Predicting wasteful spending in tree planting programs in Indian Himalaya

Pushpendra Rana[1*], Forrest Fleischman[2], Vijay Ramprasad[3] and Kangjae Lee[4]

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[1]Indian Forest Service, Talland, Shimla,
Himachal Pradesh 171002, India.
Email: pranaifs27@gmail.com

[2]Department of Forest Resources,
University of Minnesota,
1530 Cleveland Avenue North,
St Paul, MN 55108, USA.
Email: ffleisch@umn.edu

[3]Department of Forest Resources,
University of Minnesota,
1530 Cleveland Avenue North,
St Paul, MN 55108, USA.
Email: vrampras@umn.edu

[4]University of Seoul,
163, Seoulsiripdae-ro, Dongdaemun-gu,
Seoul, 02504, Republic of Korea.
Email: kasbiss@gmail.com

*Corresponding author: Pushpendra Rana
Email: pranaifs27@gmail.com

Abstract
Tree planting is widely promoted as a cost-effective nature-based climate solution, yet there are few evaluations of the implementation of tree planting. Our analysis of a unique dataset on tree planting in the Indian Himalayan state of Himachal Pradesh shows that over half of the state's budget for tree planting is wasted on plantations that are unlikely to survive and/or are poorly designed to achieve the state's goal of increasing forest cover. Himachal Pradesh (and India more generally) has been identified as a high potential area for nature-based climate solutions due to high government capacity, adequate funding, and government agencies with extensive planting experience. We combine data on the location and financial outlay for plantations, which allow us to analyze the relationship between plantations and social and biophysical conditions, with a machine learning model, trained on past land cover change, which predicts the likelihood of future tree cover loss in plantation areas. Our finding that even in this high potential area tree planting programs involve considerable wasted expenditure on ineffective plantations raises questions about optimistic assessments of the potential for tree planting to serve as a cost-effective nature-based climate solution. We suggest deemphasizing the target-based approaches that dominate present policy-making and high-profile scientific publications, which we argue are the cause of wasted expenditures in Himachal Pradesh. Instead policy-makers and scientists interested in nature-based climate solutions should focus on developing solutions that respond to local biophysical, social, and economic realities, and are implemented through transparent procedures that increase accountability to and reinforce the rights of forest dependent people.

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1. Introduction

Natural Climate Solutions have been proposed as cost-effective and low-cost carbon mitigation tools (Busch et al., 2019; Griscom et al., 2017). However socioeconomic, biophysical, and financial constraints can reduce their potential (Fleischman et al., 2020; Teo et al., 2021; Zeng et al., 2020). Tree planting is one of the most widely promoted natural climate solutions, as well as a major focus of global initiatives such as the Bonn Challenge and the UN Decade on Restoration (Bastin et al., 2019; Busch et al., 2019; Hawes, 2018), yet there is little published evidence about the impacts of tree planting programs on land cover, carbon storage, or other outcomes (Le et al., 2012)., Recent research documents high failure rates in plantation projects (Aggarwal, 2021; Asher & Bhandari, 2021; Coleman et al., 2021; Duguma et al., 2020; Fleischman et al., 2021), negative social-ecological consequences of plantations (Asher & Bhandari, 2021; Di Sacco et al., 2021; Fleischman et al., 2020; Ramprasad et al., 2020) and limited impacts of tree planting on forest cover density and rural livelihoods(Coleman et al., 2021). In this paper, we examine the practice of tree planting in the North Indian state of Himachal Pradesh to better understand how restoration-oriented tree planting is implemented.

India has been identified as a potential global forest restoration leader due to its relatively good governance and financial capacity, at least when compared to other countries in the tropics (Griscom et al., 2020). India's Nationally Determined Contribution aims to mitigate carbon equivalent to 2.5–3 billion tons CO^2e (0.61–0.73 Pg C) by 2030 with a heavy emphasis on tree planting to achieve this goal(Government of India, 2015; Singh et al., 2021). Himachal Pradesh has seen decades of investment in large-scale tree planting (Asher & Bhandari, 2021; Coleman et al., 2021; Davis & Robbins, 2018; Fleischman, 2014; Ramprasad et al., 2020; Rana & Miller, 2021), and has a longstanding reputation as one of the most well-governed states in India (Dreze, 1997; Dreze & Sen, 2002) and this combination of extensive experience and overall governance quality makes the state a "most likely case" (George & Bennett, 2005) to observe the effective implementation of tree planting programs. We use ensemble machine learning methods to predict the probability of future tree cover loss in recently planted areas in the state of Himachal Pradesh and to compare these predicted probabilities with afforestation spending and tree canopy densities. Our analysis shows that a significant portion of trees planted in recent years have been planted in locations where the potential restoration and carbon storage benefits are limited. Tree plantations that bring limited benefits may be a waste of money that could be spent on more effective mitigation measures. These results point to the importance of the design, planning, and implementation of proposed large-scale forest based climate mitigation to avoid wasted resources and potential harms to ecosystems and people.

Challenges for effective tree planting and problems in the assessment of site suitability

Tree planting programs face three challenges that can lower their effectiveness as a nature-based climate solution. First, the target-based nature of many programs may lead to a limited focus on short-term outcomes such as meeting acreage targets or evaluating seedling survivorship after 3-5 years while ignoring long-term goals such as improving tree cover or restoring ecosystems (Fleischman, 2014; Joshi et al., 2011). Second, the focus on tree planting targets may come at the expense of understanding underlying causes of forest loss and regrowth, and/or lead to unintended consequences(Sloan, 2022). This problem has been common in past approaches adopted by the international community for improving forests in the developing world: for example, Reducing Emissions from Deforestation and forest Degradation (REDD+) often fails because it focuses on changing local actors' behavior rather than addressing underlying causes of deforestation or forest degradation (Brockhaus et al., 2014; Skutsch & Turnhout, 2020), while donor-led participatory forest management often hides likely losses and hardships local communities face and fails to ensure meaningful participation of local communities (Hajjar et al., 2021; Rana & Chhatre, 2017). Third, a focus on meeting quantitative planting targets may result in planting trees where they are biophysically unsuited or not desirable for socioeconomic reasons.

Previous scholarship has underlined the importance of assessing the match between biophysical site characteristics and tree species suitability (Apps & Price, 2013; Bongers et al., 2021; FAO, 1984; Maclaren, 1996; Sathaye, 1996), yet the pressure to implement large-scale afforestation may not allow for site suitability assessments (Brancalion & Holl, 2020; Di Sacco et al., 2021; Duguma et al., 2020; Lewis et al., 2019; Veldman et al., 2015). Furthermore, while existing site assessment methods emphasize biophysical suitability, it is often social and economic limits, rather than biophysical ones, that drive restoration outcomes (Brancalion & Holl, 2020; Di Sacco et al., 2021; Duguma et al., 2020; Fleischman et al., 2020; Osborne et al., 2021). While there is abundant literature on the social and economic suitability of tree species for agroforestry systems (Kumar & Nair, 2011), species that are desirable as agroforestry crops may have limited utility for restoration in less intensively managed sites. Moreover, using multi-functional and diverse species in forest restoration projects promote productivity in the long-term compared to monoculture plantations(Bongers et al., 2021). For these reasons, some scholars have questioned widely publicized assessments that promote large-scale forest restoration as a low-cost tool for carbon mitigation without emphasizing the importance of site suitability assessments and planting of multi-functional species (Apps & Price, 2013; Bongers et al., 2021; Grainger, 1996; Lewis, Mitchard, et al., 2019; Veldman et al., 2019).

Furthermore, multi-year tree planting programs can be expensive, and annual tree planting costs are high (Brancalion et al., 2019). Ding et al estimate \$300 to \$400 billion per year is required to meet global conservation and restoration needs (Ding et al., 2017). Currently, a large portion of the proposed afforestation and reforestation consists of government-funded large-scale tree planting(Lewis et al., 2019), including in India where there is a long history of government-led afforestation(Davis & Robbins, 2018; Rana & Miller, 2021; Saxena, 1997), and where there are plans to spend \$6 billion to reforest 12% of its land by 2030 (Howard, 2016). Despite these high costs & large financial commitments, national governments and international agencies carrying out recent commitments lack robust evidence on the cost-effectiveness of nature-based solutions. Building such evidence is challenging owing to multiple nature-based benefits, the non-inclusion of trade-offs among different interventions and ecosystem services, and the changes in the provision of ecosystem services and goods over time (Seddon et al., 2020). In this paper, we evaluate the impact of 4 years of government-led tree planting programs in Himachal Pradesh using data from budget documents, plantation locations, and remotely sensed land cover change analyzed with an ensemble machine learning algorithm.

