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Exploring limits to tree planting as a natural climate solution

Pushpendra Rana [a,*], Lav R. Varshney [b]

[a] Indian Forest Service, India
[b] University of Illinois at Urbana Champaign, Department of Electrical & Computer Engineering, United States

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ABSTRACT

Large-scale tree planting has been advocated for decades in many countries as a cost-effective strategy to mitigate carbon, rejuvenate degraded landscapes, and support local livelihoods. Recent studies, however, suggest limited ecological and livelihood impacts of tree planting programs, indicating possible limits to tree planting as a natural climate solution. In this paper, we explore these carrying capacity-like limits by evaluating the site suitability of forestry landscapes of the northern Indian state of Himachal Pradesh using theory/expert-based rules and machine learning algorithms. We find that the state can only achieve a maximum of 31.54% forest cover due to socio-ecological and biophysical constraints, much less than India's goal of bringing 66% of the total geographical area of Himalayan states into forest cover. The low availability of suitable lands for growing trees, together with poor plantation site selection by forest range officers limit the use of tree planting as a sole climate mitigation strategy. To approach theoretical planting limits, we propose an ePSA (e-Plantation Site Assistant) recommendation system based on our site-suitability results to assist forest rangers in selecting suitable sites for planting trees. An initial deployment of the recommender system suggests its potential utility in shaping the long-term success of tree plantations as an effective carbon strategy in northern India and beyond. Overall, we argue that there is a need to realign over-ambitious national and international tree planting targets with actual limits from site characteristics to avoid massive wastage of funds and to obtain feasible carbon mitigation outcomes.

1. Introduction

The recent push to promote large-scale tree planting as a climate change mitigation solution has fueled a fierce debate around the nature and intensity of social-economic and ecological impacts of these programs (Bastin et al., 2019; Busch et al., 2019; Fleischman et al., 2020; Malkamäki et al., 2018). Supporters favor massive tree planting due to its cost-effectiveness and global carbon sequestration potential, whereas opponents focus on adverse effects on local livelihoods, biodiversity, and ecology (Bastin et al., 2019; Busch et al., 2019; Fleischman et al., 2020; Veldman et al., 2019).

Plantations have been shown to improve soil properties (Singh et al., 2004) and reduce carbon emissions substantially when they convert to established forests (Raza et al., 2021). On the other hand, recent studies have found limited effects of decades of tree planting on forest canopy cover and rural livelihoods (Coleman et al., 2021; Ramprasad et al., 2020). Other studies have found massive wasteful expenditure due to poor selection of plantation areas by forest rangers, mainly driven by the target-driven nature of tree-planting programs (Rana et al., 2022). Such scholarship suggests potential limits to scaling up of tree-based natural climate solutions mainly due to socio-economic, biophysical, and edaphic factors.

Despite the increasing importance of tree planting, little attention has been paid to assessing critical limits to tree-planting in forestry landscapes based on plantation site suitability. Better selection of plantation sites can help achieve higher forest cover efficiently—similar to developing energy efficiency and promoting efficient fuel substitution in the energy sector, which has shown tremendous potential in reducing carbon emissions while enhancing economic growth (Lin et al., 2022; Raza and Lin, 2022). Selecting plantation sites without assessing local biophysical, edaphic, and socioeconomic conditions can lead to poor plantation survival over the longer term (Coleman et al., 2021; Rana et al., 2022). For example, planting trees in dry, exposed, and poor soil areas may result in complete loss of planted trees in due course of time. Saplings require congenial biophysical, social, and edaphic factors; lack of any of these factors may limit the survival of saplings and lower the long-term success of the planted forest plantations. Presently, sites are mostly selected by forest frontline staff through their field scrutiny of the

* Corresponding author. Indian Forest Service, Talland, Shimla, Himachal Pradesh, 171001, India.
E-mail addresses: hp131@ifs.nic.in (P. Rana), varshney@illinois.edu (L.R. Varshney).

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potential field locations. These selections are mostly subjective with no cost-benefit analysis and no technical support available to assist in these site selection decisions, resulting in massive wasteful expenditure (Rana et al., 2022).

