


Improved household living standards can restore dry tropical forests

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Abstract

Despite multiple approaches over the last several decades to harmonize conservation and development goals in the tropics, forest-dependent households remain the poorest in the world. Durable housing and alternatives to fuelwood for cooking are critical needs to reduce multi-dimensional poverty. These improvements also potentially reduce pressure on forests and alleviate forest degradation. We test this possibility in dry tropical forests of the Central Indian Highlands where tribal and other marginalized populations rely on forests for energy, construction materials, and other livelihood needs. Based on a remotely sensed measure of forest degradation and a 5000 household survey of forest use, we use machine learning (causal forests) and other statistical methods to quantify treatment effects of two improved living standards—alternatives to fuelwood for cooking and non-forest-based housing material—on forest degradation in 1, 2, and 5 km buffers around 500 villages. Both improved living standards had significant treatment effects (-0.030 ± 0.078 , -0.030 ± 0.023 , 95% CI), respectively, with negative values indicating less forest degradation, within 1 km buffers around villages. Treatment effects were lower with increasing distance from villages. Results suggest that improved living standards can both reduce forest degradation and alleviate poverty. Forest restoration efforts can target improved living standards for local communities without conflicts over land tenure or taking land out of production to plant trees.

KEYWORDS

alternative energy, central India, dry tropical forests, forest degradation, multi-dimensional poverty, poverty alleviation

1 | INTRODUCTION

Despite decades of research and interventions to harmonize conservation and poverty alleviation goals in the tropics, successful strategies are elusive. In 1982, the third World Parks Congress in Bali adopted the principle that the needs of local people should be

integrated into protected area planning (Adams et al., 2004). With this shift away from a protectionist paradigm for conservation, policies in the 1990s promoted commercial non-timber forest products (NTFP) to improve local incomes and integrated conservation development projects (ICDP) (Campbell et al., 2010). Payments for Ecosystem Services (PES) and Reducing Emissions from

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Deforestation and Degradation (REDD+) developed in the 2000s as means to incentivize conservation.

While studies document benefits to local livelihoods in some cases, these strategies have been unable to alleviate poverty over the long term and on a large scale in the places where they have been implemented (Garnett et al., 2007; Nambiar, 2019). Areas of severe, multifaceted poverty continue to overlap with key areas for global biodiversity (Fisher & Christopher, 2007). Of the world's population living in extreme poverty, over 90 percent are dependent on forests for at least part of their livelihoods (Cheng et al., 2017; FAO & UNEP, 2020).

Many types of development undoubtedly have trade-offs with conservation, such as road expansion, dams, mines, and other infrastructure (Laurance & Arrea, 2017). However, interventions to improve living standards and health in forest-dependent households, such as alternative cooking fuels to alleviate indoor air pollution and durable housing, are potentially synergistic with reduced pressure on forests. Multi-dimensional poverty indicators consider living standards as key components of justice and poverty alleviation (Alkire & Santos, 2014; Rao & Min, 2018).

Forest and Landscape Restoration (FLR) is currently receiving considerable donor attention as a means to improve ecosystem health and human well-being. The 2021–2030 United Nations Decade of Ecosystem Restoration aims to halt the degradation of ecosystems in order to enhance livelihoods, counteract climate change, and stop the collapse of biodiversity (United Nations, 2019), while the Bonn Challenge has a global goal to restore 150 million hectares of degraded and deforested lands (Laestadius et al., 2015). These initiatives purport that improved ecosystem health contributes to livelihoods and poverty alleviation, but specific actions and policies to achieve the dual objectives remain fuzzy and are likely very context-dependent. Moreover, difficult problems such as unclear land tenure, competition for land between reforestation and food production, and biodiversity dis-benefits from mono-culture tree plantations create challenges in implementation of the restoration goals (Chazdon et al., 2021; Fischer et al., 2020; Fleischman et al., 2020).

Global and pan-tropical assessments of the potential for forest restoration to contribute to climate mitigation goals (Bastin et al., 2019; Brancalion et al., 2019; Cook-Patton et al., 2020; Griscom et al., 2017; Strassburg et al., 2020) do not generally include the place-based realities of forest dependence and needs to alleviate poverty. These analyses identify locations where reforestation is possible mainly from biophysical and economic perspectives. By excluding existing forests as targets for investments in restoration, they discount the potential for reduced forest degradation as an avenue to sequester carbon, conserve habitats, contribute to other ecosystem services, and improve livelihoods of local populations. Reforestation and afforestation to enhance carbon stocks are included in the program for Reducing Emissions from Deforestation and Degradation (REDD+), first launched by the United Nations Framework Convention on Climate Change in 2005, although these activities have not been a major focus and overall implementation of the program has not occurred on a large scale (Duchelle et al., 2018; Hein et al., 2018).