2. Data and methods

2.1. Study area, overview of tree planting and nature of data

To understand the on-the-ground impact of afforestation programs, we focus on the Indian state of Himachal Pradesh. We chose Himachal Pradesh for this study for two reasons. First, Himachal has long been one of the wealthiest, most developed, and best-governed states in India (Drèze & Sen, 1996), and therefore, it represents a strong case study for testing the hypothesis that government-led tree planting programs in India can successfully deliver forest improvements (George & Bennett, 2005). Second, we were able to obtain detailed budgetary records on afforestation programs from the Himachal Pradesh state government. The budgetary documents analyzed in this paper are usually unavailable to researchers due to official secrecy. The data used in this study became available because a Member of the state Legislature (MLA) raised a question about the afforestation spending for three years (2016 to 2019). In response to the MLA's question, state law required the Forest Department to compile and report expenditures that would not otherwise have been made public.

Himachal Pradesh has spent an estimated $248.24 million US dollars (real expenditure) on afforestation since 2002, covering an area of 236,686 Ha (Himachal Forest Statistics, 2019). The state has planted about 1.14 million hectares since 1950 to improve forest cover, livelihoods, and ecosystem services (Fig. 1). Afforestation peaked between 1985 and 1990 at 32,000 hectares per year. Since the late 1990s afforestation acreage has declined below 12,000 hectares per year. Conversely and during the same period, the total real expenditure of the state on tree planting has increased (Fig.2). During the fourth Five Year Plan (1969-1974) was only $1.31 million, which increased to $110.11 million during the eleventh Five Year Plan (2012-2017). The total expenditure of the state on tree planting during the fourth Five Year Plan (1969-1974) was only $1.31 million, which increased to $110.11 million during the eleventh Five Year Plan (2012-2017)(Himachal Forest Statistics, 2019).

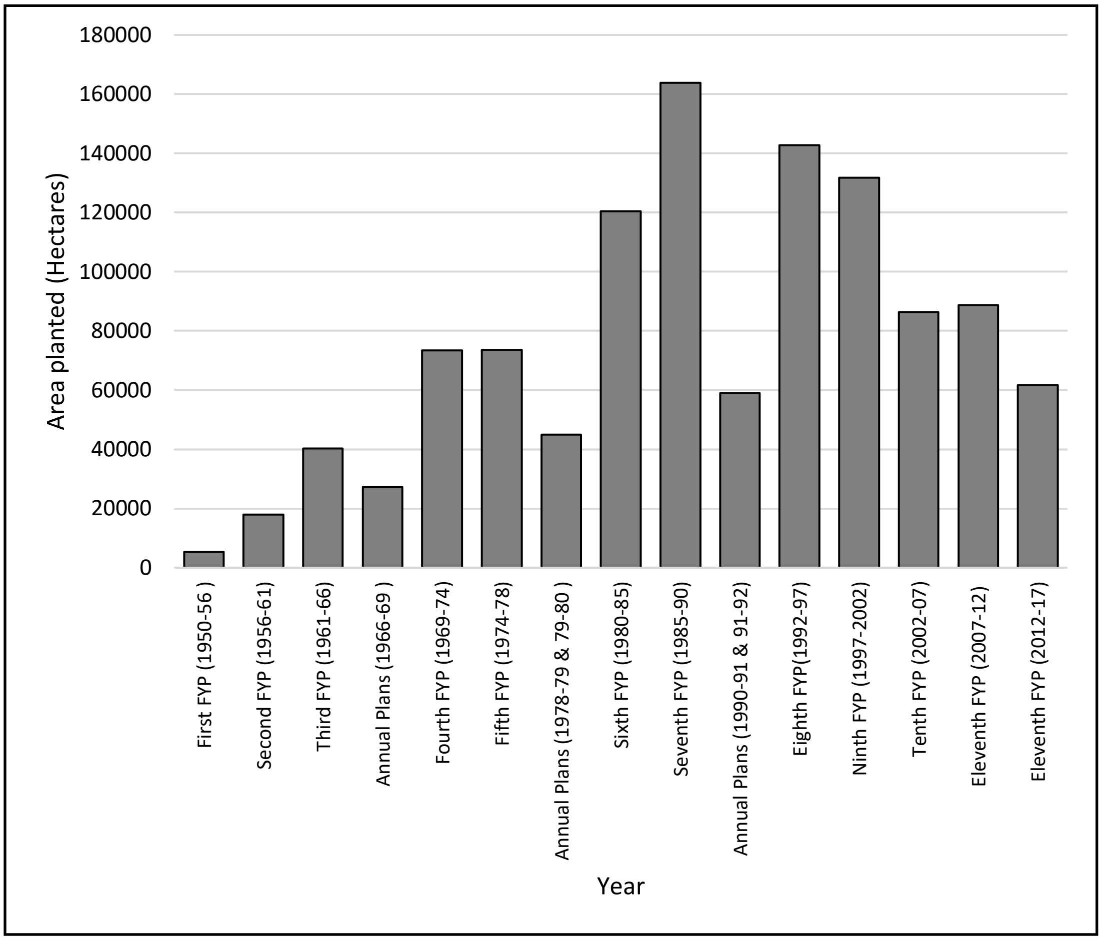

Fig. 1. Area planted in Hectares in Himachal Pradesh since 1950. Each histogram bar reflects the total area of tree planting in each of India's Five-Year Plans since 1950(Himachal Forest Statistics, 2019).

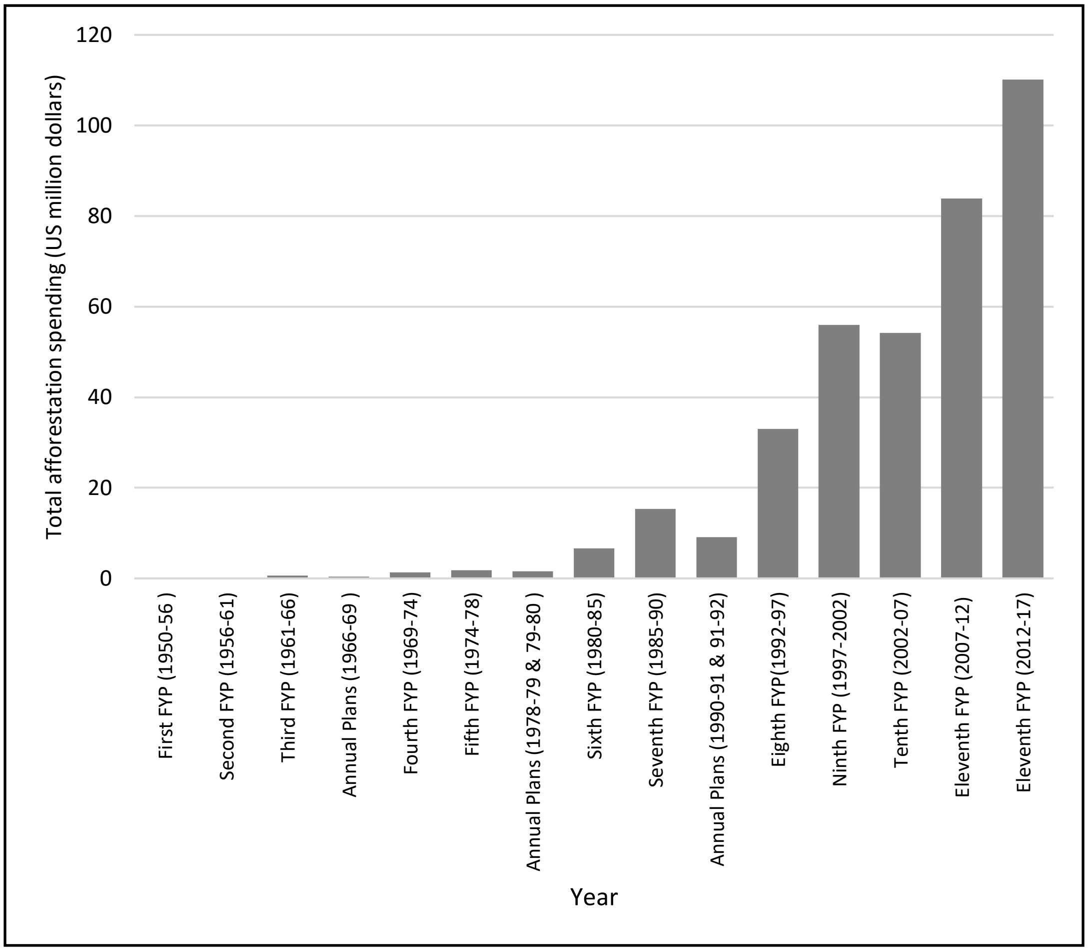

Fig. 2. Total afforestation spending in Himachal Pradesh in each of India's Five-Year Plans since 1950 (Real expenditure). The total expenditure in rupees for each period has been converted using the conversion rate of 70.92 rupees per dollar prevalent during the time of analysis(*Himachal Forest Statistics*, 2019).

To predict the relationship between afforestation budgets, activity, and effectiveness, we analyze Himachal Pradesh government documents between 2016 and 2019 that record the location of 2024 plantations and the $5.67 million spent for their planting by the Himachal Pradesh Forest Department. These plantations were planted on government-owned land by the Forest Department to improve forest cover and ecosystem services. On average, an individual plantation is 5.5 Ha in size and funded by a variety of programs including the state and central government, and donors, including the national Compensatory Afforestation Program (Saxena, 2019), the World Bank, and the German development bank, KfW. In addition to this data on plantations, we utilize 16,674 forest polygons provided by the forest department which record the location of forest department-owned land throughout most of the state to assist in analyzing afforestation spending.

