Limited effects of tree planting on forest canopy cover and rural livelihoods in Northern India

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Abstract

Many countries have adopted large-scale tree-planting programs as a climate mitigation strategy and to support local livelihoods. We evaluate a series of large-scale tree planting programs using data collected from historical Landsat imagery in the state of Himachal Pradesh in Northern India. Using this panel dataset, we use an event study design to estimate the socioeconomic and biophysical impacts over decades of these programs. We find that tree plantings have not, on average, increased the proportion of forest canopy cover, and have modestly shifted forest composition away from the broadleaf varieties valued by local people. Further cross-sectional analysis, from a household livelihood survey, shows that tree planting supports little direct use by local people. We conclude that decades of expensive tree planting programs in this region have not proved effective. This result shows that large-scale tree planting may sometimes fail to achieve its climate mitigation and livelihood goals.

Main

Many countries have begun adopting large-scale tree-planting programs based on the potential of forests to absorb carbon and support local livelihoods[1–3]. As of 2015, the extent of global tree cover from planted forests is estimated at 280 million hectares, and 12 million hectares lie within India[4]. Despite the broad appeal of planting trees, some researchers and practitioners have raised concerns about potential negative impacts of large-scale tree-planting programs on vulnerable people and diverse ecosystems[5–7]. Restoration ecologists have cautioned that tree planting should not be equated with forest restoration, but instead countries should consider diverse restoration strategies in diverse ecosystems[7]. However, forest restoration commitments made under international agreements like the Bonn Challenge and UNFCCC Paris Accords demand nationally-coordinated efforts to achieve ambitious restoration targets at immense scale[8]. As a result, much of the current nationally-pledged restoration area is set aside for large-scale tree planting[2,9]. For example, the Indian National Determined Contributions (NDC) from the Paris Accords commits "To create an additional carbon sink of 2.5 to 3 billion tonnes of CO2 equivalent through additional forest and tree cover by 2030"[10]. Understanding the impact of such policies is critical to understanding whether broader goals of forest restoration will be met[6–9,11].

Planting trees may seem like a simple activity. Yet in practice tree planting may conflict with existing land uses, particularly in densely-settled agrarian landscapes, generating significant challenges for low-level forest officers charged with implementing activities on the ground, in pursuit of the ambitious targets established at higher levels of government. We still lack rigorous quantitative studies that directly evaluate the performance of tree planting, in such a political

environment, along multiple dimensions[12–14]. This evidence gap stems from the difficulty of obtaining long-term outcome data on forest cover and rural livelihoods, and counterfactual research designs that credibly link these outcomes to policy. Policymakers need to consider evidence on the efficacy of tree planting before allocating scarce resources needed to fight climate change to such projects[15]. This study aims to provide such evidence.

We worked with rural communities to identify and map boundaries of tree planting projects and matched these to historical remote sensing-derived land cover in Kangra District of Himachal Pradesh in Northern India. Through satellite image classification, we estimate forest canopy cover and forest composition from longitudinal remote sensing at 6 points in time in 430 tree plantations from 60 randomly-selected panchayats (local governments). Our analysis shows that, on average, tree-planting projects do not increase forest canopy cover, and they modestly change forest composition away from the broadleaf varieties preferred by local people. The first result implies that tree planting has not contributed to climate-change mitigation, and the second implies that tree planting has not improved the availability of trees that support rural livelihoods.

We supplement that analysis by surveying households and comparing the livelihood contributions from different plantations. To do so, we conducted a quasi-random survey of 2400 households living proximal to plantations. We find that a small proportion of any one plantation's potential users benefit from it through fuelwood collection, fodder collection, and grazing. However, older plantations, larger plantations, and those closer to roads are used most heavily. Additionally, whereas approximately 42% of our respondents have used at least one plantation for fuelwood, fodder, or grazing, most of those plantation users rank their own dependence as low. In sum, these programs only modestly contributed to rural livelihoods.

Study Site

India provides an excellent context to assess the impact of tree-planting programs due to its long history of planting trees[16,17], continuing high-level commitment[18], prevalence of areas identified as having forest-restoration potential[19], and large number of forest-dependent people[20]. Yet recent systematic reviews on tree-planting outcomes included no studies from India[13,14], and the case studies that do exist suggest plantations may fail[21,22], endanger livelihoods[22,23], or threaten native forest cover[24–26].

India has invested vast sums of money and energy over the last 50 years to plant trees—the sixth largest effort in the world[4]. The state of Himachal Pradesh has had particular success in advancing basic development goals in a variety of areas (from health, basic welfare, education, and the environment), while a variety of local governance functions, from public service delivery to natural resource management, perform comparatively well. The Kangra District in particular has a long history of forest co-management between state actors and communities, with strong local participation and clearly defined use rights. Incidents of land dispossession from tree-planting projects which have been widely-reported by journalists working in other parts of India have not been reported there. In short, we had every reason to believe that if tree planting might be successful, we should be most likely to observe this success in this area.

Tree planting has a long history in Kangra District and traces its roots to concerns about forest degradation due to excessive harvesting of wood fuel for cooking and excessive grazing by domestic animals[27–30]. As in most of India, the tree-planting areas we study are all on government-owned land and have been undertaken by the state forest department[31]. Although there is also a history of commercially-oriented forestry in Himachal Pradesh, a ban on

99 harvesting green trees since 1986 means that commercial timber production in this region has
100 been nonexistent for the entire period under study[32]. Figure 1 shows the location of the study site.

101 **[FIGURE 1 HERE]**

102 Areas designated for forest restoration are fenced-off for the first 5 years after the initial
103 planting event and there is a moratorium on extractive uses: The forest department mandates
104 restricted access and any benefits such as grass fodder is to be harvested rather than grazed to
105 ensure the planted saplings/seedlings are not endangered. This is supposed to give the trees time
106 to grow. However, Rana and Miller show that plantations vary in overall community rule
107 adherence, the types of access rules, and post-plantation monitoring by both forest department
108 and communities.[40] For example, in some cases communities actively monitor access and
109 enforce sanctions against rule-breakers. In other cases, however, communities have removed
110 fencing and begun grazing within the 5-year moratorium. In addition to variations in rules-in-
111 use, tree plantings were initiated under several different government programs (e.g., Joint Forest
112 Management), and there is variation about the role of communities in creating and enforcing
113 rules across sites and over time. The actual rules in use tend to vary most from one panchayat to
114 the next.

115 **Impact Model**

116 We use an Event Study Design[33] to estimate the impact of these tree-planting projects on
117 forest canopy cover and forest composition. The tree plantations in our sample (n=430) were
118 established in a staggered manner over time. The establishment years range from 1965 to 2018.
119 Figure 2 shows the cumulative number of plantations, which have steadily increased since 1980.

We combine this information with dependent variables estimated using satellite image-derived land-cover data available at six time points: 1991, 1993, 1996, 1998, 2009, and 2018. These are the years for which cloud cover allowed accurate estimation of forest attributes at 30-m spatial resolution. We estimate policy impact using observed data before and after the date of the first plantation event, while controlling for a plantation's site-specific geographic characteristics and panchayat-level time trends[34,35].

[FIGURE 2 HERE]

We use the following equation to estimate the impact of plantations:

$$y_{ipt} = \alpha + Plant_{ipt}(\tau) + \theta_{pt} + \varepsilon_{ipt}.$$

Here, y_{ipt} indicates a land-cover outcome in plantation, *i*, located in panchayat, *p*, measured at time, *t*. The parameter vector θ_{pt} is a set of panchayat-year fixed effects, and ε_{ipt} is an idiosyncratic error term. Finally, $Plant_{ipt}(\tau)$ represents a policy impact function of the time τ from the establishment of a plantation (where τ is centered on zero and takes positive and negative values as years from the event). We focus on two policy impact functions: First, a flexible distributed fixed-effects impact function, created by taking dummy variables for each value of τ and estimating separate fixed effects for each year. Second, a simpler linear impact function where we include τ as a linear trend and allow that trend to vary in the years before and after plantation establishment. Below, we refer to τ as Plantation Age.

For outcomes, y_{ipt}, we examine two types of land-cover changes: forest canopy cover and forest composition. Forest composition is a proxy of the usefulness of tree species for local people: broadleaf trees provide more value as firewood and fodder for domestic animals, while

needleleaf species are less valuable for those purposes[36–39]. This relationship between broadleaf and needleleaf species and livelihoods is a characteristic of this ecosystem in the western Himalaya. Asher & Bhandari report similar findings (with slightly different species composition) from other parts of Himachal Pradesh[22], and Rana & Miller have similar findings in this area specifically[40]. The more general idea, that some species are preferred by governments or companies, while different species are preferred for local livelihoods, was proposed by Robbins[41] and has been found in other contexts as well (e.g., Chile[42]).

Using Landsat imagery, we temporally estimate the forest composition of each pixel lying within each plantation area based on four land-cover categories: percent needleleaf species cover; percent broadleaf species cover; percent mixed cover (needleleaf and broadleaf species); and percent grassland (the residual category). For the analysis presented here, we focus on the percent classified as broadleaf, the most relevant category for local people.

To estimate forest canopy cover, we combine our estimates of forest composition as outlined above with data from the Forest Survey of India (FSI) to temporally estimate the percent of each plantation area classified as having more than 40% tree canopy density ("forest canopy cover"), according to the FSI criteria[43]. We detail this process in the Methods section, and report image classification accuracies in our Supplementary Information (Tables S1-S15).

The growth trajectories of the tree plantations should, in theory, depend on the age of the plantation. In a young regenerating forest (devoid of disturbances), one would expect that stem density would be quite large during the initial years after planting, and forest canopy cover remains somewhat limited. Over time, stem density might fall while the forest canopy cover generally increases. With the Landsat imagery and FSI maps, we only measure forest canopy

cover and not stem density. But detecting growth of forest canopy cover from Landsat images will also depend on the initial conditions of the land. If land were open initially, we might observe forest canopy cover increases relatively quickly (especially under congenial site conditions). And even when forest canopy cover is greater initially, because of the long growing season in the Central and Western Himalaya, changes in forest canopy cover should be observable within a 5-9 year lag[40].

The units of analysis are *plantation-years.* We compare forest-cover observations before and after tree planting using linear regression models with standard errors clustered at the plantation level. At the plantation level, we include controls for slope, elevation, an interaction of slope and elevation, plantation size, distance to nearest road (in minutes of travel time, square root transformed to reduce skew), and an interaction of plantation size and distance to nearest road. Finally, we include 300 (=60 plantations × (6-1) time periods) panchayat-year fixed effects. There are between two and 21 plantations in each panchayat (Fig. S3 in our Supplementary Information), and some plantations are shared by multiple panchayats.

Results

We present our main results in Figure 3. We report the dummy variable impact function estimates as black dots with error bars and the linear impact function estimates as a solid blue line with a blue shaded area. Both models report 95% confidence intervals (derived from standard errors clustered on plantations). Effect sizes (y-axis) should be interpreted as differences in an outcome τ years from the establishment of the plantation (Plantation Age is truncated at ±20). The interaction between After Plantation (dummy variable indicating year after established) and Plantation Age in the linear impact function lets us estimate separate pre-

185 and post- establishment forest-cover trends. The fixed-effects impact function approach is less
186 efficient but provides more flexible effects over time. We believe the linear model presents a
187 reasonable, more efficient, approximation for these effects, but we report both in Fig. 3 for
188 reference.

189 **[FIGURE 3 HERE]**

190 Panel (a) of Fig. 3 illustrates that older plantations do not have more forest canopy cover
191 (area with canopy cover > 40%) than younger plantations. The linear effect of Plantation Age is
192 negative and close to 0, while the dummy variable impact function produces estimates that are
193 scattered across 0 and which rarely come close to meeting standard thresholds for statistical
194 significance for any given age. Even plantations in our dataset that are 20+ years old are not
195 covered by meaningfully more or less forest canopy cover than recently-planted areas. A Wald
196 test shows that pre- and post-establishment linear trends are not statistically distinguishable for
197 forest canopy cover (see Table S16 in our Supplementary Information).

198 Panel (b) reports negative effects of tree planting on broadleaf cover using both the
199 dummy variable and linear impact functions, although results are not large enough to be
200 significant at classic thresholds when using the dummy variable approach (until approx. 20 years
201 post-establishment). But, we estimate (from the linear impact model) that 20-year-old plantations
202 have ~10% less broadleaf cover than those that have just been established. A Wald test supports
203 the difference between pre- and post-establishment linear trends in broadleaf cover (Table S17).
204 Both models in Figure 3(b) provide consistent evidence against a claim that tree planting
205 *increases* the proportion of broadleaf cover.

206 In summary, establishing plantations has not improved the proportion of broadleaf cover
207 or forest canopy cover in these areas. Full regression tables from these and other specifications
208 are available in our Supplementary Information (Tables S16-S17). The results we report here are
209 robust to a variety of alternative specifications, including standard Difference-in-Differences
210 approaches and the Callaway and Sant'Anna doubly robust estimator (Table S23)[44]. In the
211 Supplementary Information we also present results for the other forest composition
212 classifications (Figures S5 and S6; Tables S18-S21). Note that our findings do not support a
213 claim that tree planting replenished threatened forest canopy cover or prevented the proportion of
214 forest canopy cover or broadleaf cover from declining more rapidly. In that case, we would see
215 stronger evidence of declining forest canopy cover or broadleaf cover in the years before
216 plantation establishment and a tempering of this trend after establishment.

217 We now move to a cross-sectional analysis of how different plantation characteristics
218 influence the livelihood support plantations currently provide. We conducted surveys of 40
219 households in each panchayat between March 2018 and May 2019. For each of the 430
220 plantations in our sample, we aggregate household survey responses from all its panchayats.
221 Because some plantations are a part of one panchayat while others are part of up to three, we
222 have data from between 40 to 120 household survey respondents for each plantation.

223 Our units of analysis are now the cross-section of 430 plantations. We consider three
224 outcomes—the number of respondents using a plantation to collect fuelwood, the number using a
225 plantation to collect fodder; and the number using a plantation to graze animals (sheep, cattle,
226 goats, and buffalo). Figure 4 presents box plots of the number of households supported by each
227 plantation in this sample. Overall, most plantations have few direct users: they support fewer

228 than 10 households in our sample for any one use. Figure S7 shows that calculating the
229 proportion of plantation users instead produces a similar pattern.

230 **[FIGURE 4 HERE]**

231 Although most of these plantations are only used by a minority of those living in one of
232 its panchayats, we show in Table S24 that 42% of our household sample uses at least one
233 plantation for at least one of these purposes (+/- 2% at a 95% confidence level). However, when
234 those plantation users rated their dependence (relative importance of this product for their
235 livelihood), only 9% indicated that their dependence on plantations was medium or high (+/-
236 1.6% at a 95% confidence level, Table S24). Plantation use for fuelwood, fodder, or grazing is
237 common, but most households receive these benefits from only a few plantations (Tables S23-
238 S24). Most households are also not highly dependent on these benefits.

