Social and ecological insights across landscape, community, and household scales:

Forest health, governance, and livelihoods in central India

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Abstract

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Forests are embedded in diverse forest governance, resource use, and resource user settings which are linked as components of social-ecological systems. **This dissertation examines forest health at a landscape scale, governance at a community scale, and livelihoods at a household scale within a social ecological system; I develop a measure of forest health, the Bare Ground Index, derived from satellite imagery and combine this with socioeconomic data to examine relationships between forest health and forest governance and livelihoods across central India.** This body of work has identified livelihood and governance approaches that provide social benefits and maintain healthy forests in central India, a landscape with globally important biodiversity and socially and historically marginalized people. This context is reflected in additional human-dominated landscapes where identifying sustainable development solutions that provide social and environmental benefits is a priority.

As forests are lost, gained, and degraded around the world, satellite data has been a powerful tool in collecting estimates of forest cover change but less widely adopted to measure forest degradation, largely due to challenges in common interpretations of operational measures.

In chapter 1, coauthors and I develop landscape-scale land cover and forest health datasets for central India. First, we identified land cover, including tree cover and bare ground, from Planet Labs Very High-Resolution satellite data using a Random Forest classifier, resulting in a 3-meter (m) thematic map with 83.00% overall accuracy. Second, we operationalize a measure of forest health and derived the Bare Ground Index (BGI), a normalized index that is a ratio of bare ground to tree cover at 90 m resolution. The BGI was mapped across forest (>10% tree cover). Although open areas occur naturally throughout the tropical dry forest of central India, results from field data indicated that the BGI served as a proxy for measuring the intensity of cattle presence in a landscape where grazing has changed forest composition. The BGI was developed as an indicator of forest health and now serves as a baseline to monitor future changes to a tropical dry forest landscape at an unprecedented spatial scale.

In chapter 2, coauthors and I integrated the BGI with socioeconomic data from surveys to households and locally elected leaders to assess forest health and governance patterns across 238 villages at the community-scale. We experimentally selected 80 total villages as treatment and control groups and used this dataset in various statistical analyses to assess the extent of exposed bare ground within forests around villages with and without local institutions involved in making decisions about the forest. Forest had less bare ground within forest where there was a local institution compared to villages without an institution at 3 and 5 kilometers (kms), distances that households traveled from the village to graze cattle or collect Non-Timber Forest Products, firewood, and fodder. Having a local forest institution was more strongly associated with bare ground within forest at 3 and 5 kms than measures of local forest use. In villages with institutions, the authority to modify rules about forest use was relatively more important than the length of time the institution had been established for bare ground within forest. Establishing formal institutions with authority over forest management is important to promote forest cover around forest-dependent communities but it is necessary to ensure that forest governance does not worsen existing socioeconomic disparities. Bare ground within forests near and far (1 and 10 kms) villages was not different in places with and without formal local institutions and was most strongly associated with local forest uses. Both formal forest institutions and forest uses like collecting firewood for cooking or wood for construction material impact forests in central India.

In my third and final chapter, coauthors and I examined firewood collection patterns and the adoption of Liquified Petroleum Gas (LPG) using surveys from 4,994 households in central India. Firewood collection is pervasive across central India's rural communities and mainly used for cooking or heating. We adopted an energy justice approach, which emphasizes questions about who does and does not have access to alternative cooking fuels, because historically marginalized groups comprise a significant portion of central India's total population. It was important to integrate social justice issues in a system where resource users experience multiple disparities, such as high levels of poverty. We found that despite overall growth in LPG use, disparities in access to clean cooking fuels remained and the probability of cooking with LPG was lowest for socially and historically marginalized households (i.e., Scheduled Tribe, Scheduled Caste, and Other Backward Caste). While 90% of LPG-using households continued to use firewood, households that have owned LPG for more years spent less time collecting firewood, indicating a waning reliance on firewood over time. This study found evidence that policies targeting communities with marginalized social groups living near forests can further accelerate LPG adoption and displace firewood use.

My thesis examined components of a social ecological system at landscape, community, and household scales. I integrated insights from across social and ecological disciplines to identify strategies for sustainable development in central India. First, I developed an operational measure of forest health. Following chapters identified characteristics of governance and livelihood interventions that present potential pathways towards achieving benefits for conservation and people. Environmental and development goals should be harmonized so that the central Indian landscape can continue to support biodiversity and people. My approach can be replicated across additional social ecological systems by linking a landscape-scale resource condition to community governance and household socioeconomic patterns.

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Dedication

To my parents; to the tiger family legacy; to the people and forests I wrote my thesis about.

Introduction

Forests are important for their roles in global biogeochemical processes, biodiversity conservation, and providing subsistence and income to millions of forest-dependent and impoverished people (Nerfa et al. 2019; Joos-Vandewalle et al. 2018). Within social ecological systems, forests are embedded in social contexts including diverse forest governance and resource use and user settings interacting at different scales (Liu et al. 2007; Ostrom, 2009; McGinnis, 2014). As forests are lost, degraded, or gained, through natural regeneration, afforestation, or restoration, around the world (Song et al. 2018; Vacutsem et al. 2021). Changes to forests present a challenge to understand and capture biophysical measures of resource condition and an opportunity to identify pathways towards sustainable development that provide multiple benefits to resources and people (DeFries et al. 2012). For example, whether resource users are involved in management or have autonomy to make and enforce rules about resource use influences resource sustainability (Dietz et al. 2003; Ostrom, 2009). International trade and overconsumption are significant drivers of deforestation along with local socioeconomic factors like forest governance and forest-dependent livelihoods (Hoang et al. 2021; DeFries et al. 2010; Lewis et al. 2015; Oldekop et al. 2020), although local demand and uses of forests do not necessarily threaten forests (Delabre et al. 2020). People in poverty inhabit the same forests that are valued for their biodiversity (Fisher et al. 2007) and local participation in forest governance has resulted in benefits to forests around the world (Slough et al. 2021; Min-Venditti et al. 2017; Oldekop et al. 2019).

Here, I introduce satellite-based methods to measure forests at the landscape scale and then provide a background to community participation in forest governance and household forest uses including collecting firewood for cooking. My first chapter derived a landscape scale measure of resource condition from satellite imagery and following chapters integrated these remote sensing products with in situ socioeconomic data at the household and community scales (Cavender-Bares et al. 2022). Sustainability has traditionally been approached through the perspective of natural resource condition (chapter 1); I integrate connections between forest health, communities, and social justice in my framing of sustainable development in subsequent chapters (Nagendra, 2018). **This dissertation examines forest health at a landscape scale, governance at a community scale, and livelihoods at a household scale within a social ecological system; I have produced a forest health indicator dataset (chapter 1) and integrated this and other satellite-derived measures of the forest with socioeconomic data to answer questions that aim to identify ways to achieve sustainable development goals for sustainable forest management (e.g. Sustainable Development Goal (SDG) 15) and access to clean energy (e.g. SDG 7) (chapters 2 and 3) in central India.** The households and communities I examine in chapters 2 and 3 provide fine-scale insights across a landscape, and landscapes are an important scale for flora, fauna, and people that live in or depend on forests (Oldekop et al. 2020; Hobbs, 1997; Daskalova et al. 2020; Opdam et al. 2018; Arroyo-Rodriguez et al. 2020).

Satellite imagery has provided insights into the presence and absence of forests at landscape and global scales (Song et al. 2018; Hansen et al. 2013). In contrast, there is no standard definition of forest degradation, a process with leads to reduced ecological functioning due to arrested succession (Ghazoul et al. 2015) and precursor to deforestation (Vancutsem et al. 2021). Structural indicators of forest degradation can include decreased biomass (Goa et al. 2020) and soil health and function (Veldkamp et al. 2020). Soil can be readily identified with satellite imagery. For example, the Normalized Difference Fraction Index integrates bare ground exposure in its measure of forest degradation using a spectral unmixing approach (Bullock et al. 2018). Globally, the amount of exposed bare ground is increasing and from 2000 to 2012, an estimated 93,896 km^2 of bare ground was gained; almost all of this conversion was human-induced (Ying et al. 2017). Despite the lack of a common interpretation of forest degradation assessed with satellite imagery (Bustamante et al. 2016), various remote sensing methods have been developed (i.e. Vancutsem et al. 2021, Bullock et al. 2018, Hansen et al. 2019). These studies use Landsat imagery (medium resolution at 30 meters), which is available from 1972 to present-day openly and free and has provided scientific and economic benefits around the world (Zhu et al. 2019). More recently, the quality and quantity of Very High Resolution (VHR) satellite imagery has increased while continued computational advancements improve the feasibility to process and analyze the data. Although not consistently openly available and free, VHR data more accurately identifies small-scale features than medium-resolution imagery and has the potential to quantitively estimate and subsequently monitor forest degradation at an unprecedented scale.

Central India was a hotspot of forest loss across India from 1985 to 2005 (Meiyappan et al. 2017), but deforestation captures shifts from forest to another land cover class and does not evaluate subtle changes within the single vegetation land cover class (e.g. forest). In chapter 1, coauthors and I develop a metric to measure exposed bare ground within forests and produce land cover and forest health datasets for the landscape. First, we identified five land covers from Planet Labs VHR (3 m) satellite imagery using a Random Forest classifier in Google Earth Engine, including tree cover, bare ground, built environment, water, and cropland. The Random Forest classifier was used because it classified land covers most accurately in an algorithm selection process where we evaluated several machine learning algorithms for discrete land cover classification on a small portion of the landscape. Second, we derived the Bare Ground Index (BGI), a normalized index that is a ratio of bare ground to tree cover at 90 m resolution across forests (>10% tree cover). The BGI was assessed with ground observations of invasive species and signs of forest use by people and cattle and developed to provide a baseline operational measure of forest health across central India. Then, I integrated the BGI with socioeconomic data on resource users and governance settings in chapter 2.

Effective forest governance is critical to maintain or improve the biophysical state of a forest. Forests can be managed under a variety of strategies such as Protected Areas under state (government) ownership and management. Forest management shared between states and local communities can be more effective for people and forests than forests under state control alone (Oldekop et al. 2015). The extent of community participation in forest management varies widely but altogether efforts to decentralize governance have provided environmental benefits. A meta-analysis from experimental sites around the world found reduced forest use and resource degradation where communities monitored natural resources (Slough et al, 2021). Community managed forests in Mexico, Costa Rica, and Thailand have resulted in more forest benefits than government managed land (Min-Vendetti et al. 2017; Agarwal, 2022). While India's forests are owned and managed by government Forest Departments, participatory management can be formalized at the village-level through institutions such as the village forest committee, *van sanrakshan samiti* in Hindi, or eco-development committee. Within sites across central India, local participation in forest governance resulted in significant positive forest outcomes (Agarwal et al. 2016; 2017).

In chapter 2, coauthors and I assessed whether global and community scale patterns showing environment benefits of community participation in forest governance was reflected at the landscape-level. We integrated the BGI developed in my first chapter as a measure of forest health with data from two surveys, one given to households across 500 villages in 2018 and another interviewing 238 local elected leaders of the same villages in 2022. The 2018 survey was used in chpaters 2 and 3. We examined patterns of forest governance across 238 villages along with household socioeconomics. To assess forest health in villages with and without local forest management institutions, we experimentally selected 80 total villages as treatment and control groups and used this dataset in a Wilcoxon rank sum test and conditional forest models. Conditional forest model results were used to estimate the relative importance of local institutions and forest uses, including collecting wood for home repairs, firewood, Non-Timber Forest Products (NTFP), and fodder and grazing cattle in the forest, on forest health. In places with local institutions, we also assessed the relative importance of the length of time a local institution had been established and whether the local institution had the authority to modify rules about forest use in forest health outcomes. Although chapter 2 focused on forest governance, resource users across central India are highly forest-dependent and results confirmed the importance of forest uses in shaping forest health across the landscape.

People depend on forests to meet basic needs even if it is hazardous to human health. For example, 2.8 billion people around the world burn biomass to meet household energy needs (Bonjour et al. 2013). Households use multiple fuels, or stack fuels, to meet energy needs; despite access to alternatives such as Liquified Petroleum Gas (LPG), biogas, and solar, firewood persists as a cooking fuel partly because of its availability (Mani et al. 2020; Kyaw et al. 2020), which can be influenced by forest condition (Njenga et al. 2021). The deaths of almost half a million people across India in 2017 were attributable to household air pollution from cooking with biomass (Balakrishnan et al. 2019) and largely burden women and children who are tasked with cooking (Cabiyo et al. 2021). In response, the Government of India has promoted the use of LPG in poor households through a *Pradhan Mantri Ujjwala Yojana*, a policy implemented in 2016.

In chapter 3, coauthors and I explore cooking fuel patterns in 4.994 households living across 500 villages in central India before and after a national-level alternative cooking fuel policy. We used an energy justice approach which emphasized questions about who does and does not have access to LPG. This approach was important because central India contains a relatively high number of historically and socially marginalized communities who face multiple disparities due to their class and community identities (Table 1). We used survey data from households within 500 villages living in forested regions collected in 2018 and a satellite-derived measure of forest availability to investigate the household determinants of LPG adoption and the timing of this adoption (pre- or post-2016). In addition, we documented patterns of firewood collection and evaluated the extent to which households acquiring LPG changed these activities.

Overall, this thesis provides a baseline measure of forest health, measuring exposed bare ground within forest, across central India and identified livelihood and governance solutions that provide social and environmental benefits. The central Indian landscape has globally important biodiversity and socially and historically marginalized people, a context reflected in additional human-dominated landscapes where identifying sustainable development solutions that have social and environmental benefits is a priority.

1.1 Study area

Central India is a landscape across 38 administrative units, known as districts, in the states of Madya Pradesh, Maharashtra, and Chhattisgarh. In addition to major urban centers –

Nagpur, Jabalpur, and Bhopal – there are numerous rural villages throughout the region where residents primarily engage in agriculture and livestock rearing as an occupation. Rural communities face higher levels of poverty, measured as a combination of health, education, and living standards, compared to the rest of India (Alkire et al. 2020). About 51 million people, living mainly in rural settings, of diverse identities live in the study area (Table 1). For example, there are more than 50 different constitutionally recognized Scheduled Tribe groups throughout central India, such as Gond or Baiga.

Forest-based economic and subsistence activities contribute substantially to households in central India (Gupta et al. 2017). Over one third (37%) of villages within the study area live within 8 km of forest (DeFries et al. 2020). Seasonal harvest of commercial NTFPs is common, such as Tendu (*Diospyros melanoxylon*) leaves or 'tendu patta,' which contribute substantially to household incomes. Other materials might be collected as fodder for livestock or for construction, particularly where communities lack more permanent, or 'pucca,' houses.

Forests across central India are tropical dry forests, which are highly threatened, contain unique biodiversity, and have close relationships with the people living in and near them (Janzen, 1988; Power et al. 2018). Many tree species are deciduous; forests can be highly heterogeneous or dominated by few species, notably Sal (*Shorea robusta*), Teak (*Tectona Grandis*), or Terminalia species (Agarwala, 2016). Central India a global priority tiger (*Panthera tigris*) conservation landscape (Sanderson et al. 2005). Although protected areas across the landscape form the foundation of biodiversity-focused management and central India has some of India's largest remaining forest patches, they are highly fragmented and 88% of central India's tree cover exists outside of formally designated protected areas (Nayak et al. 2020). Shifts in rural demographics and infrastructure development in central India are exemplary of global trends shaping forest and forest-dependent livelihoods (Oldekop et al. 2020). This forest contributes to existing connections between protected areas for tigers and other wildlife (Thatte et al. 2019; Schoen et al. 2022). Livestock grazing and fire have altered tree species composition across central India (Agarwala, 2016).

Table 1: Summary statistics of the study area. There are 38 districts in the study area (central India), 32 of which were included in the 2018 survey (as indicated by *) and another 31 included in both the 2018 and 2022 surveys (as indicated by **). The multidimensional poverty index ranges from 0 (low poverty) to 1 (high poverty) and is a combined measure of health, education, and living standards (Sharma et al. 2019). I also report the size of Scheduled Caste and Scheduled Tribe populations and percent of households (rural and total) using firewood and LPG as their primary cooking fuel by district (Registrar General and Census Commissioner of India, 2011).

State	District	Multi-dimensional poverty index	Total population	% of population Scheduled Caste	% of population Scheduled Tribe	% of rural households using firewood as a primary fuel for cooking	% of rural households using LPG as a primary fuel for cooking	% of total households using firewood as a primary fuel for cooking	% of total households using LPG as a primary fuel for cooking
Chhattisgarh	Bilaspur**	0.12	2663629	20.76	18.72	91.21	1.45	80.52	12.62
Chhattisgarh	Janjgir - Champa**	0.11	1619707	24.57	11.56	92.64	1.78	89.46	5.07
Chhattisgarh	Kabeerdham**	0.20	822526	14.56	20.31	89.96	0.66	87.54	3.61
Chhattisgarh	Korba**	0.17	1206640	10.33	40.90	93.49	2.23	71.35	15.65
Chhattisgarh	Rajnandgaon**	0.10	1537133	10.19	26.36	96.68	1.23	88.40	8.39
Madhya Pradesh	Anuppur**	0.21	749237	9.93	47.85	95.68	1.83	80.55	13.85
Madhya Pradesh	Balaghat**	0.20	1701698	7.37	22.51	96.27	1.54	90.55	6.92
Madhya Pradesh	Betul**	0.17	1575362	10.11	42.34	91.15	2.78	79.89	13.84
Madhya Pradesh	Bhopal	0.21	2371061	15.08	2.93	82.93	8.88	27.01	57.70
Madhya Pradesh	Chhatarpur	0.15	1762375	23.00	4.18	88.74	1.51	81.72	9.84
Madhya Pradesh	Chhindwara**	0.15	2090922	11.11	36.82	89.82	5.31	77.30	16.72
Madhya Pradesh	Damoh**	0.22	1264219	19.49	13.15	88.02	1.70	83.10	7.73
Madhya Pradesh	Dindori**	0.28	704524	5.65	64.69	96.84	1.01	94.84	2.71
Madhya Pradesh	East Nimar**	0.21	1310061	11.95	35.05	72.90	4.83	65.21	15.39
Madhya Pradesh	Harda	0.05	570465	16.28	27.99	86.09	8.61	74.92	19.98
Madhya Pradesh	Hoshangabad**	0.11	1241350	16.51	15.89	83.73	5.96	67.24	24.32
Madhya Pradesh	Jabalpur**	0.10	2463289	14.13	15.23	91.96	4.81	57.60	37.39
Madhya Pradesh	Katni**	0.19	1292042	12.05	24.59	95.29	2.71	84.17	13.18

Madhya Pradesh	Mandla**	0.25	1054905	4.59	57.88	96.47	2.09	90.77	7.39
Madhya Pradesh	Narsimhapur**	0.13	1091854	16.87	13.36	86.93	3.38	79.38	11.49
Madhya Pradesh	Panna**	0.21	1016520	20.46	16.81	82.21	1.91	79.70	5.69
Madhya Pradesh	Raisen**	0.17	1331597	16.96	15.40	85.20	3.14	76.74	12.58
Madhya Pradesh	Rewa**	0.17	2365106	16.25	13.19	54.05	2.44	52.56	8.36
Madhya Pradesh	Sagar**	0.17	2378458	21.09	9.33	87.80	1.97	77.19	13.44
Madhya Pradesh	Satna**	0.17	2228935	17.88	14.36	78.08	2.80	71.82	11.53
Madhya Pradesh	Sehore	0.12	1311332	20.69	11.10	88.29	3.11	79.67	12.27
Madhya Pradesh	Seoni**	0.21	1379131	9.48	37.69	91.98	2.53	85.95	8.58
Madhya Pradesh	Shahdol**	0.22	1066063	8.42	44.65	95.19	1.68	85.12	9.75
Madhya Pradesh	Umaria**	0.22	644758	9.02	46.64	96.53	1.56	89.06	8.80
Madhya Pradesh	Vidisha**	0.21	1458875	20.03	4.63	63.48	2.41	57.65	13.99
Maharashtra	Akola	0.15	1813906	20.07	5.53	67.25	10.29	55.01	27.47
Maharashtra	Amravati*	0.07	2888445	17.53	13.99	71.84	10.94	58.23	27.60
Maharashtra	Bhandara**	0.05	1200334	16.69	7.41	87.39	9.16	75.98	20.29
Maharashtra	Chandrapur**	0.09	2204307	15.80	17.67	80.01	13.29	59.69	32.60
Maharashtra	Gadchiroli**	0.12	1072942	11.25	38.71	89.47	7.30	83.89	12.62
Maharashtra	Gondiya**	0.10	1322507	13.31	16.20	91.51	4.79	82.78	13.14
Maharashtra	Nagpur**	0.03	4653570	18.65	9.40	70.83	24.15	31.96	60.23
Maharashtra	Wardha	0.11	1300774	14.52	11.49	66.64	20.51	51.36	37.67
Regional (central India)	Regional	0.16	60,730,559	14.81	23.07	85.65	4.95	73.84	16.85
National (India)	National	0.12	1,028,610,328	16.20	8.20	62.60	11.40	49.00	28.50

Chapter 1: Land cover and forest health indicator datasets for central India using very-high resolution satellite data

Progress: Under revisions for *Scientific Data*

Authors: Sarika Khanwilkar, Chris Galletti, Pinki Mondal, Johannes Urpelainen, Harini Nagendra, Yadvendradev Jhala, Qamar Qureshi, Ruth DeFries

2.1 Introduction

Forest cover changes impact global biodiversity and bio-geochemical cycles (Alkama & Cescatti, 2016; Sala et al. 2000) and livelihoods of forest-dependent people. Deforestation, the complete conversion of tree cover to another land cover, has been well-documented and quantified at regional and global scales using satellite imagery (Hansen et al. 2013). Technological developments in remote sensing methods have improved the feasibility to detect more fine-scale changes to forests; for example, Very-High Resolution (VHR) satellite data has increased the spatial resolution and amount of data available to make useful interpretations of land cover. Despite advancements in remote sensing, the scientific literature lacks a standard definition and methods for detecting and quantifying subtle 'within class' changes, such as forest degradation.

Generally, forest degradation is a change in the structure, function, or composition of a forest without complete loss of forest (GFOI, 2016). Soil health is included in different definitions of forest degradation because it is important for plant survival and growth. Additionally, lack of vegetation can lead to exposed soil (i.e. bare ground) within forests, which can alter soil moisture, water holding capacity, and nutrients (Formánek et al. 2014). The transition from tree cover to bare ground is caused by a complete loss of vegetation (Hansen et al. 2014), which may be due to resource extraction (Ying et al. 2017).

Central India is a heterogeneous mosaic of land covers that includes tree cover, exposed bare ground, water bodies, cropland, and villages and cities spanning a total geographic area of 265,330,011 km^2. While there was only a slight decrease (1.7%) in total forest cover from 2003 to 2019 in central India, there is evidence of nuanced changes to forest health; areas of open forest (canopy cover between 10% and 40%) and moderately dense forest (canopy cover between 40% and 70%), which made up a combined 83.0% of total forest in 2019, decreased by 4.9% and 7.5%, respectively, while very dense forest (canopy cover of 70% or more) increased by 30.5% (Appendix A) (Forest Survey of India, 2003 and 2019).

Tropical Dry Forest (TDF) in central India directly supports a high number of forest-dependent people (i.e. people living in and adjacent to forests and using the forest for livelihood needs and income generation), who largely belong to an officially recognized Scheduled Tribe or Scheduled Caste. Livestock rearing and agriculture are primary occupations. Livestock grazing and fire have altered tree species composition in central India, which demonstrates the important long-term impacts associated with human use of the forest (Agarwala et al. 2016). In addition, most forest-dependent households in central India collect firewood for cooking fuel (Khanwilkar et al. 2021). Another driver of forest degradation in central India is lantana (*Lantana camara*), an invasive species which most often invades forests in India where humans lop trees for wood or graze livestock (Mungi et al. 2020).

In order to quantify and map forest health in central India we first produce a high spatial resolution (3 meter (m)) land cover dataset. Several machine learning algorithms exist to classify land covers. We compared four machine learning algorithms based on an accuracy assessment and used the random forests (RF) algorithm (Breiman, 2001) to classify five land covers for central India: tree cover, bare ground, water, cropland, and built environment. Based on the classification, we develop an index (Bare Ground Index, BGI) to quantify exposed bare ground within forested regions at 90 m. We assess the BGI with ground observations of signs of degradation, which include the presence of an invasive species as well as signs of resource extraction and forest use. Land cover and BGI datasets of central India are freely available in the GeoTIFF and KML file formats, respectively; code used to classify land cover and the BGI in Google Earth Engine are also available at https://lcluc.umd.edu/metadatafiles/LCLUC-2017-PI-Defries/. To our knowledge, this was the first VHR dataset of central India.

The BGI is a metric to assess a structural indicator, exposed bare ground within forests, of forest health; it may be used as a baseline to monitor future changes to bare ground and tree cover in central India and contribute towards an operational definition of forest degradation as one of several forest health indicators (Vásquez-Grandón et al. 2018). Our approach (Figure 1) to mapping the BGI can be applied to additional forested landscapes.

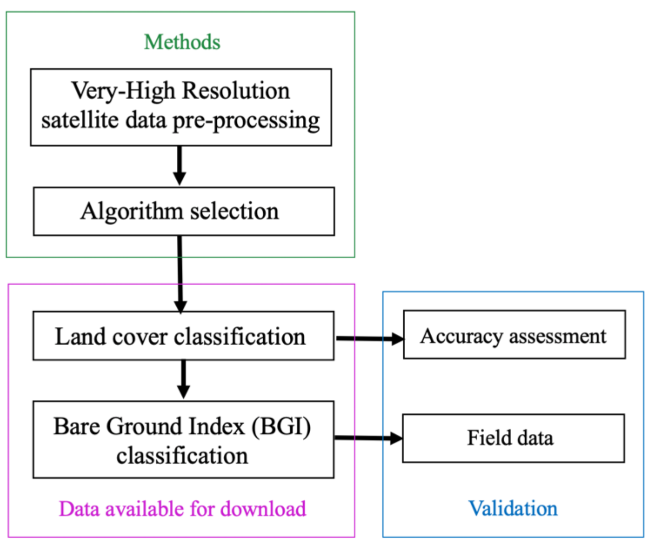

Figure 1: Flowchart depicting chapter 1. A flowchart outlining our approach to producing land cover and forest health indicator datasets in a Tropical Dry Forest using Very-High Resolution imagery.

2.2 Methods

Very-High Resolution (VHR) satellite data

Planet's PlanetScope top-of-atmosphere surface reflectance in 4 bands (Red, Green, Blue, and Near-infrared [NIR]) at 3 m resolution was used to classify land cover in central India. The four spectral bands correspond to the following wavelengths: Red (590 to 670 nm), Green (500 to 590 nm), Blue (455 to 515 nm), and NIR (780 to 860 nm). We selected and downloaded images of the study area captured between February 28 and March 5 2018 using the Planet Explorer interface. Imagery during the winter season was selected to minimize cloud cover. Rainfall is highly seasonal and concentrated during the monsoon season (mid-June to September). Many tree species are deciduous and lose their leaves before the summer (March to mid-June). The coldest and driest season is from December to February. We aimed to capture bare ground exposed throughout the year because deciduous tree species maintain leaves in the winter. The images were mosaiced and clipped (i.e. pre-processed) into 233 tiles in ArcMap and then uploaded into Google Earth Engine (GEE), which was the first step to testing algorithms, classifying land cover, and calculating the BGI.

Algorithm selection

Four of the Planet imagery tiles, covering the fieldwork region were classified using RF, Support Vector Machine (Vapnik, 1979), Boosted Decision Tree with AdaBoost, adaptive boosting (Freund and Schapire, 1996), and Kohonen's Self Organizing Map with k-means clustering (Kohonen, 1998; Li and Eastman, 2006).

Random Forest is an ensemble classification algorithm based on a collection of decision trees; the starting node, or root of the tree, considers all training data. The first and subsequent splits separate the training data into subsets by using the input features (image bands). Support

Vector Machine is a non-parametric classifier that creates a linear decision boundary for a dataset based on support vectors, a subset of the training samples. AdaBoost, short for adaptive boosting, is an ensemble method that sequentially combines the results of weak estimators, such as individual decision trees, to obtain an optimal classification (Freund and Schapire, 1996). Finally, Kohonen's Self Organizing Map with k-means clustering is an unsupervised neural network that uses competitive learning to optimize a vector of weights, or "synaptic coefficients," of a given set of neurons to minimize the distance between each input vector and its associated neuron (Kohonen, 1998; Li and Eastman, 2006).

We assessed the performance of each ML algorithm based on the overall accuracy and the kappa index, and selected RF as the best performing algorithm (Table 2). A total of 18 models were run which differed in the algorithm used and the number of samples in the training data (Appendix A) and algorithm parameters (Appendix A). The final accuracy of all models was assessed using validation data from a stratified random sample of pixels which were distributed across the four test tiles. The randomization was stratified by class and by geography. There were 5,332 total pixels assessed with a minimum of 150 pixels per class. For geographic stratification, a uniform grid was established across the corridor and pixels were randomly spread across the cells within the grid.

Table 2: Algorithm selection results. Algorithm selection was accomplished by comparing the performance of four machine learning (ML) algorithms in the land cover classification of the fieldwork region of central India. Four Planet tiles that were also used to produce the final landscape classification were classified and the Random Forest ML algorithm resulted in the highest overall accuracy and kappa index (indicated by a *).

Classification type	Algorithm	Highest overall accuracy	Kappa
Supervised	Random Forest	0.70*	0.61*
	Support Vector Machine	0.44	0.32
	Boosted Decision Tree (AdaBoost)	0.69	0.60
Unsupervised	Kohonen's Self Organizing Map	0.63	0.51

Training data for each land cover class was selected as polygons using Google Earth imagery from February 2018. Pixels within the polygons were extracted and assigned a land cover class. The same training data was used to train all three supervised algorithms. Likewise, the same validation was used to assess the accuracy of each algorithms' classification output. Models were trained using the Scikit-Learn package within Python v2.7 and parameters varied. The ML models were then applied to the images on a Linux-based high-performance computing cluster that processed each image in just over an hour.

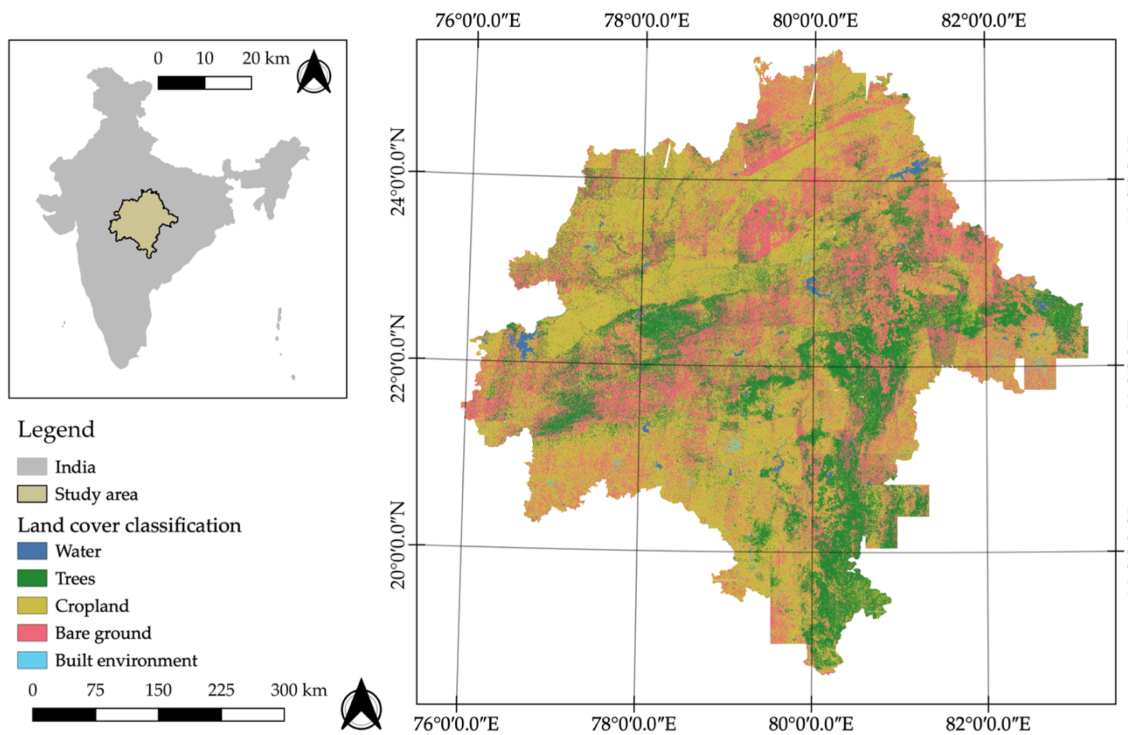

Figure 2: Land cover dataset. Very-High Resolution (3 meter) land cover map of central India. The classification was completed in Google Earth Engine and visualized in QGIS3.16.