According to Forest Department records, 2809 plantations were planted between January, 2016 and July, 2019 of which 785 plantations have missing data for afforestation spending, leaving us 2024 plantations with complete data. Further, this dataset does not contain any plantation carried out in the cold and dry desert regions of Himachal Pradesh, although other data shows that such plantations were carried out. For example, In 2016, trees were planted in Loser beat (8 Ha), Pagma beat (3 ha), and Kee beat (4.41 ha) in Spiti Valley, a cold desert mountain valley of Himachal Pradesh situated at an elevation of >3800 meters with annual precipitation of about 200 mm (Kumar et al., 2018; *Plantation Brochure*, 2017).

Exact boundaries for the 2024 tree plantations were not available. Instead, we know which forest polygon the plantation occurred in – polygons are generally larger than the plantation area. Our analysis assumes that the smaller plantation areas within the larger polygons have similar characteristics to the polygon as a whole which may introduce errors in the analysis. We believe that predicting the tree cover loss in the entire forest polygon reasonably predicts the tree cover loss in each specific plantation area as the underlying factors and contexts shaping the deforestation trajectories are likely to be similar in planted areas and in the surrounding areas falling outside these enclosures in the forest polygons. A complete replication dataset is archived at the Data Repository for the University of Minnesota (Citation omitted to anonymize document for peer review).

2.2. Methods

We conduct two analyses. First, we analyze the patterns of afforestation spending across tree canopy cover, forest tenure, and land characteristics for our studied plantation polygons (n=2024) using the budget data. Second, we develop an ensemble machine learning algorithm using data on land cover changes between 2003 and 2015 in the statewide forest department polygons (forest compartments, n=16,674), as well as a suite of predictor variables identified in the literature (Table A.1), and then employ that ensemble model to predict probable tree cover loss in our plantation polygons (n=2024).

2.2.1. Distribution of afforestation spending

We study the distribution of afforestation spending in 2,024 plantation polygons across tree canopy cover, forest tenure and land characteristics. For analyzing across tree canopy cover, we use four forest density classes given by the Forest Survey of India(Forest Survey of India, 2019). These classes are Open Forests (with 10-40% tree canopy cover), Moderately Dense Forests (40-70% tree canopy cover), Very Dense Forest (>70% tree canopy cover), and Non-Forest Areas (scattered or negligible tree growth, unproductive areas). We also analyze the spending across different forest tenure types including Reserve Forests (RF), Demarcated Protected Forests (DPF), Undemarcated Protected Forests (UPF), and Cooperative Forest Society Forests (CFS). We also study the distribution of funding across southern and northern aspects for our set of studied plantations.

Forest plantations belonged to multiple forest tenure categories with varying degrees of legal protection on the use of forest and plantation resources. Out of 2024 plantations, 233 were carried out in Reserve Forests (RFs), 1085 in Demarcated Protected Forests (DPFs), 636 in Undemarcated Protected Forests (UPFs), 23 in Cooperative Forest Society Forests (CFS), and 11 in other areas including municipal forests and community-owned lands. Tenure information was missing for the remaining 36 plantations.

Forest tenure categories differ as per the degree of protection granted under the Indian Forest Act, 1927. RFs are accorded the highest degree of protection with high restrictions on community use of forest resources. Protected Forests such as DPFs and UPFs have a limited degree of protection with higher permissible community use of forest resources. DPFs are notified by a formal notification with clear demarcation of legal forest boundaries on the ground, whereas UPFs are not notified and their boundaries are not marked on the ground leading to contested boundaries with private or village-owned lands. CFS are cooperative forest societies established by the government in the 1940s and 1950s to ensure high participation of local communities in forest protection and management through sharing of state revenue from commercial harvesting of trees or extraction of resin (Ahal, 2002). Commercial timber harvest is banned in all these tenure categories in the state since 1986 (Gouri et al., 2004).

2.2.2. Using machine learning to predict tree cover loss in studied plantations

In our second analysis, we use a dataset that records the locations of all government-owned forest polygons in Himachal Pradesh (n=16,674) to build an ensemble machine learning algorithm that predicts whether forest cover in a given polygon will decrease. We then employ that to predict probable tree cover loss in plantation polygons (n=2024). The various steps involved in building an ensemble machine learning algorithm are listed in Fig. 3.

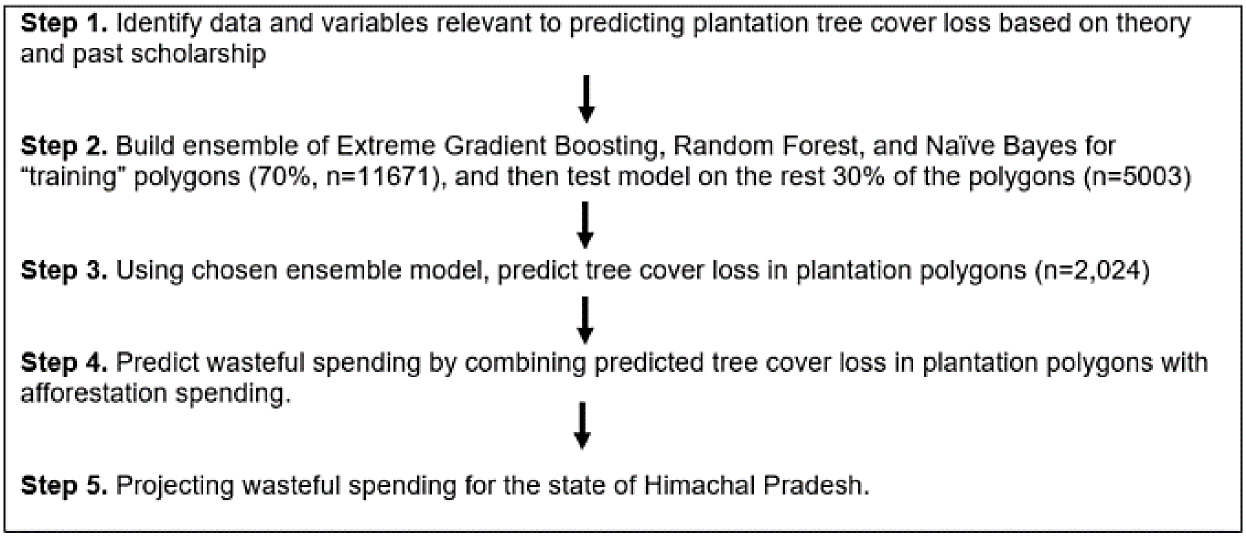

Fig. 3. A five-step approach to identify wasteful spending in afforestation programs

Dataset and variables

Our training dataset includes data on 16,674 georeferenced forest polygons in Himachal Pradesh with labeled tree cover loss outcomes for each forest polygon. Tree cover loss for each forest polygon is a binary outcome and is measured as the decline in tree canopy cover (1= tree cover loss; 0 = no loss) observed between 2003 and 2015 using Forest Survey of India data (Forest Survey of India, 2019). Himachal Pradesh Forest Department GIS Lab provided all 18,672 forest polygons (forest compartments) belonging to 33 forest divisions out of the total 43 forest divisions. We removed 1998 polygons due to missing data.

We use past tree cover loss in forest polygons (n=16,674) as a proxy for evaluating plantation survival potential – i.e. we expect that areas similar to those that lost tree cover in the past are more likely to lose tree cover in the future. We find tree cover loss a useful measure because it can be used in generalized contexts worldwide, reflects the presence of enabling site conditions that support tree establishment, and captures management practices and human use effectively on a large scale. Furthermore, while individual tree mortality is to be expected over time in tree plantations due to density-dependent mortality in a growing stand, tree cover loss reflects the overall failure of a plantation to maintain forest cover, and thereby to produce forest-based goods and services.

The predictors used in our algorithm to predict tree cover loss outcomes in our labeled dataset (n=16,674) include forest dependence attributes of neighboring populations, soil and biophysical characteristics, canopy cover before planting activity, and management practices. In the model, we included data on population, forest dependents, farmers, literates, road density, grazing density, and economic activity as indicative of higher forest dependence. These social-economic and biophysical parameters are based on theory, past scholarship, and technical studies (Agrawal & Chhatre, 2006; FAO, 1984; Rana & Miller, 2019a). For example, the model includes biophysical parameters such as temperature, moisture, rooting conditions, slope, and soil quality factors as suggested by FAO in its studies on land suitability and classification that limit long-term productive tree growth (Booth & Saunders, 1985; FAO, 1984). In addition, key demographic and social-economic variables are incorporated in the model based on past research in the region (Agrawal & Chhatre, 2006; Rana & Miller, 2019a).