239 Some plantations contribute more to local livelihoods than others. We use negative
240 binomial count regression models with panchayat fixed effects to explore within-panchayat
241 variation in plantation use. These models employ three explanatory variables: Plantation Age
242 (we focus on a linear impact function); a plantation's distance from the road in minutes of travel
243 time (square root transformed to reduce skew); and a plantation's size (logged). Select results are
244 in Table 1, and we report full results in the Supplementary Information (Table S25). Coefficients
245 from negative binomial models are difficult to directly interpret, so we instead report
246 transformations of those coefficients: the percent change in the expected number of plantation
247 users associated with a +1 increase in each explanatory variable in Panel (a). We also report
248 estimates of the impact of a large (two standard deviation) increase in these variables on the
249 count of plantation users, with other variables held at their observed values in Panel (b).

250 **[TABLE 1 HERE]**

251 Though most plantations are not heavily used, there is some variation in the amount of
252 livelihood support that different plantations provide. For instance, older plantations have
253 consistently more users for all three measures of livelihood support, although the finding for
254 fodder collection is not statistically significant. This effect of plantation age is substantively
255 small: Panel b indicates that 35-year-old plantations have 0.61 more users for fuelwood
256 collection, on average, than 11-year-old plantations (a 47% increase in the count of plantation
257 users).

258 There are more substantial effects for road distance on fuelwood and fodder collection. In
259 conjunction with our forest-cover analyses, these results imply that plantations closer to the road
260 are more useful from a livelihood perspective but are also less likely to contain the broadleaf
261 species households prefer. Finally, our results also show that a plantation's size is an important
262 predictor of its ability to jointly contribute to both environmental and livelihood goals. Larger
263 plantations have denser forest cover (Supplementary Information Table S16) and are more likely
264 to serve as a useful source of fuelwood collection.

265 **Discussion**

266 After decades of costly investments, we find no evidence that tree-planting projects
267 secured substantial benefits for carbon mitigation or livelihood support in Northern India.
268 Planting trees might seem like a straightforward way to increase carbon storage, but the process
269 of growing trees is expensive and complicated in many real-world contexts[6,45]. Our analysis
270 suggests that planting trees is an ineffective carbon-mitigation strategy in this area. This should

be interpreted in light of India's significant plans to plant trees. As discussed in our description of the study site, Himachal Pradesh is an area where we might expect such programs to be relatively effective. The fact that we do not find that plantations improve forest canopy cover or support rural livelihoods should produce serious skepticism that such programs would be widely successful elsewhere in India.

Why have these efforts to plant trees failed to improve forest canopy cover or provide species valued by local users? There are several possibilities. First, these plantations occur in densely-settled agro-pastoralist landscapes, where a variety of existing land uses limit spaces available for further tree plantations. As a result, most tree planting happens within areas that already have some tree cover, limiting the potential regrowth opportunities. Planting in cleared areas is not a viable alternative because of socioeconomic and ecological constraints of converting agricultural lands back to forests. If policymakers wish to promote forest restoration through tree planting, then the underlying social and ecological processes that led to forest degradation and loss in the first place needs to be addressed[2,5,6].

Second, forest bureaucracies have internal incentive structures focused on achieving tree-planting targets rather than sustaining longer-term socio-ecological benefits through providing support for continued tree growth[17,39]. Foresters may be incentivized to plant trees of low livelihood value precisely because they believe these trees are more likely to survive in a neglectful environment[17].

Although there are limits to generalizing this analysis beyond the study area, we note that similar constraints are likely to be present in many contexts where tree planting is proposed. This suggests that there may often be a gap between the rhetorical objectives of restoration and real-

293 world human and environmental outcomes. Although tree-planting programs are often premised
294 on the view that forests support subsistence and commercial livelihoods[1,3], our analyses raise
295 concerns about using tree planting as a straightforward cost-effective tool for sequestering
296 carbon while supporting livelihoods. While planting trees is often framed as an immediate point
297 of action for climate-change mitigation as economies pursue long-term decarbonization, our
298 findings provide empirical evidence for the need to temper these expectations[8,15]. Policymakers
299 and advocates should not assume tree-planting programs will effectively meet their carbon-
300 sequestration and livelihood goals. Although our understanding of this topic is improving, further
301 research is needed to understand the ecological, socioeconomic, and institutional conditions that
302 might make tree planting more successful[46–48].

303 **Methods**

304 This research is based on data collected between August 2017 and May 2019 in Kangra
305 district, Himachal Pradesh in northwest India. We first discuss the various types of data we
306 collected and then provide additional details on the data analysis results reported in the main
307 manuscript.

308 **Data Collection**

309 We selected four forest administrative units called 'ranges'—Palampur, Daroh,
310 Dharamsala and Shahpur—that adequately represent variation in plantation types, elevation, and
311 forest use in Kangra. We randomly selected 60 of the 181 panchayats (formalized local
312 governments consisting of a few villages and habitations) within these four ranges. Using
313 panchayats as the unit of analysis, we collected data through four research instruments that focus

314 on different aspects of communities (C-Form), households (H-Form), plantations (p-Form), and
315 plantation ecology (P-Form) for each panchayat.

316 We used this sampling frame because we wanted to maximize the potential variability in
317 forest attributes (forest composition and forest canopy cover), and we did not have *ex ante*
318 information lists on plantation locations or shapefiles. We determined that 60 was the maximum
319 feasible number of panchayats to include in our study (given our budget, the expected logistical
320 difficulty of accessing several plantations within these panchayats, and the distances between the
321 randomly-selected panchayats).

322 Data collection at each panchayat followed a sequence of steps starting with creating a
323 list of plantations in the panchayat, and then surveying communities, plantations, and households
324 in that order. Based on key-informant interviews, we created a plantation survey (p-Form) that
325 listed all plantations in the panchayat, their local names, year of planting, planted and current tree
326 species, previous and current land use, and the institutions responsible for plantation creation and
327 management.

328 Using the plantation list we randomly sampled 10 plantations in each panchayat that were
329 planted after 1980 and were greater than 5 hectares in size for detailed social-ecological survey
330 using the P-Form. If fewer than 10 plantations met our criteria, we simply sampled all
331 plantations that met the criteria. In addition to these plantations, we collected some data on all
332 plantations that were planted in 2017 irrespective of their size. In total, we discovered and
333 recorded 1250 plantations in the p-Form, but only recorded complete shapefiles and detailed
334 surveys on 430 plantations using the P-Form. The statistical analysis reported in Figure 3 is for
335 those 430 plantations with repeat measures in 6 years.

Livelihood Data

Within the 60 panchayats we created a decision tree for survey data collection. First, we collected secondary data on community demographics and conducted exploratory meetings with panchayat leaders and residents. Based on this meeting, we identified key informants who assisted in validating panchayat demographics and creating a list of households in the panchayat including names of head of household and their father, caste, and number of family members.

We randomly selected 40 households in each panchayat from the list we developed and administered surveys to each of them in Hindi. Table S7 shows a (frequency) histogram of the sampling intensity of households per panchayat. The sampling intensity is between 5%-25% across panchayats. Prior cross-site comparative forest research (e.g., the International Forestry Resources and Institutions-IFRI program) has used a sampling rule-of-thumb for 40 households per site, and our budget/time allowed for a similar number of surveys per panchayat. However, there was no formal power calculation to determine an exact household sample size necessary to detect an assumed effect size. (Power calculations were not possible because we had no good *ex ante* expectation of the plantation effect size nor good estimates of the within-panchayat versus between-panchayat variability in socioeconomic outcomes, that would be necessary to make a good power calculation with such clustered data).

Each household interview was conducted by a team of two trained field staff, one of whom solicited responses to questions in a conversation style, while the other noted the responses on a printed questionnaire form. We found that a modular questionnaire conducted as a conversation better engaged the respondents who were able to triangulate responses from memory. All household interviews were conducted at the respondent's residence with minimal

interference from non-respondents. We later entered the data on survey forms in Qualtrics software. The household-livelihood analysis reported in Figure 4 and Table 1 come from a cross-sectional analysis of 40 surveys × 60 panchayats = 2400 total households measured once.

Biophysical Data

Biophysical information is derived from multi-temporal Landsat satellite image mosaics, which are jointly analyzed with field data, as well as ancillary data. In particular, to facilitate information extraction from the Landsat time series, we exploit a Shuttle Radar Topography Mission (SRTM)-derived digital elevation model (DEM), a plantation-boundary Esri geographic information system (GIS) polygon shapefile, training/testing land-cover/forest type field polygons, and multi-temporal Forest Survey of India (FSI) forest-density maps, as ancillary spatial data for the multi-temporal Landsat image classifications.

Pairs of Landsat images in a given year are utilized to generate the respective mosaics in the time series, acquired at the limited times during which there was sufficiently minimal cloud cover, and such that the spatial extent of the study area was covered. Some characteristics of these Landsat images are summarized in Table S1 of the Supplementary Information. For Path/Row 147/38, the image-acquisition dates are: 05/10/1992, 04/27/1993, 04/03/1996, 05/27/1998, 05/09/2009, and 04/05/2018. For Path/Row 148/38, the image dates are: 05/15/1991, 05/04/1993, 04/26/1996, 04/16/1998, 04/30/2009, and 04/17/2018. For the first image pair in the time series, one image is from 1992 (05/10/1992), and the other image is from 1991 (05/15/1991), on a near-anniversary date; this is due to image-availability and cloud-cover limitations.

Regarding Landsat image pre-processing, we radiometrically calibrated the raw data (digital numbers; DNs) to units of radiance, and radiance image data were used as input to the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH®) algorithm for atmospheric correction[49], resulting in surface-reflectance images for the various image dates. For each Landsat image pair, we then mosaic the individual FLAASH-corrected images via the "Seamless Mosaic" tool in the ENVI® (The Environment for Visualizing Images®) remote-sensing digital image-processing software package. We then spatially clip the mosaicked images to just encapsulate our study area. All Landsat images are in the UTM projected coordinate system (Zone 43N; datum = WGS 1984).

In addition to the Landsat image bands, we also employ a Shuttle Radar Topography Mission (SRTM)-derived digital elevation model (DEM), with a spatial resolution of 30 meters, as another input to the image classifier. The SRTM DEM is thus also clipped to the study-area extent, and the Landsat image bands are stacked with the SRTM DEM (also in UTM, Zone 43N, WGS 84).

During 2018-2019, we delineated multiple field polygons per forest plantation via global positioning system (GPS) receiver, whereby the dominant nominal land-cover/forest type was recorded for each polygon. We employ these polygons for supervised classification algorithm training and testing. More specifically, we utilize all field-delineated polygons (from 2018-2019) for classifying the 2018 Landsat image mosaic, and in accuracy assessment, with appropriate random selection, discussed below. In order to classify the other Landsat image mosaics in the time series, we modify or remove a subset of training/testing field polygons that need modification (e.g., via modifying the polygon boundaries) or are invalid with respect to the

spatial configuration of features that are present within a given Landsat mosaic, collected earlier than 2018. Starting with the 2009 Landsat mosaic, we visually/manually interpret historical, multi-temporal, high-spatial-resolution Google Earth images, which are of a higher spatial resolution than the 30-m Landsat images, to determine which training/testing land-cover/forest type field polygons need to be modified or deleted (if no longer valid) for the purpose of classifying that Landsat image mosaic. The resultant modified/reduced set of training/testing field polygons then constitute the starting point for subsequent evaluation of the field polygon boundaries via visual interpretation of the maximally temporally corresponding Google Earth images, with reference to the next most recent Landsat image mosaic.

We repeat this procedure, progressively proceeding backwards through the Landsat time series. For the earliest Landsat dates, due to the unavailability of Google Earth images, the Landsat images themselves served as the primary source material for image interpretation, in concert with Landsat-derived vegetation index images and other ancillary data, serving as reference data for evaluating the training/testing field polygon set. Thus, uncertainty in the resultant image classifications increases progressively backward in time, particularly for the earlier Landsat image dates (i.e., 1996, 1993, and 1991). This process yields the following final training/testing field polygon counts, for each respective Landsat mosaic year: for 2018, 835 polygons; for 2009, 735 polygons; for 1998, 673 polygons; for 1996, 656 polygons; for 1993, 656 polygons; and for 1991, 656 polygons.

We use FSI forest-density (i.e., what we term canopy-cover) raster maps for the years 2001, 2005, 2009, and 2019 to provide multi-temporal forest-density reference data, where we match a given Landsat image to the temporally-closest available FSI forest-density map[43]. We

resample the FSI forest-density maps (cell size = 24 meters) via nearest-neighbor resampling to yield the same cell size as that of the Landsat image pixels (i.e., 30 meters). We reproject the forest-density rasters to the UTM projected coordinate system (Zone 43N; datum = WGS 1984), matching that of the Landsat images, and we snap the forest-density raster cells to the Landsat pixels for proper alignment. We simplify the FSI forest-density classification system by merging their "Moderately Dense Forest" (40 – 70% canopy cover) and "Very Dense Forest" (>70% canopy cover) classes to form a single "Forest Canopy Cover" class. Other classes include "Open Forest" (10% - 40%) and "Scrub" (<10%). We use these rasters in conjunction with the training/testing land-cover type field polygons (via spatial join and other GIS operations) to generate (via deep-learning classification) multi-temporal combined land-cover/canopy-cover classifications, which feature composite classes. The measure we use in the analysis of canopy cover is the proportion of the area within a tree plantation polygon that falls into the "Forest Canopy Cover" class.

We produce multi-temporal combined land-cover/canopy-cover classifications, as well as multi-temporal land-cover-only classifications (based on the training/testing field polygons). For both sets of classification trials, the Landsat image bands and the SRTM DEM are used as inputs to a deep-learning classification algorithm—i.e., a 2-D convolutional neural network (2DCNN) classifier[50].

For every classification trial, the labeled pixels are split into two pixel-sets randomly, including a training set and a testing set. We use the training set to train our classification model, and the testing set is employed for accuracy assessment. In our experiments, the ratio between training samples and testing samples is 1:1, which means that 50% of labeled samples per class

are selected for training, and the remaining labeled samples are exploited as testing samples. Note that such training-testing sample selection is a random selection, and a new random selection is implemented for each trial to ensure that different trials have different training and testing samples.

For a given Landsat image mosaic year, the classification experiments are repeated 10 times to avoid sampling bias. Regarding the accuracy assessments, we compute several accuracy metrics, described as follows: Overall accuracy (OA) is defined by calculating the ratio between the number of pixels classified correctly and the number of all pixels in the set of testing samples. Average accuracy (AA) is the average of all accuracies, computed across all classes. Also, Kappa is a statistical index for a consistency test, which can be calculated from a confusion matrix[51]. All the aforementioned accuracy-evaluation indices are be calculated by averaging those indices across all 10 replications.