The latest developments in remote sensing, geographic information systems (GIS), and machine learning (ML), however, show great promise in providing site-specific guidance to field staff in selecting the right places for planting trees. Studies have used remote sensing data coupled with GIS to locate potential tree-planting sites (Cuong et al., 2019; Wu et al., 2008), to evaluate the suitability of land for tree plantations (Basir, 2014) and agroforestry (Ahmad et al., 2017), and to specify tree species under tree plantations (Chen et al., 2019; Lahssini et al., 2015). ML has also been used to evaluate land suitability for agriculture and forestry (Loi, 2008; Sarmadian et al., 2014), to predict site index (Sabatia and Burkhart, 2014), and to predict future land use transition areas and scenarios (Grinand et al., 2020).

ML-based models can assist forest rangers in choosing socially and ecologically appropriate sites for planting trees, similar to ML applications in other fields such as prioritizing animal feed locations (Handan-Nader and Ho, 2019) and prioritizing environmental inspections (Hino et al., 2018). ML can use large social, spatial, and ecological datasets to learn patterns and then identify areas appropriate for growing trees. Moreover, ML can enable systems to continuously update their decisions based on new data from decisions and responses of users (Appel et al., 2014; Salganik, 2019; Varshney, 2016). As such, ML shows promise but also involves many challenges in the context of developing site suitability applications.

These challenges include the following. First, plantation data is highly skewed and imbalanced. Official data only covers sites selected for planting trees (positive labels) and we usually lack information about sites that rangers have rejected for planting (negative labels). Second, historical datasets on plantations do not have spatial information and so we do not know exactly where planting (sites of positive labels) happened. Moreover, plantation records are not systematic and uniform across the landscape, leading to potential biases. Third, there is significant heterogeneity in the size and site characteristics of plantation areas from one place to another, so a universal predictive plantation model may not be appropriate for all sites. Fourth, forest officials may game the system to serve their vested interests by omitting certain plantation areas as possibilities; this lack of accountability and transparency can lower the potential of plantation recommendation engines. Finally, there is a lack of large-scale, fine-resolution data on factors that influence site selection. The several sources of spatial data from government or international platforms are inadequate due to poor resolution and incompatibility among several geospatial layers. Moreover, limited financial resources and human resources restrict the large-scale collection of soil survey data and other biophysical factors at a finer scale.

Purely data-driven systems are limited (Hofman et al., 2017; Selbst et al., 2019) due to social-ecological complexity and large-scale heterogeneity that limit gathering of real or (realistic) training data that covers the universe of possibilities in a forestry landscape. If a range of factors, interactions, and feedback loops that affect planting decisions are not captured properly in data-driven models and the complex forest system is abstracted too much, the resulting incorrect classifications will have critical safety impacts on livelihoods, biodiversity, and carbon storage (Hofman et al., 2017; Mueller et al., 2019; Selbst et al., 2019; Thompson et al., 2012). In particular, existing planting site suitability classifiers are only loosely supported by data for areas of the feature space unobserved in training data, leading to wild extrapolation in such areas (Kshetry and Varshney, 2019). Even methods such as covariate shift, domain adaptation, meta-recognition (Scheirer et al., 2011), reject options, or estimating the confidence of deep learning models (Mallick et al., 2020) fail to contribute much in the presence of large-scale epistemic data uncertainty, as here. This points to addressing planting site selection not as a pure ML problem, but with a hybrid AI approach. Here, we use an *algorithm fusion* approach to AI wherein we combine theory/expert-based rules with an ML algorithm to predict site suitability for growing trees (Kshetry and Varshney, 2019).

This paper has two main objectives. First, we take a physics-based artificial intelligence (AI) approach in the form of algorithm fusion to explore limits to tree planting by analyzing site suitability in the northern Indian state of Himachal Pradesh for growing trees successfully over a longer term. Second, we use our AI approach in developing an e-Plantation Site Assistant (ePSA), a site-recommendation engine, to assist forest range officers to identify suitable blank patches inside forest areas for growing trees.

We consider limits to tree planting as akin to the notion of *carrying capacity* in mathematical ecology (Kingsland, 1995; Young, 1998) while taking socio-ecological and biophysical constraints into account. Specifically, we use traditional forestry knowledge to guide and weight features that affect site suitability scores for growing trees and use an ML model to capture large landscape-level deforestation dynamics. The overall AI system explores the potential for effective tree growth and survival due to congenial biophysical, social, and edaphic factors and maps site suitability for the entire state of Himachal Pradesh. Although fundamental limits are insightful for policymaking and planning, it is also important to have practical ways to approach those limits. Just like the Carnot limit in thermodynamics inspires and is approached by the Diesel engine design, and like the Shannon limit in information theory inspires and is approached by low-density parity-check codes in telecommunications, here we also develop recommendation algorithms for tree planting to guide forest staff in making better decisions that achieve the limits, which we also establish.