The trade-offs and synergies between poverty alleviation and conservation are particularly acute in seasonally dry tropical forests. These forests are the most endangered and least-studied tropical ecosystem with high degrees of degradation (Miles et al., 2006; Sánchez-Azofeifa & Portillo-Quintero, 2011; Sunderland et al., 2015). They face pressures from fragmentation, fire, climate change, and agricultural conversion (Miles et al., 2006). The combination of high incidence of poverty, forest dependence, and multiple pressures point to a need to understand whether interventions to alleviate poverty can be a pathway to forest regeneration.

In this paper, we quantitatively assess whether improved living standards can alleviate pressure on forests and reduce degradation for a study region in central India with dry tropical forests. Using a remotely sensed measure of degradation, 5000 household survey about forest use, and multiple statistical analyses, we address the question: “Do improved living standards (alternative energy and durable housing) reduce forest degradation around villages in the study region?”

This question is relevant to identify possible synergies between development interventions to improve living standards—such as the Ujjwala scheme launched in 2016 to provide poor households with Liquefied Petroleum Gas (LPG) for cooking (Khanwilkar et al., 2021) and government schemes to finance durable housing for poor households (Bharti, 2019)—and global forest restoration efforts. At a national level, the National Mission for a Green India (GIM) aims to increase tree cover on 5 million hectares and improve tree cover on an additional 5 million hectares (Government of India, n.d.). Opportunities to reduce local pressures on forests potentially contribute to the latter goal without increased investments in enforcement and conflicts between local people and forest management about restrictions on forest use.

In addition, we assess whether in this study region improved living standards at a local level are a pathway to forest transitions and increased forest cover. Many pathways have led to forest transitions in different countries depending on historical and geographical contexts, including labor scarcity-induced changes in land uses that shift villagers' reliance on community forests to trees on less productive croplands for fodder, fuelwood, and construction materials; commercial demand for timber; and abandonment of less productive land with structural changes from agrarian to urban economies (Marquardt et al., 2020; Meyfroidt & Lambin, 2011). From this perspective, we aim to broaden the possibilities for interventions to achieve forest restoration goals that improve forest health and simultaneously benefit the well-being of local households.

2 | DATA AND METHODS

2.1 | Study region

The study region covers ~25 million hectares (7.6% of the total land area of India) with boundaries defined by the agro-ecological zone for the Central Indian Highlands, one of twenty agro-ecological zones in the country (Gajbhiye & Mandal, 2000; Figure 1). The

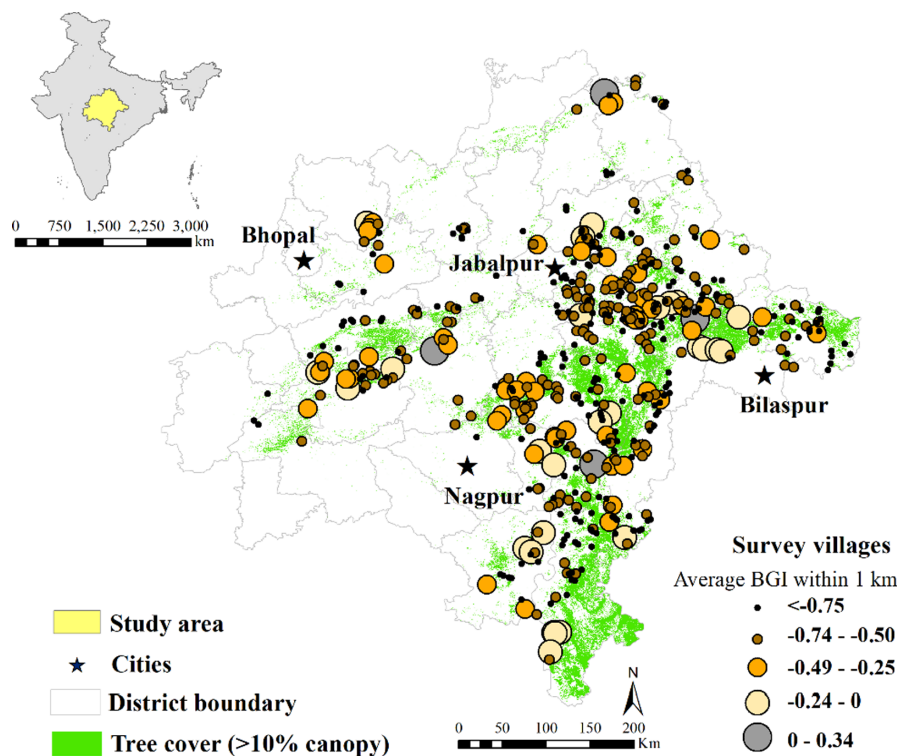


FIGURE 1 Location of study region and surveyed villages with value for Bare Ground Index (BGI). Higher value for BGI indicates higher forest degradation