Land cover classification

Each Planet tile was classified into five discrete land covers: trees, bare ground, water, cropland, and built environment (Figure 2). We identified trees and bare ground in order to derive the BGI and additional land cover types were chosen based on a field assessment completed within the fieldwork region in February 2018. Training data for each land cover class was selected as polygons using Google Earth imagery from February 2018, and additional training data was collected in the fieldwork region in February 2018 and June 2019. Pixels, 1,048,575 in total, within the polygons were extracted and assigned a land cover class (Table 3). The pixels were used as training data using RandomForest with 10 decision trees in Google Earth Engine's Classifier package and was applied to Planet imagery at 3 m scale in GEE.

Table 3: Training data. The mean and standard deviation (SD) of reflectance values of all the training data according to land cover type.

Band	Tree cover N=498,049	Bare ground N=130,756	Cropland N=95,864	Water N=215,989	Built environment N=107,917
Red, Band 1 Mean (SD)	437.67 (52.21)	1077.70 (215.90)	476.97 (75.17)	552.80 (70.18)	824.59 (130.24)
Green, Band 2 Mean (SD)	544.14 (62.57)	1312.09 (258.84)	603.97 (82.94)	673.54 (100.03)	996.97 (157.97)
Blue, Band 3 Mean (SD)	580.90 (85.51)	1733.98 (378.31)	574.24 (133.72)	675.71 (112.33)	1236.04 (225.10)
Near-infrared, Band 4 Mean (SD)	1967.48 (265.02)	2828.61 (438.59)	3336.76 (756.40)	703.57 (127.33)	2171.17 (368.07)

Bare Ground Index (BGI) classification

The BGI (Figure 3) was calculated and mapped using land cover data from the VHR land cover classification. First, we aggregated the land cover to 90 m resolution to identify forest, defined as >10% tree cover[18], and non-forest (<10% tree cover). Then, we calculated the BGI within forest.

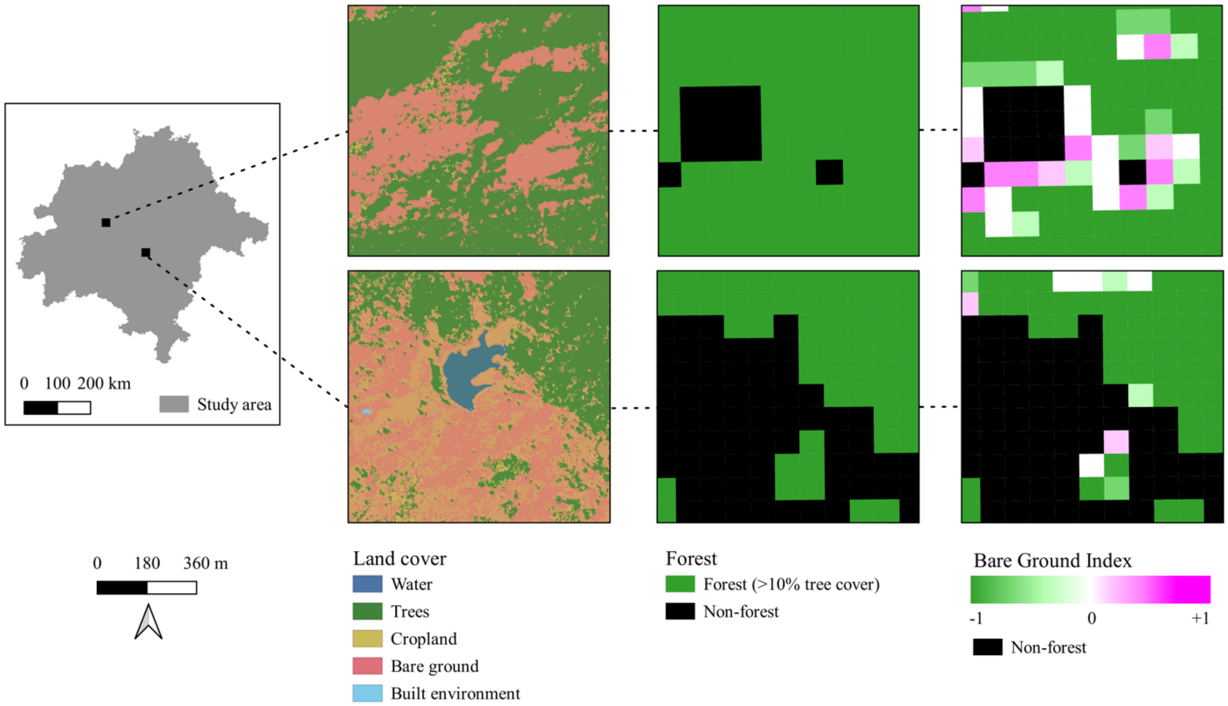

Figure 3: Visualization of the Bare Ground Index. The Bare Ground Index (BGI) was calculated and mapped in central India at 90 meter (m) resolution. The BGI was derived from the land cover classification. First, forest (>10% tree cover within a 90 m pixel) and non-forest was identified. Then, the BGI, a normalized index that ranges from -1 to +0.8, was identified within forest. White indicates pixels where the BGI equals 0. Pixels that are pink have more bare ground as compared to tree cover, whereas pixels that are green have more tree cover as compared to bare ground.

The BGI is a normalized index that ranges from -1.0 (all forest) to +0.8 (all bare ground). The maximum BGI value for a pixel is +0.8 because the BGI was only calculated within pixels that had 10% or greater tree cover. The BGI was derived from the land cover classification and calculated using the following equation (Equation 1):

$$\frac{(BareGround_i - TreeCover_i)}{(BareGround_i + TreeCover_i)} = Bare\ Ground\ Index\ (BGI) \quad (1)$$

where BGI is the Bare Ground Index (BGI) at 90 m resolution, and $TreeCover_i$ and $BareGround_i$ is the fraction of pixels within the 90 m pixel that were classified as “tree cover” and “bare ground,” respectively, in the land cover classification. The BGI classification was performed using the GEE Code Editor (www.code.earthengine.google.com) and visualized in QGIS3.16. Figure 3 shows examples of the BGI.

2.3 Results

Data Records

Data are available for download from the National Aeronautics and Space Administration's (NASA) Land Cover Land Use Change program data repository (https://lcluc.umd.edu/metadatafiles/LCLUC-2017-PI-Defries/). The 'Read_me' text file describes the available land cover and BGI classification data files. The 'StudyAreaZones' map shows the location of 233 tiles that cover the landscape; the tile number corresponds to the location and file name of available land cover ('Classified_[tile number]') and BGI ('classified_bgi_[tile number]') data.

Land cover classification accuracy

In addition to assessing the accuracy of multiple ML algorithms during algorithm selection, we conducted an accuracy assessment of the final land cover dataset following an independent resampling approach (Table 4). Geographic randomization of reference data was achieved by generating ten random points per tile (2,330 points) in R version 3.6 to ensure an unbiased reference data selection and distribution across the study area. Reference data was selected through visual interpretation of imagery in Google Earth Pro. The accuracy of the land cover classification as compared to our reference data was calculated in R version 3.6 and resulted in a 83.00% overall accuracy. The user accuracy for tree and bare ground classes were

90.21% and 52.20%, respectively; the producer accuracy for tree and bare ground classes were 88.53% and 92.08%, respectively (Table 4).

Table 4: Land cover classification error matrix. The error matrix was used to assess the accuracy of the final land cover dataset. Reference data were 10 randomized points per tile; land cover was identified from historical Google Earth imagery. The overall accuracy was 83.00%.

	Independent samples						
Land cover classification	**Tree cover**	**Bare ground**	**Built environment**	**Cropland**	**Water**	Row total	User's accuracy (%)
Tree cover	**27220**	17	56	2625	256	30174	90.21
Bare ground	1357	**12252**	156	4716	4995	23476	52.19
Built environment	1	208	**2623**	2655	7870	13357	19.64
Cropland	1111	827	569	**39984**	9274	51765	77.24
Water	1059	2	7	47	**102446**	103561	98.92
Column total	30748	13306	3411	50027	124841	222333	
Producer's accuracy (%)	88.53	92.08	76.90	79.92	82.06		

Ground validation of the BGI

In February 2020, we visited 191 locations which varied from high to low BGI in the fieldwork region (Figure 4). The season of data collection during ground validation coincided with the season that Planet satellite images were acquired, which was of particular importance to accommodate the seasonality of the region. Signs of forest use, including trails, cattle dung, and lopping, and lantana were detected at each ground validation location. These signs were categorized as 0 (no signs), 1 (1 or 2 signs), or 2 (3 or greater signs). Then, we compared the BGI values of areas with minimal to maximal signs of forest use and lantana using a Wilcoxon rank sum test, which estimates the significance of the difference between non-normally distributed data. There were significantly higher amounts ($p<0.05$) of cattle dung in places with higher values of BGI, or more bare ground than tree cover (Appendix A). There were no significant associations between the BGI and other signs of forest use.

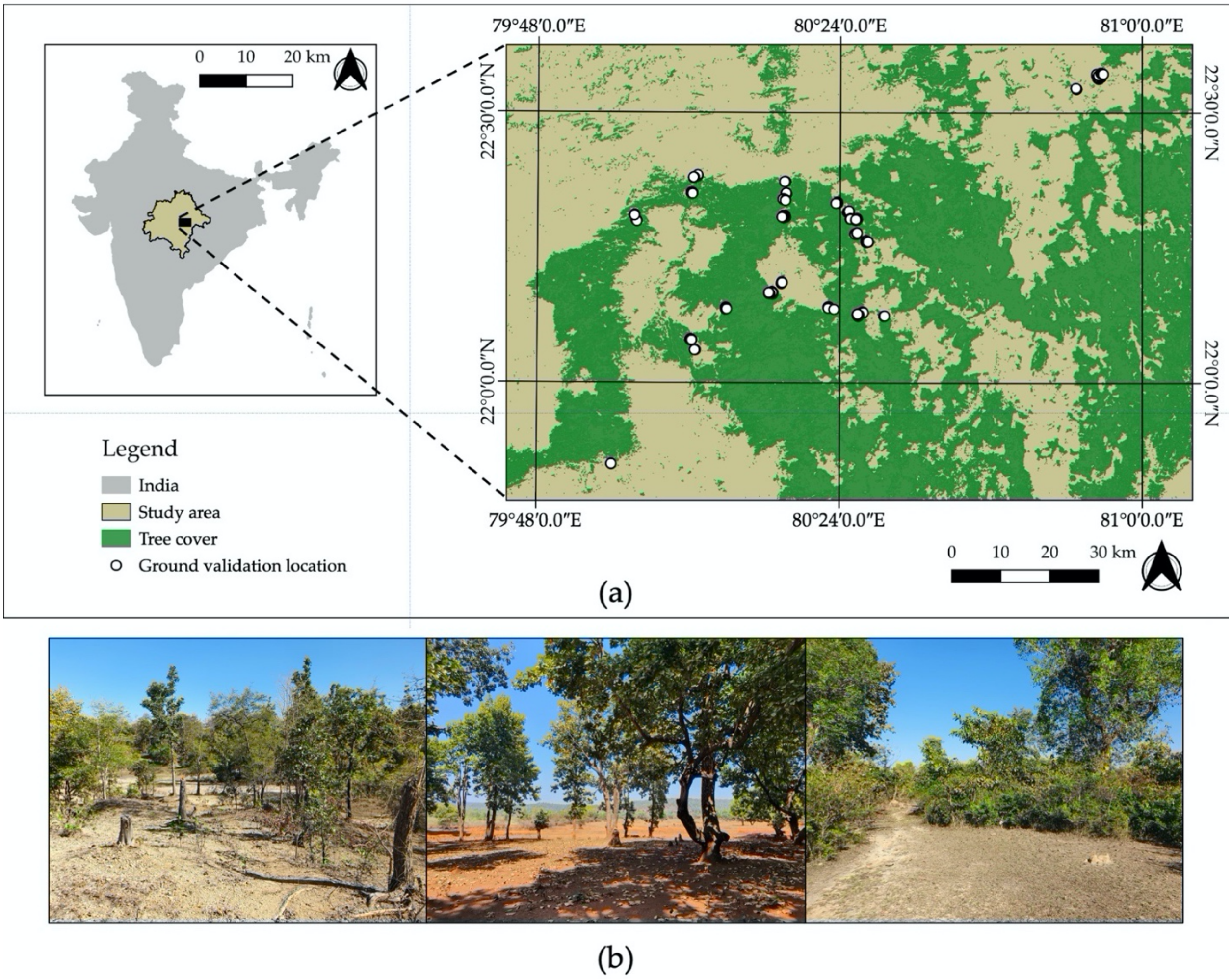

Figure 4: Ground validation map. Ground validation data was collected from the fieldwork region of the study area in February 2020 (a). Photos from ground validation locations (b) illustrate exposed bare ground within forests which we aimed to identify and map with the Bare Ground Index (BGI). Photos were taken with a Samsung Galaxy S10+. Tree cover comes from Hansen et al. 2013[2].

2.4 Discussion

There is no single remote sensing method that can measure forest health and degradation in all of its complexity. Where changes to the forest cannot be measured through changes in tree cover alone, the BGI serves as a geospatial tool to quantify and explore one characteristic of forest health. The BGI can be a valuable metric to couple with other indicators of forest health to assess and understand forest degradation and contributes to a broader need to assess and estimate changes to forest health in TDFs around the world, forests which have been understudied as compared to tropical moist or wet forests (Powers et al. 2018).

An increase in BGI is associated with increased presence of cattle dung, which we used as a proxy for intensity of cattle grazing. Stronger evidence that links the BGI directly to cattle grazing can be collected through further field research, such as direct observations of cattle grazing and a more thorough understanding of grazing patterns through social surveys. Throughout our ground surveys of the BGI, signs of forest use were prevalent across a range of values of the BGI. Such activities may continue to impact forest health below the canopy where optical data is unable to detect. We advocate for the development of additional forest heath indicators using LiDAR and SAR data, with a specific emphasis on identifying indicators of degraded forest structure and composition driven by lantana invasion, firewood collection, and human and livestock movement through the forest.

Phenological and historical examinations of the BGI would provide further insight into structural changes to the forest. We carefully considered the dates of image acquisition and ground validation due to seasonality of vegetation (see Very-High Resolution (VHR) satellite data). Although exposed bare ground occurs naturally in some locations in the study area as well of other TDFs, we measured tree cover during a season when a majority of the deciduous tree species had leaves. Historical VHR data may be used to detect long term persistence of, or changes to, the BGI. For example, transitions from tree cover to bare ground which would be indicated by increased BGI values. Future users of the BGI data and/or methods must consider inter and intra annual vegetation cycles before making interpretations and comparisons of the BGI.

It is not possible to compare the BGI of a forest across large geographies where forest types and vegetation differ. The BGI we produced was derived from five land cover classes; the tree cover class could include other forms of vegetation such as shrubs or grasses. For instance, lantana may have been classified under the tree cover class because we found greater amounts of lantana in areas with low BGI values compared to high BGI values and this difference approached significance ($p = 0.07$) (Appendix A). Bare ground was commonly misclassified as cropland or water, and built environment was largely misclassified as water.

We advocate that others adapt our methods to monitor the BGI in additional TDFs and derive the BGI from land cover classification with a larger number of vegetation classes. Deriving the BGI from a more distinctive tree cover class could help overcome potential issues of interpretation similar to the Normalized Difference Vegetation Index (NDVI), a measure of live vegetation cover, where the NDVI value is not limited to photosynthetic activity from trees alone (Agarwal et al. 2016). Finally, additional indicators of forest health in central India can be developed that incorporate locally grounded values, knowledges, and needs (Sterling et al. 2017).

Code Availability

The code classifying land cover from PlanetScope imagery and deriving the BGI was written in Google Earth Engine. The JavaScript language to classify land covers from Planetscope imagery and derive the BGI from the land cover is available as the 'Code' text file at https://lcluc.umd.edu/metadatafiles/LCLUC-2017-PI-Defries/.

Acknowledgements:

This work was supported by the NASA grant number NNX17AI24G and made possible by access to Planet Labs imagery. We thank the DeFries lab at Columbia University for support and input throughout our work and Midori Sangiolo for help in developing code to derive the BGI in GEE.

Chapter 2: Impact of governance and local forest uses on bare ground within central India's forests

Progress: In preparation

Coauthors: Sarika Khanwilkar, Johannes Urpelainen, Harini Nagendra, Ruth DeFries

3.1 Introduction

Evidence suggests that involvement of resource users in forest management and autonomy to make and enforce rules about resource use promotes forest cover and resource sustainability (Hajjar et al. 2021; Slough et al. 2021; Dietz et al. 2003; Elinor Ostrom, 2009). Community-based forest management in Mexico, Costa Rico, and Thailand was associated with positive impacts on forest cover, through decreased deforestation or increased forest area, in more instances than protected areas (Min-Venditti et al. 2017; Agarwal et al. 2022). Across Nepal, villages with community forest management experienced more social and environmental benefits through reduced poverty and deforestation than villages without community forest management (Oldekop et al. 2019).

Sustainable Development Goal 15 aims to implement sustainable management of forests and ensure sustainable use of forest resources. Maintaining healthy forests, where biophysical conditions sustain ecological functioning, are directly critical for 2.7 billion people around the world who rely on forests for housing material, water, energy, or source of income (Fedele et al.,2021). Forest-dependency can be measured along different dimensions, including the spatial relationship to forests and frequency a household member collects forest resources (Newton et al. 2016). Globally, 3.5 billion people use Non-Timber Forest Products (NTFPs) which contribute substantially to human well-being (Shackleton, et al. 2021). Forests also provide wood as construction material or food to livestock; people collect fodder or graze livestock directly in forests. Around the world, 2.8 billion people collect biomass such as firewood or charcoal to meet energy needs for cooking or heating (Bonjour et al. 2013). Community inclusion in forest management ideally provides community benefits from sustained local use of forest resources by providing control over what forest resource is harvested, by who, and when. However, social outcomes of participatory forest governance are mixed. Lack of appropriately addressing diversity within communities has further marginalized women and people or decreased forest access and rights (Calfucura, 2018; Agarwal, 2010; Killian, 2020; Rout, 2018; Kumar, 2018; Hajjar et al. 2021) and there have been higher levels of elite capture where formal community rights were initiated from outside the community (Agarwala and Ginsberg, 2017).

In postcolonial India, forests are largely controlled by state (government) forest departments. Restricted access to forests under state management has resulted in pressure shifts, where people continue to use forests for subsistence outside Protected Areas (PAs) where dense forest cover has decreased (Agarwal et al. 2016). Forest management can involve informal and formal or externally and internally directed institutions (Fleishman, 2016). Implementation or adoption of participatory forest governance policies or other development interventions related to forest management is variable across India (Bhattacharya et al. 2010). Formal decentralization of forest governance at the national level began with Joint Forest Management (JFM) in 1990, characterized by shared authority between local communities and government over government-owned forests (Bose et al. 2012; FAO, 2016). Communities with JFM vary on rules regarding harvesting of forest resources, monitoring, and compliance (Ghate and Nagendra, 2005) and individual states implement JFM, resulting in different strategies and institution names (Bhattacharya et al. 2010). However, formal and informal decentralization began before JFM at state and local scales (Agrawal and Ostrom, 2001) and historically, communities managed forests through *de facto* regimes. Communities gained *de jure* control over forest governance via the Forest Rights Act (FRA) (2006), which involves the creation of a formal community institution and recognition of rights and management to customary forest (FAO, 2016). Other formal local institutions involved in forests across India are Eco-Development Committees (EDCs), which are prioritized in the buffer zones of Protected Areas and characterized as integrated conservation and development projects (Mahanty, 2002).

In this paper, we assess relationships between formal local institutions and forest health by analyzing forest health, community governance, and household forest uses across the central region of India. In central India, forests mostly exist outside of national designated and managed protected areas; the trajectory of 88% of central India's forests will be shaped by alternative governance systems to PAs (Nayak et al. 2020). In addition, a large number of central India's communities depend on forests, with over one third (37%) of villages in central India living within 8 kilometer (km) of forest (DeFries et al. 2020). We assessed the reported existence and authority of formal committees involved in forest management and forest health across 238 villages. We then experimentally matched villages with (N=40) and without (N=40) local institutions to determine the influence of local institutions on the proportion of forest with exposed bare ground surrounding villages, quantified with a satellite-derived metric, the Bare Ground Index (BGI) (see Chapter 1). We expected to find healthier forests, or forests with less bare ground, around villages with local institutions as compared to villages without local institutions, and that the presence of a local institution was a more significant predictor of forest health than levels of forest dependency. Forest dependency was measured across five variables including percent of households grazing cattle in the forest or using wood from the forest for construction materials and average number of months per year households collect fodder, firewood, or NTFP at least once per week. This study addressed the following objectives: 1) to compare the BGI in villages with and without local institutions for forest management, 2) to assess the relative importance of local forest management institutions and local forest uses on the BGI, and 3) in villages with local forest management institutions, to assess the relative importance of institutional characteristics: the number of years the institution has been established and whether the institution has the authority to modify rules about forest use on the BGI.

3.2 Methods

This study leveraged cross-sectional structured surveys administered in 2022 to the local elected leader of villages within 8 km of forests, surveys administered in 2018 to households in those villages, and a satellite-derived measure of forest health.

Household and village sampling

We selected 500 study villages in Madhya Pradesh, Maharashtra, and Chhattisgarh according to multi-stage criteria that resulted in a representative sample. The first criteria was selection of study villages that were not in PAs but were within eight kilometers of a forested region, as defined by Hansen et al. (2013). Next, we employed a stratified sampling scheme for village selection based on the distance of that village to a town and the distance of that village to a road. Towns were identified in the 2011 Census of India as a place with a municipality, a minimum population of 5,000, population density greater than 400 people per km^2, and at least 75% of the male population employed outside the agricultural sector. Village distance to a road was calculated using the Digital Chart of the World road maps (downloaded from http://www.diva-gis.org/gdata) (Danko, 1992).

Villages were split into two groups based on whether they were above or below the median distance to nearest town. These two village groups were each further split into two groups based on whether the distance to nearest road was above or below the median of that initial grouping. This process resulted in four village groups, each farthest and closest to a road and a town, from which 125 study villages were randomly selected from each group.

Ten households in each of the 500 study villages were surveyed. Study villages consisted of multiple hamlets, or *tolas*. *Tolas* were identified by asking the village head the number of *tolas* and how many people and households were in each. Within each *tola*, households were randomly selected with the number of sampled households per *tola* matching the *tola's* relative size in the village. Households were surveyed first by selecting a random start point and direction in a *tola*, and then sampling every four to five households.

In 2018, surveys were administered to 5,000 households across 500 villages in Madhya Pradesh (N=3239), Maharashtra (N=946), and Chhattisgarh (N=809) (Table 5). Households in Madhya Pradesh represented 65% of survey households, as compared to households in Maharashtra and Chhattisgarh which were sampled at 19% and 16%, respectively, because Madhya Pradesh comprises the geographic majority of central India. In March 2022, we attempted to survey the 500 elected leaders, the sarpanch, of the same 500 villages via phone; not all were available to talk and 316 village leaders were surveyed in Madhya Pradesh (N=241), Maharashtra (N=40), and Chhattisgarh (N=35) (Table 5) between February 4th and April 16th, 2022 after the survey was piloted twice in 2021. The 316 villages surveyed in 2022 were representative of the 500 villages surveyed in 2018 because socioeconomic and environmental characteristics did not differ between villages surveyed in 2018 and 2022 (Appendix B).

Survey instruments

The 2018 survey instrument was primarily designed to assess the social structure and economic activities of households in forest-dependent communities across central India. The structured survey included questions related to household demographics, socio-economic status, natural resource use, household energy uses, and perceptions of forest status. The survey was piloted twice in 2017 within three districts of central India (Balaghat, Seoni, and Mandla).

The 2022 survey was designed to identify the presence and features of community institutions involved in making decisions about the forest. Each sarpanch was contacted via phone at least once before the survey to introduce and schedule a time for the survey. Survey questions included “how many committees do you have that make decisions about the forest?” For each committee, we asked “does this committee have the authority to modify rules about forest use?” and “when was this committee established in your village?”

A trained field team hired through MORSEL India, a social research company with experience in household questionnaires in rural India, implemented the household survey across the study area between February 2nd and March 28th, 2018. A trained team hired through MORSEL India also conducted the 2022 survey via phone. All surveys were conducted in the local language, Hindi. The 2018 household survey lasted approximately 45 minutes per household, and the 2022 survey to village leaders lasted approximately ten minutes.

Table 5: Key characteristics of 2018 and 2022 study sampling.

	Number of districts	Number of villages	Number of households	Households with woman household head
2018 survey				
Full sample	32	500	4994	1355 (27%)
Madhya Pradesh	21 (66%)	324 (65%)	3239 (65%)	1105 (82%)
Maharashtra	6 (19%)	95 (19%)	946 (19%)	83 (6%)

Chhattisgarh	5 (16%)	81 (16%)	809 (16%)	167 (12%)
2022 survey				
Full sample	31	316		
Madhya Pradesh	21 (68%)	241 (76%)		
Maharashtra	5 (16%)	40 (13%)		
Chhattisgarh	5 (16%)	35 (11%)		

Satellite-derived measure of bare ground within forest

This study evaluated forest health using a satellite-derived metric, the Bare Ground Index (BGI), that measured the amount of exposed bare ground within forest in 2018 as an outcome variable. The BGI is calculated at 90-meter resolution within forested areas (>10% tree cover) and is a value that ranges from -1.0 (all tree cover compared to bare ground) to +0.8 (all bare ground compared to tree cover) (see Chapter 1). We estimated the BGI within 1, 2, 3, 5, 8, and 10 kms of study village boundary edges.

Statistical models

Of the 316 total surveyed villages, 78 were dropped because they lacked key details about the local forest management institution or the institution was formed in 2018 or after which is after the time forest health was measured. To identify treatment and control groups for models examining villages with (treatment) and without (control) local institutions, we matched 40 control villages to 198 treatment villages using socioeconomic and environmental variables (Table 6) that influence forest health and forest livelihoods. Variables included distance to nearest town and road, the average number of cattle per household, and percent of households grazing their cattle in the forest in any season or owning Liquified Petroleum Gas. We also included direct forest uses, such as percent of households collecting wood from forest for home repair and the average number of months per year households report collecting fodder, firewood, or NTFP from the forest. Firewood, fodder, and NTFP collection was measured in months per year because forest uses varied seasonally (Khanwilker et al., 2021). We included environmental variables related to forest health including percent tree cover, percent tree cover per household, and a binary variable for whether a village was inside the buffer area of one of 20 PAs, calculated in QGIS version 3.16; these variables were calculated separately for different buffer distances from village boundary.

We ran matching separately for six different and corresponding buffer distances (1, 2, 3, 5, 8, and 10 kms) for tree cover, tree cover per household, and whether the buffer was inside a PA, resulting in 6 different datasets. Villages were matched using the "matchit" function with optimal pair matching. Optimal full matching was also tested but imbalances in the amount of household NTFP collection between treatment and control groups remained. Before matching, population, collection of NTFP, firewood, and wood for home repairs, tree cover within 3 km, and BGI within 5 km was significantly higher in places with a local institution (Appendix B).

Table 6: Variables and data sources for chapter 2. Description and data sources of variables used in matching to identify treatment and control groups. Select variables, including direct forest uses, population, tree cover, and distance to city and road, were used as predictor variables in statistical models where forest health was the outcome variable.

Variable	Description	Source	Included as predictor variable in statistical models?
Population	Number of people in village	(Government of India, 2011)	Yes
Number of cattle	Average number of cattle owned by households	2018 survey	No
Cattle feeding inside forest (%)	Average number of households reporting grazing their cattle in forest in any season	2018 survey	Yes
Fodder collection (months/year)	Average number of months per year a household spends collecting fodder from the forest	2018 survey	Yes

Firewood collection (months/year)	Average number of months per year a household spends collecting firewood from the forest	2018 survey	Yes
Non-Timber Forest Products (NTFP) collection (months/year)	Average number of months per year a household spends collecting NTFP from the forest	2018 survey	Yes
Liquified Petroleum Gas (LPG) for cooking (%)	Average number of households using LPG for cooking fuel	2018 survey	No
Wood from forest home repair (%)	Average number of households getting wood from the forest to repair their home	2018 survey	Yes
Distance to road (km)	Distance to nearest road	2018 survey	Yes
Distance to city (km)	Distance to nearest city	2018 survey, (Government of India, 2011)	Yes
Tree cover (%)	% of tree cover within 1, 2, 3, 5, 8, and 10 km of the village boundary	(Khanwilkar et al., in review)	Yes
Tree cover per household (%)	% of tree cover within 1, 2, 3, 5, 8, and 10 km of the village boundary per number of households in village	(Khanwilkar et al., in review)	No
Inside a Protected Area (PA)	1 = Buffer distance from the village boundary is inside a PA 0 = Buffer distance from village boundary is outside a PA	Overlay PA boundaries with village buffer distances (1, 2, 3, 5, 8, and 10 km)	No

After matching, there was no significant differences between the 40 treatment and 40 control groups at any buffer distance (Appendix B). For each matched dataset, we assessed the difference in median values of BGI between treatment and control groups at corresponding buffer distances using a Wilcoxon rank sum test. Conditional forest models were used to assess the relative associations between having a local forest management institution and local forest uses on forest health. We included a binary treatment variable where the baseline category was not having a local forest management institution, measures of direct forest use including percent of households collecting wood from the forest for home repair and average number of months per year households collect firewood, fodder, or NTFP, and other control variables including village population, tree cover (% within 1, 2, 3, 5, 8, and 10 kms), distance to nearest road and city (Table 6). The BGI at 1, 2, 3, 5, 8, and 10 kms was the outcome variable in all models (Appendix B); each model was run separately for each matched dataset. Appendix B – Figure S2 shows correlations between outcome and predictor variables at all distances. We also created conditional forest models that only included villages with a local institution to assess the relative associations between institution characteristics and local forest uses on forest health. Instead of a binary treatment variable for having a local forest management institution, we included two variables: the length of time a local institution had been established and a binary variable where an institution had the authority to modify rules about forest use and the baseline category was a local institution without the authority to modify rules about forest use. We used the number of years that the oldest committee was established. If one or more committees had the authority to modify rules about forest use, then this covariate was coded as 1.