India aims to mitigate 2.5–3 billion tons CO2e (0.61–0.73 Pg C) by 2030 with a heavy focus on tree planting to achieve this goal under India's Nationally Determined Contribution (Government of India, 2015; Singh et al., 2021). In this context, the Government of India has initiated several government initiatives such as Green India Mission, Compensatory Afforestation Fund Management and Planning Authority (CAMPA) (Asher and Bhandari, 2021) and even incentivized the mountainous states of northern India such as Himachal Pradesh (and other states with substantial forest cover) in the form of green bonuses or extra funds to protect forest cover and support tree planting through various programs and schemes (Busch and Mukherjee, 2018; Rana and Miller, 2021). Note that the mountainous regions also form an important water catchment drainage zone for the northern agricultural belt of India, so tree planting acts to protect soil erosion and boost water flow to agricultural regions of northern India, thereby increasing agricultural productivity. In such goals, assessing the critical limits to tree planting and then, suggesting suitable sites to grow trees through a recommendation engine can play an important role, especially since recent scholarship has shown poor survival of the plantations and massive wasteful expenditure (Coleman et al., 2021; Rana et al., 2022).

In Himachal Pradesh, this paper shows that there are substantial limits to tree-planting as a natural climate solution due to the low availability of suitable areas that can be planted to increase forest cover. Such limits are present mainly because of limiting socio-economic, ecological, biophysical, and edaphic factors, which constrain any effective growth of trees over longer term. Despite such limitations, our results show that foresters are largely planting trees in areas which are either largely unsuitable or low suitable areas in the state of Himachal Pradesh. By computing fundamental limits to tree-planting and recommending best places to plant, national and state governments can reduce the massive waste involved in current target-driven planting programs (Rana et al., 2022), which are often remnants of mismatched colonial policies (Davis and Robbins, 2018) rather than having basis in local or scientific knowledge. In this sense, and in the sense of combining traditional indigenous knowledge with modern scientific knowledge (Rana and Varshney, 2020), such AI techniques can have decolonizing impacts (Tuhiwai, 1999).

We further provide preliminary evidence on the potential utility of a recommender system in shaping the long-term success of tree plantations by ranking the lands as per their potential to grow trees. Although such a recommender system needs further ground validation and testing, its initial deployment results show its practical utility and potential use in largely similar contexts for other developing countries in assisting industrial and small-scale tree planting programs. The aim is to save money and resources by assisting forest rangers to select the best tree planting sites for carbon mitigation, so as to approach the fundamental limits of tree planting.

2. Methodology

2.1. Study area

We chose Himachal Pradesh, one of the northern states in India for the research (Fig. 1). Improving tree and forest cover has been a major priority for the Government of India since independence. The National Forest Policy of 1952 and subsequent policies consistently aim to improve forest cover to meet a variety of objectives including industrial development, increasing forest cover, rejuvenation of degraded landscapes, and livelihood generation. India aims to bring 66% geographical area in each of its Himalayan states such as Himachal Pradesh under forest cover (Joshi et al., 2011; Negi, 2009). To achieve this goal, every year, millions of hectares of forestland is planted with trees all over the Himalayan region. The increasing push to adopt tree-planting as a cost-effective and measurable climate mitigation strategy has also resulted in massive tree-planting under national, international, and donor-funded programs and projects.

Also note that since 2002, Himachal Pradesh has spent an estimated 248.24 million US dollars on tree-planting programs, covering an area of 236,686 Ha (Himachal Forest Statistics, 2019). The state has planted about 1.14 million hectares since 1950 mainly to improve forest cover through the forest department (Rana et al., 2022). The total expenditure of the state on tree planting during the period between 2012 and 2017 was $110.11 million, which is a substantial amount given the lower overall economic status of the state in the country due to its lower income and higher dependence on the Indian government for flows of funds (Himachal Forest Statistics, 2019).