landscape contains some of the largest remaining forest patches in the country (Nayak et al., 2020), which are mainly tropical dry and tropical moist deciduous forests (Champion & Seth, 1968). It includes 32 administrative districts spanning the states of Madhya Pradesh, Chhattisgarh, and Maharashtra. The Central Indian Highlands encompasses the headwaters for five major rivers that supply water downstream for agricultural and urban uses (Clark et al., 2016). The study region is also identified as a Global Priority Landscape for tiger conservation and supports ~30% of the total tiger population in India (DeFries et al., 2016; Sanderson et al., 2010).

Seventy percent of the study region's population is rural. This study focusses on the population that lives within the forest fringe (defined here as within 8 km of a forest patch >500 ha), which contains 37% of all villages in the study region (DeFries et al., 2020). The population in the forest fringe consists of small-scale farmers and communities who depend on forests for fuelwood, fodder, construction materials, and non-timber forest products (Kumar & Kushwaha, 2020). Sixty-nine percent of the population in our sample of villages in the forest fringe belongs to constitutionally recognized Schedule Caste or Scheduled Tribe categories, which includes indigenous and other marginalized groups. By comparison, 25% of India's total population falls within these categories (Baquie et al., 2020).

The vast majority of households in the sampled forest fringe villages use fuelwood as their primary energy for cooking and heating. In 2016, the government launched a nation-wide scheme (Pradhan Mantri Ujjwala Yojana) to cover costs of Liquefied Petroleum Gas (LPG) installations for women in below-poverty level households. Households are required to purchase their LPG stoves and cylinder

refills. Adoption has been uneven, likely due to the cost of refills, free availability of biomass, and cultural preferences. In the study region, households adopting LPG since 2016 are poorer, closer to forests, and less formally educated than prior to 2016, indicating the success of the program, although nearly all households continue to collect fuelwood (see section on household surveys; Khanwilkar et al., 2021).

Houses in the study region are generally made of mud, dung, and wood (known as *kutchha*) rather than concrete (known as *pucca*). *Kutchha* houses require frequent repair and maintenance using wooden beams. In 1996, the government launched a flagship program (Indira Awaas Yojana) targeted at the rural poor to provide financial assistance to families for constructing safe and durable shelter. Implementation across and within states has been fragmented. The government restructured the plan in 2016 (Pradhan Mantri Awaas Yojana) with the aim of providing *pucca* houses with basic amenities to all houseless families and those living in *kutchha* houses by 2022.

2.2 | Household surveys

We conducted 5000 household surveys in 500 forest fringe villages between January and April 2018. Villages within 8 km of forest (maximum distance people travel in the study region in a day) were selected through a stratified random sample based on distance to closest town and distance to a primary or secondary road (Figure 1). We randomly selected ten households in each sampled village. Each surveyed household responded to an approximately 45-minute interview which included questions about composition of

the household, forest use, and migration patterns. For details of the sample design and survey method, see (Baquie et al., 2020).

The survey provides data for two binary treatment effects:

Alternative energy for cooking: A response to the question “does your household use LPG for cooking?” with response options as “yes” or “no” provided data to test the effect of alternative energy on forest degradation, based on the observation that LPG is the main alternative to fuelwood in the study region. Survey responses indicate that 95% of households use fuelwood for cooking. Fifty-four percent report using LPG of which 75% also use fuelwood. Only 1.4% of households report using biogas, electric heater, induction, solar energy stoves, or other alternative energy sources for cooking.

Of the households who use LPG, 69% report that they collect wood from the forest for cooking, heating, or selling. In contrast, 83% of households who do not use LPG report that they collect wood from the forest (Figure S1).

Durable house material: Of the 5000 households in the survey, 82% of houses were *kutch*a and 18% of houses were *pucc*a or mixed. For the treatment variable in the models, we use the response to the question “is the house *pucc*a or *kutch*a?” as observed by the survey enumerator.

