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

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Abstract

Myriad scholars, policymakers, and practitioners advocate tree planting as a climate mitigation strategy and to support local livelihoods. But, is the broad appeal of tree planting supported by evidence? We report estimated impacts from decades of tree planting in Northern India. We find that tree plantings have not, on average, increased the proportion of dense forest cover, and have modestly shifted species composition away from the broadleaf varieties valued by local people. Supplementary analysis from household livelihood surveys show that, in contrast to narratives of forest dependent people being supported by tree planting, there are few direct users of these plantations and their dependence is low. We conclude that decades of expensive tree planting programs have not proved effective.

Data and materials availability: Replication data and materials for this analysis are available in the UMN Dataverse: [link posted upon final acceptance](#).

Code availability: Replication code for statistical analysis are available in the UMN Dataverse: [link posted upon final acceptance](#).

Main

Large scale tree planting is widely proposed as a central element of global climate mitigation efforts, based on the potential of new trees to absorb carbon and support local livelihoods¹⁻⁴. Despite this broad appeal, some researchers and practitioners have raised concerns about potential negative impacts of large-scale tree planting projects on vulnerable people and forest ecosystems⁵⁻⁷. Others question whether forest restoration projects will achieve their ambitious goals in the face of such challenges^{3,8-10}.

Is large-scale tree planting supported by evidence? Fundamentally, we still lack rigorous empirical studies that directly evaluate the performance of tree planting projects¹¹⁻¹³. 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 projects⁸. This study aims to provide such evidence.

We worked with rural communities to identify and map tree plantation boundaries, and matched these areas to historical land cover imagery in Kangra District of Himachal Pradesh in Northern India. Through image classification, we estimate forest density and species composition from longitudinal remote sensing at 6 point 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 dense forest cover, and they modestly change species 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 species 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 only 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, while 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, plantations only modestly contribute to rural livelihoods in our study site.

Study Site

India provides an excellent context to assess the impact of plantations due to its long history of tree planting programs^{14,15}, continuing high level commitment to tree planting¹⁶, prevalence of areas identified as having forest restoration potential¹⁷, and large number of forest dependent people¹⁸. Yet recent systematic reviews on tree planting outcomes found no studies from India^{12,13}, and the case studies that do exist suggest plantations may fail^{19,20}, endanger livelihoods^{20,21}, and threaten native forest cover²²⁻²⁴.

Tree plantations have a long history in Kangra District, and trace their roots to concerns about forest degradation due to excessive harvesting of wood fuel for cooking and excessive grazing by domestic animals²⁵⁻²⁸. As in most of India, the tree plantings we study are all on

government-owned land and have been undertaken by the state forest department²⁹. Although there is also a history of commercially oriented forestry in Himachal Pradesh, a ban on harvesting green trees since 1986 means that commercial timber production in this region has been nonexistent for the entire period under study³⁰. Figure 1 shows the location of the study site.

Figure 1. Study Site

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

Impact Model

We use an Event Study Design³¹ to estimate the impact of plantations on forest cover. The tree plantations in our sample (n=430) were established in a staggered manner over time. The establishment years of the plantations range from 1965 to 2018. Figure 2 shows the cumulative number of plantations, which have steadily increased since 1980. We combine this information with dependent variables estimated using satellite land cover data available at six time points: 1991, 1993, 1996, 1998, 2009, and 2018. These are the years for which cloud cover allowed precise estimation of forest attributes at the spatial resolution in our analysis. We estimate policy impact using observed data before and after the date when the plantation is established, while controlling for a plantation's site-specific geographic characteristics and panchayat-level time trends^{31,32}.

Figure 2. Cumulative Number of Active Tree Plantations

The cumulative number of active tree plantations over time. Years of Landsat satellite image data observations are indicated by red dashed lines.

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 density and species composition. Change in density can affect biodiversity and carbon storage⁵. Species composition estimates 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^{33–36}.

Using LANDSAT imagery, we temporally estimate the species 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 density, we combine our estimates of species composition with data from the Forest Survey of India (FSI) to temporally estimate the percent of each plantation area (e.g. percent of pixels) classified as “dense forest” (forest cover > 40% according to the FSI criteria). We detail this process in the Methods section, and report image classification accuracies in our Supplementary Information (Tables S1-S15).

Longitudinal Data

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 ($=60 \text{ plantations} \times (6-1) \text{ time periods}$) 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.

Estimation 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- and post- establishment forest cover trends. The fixed effects impact function approach is less efficient, but it provides flexible nonparametric estimates of the impact of tree planting (27). We believe the linear model presents a reasonable, more efficient, approximation for these effects, but we report both in Fig. 3 for reference.