We have chosen Himachal Pradesh to evaluate limits to tree planting and test ePSA recommendation engine for two main reasons. First, Himachal Pradesh is one of the most developed and well-governed states in northern India and is ranked second after Kerala in many human development indicators. All the requisite conditions for evaluating plantation site suitability in the state of Himachal Pradesh and for developing an effective ePSA recommendation engine to assist tree planting are present. If tree-planting does not follow site-suitability criteria and shows poor site selection in the relatively favorable social, economic, and political contexts of Himachal Pradesh, our tree-planting recommendation approach will likely be ineffective in more challenging contexts of the other northern Indian states, other parts of India, and many similar developing countries. Second, the state of Himachal Pradesh showed its commitment to move forward with site-suitability assessment and in developing this application and provided government spatial and social datasets and expert guidance to develop ePSA to prioritize tree planting patches across the state as per their tree growth potential.

2.2. Methodology – algorithm fusion

We used an algorithm fusion methodology (Kshetry and Varshney, 2019) to assess limits to tree planting based on site-suitability and to create the plantation site recommendation engine as in Fig. 2, with a further two-stage process. The first stage leverages rule-based and ML algorithms with remote sensing data to predict site suitability (Step 1 to Step 4), and the second stage uses those predictions to prioritize the most appropriate tree planting sites as per site suitability values (Step 5 and 6).

We combine forestry science knowledge with a ML classifier in the form of algorithm fusion to control epistemic uncertainty and maintain AI decision safety (FAO, 1984; Hofman et al., 2017; Kshetry and Varshney, 2019; Selbst et al., 2019). The idea is to combine theoretical and expert forestry knowledge with learned models to cover not only the known factors that affect planting decisions, but also the other known or unknown factors that affect these decisions but for which we do not have data to train purely ML models.

Algorithm fusion has two parts. First, we construct expert-based rules. We use traditional forestry knowledge to consider existing land uses by local communities, places where natural constraints restrict tree growth, and areas where existing dense vegetation limits tree planting

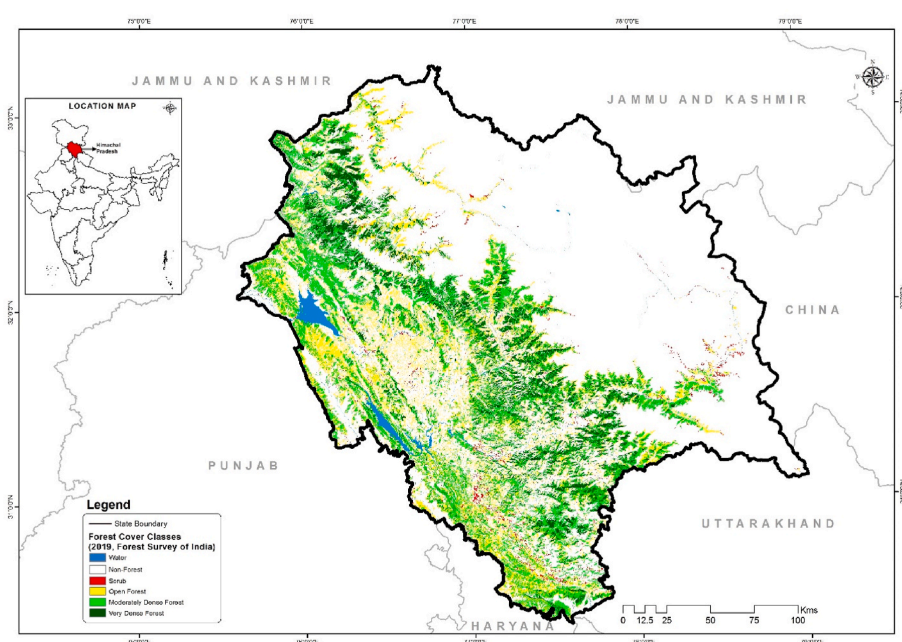


Fig. 1. Map of Himachal Pradesh, India, the study area.

Step 1. Data collection for the state of Himachal Pradesh; preprocessing of data (including geoprocessing of variables) and feature engineering for constructing expert-based rules and for machine learning models. Creation of 795,826 grid cells with area of each grid cell amounting to 265m^2 (7.0225 hectares) for the entire state.

Step 2. Application of theory/expert-based scoring rules to grids; exclusion rules for areas unfit for tree planting.

Step 3. Training of model with 16,674 forest polygons; evaluation of machine learning models (Extreme Gradient Boosting, XGBoost); predicting site suitability for 795,826 grid cells across the state of Himachal Pradesh for growing trees.