We ran 10,000 conditional trees and assessed conditional forest models from the full sample of matched data and only among villages with a local forest management institution at 1, 2, 3, 5, 8, and 10 kms using the "cforest" R function. The relative importance of variables was determined by permutation importance using the "vip" function in R. We report results from analyses at 3 and 5 kms because these buffer distances encompass the range of distances that households in study villages report to travel for grazing cattle and collecting firewood, NTFP, and fodder (Table 7), results from additional buffer distances are in the supplementary information.

Table 7: Distances reported for different forest uses in the 2018 household survey.

Forest use	Mean (SD)	Median (IQR)
NTPF collection	4.21 (2.44)	4.00 (3.00, 5.00)
Firewood collection (all seasons)	2.73 (2.02)	2.00 (1.75, 3.00)
Fodder collection	2.52 (1.50)	2.00 (2.00, 3.00)
Cattle grazing (all seasons)	2.92 (1.46)	2.50 (2.00, 3.75)

We substantiated results from conditional forest models by assessing the association of local institutions with forest health using a causal forest model and a Generalized Linear Model (GLM). Causal forest models are a supervised machine learning method designed to identify causal pathways (DeFries et al., 2021). We ran 10,000 causal trees to estimate the average treatment effect, or the difference in the mean BGI between treatment and control villages, at buffer distances using the "causal_forest" function in R. In the GLMs, we assessed the association between having a local forest management institution and forest health, controlling for forest uses and include District level Fixed Effects (FEs) using the "glm" R function.

3.3 Results

Local institutions

Of the 238 total survey villages, 83.19% (N = 198) had at least one local forest management institution and 40 villages did not have a local forest management institution (Figure 5). Most villages with a local institution had one local institution (N = 177) and 21 villages had two or more institutions and up to four. Villages with one, two, three, or four institutions did not differ significantly from one another on available socioeconomic or environmental variables except tree cover at 8 km and 13 villages with two or more institutions named the institutions (Appendix B). Of the 198 total survey villages that had a local forest management institution, the respondent reported that the committee had the authority to modify rules about forest use in 39.90% (N = 79) of villages. We did not know the name of or year that all local forest management institutions were established. Of the institutions with a known name (N = 177), the most frequently named were van suraksha samiti (22.60%, N = 40) and van samiti (18.64%, N = 33) (Table 8). Other institutions that were named in more than four villages included van vikas samiti (9.60%, N = 17), van rakshak samiti (8.47%, N = 15), van prabandhan samiti (6.78%, N = 12), van sanrakshran samiti (5.65%, N = 10), and van haq samiti (3.95%, N = 7). Most (76.27%, N =135) named institutions were created to execute JFM, including six EDCs. Eleven villages (6.21%) named forests rights committees which were created to execute the FRA. Not all named committees were directly linked to JFM or other known national participatory forest management policies. Of 125 total villages that had a local institution that was established before 2018, the oldest institution had been established 28 years ago and the average number of years an institution had been established was 7.75 years (Standard Deviation (SD): 5.32) (Appendix B).

Of the 40 villages with local institutions included in the matched datasets, 11 (27.50%) and 16 (40.00%) institutions had the authority to modify rules about forest use in the 3 and 5 km datasets, respectively (Appendix B). In the 3 and 5 km datasets, the average number of years an institution had been established was 8.04 (SD: 6.32) and 7.77 (SD: 6.07), respectively. The oldest institution included in the 3 km dataset was established 28 years ago and the oldest institution included in the 5 km dataset was established 23 years ago. Of the 40 villages with local institutions included in the 3 and 5 km datasets, 36 and 30 institutions were named, respectively (Table 8). The most frequently named institution in the 3 km dataset was van suraksha samiti (22.22%, N = 8), followed by van samiti (13.89%, N = 5), van rakshak samiti (13.89%, N = 5), and van sanrakshan samiti (11.11%, N = 4). The most frequently named institutions in the 5 km dataset were each named 5 times (16.67%) and included van suraksha samiti, van samiti, van vikas samiti, and van rakshak samiti. In the 3 km dataset, 28 institutions (77.78%) were created to execute JFM, including one EDC, and 4 institutions (11.11%) were created to execute the FRA. In the 5 km dataset, 25 institutions (83.33%) were created to execute JFM and 3 institutions (10.00%) were created to execute the FRA.

Table 8: Name, frequency, and description of local institutions that were named.

Institution name	Frequency, full sample (N = 177)	Frequency, 3 km matched dataset (N = 36)	Frequency, 5 km matched dataset (N = 30)	Description
Van suraksha samiti	40	8	5	Forest security committee aims to share responsibility of forest management between the state Forest Department and the community and originated from JFM
Van samiti	33	5	5	Forest committee is involved in various aspects of forest management and originated from JFM
Van vikas samiti	17	1	5	Forest development committee is involved in various aspects of forest management and originated from JFM
Van rakshak samiti	15	5	5	Forest protection committee aims to share responsibility of forest management between the state Forest Department and the community and originated from JFM
Van prabandhan samiti	12	3	2	Forest management committee is involved in various aspects of forest management and originated from JFM

Van sanrakshan samiti	10	4	2	Forest protection committee aims to share responsibility of forest management between the state Forest Department and the community and originated from JFM
Van haq samiti	7	3	2	Forest rights committee provides forest management authority to communities and originated from the FRA
Van aadhikar samiti	4	1	1	Forest rights committee provides forest management authority to communities and originated from the FRA
Eco development van samiti	3	1		Eco development forest committee is an integrated conservation and development initiative for villages in the buffer zones of Protected Areas and originated from JFM
Van vibhag samiti	3		1	Forest department committee
Daksha samiti	3	1		Skills committee
Gram suraksha samiti	3			Village security committee
Gram sabha samiti	3	1		General body of the community government
Gram van sabha	2			General body of the community government involved with forests
Eco vikas samiti	2			Eco development committee is an integrated conservation and development initiative for villages in the buffer zones of Protected Areas and originated from JFM
Gram vikas samiti	2	1	1	Village development committee
Gram kosh samiti	2			Village fund committee
Rauna dhaf	1			Unknown
Bindwasni van	1			Unknown
Manpur samiti	1			Unknown
Mahaveer chok samiti	1	1		Unknown

Eco samiti	1			Eco development committee is an integrated conservation and development initiative for villages in the buffer zones of Protected Areas and originated from JFM
Ikumiya samiti	1			Unknown
Van vanyashapan samiti	1	1	1	Forest management committee is involved in various aspects of forest management and originated from JFM
Tanta mukti samiti	1			Dispute resolution committee
Eco van vikas samiti	1			Eco development forest committee is an integrated conservation and development initiative for villages in the buffer zones of Protected Areas and originated from JFM
Niyantran samiti	1			Control committee
Van sewa niyantran samiti	1			Forest service control committee
Nasargik sansadhan samiti	1			Nasargik resources committee
Manushya varg sansadhan samiti	1			Human resources committee
Pesa samiti	1			Panchayats Extension to Scheduled Areas (PESA) committee created by the community government to manage forests
Samudayik van samiti	1			Community forest committee
Jalgal van sadhan samiti	1			Jalgal forest resource committee

Forest uses and the Bare Ground Index

Figure 5 illustrates the BGI within 3 km of village boundaries; the average BGI ranged from -0.68 to -0.74 and decreased with increasing distance from the village boundary (Appendix

B). On average, less exposed bare ground within forests was found at greater distances from villages. The boundaries of 38.46% (N = 93) of study villages overlapped with important areas for tiger connectivity (Appendix B).

The average number of months per year a household spent at least one week collecting fodder or NTFP per year was less than one while households spent an average of almost 7 months per year collecting firewood at least once per week. On average, 42.85% and 67.52% of households in the village grazed their cattle in the forest and collected wood from the forest for home repair, respectively (Appendix B).

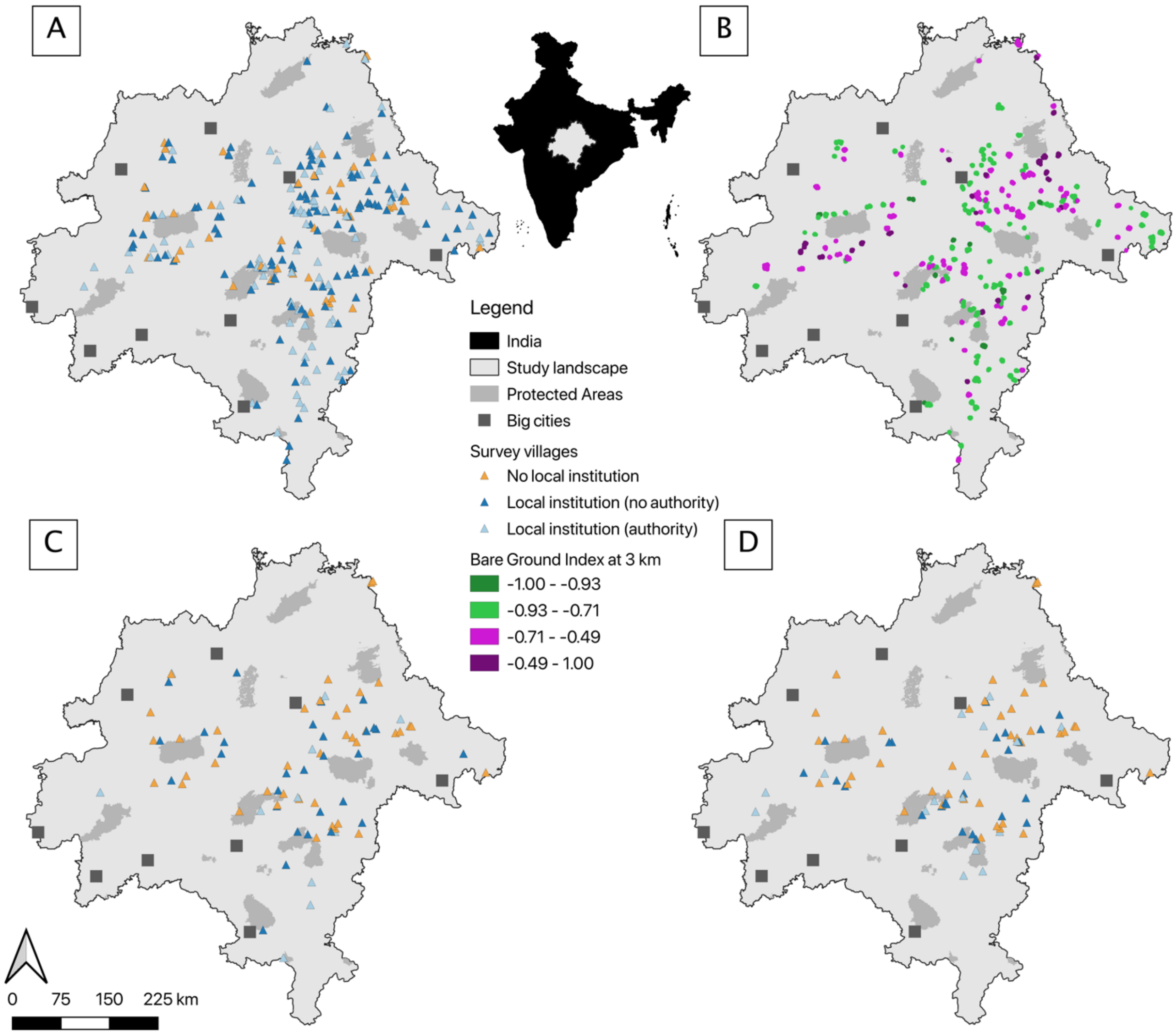

Figure 5: Survey villages and local institutions. Map of 238 survey villages (A), cities with populations greater than 88,000 people, Protected Areas, the Bare Ground Index (BGI) within 3 km of the village boundary (B), and 80 experimentally matched villages at 3 (C) and 5 km (D). There are three categories of survey villages (A, C, D), classified according to the presence of a local forest management institution and whether the institution has the authority to modify rules about forest use. Experimentally matched villages (C and D) resulted from matching 40 control villages (without a local forest management institution) to 198 treatment villages (A) using socioeconomic and environmental variables (Table 6) that influence forest health and forest livelihoods. There are four categories of BGI (B), classified according to quantile.

The Bare Ground Index in villages with and without local institutions

After statistically matching treatment and control villages (Figure 5, C and D), we found that places with a local institution were surrounded by forests with less exposed bare ground, or lower values of BGI, than control groups at all distances (Appendix B). The BGI was significantly lower by 0.08 to 0.11 units at 3 and 5 km around villages with a local institution compared to without a local institution (Figure 6).

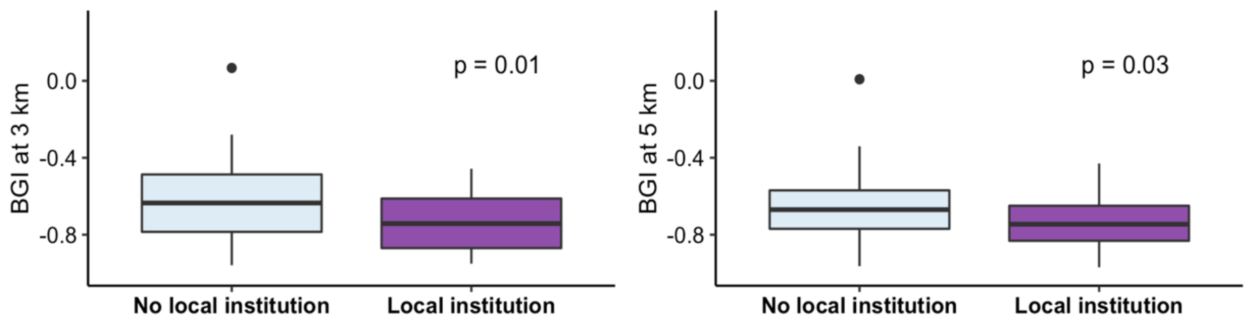

Figure 6: Forest health in places with and without local institutions. Comparing median and interquartile range values of the Bare Ground Index (BGI) at 3 and 4 km distances around villages with and without local forest management institutions. Significance values are results of Wilcoxon rank sum tests between treatment and control groups. Differences were significant ($p < 0.05$) at 3 and 5 km buffer distances.

Associations between local institutions and the Bare Ground Index

Having a local institution that makes decisions about the forest had the strongest associations with BGI at 3 and 5 km in permutation tests of conditional forest models (Figure 7). However, a local institution was not always more strongly associated with the BGI than local forest uses at other distances (Appendix B). Negative and significant values for average treatment effects from causal forest models at 3 and 5 kms indicate that there are significantly lower BGI values in villages with local forest management institutions (Appendix B). Appendix B - Figure S5 shows histograms for predicted average treatment effects at 3 and 5 kms. In generalized linear models with District level FEs, where BGI at buffer distances was the outcome variables, having a local forest management institution was significant at 5 km (Appendix B). At this distance, other covariates, including any forest uses or environmental variables, remained insignificant.

In conditional forest models that examined villages with local forest management institutions (N=40), the number of years that institution had been established or whether the institution had the authority to modify rules about forest use were included as predictor variables (Figure 8). A local institution with authority to modify rules about forest use had the strongest association with BGI within 5 km, and at all distances predicting the BGI within 8 km, the authority to modify rules was relatively more important than the number of years that institution had been established (Appendix B).

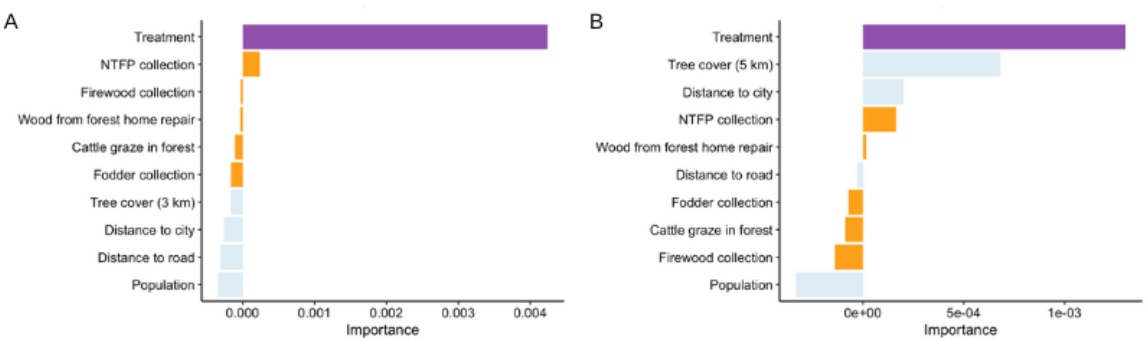

Figure 7: Relative effects of variables on forest health. Relative importance of variables in conditional forest models predicting the Bare Ground Index within 3 (A) and 5 (B) kms from all study villages (N = 80). The relative importance was determined by permuting values for each variable. The treatment variables are colored purple and variables measuring forest uses are colored orange.

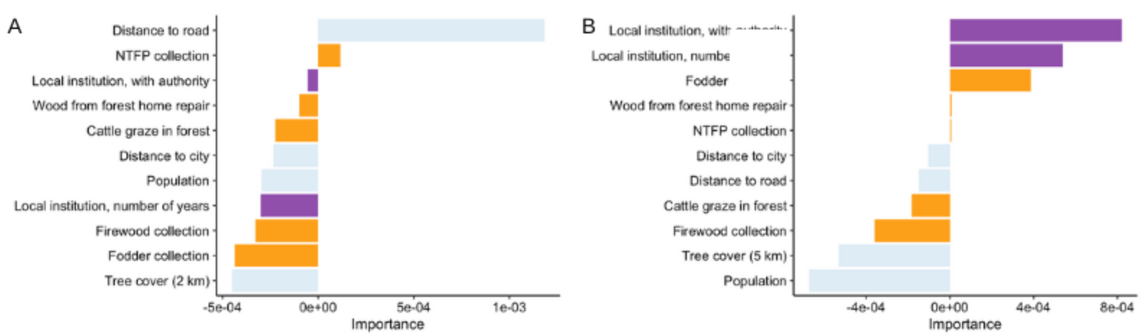

Figure 8: Relative effects of institutional variables on forest health. Relative importance of variables in conditional forest models predicting the Bare Ground Index within 3 (A) and 5 (B) kms from villages that had a local forest management institution (N = 40). The relative importance was determined by permuting values for each predictor variables. Variables that are characteristics of local institutions are colored purple and variables measuring forest uses are colored orange.

3.4 Discussion

Results confirm the significance of formal local institutions in promoting forest health around communities at distances people are using the forest for a variety of income and subsistence activities in central India. We considered low amounts of exposed bare ground within forest (low BGI) to indicate a healthier forest as compared to forest with high amounts of exposed bare ground (high BGI). Local forest uses continued to influence forest health near and far villages, also strengthening evidence for the potential that development interventions aiming to reduce dependency on forests for firewood and wood for housing material in households is important to prevent exposed bare ground within forests.

We found healthier forests between 1 and 8 km around villages with local institutions as compared to villages with comparable socioeconomics and amounts of local forest uses and without local institutions (Figure 6). In forest at 3 and 5 km around villages, having a local forest management institution was more significantly associated with forest health than local forest uses in conditional forest models that ranked the importance of variables (Figure 7). Our landscape-wide results substantiate evidence from previous work within central India that identified positive indicators of forest condition associated with people's involvement in forest management (Agarwal, 2016 and 2017). Further, having a local institution was the only significant predictor in the generalized linear model predicting BGI at 5 km and local forest uses were not significant at any distance (Appendix B). In causal forests models predicting the BGI at 3, 5, and 8 km, the treatment effect of having a local institution involved in forest management was significant and negative (Appendix B).

In communities with a local institution, our results show that having the authority to modify rules about forest use was more strongly associated with forest health than the number of years a local institution had been established (Figure 8). Local forest uses and forest monitoring within communities with JFM institutions can vary widely (Ghate and Nagendra, 2005) and JFM has been criticized for its ineffectiveness of implementation on the ground due to lack of monitoring (Singh et al. 2011) and variable forest outcomes (Behere, 2009). Not all local institutions we captured in the survey or that were included in the 3 and 5 km datasets were formed as JFM institutions (Table 8). A majority of local institutions included in statistical analyses were created to execute JFM; for example, 77.78% of institutions in the 3 km dataset 83.33% of institutions in the 5 km dataset were JFM institutions. Despite the variability in formal institutions and the degree of community participation in formal institutions and on the ground implementation, which we did not measure, our results indicate that having a local institution with authority over forests is more important than an institution that exists but does not have authority, even if such an institution has existed for a long time.

At 1 and 10 km, the number of households collecting wood from the forest for home repairs and the number of months per year households collect firewood were the most important variable in determining forest health, respectively (Appendix B). At these distances, forest health was not significantly different between villages with and without local institutions. Our work contributes evidence about the potential for reduced forest dependency to provide social (Khanwilkar et al. 2021) and environmental benefits (DeFries et al. 2021) in central India. Importantly, while local uses of forest resources are related to the function and health of forests, global, national, and regional trends like market demands, resource extraction, or infrastructure development also have substantial effects on forests and forest livelihoods (Lewis et al. 2015).

This study had several limitations. First, our research was limited to examining the presence and decision-making authority of formal institutions as reported by the sarpanch. The name of an institution alone provided limited information and we were not able to identify a connection between all institutions that a sarpanch named as being involved in forest management and known policies about participatory forest governance. Due to local variation in the names of institutions executed for JFM, we may have underestimated the number of institutions that originated from JFM (Table 8). In addition, sarpanch named institutions involved in other or additional governance matters, such as the gram sabha samiti or daksha samiti. We did not capture the extent of involvement that non-JFM institutions had in forest management. Greater attention is needed to characteristics of formal local institutions that lead to healthier forests, like a network analysis of participation in formal institutions (Friedman et al., 2020) or greater detail about the implementation of local institutions and the extent of their authority over decision-making. Further research can also focus on the forest officials who implement formal institutions and share authority with communities (Fleishmann, 2016). Both treatment and control groups in our study may have included villages with informal institutions involved in forest governance. We recommend similar studies on forest governance and health in central India that compare environmental outcomes across informal institutional settings. In central India, community-initiated management was more effective in monitoring forests and managing grazing than top-down institutions (Ghate and Nagendra, 2005). Based on the names of local institutions (Table 8), our study captured associations most related to government-directed forest governance policies like JFM rather than alternative management approaches that provide greater forests rights and ownership to local people through community forest rights; only 6.21% (N = 11) of institutions were forest rights committees. Of the 40 villages with local institutions included in the 3 and 5 km datasets, 3 and 4 institutions were forests rights committees, respectively. Second, we used multiple methodologies to identify pathways of causality based on observational data and do not capture the impacts of forest health on forest management and forest uses. Before statistically matching treatment and control groups, villages with local institutions had higher amount of firewood, NTFP, and wood for housing collection as well as higher amounts of tree cover and healthier forests compared to villages without local institutions (Appendix B). Comparing the magnitude of forest health impacts from governance and livelihoods requires greater understanding into feedbacks between forest uses and governance. Second, there are increasing attempts to identify win-win governance systems that meet social and environmental goals (McKinnon et al. 2016). Our research found environmental benefits from formal local institutions but did not examine the extent of participation, dimensions of equitable participation in governance, or economic and human well-being outcomes. The socioeconomic implications of formal, participatory forest governance in central India are important to consider for communities and governments who implement such policies to ensure forest governance does not further marginalize and exclude socially and historically underrepresented groups. Third, Finally, our outcome variable was a single metric, the BGI, which measured exposed bare ground in forest. The BGI is a relevant indicator of forest condition in central India because exposed bare ground impacts vegetation and ecological functioning; however, our analyses excluded other measures of forest health such as forest structure and species diversity and abundance.

Conclusion

Previous work has shown the importance of livelihood and governance approaches to healthy forests in central India separately; durable housing materials and LPG ownership were significantly associated with healthy forests in villages across the landscape (DeFries et al. 2021) and at sites within the study area, Agarwal (2016, 2017) found environmental benefits to local participation in forest governance. We examined the relative associations of formal institutions and local forest uses on exposed bare ground within forest surrounding villages at distances that people travel for forest products and found that institutions were more significant for forest health than forest uses. However, this result was not reflected for forest health at all distances, and local forest uses were more significantly associated with forest health near or far village boundaries. Both involving and giving authority to local people in formal institutions and displacing forest uses can promote healthy forests. Such interventions can be targeted in ecologically valuable localities within central India, such as in villages that overlap with tiger connectivity areas.

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Chapter 3: Firewood, forests, and fringe populations: Exploring the inequitable socioeconomic dimensions of Liquified Petroleum Gas (LPG) adoption in India

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4.1 Introduction

Globally, 2.8 billion people, often the world's poorest and most marginalized, burn biomass to meet their daily household energy needs (Boujour et al. 2013). Inefficiently burning traditional solid biomass – firewood, coal, agricultural residue, and dung –for cooking and heating has substantial negative impacts on public health and the environment. Exposure to household air pollution (HAP) from the incomplete combustion of biomass is one of the greatest global environmental health risks, estimated to account for 2.3 million premature deaths each year (Murray et al. 2020). The extraction of biomass can also hinder forests' ability to provide a healthy ecosystem for people by contributing to forest degradation, deforestation, and climate change around the world (Bailis et al. 2015; 2017; Bond et al. 2004). In recent decades, clean cooking fuels such as Liquified Petroleum Gas (LPG) have been an important tool for programs and policies aiming to deliver its multiple benefits, including: improved air quality, climate change mitigation, and reduced biomass demand. For example, Sustainable Development Goal 7 aims for affordable and sustainable energy availability, which includes accelerating the access to clean and safe cooking fuels. However, achieving sustainable development will require an understanding of who has access to clean cooking and how that access changes the use of traditional solid biomass.

Traditional biomass-based cooking is widespread across India. In 2011, about half of India's households used firewood as their primary cooking fuel and 12% used it as a secondary fuel, totaling 150 million households (Office of the Registrar General & Census Commissioner, 2013). However, the burden of biomass use in India is unequal across gender, social groups, and regions. Recognizing specific groups of stakeholders with unequal access to clean cooking fuel – a key tenet of energy justice (Jenkins et al. 2016) – is necessary to address the equity in promoting clean cooking and sustainable development.

Attaining the multiple benefits of fuel transitions requires that clean cooking fuels significantly displace traditional biomass use. However, studies from around the world and in India show that households rarely cease to use their traditional cooking practices when they adopt cleaner cooking technologies (Cheng et al. 2014; Dickinson et al. 2019; Gupta et al. 2020; Masera et al. 2015; Shankar et al. 2020; Velho et al. 2019). There are multiple reasons households may continue to use biomass after acquiring a cleaner fuel, a practice termed fuel stacking, including: household economics, individual preferences, and specific energy end uses. Historically, high costs and low availability of clean cooking fuels have limited the penetration into regions with significant household reliance on biomass (Kumar et al. 2016; Puzzulo et al. 2019; 2016; Quinn et al. 2018), largely excluding poor and marginalized households. In contrast, the availability of biomass as a monetary-cost-free alternative cooking fuel is often considered a driver of continued traditional cooking practices (Jagadish and Dwivedi, 2018).

Quantitative and qualitative evidence suggests that biomass availability can affect fuel collection time and effort, thereby influencing household fuel choices, including the decision to adopt cleaner fuels (Bandyopadhyay et al. 2011; Behera et al. 2015; Cooke et al. 2008). In previous quantitative studies seeking to understand the association between biomass availability and cooking fuel choice, biomass availability has been defined in several different ways, including: proxies for assessing geographic variabilities in fuel choice that might be due to biomass availability (Gregory and Stern, 2014; Rehfuess et al. 2010), distance to the nearest forest (Heltberg, 2005; Jumbe and Angelsen, 2011; Turker and Kaygusuz, 2001), time spent on fuel collection (Chen et al. 2006; Dendup annd Arimura et al 2019), forest area per person, perceived convenience and reliability of biomass fuel supply (Gupta and Kohlin, 2006), and satellite-derived measures of biomass availability or forest cover (Jagger and Kittner, 2017; Jagger and Shively, 2014). While not as well characterized as individual and household determinants of fuel choice, characterizing the supply-side determinants of fuel choice can inform the motivations for continued biomass use after clean cooking fuel adoption and use. Given that even limited traditional biomass-based cooking can lead to high health risks and continued environmental and climate impacts (Johnson and Chiang, 2015), displacing household biomass use with clean fuels can havae substantial implications for health, environmental, and climate burdens. Efforts to understand the extent to which LPG use and biomass availability modifies biomass collection patterns can help us achieve this goal by identifying strategies to curb continued household biomass combustion.

Disparities in India's cooking fuel

India's rural households (71% of the country) are more dependent on firewood and have limited access to LPG as compared to urban households (62% vs. 21% in 2011, respectively) (Office of the Registrar General & Census Commissioner, 2013). Among rural households, wealth and formal educational attainment are strongly positively associated with using LPG (Rao and Reddy, 2007; Gould and Urpelainen, 2020a; Meghwani et al. 2019; Lewis and Pattanayak, 2012; Muller and Yan, 2018). Recent evidence also indicates that stable, salaried incomes as compared to more seasonal agricultural or day labor are associated with LPG ownership (Mani et al. 2020). Furthermore, clean cooking adoption, much like cooking itself, is gendered. Women are primarily responsible for cooking and biomass collection, disproportionately facing the negative health and well-being burdens of biomass cooking. And yet, men often control finances. There is evidence that when women are involved in decision-making then a household is more likely to have LPG in rural India (Gould and Urpelainen, 2019).

Further, tribe and caste status have been an important determinant of LPG access in communities. India's Scheduled Tribe (ST) or Scheduled Caste (SC) communities, terms in the Indian Constitution that describe a diverse group of historically marginalized Indigenous and religious communities, are highly reliant on biomass and are socioeconomically disadvantaged. For example, the human development index and human poverty index, composite measures of life expectancy, education level, and standard of living, is lower in ST communities than the rest of India (Sarkar et al. 2006). ST and lower caste households have low rates of clean cooking fuel adoption (Pandey and Chaubal, 2011). An analysis of the National Sample Survey data (2011-2012) found that ST and SC households were 9% less likely to own LPG as compared to non-ST or non-SC households (Saxena and Bhattacharya, 2018).

There are a high number of ST and other non-general caste households in the forested regions of central India, the study area. In central India, households have traditionally met their subsistence and livelihood needs with forest resources. For example, in rural households in Madhya Pradesh located within a distance of two kilometers of the forest, more than half of households were ST or SC and they derived 49% of their income from forest products (Bahuguna, 2000).

Households in central India are heavily reliant on biomass for meeting their household energy needs. In 2011, 86% of rural households in central India used firewood as their primary cooking fuel, compared to 63% of all rural Indian households, while only 5% relied on LPG (Table 1). Households living near forests can collect firewood at no monetary cost, which may be a barrier to investing in an alternative, more costly cooking fuel (Heltberg et al. 2000; Malakar et al. 2018). Still, while not monetarily costly, these households devote effort and time to collect firewood.

LPG expansion and fuel stacking

India has pioneered several ambitious clean cooking fuel programs to address the high burden of biomass cooking in rural households in recent years. Notably, the Government of India, through *Pradhan Mantri Ujjwala Yojana* (PMUY), has provided about 80 million LPG connections to below poverty line households since 2016 (Ministry of Petroleum and Natural Gas, 2019c). PMUY beneficiaries – exclusively women – have their LPG cylinder deposit and regulator and installation charges covered by the program (1,600 Indian Rupees (INR) in total; 23 United States Dollar (USD)[1]). Still, households are required to purchase a double-burner LPG stove (approximately 1,000 INR; 14 USD) and their first LPG refill (500 INR; 7 USD), with optional loan assistance.