In the households with *kutch*a houses, 80% responded “forest” to the question “where do you get wood to repair your house?” with options as depot, forest, market, or other. In the *pucc*a and mixed households, 33% responded “forest” (Figure S2).

The surveys also provided data for household-level predictor variables that potentially affect forest degradation and confound the effect of the treatment variables, including number of cattle owned, whether cattle graze in the forest, fodder and NTFP (non-timber forest product) collection, and whether households get wood for repair and energy from the forest (Table 1).

2.3 | Satellite data and GIS layers

We derived measures of forest cover and forest degradation from high-resolution (3m) remote sensing imagery from Planet Labs, Inc. We first classified the landscape into five land covers (tree cover, bare ground, water, built environment, and cropland) with a random forest classifier and training data from field observations and very high-resolution data. We aggregated the classification result to 90m resolution and calculated the % of bare ground and % tree cover in each 90-m grid cell. We derived a forest mask defined as grid cells with greater than 10% tree cover. In each grid cell identified as forest, we calculate a Bare Ground Index (BGI) as a normalized ratio of bare ground to tree cover (bare ground minus tree cover divided by bare ground plus tree cover). BGI can vary from -1 (full tree cover) to $+0.8$ (all bare ground aside from 10% tree cover).

Field validation indicates that the BGI is a reasonable proxy for intensity of human use (Baquie et al., 2020). Although some studies suggest that dry deciduous forests of India, particularly central India, are savanna where low canopy cover is natural (Ratnam et al., 2011,

2016), we found that exposed bare ground within forests (>10% tree cover) and without grass or understory is related to degradation from human use. Analyses of satellite data were carried out in Google Earth Engine.

Additional village-level layers (distance from road and distance from closest town) were derived from GIS analysis to capture potential differences in pressures on forests due to proximity to economic activities and access by outsiders (Table 1). We also include the proportion of the buffer within a protected area boundary to account for potentially restricted access to forests within protected areas.

Buffers at 1, 2, and 5 km were derived from the boundaries of village polygons. We chose 5 km as the distance based on the 95% percentile of the distance that people report in the surveys to graze cattle and collect fuelwood, non-timber forest products, and fodder (Table S1). Although the Forest Department identifies forest areas for villagers to use, our experience indicates that villagers are often not aware of these locations and rather use forests in closest proximity (Agarwala et al., 2016). We expect that most local use of forests would be within 5 km with increased use in closer proximity to villages.

2.4 | Statistical models

To derive treatment and control groups for the models, we matched households with the variables in Table 1 for each of the two treatment variables. We chose variables that plausibly have a direct effect on forest degradation, such as number of cattle and NTFP collection, rather than variables that could indirectly be related to forest use such as education and income as analyzed elsewhere from the household surveys (Baquie et al., 2020; Velho et al., in press).

For each of the two pairs of treatment and control groups, we included the other treatment variable in the match along with the predictor variables. This process resulted in treatment and control groups for each treatment that vary in the numbers of observations (Table S2). We matched the households in R with the “matchit” function with optimal full matching (Stuart & Green, 2008).

We assessed significance of associations between treatment effects and outcomes for two treatment effects and three outcomes: average BGI in 1 km, 2 km, and 5 km buffers around village polygons. The result is six separate models. To assess whether results are consistent across methods, we used three different approaches:

1. Wilcoxon tests to determine the significance of differences in median values for average BGI in 1 km, 2 km, and 5 km buffers for each of the two treatment-control groups. Variance estimates were clustered by village. We used the R package “clusrank.”

2. Causal forests, a machine learning method to derive treatment effects. Machine learning provides non-parametric methods to identify patterns in large data sets. Causal forests is one method within supervised machine learning (e.g., regression