Step 4. Algorithm fusion to incorporate both expert/theory-based and machine learning rules in predicting the final suitability score for each of the 795,826 grid cells; mapping the plantation site suitability score for the entire state.

Step 5. Using predictions to prioritize the most appropriate tree planting sites as per suitability score; assessment of 1547 tree plantations planted during 2020 in the state of Himachal Pradesh based on site suitability score.

Step 6. Development of a mobile-based application (e-Plantation Site Assistant (ePSA)) to assist forest ranger officers to select suitable sites for growing trees; its initial deployment and field validation through a user study

Fig. 2. Overview of methods.

(FAO, 1984). We also include rules based on the extent and change of tree cover, slope, aspect, elevation, soil quality, and nearness to habitations in our scoring algorithm to predict the site suitability of each studied forest grid cell. These rules originate from theory, past scholarship, and technical studies (FAO, 1984; Rana and Varshney, 2020a). We use satellite data from various national and international sources, perform feature engineering, and create relevant indicators that may influence the site suitability of the location.

Second, we further employ ML trained on a large set of features ($n =$ 31) to capture landscape-level deforestation dynamics to properly account for factors that lead to tree cover loss in any landscape, a process that is largely outside the ability of human-derived traditional knowledge to capture. These two pieces are then used together via algorithm fusion. We have used QGIS, ArcGIS, and Python capabilities to process the geospatial data and to make it useable for developing this application.

2.2.1. *Data collection: feature engineering*

We collect spatial data on 18,672 forest polygons (forest compartments) from Himachal Pradesh Forest Department GIS Lab, out of which we removed 1998 polygons due to missing data. We used the rest of the 16,674 forest polygons to build our ML model. These forest polygons record the location of the forest department-owned land throughout the state. Plantations occur inside these forest polygons, and we assume that training our ML model at the level of forest polygons reasonably predict the plantation suitability score for the entire state.

Open access spatial datasets related to social, biophysical, and ecological factors that associate with the long-term success of tree planting were used to create various features used in the recommendation engine. These features were identified based on theory and expert knowledge that determine the availability of blank areas as well as suitability for the long-term successful growth of trees (for details, please refer to Supplementary Tables S1 and S2). We used guidance from the Food and Agriculture Organization and traditional forestry knowledge from forestry field staff to evaluate limits to tree planting and to inform our recommendation system (Booth and Saunders, 1985). Trees require adequate temperature, moisture, nutrients, aeration, appropriate radiation, and a rooting environment as well as the absence of conditions such as adverse soil, climatic, and other conditions such as attack by pests and diseases (FAO, 1984).

Variables included in the site suitability assessment and recommendation engine include forest cover data from the Forest Survey of India (FSI), which has time series cover data on tree density classes. These classes include open forest (10–40% canopy density), moderately dense forest (40–70%), very dense forest (>70%), non-forest, scrub, and water. The prior extent of vegetation is a critical factor that determines the extent and possibility of growing trees in any landscape. Open forest patches are potential spots for growing trees, provided they are not natural blanks or rocky lands, and there are no other biophysical limits that constrain the successful growth of trees.

Other important factors that determine the growth of trees include elevation, slope, and aspect of plantations. Elevation beyond the tree line (~3800 m) and the presence of southern slope both prevent any productive tree growth. We use soil depth and soil carbon (organic and inorganic) as critical determinants that guide whether trees will grow and establish over the long term. Higher soil depth and soil carbon facilitate the successful establishment of plantations due to the higher availability of soil nutrients, soil moisture, and humus. We have used the number of villages in the vicinity of the assessed forest grid cell (forest patch) as indicative of higher resource use, which can restrict the success of tree planting over the long term. In addition, we collected spatial data for roads, urban areas, water bodies, snow, agriculture, grasslands, and desert areas (Trans Himalaya) from open-source spatial datasets (please refer to Supplementary Tables S1 and S2).

We created a 265 m^2 grid (7.0225 ha) for the entire state of Himachal Pradesh using QGIS for recommending growing of trees at the grid level. This size of the grid cell is used at 7.0225 ha so that each recommended grid cell must have at least 3–5 ha of area that can be planted. A total of 795,826 grid cells were created. Critical value ranges for various variables used in the analysis differ across various landscapes and even within grid cells due to variation in biophysical, ecological, and socioeconomic context, therefore it is not feasible to give specific within grid-level details for each variable (FAO, 1984). We use a single value for each variable for each grid cell to facilitate analysis. We store these variables in the PostgreSQL database and then use the PostGIS extension to create various features for each grid cell using Python. The spatial data was geoprocessed in QGIS and ArcMap.