The Government of India now estimates that 95% of Indian households have access to LPG, thanks in large part to PMUY (Comptroller and Auditor General of India, 2019). An analysis of panel survey data collected in 2015 and then in 2018 (ACCESS) in six energy-poor north Indian states shows that access to LPG has increased for marginalized populations. The proportion of SC and ST households using LPG increased by 43% and 30%, respectively (Patnaik annd Jha, 2020). ACCESS data collected in Madhya Pradesh – located in central India –

shows that 59% of households acquiring LPG between 2015 and 2018 did so via PMUY (Mani et al. 2018). Although access to LPG increased for SC households, LPG adoption has lagged among ST households (Pelz et al. 2021).

While PMUY has helped to overcome the initial hurdles of LPG stove and connection access and affordability, the program does not address LPG use after adoption. Recent evidence shows that PMUY beneficiaries use LPG less than general customers across multiple contexts (Mani et al 2020; Comptroller and Auditor General of India, 2019; Kar et al 2019; Gould et al 2020b). LPG cylinder refill costs remain barriers to sustained LPG use and may be exacerbated by the seasonality of income, community or cultural norms, or biomass availability (Gould and Urpelainen, 2018; Mani et al. 2020). Still, there is some evidence to suggest the longer a household has LPG, the larger a role it has in the household (Mani et al. 2020; Sharma et al. 2019).

Study objectives

This study combines household-level and remotely-sensed satellite data to understand socioeconomic and environmental drivers of cooking fuel choice and firewood collection in rural Indian households living near forests in central India. The region remains highly forested and there are a high number of ST, SC and OBC households that have long relied on forest resources for consumption and livelihoods. The diffusion of LPG after PMUY and patterns of fuel stacking in communities within forested regions remains unknown. This study population is of particular interest for jointly evaluating the socioeconomic and environmental drivers of fuel choices and firewood collection in traditionally disadvantaged populations, which is an important consideration to implement socially inclusive clean cooking fuel policy.

Our study contributes to understanding LPG adoption and clean cooking transitions by collecting and analyzing cooking fuel data from marginalized, forest-dependent populations where households cook with both LPG and firewood. The study addresses the following objectives: 1) to examine the socioeconomic and environmental drivers of the use of LPG for cooking before and after PMUY was implemented and 2) to assess the influence of LPG ownership over time on seasonal household firewood collection patterns. We address these objectives through analysis of household surveys from approximately 5,000 households living near forests in central India.

4.2 Methods

This study leveraged cross-sectional structured surveys administered to rural households living within 8 km of forests in central India from February to March 2018. Household sampling and survey instrument details are outlined in Section 3.2 Methods. We assessed the association between household characteristics, cooking fuel use, and firewood collection patterns. We also used published data on vegetation to incorporate availability of forest in our understanding of cooking fuel patterns.

Household Sampling

Of 5,000 households surveyed in 2018, six households missing variables used in analyses were dropped in the present study. These households did not differ significantly from households included in analysis on available socio-economic or household energy use variables.

Satellite-Derived Measure of Forest Availability

We used gridded forest cover data (percent tree cover at 30-meter resolution) from the Global 2010 Tree Cover product to estimate village-level forest availability (Hansen et al. 2013). We obtained boundaries identifying the borders of each study village from ML Infomap Pvt. Ltd.

(https://www.mlinfomap.com/Main/indiamaps.html). We estimated the percent tree cover within 2.74 kilometers of study village boundary edges in addition to forest inside village boundaries. We excluded forest cover within PAs because of restricted access to this forest (see *Understanding the perception that firewood collection has become more difficult*). We specified a 2.74-kilometer buffer because this was the mean distance reported by households to travel on average to collect firewood across all seasons (summer, monsoon, post-monsoon, winter) (Appendix C). In doing so, we expect to capture the majority of trips commonly taken to collect firewood. We tested additional buffer distances (1 km, 2 km, 3 km, 5 km, 8 km, and 10 km), including the median reported distance traveled of 2.0 km, to evaluate for potential threshold distances at which forest cover does not affect collection patterns. However, 2.74 kilometers was selected because it explained the most variance in firewood collection across all seasons (along with 3 km). The 2.0 and 2.74 km buffer resulted in a lower Akaike Information Criterion than 3 km in logistic regressions where LPG ownership was the outcome variable (Appendix C).

Outcome Variables

The present study evaluated three outcomes central to patterns of cooking fuel use and collection: 1) the use of LPG for cooking, 2) when LPG was acquired (before or after 2016), and 3) the time spent collecting firewood. These outcomes were used to examine recent LPG adoptions and identify fuel stacking patterns in households that use LPG and firewood for cooking.

Use of LPG for cooking. Households were asked "Does your household use LPG for cooking?" Responses were used as a binary outcome variable in a multilevel logistic regression to determine the household and ecological characteristics associated with the use of LPG for cooking. Responses about firewood collection (see below) indicate that households are not exclusively using LPG.

LPG ownership after 2016. Households who used LPG for cooking (N=2276) were asked, "When did you start using it?" These responses were categorized: 1) Before 2013, 2) 2013, 3) 2014, 4) 2015, 5) 2016, and 6) 2017. Responses were further grouped based on LPG adoption before (pre-2016) or after (2016 or 2017) PMUY. In Madhya Pradesh, PMUY was launched on July 4th, 2016 (Ministry of Petroleum and Natural Gas, 2016a). PMUY was launched in Maharashtra on October 7th, 2016 (Ministry of Petroleum and Natural Gas, 2016b) and Chhattisgarh on August 13th, 2016 (Government of Chhattisgarh, 2016). This pre- or post-PMUY binary variable was used as an outcome in a multilevel logistic regression to assess variations in the determinants of LPG adoption before or after PMUY. In a sensitivity analysis, we re-specify the post-PMUY period to only include 2017. We observe no meaningful deviation in the associations between covariates and the outcome (Appendix C). We assume that households that adopted LPG after 2016 received LPG as a direct result of the policy, although LPG adoption could be influenced by other factors.

Firewood Collection. Participants, including respondents who used LPG for cooking, were asked about their firewood collection patterns during each season of the year to assess the intensity of firewood collection and its variability in time. Seasons were defined as: summer (April – June), monsoon (July – September), post-monsoon (October – November), and winter (December – March). Specifically, participants were asked for each season: "In a typical week, how many days did you or a person in the household visit the forest to collect firewood?"

Participants reporting firewood collection trips were then asked, "On average, how many hours did you or a person in the household spend collecting firewood on one day?" These two variables were multiplied to compute the outcome variable hours of firewood collection per week. Seasonal patterns in firewood collection required stratified analysis for the monsoon season, when much less firewood collection was reported, to determine associations with LPG ownership (see *Characteristics of firewood collection*).

Statistical Approach

First, we assess the association between household characteristics, including income and socioeconomic status, education, and forest availability, and the use of LPG for cooking (Equation 2). Among LPG owners, we then aimed to understand the differences between households that adopted LPG before or after PMUY (Equation 3). In our third model (Equation 4), we assess the association between year of LPG adoption and changes in time spent collecting firewood, controlling for other covariates. Equations are described below:

$$\log\left(\frac{P(LPG\ for\ cooking_{ij})}{P(1 - LPG\ for\ cooking_{ij})}\right) = \beta_0 + \beta_1 \cdot X_i + \varepsilon_i \tag{2}$$

$$\log\left(\frac{P(LPG\ ownership\ in\ 2016\ or\ 2017_{ij})}{P(1 - LPG\ ownership\ in\ 2016\ or\ 2017_{ij})}\right) = \beta_0 + \beta_1 \cdot X_i + \varepsilon_i \tag{3}$$

$$Firewood\ Collection\ hrs/week_{ij} = \beta_0 + \beta_1 \cdot LPG_{Year_i} + \beta_2 \cdot Y_i + \varepsilon_{ij} \tag{4}$$

where X_i is a matrix of covariates identified from reviews of the clean cooking fuel adoption and use literature (Puzzolo et al. 2016; Quinn et al. 2018; Lewis and Pattanayak, 2012; Muller and Yan, 2018), as well as evidence of correlations with both the outcome and explanatory variables of interest in the study data (Appendix C). Y_i, the matrix of covariates used in Equation 4, only includes X_i covariates that were statistically significantly ($P < 0.05$) associated with LPG ownership in Equation 2. The covariates are described in Table 9. We report models with district-level fixed effects[3] (District FEs) to account for potential residual spatial confounding, as carried out elsewhere (Baland et al. 2010; Lobell et al. 2012). Models with District FEs additionally explained more variance in the outcome variables than those without District FEs (Appendix C). Additionally, we present results from the predicted probabilities of LPG ownership for continuous covariates modeled in Equations 1 and 2 (Appendix C). All analyses were carried out in R version 3.5.0 (R Core Team, 2018) using the MASS (Venables and Ripley, 2002), lme4 (Bates et al. 2015), and margins (Leeper, 2018) packages.

Table 9: Variables used in chapter 3. Description of covariates used in statistical models.

Covariate	Variable type	Description
Year of LPG ownership (2013 or earlier, 2014-2015, or 2016-2017)?	Binary	Responses to the question "When did you start using LPG?" were grouped into four categories based on similarities in household characteristics: 1) No LPG; 2) Acquired LPG in 2013 or earlier; 3) Acquired LPG in 2014-2015; and 4) Acquired LPG in 2016-2017 (Table 10). No LPG used for cooking was a baseline category. This variable was included exclusively in Equation 4.
Monthly expenditure (INR)	Continuous	Wealth has been positively associated with cleaner cooking uptake around the world (Gupta and Kohlin, 2006; Baiyegunhi and Hassan, 2014). However, consistent incomes are rare in many poor and rural communities in India and globally (Davis et al. 2010). Therefore, we utilized monthly household expenditures, which is a reliable predictor of wealth used in previous studies (Muller and Yan, 2018; Aklin et al. 2016). This covariate was log transformed and standardized in analyses (Mean = 0, Standard deviation (SD) = 1).
Has money in a bank account?	Binary	In this study sample, having money in a bank account is an additional measure of wealth and capital. Baseline category was not having money in a bank account in the past year[4].
Has saved money?	Binary	Having money to save is another measure of wealth and capital. Baseline category was not having money to save in the past year.
Woman as household head?	Binary	Because of the gendered nature of cooking and decision-making in rural Indian households, households headed by woman may be more likely to adopt cleaner cooking technologies (Behera et al. 2015; Gupta and Kohlin, 2006; Gould and Urpelainen, 2019; Heltberg, 2004; Hou et al. 2018; Mottaleb et al. 2017). In addition, women are the primary collectors of firewood and the beneficiaries

		targeted by PMUY. Baseline category is having a man as a household head[5].
Caste (ST, SC, or OBC)?	Binary	We use general (or forward) caste as the baseline category. Other categories include Scheduled Tribe, Scheduled Caste, and Other Backward Class. Caste has been associated with cooking fuel choice in other case studies in India (Gould and Urpelainen, 2019; Menghwani et al. 2019; Gould and Urpelainen, 2019; Saxena and Bhattacharya, 2018).
Education of the survey respondent (primary/secondary, high school, or intermediate and above)?	Binary	Education of the household head has been strongly positively associated with clean cookstove ownership in India previously (Gould and Urpelainen, 2019; Gould and Urpelainen, 2019; Baiyegunnhi annd Hassan, 2014; Farsi et al. 2007). Baseline category is no formal education, with additional categories being completed (i) Primary/Secondary school, (ii) High School, and (iii) Intermediate and above.
Increased difficulty in firewood collection?	Binary	We assessed changes in perceived difficulty of firewood collection. Participants were asked "Over the last five years, has it become easier or harder to collect firewood?" Responses were coded into five categories: 1) much easier, 2) somewhat easier, 3) stayed constant, 4) somewhat harder, and 5) much harder. A majority (88%) of respondents reported firewood collection as getting somewhat harder or much harder thus we recoded responses to be used as a binary variable where the baseline category was "stayed constant," "somewhat easier," or "much easier." The correlation coefficient of a binary variable created from a collapsed Likert scale and the original scale is between 0.8 to 0.9, and such a variable transformation is appropriate where nuances of the response are not critical for interpretation (Jeong, 2016).
Forest availability (% tree cover)	Continuous	Percent tree cover within a buffer distance of each study village and outside a PA was log transformed and standardized to use as a covariate in analyses (see Satellite-derived measure of forest availability for more details).
Distance to road (km)	Continuous	Distance to nearest road (km) at the time of the survey was calculated at the village level using OpenStreetMap (OSM) road data. We consider distance to the nearest road as an indicator of access to LPG cylinder refills. To obtain historical road data from our study region, we used the Overpass API tool (Olbricht, 2018) using a bounding box of 17.7° to 26.4° N; 74.9° to 84.1° E to allow for a 1° buffer around the study region. Second, the Osmium tool (Topf, 2020) was used to extract historical OSM road layers last updated February 28th, 2018. This covariate was log transformed and standardized in analyses.

Qualitative Data

We provide context to firewood collection using responses from the open-ended question "Why do you think it has become easier/harder to collect firewood?" Responses were transcribed in the local language by field staff at the time of data collection and then hand coded according to emergent themes. Quotes and themes were then translated to English by a bilingual member of the research team.

4.3 Results

Of the 500 study villages, there were 35 villages (7%) where no households used LPG for cooking and only four villages where all households used LPG for cooking. There was substantial variation in LPG use across study villages, as well as year of LPG uptake (Figure 9).

Nearly half of households (46%) reported the use of LPG for cooking at the time of the survey in early 2018. Three-quarters of households with LPG reported to have acquired the stove and connection in 2016 or 2017. Households that reported acquiring LPG more recently were less wealthy, more likely to be ST, near more forest, and had lower levels of formal education than those that adopted LPG in 2013 or before (Table 10). Households that reported acquiring LPG between 2016-2017 were similar to households that reported to not cook with LPG. Of households that owned LPG, 90% also reported cooking with firewood and 68% collected firewood in at least one season through the year. More than half of study households (57%) were ST, over a quarter were OBC (27%), and 12% were SC; only 4% of households were general caste.

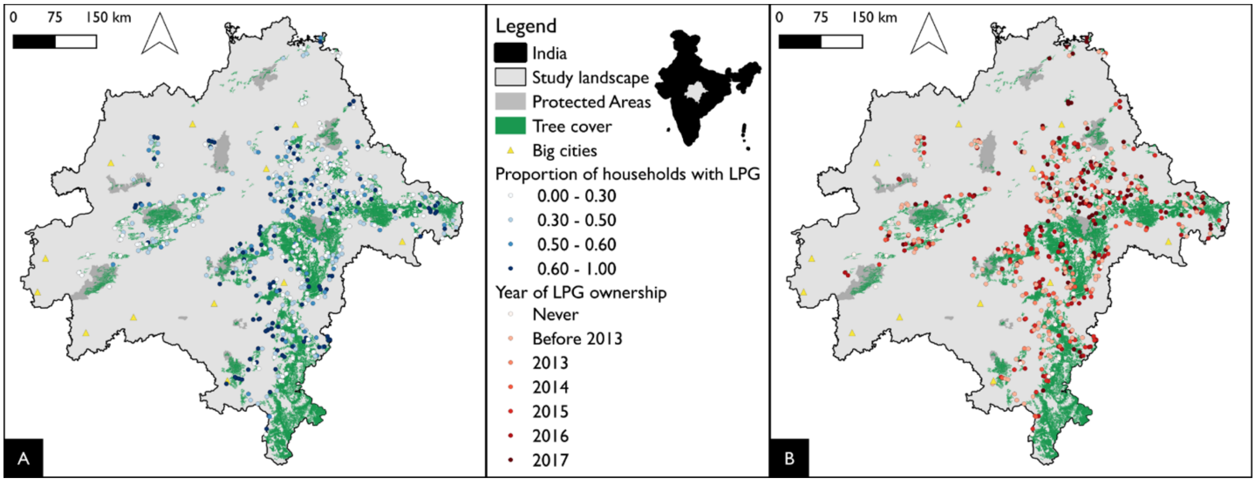

Figure 9. 2018 survey villages and Liquified Petroleum Gas ownership. Map of 500 survey villages, indicated as colored circles, cities with populations greater than 88,000 people, protected areas, and tree cover in central India. Tree cover data is from Hansen et al. (2013). Fig. 1A. The color of each village indicates the proportion of surveyed households which use Liquified Petroleum Gas (LPG) for cooking, where darker shades of blue represent a higher proportion. There are four categories of proportion of households cooking with LPG, classified according to quantile. Fig. 1B. The color of each village indicates the first year in which LPG was used for cooking by households within that village, where darker shades of red represent more recent years. Except in the 35 villages where LPG was not used by any household, LPG was available in all villages in 2017.

Table 10: Summary statistics of households, by year of LPG adoption.

	Full sample	**2013 or before**	**2014-2015**	**2016-2017**	**No LPG**
Sample Size, N (%)	4994 (100%)	270 (5%)	277 (6%)	1729 (35%)	2718 (54%)
Age of Respondent, Mean (SD)*	42.0 (13.3)	43.2 (14.4)	41.6 (13.4)	41.9 (13.1)	41.9 (13.31
Woman as household head, N (%)*	1355 (27%)	56 (21%)	46 (17%)	468 (27%)	785 (29%)
Man Chief Wage Earner, N (%)*	4476 (90%)	250 (93%)	261 (94%)	1551 (90%)	1104 (89%)
Respondent education, N (%)*					
High School	564 (11%)	41 (15%)	56 (20%)	212 (12%)	255 (9%)
Intermediate or Greater	534 (11%)	104 (39%)	54 (19%)	162 (9%)	214 (8%)

No Formal Education	2021 (40%)	48 (18%)	59 (21%)	656 (38%)	1258 (46%)
Primary/Secondary	1875 (38%)	77 (29%)	108 (39%)	699 (40%)	991 (36%)
Household Caste, N (%)*					
General	198 (4%)	42 (16%)	20 (7%)	59 (3%)	77 (3%)
Other Backward Caste	1338 (27%)	105 (39%)	109 (39%)	465 (27%)	659 (24%)
Schedule Caste	608 (12%)	43 (16%)	39 (14%)	219 (13%)	307 (11%)
Scheduled Tribe	2850 (57%)	80 (30%)	109 (39%)	986 (57%)	1675 (62%)
Monthly Expenditure (INR), Mean (SD)*	3785 (2846)	6206 (4417)	4843 (3511)	3745 (2317)	3462 (2736)
Monthly Expenditure (USD), Mean (SD)	54 (41)	89 (63)	69 (50)	54 (33)	49 (39)
Tree cover (%), Mean (SD)*	5.64 (7.21)	3.48 (4.93)	4.10 (6.04)	5.42 (6.78)	6.28 (7.56)
Distance to Road (km), Mean (SD)	1.69 (2.35)	1.28 (2.03)	1.58 (2.23)	1.72 (2.44)	1.73 (2.33)
Has Saved Money?, N (%)*	1457 (29%)	131 (49%)	89 (32%)	522 (30%)	715 (26%)
Has Money in a Bank Account?, N (%)*	1822 (36%)	153 (3%)	107 (2%)	669 (13%)	893 (18%)

* Indicates that there was a statistically significant difference between the households depending on year of LPG adoption at $P < 0.05$ in ANOVA. SD is standard deviation.

Determinants of using LPG for cooking

Households that used LPG were wealthier, better educated, and had higher odds of being general caste than those without LPG (Figure 10). Controlling for other covariates, the probability of cooking with LPG was higher by 15 percentage points (95% CI: 10 – 20 percentage points), 12 percentage points (95% CI: 7.6 – 17 percentage points), and 6.2 percentage points (95% CI: 3.1 – 9.3 percentage points) if the household head was educated at the intermediate or above, high school, or primary/secondary level, respectively, as compared to a household headed by a person with no formal education. In addition, the probability of using LPG was significantly positively associated with higher monthly expenditure (Appendix C).

Households belonging to the Scheduled Tribe (ST) caste, which comprised almost 60% of the study sample, had the lowest odds of having LPG at the time of the survey, as compared to the other castes (Scheduled Caste (SC), Other Backward Class (OBC), and general caste). Accounting for other household characteristics and covariates, the probability of using LPG was lower by 14 percentage points (95% CI: 6.5 – 21 percentage points) if a household was ST as compared to a household belonging to the general caste. Similarly, the probability of using LPG was 9.3 percentage points (95% CI: 2.0 – 17 percentage points) and 6.6 percentage points (95% CI: 1.3 – 15 percentage points) lower for OBC and SC households, respectively, as compared to belonging to the general caste.

In addition to household characteristics, some contextual environmental variables were associated with using LPG. The probability of using LPG was significantly negatively associated with higher tree cover (Appendix C). For every additional percent of tree cover nearby a village, the probability of using LPG decreased by 4.1 percentage points (95% CI: 2.5 – 5.7 percentage points). Participants stating that firewood collection had increased in difficulty in the past five had a 4.4 percentage point (95% CI: 0.0 – 8.6 percentage point) lower probability of using LPG as compared to those that did not perceive firewood collection to have become more difficult.

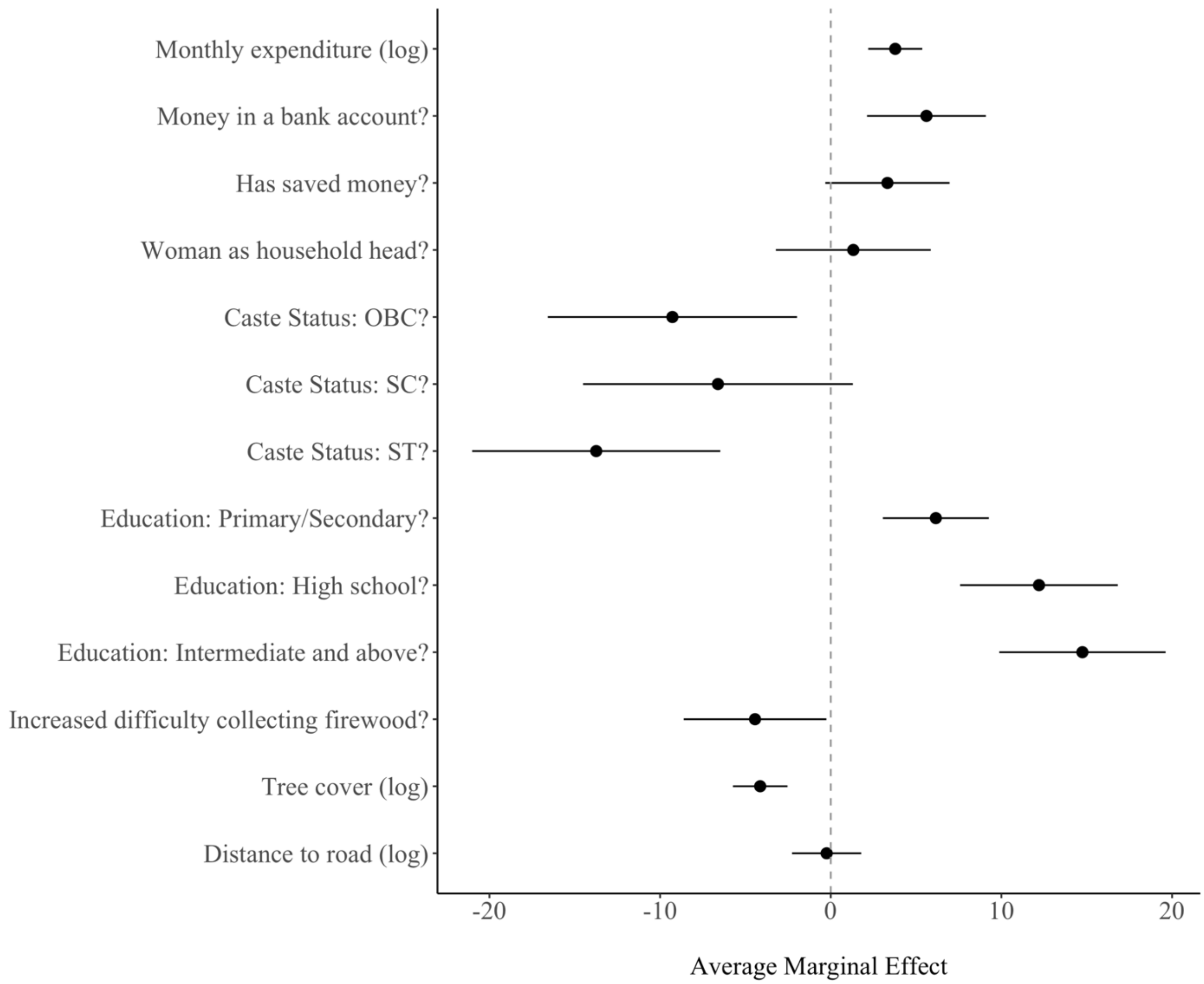

Figure 10: Liquified Petroleum Gas ownership. Coefficient plot for logistic regression with District fixed effects assessing the household and ecological characteristics that are associated with LPG ownership. Points represent coefficients of average marginal effects (percentage point change in the probability of LPG ownership) and whiskers show 95% confidence intervals.

Explaining the timing of LPG adoption

Of all LPG users in the study sample, households that adopted LPG in 2016 or after were poorer, less educated, and had higher odds of being from a non-general caste than those that adopted LPG before PMUY (Figure 11). Controlling for other covariates, households that belonged to the Scheduled Tribe caste had an 18 percentage point (95% CI: 11 – 25 percentage point) higher probability of acquiring LPG after PMUY as compared to a household in the general caste. Similarly, households belonging to the Scheduled Caste or Other Backward Class had higher probabilities of acquiring LPG after PMUY, though somewhat lower than those in the ST caste.

The level of formal education of household members and monthly expenditures were both positively associated with having adopted LPG prior to 2016 (those that are considered general consumers as opposed to likely being PMUY beneficiaries). For example, a household headed by a person that had completed an education at the intermediate level or above had 15 percentage points (95% CI: 10 – 20 percentage points) higher probability of acquiring LPG prior to PMUY as compared to a household headed by a person with no formal education. Similarly, the probability of LPG ownership prior to PMUY was significantly positively associated to monthly expenditure (Appendix C).

Households acquiring LPG after the beginning of PMUY had greater village-level forest cover than those that acquired LPG before PMUY. The use of LPG for cooking after 2016 was greater for households with high forest availability, whereas we had observed a significant negative association between nearby tree cover and the use of LPG across all years (Appendix C). LPG ownership after 2016 was also higher in households that perceived increased difficulty in firewood collection over the last 5 years.

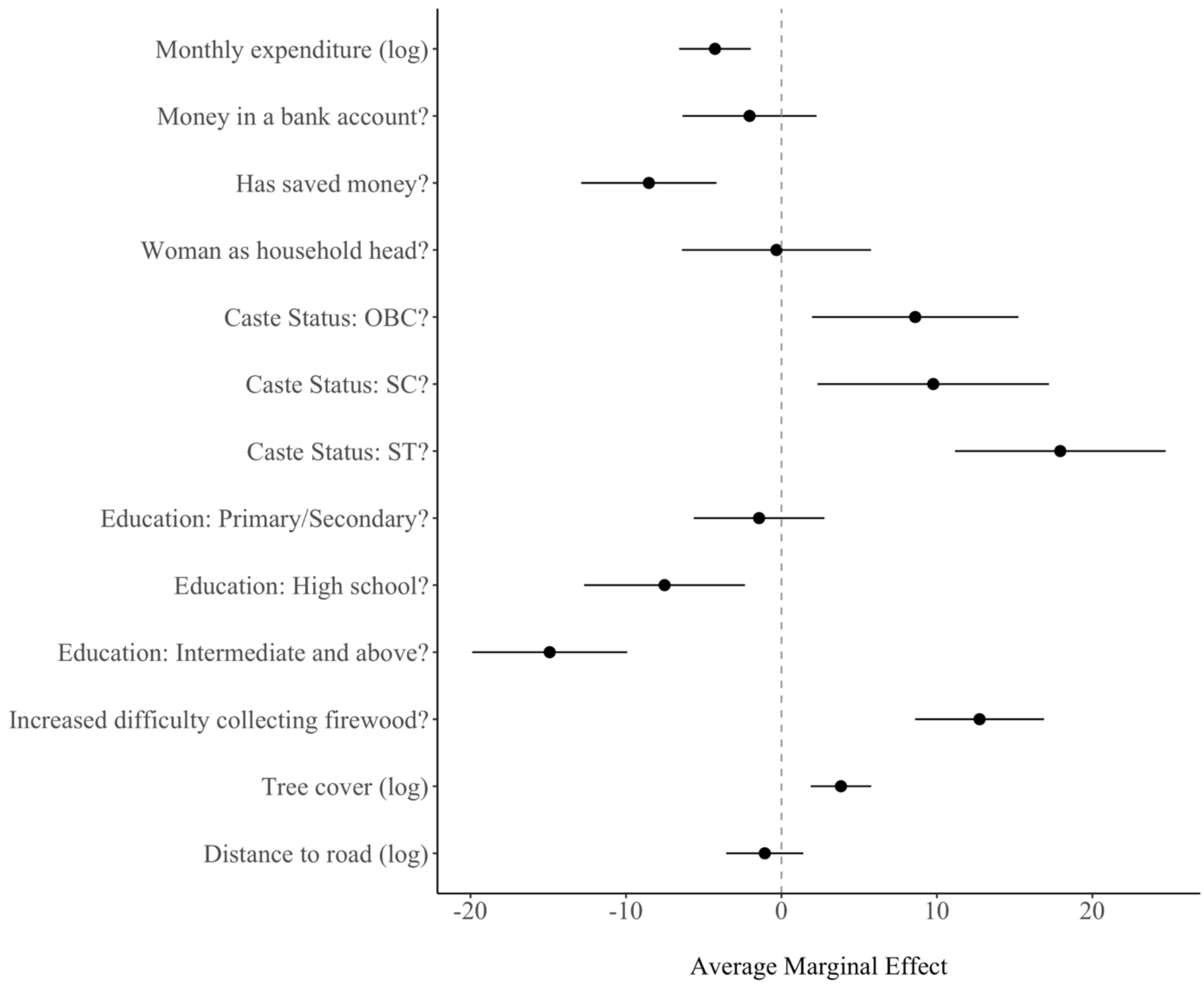

Figure 11: Recent adoptions of Liquified Petroleum Gas. Coefficient plot for logistic regression with District Fixed Effects assessing the household characteristics that are associated with adopting LPG in 2016 or 2017. Points represent coefficients of average marginal effects (percentage point change in the probability of adopting LPG in 2016 or 2017) and whiskers show 95% confidence intervals.

Characteristics of firewood collection

Almost all households (95%) in the study sample reported that they use firewood for cooking at some point during the year. Nearly 70% of households reported weekly firewood collection during the summer, post-monsoon, and winter seasons, but only 33% of households reported weekly firewood collection during the monsoon season (Table 10). Households reporting to collect firewood during the summer, post-monsoon, or winter generally collected firewood during all three seasons. Almost all households (93%) reporting to collect firewood during the monsoon season collected firewood throughout the entire year.

The average distance traveled for firewood was 2.74 km (Standard Deviation (SD): 2.02) and the median distance was 2 km (interquartile range: 1.75 – 3.00 km) (Appendix C). Distance traveled for firewood did not differ significantly across seasons of the year, suggesting that households might acquire wood from the same locations throughout the year.

On average, households that collected firewood at some point during the year reported to spend 15 hours (SD: 11, Median = 12) per week collecting firewood during the summer, post-monsoon, and winter seasons, with the greatest amount of firewood collection time during the winter and the least amount of time during the monsoon season (Table 11). Only a relatively small number of households (2.2% across all seasons and 3.0% in winter) reported to explicitly collect firewood for space heating purposes.