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 dense forest 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 dense forest 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.

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

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

In summary, establishing plantations has not improved the proportion of broadleaf cover or dense forest cover in these areas. Full regression tables from these and other specifications (Tables S16-S17) are available in our Supplementary Information. The results we report here are robust to a variety of alternative specifications. In the Supplementary Information we also present results for the other land cover classifications (Figures S5 and S6; Tables S18-S21). Note

that our findings do not support a claim that tree planting replenished threatened forest cover or prevented the proportion of dense forest or broadleaf cover from declining more rapidly. In that case, we would see stronger evidence of declining dense or broadleaf cover in the years before plantation establishment and a tempering of this trend after establishment.

Livelihood support

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

Our units of analysis are now the cross-section of 430 plantations. We consider three outcomes—the number of respondents using a plantation to collect fuelwood, the number using a plantation to collect fodder; and the number using a plantation to graze animals (sheep, cattle, goats, and buffalo). Figure 4 presents box plots of the number of households supported by each plantation in this sample. Overall, most plantations have few direct users: they support fewer than 10 households in our sample for any one use. Figure S7 shows that calculating the proportion of plantation users instead produces a similar pattern.

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).

While most of these plantations are only used by a minority of those living in one of its panchayats, we show in Table S23 that 42% of our household sample uses at least one plantation for at least one of these purposes (+/- 2% at a 95% confidence level). However, when those plantation users rated their dependence, only 9% indicated that their dependence on plantations was medium or high (+/- 1.6% at a 95% confidence level). 91% of respondents who use plantations for fuelwood, fodder, or grazing rank their dependence as low (Table S23). In sum, while plantation use for fuelwood, fodder, or grazing is common, most households receive these benefits from only a few plantations (Tables S23-S24). Most households are also not highly dependent on these benefits.

Analysis of livelihood benefits

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

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, 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.

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

There are more substantial effects for road distance on fuelwood and fodder collection. In conjunction with our forest cover analyses, these results imply that plantations closer to the road

are more useful from a livelihood perspective, but are also less likely to contain the broadleaf species households prefer. Finally, our results also show that a plantation's size is an important predictor of its ability to jointly contribute to both environmental and livelihood goals. Larger plantations have denser forest cover (Supplementary Information Table S16) and are more likely to serve as a useful source of fuelwood collection.

Discussion

After decades of costly investments, we find no evidence that tree planting projects secured additional benefits for carbon mitigation or livelihood support in Northern India. Planting trees might seem like a straightforward way to increase carbon storage, but the process of growing trees is expensive and complicated^{6,37}. Our analysis suggests that planting trees may be a less useful carbon mitigation strategy than its proponents claim¹.

Why have these efforts to plant trees failed to improve forest conditions? 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. Cleared areas are not a viable alternative because of socioeconomic and ecological constraints of converting productive 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 in the first place needs to be addressed^{3,5,6}.

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^{15,36}. 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 environment¹⁵.

While forest plantation and restoration programs are often premised on the view that healthy ecosystems are better able to support subsistence and commercial livelihoods^{2,4}, our analyses raise critical concerns about plantations as a straightforward, cost-effective strategy for sequestering carbon while supporting the poor. While planting trees is often framed as an immediate point of action for climate change mitigation as economies pursue long-term decarbonization, our findings provide empirical evidence for the need to temper these expectations^{8,10}. Policymakers and advocates should not just assume tree planting programs will effectively meet their carbon sequestration and livelihood goals. Although our understanding of this topic is improving, further research is needed to understand the ecological, socioeconomic, and institutional conditions that might make tree planting more successful^{38–40}.

Methods

This research is based on data collected between August 2017 and May 2019 in Kangra district, Himachal Pradesh in northwest India. The objective of the data collection was to examine the connections between livelihoods and plantations in diverse social contexts and forest landscapes. We first discuss the various types of data we collected and then provide additional details on the data analysis results reported in the main manuscript.

Data Collection

We selected four forest administrative units called ‘ranges’—Palampur, Daroh, Dharamsala and Shahpur—that adequately represent variation in plantation types, elevation, and forest use in Kangra. We randomly selected 60 of the 181 panchayats (formalized local governments consisting of a few villages and habitations) within these four ranges (i.e. block randomization, 15 panchayats per range). Using panchayats as the unit of analysis, we collected data through four research instruments that focus on different aspects of communities (C-Form), households (H-Form), plantations (p-Form), and plantation ecology (P-Form) for each panchayat.