2.2.2. *Rule-based metrics and scoring*

First, we used guardrails in the form of exclusion rules, which are based on traditional forestry knowledge to identify blank patches for growing trees in the state. We then exclude areas that are covered with grasslands, alpine or sub-alpine pastures, natural blanks, snow, water bodies, agriculture, urban areas, roads, and highways from the potential areas available for tree planting. We also exclude areas with very dense forests, those falling inside 'Trans Himalaya', dry desert zone, and with elevation more than 10,000 feet from mean sea level.

Natural blanks are areas that are devoid of any vegetation for a long time due to critical limits to tree growth imposed by local environmental and biophysical limits. We identify forest patches (grid cells) falling inside such natural blank areas by using a set of expert or traditional forestry rules based on changes in tree density between 2001 and 2019. We identify natural blanks by calculating the change in the tree canopy density for open forest (10–40% density), moderately dense forest (40–70%) and very dense forests (>70% density) and for non-forest, scrub and water categories for each forest patch (grid cell) for various combinations (change in each category between 2001 and 2003; between 2003 and 2005; between 2005 and 2009; between 2009 and 2013; between 2013 and 2015; between 2015 and 2019) as per Forest Survey of India satellite data (Forest Survey of India, 2019). Forest patches or grids with zero value and witnessing no change in zero values for above categories and for respective time periods are categorized as natural blanks as those that are devoid of any tree growth.

Finally, we created rule-based scores for each grid cell based on theory and expert advice from several senior forest officers and frontline field staff. The rubric for scoring grid cells based on expert/theory is given in Table S2. To store and query spatial datasets, we used the PostgreSQL database and its extension called PostGIS, which adds support for geographic objects to the PostgreSQL open-source object-relational database. We created different features based on our spatial queries, which were run on PostGIS using Python.

2.2.3. Model building and evaluation

To build our ML model, we use a dataset comprising of 16,674 forest polygons in Himachal Pradesh that records the location of all government-owned land and then, employ our ML model to predict plantation site suitability for each of the 795,826 grid cells in the entire state.

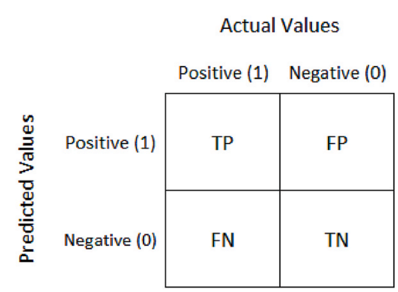
2.2.3.1. Dataset and variables. We use a training dataset comprising of spatial data on 16,674 georeferenced forest polygons in Himachal Pradesh with labeled tree cover loss (deforestation) outcomes for each forest polygon. The labeled tree cover loss outcome is a binary outcome and is measured as the decline in tree canopy cover (1 = tree cover loss; 0 = no tree cover loss) between 2003 and 2015 as reported by Forest Survey of India.

In our analysis, we use past tree cover loss in our studied forest polygons (n = 16,674) as a proxy for evaluating plantation site suitability in 795,826 grid cells across the state of Himachal Pradesh. In other words, we expect that areas similar to those that have lost tree cover or experienced deforestation are more likely to lose tree cover in the future, and therefore are likely to have lower plantation site suitability for growing trees. Exploring changes in tree cover loss is a useful metric as it can be used under diverse contexts worldwide, reflect and take into consideration multiple factors and processes including management and human use that shape the suitability of a particular site to grow and establish trees and maintain forest cover over long-term.

Our predictors in the ML model include socio-economic and biophysical parameters, as identified from the theory, technical studies, and past scholarship. These include human forest dependence attributes as indicated by population, number of forest dependents, level of literacy, grazing density, road density, number of farmers and economic activity in addition to soil and biophysical characteristics. Data on social indicators was calculated either by summing up the corresponding values of census villages (for population, farmers, literates, forest dependence) or by averaging (for grazing density, road density and economic activity), which were found within a particular forest polygon. In addition, we included baseline data on land use (forest cover, cropland, grassland or bare-land), data on soil quality (soil depth, soil carbon, soil pH, bulk density, cation exchange capacity, and available soil water capacity), and information on altitude, slope, temperature, precipitation, area and forest fires in our predictive model. For more details, please refer to our Supplementary Materials.