Data on these social indicators were calculated based on values of census villages that were circumscribed within forest polygons under study. Values for population, forest dependence, farmers, and literates were summed up, whereas values for road density, grazing density, and economic activity across villages were averaged within forest polygons. Baseline data on forest cover, cropland, grassland, and the bare-land area within each forest polygon was also included. Soil quality factors included in the model are soil depth, soil carbon, soil organic carbon, bulk density, cation exchange capacity, soil PH, and available soil water capacity. In addition, we included information on altitude, slope, area, precipitation, temperature, and forest fires in the predictive model. More details about the model predictors are provided in the *SI Appendix A,* Table A.1.

Building ensemble model using forest polygons (n=16,674)

We first build an ensemble of Extreme Gradient Boosting, Random Forest, and Naïve Bayes to generate tree cover loss predictions for forest polygons (n= 16,674). In the model, we assign tree cover loss as positive and tree cover gain as negative values, and then randomly split the data into a “training” dataset (70%) and a “test” dataset (30%). We develop the predictive algorithm for the training dataset and then, use the resulting algorithm to generate tree cover loss predictions for the test dataset for validation. In the model, we use 10-fold cross-validation on the training dataset using three different models (Extreme Gradient Boosting, Random Forest, and Naïve Bayes). We center and scale the variables, reduce the multi-dimensionality of the algorithm using principal component analysis (PCA), exclude near-zero variance and highly correlated predictors to enhance the performance of the algorithm. We also optimize ROC (Receiver Operating Characteristics) for our three machine-learning models. Please refer to supplementary text for more details for these three models (*SI Appendix A*).

Then we train a stacked ensemble model on these three meta-models (Extreme Gradient Boosting, Random Forest, and Naïve Bayes) with a boosted decision-tree algorithm to maximize recall. Our model puts more value on recall as missing a true positive (tree cover loss) may lead to serious ramifications for biodiversity and forest cover in the area. Our chosen stacked ensemble model resulted in higher values for balanced accuracy (unbalanced nature of our test set), recall, and specificity. The chosen model parameters include Stacked Ensemble Model: Predictive accuracy is 64% (95% Confidence intervals: 62 to 65%). Kappa = 0.24; Sensitivity = 0.74; Specificity = 0.50; Precision = 0.66; Recall = 0.74; F1 = 0.69.

Using ensemble model to predict tree cover loss in plantation polygons (n=2,024)

Finally, we use our selected ensemble model to predict tree cover loss probabilities for 2024 plantation polygons, which we believe reasonably predicts the tree cover loss in the plantations occurred inside these polygons. The tree cover loss probability for these plantation polygons ranges from 0 to 100%.

Predicting wasteful spending in plantation polygons (n=2,024) and for Himachal Pradesh

We then predict wasteful spending in our 2,024 plantation polygons by comparing predicted tree cover loss with the budget spent in planting inside these polygons. For example, if the forest department spent $10,000 planting trees in 10 hectares of land inside a plantation polygon and our model predicts a 50% probability of tree cover loss we consider this a likelihood of 50% wasteful spending.

We then project wasteful spending for the state of Himachal Pradesh combining the ML-based predicted tree cover loss with forecasts of spending till 2030. This projection is useful for policy since the Himachal Pradesh Forest Department has set ambitious tree-planting targets to meet India's Sustainable Development Goal (SDGs) and other international afforestation commitments: to bring 30% (up from the current 27.72%) of its total geographical area (55, 673 km^2) under forest cover by 2030 (Times of India, 2020). To meet this goal, the Forest Department planned to plant trees in 12,000 hectares in 2020 and then increase it to 15,000 hectares every year beginning 2021 till 2030, totaling to 162,000 hectares by 2030. The projections for the per hectare cost of planting trees are based on a 10% annual increase in the present amount of spending per hectare.

We also created an interpolated tree cover loss probability layer using predicted tree cover loss probabilities of 2024 plantation polygons using Kriging to graphically represent the distribution of future tree cover loss probabilities for plantations across the state of Himachal Pradesh (Fig. 4). We used Ordinary Kriging with a stable prediction model in the Geostatistical Analyst tool in ArcMap (10.7.1) to generate the interpolated tree cover loss. We chose the model based on normality and anisotropy parameters. Our Kriging model semivariogram has 12 lags with a lag size of 651.27 meters with a standard neighborhood type (max neighbors = 4, minimum neighbors =2). The prediction model has a root mean square error of 0.14 and a root mean square standardized error of 1.01.

Limitations

Ensemble machine learning algorithms are becoming increasingly popular to generate insights concerning research questions in various disciplines including social sciences(Jean et al., 2016; Watmough et al., 2019), health sciences (Einav et al., 2018), and natural resource management (Engler et al., 2013; Tehrany et al., 2019). Although machine learning approaches offer a powerful tool to learn, analyze and draw inferences from patterns in the data, and to develop useful predictions about the phenomenon understudy in a larger landscape, they are generally employed to make predictions rather than provide causal inference (Mullainathan & Spiess, 2017; Rana & Miller, 2019b). These projections may not fully incorporate the complex present and future social-ecological dynamics of deforestation and forest degradation due to the non-inclusion of relevant predictors related to forest-agriculture or resource use dynamics (Mullainathan & Spiess, 2017; O'Neill & Weeks, 2018; Rana & Varshney, 2020), which may lessen the generalizability of our findings to other settings.

3. Results

Our results indicate that much afforestation spending in Himachal Pradesh is wasteful (Fig. 4 and 5). Wasteful spending is a result of tree planting in the following 4 types of places: 1) non-forest unproductive areas, where tree cover loss is likely to be high due to poor edaphic, biophysical, or social factors (47.7% of plantation spending between 2016 and 2019, $2.7 million), 2) forests with extensive southern exposure, where dryness is likely to limit growth (33%, $1.86 million), 3) forests where contested land tenure is likely to lead to conflicts with local communities that may lead to tree cover loss (28.9%, $1.64 million), and 4) forests that already have more than 40% canopy cover, where planting is likely to be unnecessary to maintain forest cover (38.1%, 2.6 million). In contrast, only 14.1% of spending is likely to be effective, with tree planting happening in areas of low-density forest (density between 10-40%), which are likely to be degraded forests having high reforestation potential. Because our information is not sufficiently spatially explicit, we cannot calculate the total area that is likely to be subject to wasteful spending, but these figures indicate that at a minimum, more than half of all spending is likely to be wasteful (see Fig. 4).

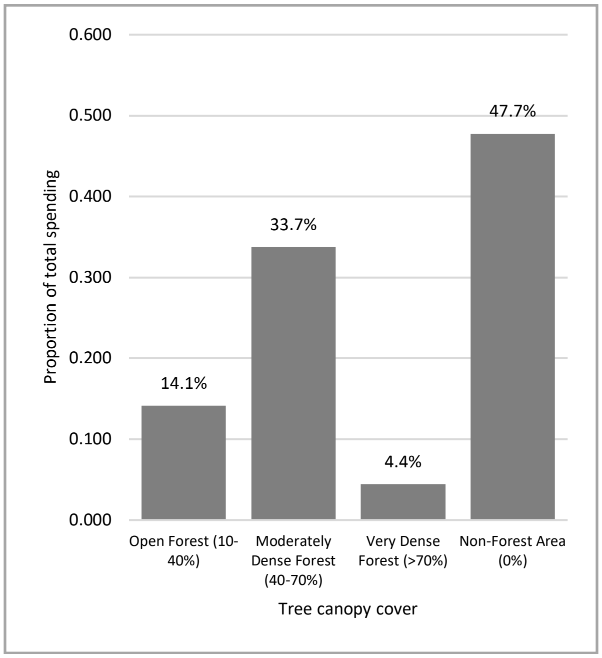

Fig 4 (a)

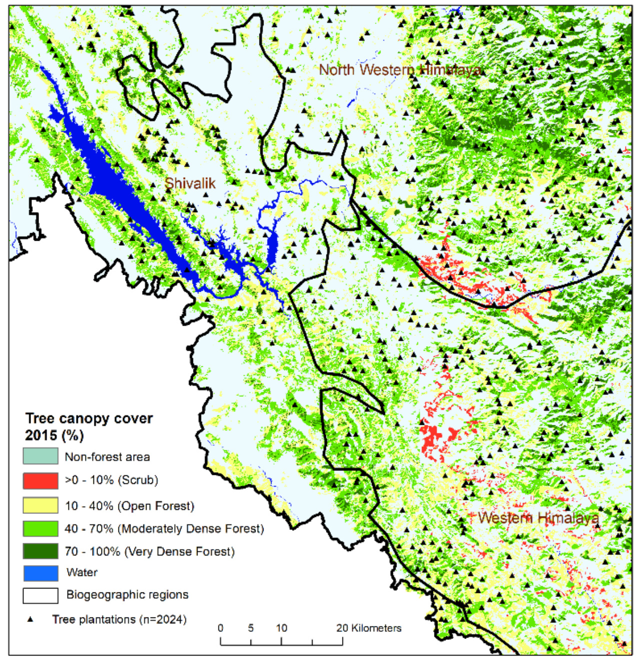

Fig 4 (b)

Fig. 4. Afforestation spending distribution by tree canopy cover in studied tree plantation polygons (n = 2024). Fig. 4 (a) shows that much of the afforestation spending is going to forests that already have more than 40% canopy cover, where planting is likely to be unnecessary to maintain forest (38.1%). Only 14.1% of spending goes to areas of low-density forest (density between 10-40%), where reforestation potential is most likely to be high. Fig. 4 (b) shows the spatial distribution of plantation polygons (n = 2024) with tree canopy cover in a magnified portion of the studied area (Forest Survey of India, 2019). (2-column fitting image, color)

Furthermore, a large share of planting occurred in areas where our algorithm predicts a high probability of tree cover loss. Between January 2016 and July 2019, 59.9% of the afforestation spending occurred where the probability of experiencing tree cover loss was greater than 50% and 35.6% of spending was in areas where the probability of tree cover loss was more than 60%. 23.3% of afforestation spending is directed to areas where the probability of tree cover loss was greater than 70% (Fig. 5, Table 1).