For the multi-temporal combined land-cover/canopy-cover classifications, accuracy-assessment results are given in Tables S2-S7 in the Supplementary Information. For most years, there are 15 classes, which are given in Tables S2-S7. However, note that the "Needleleaf Open Forest Cover" class is not part of the 2009 classification, and the "Grassland Open Forest Cover" class is not part of both the 2009 and 2018 classifications. Those classes are not part of those respective classifications because they did not exist in the training/testing polygons, after being combined with the canopy-cover data, for those Landsat mosaic years. This may at least partly be due to error associated with the FSI maps. Post-classification change detection[52] was performed on a pairwise basis, based on the 2DCNN-classified image mosaics. Accuracy

assessment is only performed based on results and data within the forest-plantation boundaries—specifically, within those field polygons randomly selected for testing.

Regarding the multi-temporal land-cover-only classifications (that do not include canopy-cover information in the classes), those classes are: needleleaf forest, broadleaf forest, mixed forest, and grassland. The quantitative classification accuracy-assessment results for the various Landsat image dates in our time series using this classification system are shown in our Supplementary Information in Tables S9-S14. With a smaller number of classes involved, we find that these classification accuracies are higher than the results based on the composite land-cover/canopy-cover classes. Thus, these multi-temporal classified images and the quantified changes that were detected based on those classifications serve as the basis for subsequent statistical analyses of land-cover change. As noted, we also perform pairwise change-detection analyses based on the multi-temporal land-cover classified images, and some of those results are summarized in Table S15.

Data Analysis

Forest-cover analysis

We estimate an effect of tree planting on forest canopy cover and forest composition by comparing newly-established plantations (planted at time $\tau = 0$) with plantations already in existence ($\tau > 0$) for different periods of time. Similarly, we compare recently-established plantations to areas that will be planted in the future ($\tau < 0$) to look for noteworthy pre-establishment trends in forest canopy cover and forest composition. Our units of analysis are the 430 plantations in this study in six different years (1991, 1993, 1996, 1998, 2008, and 2009), yielding 2,580 observations total (plantation-years).

First, we consider including a simple binary variable in our models that indicates whether *Plantation Age* is greater than 0 (*After Plantation*). This yields a difference-in-differences analysis of the impacts of tree planting (Model 1 in Tables S16-S21). Second, we allow *Plantation Age* to have separate linear effects on our outcome measures in the years before and after planting (Model 2). We accomplish this by including *Plantation Age* in the model, interacted with *After Plantation*. Third, we consider constructing dummy variables for each value of *Plantation Age* and including all these dummies in our regression models (Model 3). Finally, we allow *Plantation Age* to have separate curvilinear effects on our outcome measures in the years before and after planting (Model 4). This is an extension of our second approach. We highlight the second and third impact functions in the main text.

We use a Wald test on the output of Model 2 to compare the estimated linear effects of *Plantation Age* in the years before and after planting for each outcome measure. Specifically, we test a restriction that both estimated linear trends are equivalent. Tables S16-S21 in our Supplementary Information present our regression results for all outcome measures. Results presented in Tables S16 and S17 are used to construct Figure 3 in the main text. Fig. S5 and S6 in our Supplementary Information provide figures comparable to Fig. 3 for outcome measures not discussed in the main text.

Plantation-use analysis

506 For these analyses, our units are a cross-section of the 430 panchayats considered in the
507 forest-cover analysis. For each plantation, we aggregate household-survey responses from all the
508 panchayats of which it is a part (based on key-informant interviews). Some plantations are a part
509 of two or three panchayats. As a result, each of the 430 plantations considered in this study are
510 available to between 40 and 120 respondents. Our outcome measure for each plantation is the
511 number of household-survey respondents that indicated using it for: fuelwood collection; fodder
512 (animal feed) collection; and grazing animals.

513 We use negative binomial regression (NB) models to explain variation in the number of
514 users across plantations. We prefer a NB model over other count regression models. Model fit
515 comparisons show that a NB model (AIC 1286.604, BIC 1306.923) outperforms a Poisson
516 regression model (AIC 1693.154, BIC 1709.41) and either modestly underperforms or modestly
517 outperforms a zero-inflated negative binomial regression model (AIC 1286.199, BIC 1322.773)
518 depending on the metric considered.

519 We employ three explanatory variables: Plantation Age (the linear impact function);
520 distance from the road in minutes (square root); and plantation size in hectares (logged). We also
521 include panchayat fixed effects (we do not use these fixed effects in the AIC/BIC comparisons).
522 Introducing fixed effects into some nonlinear regression models can produce bias through the
523 "incidental parameters problem." However, simulation evidence suggests that in a NB model
524 fixed effects bias standard errors and not coefficient estimates[53]. We implement a standard error
525 correction those authors recommend.

526 We present the results from all three negative binomial regression models in Table S25 of
527 our Supplementary Information. In Table 1 of the main text, we report transformations of these

coefficients in Panel A rather than the coefficients themselves. Applying the following equation to a negative binomial regression coefficient β_X for some variable X yields the percent change in the expected count associated with a unit increase in X: $100 \times [e^{\beta_X} - 1]$. For Panel B of Table 1, we calculate the change in the expected count of plantation users associated with a large increase in each explanatory variable. We define a large increase as an increase of 2 standard deviations from that explanatory variable's first quartile, and hold other explanatory variables at their observed values.

Data Availability

Replication data and materials for this analysis are available in the Data Repository for University of Minnesota: https://conservancy.umn.edu/handle/11299/220402. Replication code for statistical analysis is also available in the Data Repository for University of Minnesota: https://conservancy.umn.edu/handle/11299/220402.

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Authors contributions

FF, EC, VR, HF, and PR conceived the study, and FF oversaw data collection. VR led survey data collection, and VG and RR contributed. AF and BG oversaw geospatial processing with AM contributing. EC and BS designed and conducted the data analysis, with feedback from other authors. EC led revision of the final manuscript, and BS, VR, HF, PR, AF, BG, CRS, and FF contributed to writing the manuscript and SI.

Competing interests

There are no competing interests.

Figure Legends/Captions

Figure 1. Study Site. We block-randomized selection of 60 study panchayats from four ranges within the Kangra district of Himachal Pradesh, India.

Figure 2. Cumulative Number of Active Tree Plantations. The cumulative number of active tree plantations over time. Years of Landsat satellite image observations are indicated by red dashed lines.

Figure 3. The Effects of Plantations on Land Cover. Estimated linear and dummy variable impacts with 95% confidence intervals. Panel (a) shows no significant difference in percent forest canopy cover when comparing the years prior to the establishment of the plantation ($\tau < 0$)with the time when it was established ($\tau = 0$). Similarly, there is no significant difference when considering percent forest canopy cover in the years after the plantation was established ($\tau > 0$). These results are consistent with both the more flexible impact model and the linear model. Panel (b) shows no significant difference in broadleaf composition when comparing the years prior to the establishment of the plantation ($\tau < 0$) with the time when it was established ($\tau = 0$). However, there is a decline in broadleaf composition in the years after the plantation was established ($\tau > 0$). This decline is consistent in both the more flexible impact model and the linear model, although the assumed structure of the linear model provides more precise estimates (narrower confidence intervals) that reach standard significance thresholds over the entire post-establishment timeframe.

Figure 4. Box plots for plantation use outcome measures. These box plots illustrate the distribution of our outcome measures in the plantation use regression analyses. The outcomes are the count of respondents using a plantation for fuelwood collection, the count using it for fodder collection, and the count using it for grazing. The box plots are only calculated for counts greater than 0. Boxplots center line is the median, box limits are the upper and lower quartiles, whiskers are 1.5x interquartile range, and points are outliers. We provide the number of non-zero observations for each outcome measure in the legend (out of 430 observations total).

Tables

Table 1. Results from fixed-effects negative binomial regressions of plantation use.

(a)
Percent change in the number of users due to a +1 unit change in the explanatory variable (p-values in parentheses)

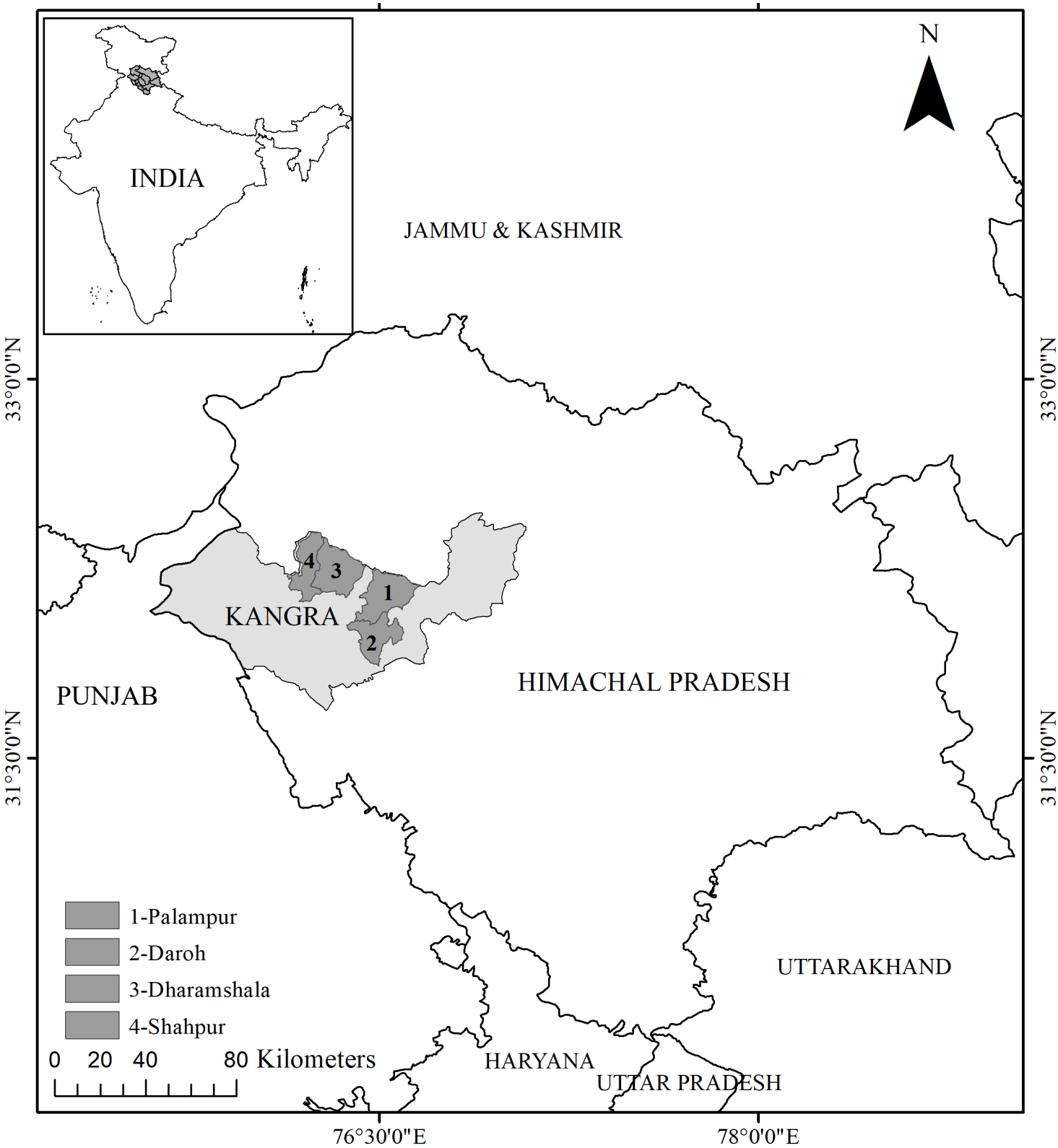
Variable	Fuelwood	Fodder	Grazing
Plantation age	+1.98% (0.01)	+0.28% (0.73)	+2.52% (<0.01)
Minutes from the road (sqrt)	-10.27% (0.01)	-8.53% (0.01)	-4.58% (0.12)
Plantation area (log)	+49.62% (<0.01)	+29.94% (0.10)	+11.13% (0.53)

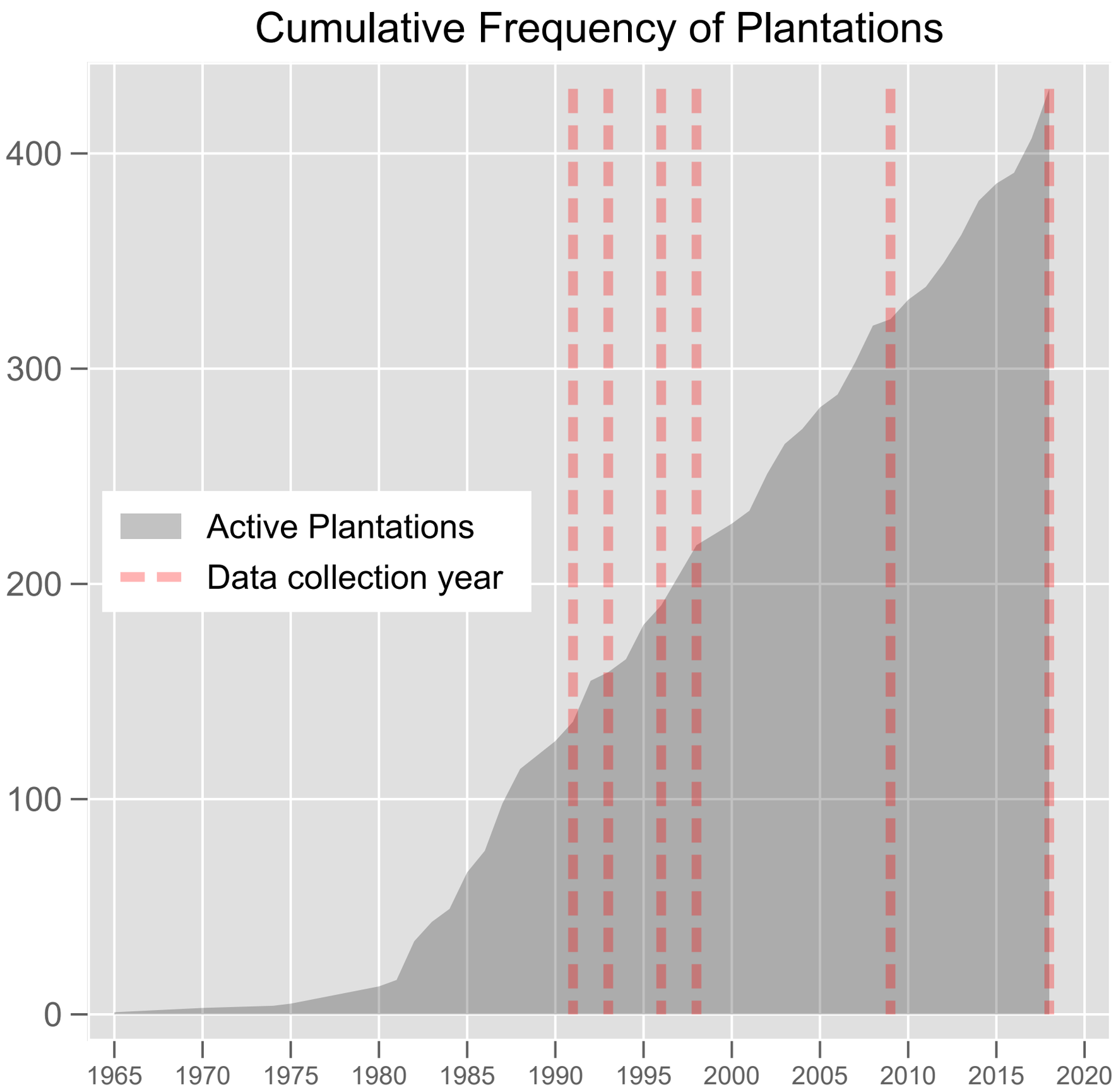
(b)
Estimated change in the number of users from a +2 standard deviation unit change in the explanatory variable, with other variables held at their observed values

