durability / aesthetics Food as good or better Other (ALLOW TEXT)
o.	Name two things you dislike about this stove	MAKE THIS MULTI-CHOICE BASED ON LIST Slower Dirty MORE smoke Uses more fuel Can't do space heating Not Durable / Doesn't look nice Food not as good Other (ALLOW TEXT)

p.	[If not mentioned in likes/dislikes] Does the new stove cook food faster, slower, or no change?	□ Faster □ Slower □ No change
q.	Did the stove change your cooking or heating patterns in any way? (e.g. timing or frequency of cooking, order of food cooked, type of foods cooked, use of other stoves, etc)	□ No □ Yes (describe)
r.	How many days per week do you use your stove ?	1-2 3-4 5-7
s.	What, if anything, do you usually use your new stove for?	

For each fuel listed in 3.c and d describe the stoves used - check all that apply, specify main use (cooking, heating, or both) and indicate location (1=indoor kitchen; 2=bedroom; 3=sitting room; 4=outdoor kitchen; 5=other (specify))

Fuel type		Stove type	Purpose and location
t.	Wood	□ Mud stove □ Tripod stove (Sthanay) □ Traditional tandoor □ Traditional tandoor □ Other (specify): _______________	□ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___
u.	Crop residue/coconut husk	□ Mud stove □ Tripod stove (Sthanay) □ Traditional tandoor □ Traditional tandoor □ Other (specify): _______________	□ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___
v.	Dung cakes	□ Mud stove □ Tripod stove (Sthanay) □ Traditional tandoor □ Traditional tandoor □ Other (specify): _______________	□ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___
w.	Other solid fuels (coal/coke/lignite charcoal, etc)	□ Mud stove □ Tripod stove (Sthanay) □ Traditional tandoor □ Traditional tandoor □ Other (specify): _______________	□ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___
x.	Kerosene	□ Wick stove □ Jet stove □ Other (specify): __________________	□ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___
y.	LPG	□ Single burner □ Double burner □ Other (specify): __________________	□ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___

z.	Electricity	□ Tea kettle □ Rice cooker □ Single burner - resistance □ Single burner - induction □ Double burner - resistance □ Double burner - induction □ Other (specify): ________________	□ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___ □ Cooking □ Heating □ Both Location ___

4. Fuelwood collection and use [enumerators should remind the respondent that this data will not be shared with forest department and that responses are purely confidential and there will be no repercussions for responses that reflect improper wood harvesting] *(also the change questions will be "since stove" for treatment, and use "past year" for control)*

a.	Have wood species you use changed since the new stove (past year)?	□ Yes □ No
b.	Do you collect fuelwood, purchase fuelwood, or both?	□ Purchase only → Complete 6.d-6.i, then skip to **Error! Reference source not found.** □ Collect only → Skip to 4.i and complete section from there □ Both → complete the rest of this section
c.	On average how many times a month do you buy wood?	
d.	Has this buying pattern changed in the past year (or since stove?)	□ Quantity □ More □ Same □ Less □ Frequency □ More □ Same □ Less If answers to both are "same" skip to 6.l. If answers are "more" or "less", continue to 6.f
e.	What is the average unit bought each time? (define whether unit is headload, oxcart, other)	_________ (headload, oxcart, other)
f.	Has this average unit bought each time changed in the past year (or since stove?)	□ Quantity _________ (headload, oxcart, other) □ More □ Same □ Less □ Other (Specify)__________________
g.	How long does this unit typically last?	Winter _________ (days, weeks, months) Summer _________ (days, weeks, months) Monsoon _________ (days, weeks, months)

h.	How much do you pay for the wood?	____ Rs per (headload, oxcart, other)
i.	On what type of land do you collect wood?	□ Own farm/orchard □ Other person's farm/orchard □ Community woodlot/forest □ Gov't forest □ Roadside or other common area (non-forest) □ Other (specify): ___________________________
j.	Has the type of land that you collect wood on changed in the past year (or since stove)?	□ Yes (wha was previous type) □ Own farm/orchard □ Other person's farm/orchard □ Community woodlot/forest □ Gov't forest □ Roadside or other common area (non-forest) □ Other (specify): _______ □ No (if No, skip to 6.m)
k.	Why has the type of land that you collect wood on changed in the past year (or since stove)?	□ Quantity required: explain___________ □ Time: explain___________ □ Regulations: (example not allowed in forest anymore)___________ □ External factors: (example fire in forest) □ Other (Specify)__________________
l.	Do you typically cut live trees, prune live trees, or collect dead wood? Note, cutting live trees or pruning branches, leaving the wood to dry, and collecting it days, weeks or months later would be considered cutting or pruning. Collecting dead wood only applies to collecting woody material that fell naturally.	Check all that apply: □ Cut live trees □ Prune live trees □ Collect dead branches
m.	Has this method of cutting/pruning and/or collecting wood changed in the past year (since stove)?	□ Cut live trees □ More □ Same □ Less Why: explain________________ □ Prune live trees □ More □ Same □ Less Why: explain________________ □ Collect dead branches □ More □ Same □ Less Why: explain________________