TABLE 1 Treatment and predictor variables and data sources used in the models

	Description	Data source
Treatment variables		
Alternative energy for cooking	1=household uses LPG 0=household does not use LPG	survey
Durable house material	1=pucca or mixed house material 0=kutchra house	survey
Predictor variables		
Number of cattle	Number of cattle owned by household	survey
Cattle feeding outside forest	1=cattle graze in forest in any season 0=cattle do not graze in forest	survey
Fodder collection from forest (months/year)	Number of months per year household collects fodder from forest	survey
NTFP collection (months/year)	Number of months per year household collects non-timber forest products	survey
Get wood from forest to repair house	1=get wood from forest for repair 0=get wood from other source (depot, market) or do not use wood for repair	survey
Get wood from forest for energy	1=get wood from forest for cooking, heating, lighting, or selling 0=do not get wood from forest	survey
Distance of village from road (km)	Distance of village from primary or secondary road	(DIVA-GIS)
Distance of village from town (km)	Distance from closest town or city as defined by 2011 census	(Government of India, 2011)
Forest per household (%) in 1km buffer	% of 1 km buffer around village with >10% tree cover per number of households in village	Planet Lab classification
Forest per household (%) in 2km buffer	% of 2 km buffer around village with >10% tree cover per number of households in village	Planet Lab classification
Forest per household (%) in 5km buffer	% of 5 km buffer around village with >10% tree cover per number of households in village	Planet Lab classification
% forest in 1 km buffer	% of 1 km buffer around village with >10% tree cover	Planet Lab classification
% forest in 2 km buffer	% of 2 km buffer around village with >10% tree cover	Planet Lab classification
% forest in 5 km buffer	% of 5 km buffer around village with >10% tree cover	Planet Lab classification
% 1km buffer in PA	% of 1km buffer around village within boundary of Protected Area	Overlay PA boundaries on village buffer
% 2km buffer in PA	% of 2km buffer around village within boundary of Protected Area	Overlay PA boundaries on village buffer
% 5km buffer in PA	% of 5km buffer around village within boundary of Protected Area	Overlay PA boundaries on village buffer

Note: Outcome variables for the models are the Bare Ground Index at 1 km, 2 km, and 5 km buffers around village polygons. See Tables S2 and S3 for values of variables for treatment and control groups.

trees, random forests, and LASSO; Athey & Imbens, 2016). The method is intended to specifically identify heterogeneous causal relationships from data sets without prior assumptions about causality. The main difference between decision (for categorical response variables) or regression (for continuous response variables) trees (Breiman et al., 1984) and causal trees is that the

former is designed to maximize predictive capability with “if-then” rules without the goal of causal discovery. Causal decision trees are designed to reveal causal pathways for outcomes among heterogeneous groups and identify treatment effects of interventions while eliminating the effect of confounding variables. Causal inference with causal decision trees is increasingly used to

determine treatment effects in health studies, social sciences, and other applications, for example (Athey & Wager, 2019; Biesbroek et al., 2017; Davis & Heller, 2017).

Algorithms for causal decision trees differ from standard decision trees by deriving the paths in the tree so that each predictor variable has a causal relationship with the outcome variable through classic statistical tests for partial associations. The variable is included only if it has a statistically significant relationship with the outcome variable. While this approach can lessen the predictive capability on unseen cases compared with supervised classification approaches such as decision trees and random forests, the benefit is that the causal relationships contain information about the conditions in which a causal relationship holds, so that the results are more actionable and suitable for decision support and intervention planning (Li et al., 2016). The treatment effect is determined by running the tree on an “honest” sample by deriving the tree from one random sub-sample, pruning the tree to avoid over-fitting, and applying the tree to another random sub-sample. The average treatment effect is derived from the difference from the mean BGI in each leaf in the tree for treatment and control observations.

Causal forests run many iterations of causal trees, similar to random forests. For each treatment effect, we ran 10,000 causal trees with predictors in Table 1 to derive histograms of the average treatment effects for each of three outcomes: average BGI in 1 km, 2 km, and 5 km buffers around village polygons. Following (Athey & Wager, 2019), we use the village variable to cluster samples. After first generating a forest with all variables, we run a second causal forest with only the variables with variable importance values above the mean so that the forest makes splits on important variables. We use the R function “causal_forest.”

3. General linear models with all variables in Table 1 to test the significance of the treatment variables. Prior to running the models, we checked co-linearity to eliminate variables with Pearson's correlation coefficient >0.5 and Variable Inflation Factor >5 and scaled all predictor variables. We use R function “glm.cluster” with errors clustered by village.

3 | RESULTS

For each of the methods to test differences between treatment and control groups for two living standard treatment variables (alternative energy for cooking and durable house material), we find that households with improved living standards are significantly related to less forest degradation in 1 km, 2 km, and 5 km buffers around their villages.

Wilcoxon tests of the difference in buffers' median BGI between treatment and control groups are significant for all treatment variables in the buffers (all $p < 0.05$ except durable house material in 5 km buffer with $p < 0.10$). Treatment groups have lower BGI (less forest degradation) than control groups (Table 2). As expected, BGI values are lower with increasing buffer distances reflecting higher forest degradation closer to villages.