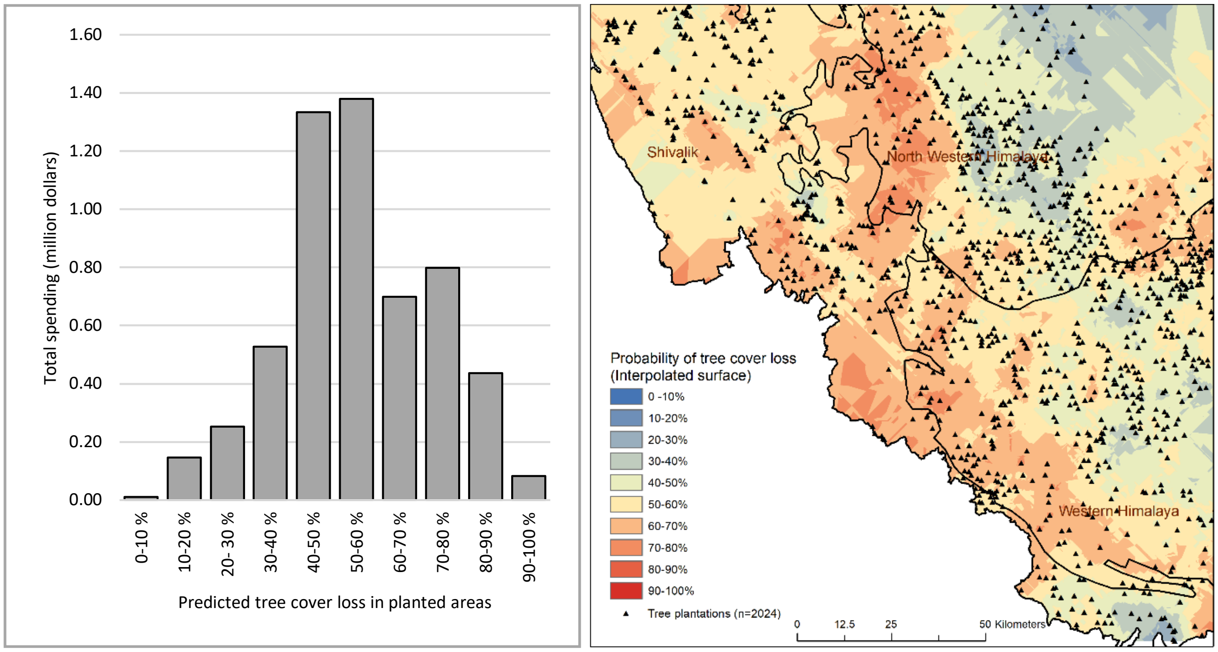

Fig. 5 (a) Fig. 5 (b)

Fig. 5. Afforestation spending and predicted forest cover loss in studied tree plantation polygons (n=2024). Fig. 5 (a) shows the distribution of afforestation spending as related to predicted tree cover loss in plantation polygons. Fig. 5 (b) shows the graphical representation of the distribution of predicted probabilities of tree cover loss for plantations in a magnified portion of the studied region. The interpolated surface with the probability of tree cover loss has been calculated using ordinary kriging with the tree cover loss probabilities of 2024 plantation polygons. (2-column fitting image, color).

Table 1 shows the distribution of predicted plantation tree cover loss by several planting locations, area and trees planted, and afforestation spending by Himachal Pradesh Forest Department in 2024 plantation polygons between 2016 and 2019. We found that in areas with a higher likelihood of tree cover loss (>50%), 5.93 million saplings were planted in 1216 plantation locations involving a total acreage of 6775 hectares by forest officials in the state of Himachal Pradesh during our study period (Table 1). For our sample of 2024 plantations, 59.9% of total state expenditure on planting, or $3.4 million, could have been saved by not planting in areas with more than 50% predicted tree cover loss (Table 1).

Table 1. Distribution of predicted plantation tree cover loss by the number of planting locations, area and trees planted, and afforestation spending

Predictive tree cover loss in plantation polygons	Number of locations planted during 2016-2019	Total area planted (Hectares)	Total trees planted (Number)	Spending by in million US dollars
0-10 %	2	15.00	13500	0.01
10-20 %	49	297.27	284497	0.15
20- 30 %	99	521.28	479358	0.25
30-40 %	203	1024.21	973158	0.53
40-50 %	455	2545.66	2299789	1.33
50-60 %	486	2838.35	2479752	1.38
60-70 %	257	1363.22	1227029	0.70
70-80 %	302	1613.60	1426436	0.80
80-90 %	144	801.66	667038	0.44
90-100 %	27	158.87	129382	0.08

Our results indicate that most of the afforestation funding is going to Demarcated Protected Forests (51.8%), followed by Undemarcated Protected Forests (28.9%) and Reserve Forests (15.32%) In contrast, Cooperative Forest Society Forests receive a small fraction of afforestation funding (1.14%) (Fig. 6).

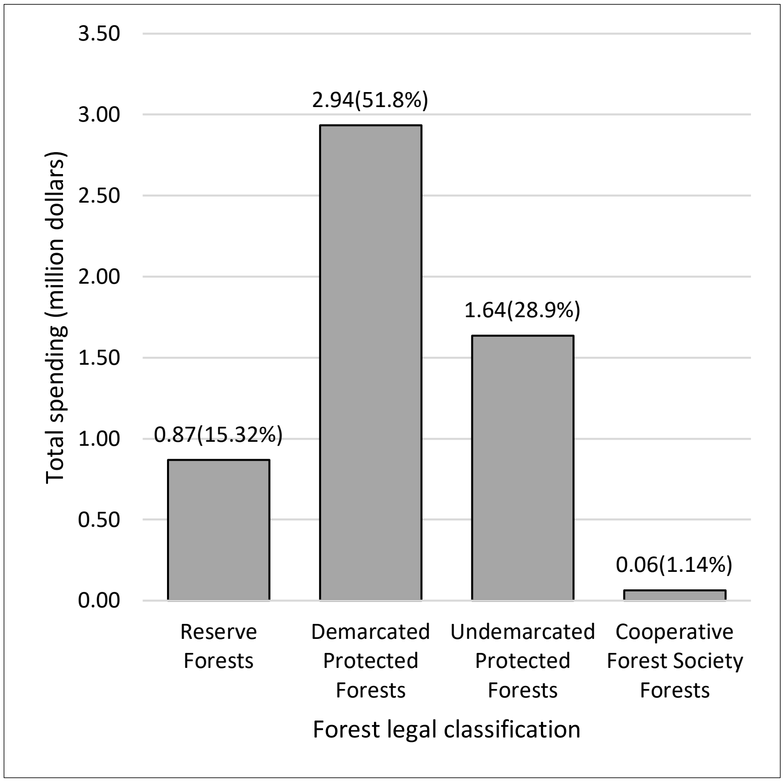

Fig. 6. Afforestation spending distribution by management types in studied tree plantation polygons (n =2024). This figure shows that most of the afforestation spending is going to Demarcated and undemarcated plantation polygons, followed by reserve forest polygons. Cooperative Forest Society forest polygons receive a meager amount of afforestation spending. Other categories not shown in the graph include plantations grown in municipal forest and community-owned areas ($ 0.3 million, 0.6%) and those with missing values for tenure ($0.13 million, 2.3%).

Table 2 shows the distribution of tree species in terms of planted area between 1950 and 2017 based on the analysis of the government records (*Himachal Forest Statistics*, 2019). Since 1950, 44.1% of the total planted area in the state of Himachal is of species that have high commercial value for their timber production (e.g. *Pinus roxburghii*, *Tectona grandis*, *Pinus wallichiana, Cedrus deodara)*, but which are less valuable than other species for widespread household uses such as fuelwood, fodder, or food. In terms of total acreage, an area of 500,873 hectares has been planted with timber-oriented trees with little direct benefit to local communities (Himachal Forest Statistics, 2019) This focus on commercial timber species may lead to public disengagement: local people do not benefit from commercial timber harvest both because profits from timber harvests primarily go to the state government rather than local communities, and also because commercial timber felling has been banned in the state since 1986. Public disengagement may contribute to higher tree cover loss in planted areas (Table 2).