Table 11: Summary of household firewood collection patterns by season.

	Summer	Post-monsoon	Winter	Monsoon
Households reporting weekly firewood collection, N (%)	3465 (69%)	3442 (69%)	3384 (68%)	1661 (33%)
Purpose of firewood collection, N (%)				
Cooking	3440 (99%)	3419 (99%)	3252 (96%)	1645 (99%)
Selling	22 (1%)	18 (1%)	18 (1%)	13 (1%)
Heating	3 (<1%)	5 (<1%)	112 (3%)	3 (<1%)
Number of days per week				
Mean (SD)	3.52 (1.91)	3.22 (1.83)	3.73 (1.89)	2.50 (1.47)
Median (IQR)	3 (2, 5)	3 (2, 4)	3 (2, 5)	2 (1, 3)
Number of hours per day				
Mean (SD)	4.51 (1.76)	4.46 (1.83)	4.54 (1.82)	4.06 (1.79)
Median (IQR)	4 (3, 5)	4 (3, 5)	4 (3, 5)	4 (3, 5)
Number of hours per week				
Mean (SD)	16.48 (12.44)	14.78 (11.38)	17.82 (13.17)	10.20 (8.26)
Median (IQR)	12 (8, 21)	12 (6, 20)	15 (8, 24)	8 (5, 12)

SD is standard deviation and IQR is interquartile range.

Understanding the perception that firewood collection has become more difficult

Qualitative results indicate that restricted access to firewood and a lack of forest were the top reasons for perceived increased difficulty in firewood collection. Yet, the average amount of forest outside of PAs within 2.74 km of villages where households reported increased difficulty in firewood collection over the last 5 years was significantly higher than for households who reported that firewood collection had gotten easier or not changed (Appendix C). To account for this non-intuitive relationship, we included both forest availability and increased difficulty collecting firewood as covariates as we believe both encompass important aspects of decision-making related to cooking fuel use. The perceived change in difficulty to collect firewood variable captures perceived shifts in environmental conditions rather than a more objective measure of firewood availability.

Although access to PAs varies spatially, 52% of survey respondents stated that restricted access to firewood was one of the top reasons for increased difficulty in firewood collection. Those who discussed restricted specifically mentioned the “forest department,” “forest guards,” “forest officer,” “government,” or “village committee” as enforcing these restrictions. For example, “forest department do not allow us to take the firewood from the forest,” “government started to protect forest areas,” and “village committee not allowing us to go into forest.” Therefore, we excluded forest cover within PAs in our measure of forest available for firewood collection. Only 4% of villages contained a PA within 2.74 km of their boundary. The lack of forest was also discussed in 28% of responses as a driver of the increased difficulty in collecting firewood. For example, “There is no firewood in the forest these days” and “much less firewood in the forest and we are not allowed to enter into the forest.”

Determinants of firewood collection patterns

In response to the distinct seasonal pattern in firewood collection, we conducted analyses that considered firewood collection per week as the outcome for the monsoon season and the average time across summer, post-monsoon, and winter seasons separately. The use of LPG for cooking was significantly negatively associated with the number of hours per week spent collecting firewood, accounting for other covariates (Figure 12). In the summer, post-monsoon, and winter seasons, households without LPG spent 17 hours (SD: 11, Median = 14) per week collecting firewood compared to households with LPG that spent 13 hours (SD: 9.5, Median = 9.8) per week (Table 12).

The more years a household owned LPG, the stronger the negative association of LPG use was with reported time collecting firewood. For example, households that adopted LPG in 2013 or before reported spending 53% fewer (95% CI: 47 – 59%) hours per week collecting firewood than households without LPG in the summer, post-monsoon, and winter seasons. Similarly, households adopting LPG in 2014 – 2015 and those in 2016 – 2017 spent 46% less (95% CI: 39 – 53%) and 14% less (95% CI: 8.6 – 19%) time collecting firewood than households without LPG, respectively. While the percent change in time spent collecting firewood was not meaningfully different between the "adopted LPG in 2013" and the "adopted LPG in 2014 – 2015" categories, both of these groups reported spending significantly less time collecting firewood than households adopting LPG in "2016 – 2017." These households (2016 – 2017 adopters), in turn, spent significantly less time collecting firewood than households that did not use LPG. We observe consistent results when carrying out analyses for time spent collecting firewood during the monsoon season, but with attenuated effect sizes, perhaps owing to comparatively less overall firewood collection during this season.

Monthly expenditure, level of formal education, and household tribe and caste status were associated with time spent collecting firewood. The reported time spent collecting firewood each week was shorter by 4.7% (95% CI: 1.9 – 7.4%) with every 1% increase in monthly expenditure. Compared to a household with no formal education, when the household head obtained a primary or secondary, high school, or intermediate and above education, the household spent 6.5% (95% CI: 0.1 – 12%), 13% (95% CI: 4.2 – 21%), and 33% (95% CI: 25 – 39%) less time collecting firewood, respectively. Scheduled Tribe households spent 51% more (95% CI: 29 – 76%) hours collecting firewood than those in the general caste. In addition, SC and OBC households spent 41% (95% CI: 19 – 67) and 18% (95% CI: 1.5 – 38) more hours collecting firewood than those in the general caste, respectively.

Village-level tree cover and the perception that firewood collection had gotten more difficult over the last five years were associated with time spent collecting firewood. Accounting for other covariates, 1% greater forest cover was associated with 26% (95% CI: 22 – 30%) more reported firewood collection time. Households reporting increased difficulty in firewood collection reported to spend 67% more (95% CI: 53 – 82%) time collecting firewood as compared to households that did not perceive increased difficulty.

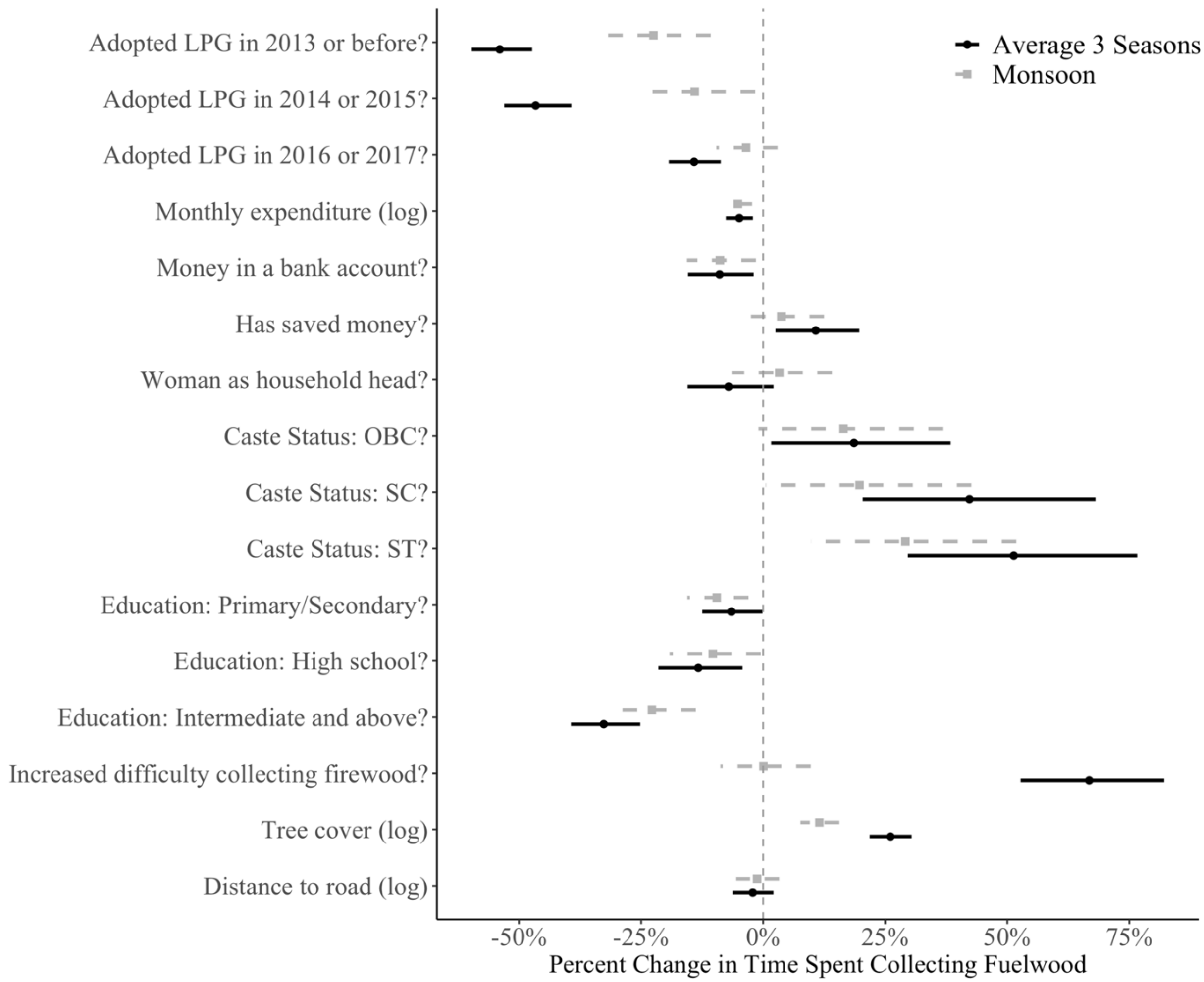

Figure 12: Liquified Petroleum Gas effects firewood collection. Coefficient plots for OLS regressions with District Fixed Effects. Regressions assessed the association between LPG ownership and time spent collecting firewood averaged across three seasons (summer, post-monsoon, and winter) and in monsoon. Points represent exponentiated coefficient estimates (percent change in time spent collecting firewood) and whiskers show 95% confidence intervals.

Table 12: Hours spent collecting firewood per week by season and timing of LPG adoption.

	2013 or before	**2014-2015**	**2016-2017**	**No LPG**
N	270	277	1729	2718
Summer, post-monsoon, and winter				
Mean (SD)	12.79 (10.54)	10.75 (6.92)	15.74 (11.05)	16.50 (11.18)
Median (IQR)	8.17 (6.00, 16.00)	8.83 (6.00, 13.92)	12.33 (7.75, 20.67)	14.00 (8.00, 21.50)

Monsoon				
Mean (SD)	9.55 (7.51)	9.07 (6.63)	10.50 (8.03)	10.12 (8.50)
Median (IQR)	7.00 (4.25, 12.00)	8.00 (4.00, 12.00)	8.00 (5.00, 14.00)	8.00 (5.00, 12.00)

SD is standard deviation and IQR is interquartile range.

4.4 Discussion

This study examines LPG use and firewood collection in marginalized populations living in forested regions within central India. Education, monthly household expenditures, and tribe and caste status were strongly associated with the use of LPG. In particular, households belonging to the Scheduled Tribe designation had the lowest probability of using LPG, had adopted LPG most recently, and reported to spend the most time collecting firewood, even after controlling for other covariates. While almost all LPG users continue to collect and cook with firewood, more years cooking with LPG was associated with less firewood collection, suggesting a waning reliance on firewood for cooking. Finally, households near higher tree cover had lower odds of using LPG, adopted LPG more recently, and spent more time collecting firewood.

While India's energy policies have focused more on expanding clean cooking than equitable access, our study finds LPG ownership increased in marginalized, less-formally educated, and poor households after PMUY. Of all households that use LPG for cooking, a ST household was 18 percentage points more likely to have acquired LPG after PMUY as compared to a general caste household. Nonetheless, the probability of using LPG overall for cooking was 7 – 14 percentage points lower among SC, OBC, and ST households as compared to general cate households. We contribute to growing evidence that, despite overall growth in LPG use owing to PMUY, disparities in access to cleaner cooking remain between social groups and across wealth gaps in India (Pelz et al. 2021; Kumar et al. 2020; Aklin et al. 2020).

Consistent with case studies around the world that show the persistent role of biomass for cooking after the introduction of a clean fuel (Shankar et al. 2020; Quinn et al. 2018), households in central India continue to rely on firewood for cooking despite the recent penetration of LPG. And yet, approaching the near-complete cessation of biomass use is a top priority to achieve cleaner indoor air (Johnson and Chiang et al. 2015; Pope et al, 2017). However, the associations we find between length of time a household owns clean cooking fuel and traditional firewood collection are encouraging for future clean energy adoption and use in India. Still, ST, SC, and OBC households spent 18% – 51% more time collecting firewood than general caste households in central India, even after controlling for years of LPG ownership and economic and demographic characteristics.

This study reached a population that lives in villages within forested regions, where households generally rely strongly on nearby forest products. Our results suggest that in central India, biomass availability promotes firewood collection and hinders LPG use, and there should be further research on these associations. There is evidence from other regions of India that indicates that replacing firewood as a cooking fuel can generate positive environmental outcomes. For example, in South India, forest biomass was greater around communities where households cook with biogas (Agarwala et al. 2017). Including communities living near forest in LPG expansion policies can expand the use of LPG in households that traditionally rely on biomass and may otherwise be unlikely to fully substitute firewood with LPG. In central India, households near higher forest cover were more likely to own LPG after PMUY than other households with LPG. Expanding LPG ownership in households within forested regions should continue and be prioritized as a selection criterion for future LPG promotion policies.

Rural India is comprised of diverse communities where further attention on equity could help achieve energy justice. One potential strategy for increased LPG use would be targeted LPG subsidies or enhanced availability of LPG cylinder refills for specific groups and regions. For example, the amount of LPG subsidy might be linked to the highest education level attained by the household head, caste status, or monthly expenditures. While our study was restricted to largely ST and other lower caste communities in central India, our results have broader implications by motivating additional place-based analyses of barriers to clean cooking fuel adoption in recognition of the importance of household-level socioeconomic characteristics on cooking fuel choice.

The ability to afford clean cooking fuel is affected by income, which for the marginalized, rural populations in central India has traditionally depended on the extraction of forest goods. Increasing employment opportunities for this population can increase their capacity to use LPG and alleviate the burden of collecting firewood, which requires substantial time and effort. Women and children, household members who are generally responsible for firewood collection, in particular could experience further benefits along with a decreased burden of biomass collection. As argued elsewhere (Mani et al. 2020), clean cooking policies should consider the role of broader rural economic development and efforts to enhance education and women's empowerment. A multifaceted approach to increase the use of clean cooking fuels that includes generating employment and providing education opportunities will have widespread benefits beyond clean energy access such as human capital development and gender equality. In central India, the ST and other lower caste communities who face disparities in education and poverty would particularly benefit from a comprehensive rural development and clean cooking program.

Limitations and future areas of research

This study has a few limitations worth noting. First, we do not have multiple measures of cooking fuel use or firewood collection patterns over time. The cross-sectional nature of our study is limiting in two main ways: (1) we are limited in assessing self-reported historical patterns so we cannot capture the changing trade-offs between LPG and firewood use in the years since LPG adoption (e.g., waning reliance on firewood) and (2) we do not capture the precise seasonal patterns of cooking fuel use (e.g., LPG used more in the rainy season) and the corresponding seasonal determinants of fuel use (e.g., variable fuel availability, time-varying incomes). Panel surveys that visit households more than once over the course of many years and studies employing high-frequency surveys across a full year can offer valuable insights into the trajectories of fuel consumption patterns and their determinants (Gould et al, 2020b; Mani et al. 2020; Lam et al. 2017; Carter et al, 2020).

While self-reported measures of cooking fuel use are at risk of survey bias because LPG is socially desirable across India, we do not use continuous measures of LPG use, such as cylinder refills per year, that may be at risk of over-reporting (Kar et al. 2020). It is unlikely that participants differentially reported firewood collection based on ownership of LPG particularly because we calculate time spent collecting firewood using two questions (number of days visiting the forest and hours per trip). Nonetheless, while our comparisons across groups are not likely to be systematically biased, estimates of firewood collection intensity may contain errors and should be interpreted with caution.

Additionally, in our focus on forest-fringe communities, we specifically asked participants if they collected firewood from the forest at least weekly. However, about 20% of households did not report to collect firewood from the forest on a weekly basis during any season of the year. While we do not know how these households acquired firewood for their energy needs, there are a few possibilities: (1) they collected firewood less frequently than once per week; (2) they did collect firewood but not from the forest; (3) they received firewood from friends or family free of cost; or (4) they purchased firewood. Reported collection of firewood from the forest for sale was very rare in our sample (~1%), however, it is possible that firewood collection for sale was underreported due to the illicit nature of that activity. Nonetheless, future studies should investigate the possibility of less frequent firewood collection, firewood collection from non-forest sources, and the potential for a rural firewood market.

Additional limitations are that precise locations for firewood collection was not recorded and tree cover instead of biomass was used as a proxy for firewood availability. Greater specificity on firewood collection location and measures of biomass within those locations could enable even more precise estimates of the effects of biomass availability on household energy choices. We also find a mismatch between our satellite-derived measure of forest availability and perceptions of firewood availability. Households reporting increased difficulty in firewood collection in the last five years also lived near greater tree cover as compared to households who reported no change or increased ease in firewood collection. Change in perceptions of the ease of firewood collection does not directly represent the burden of firewood collection. Highly forested areas may be more likely to become less forested – and therefore firewood collection more difficult – than areas with already reduced forest availability. In addition, the ease of firewood collection may be determined by more factors than availability of forest, such as forest management systems that occur outside of PAs or interactions with neighboring communities. Finally, perceptions of environmental change, such difficulty in firewood collection, may be constructed from socio-cultural practices or cognitive biases and influenced by survey questions (Grunblatt et al. 2017; Pyhala et al. 2016).

Additional research on drivers of perceptions of firewood availability and how households make cooking fuel decisions based on these perceptions along with availability of biomass may provide clarity into strategies for reducing the use of biomass-based fuels in forest-fringe communities that stack fuels. Furthermore, future studies could employ temporally-resolved forest cover measures and multiple surveys to enable panel models capable of capturing assessing forest cover dynamics and within-household shifts in fuel choices, firewood collection patterns, and perceived changes in firewood availability. The continued collection and demand for firewood, socioeconomic drivers of LPG ownership, and differences between measured and perceived biomass availability indicate complexities in behavioral transitions and energy access that impact cooking fuel use and require further exploration.

Our research contributes to a broader understanding of fuel stacking and incorporates tenets of energy justice into clean cooking fuel access within India. In households that use LPG and firewood to cook, the time spent to collect firewood was lowest among households that owned LPG the longest. Even households that adopted LPG most recently (2016 – 2017) spent significantly less time collecting firewood than households without LPG. While PMUY increased access to LPG in Indian households overall, and in our study sample, disparities in LPG access for ST and OBC populations remain. In addition to the disparities in LPG access that rural Indian households face by social group, we find that education level, income, and proximity to forest impact the use of LPG. Our findings suggest that incorporating an explicit motive to address inequitable access for marginalized stakeholders in PMUY may further expand LPG access, displace firewood use, and ultimately improve livelihoods in central India. Similar approaches that examine barriers and inequalities in social groups can inform targeted clean cooking fuel expansion policies around the world.

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Conclusion

Tropical forests provide housing material, water, energy, or income opportunities to 2.7 billion people (Fedele et al. 2021) in addition to supporting significant amounts of biodiversity (Giam, 2017). Tropical dry forests, characterized by lower rainfall and intense dry seasons, in particular are highly threatened, contain endemic flora and fauna, and have close relationships with the people living in and near them (Power et al. 2018). This thesis examined the central Indian landscape at multiple scales through a social ecological framework; I developed a satellite-derived indicator of forest condition at the landscape level and combined remote sensing products with socioeconomic variables measured directly through surveys to households and elected leaders to assess relationships. My study area, central India, is a human-dominated landscape with tropical dry forest where socioeconomically marginalized communities use the same forests as species of global conservation concern (i.e. tigers). This context is reflected in additional landscapes where sustainable development must integrate land use needs of humans and biodiversity. Approaching forests and sustainable development at the landscape scale is useful to examine environmental, governance, and social patterns and interactions (Opdam et al. 2018).

This work contributes to developing our understanding of linkages between forests, forest governance, resource use, and resource user settings in social ecological systems. A forest health dataset, the Bare Ground Index, was developed to measure exposed bare ground within forests and results from chapter 2 and 3 identified social and environmental benefits from livelihood and governance approaches in central India. Formal community institutions with authority to make decision about forests promoted healthier forests, measured as forests with less exposed bare ground, at moderate distances (3 to 8 km) from villages whereas household forest uses were the most important variables for forest health at 1 and 10 km distances. Socially marginalized households across central India have recently gained access to alternative cooking fuels and although firewood for cooking has not been replaced, Liquified Petroleum Gas (LPG) ownership significantly reduced firewood collection. Multiple sustainable development solutions can promote healthy forests across central India, including establishing formal community institutions with authority over forest management and improving forest-dependent livelihoods through access to LPG. Given our work from chapter 2 did not explore socioeconomic dimensions of participation and impacts of local forest management institutions, our work provides evidence to prioritize LPG access for environmental and social benefits.

In chapter 1, coauthors and I produced a very high resolution (3 meter) 2018 land cover and 90 m resolution forest health dataset for the central Indian landscape. We used a discrete classification method on optical imagery to calculate bare ground and tree cover and derive the Bare Ground Index (BGI) in Google Earth Engine. The overall accuracy of the thematic land cover map was 83%. The Random Forest classifier was selected as the most accurate algorithm during a selection stage where we evaluated the classification performance of four machine learning algorithms (Random Forest, Support Vector Machine, Boosted Decision Tree with AdaBoost, adaptive boosting, and Kohonen's Self Organizing Map with k-means clustering) on a small portion of the landscape. We also assessed the BGI through ground validation (February 2020) and found significantly higher signs of cattle (cattle dung) in forests with higher values of BGI, or more bare ground than tree cover, as compared to healthier forests. Cattle dung served as a proxy for measuring the intensity of cattle presence. Signs of forest use were prevalent across forests of high to low BGI and there is a lot of scope to expand our work to operationalize the monitoring of forest degradation.

Access to data and analysis tools and technological developments will continue to improve the feasibility to measure and monitor structural forest degradation at large scales (Sasaki and Putz, 2009). LiDAR and other 3D imaging methods can also be harnessed to interpret forest health in central India and particularly helpful in other forest systems where uses like firewood collection mainly occur under the tree canopy. I used Planet Labs 3 m imagery at 4 bands in a discrete classification in chapter 1 and imagery is now available in 8 bands. Such increased spectral resolution expands the suitability of very-high resolution satellite data for use in spectral unmixing approaches to calculate the BGI and other measures of forest health such as the Normalized Degradation Fraction Index (Bullock et al. 2018). The datasets produced in chapter 1 have been used in studies examining socioeconomic relationships with forests across central India (DeFries et al. 2020; Baquei et al. 2021) and will continue to serve in capacities to contribute to important tropical forest landscape scale research (Daskalova et al. 2020; Mitchard, 2018) because the dataset is available free and open. For example biophysical changes to forests can span decades and the 2018 BGI dataset can be a baseline for future analyses. In addition, the code used to classify imagery and develop the BGI datasets using Google Earth Engine, a cloud-based platform that has improved the capacity for geospatial analysis (Gorelick et al. 2017) is available open and free. Developing accessible methodologies was a step towards empowering non-traditional experts, like government resource managers and non-governmental organization employees, to engage in forest monitoring across central India.

In chapter 2, coauthors and I found evidence for formal community institutions to maintain healthy forests, through associations with decreased amount of exposed bare ground within forest. Of 238 total survey villages across central India, 83% (N = 198) had a local forest management institution and less than half (40%, N = 79) had the authority to modify rules about forest use. About half of households across all villages grazed their cattle in the forest or collected wood from the forest for home repairs; households collected firewood at least once per week across an average of seven months per year, which was relatively high compared to Non-Timber Forest Product (NTFP) or fodder collection. After statistically matching villages (N = 80), we found that forests were healthier, or had less exposed bare ground, at 3 and 3 km of village boundaries where there was a formal local forest management institution compared to villages without a local institution. These distances correspond to the distances that households report traveling for local forest uses. The importance of a local institution for forest health was further confirmed in conditional forest models, where a local institution was more important than direct forest uses in predicting forest health at 3 and 5 km. In conditional forest models that only included villages (N = 40) that were included in matched datasets and had an institution, we found that an institution's authority to modify rules about forest use was relatively more important for forest health than the length of time the institution had been established. Results contribute a landscape-wide analysis to growing work from places within central India where positive indicators of forest condition have been associated with people's involvement in forest management (Agarwal, 2016 and 2017). While multiple methods show that formal local institutions have significantly influenced forest health around communities in central India, forest uses are still important in shaping forest health because collecting wood for housing material and firewood were the most important variables for forest health at distances near (within 1 km) and far (within 10 km) the village, respectively. Sustainable development approaches, such as participatory community governance, are not a single solution (Meyfroidt et al. 2022).

Multiple methods were employed to identify significant links between governance and forest health but I was not able to account for feedbacks that encompass the ways forest health influences governance and livelihoods. In addition, further work should explore mechanisms behind our results that identified the importance of formal local institutions for forest health outcomes. This chapter was limited to collecting data on formal institutions although communities around central India have informal institutions and traditions that influence the forest. Although community forest management can benefit forests, evidence of the social benefits of community governance is mixed because it can worsen other pre-existing socioeconomic inequalities (Bhattacharya et al. 2010; Calfucura, 2018; Agarwal, 2010; Killian and Hyle, 2020). For example, where forest users had a role in forest management there were improved forest cover and household incomes but decreased forest access and resource rights (Hajjar et al. 2021). Participatory forest governance models across India have excluded women (Rout, 2018). Follow up work could examine the relationships between formal and informal governance and forest health, how formal institutions change household forest uses, and issues of social equity by identifying who is and is not participating in forest governance. We require more work on the socioeconomic implications of participatory governance across central India to ensure that formal community institutions and other methods of participation do not exacerbate existing gender and caste disparities.

In chapter 3, coauthors and I identified an opportunity to decrease disparities in clean cooking fuel access across central India and promote potential environmental benefits from decreased firewood dependency. By early 2018, LPG was used for cooking in half (46%) of the 4,994 households living across 500 villages. Yet, fuel stacking remained the predominant cooking fuel strategy with 90% of LPG-owning households continuing to cooking firewood. Almost all (96%) of the study households identified as a marginalized social group, either Scheduled Tribe, Scheduled Caste, or Other Backward Caste; the probability of using LPG for cooking was 7 – 14 percentage points lower among these households and they spent 18% – 51% more time collecting firewood as compared to general caste households. However, after 2016, when India enacted *Pradhan Mantri Ujjwala Yojana* (PMUY), access to LPG increased for marginalized households. Specifically, Scheduled Tribe households had a 18 percentage point higher probability of acquiring LPG after 2016 as compared to a household in the general caste. We also found significant reductions in firewood collection in households that owned LPG and reductions corresponded to the numbers of years LPG was owned. Households that adopted LPG in 2013 or before, 2014 – 2015, or 2016 – 2017 spent 53%, 46%, and 14% fewer hours per week collecting firewood than households without LPG in the summer, post-monsoon, and winter seasons, respectively. Policies targeting communities with marginalized social groups living near forests can further accelerate LPG adoption and displace firewood use.

Livelihood interventions such as clean cooking fuel policies that aim to reduce the human health impacts from cooking with firewood have the potential for combined social and environmental benefits. My work showed that marginalized households have benefitted from PMUY and decrease firewood collection with ownership, an important contribution to literature which has mostly focused on barrier to energy access (Jeuland et al. 2021). Across India, firewood collection has been associated with local degradation (DeFries et al. 2010) and in central India, LPG ownership was significantly associated with healthier forests (DeFries et al.

2021). More direct ways to measure the potential environmental payoffs from decreased firewood collection due to LPG ownership still need to be fully explored. For example, revisiting villages with older versus more recent LPG adoption trends and combine household survey data with vegetation plots along with the BGI. India imports most of its oil and the price and availability of LPG at the national level is under the influence of fluctuations in global oil supply and prices (Alam et al. 2019). Despite this reliance, LPG continues to be an important development and energy transition strategy towards a non-zero or decarbonized system (Rosenthal et al. 2018), a “transition fuel” (Safari et al. 2019), because of its widespread adoption across India compared to other fuels. Similar research examining disparities in energy development policies in social and ecological systems can help to promote just energy transitions around the world.

Results of this thesis are limited in identifying mechanisms to explain significant associations. When it becomes possible to measure the change in BGI over a significant time period, such as 5 to 10 years, corresponding longitudinal surveys to households and village leaders will make additional causal analyses on forest health and socioeconomic and governance factors feasible. Changing rural demographics will continue to alter forests and forest livelihoods in central India and in social ecological systems around the world (Oldekop et al. 2020). Panel data as well as accounting for different types of values placed on forests, including biocultural and commercial, will help understand social ecological systems in transition (Rasmussen et al. 2017). In chapters 2 and 3, I use measures of forest and forest health at buffer distances around forests because the precise spatial extent of forest areas in central India used by local people for specific purposes or governed in some extent by communities was and remains unknown. Extensive efforts to map boundaries of locally important forests areas around communities in central India would aid our efforts of evaluating interactions with community governance and livelihood changes. Forest management boundaries alone do not indicate where people travel and use the forest and are not always available; people's movements in central India's forests are influenced by wildlife (Read et al. 2021). Therefore, such mapping should be participatory and involve forest users. In combination with the fine-scale measures of the amount of time households spend using forests from the 2018 survey, spatial data on locally important forests could deepen our knowledge of forest-dependency across central India. In addition, employing ethnographic methods to record and incorporate landscape histories and documenting local values (Ekblom et al. 2019) will advance our understanding of forest health and social ecological relationships in central India. There remains a need to approach the social and ecological relationships within central India in a multidimensional systems framework rather than as separate but related links (chapters 2 and 3). Finally, focusing on local drivers of changes to forest health such as governance and local livelihoods can detract from relatively more important large-scale drivers of degradation and may be counterproductive to forest conservation (Delabre et al. 2020).

Overall, this thesis produced open and available land cover and forest health datasets across a tropical human-dominated landscape along with fine-scale (village and community level) evidence to strengthen our understanding of a social ecological system in the central India context. High-resolution datasets produced from chapter 1 will continue to serve as a resource to understand land use and forest health and contributes to a broader set of literature that operationalizes measures of forest structure with optical data. Together, chapters 2 and 3 identified governance and livelihood interventions as effective strategies to achieve benefits for people and forests. Formal community institutions involved in forest management significantly benefitted forests and combined evidence from chapter 2 and 3 suggest environmental and social benefits from reduced firewood collection achieved through LPG adoption. The same livelihood and governance approaches identified and discussed here will not produce similar outcomes in other systems. Rather, this thesis presents a useful approach to linking a relevant landscape-scale resource condition to key community and household socioeconomic patterns to identify potential sustainable development synergies in social and ecological systems.

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Appendix A: Supplementary information for chapter 1

Supplementary Table 1. There were 38 districts in the study area. We report on total forest cover, open forest (land with tree cover of canopy density between 10% and 40%), moderately dense forest (land with tree cover of canopy density between 40% and 70%), and very dense forest (land with tree cover of canopy density above 70%) in 2003 and 2019 for 37 districts in central India. Madhya Pradesh's Annapur district had no data in 2003 so we do not include forest cover data from this district. Source: Forest Survey of India, 2003 and 2019.