n.	Has the time for fuelwood collection changed since the stove (past year)?	□ time has increased. If so, then by approximately □ < 1 hr □ 1-2 hr □ > 2 hr □ Time has decreased. If so, then by approximately □ < 1 hr □ 1-2 hr □ > 2 hr □ no change
o.	Has there been a change in the quantity of fuelwood used per week?	□ Yes (then answer 6.r) □ More □ Same □ Less □ No (proceed to question 7)
p.	Why? (Let them suggest first)	□ new stove: (e.g. LPG, Induction, or new wood stove leads to wood savings) □ number of HH members: explain____________ □ time: (example more time so cook more)_____ □ money: (e.g. HH has had a change in income, now consumes more/less food) □ Other – specify ______________________________

5. Social network questions

a) Have you talked to your friends and family about your new stove? □ Yes

□ No

If yes, go to 7b, else move to 7c.

b) If yes, name some people you spoke to you about **<u>your new cookstove</u>**?

Name	Gender	Age	Village Name	Relationship to the respondent	Opinion of new stove (use multi-choice below table)

0 - Don't like it and won't get one

1 - Indifferent to it

2 - Not sure if they like it, want to try first

3 - Like it but don't want to get one

4 - Like it and want to get the new cookstove

5 - Not sure of their opinion

c) Have you seen new cookstoves **<u>distributed by the project in the homes of friends or familiy or have they spoken to you about them</u>**?

□ Yes

□ No

If yes, go to 7d, else move Section 8.

d) If yes, name some people who spoke to you about their new cookstove/s? Also name the cookstove/s that were spoken about.

Name	Gender	Age	Village Name	Relationship to the respondent	Cookstove spoken about

6. Abhisek's questions - stress that these questions only apply to LPG.

a. Do you use LPG regularly? For example, do you cook most of your meals with LPG during the summer and/or use about 3 cylinders per year?

□ Yes

□ No

If yes, go to 8b, otherwise go to 8h.

b. How do you feel about cooking with LPG?

- ○ Very pleasant
- ○ Slightly pleasant

- ○ Neither pleasant nor unpleasant
- ○ Slightly unpleasant
- ○ Very unpleasant

c. What do you think about cooking with LPG?

- ○ Very useful
- ○ Slightly useful
- ○ Neither useful nor harmful
- ○ Slightly Harmful
- ○ Very harmful

d. Can you think of people whose opinion you value; they could be family members, or people who you know from within or outside the community.

□ Yes

□ No

If no, go to f.

e. Do the people whose opinion you value think you should use at least three cylinders a year and cook with LPG for your family?

- ○ Definitely Yes
- ○ Probably Yes
- ○ I don't know
- ○ Probably No
- ○ Definitely No

f. Do the people whose opinion you value cook with LPG for their family?

- ○ Definitely Yes
- ○ Probably Yes
- ○ I don't know
- ○ Probably No

- ○ Definitely No

g. Are you confident that you can continue using LPG the way you are right now.

(Prompt such as think about cost availability, access, weather, family circumstance)

END!

h. How would you feel about cooking with LPG if you were to start using it regularly?
   - ○ Very pleasant
   - ○ Slightly pleasant
   - ○ Neither pleasant nor unpleasant
   - ○ Slightly unpleasant
   - ○ Very unpleasant

i. What would you think about cooking with LPG regularly?
   - ○ Very useful
   - ○ Slightly useful
   - ○ Neither useful nor harmful
   - ○ Slightly Harmful
   - ○ Very harmful

j. Can you think of people whose opinion you value; they could be family members, or people who you know from within or outside the community.

□ Yes

□ No

If no, go to m.

k. Do the people whose opinion you value think you should use at least three cylinders a year and cook with LPG for your family?
   - ○ Definitely Yes
   - ○ Probably Yes

- ○ I don't know
- ○ Probably No
- ○ Definitely No

l. Do the people whose opinion you value cook with LPG for their family?

- ○ Definitely Yes
- ○ Probably Yes
- ○ I don't know
- ○ Probably No
- ○ Definitely No

m. Are you confident that you can continue using LPG the way you are right now.

(Prompt such as think about cost availability, access, weather, family circumstance)