Table 2. Distribution of tree species in terms of planted area between 1950 and 2017

Planted tree species (local names)	Botanical names	Total area planted (1950 to 2017) (Hectares)	Timber species vs. Fuelwood/fodder/food species
Deodar	*Cedrus deodara*	157018	Timber species
Kail	*Pinus wallichiana*	13635	Timber species
Fir and Spruce	*Abies pindrow* (Fir), *Picea smithiana* (Spruce)	18810	Timber species
Chil	*Pinus roxburghii*	285628	Timber species
Walnut	*Juglans regia*	4480	Timber species
Willow	*Salix* spp.	11353	Timber species
Khair	*Acacia catechu*	181236	Heartwood (commercial)
Shisham	*Dalbergia sissoo*	25782	Timber species
Bamboo	*Bambusa nutans*, *Dendrocalamus hamiltonii*, *D. strictus*	15680	Fuelwood/fodder species
Poplar	*Populus deltoids, P. ciliata, P. alba*	15300	Fuelwood species
Robinia	*Robinia pseudoacacia*	54110	Fuelwood/fodder species
Leucenea	*Leucaena leucocephala*	5581	Fuelwood/fodder species
Kachnar	*Bauhinia variegata*	6551	Fuelwood/fodder/food species
Ban Oak	*Quercus leucotrichophora*	2494	Fuelwood/fodder species
Amla	*Phyllanthus emblica*	3360	Fuelwood/fodder/food species
Daroo	*Punica granatum*	2579	Fuelwood/food species
Other broadleaf species	*Morus alba, Punica cornuta, Grewia optiva,* etc.	333414	Fuelwood/fodder species
Total		1137011	

Based on a forecasting model (Table 3) we project that if the government of Himachal Pradesh maintains status quo expenditure, it will spend $167.37 million between 2020 and 2030 on planting trees. Adopting policy reforms that avoid planting in areas that already have more than 40% tree canopy cover, i.e. where planting is unlikely to contribute to improved forest cover or quality, would save $63.60 million, and tree-planting programs that avoid areas with greater than a 50% probability of tree cover loss would save $100.43 million, all while providing more benefits than the current program, as trees not planted under these reforms would be trees with a low probability of survival due to their growth in areas with a high likelihood of tree cover loss, and trees planted in areas where survival is low may be leading to the loss of native grasslands and savannas (Joshi et al., 2018; Ratnam et al., 2011, 2016) (Table 3).

Table 3. A forecast of tree planting targets and associated wasteful spending in Himachal Pradesh between 2020 and 2030

Year	Total plantation target (hectares)	Per hectare cost of planting trees (US dollars)	Total afforestation spending (US million dollars)	Projected waste if areas >50% probability of tree cover loss are planted (US million dollars)	Projected waste if forests that already have more than 40% tree canopy cover are planted (US million dollars)
	I	II	III	IV	V
2020	12000	608.73	7.30	4.38	2.78
2021	15000	669.60	10.04	6.03	3.82
2022	15000	736.56	11.05	6.63	4.19
2023	15000	810.22	12.15	7.29	4.62
2024	15000	891.24	13.37	8.02	5.08
2025	15000	980.37	14.71	8.82	5.59
2026	15000	1078.40	16.18	9.71	6.15
2027	15000	1186.24	17.79	10.68	6.76
2028	15000	1304.87	19.57	11.74	7.44
2029	15000	1435.35	21.53	12.92	8.18
2030	15000	1578.89	23.68	14.21	8.99
Total	1,62,000		167.37	100.43	63.6

4. Discussion & Conclusion

Our results show that poor implementation of tree planting-based natural climate solutions can result in significant wasteful expenditure. Despite strong governance and high financial capacity in our study area, we find that tree plantations are at risk of failure because of (a) poor biophysical suitability, (b) unclear or inappropriate goal and programmatic mandates, and (c) lack of community involvement, resulting in substantial waste of financial resources and tree planting efforts. Our results are consistent with several recent studies of tree planting in Himachal Pradesh that use different datasets and methods, but also find that tree planting programs have disappointing outcomes (Aggarwal, 2021; Asher & Bhandari, 2021; E. A. Coleman et al., 2021). Together these results suggest that tree planting programs may not help India achieve its National Mitigation Potential (Griscom et al., 2020) without significant changes.

More broadly, our results raise questions about optimistic assessments of the potential for natural climate solutions globally (Bastin et al., 2019; Strassburg et al., 2020). This is because Himachal Pradesh represents a best-case scenario for tree planting in the global south: good governance, generous funding, and an implementing agency with decades of tree planting experience. All these supportive contexts appear insufficient. We suggest that wasteful spending may be caused by a focus on target-based program implementation (see Fleischman, 2014), which favor outcome metrics such as area treated or the number of trees planted while offering limited guidance on how and where to plant trees in the context of varying biophysical and socioeconomic suitability (Apps & Price, 2013; Bastin et al., 2019; Brancalion & Holl, 2020; Lewis et al., 2015).

The extent of wasteful expenditure from ineffective land restoration programs. For example, the Bonn Challenge launched in 2011 aims to bring 350 million hectares of degraded lands under restoration by 2030 (Erbaugh & Oldekop, 2018; Suding et al., 2015). Under this

Challenge, 61 countries have pledged to restore 210 million hectares of degraded and deforested land. With an average restoration cost of $1000 per hectare, these countries would spend about $ 201 billion by 2030 to restore their degraded landscapes. Even a conservative estimate of 10% wasteful spending due to the planting of trees on unsuitable lands in these countries can lead to a total wasteful expenditure of about $20 billion by 2030. If the losses are equal to what our model finds in Himachal, then the extent of wasteful expenditure might be as high as $100 billion over the next ten years in these countries. Such high levels of waste seem more likely given the forest governance challenges common in much of the developing world, including corruption, failure to follow tree-planting guidelines, and poor local participation (Afroz et al., 2016; Brancalion & Holl, 2020; Fagan et al., 2020).

Our research suggests that nature-based solutions may become more effective when they address three main challenges identified in this research: site unsuitability, lack of engagement with forest-dependent communities, and program design that emphasizes treatment area over fit with local biophysical and social contexts.

First, we found that tree planting programs in our study area do not consider site suitability. We show that planting is targeted towards areas with high tree cover, where planting is unlikely to contribute to programmatic goals of increasing tree cover, or where the probability of tree cover loss due to unsupportive biophysical and socio-economic contexts is high. Planting in areas with high existing tree cover can have valid silvicultural justifications such as gap filling, enrichment planting, or restocking valuable species. For example, some silvicultural practices may require growing trees in moderately dense forests (MDFs, 40-70% tree canopy density) or gap-filling in very dense forests (VDFs, >70% tree canopy density). These plantings may be targeted to replace selectively harvested trees in mature forests, replace inadequate natural regeneration, introduce desired tree species, enhance biodiversity in established stands or protect vulnerable and sliding zones (Bettinger et al., 2016; Evans, 2009). With a ban on commercial timber harvest in Himachal Pradesh, there should be, in theory, no need to replace selectively harvested trees, since trees are not supposed to be harvested. Furthermore, our data show that the vast majority of tree planting in Himachal Pradesh is of a small number of already common species, so plantings in dense forests are unlikely to significantly increase biodiversity.

Second, tree planting budgets and activities do not adequately engage with rural communities. While community participation has been consistently identified as one of the strongest predictors of forest sustainability in South Asia and beyond (Persha et al., 2011; Saxena, 1997; Somanathan et al., 2009), and in the success of forest restoration efforts (Erbaugh et al., 2020), only *1.14%* of tree planting funding ($0.06 million) supported community-managed forests (Fig. 6). This systemic neglect of community participation in afforestation programs is also reflected in the omission of tree species such as *Grewia optiva, Anogeissus latifolia,* and *Bauhinia variegata* that are valued by communities for their contribution to multiple livelihood needs. *Quercus leucotrichophora* (Ban Oak), a naturally abundant species which is highly valued for both fodder and fuelwood and supports more biodiversity than most other native species (Shahabuddin, 2018; Shahabuddin & Thadani, 2018; Singh et al., 2014) was planted on only 2494 hectares, approximately one hundred times less than *Pinus roxburghii* (Chir Pine), which has little livelihood or biodiversity benefit and is more susceptible to forest fires. Although, our analysis dichotomizes species valued primarily for commercial timber harvest, such as Chir Pine versus those valued for fodder, fuelwood, or food, such as Ban Oak, in ways that may simplify forest diversity's contribution to livelihood use, the favoring of timber species follows global trends. Commercial timber species dominate plantation programs in the tropics and subtropics, including *Eucalyptus (31%), Pinus (27%), Acacia (6%),* *Tectona grandis (6%),* and *Cupressus* (1%) (Kindt et al., 2021). This is particularly surprising given that commercial timber harvest was banned in this region 30 years before the start of our study period.