State	District	Total Forest Cover 2003	Open Forest 2003	Moderately Dense Forest 2003	Very Dense Forest 2003	Total Forest Cover 2019	Open Forest 2019	Moderately Dense Forest 2019	Very Dense Forest 2019
Madhya Pradesh	Chhatarpur	1706	862	803	41	1758.55	756.97	817.52	184.06
Madhya Pradesh	Panna	2728	1069	1595	64	2742.71	1181.44	1478.26	83.01
Madhya Pradesh	Sagar	2922	1198	1722	2	2794.54	1651.97	1141.57	1
Madhya Pradesh	Damoh	2678	1769	903	6	2587.18	1739.39	845.79	2
Madhya Pradesh	Satna	1678	717	942	19	1752.9	831.2	909.7	12
Madhya Pradesh	Rewa	708	474	224	10	781.15	333.57	386.58	61
Madhya Pradesh	Umaria	1872	528	1108	236	2022.58	548.05	1096.22	378.31
Madhya Pradesh	Vidisha	902	375	495	32	777.46	431.55	344.91	1
Madhya Pradesh	Bhopal	312	215	97	0	328.67	207.75	120.92	0
Madhya Pradesh	Sehore	1464	724	740	0	1357.9	719.15	614.85	23.9
Madhya Pradesh	Raisen	2732	1084	1569	79	2676.26	1346.75	1306.51	23
Madhya Pradesh	Betul	3537	1551	1844	142	3663.7	1495.22	1938.14	230.34
Madhya Pradesh	Harda	1045	446	598	1	956.26	409.57	527.69	19
Madhya Pradesh	Hoshangabad	2402	849	1292	262	2422.65	780.44	1370.32	271.89
Madhya Pradesh	Katni	1191	625	477	89	1361.3	658.82	608.58	93.9
Madhya Pradesh	Jabalpur	1078	620	408	50	1113.93	570.43	502.5	41
Madhya Pradesh	Narsimhapur	1374	783	517	74	1342.76	624.42	657.34	61
Madhya Pradesh	Dindori	2643	592	1478	573	3031.96	663.85	1281.17	1086.94
Madhya Pradesh	Mandla	2732	980	1309	443	2577.51	795.15	1091.05	691.31
Madhya Pradesh	Chhindwara	4409	1838	2368	203	4588.01	1938.98	2027.09	576.94
Madhya Pradesh	Seoni	3038	1387	1412	239	3069.59	1041.37	1791.14	237.08
Madhya Pradesh	Balaghat	4859	1682	2547	630	4932.06	883.84	2638.97	1409.25
Madhya Pradesh	Shahdol	2483	893	1491	99	1970.71	1028.17	820.54	122

Madhya Pradesh	East Nimar	3580	1479	2058	43	2089.12	784.52	1156.8	147.8
STATE TOTAL		54073	22740	27997	3337	52699.46	21422.57	25474.16	5757.73
Maharashtra	Akola	321	195	111	15	340.37	220.93	108.44	11
Maharashtra	Amravati	3069	997	1395	677	3167.77	1087.35	1461.53	618.89
Maharashtra	Wardha	824	386	438	0	861.95	441.95	410.03	9.97
Maharashtra	Nagpur	1984	664	961	359	2000.38	696.76	902.56	401.06
Maharashtra	Bhandara	886	223	526	137	998.92	264.93	563.13	170.86
Maharashtra	Gondiya	2160	461	887	812	1938.59	317.75	732.23	888.61
Maharashtra	Gadchiroli	10069	2143	3725	4201	9916.94	1909.92	3307.73	4699.29
Maharashtra	Chandrapur	3940	1039	1639	1262	4054.46	1171.99	1559.44	1323.03
STATE TOTAL		23253	6108	9682	7463	23279.38	6111.58	9045.09	8122.71
Chhattisgarh	Korba	3358	1023	2186	149	3393.7	877.08	2313.62	203
Chhattisgarh	Janfgir-Champa	157	102	51	4	149.89	125.76	22.13	2
Chhattisgarh	Bilaspur	2504	600	1682	222	2456.89	522.7	1539.19	395
Chhattisgarh	Kabeerdham	1621	375	1246	0	1548.72	385.79	1083.84	79.09
Chhattisgarh	Rajnandgaon	2548	818	1727	3	2535.18	754.67	1749.51	31
STATE TOTAL		10188	2918	6892	378	10084.38	2666	6708.29	710.09
STUDY AREA TOTAL		**87514**	**31766**	**44571**	**11178**	**86063.22**	**30200.15**	**41227.54**	**14590.53**

Supplementary Table 2. Overall accuracy and kappa index for a total of 18 models which were run using Random Forest, Support Vector Machine, Boosted Decision Tree (AdaBoost), or Kohonen's Self Organizing Map with k-means clustering. Models differed in the algorithm used, the number of samples in the training data, and algorithm parameters. Algorithm parameters are specific in Appendix A - Table S3. For each algorithm, the highest overall accuracy and kappa index is in bold, these four models are reported in Table 2. * denotes the model with highest overall accuracy and kappa index, run using the Random Forest algorithm.

Algorithm	# of samples in training data	Model	Overall Accuracy	Kappa
Random Forest	6,000 pixels	1	0.694	0.606
		2	0.692	0.606
		3	0.693	0.605
	18,000 pixels	4	**0.697***	**0.610***
		5	0.695	0.608
		6	0.696	0.609
	Polygons	7	0.693	0.602
		8	0.690	0.598
		9	0.696	0.606
Support Vector Machine	6,000 pixels	10	0.378	0.267
		11	0.427	0.315
	18,000 pixels	12	0.388	0.279
		13	**0.435**	**0.324**
Boosted Decision Tree (AdaBoost)	6,000 pixels	14	**0.687**	**0.597**
	18,000 pixels	15	0.680	0.588
Kohonen's Self Organizing Map	-	16	0.622	0.507
		17	**0.631**	**0.514**
		18	0.556	0.416

Supplementary Table 3. The name of model parameters that were varied. Specific model parameters are listed in Appendix A - Table S4, S5, and S6.

Classification Type	Model Name	Algorithm	Parameters
Supervised Classifications	1	Random Forest	Number of trees (n_estimators)
	2		
	3		
	4		
	5		
	6		
	7		
	8		
	9		
	10	Support Vector Machine	RBF kernel: C, error rate
	11		
	12		Polynomial kernel: C, degree
	13		
	14	Boosted Decision Tree (Adaboost)	n_estimators, learning rate
	15		
Unsupervised Classifications	16	Kohonen's Self Organizing Map with k-means clustering	Number of output neurons
	17		
	18		

Supplementary Table 4. Model parameters for models 1 to 0 (run using Random Forest algorithm).

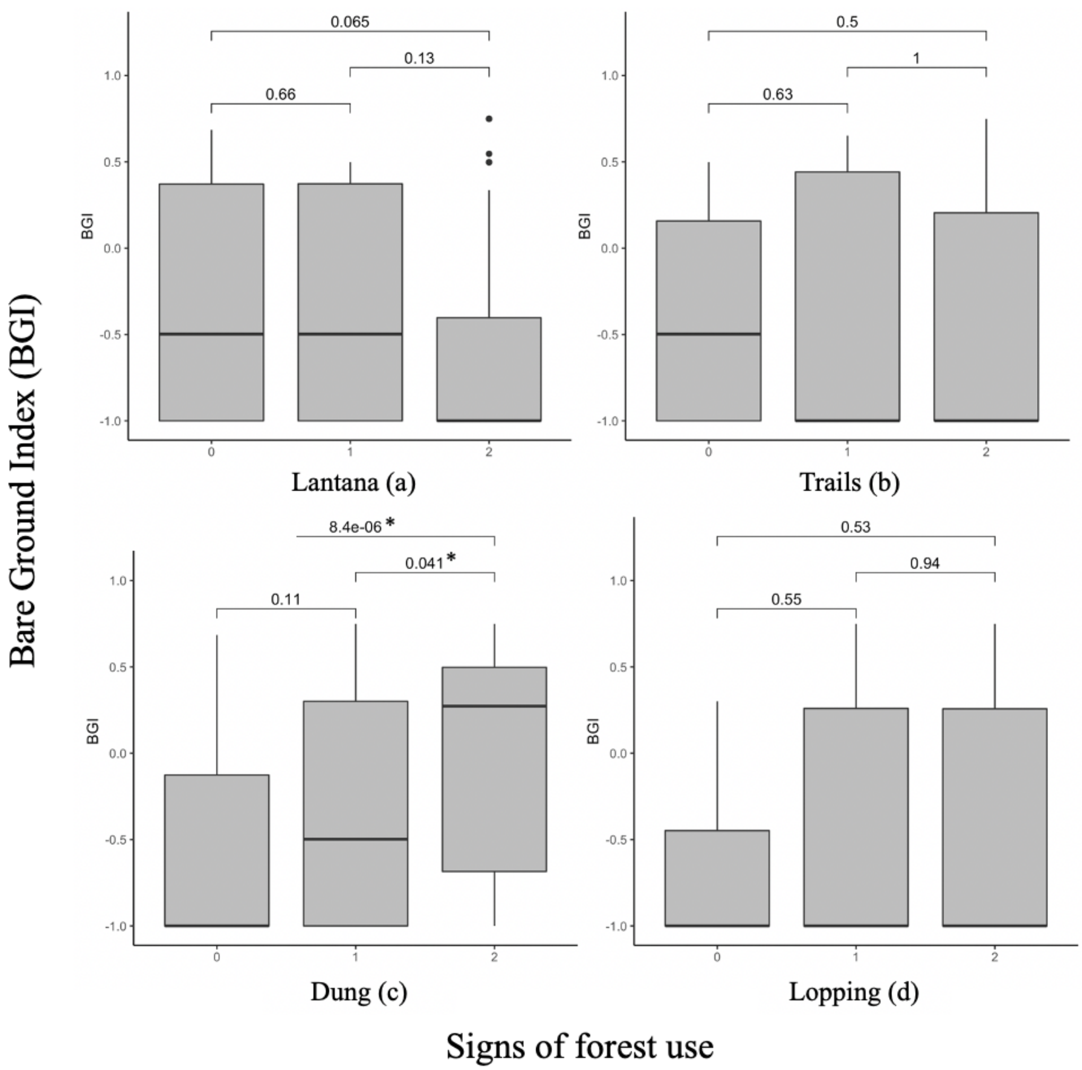
Model	Number of trees
1, 4, and 7	50
2, 5, and 8	100
3, 6, and 9	200

Supplementary Table 5. Model parameters for models 10 to 13 (run using the Support Vector Machine algorithm).

Model	**C**	**gamma**	**Degree**
10 and 12	800	0.90	-
11 and 13	1000	-	1

Supplementary Table 6. Model parameters and quantization error for models 16, 17, and 18 (run using the Kohonen's Self Organizing Map algorithm).

Parameters	Model #		
	16	**17**	**18**
Output layer neurons:	100	225	400
Min learning rate:	0.5		
Max learning rate:	1		
k-means clustering:	yes		
Max no. of output clusters:	32		
Quantization error:	0.0197	0.017	0.015
Iterations:	12,715,912		



Supplementary Figure 1. The average values of the Bare Ground Index (BGI) in ground validation locations according to the level (0, 1 or 2) of signs of forest use. Validation locations were identified at the center of any given 90 meter pixel and signs of forest use within a 15 m radius of the point were recorded. Signs of forest use included lantana (a), trails (b), cattle dung (c), and tree lopping (d) and were categorized as 0 (no signs), 1 (1 or 2 signs), or 2 (3 or greater signs) for the same use type. Plots show the mean and the interquartile range (in gray) of the BGI. We compared the average BGI values of areas with different levels of forest use using a Wilcoxon rank sum test. * denotes a p < 0.05. There was a significant positive association between the presence of cattle dung and BGI.

Appendix B: Supplementary information for chapter 2

Table S1. Key characteristics of villages surveyed in 2018 (N = 500) and 2022 (N = 238). * indicates significant differences at p < 0.05 between places surveyed in 2022 and 2018, there were no significant differences.

	2022 sarpanch survey (N=238)	2018 household survey (N=500)
Number of districts, full sample	31	32
Districts in Madhya Pradesh (% of full sample)	21 (68%)	21 (66%)
Districts in Maharashtra (% of full sample)	5 (16%)	6 (19%)
Districts in Chhattisgarh (% of full sample)	5 (16%)	5 (16%)
Number of villages, full sample	316	500
Villages in Madhya Pradesh (% of full sample)	241 (76%)	324 (65%)
Villages in Maharashtra (% of full sample)	40 (13%)	95 (19%)
Villages in Chhattisgarh (% of full sample)	35 (11%)	81 (16%)
Population		
Mean (SD)	905.55 (784.71)	885.01 (1055.60)
Median (IQR)	650.00 (385.50, 1200.00)	600.00 (350.00, 1100.00)
Cattle feeding inside forest (% of households)		
Mean (SD)	42.82 (25.95)	45.90 (24.97)
Median (IQR)	40.00 (20.00, 60.00)	50.00 (30.00, 70.00)
Fodder collection (months/year)		

Mean (SD)	0.69 (0.87)	0.71 (0.90)
Median (IQR)	0.30 (0.00, 1.10)	0.40 (0.00, 1.10)
Firewood collection (months/year)		
Mean (SD)	6.89 (2.91)	7.17 (2.72)
Median (IQR)	7.70 (5.00, 9.07)	7.80 (5.77, 9.20)
Liquified Petroleum Gas used for cooking (% of households)		
Mean (SD)	46.51 (24.27)	45.58 (24.91)
Median (IQR)	50.00 (30.00, 60.00)	50.00 (30.00, 60.00)
Non-Timber Forest Products (NTFP) collection (months/year)		
Mean (SD)	0.65 (0.56)	0.71 (0.54)
Median (IQR)	0.60 (0.20, 1.00)	0.70 (0.27, 1.00)
Wood from forest home repair (% of households)		
Mean (SD)	67.48 (27.30)	70.72 (26.38)
Median (IQR)	70.00 (50.00, 90.00)	80.00 (50.00, 90.00)
Distance to road (km)		
Mean (SD)	10.32 (7.68)	10.09 (8.12)
Median (IQR)	8.38 (3.82, 15.44)	8.08 (3.14, 15.48)
Distance to city (km)		
Mean (SD)	92.52 (30.68)	91.08 (30.30)
Median (IQR)	97.04 (72.81, 116.93)	94.05 (71.37, 114.26)
Tree cover at 1 km (%)		
Mean (SD)	33.94 (24.40)	35.45 (26.15)
Median (IQR)	29.33 (14.67, 50.38)	30.09 (13.86, 54.65)
Tree cover at 2 km (%)		
Mean (SD)	34.94 (23.19)	36.47 (24.88)
Median (IQR)	31.32 (17.61, 48.04)	33.08 (16.77, 52.43)
Tree cover at 3 km (%)		
Mean (SD)	35.98 (22.06)	37.39 (23.72)
Median (IQR)	33.15 (20.01, 48.58)	34.69 (18.73, 52.21)
Tree cover at 5 km (%)		
Mean (SD)	37.85 (20.32)	38.89 (21.78)

Median (IQR)	35.69 (23.14, 48.47)	36.20 (21.97, 53.06)
Tree cover at 8 km (%)		
Mean (SD)	39.40 (17.93)	40.27 (19.69)
Median (IQR)	37.14 (27.38, 49.96)	38.25 (26.26, 53.02)
Tree cover at 10 km (%)		
Mean (SD)	39.09 (15.22)	39.83 (16.75)
Median (IQR)	37.98 (27.88, 48.05)	38.51 (27.99, 50.12)
BGI at 1 km		
Mean (SD)	-0.68 (0.21)	-0.68 (0.23)
Median (IQR)	-0.70 (-0.83, -0.58)	-0.72 (-0.85, -0.58)
BGI at 2 km		
Mean (SD)	-0.69 (0.19)	-0.69 (0.21)
Median (IQR)	-0.71 (-0.83, -0.57)	-0.73 (-0.85, -0.59)
BGI at 3 km		
Mean (SD)	-0.70 (0.17)	-0.70 (0.19)
Median (IQR)	-0.72 (-0.83, -0.60)	-0.73 (-0.84, -0.60)
BGI at 5 km		
Mean (SD)	-0.71 (0.16)	-0.72 (0.16)
Median (IQR)	-0.74 (-0.82, -0.62)	-0.74 (-0.84, -0.62)
BGI at 8 km		
Mean (SD)	-0.73 (0.13)	-0.73 (0.14)
Median (IQR)	-0.75 (-0.83, -0.65)	-0.76 (-0.84, -0.65)
BGI at 10 km		
Mean (SD)	-0.74 (0.11)	-0.75 (0.11)
Median (IQR)	-0.75 (-0.82, -0.66)	-0.76 (-0.83, -0.67)

Table S2. Key characteristics of the full sample (N = 238) of surveyed villages. * indicates significant differences at p < 0.05 between places with and without local forest management institutions.

	No local forest management institution (N=40)	Local forest management institution (N=198)	Full sample (N=238)
Population*			
Mean (SD)	1267.62 (1208.38)	832.40 (647.87)	905.55 (784.71)
Median (IQR)	700.00 (500.00, 1700.00)	650.00 (350.00, 1100.00)	650.00 (385.50, 1200.00)
Cattle feeding inside forest (%)			
Mean (SD)	42.25 (31.01)	42.97 (24.97)	42.85 (26.01)
Median (IQR)	35.00 (10.00, 70.00)	40.00 (20.00, 60.00)	40.00 (20.00, 60.00)
Fodder collection (months/year)			
Mean (SD)	0.75 (0.81)	0.67 (0.88)	0.69 (0.87)
Median (IQR)	0.55 (0.08, 1.10)	0.30 (0.00, 1.10)	0.30 (0.00, 1.10)
Liquified Petroleum Gas used for cooking (% of households)			
Mean (SD)	44.75 (23.31)	46.89 (24.50)	46.53 (24.27)
Median (IQR)	50.00 (30.00, 60.00)	50.00 (30.00, 60.00)	50.00 (30.00, 60.00)
Firewood collection (months/year)*			
Mean (SD)	5.78 (3.07)	7.12 (2.83)	6.89 (2.91)
Median (IQR)	5.95 (3.30, 8.45)	7.85 (5.40, 9.20)	7.70 (5.00, 9.07)
Non-Timber Forest Products (NTFP) collection (months/year)*			
Mean (SD)	0.36 (0.40)	0.71 (0.56)	0.65 (0.56)
Median (IQR)	0.20 (0.00, 0.53)	0.70 (0.20, 1.00)	0.60 (0.20, 1.00)
Wood from forest home repair (% of households)*			
Mean (SD)	59.00 (31.03)	69.24 (26.29)	67.52 (27.35)

Median (IQR)	70.00 (30.00, 90.00)	75.00 (50.00, 90.00)	70.00 (50.00, 90.00)
Distance to road (km)			
Mean (SD)	9.77 (7.77)	10.43 (7.68)	10.32 (7.68)
Median (IQR)	7.34 (3.77, 13.45)	8.50 (3.88, 15.52)	8.38 (3.82, 15.44)
Distance to city (km)			
Mean (SD)	94.62 (27.68)	92.09 (31.30)	92.52 (30.68)
Median (IQR)	98.46 (80.86, 113.73)	95.95 (70.82, 116.93)	97.04 (72.81, 116.93)
Tree cover at 1 km (%)*			
Mean (SD)	26.51 (20.86)	35.44 (24.83)	33.94 (24.40)
Median (IQR)	20.33 (12.78, 38.26)	30.84 (16.00, 52.10)	29.33 (14.67, 50.38)
Tree cover at 2 km (%)*			
Mean (SD)	27.08 (18.97)	36.53 (23.68)	34.94 (23.19)
Median (IQR)	23.39 (14.14, 36.35)	33.55 (17.73, 50.46)	31.32 (17.61, 48.04)
Tree cover at 3 km (%)*			
Mean (SD)	28.85 (18.04)	37.42 (22.56)	35.98 (22.06)
Median (IQR)	26.67 (16.05, 36.63)	34.37 (20.49, 49.24)	33.15 (20.01, 48.58)
Tree cover at 5 km (%)			
Mean (SD)	33.12 (17.21)	38.81 (20.80)	37.85 (20.32)
Median (IQR)	31.86 (20.28, 42.39)	35.91 (24.17, 50.27)	35.69 (23.14, 48.47)
Tree cover at 8 km (%)			
Mean (SD)	36.58 (15.53)	39.97 (18.35)	39.40 (17.93)
Median (IQR)	32.78 (25.82, 44.56)	37.75 (27.69, 50.20)	37.14 (27.38, 49.96)
Tree cover at 10 km (%)			
Mean (SD)	37.86 (13.79)	39.34 (15.51)	39.09 (15.22)
Median (IQR)	36.45 (28.53, 46.19)	38.78 (27.70, 49.60)	37.98 (27.88, 48.05)
BGI at 1 km*			
Mean (SD)	-0.61 (0.25)	-0.69 (0.20)	-0.68 (0.21)
Median (IQR)	-0.61 (-0.81, -0.45)	-0.70 (-0.83, -0.60)	-0.70 (-0.83, -0.58)

BGI at 2 km*			
Mean (SD)	-0.61 (0.24)	-0.70 (0.17)	-0.69 (0.19)
Median (IQR)	-0.60 (-0.79, -0.46)	-0.72 (-0.84, -0.60)	-0.71 (-0.83, -0.57)
BGI at 3 km*			
Mean (SD)	-0.63 (0.21)	-0.71 (0.16)	-0.70 (0.17)
Median (IQR)	-0.63 (-0.78, -0.49)	-0.73 (-0.84, -0.61)	-0.72 (-0.83, -0.60)
BGI at 5 km*			
Mean (SD)	-0.66 (0.18)	-0.72 (0.15)	-0.71 (0.16)
Median (IQR)	-0.67 (-0.77, -0.57)	-0.74 (-0.82, -0.64)	-0.74 (-0.82, -0.62)
BGI at 8 km			
Mean (SD)	-0.70 (0.14)	-0.73 (0.13)	-0.73 (0.13)
Median (IQR)	-0.70 (-0.78, -0.63)	-0.76 (-0.83, -0.65)	-0.75 (-0.83, -0.65)
BGI at 10 km			
Mean (SD)	-0.72 (0.11)	-0.74 (0.11)	-0.74 (0.11)
Median (IQR)	-0.73 (-0.80, -0.64)	-0.75 (-0.82, -0.67)	-0.75 (-0.82, -0.66)

Table S3. Key characteristics of villages in matched dataset at 1 km. There were no differences between treatment and control groups in these key characteristics.

	No local forest management institution (N=40)	Local forest management institution (N=40)	Full sample (N=80)
Population			
Mean (SD)	1248.85 (1218.24)	1110.72 (759.02)	1178.91 (1007.93)
Median (IQR)	700.00 (500.00, 1650.00)	1025.00 (450.00, 1503.50)	700.00 (475.00, 1557.00)
Cattle feeding inside forest (%)			
Mean (SD)	43.08 (30.96)	49.25 (26.15)	46.20 (28.61)
Median (IQR)	40.00 (10.00, 70.00)	55.00 (30.00, 70.00)	50.00 (20.00, 70.00)
Fodder collection (months/year)			
Mean (SD)	0.77 (0.82)	0.88 (1.12)	0.83 (0.98)
Median (IQR)	0.60 (0.15, 1.10)	0.35 (0.10, 1.27)	0.50 (0.10, 1.20)
Firewood collection (months/year)			
Mean (SD)	5.78 (3.11)	6.55 (3.02)	6.17 (3.07)
Median (IQR)	6.00 (3.30, 8.50)	7.35 (4.18, 8.75)	6.90 (3.65, 8.65)
Non-Timber Forest Products (NTFP) collection (months/year)			
Mean (SD)	0.37 (0.41)	0.39 (0.37)	0.38 (0.39)
Median (IQR)	0.20 (0.00, 0.55)	0.30 (0.08, 0.62)	0.30 (0.00, 0.60)
Wood from forest home repair (%)			
Mean (SD)	45.64 (22.92)	43.50 (23.38)	44.56 (23.03)
Median (IQR)	50.00 (30.00, 60.00)	50.00 (27.50, 60.00)	50.00 (30.00, 60.00)
Distance to road (km)			

Mean (SD)	58.72 (31.39)	62.25 (25.97)	60.51 (28.64)
Median (IQR)	70.00 (30.00, 90.00)	60.00 (50.00, 80.00)	60.00 (40.00, 80.00)
Distance to city (km)			
Mean (SD)	9.26 (7.15)	9.01 (5.98)	9.13 (6.54)
Median (IQR)	7.34 (3.74, 12.99)	7.69 (4.04, 14.06)	7.34 (3.74, 13.55)
Population			
Mean (SD)	94.58 (28.04)	92.79 (31.93)	93.67 (29.89)
Median (IQR)	98.87 (80.54, 115.01)	98.33 (78.91, 116.31)	98.87 (79.83, 116.58)
Tree cover at 1 km (%)			
Mean (SD)	27.19 (20.68)	26.86 (21.58)	27.02 (21.01)
Median (IQR)	21.37 (13.39, 39.59)	23.61 (11.73, 38.09)	23.14 (12.45, 39.59)

Table S4. Key characteristics of villages in matched dataset at 2 km. There were no differences between treatment and control groups in these key characteristics.

	No local forest management institution (N=40)	Local forest management institution (N=40)	Full sample (N=80)
Population			
Mean (SD)	1267.62 (1208.38)	1212.92 (797.40)	1240.28 (1017.60)
Median (IQR)	700.00 (500.00, 1700.00)	1200.00 (537.50, 1600.00)	825.00 (500.00, 1625.00)
Cattle feeding inside forest (%)			
Mean (SD)	42.25 (31.01)	45.50 (25.31)	43.88 (28.17)
Median (IQR)	35.00 (10.00, 70.00)	45.00 (27.50, 60.00)	40.00 (20.00, 70.00)
Fodder collection (months/year)			
Mean (SD)	0.75 (0.81)	1.01 (0.99)	0.88 (0.91)
Median (IQR)	0.55 (0.08, 1.10)	0.90 (0.00, 1.72)	0.60 (0.00, 1.25)
Firewood collection (months/year)			
Mean (SD)	5.78 (3.07)	6.04 (3.15)	5.91 (3.09)
Median (IQR)	5.95 (3.30, 8.45)	6.55 (3.90, 8.53)	6.20 (3.38, 8.45)
Non-Timber Forest Products (NTFP) collection (months/year)			
Mean (SD)	0.36 (0.40)	0.43 (0.37)	0.39 (0.39)
Median (IQR)	0.20 (0.00, 0.53)	0.40 (0.00, 0.80)	0.30 (0.00, 0.72)
Wood from forest home repair (%)			
Mean (SD)	44.75 (23.31)	45.75 (26.40)	45.25 (24.75)
Median (IQR)	50.00 (30.00, 60.00)	50.00 (27.50, 60.00)	50.00 (30.00, 60.00)

Distance to road (km)			
Mean (SD)	59.00 (31.03)	61.75 (24.27)	60.38 (27.72)
Median (IQR)	70.00 (30.00, 90.00)	60.00 (47.50, 80.00)	65.00 (40.00, 82.50)
Distance to city (km)			
Mean (SD)	9.77 (7.77)	9.63 (7.99)	9.70 (7.83)
Median (IQR)	7.34 (3.77, 13.45)	6.96 (3.20, 14.25)	7.08 (3.48, 14.10)
Population			
Mean (SD)	94.62 (27.68)	91.13 (29.65)	92.88 (28.56)
Median (IQR)	98.46 (80.86, 113.73)	96.59 (66.75, 114.43)	97.74 (73.23, 114.43)
Tree cover at 2 km (%)			
Mean (SD)	27.08 (18.97)	28.44 (17.96)	27.76 (18.36)
Median (IQR)	23.39 (14.14, 36.35)	29.15 (16.78, 37.13)	25.94 (15.26, 37.11)

Table S5. Key characteristics of villages in matched dataset at 3 km. There were no differences between treatment and control groups in these key characteristics.

	No local forest management institution (N=40)	Local forest management institution (N=40)	Full sample (N=80)
Population			
Mean (SD)	1267.62 (1208.38)	1033.30 (725.59)	1150.46 (997.32)
Median (IQR)	700.00 (500.00, 1700.00)	1025.00 (425.00, 1500.00)	700.00 (450.00, 1525.00)
Cattle feeding inside forest (%)			
Mean (SD)	42.25 (31.01)	39.25 (26.83)	40.75 (28.85)
Median (IQR)	35.00 (10.00, 70.00)	40.00 (20.00, 60.00)	40.00 (17.50, 70.00)
Fodder collection (months/year)			
Mean (SD)	0.75 (0.81)	0.73 (0.85)	0.74 (0.83)
Median (IQR)	0.55 (0.08, 1.10)	0.35 (0.00, 1.20)	0.45 (0.00, 1.20)
Firewood collection (months/year)			
Mean (SD)	5.78 (3.07)	5.87 (3.32)	5.83 (3.18)
Median (IQR)	5.95 (3.30, 8.45)	6.15 (2.77, 8.45)	5.95 (3.30, 8.45)
Non-Timber Forest Products (NTFP) collection (months/year)			
Mean (SD)	0.36 (0.40)	0.32 (0.33)	0.34 (0.37)
Median (IQR)	0.20 (0.00, 0.53)	0.30 (0.00, 0.53)	0.25 (0.00, 0.53)
Wood from forest home repair (%)			
Mean (SD)	44.75 (23.31)	43.50 (24.55)	44.12 (23.80)

Median (IQR)	50.00 (30.00, 60.00)	50.00 (30.00, 60.00)	50.00 (30.00, 60.00)
Distance to road (km)			
Mean (SD)	59.00 (31.03)	53.75 (26.28)	56.38 (28.69)
Median (IQR)	70.00 (30.00, 90.00)	50.00 (40.00, 72.50)	50.00 (37.50, 80.00)
Distance to city (km)			
Mean (SD)	9.77 (7.77)	10.53 (7.96)	10.15 (7.82)
Median (IQR)	7.34 (3.77, 13.45)	7.82 (4.44, 14.92)	7.34 (4.13, 14.10)
Population			
Mean (SD)	94.62 (27.68)	93.08 (30.52)	93.85 (28.96)
Median (IQR)	98.46 (80.86, 113.73)	100.72 (67.28, 119.10)	99.05 (75.84, 117.79)
Tree cover at 3 km (%)			
Mean (SD)	28.85 (18.04)	31.82 (24.11)	30.34 (21.21)
Median (IQR)	26.67 (16.05, 36.63)	25.95 (9.48, 47.18)	26.26 (12.74, 40.29)

Table S6. Key characteristics of villages in matched dataset at 5 km. There were no differences between treatment and control groups in these key characteristics.