TABLE 2 Results of Wilcoxon test for differences in Bare Ground Index (BGI) between treatment and control groups for two living standards

	Alternative energy for cooking		Durable house material	
	Treatment	Control	Treatment	Control
BGI in 1 km buffer	-0.73*	-0.70*	-0.74**	-0.72**
BGI in 2 km buffer	-0.74**	-0.72**	-0.72*	-0.75*
BGI in 5 km buffer	-0.75**	-0.73**	-0.75 [#]	-0.74 [#]

Note: Values are median BGI in 1 km, 2 km, and 5 km buffers around villages. Lower BGI values indicate less forest degradation. See Table S2 for numbers of observations and balance of treatment and control groups. p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

Results from causal forests, with Bare Ground Index in 1 km buffer as the outcome variable, indicate treatment effects of -0.030 ± 0.018 (95% CI) for alternative energy for cooking and -0.030 ± 0.023 for durable house material. Figure 2 shows the histogram of the treatment effects in the causal trees (Figures S3 and S4 are histograms for outcome variables BGI in 2 km and 5 km buffers). Negative values for treatment effects indicate that households in the treatment group have lower BGI values (less forest degradation) than households in control groups.

Average treatment effects from causal forests are similar for both treatments—alternative energy for cooking and durable house material—in the 1 km buffer. The effect declines in the 5 km buffer, particularly for durable housing material, suggesting that people obtain fuelwood further from the village than they do for house material (Figure 3).

Variable importance values from the causal forests indicate that percent of forest per household and percent of forest in buffers around villages, as well as distance of village from towns and roads, are generally the most important variables to predict forest degradation (Tables S3 and Table S4). Other variables related to household forest use are less relevant.

For the generalized linear model, percent forest per household in 1 km, 2 km, and 5 km buffers was co-linear. Similarly, percent forest in buffer in the three buffers was co-linear. We consequently used the buffer distance corresponding to the buffer distance for average BGI in each model. Model results reinforce the conclusion from causal forests that both absolute percent and per household availability of forest are important variables explaining degradation. In agreement with the causal forest and Wilcoxon tests, the treatment effect of alternative energy for cooking is significant and associated with lower BGI (less degradation) at 1 km, 2 km, and 5 km buffer distances. Durable house material is marginally significant for the 1 km buffer and not significant for the other two buffer distances (Table 3).

In sum, the three methods together provide strong evidence that households with non-fuelwood, alternative energy for cooking are

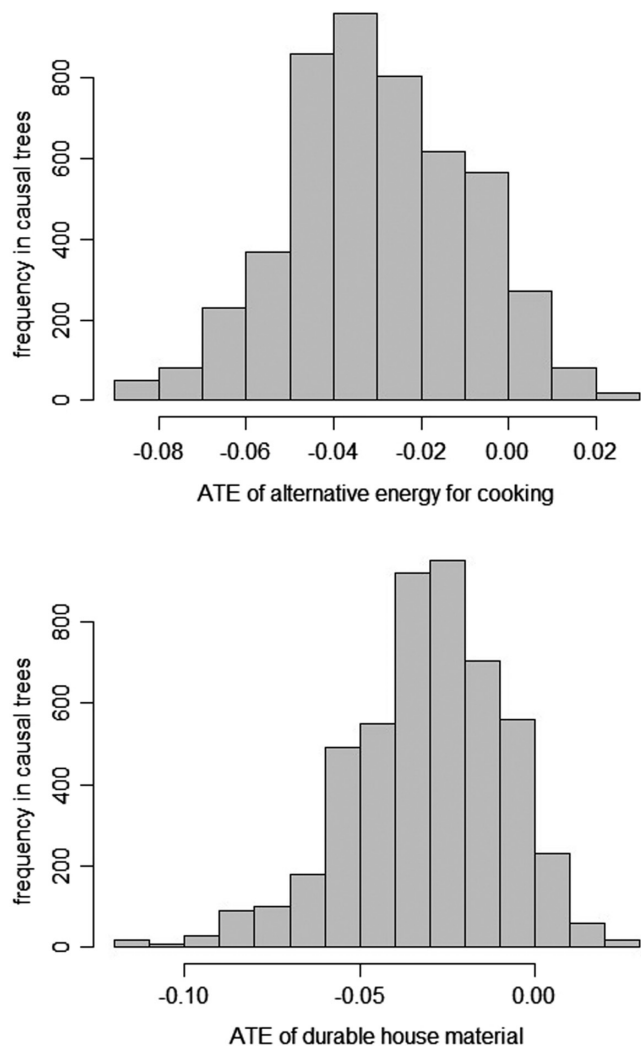


FIGURE 2 Histograms of average treatment effects (ATE) from causal forests for alternative energy for cooking (top) and durable house material (bottom). Outcome variable is average Bare Ground Index in 1 km buffer around village. Note differences in scale for x-axes. See Figures S1 histograms of ATEs for 2 km and 5 km buffers

associated with less forest degradation up to at least a 5 km buffer around villages. Durable housing material is related to reducing forest degradation in close proximity to villages but less significant with distance from village.