Nearly one-third of afforestation spending (28.9%) is devoted to planting in forests with contested land tenure, which further aggravates problems for local communities located near lands formally classified as Undemarcated Protected Forests (UPF, Fig. 6). Planting trees in UPFs threatens local livelihoods more than in other forest ownership classes because these lands provide important uses such as grazing cattle, cultural and traditional uses such as organizing religious fairs of the village, and harvesting minor forest products such as fruits, berries, or medicinal plants. Furthermore, UPFs form a central part of migratory routes that pastoralists use in Himachal Pradesh, and tree-planting programs that are not sensitive to the needs of pastoralists fail to support both plantations and pastoralists (Ramprasad et al., 2020).

In areas with contested tenure and competing use, plantations are less likely to survive. This is because where plantations threaten livelihoods or are perceived as illegitimate because of contested land tenure, plantation users are less likely to protect and nurture plantations. Instead in contested areas, users are more likely to remove fencing, light fires, and/or not monitor and protect plantations against fire and grazing (Asher & Bhandari, 2021; Rana & Miller, 2021). Tree planting in highly contested contexts \can lead to unfavorable social-ecological outcomes especially restricting community access to forest resources including grazing, fodder, or fuelwood (Aggarwal, 2020; Asher & Bhandari, 2021; Ramprasad et al., 2020; Rana & Miller, 2021).

Third, current tree planting programs emphasize achieving acreage and tree-based targets rather than achieving effective forest restoration or livelihood improvement. For example, Compensatory Afforestation Fund Management and Planning Authority (CAMPA) is a flagship program of the Government of India to reforest and restore forest landscapes to compensate for the loss of forest cover due to construction of large-scale infrastructure, hydel-power or other industrial projects(Asher & Bhandari, 2021). This program has spent billions of dollars, but without a focus on situating tree planting within either broader silviculture-based or landscape-based restoration programs. CAMPA rarely considers social, economic or biophysical contexts (Asher & Bhandari, 2021; Borah et al., 2018; Ravi & Priyadarsanan, 2015), Instead targeting goals for acreage treated or trees planted without regard to the appropriateness of such treatments. These target-based approaches incentivize government agencies to plant trees that are easy to propagate, such as Chir Pine, rather than more locally valued species that may be harder to propagate, such as Ban Oak, and also disincentivize the time-consuming work of engaging with the local community and identifying suitable sites (Fleischman 2014).

We suggest that natural climate solutions that rely on forest restoration may avoid these problems by financing site-specific interventions developed by affected forest-dependent peoples, and by focusing on genuine measures of outcomes – such as improvements in biodiversity, livelihoods, carbon storage, and other benefits, rather than counting inputs such as acreage treated or trees planted. Such an approach may require constraining our expectations: a recent study in South East Asia finds only a fraction of climate mitigation potential (0.3-18%) of reforestation estimated based on biophysical suitability is achievable due to financial, land use, and operational constraints (Zeng et al., 2020). If this results in less total planting, this should be conceived of as a benefit, as money not spent on wasteful planting can be reallocated towards more beneficial uses. In the Indian context, recognition of community forest rights under the 2006 Forest Rights Act may provide a means to enable forest-dependent people to design restoration strategies.

Governments and donors can support the local development of site-specific restoration by providing information and technical assistance to a wide range of stakeholders involved in forest restoration. For example, a smartphone mobile app that predicts the probability of a given forest patch for supporting long-term tree growth developed using the same data analyzed in this paper is now being used by the state of Himachal Pradesh (Rana & Varshney, 2020). This app assists forest officials to locate the best land for growing trees based on site characteristics. All stakeholders including local communities, political representatives, NGOs, and donors can monitor and evaluate the planting site decisions made using this app. Similar efforts in other places may help scale-up global restoration efforts to achieve the climate mitigation potential of Natural Climate Solutions while strengthening transparency and accountability. In sum, more careful site and species selection, and restoration practice may reduce the wasteful expenditure of tree planting-based climate solutions while benefitting local biodiversity and rural livelihoods.

Researchers and communities could help government and non-government actors identify priority areas for tree planting that minimize wasteful expenditure, maximize co-benefits, and avoid wasteful spending to maximize benefits from Natural Climate Solutions (Brancalion et al., 2019; Brancalion & Holl, 2020; Erbaugh et al., 2020; Fagan et al., 2020). Wasteful afforestation/reforestation spending is particularly troubling because it reduces the availability of funding for other climate mitigation and adaptation priorities while at best accomplishing much less than stated goals. Re-allocating budgets obtained from avoided afforestation is promising. In developing country contexts, activities that support climate adaptation and mitigation, welfare and social security nets, education, women's empowerment, and wellbeing are some high priority policy items that are better addressed instead of planting trees where they cannot thrive.

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Appendix A

Supplementary Materials for

Predicting wasteful spending in tree planting programs in Indian Himalaya

This file includes:

Supplementary text
Table A.1
Figure A.1
SI References

Supplementary text

Methods:

Predictive Algorithm

We develop a predictive algorithm that forecasts probability of tree cover loss based on fit of an area for plantation activity, which assist in estimating wasteful expenditure – i.e. money spent planting trees in places where survivorship is unlikely.

We use an ensemble of Extreme Gradient Boosting, Random Forest and Naïve Bayes to generate tree cover loss predictions for studied forest polygons (n= 16,674). In the model, we assign tree cover loss as positive and tree cover gain as negative values, and then randomly split the data into a "training" dataset (70%) and a "test" dataset (30%). We develop the predictive algorithm for the training dataset and then, use the resulting algorithm to generate tree cover loss predictions for the test dataset.

In the model, we use 10-fold cross validation on the training dataset using three different models (Extreme Gradient Boosting, Random Forest and Naïve Bayes). We center and scale the variables, reduce multi-dimensionality of the algorithm using principal component analysis (PCA), exclude near-zero variance and highly correlated predictors to enhance the performance of algorithm. We also optimize ROC (Receiver Operating Characteristics) for our three machine-learning models.

Our chosen parameters for each model are:

(i) eXtreme Gradient Boosting: We use 10-fold cross validation and ROC is used to select the optimal model using the largest value (0.64). Sensitivity of the model is 0.78. The final values for the selected model includes: nrounds = 100, max_depth = 2; eta = 0.3; colsample_bytree = 0.8; min_child_weight = 1 and subsample = 0.75.

(ii) Random forest: The model include 10-fold cross validation. ROC was used to select the optimal model using value (0.64). Sensitivity is 0.75. Final mtry =2.

(iii) Naïve Bayes: We use 10-fold cross validation. ROC is used as a parameter to select the model with the largest value (0.62). We obtain sensitivity as 0.73. The final values of the model include: laplace =0; usekernel = TRUE and adjust =1.

Then, we train a stacked ensemble model on these three meta-models with a boosted decision-tree algorithm with the objective of maximizing recall. Our model put more value on recall as missing a true positive (tree cover loss) may lead to serious ramifications for biodiversity and forest cover in the area. Our chosen stacked ensemble model resulted in higher values for balanced accuracy (unbalanced nature of our test set), recall and specificity. The chosen model parameters include: Stacked Ensemble Model: Predictive accuracy is 64% (95% Confidence intervals: 62 to 65%). Kappa = 0.24; Sensitivity = 0.74; Specificity = 0.50; Precision = 0.66; Recall = 0.74; F1 = 0.69. Finally, we use our selected ensemble model to estimate predicted tree cover loss probabilities for a new set of 2024 plantation polygons (planted between January, 2016 and July, 2019) and compare these predicted probabilities with afforestation spending and tree canopy densities.

We also created an interpolated tree cover loss probabilities using predicted tree cover loss probabilities of 2024 plantation polygons using Kriging. We used Ordinary Kriging with stable prediction model in Geostatistical Analyst tool in ArcMap (10.7.1) to generate the interpolated tree cover loss. We chose the model on the basis of normality and anisotropy parameters. Our Kriging model semivariogram has 12 number of lags with a lag size of 651.27 meters with a standard neighborhood type (max neighbors = 4, minimum neighbors =2). The prediction model has a root mean square error of 0.14 and a root mean square standardized error of 1.01. Additional details on predictors of the potential tree cover loss are provided in the *SI Appendix A,* Table A.1.

We find that our calculated predicted tree cover loss varies in expected ways with individual forest polygon characteristics. For example, we found our predicted tree cover loss probabilities to vary linearly with the proportion of area under southern aspect in each plantation polygon (Fig. A.1). This finding validates our model since south-facing lands in the western Himalayas have microclimates less conducive to productive tree growth, with greater solar radiation and wind exposure leading to higher rates of evapotranspiration and decreased soil moisture, organic carbon, and soil microflora, in turn leading to higher values of predicted tree cover loss. Moreover, the performance of our algorithm is comparable to other recent prediction algorithms that explain social-ecological phenomenon such as poverty (Jean et al., 2016; Watmough et al., 2019).