Variable and change	Plantation use	Change in count	95% CI
Plantation age (11 to 35)	Fuelwood	+0.61	0.14, 1.08
Road minutes, sqrt. (0 to 6)	Fuelwood	-0.84	-1.35, -0.32
Plant. area, log (1.61 to 2.95)	Fuelwood	+0.80	0.09, 1.53

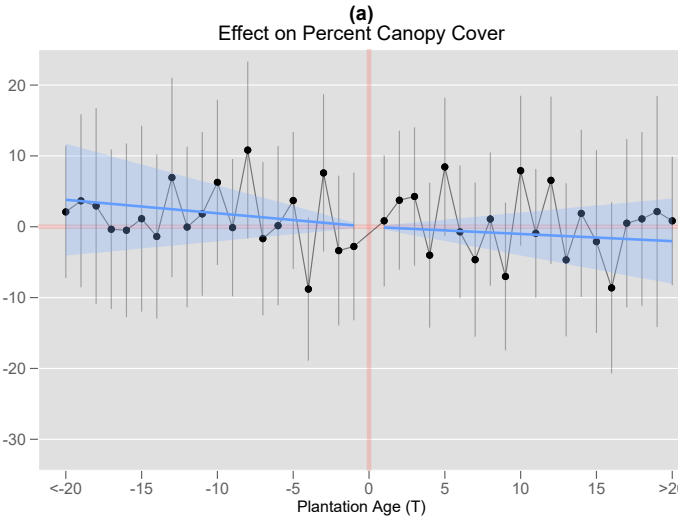
For the 430 plantations in this analysis, we estimate a negative binomial regression of the count of users with panchayat-level clustered standard errors adjusted. In addition to the explanatory variables below, we also estimate panchayat fixed effects, which means that our results draw on variation among plantations in the same panchayat. (a) We use the results of those regressions to calculate the percent change in the expected count of plantation users associated with an increase of 1 in each explanatory variable. We present p-values in parentheses (two-tailed hypothesis tests). Full regression tables are available in our Supplementary Information Table S26, and more details on estimation are available in our Methods section. (b) Examples of the effect of substantively interesting changes in several variables on the expected count of plantation users. For these continuous variables we calculate change in the expected count due to a +2SD increase, starting from the variable's 1st quartile. See summary statistics in Table S9. We use the observed values approach to hold constant the effects of other variables.

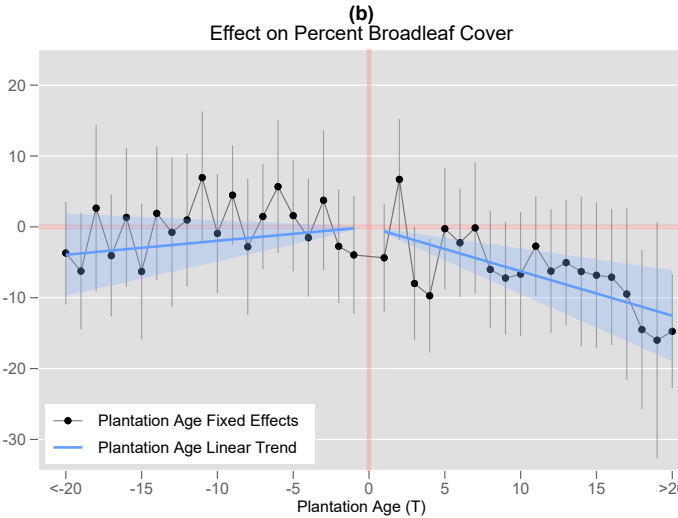
Study Area in Himachal Pradesh, India

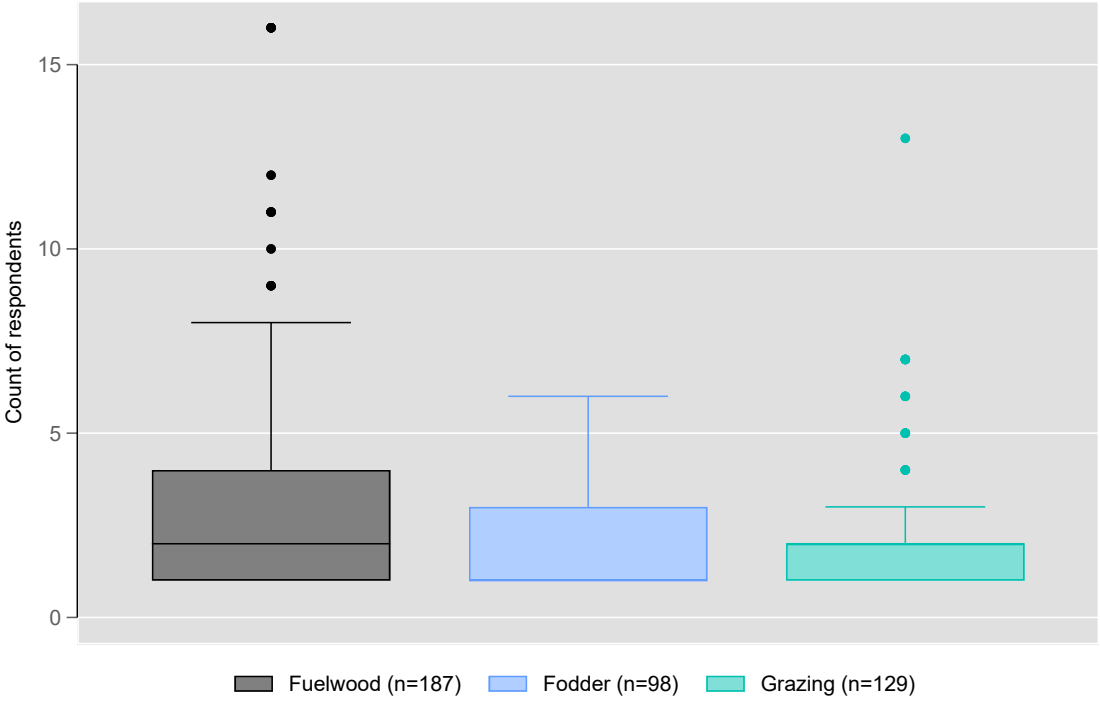




Note: 430 total plantations


(a)
Effect on Percent Canopy Cover
20
10
0
-10
-20
-30
<-20
-15
-10
-5
0
5
10
15
>20
Plantation Age (T)


(b)
Effect on Percent Broadleaf Cover
20
10
0
-10
-20
-30
Plantation Age Fixed Effects
Plantation Age Linear Trend
<-20
-15
-10
-5
0
5
10
15
>20
Plantation Age (T)


Count of respondents
0
5
10
15
Fuelwood (n=187)
Fodder (n=98)
Grazing (n=129)

Supplementary Information for:

Decades of tree planting in Northern India had little effect on forest canopy cover and rural livelihoods

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This PDF file includes:

Table S1. Landsat images used in the analysis.

Year of Acquisition	Path/Row	Cloud Cover	Sensor	Processing Level
1991	147/038	2.0%	Landsat 5 TM	L1TP
	148/038	2.0%	Landsat 5 TM	L1TP
1993	147/038	1.0%	Landsat 5 TM	L1TP
	148/038	1.0%	Landsat 5 TM	L1TP
1996	147/038	3.0%	Landsat 5 TM	L1TP
	148/038	0.0%	Landsat 5 TM	L1TP
1998	147/038	3.0%	Landsat 5 TM	L1TP
	148/038	1.0%	Landsat 5 TM	L1TP
2009	147/038	3.0%	Landsat 5 TM	L1TP
	148/038	1.0%	Landsat 5 TM	L1TP
2018	147/038	2.56%	Landsat 8 OLI	L1TP
	148/038	1.41%	Landsat 8 OLI	L1TP

Landsat images used in the analysis (year of acquisition, Path/Row, cloud cover, sensor, and processing level). L1TP denotes the Level-1 precision- and terrain-corrected product.

Table S2. Classification accuracies of the 1991-pair Landsat image (%).

Class (Class No.)	2DCNN
Needleleaf Open Forest Cover (1)	**61.36±6.93**
Needleleaf Scrub (2)	**62.07±6.77**
Needleleaf Forest Canopy Cover (3)	**77.79±2.99**
Broadleaf Open Forest Cover (4)	**66.48±6.61**
Broadleaf Scrub (5)	**63.00±5.59**
Broadleaf Forest Canopy Cover (6)	**75.13±1.95**
Grassland Scrub (7)	**83.53±5.96**
Mixed Open Forest Cover (10)	**63.22±4.06**
Mixed Scrub (11)	**67.18±3.21**
Mixed Forest Canopy Cover (12)	**75.23±3.46**
Grassland Open Forest Cover (15)	**59.77±14.37**
OA	**71.36±0.96**
AA	**68.61±7.59**
Kappa	**65.98±1.08**

The accuracies of 2DCNN land-cover/canopy-cover classification of the 1991-pair Landsat image (%).

Table S3. Classification accuracies of the 1993-pair Landsat image (%).

Class (Class No.)	2DCNN
Needleleaf Open Forest Cover (1)	**53.89±3.49**
Needleleaf Scrub (2)	**54.57±4.04**
Needleleaf Forest Canopy Cover (3)	**72.95±2.08**
Broadleaf Open Forest Cover (4)	**66.41±5.27**
Broadleaf Scrub (5)	**50.49±4.82**
Broadleaf Forest Canopy Cover (6)	**69.61±3.49**
Grassland Scrub (7)	**77.77±2.43**
Mixed Open Forest Cover (10)	**56.56±3.36**
Mixed Scrub (11)	**58.36±1.69**
Mixed Forest Canopy Cover (12)	**67.40±1.33**
Grassland Open Forest Cover (15)	**53.76±9.33**
OA	**64.99±0.83**
AA	**61.98±8.73**
Kappa	**58.11±1.00**

The accuracies of 2DCNN land-cover/canopy-cover classification of the 1993-pair Landsat image (%).

Table S4. Classification accuracies of the 1996-pair Landsat image (%).

Class (Class No.)	2DCNN
Needleleaf Open Forest Cover (1)	**59.43±6.68**
Needleleaf Scrub (2)	**58.13±5.10**
Needleleaf Forest Canopy Cover (3)	**70.96±3.23**
Broadleaf Open Forest Cover (4)	**71.34±7.84**
Broadleaf Scrub (5)	**60.28±7.77**
Broadleaf Forest Canopy Cover (6)	**78.15±4.36**
Grassland Scrub (7)	**78.18±6.04**
Mixed Open Forest Cover (10)	**59.61±4.18**
Mixed Scrub (11)	**65.25±3.18**
Mixed Forest Canopy Cover (12)	**71.35±1.84**
Grassland Open Forest Cover (15)	**66.96±17.90**
OA	**68.79±1.08**
AA	**67.24±7.01**
Kappa	**62.83±1.25**

The accuracies of 2DCNN land-cover/canopy-cover classification of the 1996-pair Landsat image (%).

Table S5. Classification accuracies of the 1998-pair Landsat image (%).

Class (Class No.)	2DCNN
Needleleaf Open Forest Cover (1)	**58.87 ± 3.52**
Needleleaf Scrub (2)	**59.61 ± 5.04**
Needleleaf Forest Canopy Cover (3)	**74.46 ± 2.83**
Broadleaf Open Forest Cover (4)	**67.79 ± 3.075**
Broadleaf Scrub (5)	**66.44 ± 7.55**
Broadleaf Forest Canopy Cover (6)	**73.11 ± 4.11**
Grassland Scrub (7)	**85.11 ± 4.07**
Mixed Open Forest Cover (10)	**60.12 ± 8.00**
Mixed Scrub (11)	**65.42 ± 3.15**
Mixed Forest Canopy Cover (12)	**71.00 ± 5.26**
Grassland Open Forest Cover (15)	**61.88 ± 7.82**
OA	**68.71 ± 2.04**
AA	**67.62 ± 7.57**
Kappa	**62.69 ± 2.58**

The accuracies of 2DCNN land-cover/canopy-cover classification of the 1998-pair Landsat image (%).

Table S6. Classification accuracies of the 2009-pair Landsat image (%).

Needleleaf Scrub (2)	**60.15 ± 5.87**
Needleleaf Forest Canopy Cover (3)	**75.58 ± 3.61**
Broadleaf Open Forest Cover (4)	**62.53 ± 13.82**
Broadleaf Scrub (5)	**70.21 ± 4.13**
Broadleaf Forest Canopy Cover (6)	**66.20 ± 4.99**
Grassland Scrub (7)	**80.00 ± 5.51**
Mixed Open Forest Cover (10)	**53.00 ± 9.09**
Mixed Scrub (11)	**64.04 ± 4.13**
Mixed Forest Canopy Cover (12)	**72.70 ± 2.78**
OA	**68.32 ± 2.03**
AA	**67.16 ± 7.86**
Kappa	**61.76 ± 2.37**

The accuracies of 2DCNN land-cover/canopy-cover classification of the 2009-pair Landsat image (%).

Table S7. Classification accuracies of the 2018-pair Landsat image (%).

Class (Class No.)	2DCNN
Needleleaf Open Forest Cover (1)	**52.94 ± 7.20**
Needleleaf Scrub (2)	**62.64 ± 9.48**
Needleleaf Forest Canopy Cover (3)	**74.68 ± 6.47**
Broadleaf Open Forest Cover (4)	**58.80 ± 6.01**
Broadleaf Scrub (5)	**66.34 ± 4.45**
Broadleaf Forest Canopy Cover (6)	**71.65 ± 2.99**
Grassland Scrub (7)	**83.73 ± 5.16**
Mixed Open Forest Cover (10)	**56.45 ± 4.15**
Mixed Scrub (11)	**70.42 ± 3.97**
Mixed Forest Canopy Cover (12)	**72.86 ± 2.52**
OA	**70.33 ± 0.98**
AA	**67.05 ± 8.95**
Kappa	**63.44 ± 1.30**

The accuracies of 2DCNN land-cover/canopy-cover classification of the 2018-pair Landsat image (%).