4 | DISCUSSION AND CONCLUSIONS

Results from this analysis indicate that, in this study region, improved living standards that reduce reliance on forest resources could both benefit households and improve health of the forests. Unlike reforestation, poverty alleviation through improved living standards provides an approach that does not clash with land tenure or competition for land needed for food security and other uses. The results of this paper provide evidence that, in addition to cash transfers shown to reduce deforestation in Indonesia (Ferraro &

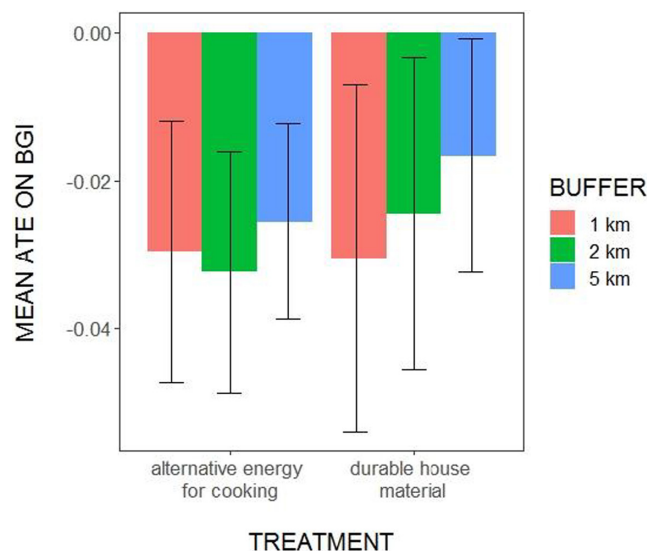


FIGURE 3 Mean values from causal forests for Average Treatment Effects (ATE) for two treatments with outcome as Bare Ground Index in 1 km, 2 km, and 5 km buffers around village. Negative values of mean ATE indicate less forest degradation with treatment. Error bars are 95% confidence intervals

Simorangkir, 2020), a multi-dimensional poverty perspective with a focus on living standards could likewise simultaneously achieve goals for human well-being and conservation without potentially harmful forest use restrictions on local people. Strategies with a primary objective to improve livelihoods provide alternatives to forest carbon and other conservation projects, which can have negative impacts on livelihoods (Aggarwal & Brockington, 2020).

Results also indicate that forest available to households is insufficient to sustainably support livelihood needs with current levels of forest use. Three statistical methods collectively provide strong evidence that alternative energy for cooking is associated with reduced forest degradation. Similar impacts of clean cook stoves have been found, for example, in the Indian state of Karnataka (Agarwala et al., 2017) and the Democratic Republic of Congo (Kahlenberg et al., 2020), but most studies focus on health rather than environmental impacts (Jeuland et al., 2021).

Eighty-three percent of surveyed households obtain wood from forests for cooking and have not yet adopted alternatives such as LPG (Figure S1). A large potential exists in this landscape to reduce forest dependence, improve indoor air quality, and achieve other benefits from alternative energy sources (Anderman et al., 2015; Ranjan, 2019; Singh et al., 2017). Durable housing would reduce dependence on forests for construction for 66% of households (Figure S2).

This study uses LPG as the treatment case for alternatives to energy for cooking and *pucca* concrete houses as alternatives to forest-based house construction. Each of these alternatives potentially creates other problems and displaces environmental impacts. LPG, although increasingly adopted in the study region (Khanwilkar et al., 2021), is expensive for households, and cylinders require refilling. Moreover, nationally, natural gas requires dependence on imports

TABLE 3 Coefficients and standard errors clustered by village (parentheses) for treatment and predictor variables from generalized linear models with outcome variables for average Bare Ground Index (BGI) in 1 km, 2 km, and 5 km buffers around villages