2.2.3.2. Building and evaluating XGBoost model using forest polygons (n = 16,674). We build a XGBoost model to generate tree cover loss predictions for our studied polygons (n = 16,674). In our model, we assign tree cover loss as positive values (mortality; tree cover loss = 1; no tree cover loss = 0) and then, randomly split the data into a "training" dataset (80%) and a "test" dataset (20%) using *scikit-learn* in Python. We develop the XGBoost predictive model using the training dataset and then employ the resulting model to predict tree cover loss probability for the test dataset for model validation. We use 100 trees in building our XGBoost model and keep other parameters as their default values due to small sample size. We import XGBClassifier from XGBoost library in Python to build our model. Given the heterogeneity of features and the fact that some of the features are categorical, we focused on decision-tree based ensemble-based methods. In this analysis, we tried two models: Random Forest (Breiman, 2001) and XGBoost (Chen and Guestrin, 2016) under standard parameters and finally, selected XGBoost model based on performance metric.

We evaluated the performance of our models based on confusion matrix based on the criteria of precision and recall. Confusion matrix is performance metric for classification-based machine learning problems wherein the outcome can be two or more classes.



Where:

True Positive (TP): Algorithm predicted positive class and it is true
True Negative (TN): Algorithm predicted negative class and it is true
False Positive (FP): Algorithm predicted positive class and it is false
False Negative (FN): Algorithm predicted negative class and it is false.

Precision is the ratio of the actual positive classes out of all the positive classes predicted correctly, i.e. TP/TP+FP, whereas Recall is the ratio of the correct predicted classes out of the all the positive classes, i.e. TP/TP+FN. We used 3-folds cross validation and evaluate its recall and precision attributes with a focus on maximizing recall. In our case, we believe recall is more valuable compared to precision as missing a true positive (tree cover loss) may lead to serious ramifications for biodiversity and forest cover in the area.

The XGBoost model we develop has the following performance: Predictive accuracy = 67.92%; Recall for tree cover loss (mortality) = 0.57; precision = 0.63; f1-score = 0.59). Finally, we use our selected XGBoost model to predict tree cover loss probability for 795,826 grid cells (for entire state). Based on this probability, we calculate the plantation site suitability score for each of the grids, which ranges from 0 to 100%.

In cases where there are multiple grid cells within a compartment, we consider all these grid cells to have an increase (or decrease) in tree cover loss if we found an increase (or decrease) in tree cover loss in that compartment. In cases where a single grid cell is present in multiple compartments, we used the prediction results for the compartment with the largest coverage for that grid cell.

ML-based analysis at the forest polygon level is done to incorporate deforestation (tree cover loss) dynamics and associated factors and processes operating at the landscape level. Incorporation of the deforestation probabilities in the tree planting recommendation engine along with expert-based rules make the engine more powerful in predicting site suitability classes for growing trees.

2.2.3.3. Robustness tests for the model. Initially, we start with Random Forest and XGBoost predictive models and evaluate their corresponding performance using 3-folds cross validation. We import RandomForestClassifier from *sklearn.ensemble* python API to build Random Forest model using 100 trees. We then compare and evaluate the comparative performance of Random Forest and XGBoost model using 3-folds cross-validation and the corresponding classification summary. Our XGBoost model performed better than Random Forest model in terms of recall (Recall: XGBoost = 0.57; Random Forest = 0.55). In other words, our chosen model can help identify tree cover loss outcomes (a true positive) better than Random Forest and hence, can be suitable to effectively assessing tree cover loss outcomes in the area.

2.2.4. Algorithm fusion

Finally, we used scoring rules for each grid cell in terms of its suitability to grow trees in terms of the presence of blank areas for planting and the site suitability of a site to support tree growth.

Let X_1 to X_n be scoring variables for the forest grid cells (parcels) of size 7.0225 ha (795,826 grid cells) created for the entire state of Himachal Pradesh. Let S_1 to S_n be the site suitability scores for each of forest grid cell based on the expert/theory rules. Let M_1 to M_n be the site suitability scores for each forest grid cell based on the machine learning model. The final score for each grid cell is weighted with 90% weight given to the score from theory/expert-based rules and 10% weight given to the ML-driven score, $X_i = 0.9S_i + 0.1M_i$. We will describe how we choose these weights shortly.