Table S8. Change summary for the composite land-cover/canopy-cover classes.

Years	Class with the largest change in extent (# of pixels)	Classes with the largest net increase and net decrease in extent (# of pixels)	Class with the largest change in extent (% of pixels)	Classes with the largest net increase and net decrease in extent (in %)
1991 to 1993	Mixed Scrub Class 11 (3435, 3.09 km^2)	Mixed Open Forest Cover Class 10 (+1196, +1.08 km^2) Needleleaf Scrub Class 2 (-598, -0.54 km^2)	Needleleaf Open Forest Cover Class 1 (71.99%)	Grassland Open Forest Cover Class 15 (+143.85%) Needleleaf Open Forest Cover Class 1 (-23.46%)
1993 to 1996	Broadleaf Forest Canopy Cover Class 6 (3798, 3.42 km^2)	Mixed Scrub Class 11 (+1577, +1.42 km^2) Broadleaf Forest Canopy Cover Class 6 (-1589, -1.43 km^2)	Grassland Open Forest Cover Class 15 (83.91%)	Needleleaf Scrub Class 2 (+23.19%) Grassland Open Forest Cover Class 15 (-77.29%)
1996 to 1998	Mixed Scrub Class 11 (4.48 km^2)	Broadleaf Forest Canopy Cover Class 6 (+3.15 km^2) Mixed Forest Canopy Cover Class 12 (-1.92 km^2)	Needleleaf Scrub Class 2 (76.63%)	Grassland Open Forest Cover Class 15 (+172.22%) Needleleaf Scrub Class 2 (-25.63%)
1998 to 2009	Broadleaf Forest Canopy Cover Class 6 (4.84 km^2)	Needleleaf Scrub Class 2 (+1.61 km^2) Mixed Open Forest Cover Class 10 (-1.31 km^2)	Broadleaf Open Forest Cover Class 4 (92.00%)	Needleleaf Scrub Class 2 (+88.81%) Broadleaf Open Forest Cover Class 4 (-77.65%)
2009 to 2018	Mixed Scrub Class 11 (6.18 km^2)	Mixed Forest Canopy Cover-Class 12 (+6.17 km^2) Mixed Scrub Class 11 (-4.62 km^2)	Needleleaf Scrub Class 2 (94.81%)	Broadleaf Open Forest Cover Class 4 (+190.97%) Needleleaf Scrub Class 2 (-81.14%)
1991 to 2018	*Mixed Scrub Class 11 (5.08 km^2)*	*Mixed Forest Canopy Cover Class 12 (+4.10 km^2)* *Mixed Scrub Class 11 (-3.23 km^2)*	*Needleleaf Scrub Class 2 (94.59%)*	*Needleleaf Open Forest Cover Class 1 (+47.80%)* *Needleleaf Scrub Class 2 (-74.36%)*

Summary of those composite land-cover/canopy-cover classes that underwent the largest changes between successive intervals. Only the most changed class is considered for each statistical variable, and only those classes that existed in both Landsat image-mosaic years are considered for the change-detection analysis. A positive difference means the class size increased, and a negative difference means the class size decreased.

Table S9. Classification accuracies of the 1991-pair Landsat image mosaic (%).

Class	2DCNN
Needleleaf Forest	**86.01±2.50**
Broadleaf Forest	**84.65±2.99**
Mixed Forest	**84.62±1.84**
Grassland	**85.93±3.45**
OA	**84.91±1.38**
AA	**85.30±0.66**
Kappa	**76.10±2.17**

The accuracies of 2DCNN land-cover classification of the 1991-pair Landsat image mosaic (%).

Table S10. Classification accuracies of the 1993-pair Landsat image mosaic (%).

Class	2DCNN
Needleleaf Forest	**86.61±3.73**
Broadleaf Forest	**83.79±3.01**
Mixed Forest	**84.41±1.29**
Grassland	**86.54±5.26**
OA	**84.73±0.88**
AA	**85.34±1.25**
Kappa	**75.80±1.33**

The accuracies of 2DCNN land-cover classification of the 1993-pair Landsat image mosaic (%).

Table S11. Classification accuracies of the 1996-pair Landsat image mosaic (%).

Class	2DCNN
Needleleaf Forest	**82.89±2.66**
Broadleaf Forest	**83.27±3.05**
Mixed Forest	**82.67±2.62**
Grassland	**85.05±3.68**
OA	**82.73±1.02**
AA	**83.47±0.94**
Kappa	**72.49±1.95**

The accuracies of 2DCNN land-cover classification of the 1996-pair Landsat image mosaic (%).

Table S12. Classification accuracies of the 1998-pair Landsat image mosaic (%).

Class	2DCNN
Needleleaf Forest	**85.51±4.01**
Broadleaf Forest	**75.13±5.07**
Mixed Forest	**84.69±1.69**
Grassland	**86.95±6.69**
OA	**82.50±1.29**
AA	**83.07±4.65**
Kappa	**72.47±2.06**

The accuracies of 2DCNN land-cover classification of the 1998-pair Landsat image mosaic (%).

Table S13. Classification accuracies of the 2009-pair Landsat image mosaic (%).

Class	2DCNN
Needleleaf Forest	**85.38±3.35**
Broadleaf Forest	**82.83±2.41**
Mixed Forest	**82.81±1.29**
Grassland	**82.40±3.87**
OA	**83.25±0.87**
AA	**83.36±1.18**
Kappa	**73.50±1.33**

The accuracies of 2DCNN land-cover classification of the 2009-pair Landsat image mosaic (%).

Table S14. Classification accuracies of the 2018-pair Landsat image mosaic (%).

Class	2DCNN
Needleleaf Forest	**80.75±2.62**
Broadleaf Forest	**84.25±2.91**
Mixed Forest	**81.19±2.13**
Grassland	**87.71±3.29**
OA	**81.78±0.79**
AA	**83.48±2.79**
Kappa	**70.95±1.48**

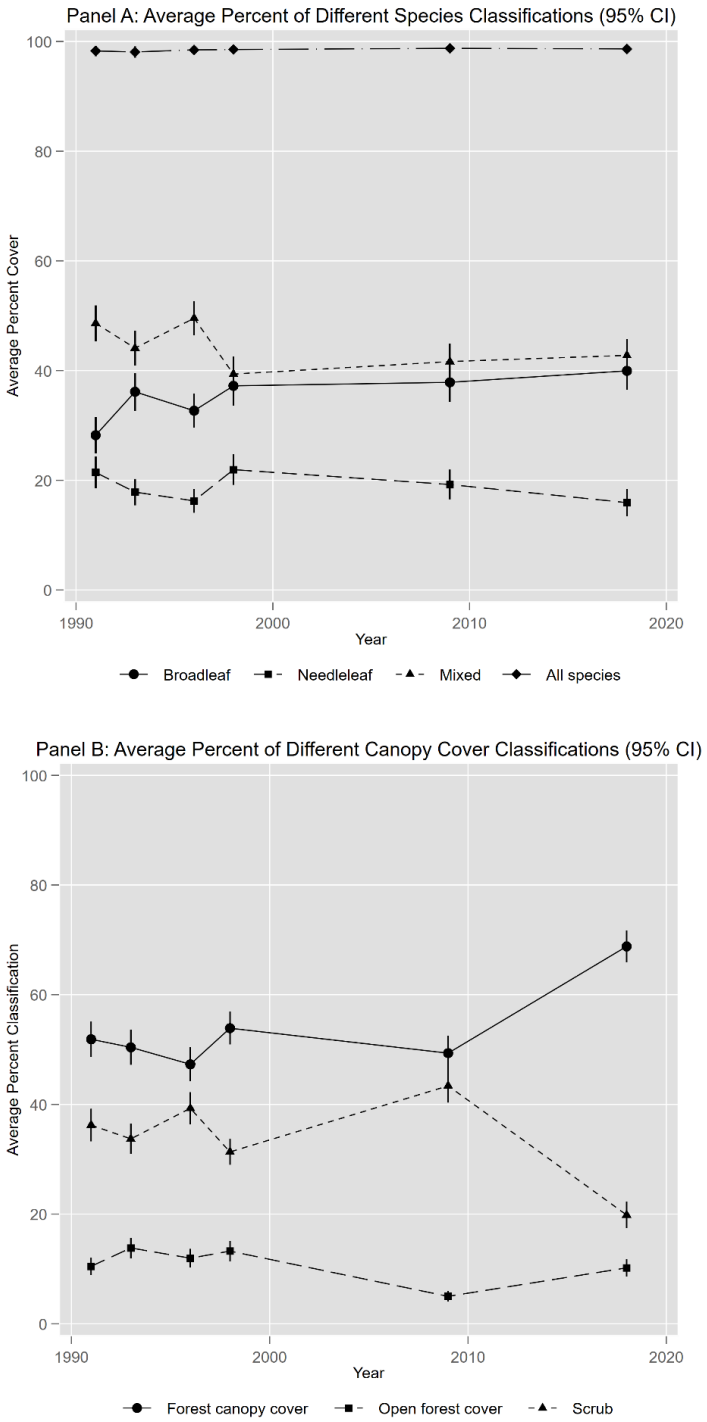
The accuracies of 2DCNN land-cover classification of the 2018-pair Landsat image mosaic (%).

Table S15. Land change summary measures based on image classifications.

Years	Class Changes (Most changed) in Pixel Count	Image Differences (Most changed) in Pixel Count	Class Changes (Most changed) in Percentage	Image Differences (Most changed) in Percentage
1991 to 1993	Needleleaf Forest (1267)	Broadleaf (+457) Needleleaf Forest (-415)	Needleleaf Forest (29.85%)	Grassland (+14.21%) Needleleaf Forest (-9.78%)
1993 to 1996	Mixed Forest (1756)	Mixed Forest (+284) Needleleaf Forest (-275)	Grassland (36.68%)	Mixed Forest (+2.67%) Needleleaf Forest (-7.42%)
1996 to 1998	Mixed Forest (2598)	Pure Needle (+791) Mixed Forest (-513)	Broadleaf Forest (41.00%)	Needleleaf Forest (+22.25%) Grassland (-7.90%)
1998 to 2009	Mixed Forest (2333)	Pure Broad (+457) Mixed Forest (-319)	Grassland (40.72%)	Broadleaf Forest (+12.31%) Grassland (-16.52%)
2009 to 2018	Mixed Forest (2105)	Broadleaf Forest (+802) Needleleaf Forest (-601)	Grassland (44.479%)	Broadleaf Forest (+19.23%) Needleleaf Forest (-13.86%)
1991 to 2018	*Mixed Forest (2850)*	*Broadleaf Forest (+1564) Mixed Forest (-815)*	/	*Broadleaf Forest (+45.89%) Grassland (-29.93%)*

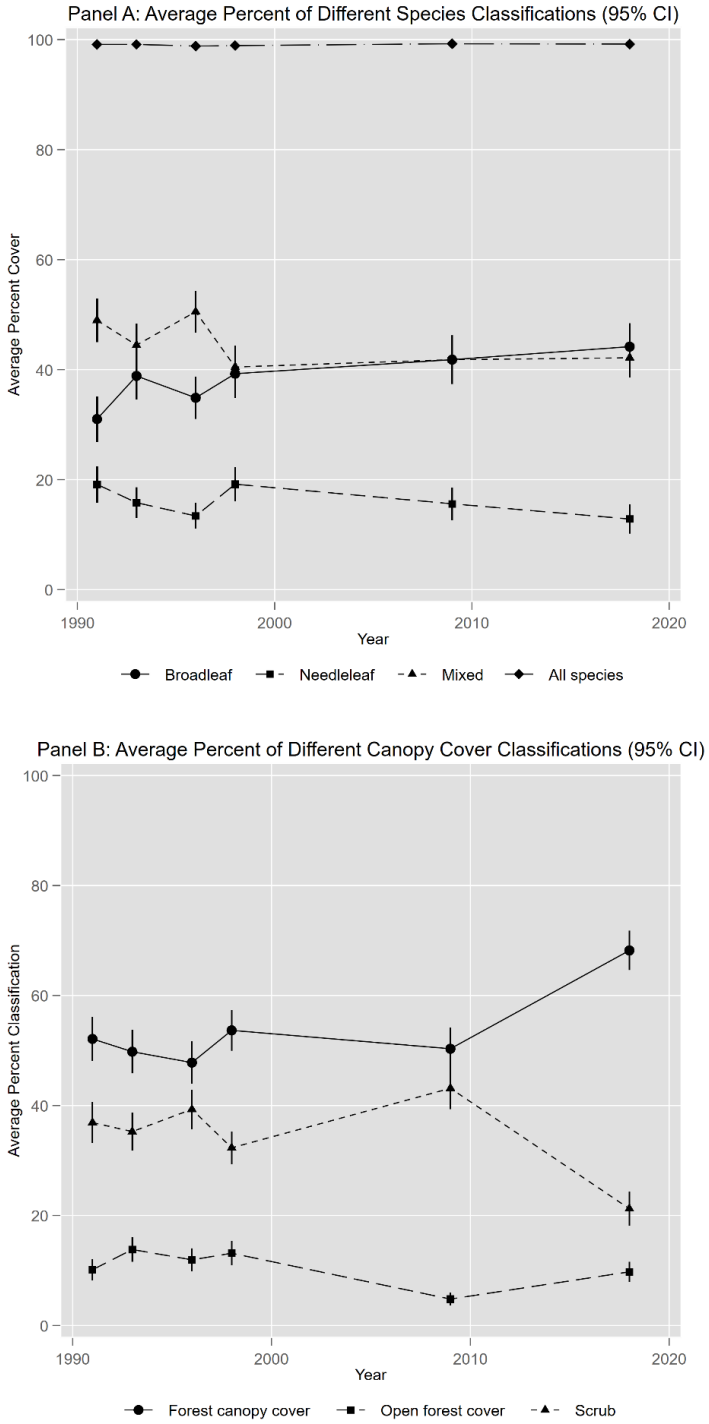
Summary measures of land change across the 60 plantations from 1991 to 2018, based on the land-cover classified images. Specifically, this table provides a summary of those land-cover classes that underwent the largest changes between successive intervals. Only the most changed class is considered for each statistical variable. Class Changes refers to the total number of initial state pixels that changed classes. Image Differences is the difference in the total number of equivalently-classed pixels in the two images, computed by subtracting the Initial State Class from the Final State Class Totals. A positive difference means the class size increased, and a negative difference means the class size decreased.