	No local forest management institution (N=40)	Local forest management institution (N=40)	Full sample (N=80)
Population			
Mean (SD)	1267.62 (1208.38)	1170.88 (756.22)	1219.25 (1002.76)
Median (IQR)	700.00 (500.00, 1700.00)	1050.00 (637.50, 1625.00)	810.00 (500.00, 1700.00)
Cattle feeding inside forest (%)			
Mean (SD)	42.25 (31.01)	47.00 (27.38)	44.62 (29.16)
Median (IQR)	35.00 (10.00, 70.00)	50.00 (30.00, 60.00)	45.00 (20.00, 70.00)
Fodder collection (months/year)			
Mean (SD)	0.75 (0.81)	0.87 (0.96)	0.81 (0.89)
Median (IQR)	0.55 (0.08, 1.10)	0.50 (0.10, 1.20)	0.50 (0.10, 1.20)
Firewood collection (months/year)			
Mean (SD)	5.78 (3.07)	6.41 (3.07)	6.10 (3.07)
Median (IQR)	5.95 (3.30, 8.45)	6.50 (4.25, 9.38)	6.20 (3.48, 8.62)
Non-Timber Forest Products (NTFP) collection (months/year)			
Mean (SD)	0.36 (0.40)	0.43 (0.43)	0.40 (0.42)
Median (IQR)	0.20 (0.00, 0.53)	0.30 (0.00, 0.72)	0.30 (0.00, 0.70)
Wood from forest home repair (%)			
Mean (SD)	44.75 (23.31)	40.75 (26.45)	42.75 (24.85)
Median (IQR)	50.00 (30.00, 60.00)	40.00 (20.00, 60.00)	40.00 (30.00, 60.00)

Distance to road (km)			
Mean (SD)	59.00 (31.03)	60.75 (29.21)	59.88 (29.96)
Median (IQR)	70.00 (30.00, 90.00)	65.00 (47.50, 80.00)	70.00 (40.00, 82.50)
Distance to city (km)			
Mean (SD)	9.77 (7.77)	11.30 (8.70)	10.53 (8.23)
Median (IQR)	7.34 (3.77, 13.45)	10.06 (4.34, 15.95)	8.69 (3.79, 14.16)
Population			
Mean (SD)	94.62 (27.68)	97.57 (28.16)	96.10 (27.78)
Median (IQR)	98.46 (80.86, 113.73)	105.19 (86.46, 121.16)	99.10 (85.65, 117.80)
Tree cover at 5 km (%)			
Mean (SD)	33.12 (17.21)	36.78 (21.09)	34.95 (19.21)
Median (IQR)	31.86 (20.28, 42.39)	31.22 (22.86, 43.15)	31.25 (21.51, 43.15)

Table S7. Key characteristics of villages in matched dataset at 8 km. There were no differences between treatment and control groups in these key characteristics.

	No local forest management institution (N=40)	Local forest management institution (N=40)	Full sample (N=80)
Population			
Mean (SD)	1267.62 (1208.38)	1175.17 (746.10)	1221.40 (998.91)
Median (IQR)	700.00 (500.00, 1700.00)	1000.00 (592.50, 1625.00)	900.00 (500.00, 1700.00)
Cattle feeding inside forest (%)			
Mean (SD)	42.25 (31.01)	44.22 (27.95)	43.24 (29.35)
Median (IQR)	35.00 (10.00, 70.00)	40.00 (20.00, 70.00)	40.00 (20.00, 70.00)
Fodder collection (months/year)			
Mean (SD)	0.75 (0.81)	0.67 (0.91)	0.71 (0.86)
Median (IQR)	0.55 (0.08, 1.10)	0.30 (0.00, 1.00)	0.40 (0.00, 1.02)
Firewood collection (months/year)			
Mean (SD)	5.78 (3.07)	6.20 (3.02)	5.99 (3.03)
Median (IQR)	5.95 (3.30, 8.45)	7.00 (3.25, 8.72)	6.40 (3.30, 8.62)
Non-Timber Forest Products (NTFP) collection (months/year)			
Mean (SD)	0.36 (0.40)	0.38 (0.41)	0.37 (0.41)
Median (IQR)	0.20 (0.00, 0.53)	0.30 (0.00, 0.62)	0.25 (0.00, 0.60)
Wood from forest home repair (%)			
Mean (SD)	44.75 (23.31)	41.61 (25.17)	43.18 (24.16)

Median (IQR)	50.00 (30.00, 60.00)	40.00 (20.00, 60.00)	40.00 (30.00, 60.00)
Distance to road (km)			
Mean (SD)	59.00 (31.03)	61.75 (27.26)	60.38 (29.05)
Median (IQR)	70.00 (30.00, 90.00)	65.00 (40.00, 80.00)	70.00 (40.00, 82.50)
Distance to city (km)			
Mean (SD)	9.77 (7.77)	9.64 (7.57)	9.71 (7.62)
Median (IQR)	7.34 (3.77, 13.45)	7.41 (3.28, 14.48)	7.34 (3.53, 13.84)
Population			
Mean (SD)	94.62 (27.68)	91.41 (30.73)	93.02 (29.10)
Median (IQR)	98.46 (80.86, 113.73)	94.62 (76.29, 112.98)	97.43 (77.91, 113.23)
Tree cover at 8 km (%)			
Mean (SD)	36.58 (15.53)	38.13 (20.60)	37.35 (18.14)
Median (IQR)	32.78 (25.82, 44.56)	33.77 (24.86, 48.69)	33.48 (25.40, 47.03)

Table S8. Key characteristics of villages in matched dataset at 10 km. There were no differences between treatment and control groups in these key characteristics.

	No local forest management institution (N=40)	Local forest management institution (N=40)	Full sample (N=80)
Population			
Mean (SD)	1267.62 (1208.38)	1227.12 (947.67)	1247.38 (1079.18)
Median (IQR)	700.00 (500.00, 1700.00)	1100.00 (450.00, 1725.00)	950.00 (487.50, 1700.00)
Cattle feeding inside forest (%)			
Mean (SD)	42.25 (31.01)	39.50 (29.26)	40.88 (29.99)
Median (IQR)	35.00 (10.00, 70.00)	30.00 (20.00, 60.00)	30.00 (17.50, 70.00)
Fodder collection (months/year)			
Mean (SD)	0.75 (0.81)	0.86 (0.81)	0.80 (0.81)
Median (IQR)	0.55 (0.08, 1.10)	0.60 (0.10, 1.42)	0.60 (0.10, 1.20)
Firewood collection (months/year)			
Mean (SD)	5.78 (3.07)	5.46 (3.27)	5.62 (3.16)
Median (IQR)	5.95 (3.30, 8.45)	5.10 (2.77, 8.40)	5.55 (3.08, 8.45)
Non-Timber Forest Products (NTFP) collection (months/year)			
Mean (SD)	0.36 (0.40)	0.35 (0.42)	0.36 (0.41)
Median (IQR)	0.20 (0.00, 0.53)	0.15 (0.00, 0.55)	0.20 (0.00, 0.53)
Wood from forest home repair (%)			
Mean (SD)	44.75 (23.31)	49.75 (25.57)	47.25 (24.44)
Median (IQR)	50.00 (30.00, 60.00)	50.00 (37.50, 70.00)	50.00 (30.00, 60.00)

Distance to road (km)			
Mean (SD)	59.00 (31.03)	56.75 (28.95)	57.88 (29.84)
Median (IQR)	70.00 (30.00, 90.00)	50.00 (40.00, 80.00)	50.00 (30.00, 82.50)
Distance to city (km)			
Mean (SD)	9.77 (7.77)	10.61 (7.69)	10.19 (7.69)
Median (IQR)	7.34 (3.77, 13.45)	8.25 (3.41, 17.93)	7.88 (3.65, 15.48)
Population			
Mean (SD)	94.62 (27.68)	91.56 (32.43)	93.09 (30.00)
Median (IQR)	98.46 (80.86, 113.73)	95.75 (66.62, 116.21)	97.23 (74.09, 116.21)
Tree cover at 10 km (%)			
Mean (SD)	37.86 (13.79)	38.22 (14.61)	38.04 (14.12)
Median (IQR)	36.45 (28.53, 46.19)	36.41 (27.13, 45.70)	36.45 (27.82, 45.92)

Table S9. Summary statistics of BGI at buffer distances from matched datasets (N = 80).

Buffer distances	**1 km**	**2 km**	**3 km**	**5 km**	**8 km**	**10 km**
Mean (SD)	-0.64 (0.22)	-0.66 (0.21)	-0.68 (0.19)	-0.70 (0.16)	-0.73 (0.13)	-0.74 (0.11)
Median (IQR)	-0.65 (-0.83, -0.51)	-0.69 (-0.83, -0.52)	-0.69 (-0.84, -0.60)	-0.71 (-0.81, -0.61)	-0.75 (-0.80, -0.65)	-0.75 (-0.82, -0.66)

Table S10. Key characteristics of surveyed villages with one or more formal local institution involved in forest management * indicates a significant difference between places with 1, 2, 3, or 4 local institutions.

	1 local institution (N=177)	2 local institutions (N=15)	3 local institutions (N=4)	4 local institutions (N=2)	Full sample (N=238)
Population					
Mean (SD)	843.98 (663.75)	786.67 (460.38)	700.00 (739.37)	415.00 (261.63)	832.40 (647.87)
Median (IQR)	650.00 (350.00, 1100.00)	650.00 (475.00, 1100.00)	400.00 (350.00, 750.00)	415.00 (322.50, 507.50)	650.00 (350.00, 1100.00)
Cattle feeding inside forest (%)					
Mean (SD)	42.82 (24.99)	42.00 (24.84)	52.50 (35.94)	45.00 (7.07)	42.97 (24.97)
Median (IQR)	40.00 (20.00, 60.00)	50.00 (30.00, 60.00)	65.00 (45.00, 72.50)	45.00 (42.50, 47.50)	40.00 (20.00, 60.00)
Fodder collection (months/year)					
Mean (SD)	0.70 (0.87)	0.63 (1.11)	0.15 (0.24)	0.00 (0.00)	0.67 (0.88)
Median (IQR)	0.30 (0.00, 1.20)	0.10 (0.00, 0.40)	0.05 (0.00, 0.20)	0.00 (0.00, 0.00)	0.30 (0.00, 1.10)
Liquified Petroleum Gas used for cooking (% of households)					
Mean (SD)	7.10 (2.87)	7.33 (2.47)	6.45 (3.75)	8.15 (0.35)	7.12 (2.83)
Median (IQR)	7.80 (5.40, 9.20)	7.70 (5.85, 8.75)	8.05 (5.78, 8.72)	8.15 (8.03, 8.28)	7.85 (5.40, 9.20)
Firewood collection (months/year)					
Mean (SD)	46.69 (24.46)	46.00 (25.01)	42.50 (25.00)	80.00 (0.00)	46.89 (24.50)

Median (IQR)	50.00 (30.00, 60.00)	50.00 (25.00, 70.00)	45.00 (32.50, 55.00)	80.00 (80.00, 80.00)	50.00 (30.00, 60.00)
Non-Timber Forest Products (NTFP) collection (months/year)					
Mean (SD)	0.69 (0.53)	0.79 (0.85)	0.95 (0.75)	1.40 (0.00)	0.71 (0.56)
Median (IQR)	0.60 (0.20, 1.00)	0.50 (0.15, 1.10)	1.10 (0.52, 1.52)	1.40 (1.40, 1.40)	0.70 (0.20, 1.00)
Wood from forest home repair (% of households)					
Mean (SD)	68.59 (26.94)	76.67 (17.59)	62.50 (26.30)	85.00 (21.21)	69.24 (26.29)
Median (IQR)	70.00 (50.00, 90.00)	80.00 (65.00, 90.00)	60.00 (40.00, 82.50)	85.00 (77.50, 92.50)	75.00 (50.00, 90.00)
Distance to road (km)					
Mean (SD)	10.45 (7.77)	9.03 (6.25)	13.05 (7.25)	14.58 (13.29)	10.43 (7.68)
Median (IQR)	8.37 (3.68, 15.53)	8.65 (3.99, 11.54)	12.01 (7.81, 17.25)	14.58 (9.88, 19.28)	8.50 (3.88, 15.52)
Distance to city (km)					
Mean (SD)	92.85 (30.88)	85.39 (37.52)	82.46 (36.70)	94.77 (14.65)	92.09 (31.30)
Median (IQR)	97.09 (70.42, 117.02)	92.08 (61.67, 115.72)	93.28 (77.14, 98.59)	94.77 (89.59, 99.95)	95.95 (70.82, 116.93)
Tree cover at 1 km (%)					
Mean (SD)	35.33 (24.71)	29.61 (19.11)	57.42 (43.92)	45.15 (21.15)	35.44 (24.83)
Median (IQR)	31.13 (15.89, 52.25)	26.25 (16.54, 35.22)	67.25 (33.58, 91.09)	45.15 (37.67, 52.62)	30.84 (16.00, 52.10)

Tree cover at 2 km (%)					
Mean (SD)	36.57 (23.55)	28.71 (17.06)	56.00 (42.84)	52.84 (17.13)	36.53 (23.68)
Median (IQR)	33.78 (17.91, 51.16)	27.91 (15.83, 36.63)	65.92 (31.99, 89.93)	52.84 (46.78, 58.89)	33.55 (17.73, 50.46)
Tree cover at 3 km (%)					
Mean (SD)	37.42 (22.32)	29.68 (16.73)	55.47 (41.97)	59.22 (14.78)	37.42 (22.56)
Median (IQR)	34.74 (20.84, 49.27)	30.69 (16.71, 34.45)	65.48 (32.89, 88.06)	59.22 (54.00, 64.45)	34.37 (20.49, 49.24)
Tree cover at 5 km (%)					
Mean (SD)	38.62 (20.31)	32.71 (17.46)	57.08 (40.94)	64.69 (10.72)	38.81 (20.80)
Median (IQR)	35.79 (24.26, 50.20)	32.15 (20.67, 40.80)	67.79 (38.78, 86.09)	64.69 (60.90, 68.48)	35.91 (24.17, 50.27)
Tree cover at 8 km (%)*					
Mean (SD)	39.78 (17.82)	34.58 (16.42)	57.52 (36.72)	62.34 (2.10)	39.97 (18.35)
Median (IQR)	38.02 (27.82, 50.15)	29.86 (25.59, 41.60)	65.40 (44.52, 78.40)	62.34 (61.59, 63.08)	37.75 (27.69, 50.20)
Tree cover at 10 km (%)					
Mean (SD)	39.25 (15.06)	35.32 (16.31)	50.87 (28.89)	54.65 (5.01)	39.34 (15.51)
Median (IQR)	38.97 (27.98, 48.07)	32.09 (25.19, 41.41)	56.08 (44.71, 62.24)	54.65 (52.88, 56.42)	38.78 (27.70, 49.60)
BGI at 1 km					
Mean (SD)	-0.69 (0.20)	-0.65 (0.16)	-0.77 (0.16)	-0.56 (0.04)	-0.69 (0.20)
Median (IQR)	-0.72 (-0.85, -0.61)	-0.67 (-0.77, -0.59)	-0.74 (-0.87, -0.65)	-0.56 (-0.58, -0.55)	-0.70 (-0.83, -0.60)

BGI at 2 km					
Mean (SD)	-0.70 (0.18)	-0.67 (0.14)	-0.75 (0.18)	-0.68 (0.06)	-0.70 (0.17)
Median (IQR)	-0.74 (-0.84, -0.61)	-0.68 (-0.78, -0.59)	-0.75 (-0.87, -0.63)	-0.68 (-0.70, -0.66)	-0.72 (-0.84, -0.60)
BGI at 3 km					
Mean (SD)	-0.71 (0.17)	-0.69 (0.13)	-0.78 (0.14)	-0.69 (0.10)	-0.71 (0.16)
Median (IQR)	-0.74 (-0.84, -0.61)	-0.70 (-0.77, -0.60)	-0.78 (-0.87, -0.68)	-0.69 (-0.73, -0.66)	-0.73 (-0.84, -0.61)
BGI at 5 km					
Mean (SD)	-0.72 (0.15)	-0.71 (0.11)	-0.84 (0.08)	-0.71 (0.11)	-0.72 (0.15)
Median (IQR)	-0.74 (-0.82, -0.63)	-0.71 (-0.77, -0.66)	-0.83 (-0.89, -0.78)	-0.71 (-0.75, -0.67)	-0.74 (-0.82, -0.64)
BGI at 8 km					
Mean (SD)	-0.73 (0.13)	-0.72 (0.12)	-0.87 (0.05)	-0.71 (0.13)	-0.73 (0.13)
Median (IQR)	-0.76 (-0.83, -0.65)	-0.72 (-0.79, -0.64)	-0.86 (-0.90, -0.83)	-0.71 (-0.76, -0.67)	-0.76 (-0.83, -0.65)
BGI at 10 km					
Mean (SD)	-0.74 (0.11)	-0.73 (0.13)	-0.85 (0.06)	-0.74 (0.10)	-0.74 (0.11)
Median (IQR)	-0.75 (-0.82, -0.66)	-0.71 (-0.80, -0.67)	-0.86 (-0.89, -0.82)	-0.74 (-0.78, -0.71)	-0.75 (-0.82, -0.67)

Table S11. Committees from 13 villages where there was two or more committees identified and named as involved in making decisions about the forest.

Places with more than 1 committees:
Van haq samiti, gram sabha samiti, daksha samiti
Van prabandhan samiti, Gram surakshi samiti
Gram van suraksha samiti, Gram van sabha
Gram van suraksha samiti, Gram van samiti
Van adhikar samiti, van suraksha samiti
Eco samiti, van samiti
Gram koch samiti, Van sewa niyantran samiti, Nasargik sansadhan samiti, Manusha varg sansadhan samiti
Pesa samiti, Samudayik van samiti, Taluka van samiti
Van haq samiti, daksha samiti
Gram suraksha samiti, Gram van samiti
Gram vikas samiti, van samiti
Van samiti, Jalgal van sadhan samiti
Van haq samiti, Gram sabha, Niyanntran samiti, Daksha samiti

Table S12. Characteristics of local forest management institutions, from matched datasets at buffer distances and from select villages that answered the questions about committees from the 236 full sample villages (pre-matching).

Buffer distances	**1 km (N = 26)**	**2 km (N = 22)**	**3 km (N = 25)**	**5 km (N = 25)**	**8 km (N = 26)**	**10 km (N = 25)**	**Full sample (N = 125)**
Local institution with authority? %, N	44.44%, 8	36.36%, 8	24.00%, 6	44.00%, 11	38.46%, 10	48.00%, 12	36.00%, 45
Number of years a local forest management institution has been established							
Mean (SD)	6.31 (4.38)	7.86 (6.70)	8.04 (6.32)	7.77 (6.07)	7.92 (4.69)	7.2 (4.29)	7.75 (5.32)
Median (IQR)	6.5 (0.6, 12.5)	6.5 (-1.75, 14.75)	7 (-2, 16)	7 (-3, 17)	7 (-0.75, 14.75)	7 (2, 12)	7 (-1, 15)

Table S13. Median and interquartile ranges of the Bare Ground Index (BGI) at buffer distances around villages with and without local forest management institutions. Significance values are results of Wilcoxon rank sum tests between treatment and control groups. Differences were significant (* = p < 0.10, ** = p < 0.05) at 2, 3, 5, and 8 km buffer distances.

Buffer distances	1 km	2 km	3 km	5 km	8 km	10 km
With a local forest management institution	-0.70 (-0.46, -0.94)	-0.72** (-0.47, -0.97)	-0.72* (-0.48, -0.96)	-0.74* (-0.54, -0.94)	-0.76* (-0.57, -0.95)	-0.74 (-0.58, -0.90)
Without a forest management institution	-0.62 (-0.25, -0.99)	-0.60** (-0.28, -0.92)	-0.64* (-0.35, -0.93)	-0.67* (-0.48, -0.86	-0.70* (-0.55, -0.85)	-0.72 (-0.55, -0.89)

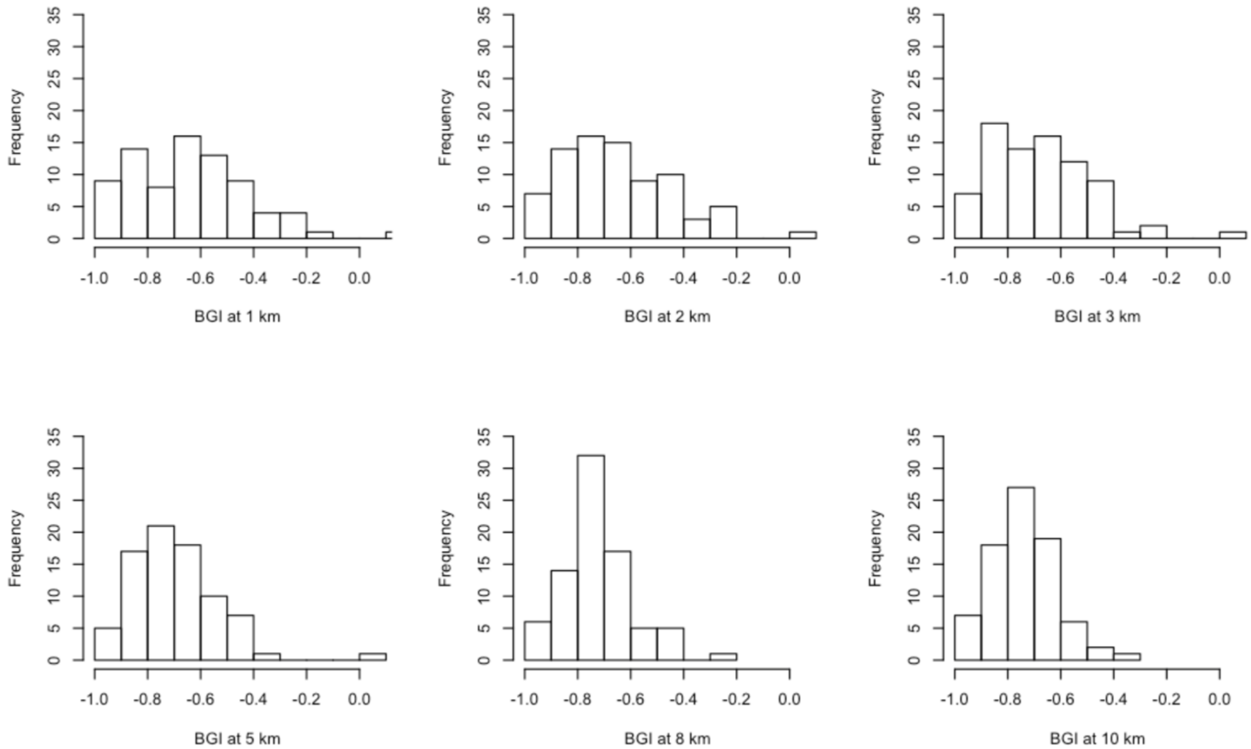


Figure S1. Histograms showing the distribution of the Bare Ground Index (BGI) at 1, 2, 3, 5, 8, and 10 kms from village boundaries in matched datasets (N = 80). The BGI at buffer distances was the measure of forest health and used as the outcome variable in causal forest models, Generalized Linear Models (GLMs), and conditional forest models.

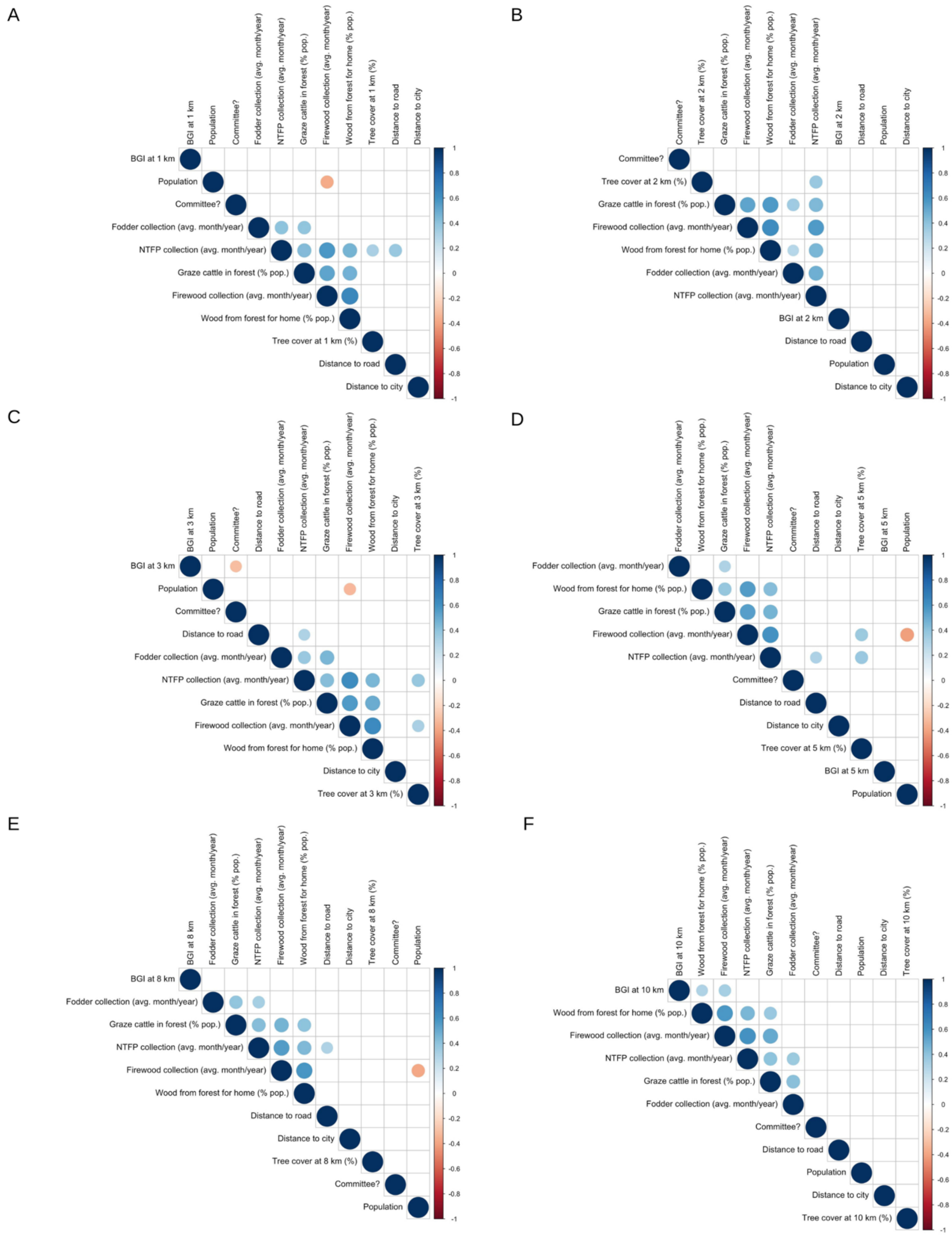


Figure S2. Correlation matrix of outcome and predictor variables at buffer distances of 1 (A), 2 (B), 3 (C), 5 (D), 8 (E), and 10 (F) kms.

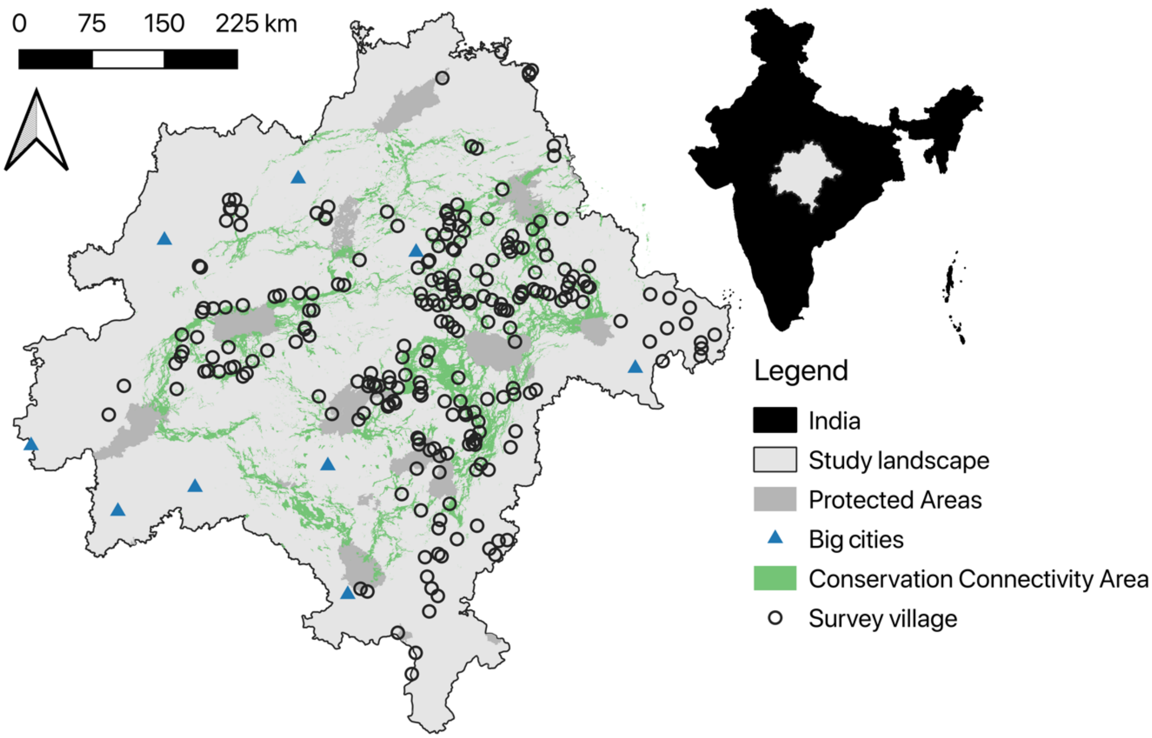


Figure S3. Map of 238 survey villages, cities with populations greater than 88,000 people, Protected Areas, and Conservation Connectivity Areas for tigers from Schoen et al. (2022).

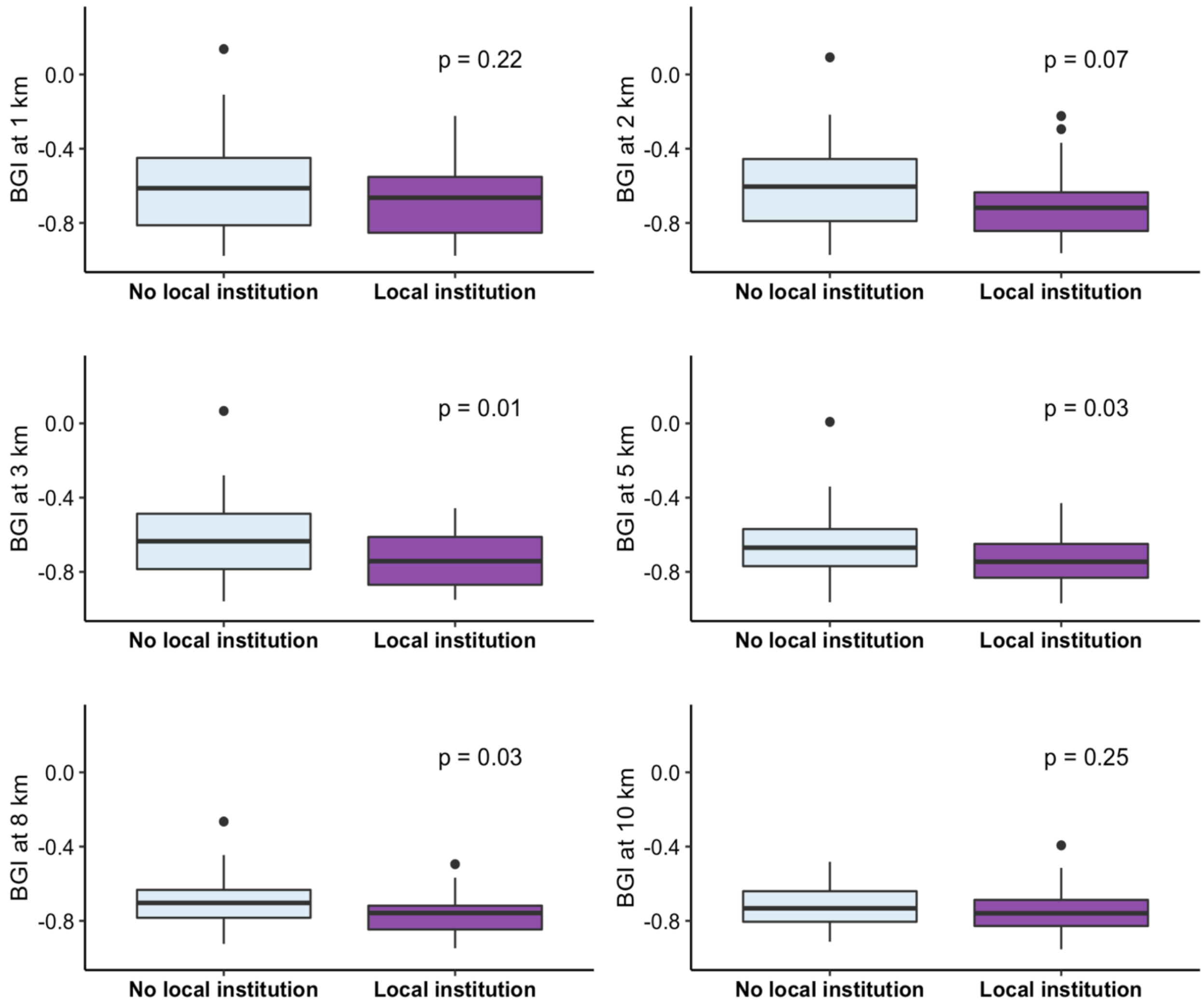


Figure S4. Between 1 and 8 km of the village boundary, there was significantly lower median BGI around villages with local forest management institutions as compared to villages without local institutions (Figure 6). Between 1 and 8 km, the BGI was significantly lower by 0.06 to 0.12 units around villages with a local institution.