Table A.1. Predictor variables and their sources

Variable	**Description**	**Unit of measurement**	**Sources of data**
Number of households	Number of households	Total number of HHs in villages that are inside a forest polygon	Census (2001), India, http://censusindia.gov.in/ (*Census of India, 2001*, 2001)
Total population	Total population	Total population of the villages that fall inside a forest polygon	Census (2001), India, http://censusindia.gov.in/ (*Census of India, 2001*, 2001)
Number of farmers	Number of cultivators (farmers)	Total number of farmers in villages that fall inside a forest polygon	Census (2001), India, http://censusindia.gov.in/ (*Census of India, 2001*, 2001)

Variable	Description	Unit of measurement	Sources of data
Number of marginal people (scheduled caste population)	Scheduled caste population	Total number of total SC population in villages that fall inside a forest polygon	Census (2001), India, http://censusindia.gov.in/ (*Census of India, 2001*, 2001)
Number of literates	Total number of literates	Total number of literates in villages that fall inside a forest polygon	Census (2001), India, http://censusindia.gov.in/ (*Census of India, 2001*, 2001)
Number of unemployed people	Total marginal workers	Total number of marginal workers in villages that fall inside a forest polygon	Census (2001), India, http://censusindia.gov.in/ (*Census of India, 2001*, 2001)
Economic activity	2003–2008, 0.56 km spatial resolution	1 to 63 (values) (Average for villages that fall inside a forest polygon)	Version 4 DMSP-OLS Nighttime Lights Time Series (https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html) (n.d.-b)
Road density	Road density,	Km/km^2 (Average for villages that fall inside a forest polygon)	CIESIN (Data Center in NASA's Earth Observing System Data and Information System (EOSDIS)) (https://sedac.ciesin.columbia.edu/data/sets/browse)(n.d.-a)
Number of small landholdings	Number of small land-holdings less than 0.5 ha	Number of smallholdings less than 0.5 ha in Census Tehsils where that forest polygon falls.	Agricultural census (2005), India (*Agricultural Census, 2005*, n.d.)
Grazing density	Number of grazing animals (buffaloes, goats, sheep, cattle)/area of the tehsil in ha	Number/ha (Average for villages that fall inside a forest polygon)	Livestock census (2007), India (*Livestock Census | Department of Animal Husbandry & Dairying*, n.d.)
Area of forest polygon	Area of the forest polygon	ha	Forest records, HP Forest Department, India
Area under crop acreage	2000, 30 m resolution	ha	(Chen et al., 2015)
Area under grass coverage	2000, 30 m resolution	ha	(Chen et al., 2015)
Area under bare land acreage	2000, 30 m resolution	ha	(Chen et al., 2015)
			(Wieder et al., 2014)

Variable	Description	Unit of measurement	Sources of data
Soil depth	2000, reference soil depth, average	cm	(Wieder et al., 2014)
Available soil water capacity	2000, available soil water storage capacity, average	Coded values 1 to 7; 1 = 15 cm water per m of the soil unit, 2 = 12.5 cm, 3 = 10 cm, 4 = 7.5 cm, 5 = 5 cm, 6 = 1.5 cm, 7 = 0 cm.	(Wieder et al., 2014)
Topsoil Carbon Content	Topsoil and subsoil carbon content (T_C and S_C) are based on the carbon content of the dominant soil type in each regridded cell rather than a weighted average.	kg C m-2	(Wieder et al., 2014)
Subsoil Carbon Content		kg C m-2	(Wieder et al., 2014)
Topsoil Organic Carbon		% weight	(Wieder et al., 2014)
Subsoil Organic Carbon		% weight	(Wieder et al., 2014)
PH (Top Soil)	Topsoil pH (in H2O)	-log(H+)	(Wieder et al., 2014)
Top Soil Bulk Density	Reference bulk density values are calculated from equations developed by Saxton et al. (1986) that relate to the texture of the soil only.	kg dm-3	(Wieder et al., 2014)
Top Soil Cation Exchange Capacity	Cation exchange capacity of the clay fraction in the topsoil	cmol per kg	(Wieder et al., 2014)
Sub Soil Cation Exchange Capacity	Cation exchange capacity of the clay fraction in the subsoil	cmol per kg	(Wieder et al., 2014)
Location (altitude)	2000, 90 m resolution	m	SRTM (Shuttle Radar Topography Mission), 90 m resolution, 2000 (*SRTM 90m Digital Elevation Database v4.1*, 2017)
Slope	2000, 90 m resolution	degree	SRTM (Shuttle Radar Topography Mission), 90 m resolution, 2000 (*SRTM 90m Digital Elevation Database v4.1*, 2017)
Baseline forest cover (FC_2003HA)	2003, 24 m resolution	Forest cover = Open forest + Moderately dense forest + Very dense forest	Forest Survey of India, 2005 (Forest Survey of India, 2019)

Variable	Description	Unit of measurement	Sources of data
Number of forest fires	2003–2008	Number	NASA, active fire data, MODIS C6 (*FIRMS*, n.d.)
Temperature	2001–2008, 30 km resolution, average	°C	CRU (Climatic Research Unit) TS dataset, version 4.0, gridded dataset of monthly terrestrial surface climate http://www.cru.uea.ac.uk/ (Harris et al., 2014)
Precipitation	2001–2008, 30 km resolution, average	mm	CRU (Climatic Research Unit) TS dataset, version 4.0, gridded dataset of monthly terrestrial surface climate http://www.cru.uea.ac.uk/ (Harris et al., 2014)
Land surface temperature	2001–2008, 5.5 km spatial resolution, average	K	MODIS/Aqua Land Surface Temperature/Emissivity Monthly L3 Global CMG V005 (*Global Change Master Directory (GCMD)*, n.d.)
Outcomes (O)			
Tree cover loss	24 m resolution FC_CHANGE15_03 = FC_2015HA – FC_2003HA	If FC_CHANGE15_03< 0, Tree cover loss = 1, Otherwise = 0	Forest Survey of India (2005); Forest Survey of India (2017) (Forest Survey of India, 2019)

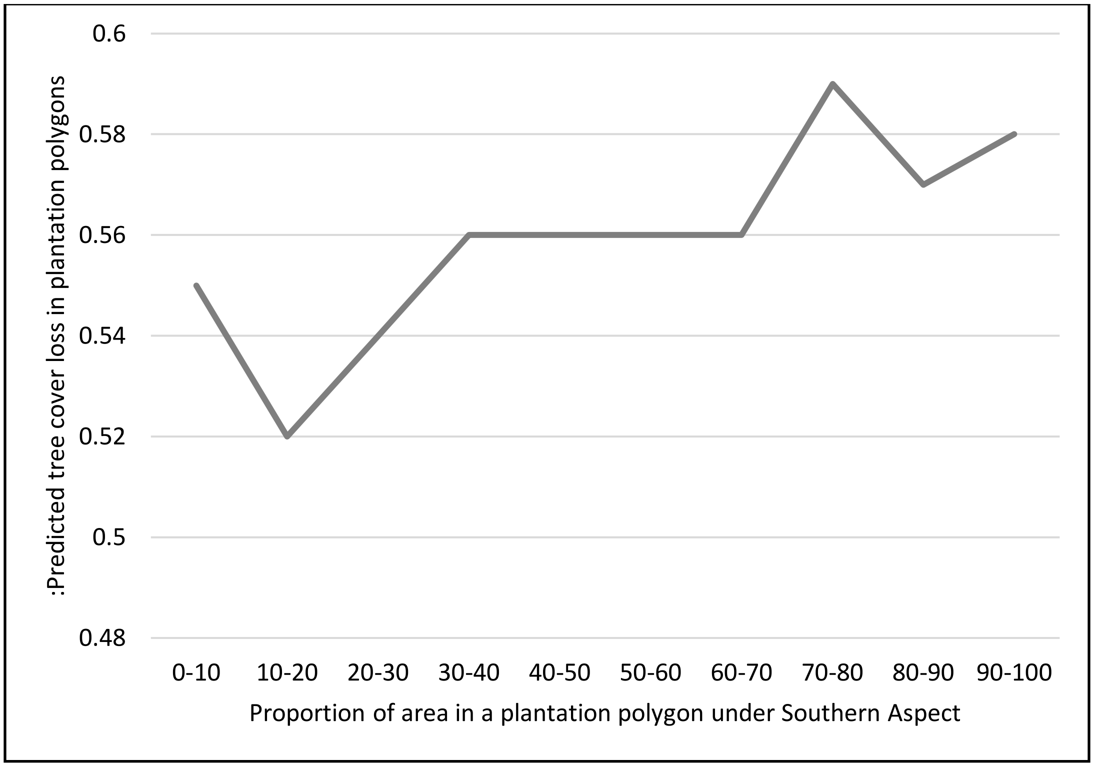

Figure A.1. Proportion of area under southern aspect and predicted tree cover loss. The relationship between the proportion of area under southern aspect in studied plantation polygons (n=2024) and the predicted tree cover loss. We find a linear relationship between the proportion of area in a plantation polygon under southern slope and the estimated predicted tree cover loss probabilities as suggested by our ensemble model. This finding validates our model since south-facing lands in the western Himalayas have microclimates that do not support vegetation growth leading to higher values of predicted tree cover loss. This is because, these lands are more exposed to solar radiation and winds that promote higher rates of evapotranspiration decreasing soil moisture, organic carbon, and soil microflora.

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