Fig. S1. Average forest cover trends across plantation areas



This figure presents the average value of each forest cover classification across all plantation areas in our sample within each year. We use points to represent the timing of our actual measurements and connect them with lines to help readers visualize trends. Spikes around the points represent 95% confidence intervals for our estimates.

Fig. S2. Average forest cover trends across plantation areas not yet established in 1991



This figure presents the same information as Fig. S1 but calculated in a restricted sample: plantation areas that did not yet have an established plantation on them in 1991.

Fig. S3. Histogram of the number of plantations in all 60 panchayats

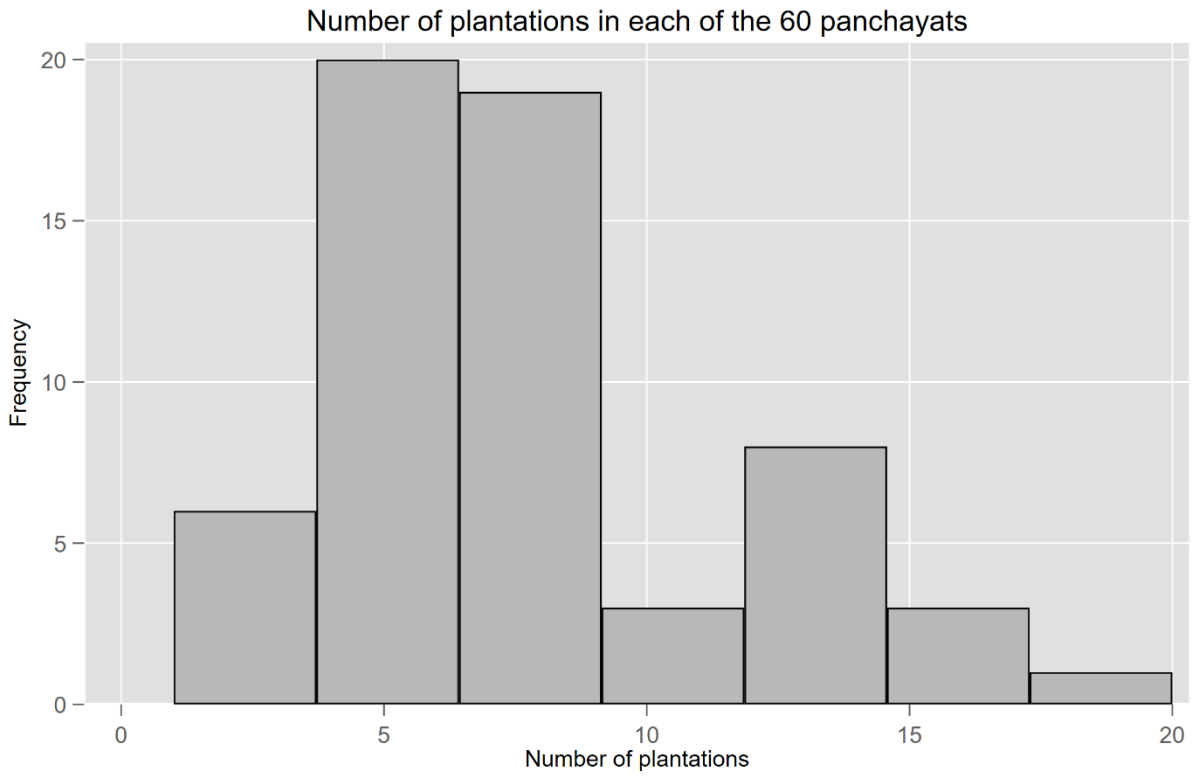


Fig. S4. Forest canopy cover over time for each plantation in one study panchayat

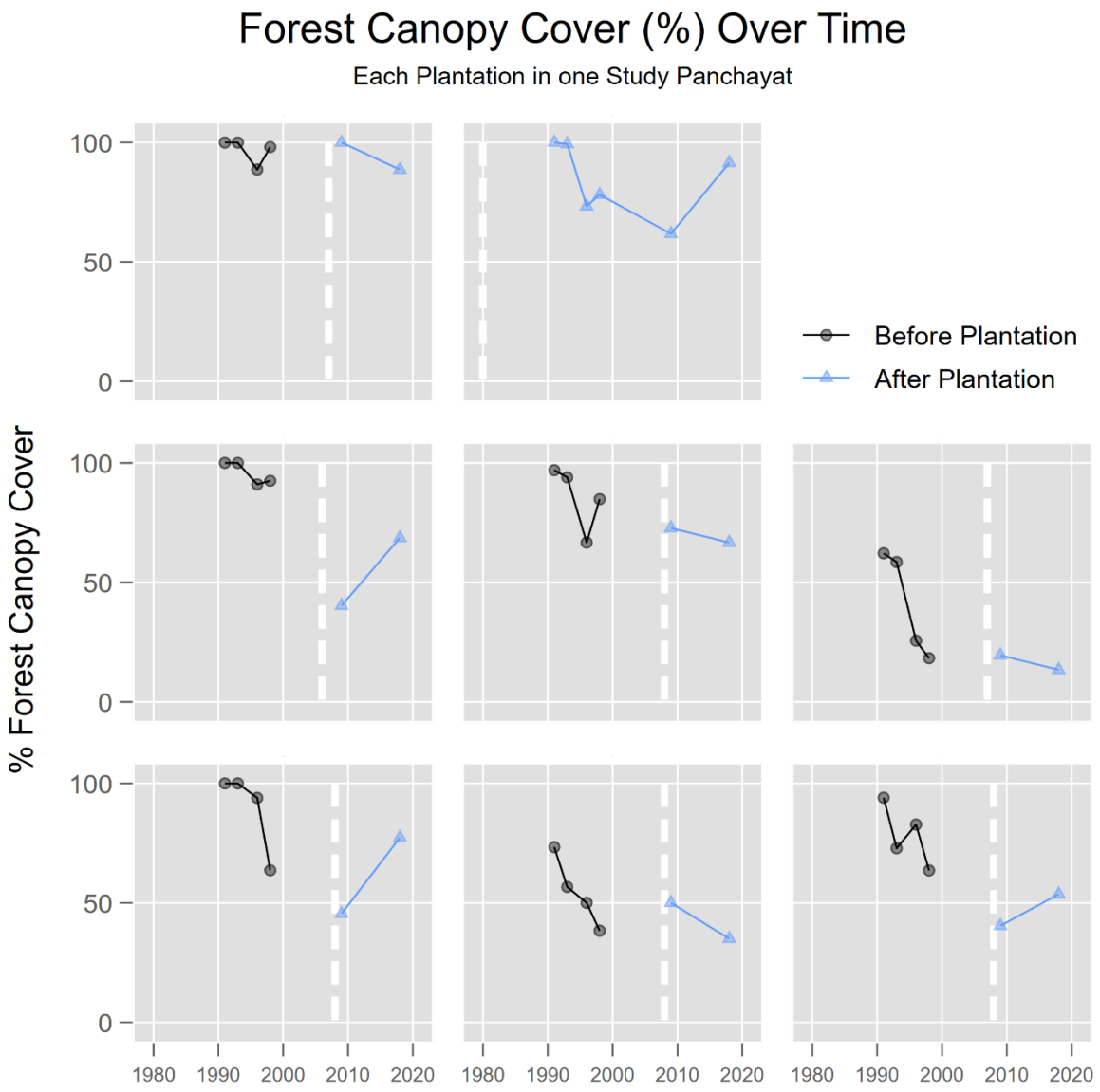


Table S16. Forest canopy cover regression results

	(1) Model 1 b/se	(2) Model 2 b/se	(3) Model 3 b/se	(4) Model 4 b/se
After Plantation	-0.606	2.133		4.876
	(2.29)	(2.27)		(3.32)
After Plantation x Plantation Age		0.089		-0.110
		(0.20)		(0.96)
After Plantation x Plantation Age^2				0.036
				(0.04)
Plantation Age		-0.191		-0.478
		(0.20)		(0.69)
Plantation Age^2				-0.014
				(0.03)
sqrt(Distance)	-0.043	-0.031	-0.071	-0.036
	(0.53)	(0.53)	(0.52)	(0.53)
log(Area)	4.516**	4.931**	5.096**	4.861**
	(1.72)	(1.83)	(1.82)	(1.84)
sqrt(Distance) x log(Area)	0.129	0.083	0.122	0.086
	(0.59)	(0.59)	(0.59)	(0.59)
log(Slope)	5.858	5.747	5.924	5.732
	(4.64)	(4.61)	(4.56)	(4.61)
log(Elevation)	27.538**	27.580**	27.607**	27.690**
	(10.26)	(10.24)	(10.18)	(10.24)
log(Slope) x log(Elevation)	-43.686***	-43.783***	-43.541***	-43.879***
	(11.25)	(11.18)	(11.12)	(11.19)
Constant	43.040***	41.400***	42.798***	40.423***
	(5.76)	(5.77)	(6.56)	(6.07)
Plantation Age FE	*No*	*No*	*Yes*	*No*
Panchayat-Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Plantations	430	430	430	430
Total Obs.	2580	2580	2580	2580
R-Squared	0.464	0.464	0.475	0.465

Forest canopy cover regression results for models described in the main text (Models 2-3), a model that simply includes a binary term for active plantations (Model 1), and a model that considers a quadratic effect of Plantation Age (Model 4). Estimates in the table above are coefficient estimates, with standard errors (clustered at the plantation level) in parentheses.

We use a Wald test to explore whether the effect of Plantation Age in Model 2 differs in the pre- and post-establishment periods. This yields a F-statistic of 0.58, and a p-value of 0.447.

Table S17. Broadleaf species cover regression results

	(1) Model 1 b/se	(2) Model 2 b/se	(3) Model 3 b/se	(4) Model 4 b/se
After Plantation	-5.395***	-1.801		-3.096
	(1.61)	(1.91)		(2.81)
After Plantation x Plantation Age		-0.824***		1.563*
		(0.20)		(0.74)
After Plantation x Plantation Age^2				-0.008
				(0.03)
Plantation Age		0.197		-0.905
		(0.15)		(0.52)
Plantation Age^2				-0.050*
				(0.02)
sqrt(Distance)	2.332***	2.325***	2.345***	2.311***
	(0.40)	(0.40)	(0.40)	(0.40)
log(Area)	0.601	1.036	0.769	0.850
	(1.59)	(1.61)	(1.57)	(1.58)
sqrt(Distance) x log(Area)	-0.650	-0.688	-0.619	-0.651
	(0.40)	(0.40)	(0.41)	(0.41)
log(Slope)	0.838	0.569	0.700	0.705
	(3.30)	(3.29)	(3.28)	(3.30)
log(Elevation)	-53.811***	-52.769***	-53.493***	-53.195***
	(11.25)	(11.14)	(10.83)	(11.14)
log(Slope) x log(Elevation)	22.028*	21.289*	21.766*	21.306*
	(10.49)	(10.54)	(10.50)	(10.61)
Constant	28.739***	31.746***	30.111***	28.489***
	(5.56)	(5.46)	(5.86)	(5.29)
Plantation Age FE	*No*	*No*	*Yes*	*No*
Panchayat-Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Plantations	430	430	430	430
Total Obs.	2580	2580	2580	2580
R-Squared	0.464	0.464	0.475	0.465

Broadleaf species cover regression results for models described in the main text (Models 2-3), a model that simply includes a binary term of active plantations (Model 1), and a model that considers a quadratic effect of Plantation Age (Model 4). Estimates in the table above are coefficient estimates, with standard errors (clustered at the plantation level) in parentheses.

We use a Wald test to explore whether the effect of Plantation Age in Model 2 differs in the pre- and post-establishment periods. This yields a F-statistic of 10.69, and a p-value of 0.001.

Table S18. Needleleaf species cover regression results

	(1) Model 1 b/se	(2) Model 2 b/se	(3) Model 3 b/se	(4) Model 4 b/se
After Plantation	4.466*	-0.721		2.682
	(2.05)	(1.75)		(2.45)
After Plantation x Plantation Age		0.588**		0.801
		(0.20)		(0.83)
After Plantation x Plantation Age^2				0.046
				(0.03)
Plantation Age		0.001		-0.604
		(0.15)		(0.59)
Plantation Age^2				-0.028
				(0.03)
sqrt(Distance)	-1.638***	-1.643***	-1.642***	-1.652***
	(0.41)	(0.41)	(0.42)	(0.42)
log(Area)	0.640	-0.057	-0.011	-0.187
	(1.62)	(1.62)	(1.63)	(1.63)
sqrt(Distance) x log(Area)	-0.476	-0.407	-0.428	-0.396
	(0.42)	(0.42)	(0.42)	(0.42)
log(Slope)	-8.059	-7.751	-7.836	-7.744
	(4.36)	(4.38)	(4.38)	(4.39)
log(Elevation)	19.595*	18.722*	18.459*	18.784*
	(8.56)	(8.37)	(8.38)	(8.40)
log(Slope) x log(Elevation)	-37.294***	-36.619***	-36.614***	-36.744***
	(9.71)	(9.81)	(9.83)	(9.82)
Constant	25.542***	24.493***	24.704***	22.535***
	(5.14)	(5.13)	(5.38)	(5.09)
Plantation Age FE	*No*	*No*	*Yes*	*No*
Panchayat-Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Plantations	430	430	430	430
Total Obs.	2580	2580	2580	2580
R-Squared	0.464	0.464	0.475	0.465

Needleleaf species cover regression results for models described in the main text (Models 2-3), a model that simply includes a binary term of active plantations (Model 1), and a model that considers a quadratic effect of Plantation Age (Model 4). Estimates in the table above are coefficient estimates, with standard errors (clustered at the plantation level) in parentheses.

We use a Wald test to explore whether the effect of Plantation Age in Model 2 differs in the pre- and post-establishment periods. This yields a F-statistic of 3.74, and a p-value of 0.0536.

Table S19. Mixed species cover regression results

	(1) Model 1 b/se	(2) Model 2 b/se	(3) Model 3 b/se	(4) Model 4 b/se
After Plantation	-0.578	1.866		-0.002
	(2.21)	(2.20)		(2.97)
After Plantation x Plantation Age		0.236		-2.408**
		(0.19)		(0.92)
After Plantation x Plantation Age^2				-0.035
				(0.03)
Plantation Age		-0.244		1.453*
		(0.18)		(0.62)
Plantation Age^2				0.078*
				(0.03)
sqrt(Distance)	-1.667**	-1.653**	-1.678**	-1.630**
	(0.55)	(0.55)	(0.55)	(0.55)
log(Area)	-0.382	0.006	0.222	0.318
	(1.64)	(1.73)	(1.74)	(1.73)
sqrt(Distance) x log(Area)	0.430	0.385	0.347	0.337
	(0.70)	(0.71)	(0.70)	(0.71)
log(Slope)	9.125	9.047	9.006	8.902
	(5.22)	(5.23)	(5.21)	(5.25)
log(Elevation)	18.283	18.156	19.374	18.534
	(10.70)	(10.76)	(10.50)	(10.71)
log(Slope) x log(Elevation)	17.052	17.067	16.445	17.167
	(12.13)	(12.16)	(12.07)	(12.23)
Constant	46.139***	43.819***	45.379***	48.992***
	(6.11)	(6.07)	(6.39)	(6.08)
Plantation Age FE	*No*	*No*	*Yes*	*No*
Panchayat-Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Plantations	430	430	430	430
Total Obs.	2580	2580	2580	2580
R-Squared	0.464	0.464	0.475	0.465

Mixed species cover regression results for models described in the main text (Models 2-3), a model that simply includes a binary term of active plantations (Model 1), and a model that considers a quadratic effect of Plantation Age (Model 4). Estimates in the table above are coefficient estimates, with standard errors (clustered at the plantation level) in parentheses.