Data collection followed a sequence of steps starting with creating a list of plantations in the panchayat, and then surveying communities, plantations, and households in that order. We found that the most challenging aspect of connecting plantations to livelihoods was to disaggregate and uniquely identify the different plantations in the panchayat, determine their locations, and estimate their areas, planting years and management details. To solve this challenge, we identified key informants (e.g. forest stewards or Rakhas, forest field staff,

members of forest institutions, community leaders, etc.) in each panchayat who were knowledgeable about the location and its tree planting history. Based on these key-informant interviews we created a plantation survey (p-Form) that listed all plantations in the panchayat, their local names, year of planting, planted and current tree species, previous and current land use, and the institutions responsible for plantation creation and management.

Using the plantation list (p-Form) we randomly sampled 10 plantations in each panchayat that were planted after 1980 and were greater than 5 hectares in size for detailed social-ecological survey using the P-Form. If fewer than 10 plantations met our criteria, we simply sampled all plantations that met the criteria. In addition to these plantations, we collected data on all plantations that were planted in 2017 irrespective of their size. In total, we listed 1250 plantations in the p-Form and surveyed 430 plantations using the P-Form. The statistical analysis reported in Figure 3 is for those 430 plantations with repeat measures in 6 years.

Institutional Data

We conducted preliminary meetings with local representatives in each panchayat, and organized an informal group meeting with other officials. During this meeting, we collected information on active institutions, including civic society and market actors. We used these meetings to gather demographic data and identify key informants such as the forest guard, Rakha, or retired officials who could recollect and narrate the landscape history of the panchayat. We then conducted a series of meetings with identified key informants. We conducted transect walks with the key informants through key areas of the panchayat in order to create a cognitive resource and asset map of the panchayat that listed all key landmarks (e.g., child care center, temple etc.,) institutions (e.g., veterinary clinic, forest guard hut etc.,) natural resources (e.g.,

streams, pastures etc.,) habitations (e.g., clusters of households, hamlets etc.,) and plantations. We triangulated this information from multiple sources and generated a list of plantations and institutions that would be used during the household interview and plantation ecological survey.

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. 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 x 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 correction⁴¹, 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 are in need of 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 utilize FSI forest-density 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. 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 the “Moderately Dense Forest” (40 – 70% canopy cover) and “Very Dense Forest” (>70% canopy cover) classes to form a single “Dense Forest” class. Other forest-density classes include Open Forest (10% - 40%) and Scrub (<10%). We use the forest-density 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/forest-density classifications, which feature composite classes.

We actually produce multi-temporal combined land-cover/forest-density 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) classifier⁴².

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 matrix⁴³. All the aforementioned accuracy-evaluation indices are calculated by averaging those indices across all 10 replications.

For the multi-temporal combined land-cover/forest-density 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” class is not part of the 2009 classification, and the “Pasture Open Forest” 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 forest-density data, for those Landsat mosaic years. This may at least partly be due to error associated with the FSI maps. Post-classification change detection⁴⁴ 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 forest-density information in the classes), those classes are: needleleaf forest, broadleaf forest, mixed forest, and pasture. 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/forest-density 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 density and species 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 density and species 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 of 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 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

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

We use negative binomial regression (NB) models to explain variation in the number of users across plantations. We prefer a NB model over other count regression models. Model fit

comparisons show that a NB model (AIC 1286.604, BIC 1306.923) outperforms a Poisson regression model (AIC 1693.154, BIC 1709.41) and either modestly underperforms or modestly outperforms a zero-inflated negative binomial regression model (AIC 1286.199, BIC 1322.773) depending on the metric considered.

The goal of this analysis is to determine whether plantation characteristics considered in our forest cover analyses also explain variation in plantation use. We employ three explanatory variables: Plantation Age (the linear impact function); distance from the road in minutes (square root); and plantation size in hectares (logged). We also include panchayat fixed effects (we do not use these fixed effects in the AIC/BIC comparisons). Introducing fixed effects into some nonlinear regression models can produce bias through the “incidental parameters problem.” However, simulation evidence suggests that in a NB model fixed effects bias standard errors and not coefficient estimates⁴⁵. We implement a standard error correction those authors recommend.

We present the results from all three negative binomial regression models in Table S25 of 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.

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Figures

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 data 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 dense forest cover when comparing the years prior to the establishment of the plantation ($T < 0$) with the time when it was established ($T = 0$). Similarly, there is no significant difference when considering percent dense forest cover in the years after the plantation was established ($T > 0$). 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 ($T < 0$) with the time when it was established ($T = 0$). However, there is a decline in broadleaf composition in the years after the plantation was established ($T > 0$). 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).

Supplementary Files

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