Variable	BGI in 1 km buffer	BGI in 2 km buffer	BGI in 3 km buffer
Treatment: Alternative energy for cooking	-0.010 (0.004)*	-0.013 (0.004)**	-0.011 (0.003)**
Treatment: Durable housing material	-0.010 (0.004)#	-0.005 (0.004)	-0.000 (0.003)
Cattle feeding outside forest	-0.010 (0.005)#	-0.006 (0.050)	-0.000 (0.003)
Number of cattle	-0.006 (0.004)	0.007 (0.004)#	0.004 (0.003)
Fodder collection from forest (months/year)	-0.000 (0.004)	-0.001 (0.003)	0.000 (0.002)
NTPF collection (months/year)	-0.001 (0.005)	-0.010 (0.005)	0.000 (0.004)
Get wood from forest for energy	0.011 (0.006)	0.010 (0.005)*	0.001 (0.004)*
Get wood from forest to repair house	0.010 (0.005)*	0.010 (0.005)*	0.001 (0.003)*
Forest per household (%) in 1km buffer	-0.018 (0.009)#	n.a.	n.a.
Forest per household (%) in 2km buffer	n.a.	-0.016 *(0.008)	n.a.
Forest per household (%) in 5km buffer	n.a.	n.a.	-0.001 (0.007)
% forest in 1 km buffer	-0.056 (0.012)***	n.a.	n.a.
% forest in 2 km buffer	n.a.	-0.052 (0.011)***	n.a.
% forest in 5 km buffer	n.a.	n.a.	-0.041 (0.008)***
% 1km buffer in PA	0.006 (0.001)***	0.010 (0.001)***	0.000 (0.001)**
% 2km buffer in PA	-0.005 (0.006)	-0.013 (0.005)	-0.018 (0.004)**
% 5km buffer in PA	-0.004 (0.010)	0.000 (0.009)	0.000 (0.007)
Distance of village from town (km)	0.033 (0.011)**	0.030 (0.010)**	0.019 (0.008)
Distance of village from road (km)	-0.002 (0.011)	-0.003 (0.010)	0.000 (0.008)

Note: Negative coefficients indicate less forest degradation (lower BGI) with increasing value of variable. See Table 1 for description of variables. "n.a." indicates that variable was not included due to co-linearity. *p* values are *** <0.001, ** <0.01, * <0.05, and # <0.10. *n* = 4940.

and prices are subject to market fluctuations. India imports approximately forty-five percent of its natural gas consumption (Hameed, 2020). Other alternative energy sources, including biogas from dung and household waste, could be suitable for reducing pressures on forests and improving indoor air quality while avoiding dependence on natural gas supplies. Likewise, *pucca* houses are concrete, which retain heat in a hot climate and do not have the air flow and communal courtyards of traditional houses. Construction with concrete is also a source of greenhouse gas emissions. If people want to remain living in *kutcha* houses, wood for construction could come from woodlots or depots rather than forests surrounding villages to avoid forest loss (Temudo et al., 2019). In sum, multiple options could improve living standards and improve forest health while minimizing other undesirable outcomes and displacing environmental impacts to other locations.

This study has several limitations. It suggests causality through the designation of treatment and control groups and the use of machine learning causal methods. However, causality is not completely assured. The possibility for an alternative interpretation of reverse causality exists if less forest degradation caused adoption of LPG or construction of *pucca* houses, rather than the other way around.

Logically, however, one would not expect that lower degradation would promote adoption of these alternatives. A more plausible explanation is that alternative energy and construction material lead to less dependence on forests and reduced forest degradation. Time series of forest degradation and forest use with control and treatment groups would provide a basis for stronger conclusions, but such time series are not available. A time series would also provide insight into questions about whether forest regeneration can occur naturally with the alleviation of human pressures, how long forest regeneration requires, and whether active forest regeneration is needed to restore these dry tropical forests. In addition, we cannot distinguish whether living standards vary due to government policies, such as schemes to promote LPG adoption and durable housing, or to increased income for individual households. Another limitation is that the remotely sensed proxy for forest degradation, the Bare Ground Index, captures exposed ground but does not capture other forms of degradation such as invasive species or mono-culture plantations.

This study adds to the growing literature that quantitatively evaluates livelihood impacts from forest conservation interventions, for example (Ferraro & Simorangkir, 2020; Jayachandran et al., 2017).

It also points to a critical need to re-evaluate the goals for forest restoration and place living standards of forest-dependent people as a central consideration for where, how, and what interventions governments and civil society pursue to improve carbon sequestration and other ecosystem services from forests.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the Dryad Digital Repository: <https://doi.org/10.5061/dryad.44j0zpcdg> (DeFries et al., 2021). The classified satellite data are available through the NASA Land Cover and Land Use Change data portal at <https://lcluc.umd.edu/metadatafiles/LCLUC-2017-PI-Defries/>.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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