We use a Wald test to explore whether the effect of Plantation Age in Model 2 differs in the pre- and post-establishment periods. This yields a F-statistic of 2.16, and a p-value of 0.142.

Table S20. Open forest cover regression results

	(1) Model 1 b/se	(2) Model 2 b/se	(3) Model 3 b/se	(4) Model 4 b/se
After Plantation	0.907	0.088		0.760
	(1.19)	(1.86)		(2.21)
After Plantation x Plantation Age		0.183		0.733
		(0.16)		(0.53)
After Plantation x Plantation Age^2				0.011
				(0.02)
Plantation Age		-0.043		-0.437
		(0.15)		(0.38)
Plantation Age^2				-0.018
				(0.02)
sqrt(Distance)	-0.127	-0.125	-0.113	-0.131
	(0.23)	(0.23)	(0.24)	(0.23)
log(Area)	-1.512	-1.612	-1.857	-1.686
	(0.98)	(0.99)	(0.99)	(0.99)
sqrt(Distance) x log(Area)	-0.233	-0.224	-0.218	-0.214
	(0.28)	(0.29)	(0.29)	(0.29)
log(Slope)	0.066	0.126	0.019	0.156
	(1.86)	(1.85)	(1.83)	(1.83)
log(Elevation)	-0.397	-0.629	-0.386	-0.699
	(4.41)	(4.41)	(4.42)	(4.39)
log(Slope) x log(Elevation)	8.564*	8.729*	8.827*	8.698*
	(3.76)	(3.75)	(3.79)	(3.75)
Constant	10.348***	9.689**	9.712**	8.477**
	(2.80)	(3.12)	(3.67)	(3.21)
Plantation Age FE	*No*	*No*	*Yes*	*No*
Panchayat-Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Plantations	430	430	430	430
Total Obs.	2580	2580	2580	2580
R-Squared	0.464	0.464	0.475	0.465

Open forest cover regression results for models described in the main text (Models 2-3), a model that simply includes a binary term of active plantations (Model 1), and a model that considers a quadratic effect of Plantation Age (Model 4). Estimates in the table above are coefficient estimates, with standard errors (clustered at the plantation level) in parentheses.

We use a Wald test to explore whether the effect of Plantation Age in Model 2 differs in the pre- and post-establishment periods. This yields a F-statistic of 0.59, and a p-value of 0.441.

Table S21. Scrub cover regression results

	(1) Model 1 b/se	(2) Model 2 b/se	(3) Model 3 b/se	(4) Model 4 b/se
After Plantation	-1.814	-3.034		-6.052
	(2.02)	(2.09)		(3.09)
After Plantation x Plantation Age		-0.305		-0.923
		(0.18)		(0.82)
After Plantation x Plantation Age^2				-0.043
				(0.03)
Plantation Age		0.211		0.979
		(0.18)		(0.62)
Plantation Age^2				0.036
				(0.03)
sqrt(Distance)	-0.752	-0.764	-0.738	-0.752
	(0.44)	(0.44)	(0.44)	(0.44)
log(Area)	-2.231	-2.446	-2.379	-2.290
	(1.45)	(1.54)	(1.53)	(1.55)
sqrt(Distance) x log(Area)	-0.603	-0.577	-0.624	-0.594
	(0.43)	(0.43)	(0.42)	(0.44)
log(Slope)	-3.493	-3.479	-3.592	-3.508
	(4.54)	(4.53)	(4.51)	(4.53)
log(Elevation)	-42.368***	-42.109***	-42.120***	-42.094***
	(7.66)	(7.66)	(7.62)	(7.69)
log(Slope) x log(Elevation)	36.706***	36.576***	36.247***	36.692***
	(9.63)	(9.61)	(9.55)	(9.60)
Constant	46.784***	48.969***	47.733***	51.402***
	(4.84)	(4.98)	(5.59)	(5.15)
Plantation Age FE	*No*	*No*	*Yes*	*No*
Panchayat-Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Plantations	430	430	430	430
Total Obs.	2580	2580	2580	2580
R-Squared	0.464	0.464	0.475	0.465

Scrub cover regression results for models described in the main text (Models 2-3), a model that simply includes a binary term of active plantations (Model 1), and a model that considers a quadratic effect of Plantation Age (Model 4). Estimates in the table above are coefficient estimates, with standard errors (clustered at the plantation level) in parentheses.

We use a Wald test to explore whether the effect of Plantation Age in Model 2 differs in the pre- and post-establishment periods. This yields a F-statistic of 2.38, and a p-value of 0.124.

Table S22. Summary statistics for variables in forest cover regressions

Variables	Obs	Mean	Std. Dev.	Min	Max	p1	p99	Skew.	Kurt.
Percent forest canopy	2580	53.607	33.142	0	100	0	100	-.12	1.641
Percent broadleaf	2580	35.347	36.144	0	100	0	100	.67	1.932
After Plantation	2580	.54	.498	0	1	0	1	-.162	1.026
Plantation Age	2580	.991	13.08	-20	20	-20	20	-.117	1.819
Distance to road (minutes)	2580	13.598	33.916	0	220	0	180	3.929	18.893
sqrt(Distance)	2580	2.089	3.039	0	14.832	0	13.416	1.971	7.179
Area (hectares)	2580	8.401	5.52	.1	40	.5	30	2.374	10.82
log(Area)	2580	1.943	.668	-2.303	3.689	-.693	3.401	-1.72	12.879
Slope	2580	19.099	7.573	2.49	43.223	3.645	37.889	.628	3.265
log(slope)	2580	2.862	.445	.912	3.766	1.293	3.635	-1.04	5.7
Elevation	2580	1048.491	460.992	523.591	2807.74	562.531	2423.862	1.32	3.955
log(elevation)	2580	6.875	.384	6.261	7.94	6.332	7.793	.777	2.47

Table S23. Alternative land cover estimation

Outcome measure	Controls	ATT	Std. error	95% CI, lower	95% CI, upper
Percent forest canopy cover	No	-2.85	2.29	-7.33	1.63
Percent broadleaf cover	No	-2.19	2.36	-6.81	2.43
Percent forest canopy cover	Yes	-2.89	2.13	-7.06	1.27
Percent broadleaf cover	Yes	0.10	2.13	-4.07	4.27

Motivated in part by concerns about the accuracy and interpretability of two-way fixed effects estimators, Callaway and Sant'Anna (2020)[1] present a framework for generalizing difference-in-differences (DID) estimation outside of the canonical two-period setup. Their method allows estimating DID effects in the presence of more than two time periods, staggered adoption, and a parallel trends assumption that is conditional on covariates. This method provides a way for analysts to flexibly calculate different kinds of DID effects by varying how they aggregate *group-time average treatment effects*—average treatment effects among units in a sample who became treated at specific time points.

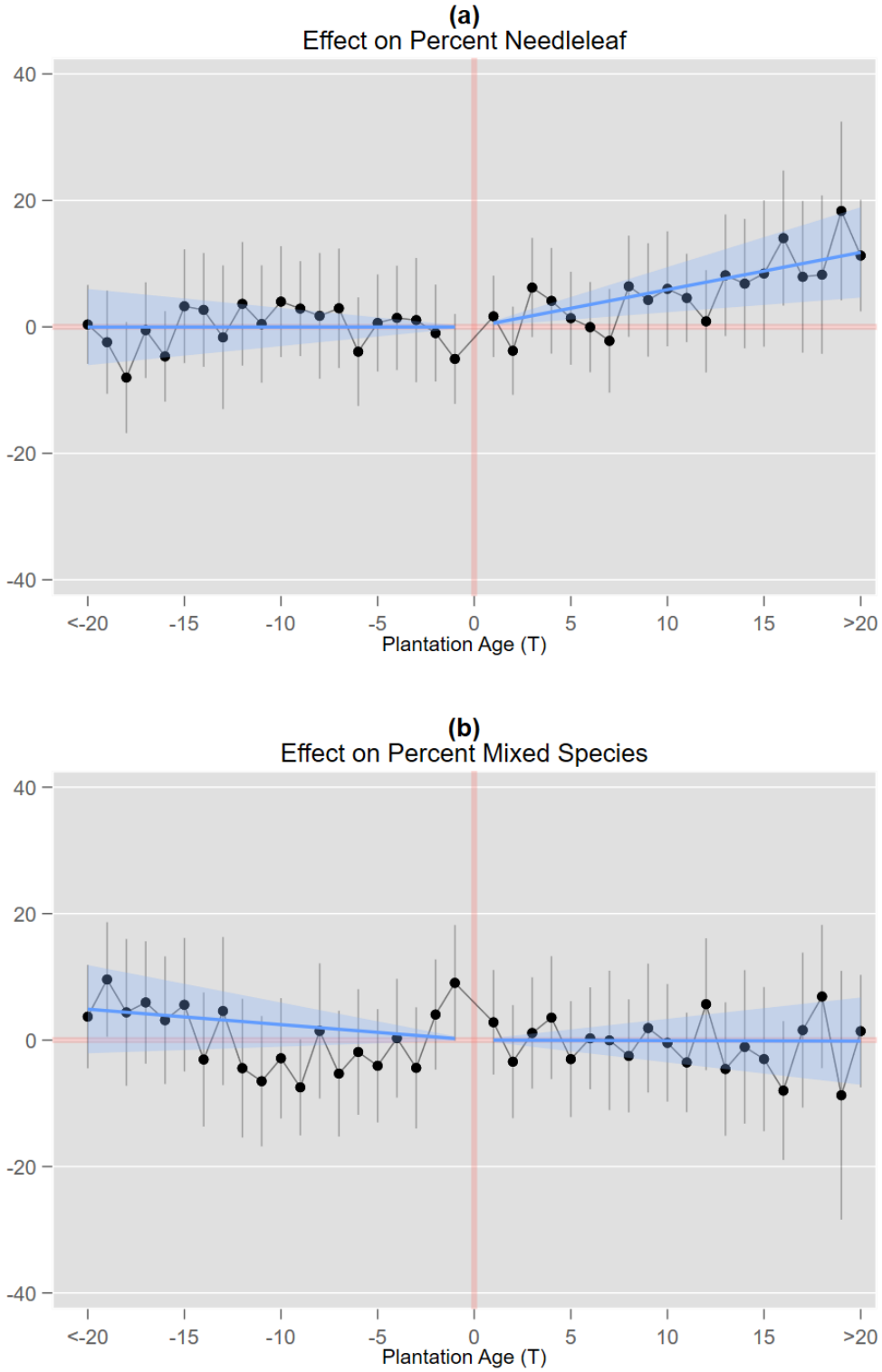
We use code developed by these authors for the R statistical programming language to demonstrate that applying their strategy yields similar conclusions to those we present in the main text. We focus on a method Callaway and Sant'Anna (2020) provide for computing a single average treatment effect on the treated (ATT) across an entire sample. This is analogous to Model 1 in Tables S16-S22; it shows us an average effect of tree planting in the years after plantation establishment, relative to the years before plantation establishment.

Applying this method requires defining a reference group of control units. We elect to use not-yet-treated units as our controls: areas for which we have forest cover classifications before a plantation had been established. This requires dropping the 136 plantations that already existed in 1991 from this analysis. Applying this method also requires choosing an estimator. We elect to use the "doubly robust" estimator Callaway and Sant'Anna (2020) discuss. Finally, we produce results both with and without the covariates we use in the analyses in Tables S16-S22 (an interaction of distance from the road and plantation area; an interaction of slope and elevation).

The results in Table S23 are consistent with the substantive conclusions that follow from the estimation strategy we use in the main text. The estimated effect of tree planting on the percent of forest canopy cover and broadleaf cover in these plantation areas is small. Moreover, the 95% confidence intervals contain values that are substantively negligible given our study timeframe.

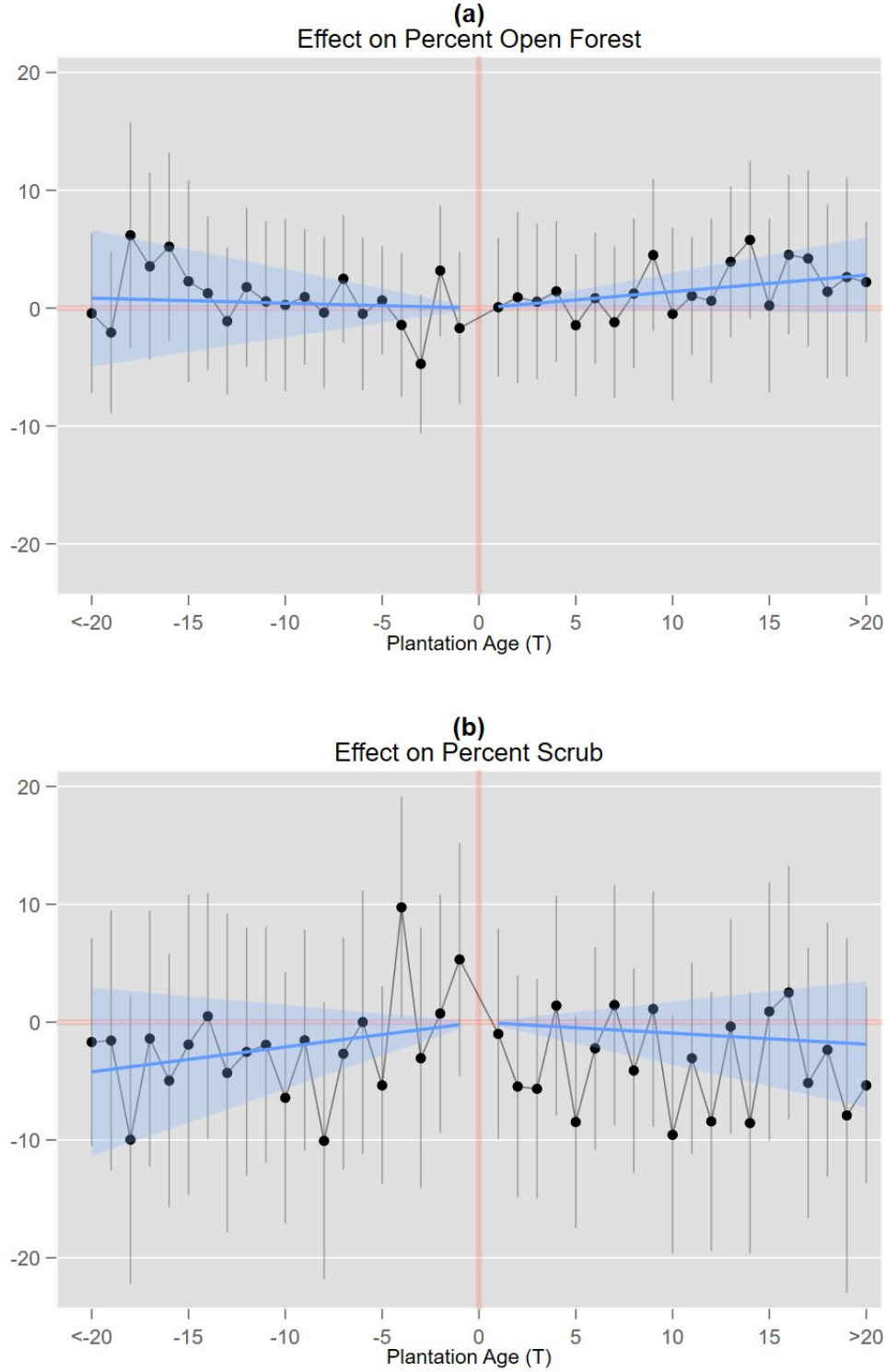
[1] Reference 44 in the main text.