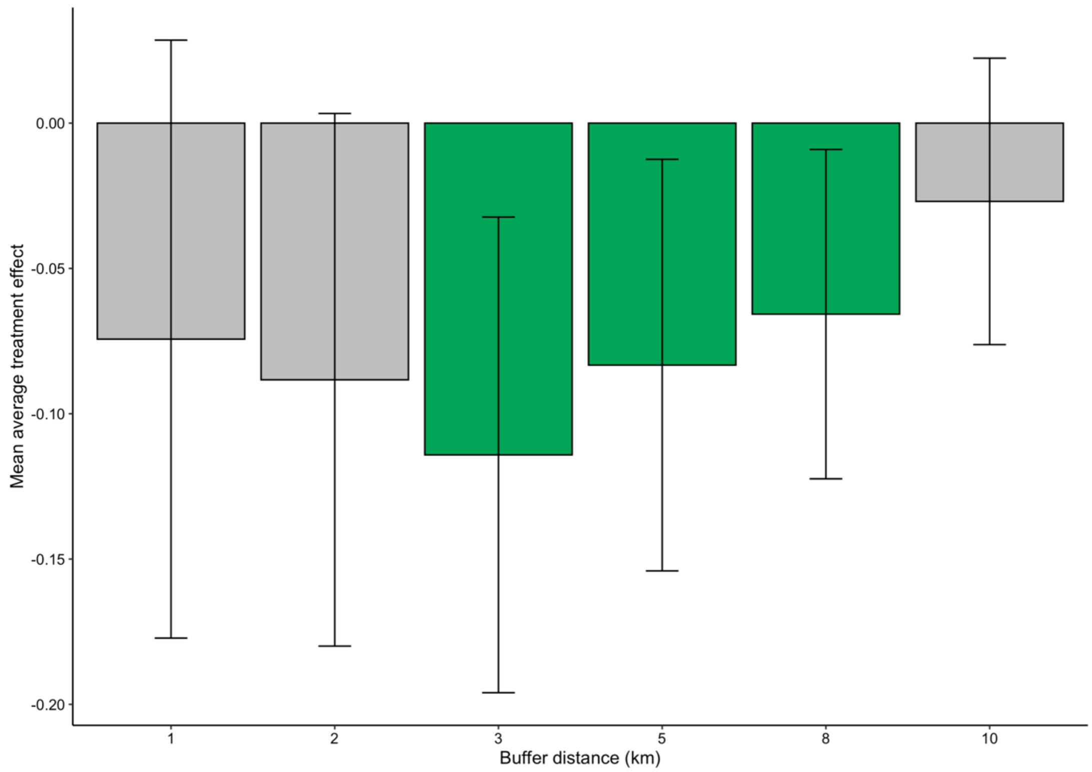


Figure S5. Mean average treatment effect values from causal forest models at all buffer distances; green indicates where the treatment effect was significant at 3, 5, and 8 kms. Error bars are 95% confidence intervals.

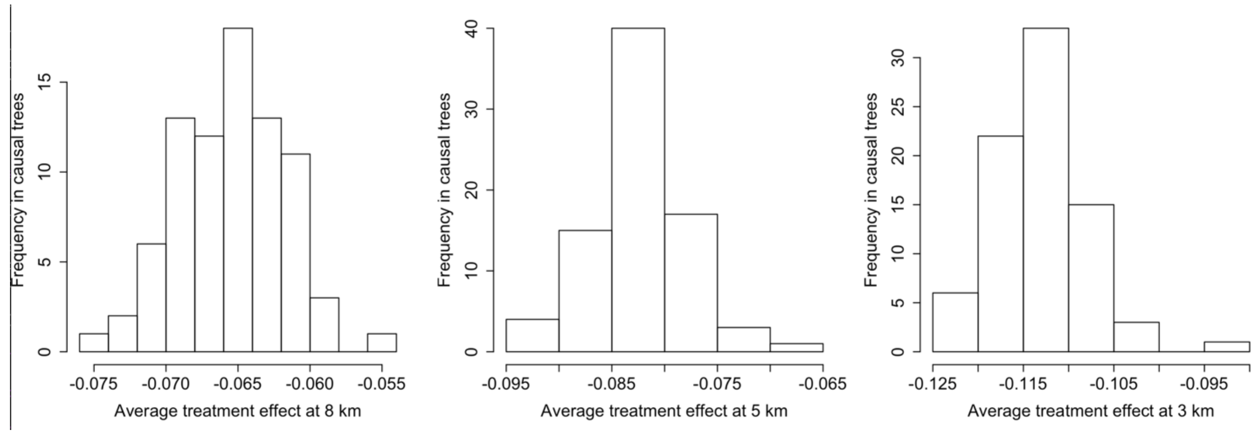


Figure S6. Histograms for the predicted average treatment effect in causal forest models at buffer distances where treatment was significant (3, 5, and 8 km).

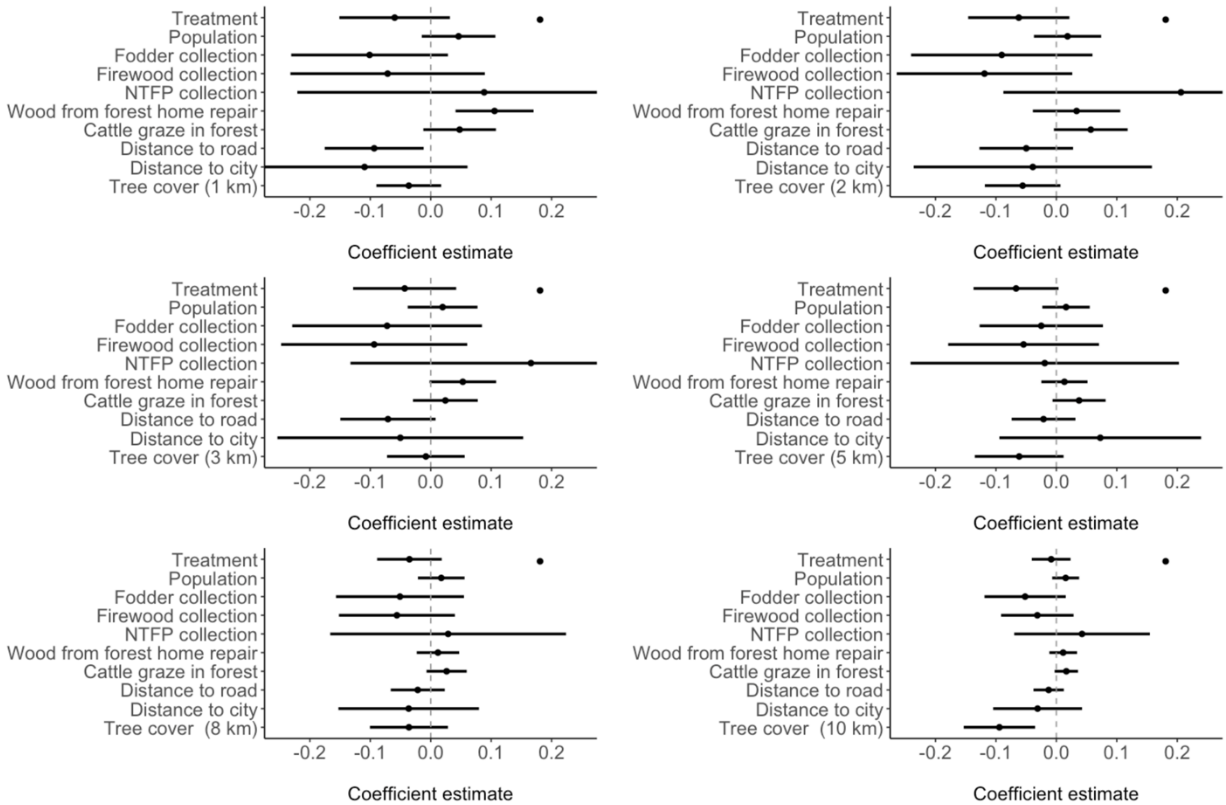


Figure S7. Coefficient plots for generalized linear regression models with District-level fixed effects assessing the associations of variables with forest health at all buffer distances. Points represent coefficients and whiskers show 95% confidence intervals.

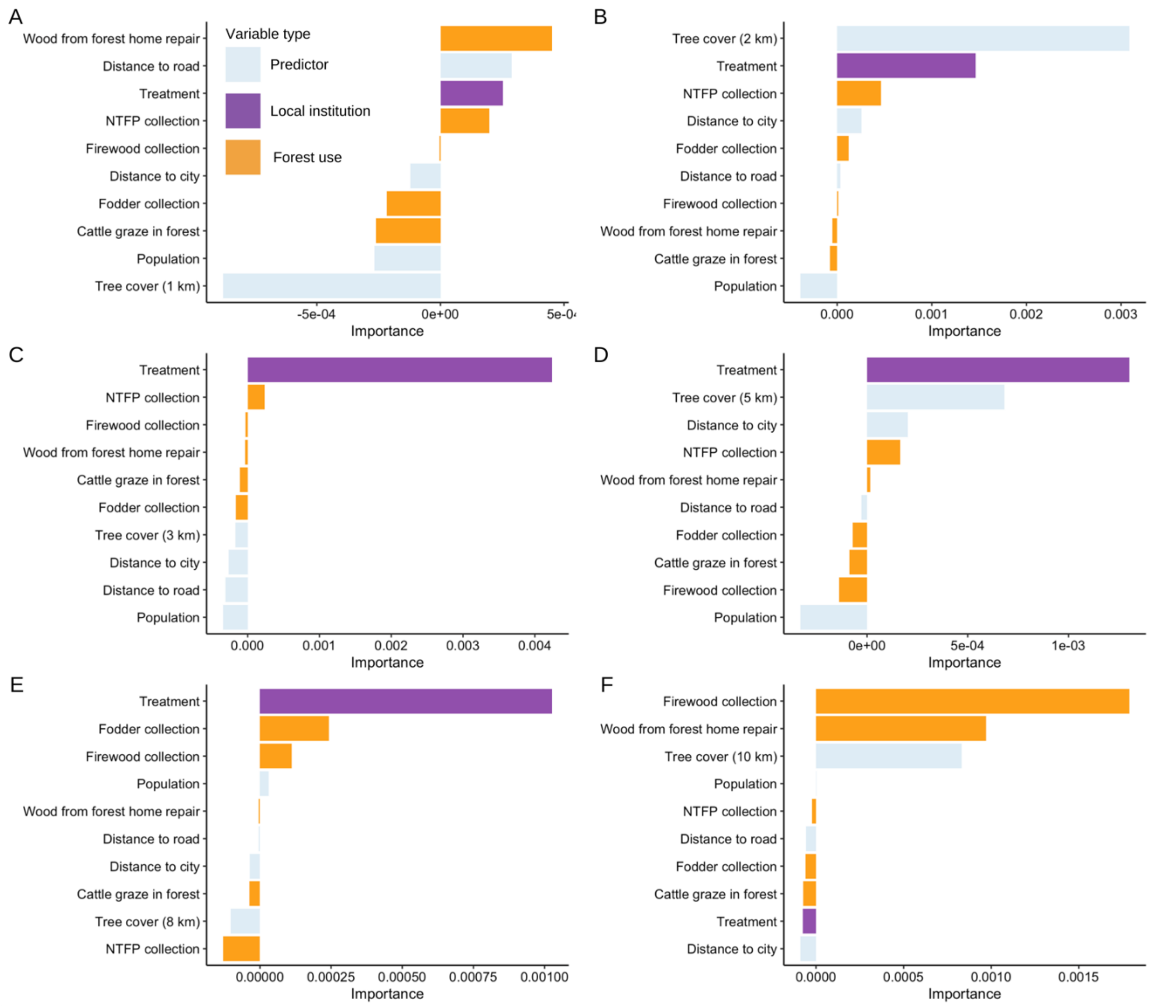


Figure S8. Relative importance of variables in conditional forest models predicting forest health at buffer distances of 1 (A), 2 (B), 3 (C), 5 (D), 8 (E), and 10 (F) kms from all study villages (N=80). The relative importance was determined by permuting values for each variable. The treatment variable is colored purple and variables measuring forest uses are colored orange.

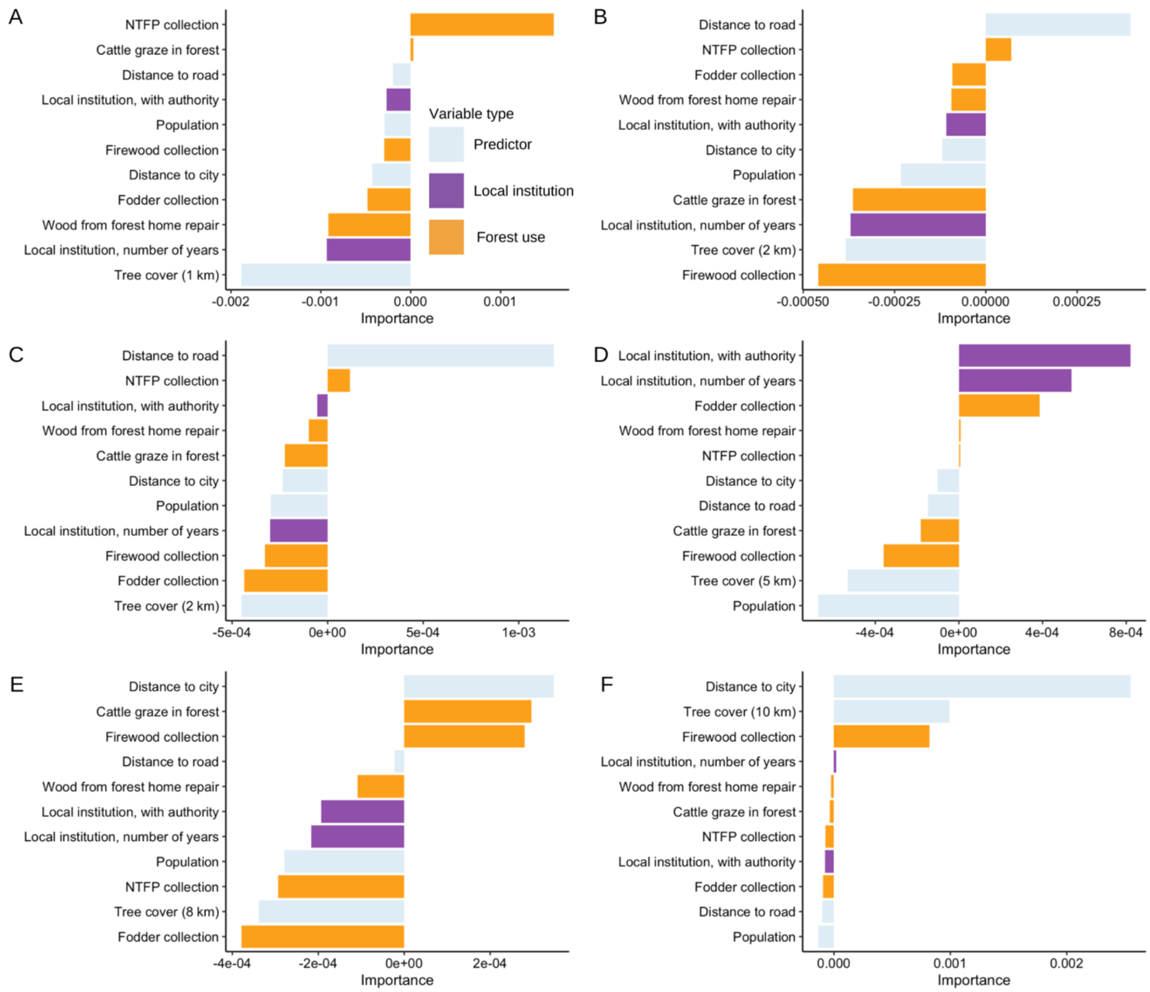


Figure S9. Relative importance of variables in conditional forest models predicting forest health at buffer distances of 1 (A), 2 (B), 3 (C), 5 (D), 8 (E), and 10 (F) kms only from villages that had a local forest management institution (N=40). The relative importance was determined by permuting values for each predictor variable. Variables that are characteristics of local forest management institutions are colored purple and variables measuring forest uses are colored orange.

Appendix C: Supplementary information for chapter 3

Table S1. Summary of distance traveled for firewood collection by season and all seasons combined. Only households reporting a distance traveled for firewood collection greater than 0 kilometers were retained for these statistics. The percent is calculated from the number of households reporting a travel distance of greater than 0 kilometers for a given season out of the total number of households (4994) included in our study.

	Summer	**Post-monsoon**	**Winter**	**Monsoon**	**All seasons**
Households reporting distance greater than 0, N (%)	4987 (99.9)	4985 (99.8)	4990 (99.9)	4982 (99.8)	4982 (99.8)
Distance traveled (km)					
Mean (SD)	3.03 (2.14)	2.97 (2.26)	3.06 (2.19)	2.73 (2.09)	2.74 (2.02)
Median (IQR)	3.0 (2.0, 4.0)	2.0 (2.0, 4.0)	3.0 (2.0, 4.0)	2.0 (2.0, 3.0)	2.0 (1.8, 3.0)

SD is standard deviation and IQR is interquartile range.

Table S2. Model results comparing the Akaike Information Criterion (AIC) and Multiple R-squared (R^2) value of models using tree cover (%) at distance of 1, 2, 2.74, 3, 5, 8, and 10 km.

	Equation 1 AIC	Equation 2 AIC	Equation 3, R^2 (average of 3 seasons, %)	Equation 3, R^2 (monsoon, %)
1 km	6536.12	2149.53	33.75	10.12
2 km	6536.97	2149.04	34.14	10.11
2.74 km	6540.34	2150.86	34.32	10.17
3 km	6541.90	2151.14	34.36	10.19
5 km	6545.69	2152.09	34.41	10.10
8 km	6552.95	2156.66	33.43	9.80
10 km	6558.39	2163.69	32.24	9.52

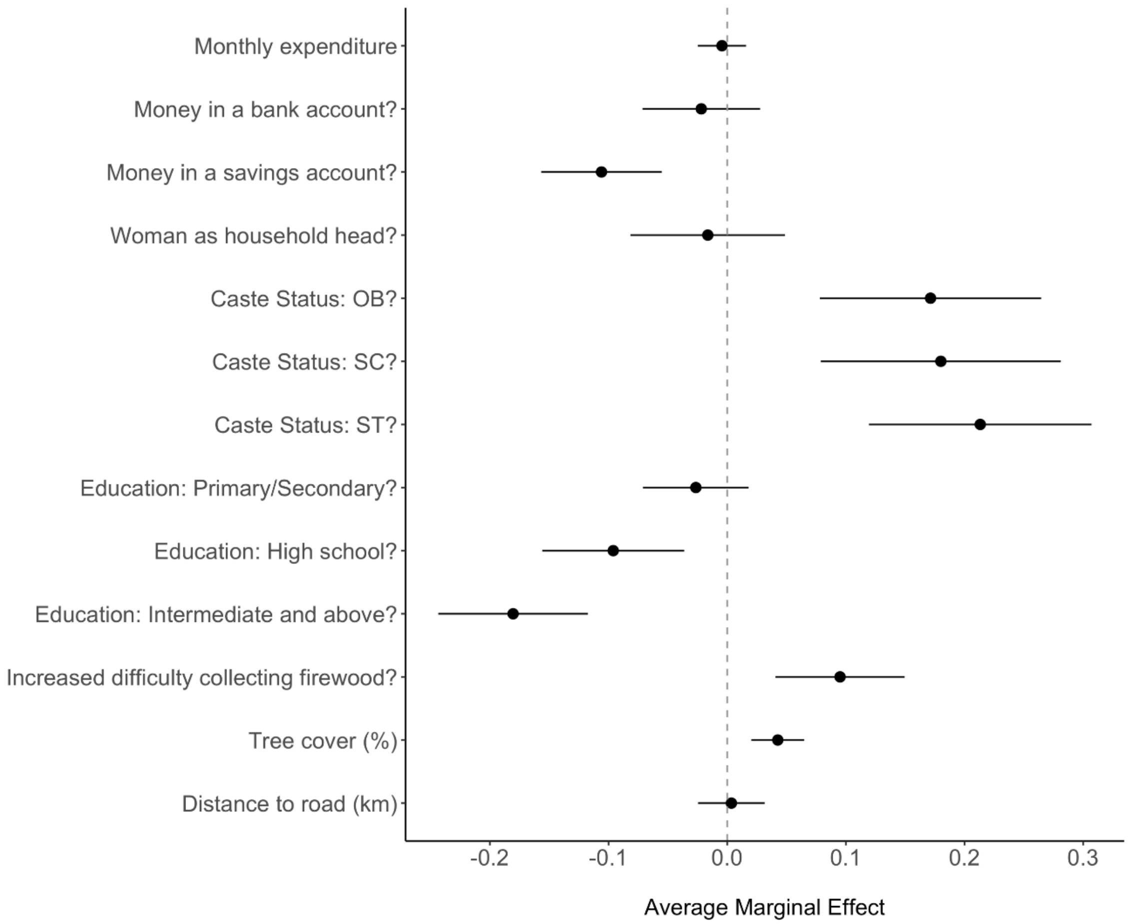


Figure S1. Coefficient plot for logistic regression with District Fixed Effects assessing the household characteristics that are associated with adopting LPG in 2017. Points represent coefficients of average marginal effects (percentage point change in the probability of adopting LPG in 2017) and whiskers show 95% confidence intervals. Compared to the final model (Figure 3), where we predicted LPG ownership in 2016 and 2017, monthly expenditure loses its significance in predicting LPG ownership in 2017. However, the relationships between the covariates and the outcome are the same when predicting LPG ownership in 2016 and 2017 versus 2017.

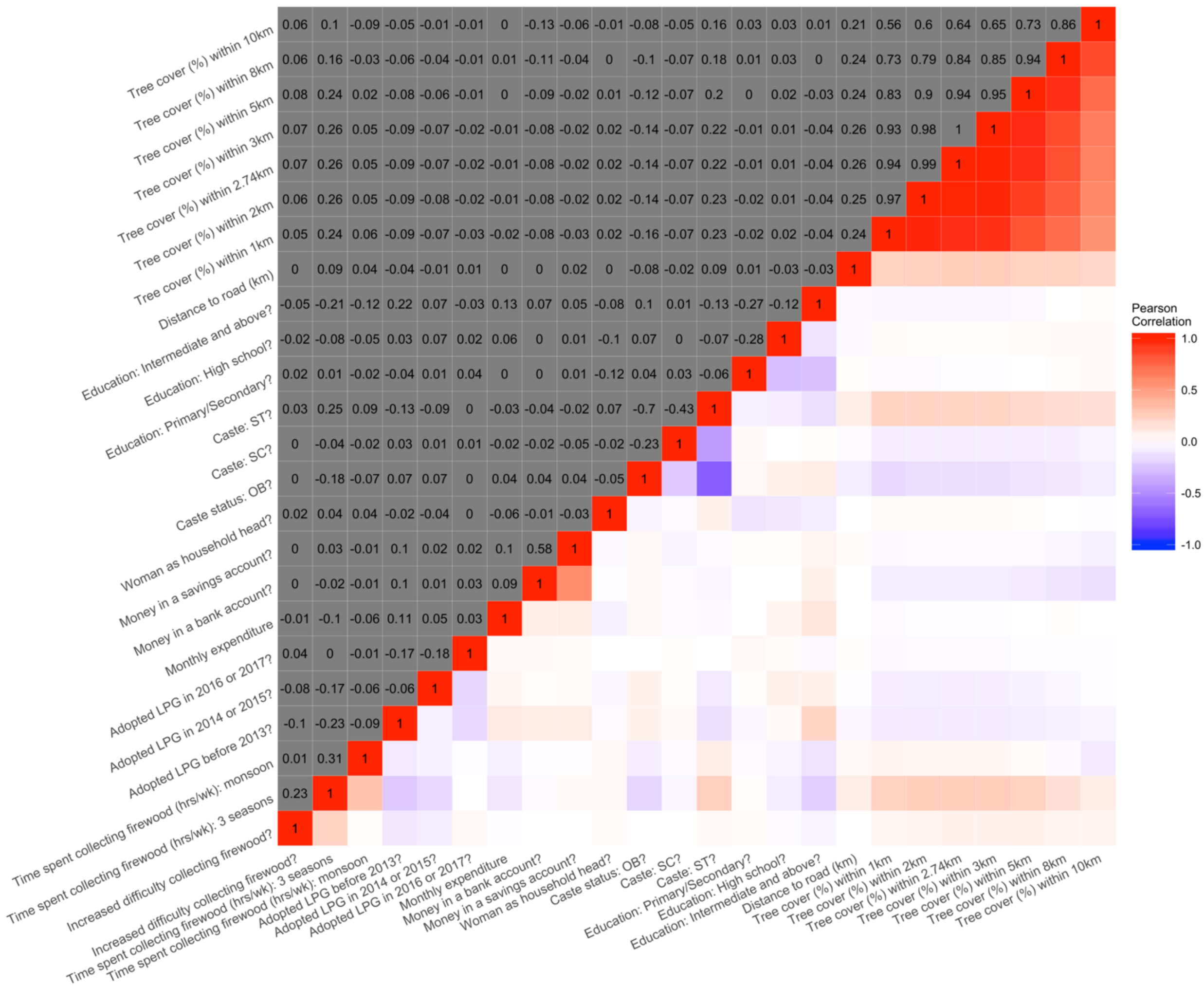


Figure S2. Correlation matrix of outcome and predictor variables.

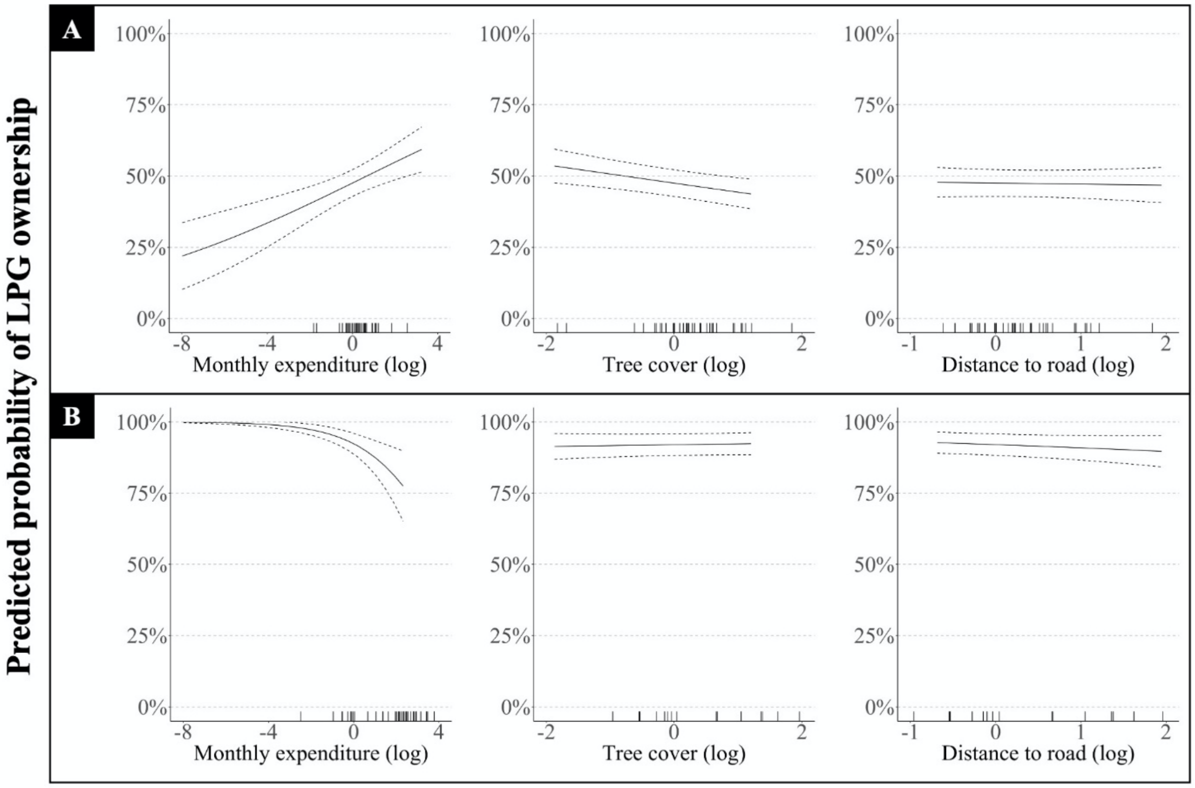


Figure S3. Conditional predicted probabilities of LPG ownership with 95% confidence intervals (dashed black lines) by monthly expenditure, tree cover, and distance to road for all households (A) and households that owned LPG (B). Monthly expenditure, tree cover, and distance to road are presented in their log and standardized form. Tick marks on the x-axis indicate all individual data points. Monthly expenditure and tree cover were significantly associated with LPG ownership in Equations 1 and 2.

Table S3. Models results comparing the Akaike information criterion (AIC) and Multiple R-squared (R2) value of models with and without District Fixed Effects (FEs).

	With District FEs	Without District FEs
Equation 1		
AIC	6540.34	6677.35
Equation 2		
AIC	2150.86	2219.00
Equation 3		
Post-monsoon, summer, and winter		
R^2	34.32%	23.21%
Monsoon		
R^2	10.17%	3.71%

Table S4. Models results comparing the Akaike information criterion (AIC) and Multiple R-squared (R^2) value of models with and without the covariate "Has money in a bank account?"

	With "Has money in a bank account"	Without "Has money in a bank account"
Equation 1		
AIC	6540.34	6548.21
Equation 2		
AIC	2150.86	2149.72
Equation 3		
Rabi, summer, and winter		
R^2	34.41%	34.32%
Monsoon		
R^2	10.18%	10.08%

Table S5. Percent tree cover within 2.74 km of a village boundary according to whether or not a household perceived increased difficulty in firewood collection over the last 5 years.

	Increased difficulty	**Increase ease or no change**
Sample size, N (%)	4391 (88)	603 (12)
Tree cover (%) within 2.74 km of village*		
Mean (SD)	5.72 (7.20)	5.03 (7.21)
Median (IQR)	3.28 (0.85, 7.51)	1.77 (0.19, 6.91)

* Indicates a statistically significant difference between the households depending on whether or not they perceived an increase in difficulty of firewood collection at $P < 0.05$ in ANOVA. SD is standard deviation and IQR is interquartile range.