Fig. S5. Impact of tree planting on other forest composition classifications



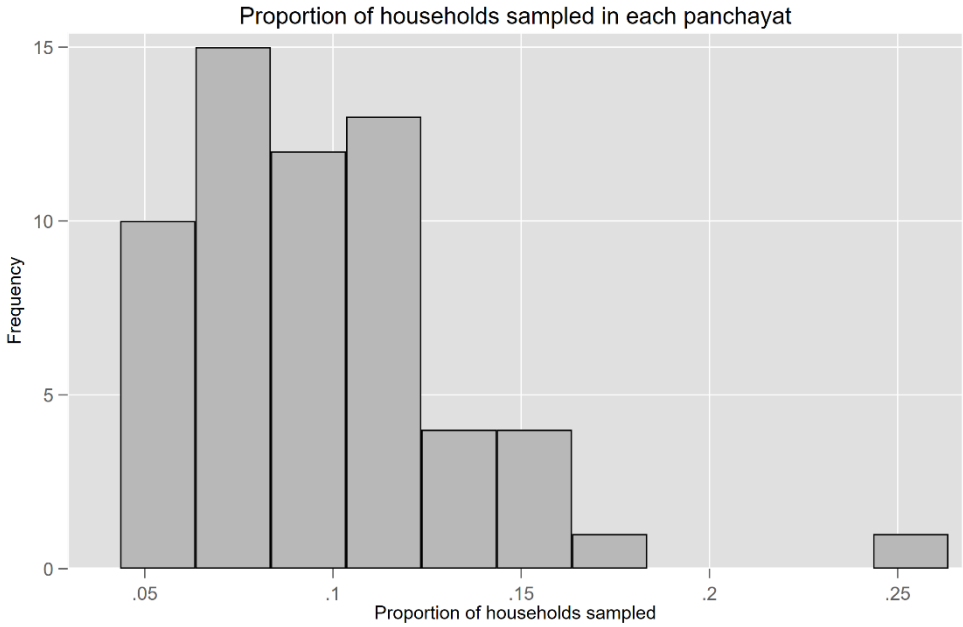
This figure replicates Figure 3 from the main text for the other species cover classifications: needleleaf species cover and mixed species cover (both needleleaf and broadleaf).

Fig. S6. Impact of tree planting on other forest canopy classifications



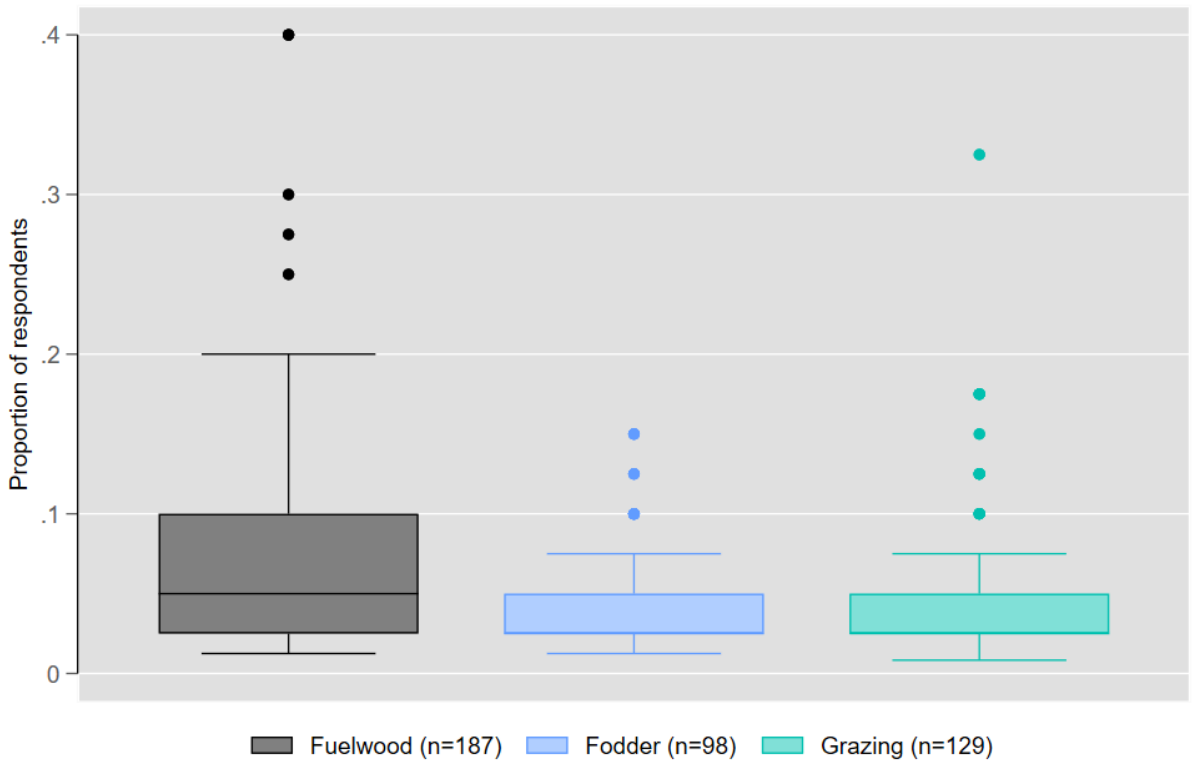
This figure replicates Figure 3 from the main text for the other canopy-cover classifications: open forest cover (canopy cover between 40% and 10%); and scrub (canopy cover <10%).

Fig. S7. Proportion of surveyed households in each panchayat



We divide 40 (the number of household surveys we conducted in each panchayat) by the number of total households in each panchayat. The resulting estimates are presented in this histogram, as a measure of sampling intensity within each panchayat.

Fig. S8. Box plots of the proportion of plantation users



Box plots illustrating variation in the proportion of respondents who use each plantation. The count of plantations with 1 or more users for each purpose in our sample are listed in parentheses.

Table S24. Summary information on plantation use and dependence

	Proportion (of *N*)	*N*	Std. Err.	95% CI, lower	95% CI, upper
Panel A: Proportion Plantation users (fuelwood, fodder, grazing)					
Overall	0.424	2,400	0.01	0.404	0.444
Income terciles					
- Low income	0.605	833	0.02	0.571	0.638
- Middle income	0.420	767	0.02	0.385	0.455
- High income	0.239	800	0.02	0.21	0.27
Midday meal access					
- Yes	0.736	314	0.02	0.684	0.782
- No	0.377	2,086	0.01	0.356	0.398
Scheduled Caste/Tribe					
- Yes	0.617	741	0.02	0.581	0.651
- No	0.338	1,695	0.01	0.315	0.361
Panel B: Proportion Dependence (among plantation users for fuelwood, fodder, and grazing)					
Overall	0.094	1,008	0.01	0.078	0.114
Income terciles					
- Low income	0.106	498	0.01	0.082	0.137
- Middle income	0.088	319	0.02	0.061	0.124
- High income	0.073	191	0.02	0.044	0.120
Midday meal access					
- Yes	0.127	228	0.02	0.09	0.177
- No	0.085	780	0.01	0.067	0.106
Scheduled Caste/Tribe					
- Yes	0.12	450	0.02	0.093	0.153
- No	0.073	558	0.01	0.054	0.098
Panel C: Importance of Plantations for Livelihoods (among plantation users)					
Experienced a livelihood shock	0.263	1,008	0.01	0.237	0.291
- Plantations helped at least a little	0.230	265	0.03	0.183	0.285
- Plantations helped substantially	0.057	265	0.01	0.034	0.092
Plantation decline bad for livelihood	0.014	1,008	0.004	0.008	0.023

For each of the 2,400 respondents to our household surveys, we construct a binary variable representing whether they use at least one plantation in this region (including plantations in our sample that were not selected for remote sensing) for one of the three uses discussed in the main text: fuelwood collection, fodder collection, and grazing. We call this *Plantation Use*. The first

row in Panel A shows the proportion of all respondents who use at least one plantation for at least one of those three purposes, along with standard errors and confidence intervals. Roughly half of our respondents use at least one plantation for at least one of those three purposes.

The following seven rows show the proportion of plantation users among different subgroups of respondents. First, we group respondents into terciles based on their reported annual household income: low income, middle income, and high income. Then, we group respondents according to whether they have access to a government assistance program that provides midday meals. Finally, we group respondents based on whether they are of a Scheduled Caste or Scheduled Tribe. Low income respondents, respondents with access to meal assistance, and scheduled caste respondents appear more likely to rely on plantations. A comparison of confidence intervals across categories within the same group (e.g., low income vs high income) suggests that these differences in plantation use are meaningful.

Next, we construct a variable called *Dependence* for the 1,017 respondents who use at least one plantation for fuelwood, fodder, or grazing. We base this variable on a survey question asking respondents how much they depend on each plantation in their panchayat. There were five possible responses: *not dependent*; *low*; *medium*; *high*; *no response*. *Dependence* takes a value of 1 for respondents who indicated that their dependence on plantations was either moderate or high. We drop information from nine respondents who answered "no response" when asked about their dependence.

The first row of Panel B shows the proportion of plantation users who indicate being dependent on those plantations, along with standard errors and confidence intervals. Once again, we follow with estimates for different subgroups of respondents. Here, differences across subgroups are not as striking.

Finally, we present information in Panel C that explores the relationship between plantations and respondents' livelihoods in more detail. This helps add context to the results from Panel B. In our household surveys, we asked respondents whether they have experienced different shocks or stressors that could threaten a household's livelihood: drought; fire; flood/rain/landslide; livestock death; rise in prices of food or agricultural inputs; fall in sale prices of crops; loss of land; and the illness or death of household member. We calculate the number of respondents who experienced at least one of these. We also asked respondents whether plantations helped them recover from any of these shocks or stressors. The possible responses were: *did not help*, *a little bit*, *helped somewhat*, *equally important with other steps*, and *more important than other steps*.

We subset to respondents who use plantations for fuelwood, fodder, or grazing, as in Panel B. Next, we calculate the number of plantation users who experienced one of these shocks, and who state that plantations helped them recover from this shock at least *a little bit.* After that, we redo this calculation while only considering respondents who indicate that plantations helped *somewhat* or more. We call this second measure "helped substantially" in Table S24. Lastly, we also asked respondents how they predict that their main or secondary livelihoods would change if the benefits they currently receive from plantations decrease in the future (*i.e.*, if plantations themselves go into decline). We calculate the number of plantation users who indicate that their

livelihoods will *decrease greatly* or *decrease somewhat* (rather than *remain the same* or *increase somewhat*) if plantations decline.

Panel C shows that roughly 25% of the plantation users in our samples experienced at least one shock to their livelihoods. Of the 265 respondents who had, about 20% indicate that plantations helped in their recovery from these shocks, at least a little. However, only about 5% of respondents indicate that plantations helped a substantial amount. In most cases plantation benefits play only a small role in a household's recovery from a shock to its members' livelihoods. Finally, Panel C shows that only around 1% of the plantation users in our sample indicate that they expect their livelihoods to be threatened if plantations go into decline.

Table S25. Number of plantations used by households

Number of plantations a household uses for fuel, fodder, or grazing	Frequency	Percent	Cumulative
1	698	68.63	68.63
2	231	22.71	91.35
3	63	6.19	97.54
4	14	1.38	98.92
5	8	0.79	99.71
6	1	0.10	99.80
7	2	0.20	100.00
Total	1017	100.00	

Across all respondents who use at least one plantation for fuelwood, fodder, or grazing, we tabulated the total number of plantations their household uses for those three purposes. In other words, for each household that indicates using at least one plantation, we count the number of *household-plantation* pairs that involve plantation use for fuelwood, fodder, or grazing.

The result shows that although some outlier households use multiple plantations for the three benefits we highlight, by and large most households use only one or two.

Table S26. Negative binomial regression table for results reported in Table 1

Household use of plantations--Negative binomial models

	(1) Fuel	(2) Fodder	(3) Grazing
Plantation age	0.0196**	0.00278	0.0249**
	(0.00739)	(0.00800)	(0.00790)
sqrt(Distance)	-0.108**	-0.0872**	-0.0468
	(0.0313)	(0.0333)	(0.0303)
log(Area)	0.403**	0.262	0.106
	(0.155)	(0.160)	(0.164)
Constant	-2.776**	-3.209**	-3.587**
	(0.471)	(0.510)	(0.500)
Panchayat FE	Yes	Yes	Yes
N	430	430	430

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Coefficient estimates from within-panchayat negative binomial regression results (i.e., regression results using panchayat fixed effects and a limited sample of explanatory variables). Panel A results in Table 1 in the main text are transformations of these coefficients (see our Materials and Methods). Panel B results are calculated using these coefficients.

Table S27. Summary statistics for livelihood explanatory variables

Variables	Obs	Mean	Std. Dev.	Min	Max	p1	p99	Skew.	Kurt.
Plantation age	430	20.909	11.92	2	55	2	45	.041	1.942
Distance to road in minutes	430	13.598	33.949	0	220	0	180	3.929	18.893
sqrt(Distance)	430	2.089	3.042	0	14.832	0	13.416	1.971	7.179
Area in hectares	430	8.401	5.525	.1	40	.5	30	2.374	10.82
log(Area)	430	1.943	.668	-2.303	3.689	-.693	3.401	-1.72	12.879
Number of surveyed households	430	43.535	11.69	40	120	40	80	3.178	12.248