The site suitability score ranges from 0 to 100, for each forest grid cell/parcel. Based on this score, we divide the entire area available in the state into four FAO-based suitability categories to assist tree-planting decisions of forest rangers (FAO, 1984). High suitability category includes areas with a high probability of achieving established plantations due to largely supportive soil and other site quality conditions. Medium suitability category represents areas with an above-average probability of achieving established plantations due to moderate availability of open areas for growing trees and modest soil, other site quality conditions, and human dependence pressure. Low suitability areas are those with lowest probability of achieving established plantations due to inadequate soil and other site quality conditions, low availability of open areas for growing trees and plausible human dependence pressure. Finally, largely unsuitable category represents areas that are almost inappropriate areas for long-term establishment of plantations due to severe soil and other site quality constraints, and higher plausible human dependence pressure.

Any forest grid cell with score more than 70 is categorized as *high suitability*, score between 40 and 70 is categorized as *medium suitability*, positive scores up to 40 are categorized as *low suitability*, and grid cells with zero scores are categorized as *largely unsuitable.*

Our choices of weights for expert/theory and ML-driven scores are influenced by large-scale epistemic uncertainties (unknown unknowns) in data-driven assessment of suitability of forestry landscapes for growing trees. That is, available data does not capture many aspects of the socio-ecological and biophysical factors that influence site suitability, but centuries of human experience as distilled into expert Indian Forest Service knowledge do. On the other hand, human knowledge is unable to take large compartment-scale deforestation dynamics into account. As such, traditional knowledge and data-driven ML approaches are complementary.

To determine the weighting between traditional knowledge rules and the ML algorithm (our final result is 90% for traditional knowledge and 10% for ML), it would have been best to do formal parameter tuning to measure performance criteria like error probability, but ground truth was lacking to do this, as one must actually plant trees and see how they grow. Instead in our informal parameter tuning approach, we still varied the weighting parameter (among all possible 10% jumps) but measured the proportions of area classified to different land suitability categories. This distribution of total forestland among different categories [largely unsuitable, low suitability, medium suitability and high suitability] was then matched to the distributional assessments previously developed by the Indian Forest Service for the state of Himachal Pradesh (Himachal Forest Statistics, 2019) (Table 1).

According to Indian Forest Service, out of the total recorded forest area in the state (37,948 km^2), nearly 16,376 km^2 is under pasture, barren lands, and perpetual snow. This leaves 21,572 km^2 where there is some potential of tree growth with variable densities (Himachal Forest Statistics, 2019). Out of this tree growth potential estimate, 3113 km^2 is under very dense forest and 315 km^2 is under scrub, bushes, and other perennial shrubs (Forest Survey of India, 2019). Both of these categories have been excluded from the site suitability estimation, leaving a potential tree growth area of 18,144 km^2. Our site suitability application estimated a total tree growth potential area of 17,559 km^2. We attribute the difference (585 km^2) to methodological limitations in tree growth estimations by the Indian Forest Service, which fails to capture the few scattered trees existing on largely unsuitable landscapes, which are not fit for any potential tree growth in largely unsuitable category (Forest Survey of India, 2019).

We also collect spatial locations for 1547 plantations grown during 2020 throughout the state from Himachal Pradesh GIS lab to assess their suitability for successful tree planting based on our site suitability classification scores.

3. Results and discussion

3.1. Limits to tree-planting in Himachal Pradesh

Fig. 3 shows a portion of the state of Himachal Pradesh with site suitability classification for growing trees for grids under study.

Our results show that 68.46% (38,114 km^2) of the total area (55,673 km^2) in the state of Himachal Pradesh is highly unsuitable for growing trees and the remaining 31.54% area (17,559 km^2) can support some tree growth based on site suitability categories. Within 31.54% of the geographical area, we found 15.70% (8740.66 km^2) has low suitability, 14.14% (7872.16 km^2) has medium suitability, and 1.68% (935.31 km^2) has high suitability for tree planting in the state of Himachal Pradesh. Tree planting can show better results in medium to high suitability areas. With more financial and technical support, it may be possible to bring low suitable areas (15.70%, 8740.66 km^2) under tree plantations with low density.

As per the Forest Survey of India (2019) report, Himachal Pradesh has a total area of 15,433 km^2 under forest cover, which leaves about 2126 km^2 for potential tree plantations with low to moderate planting densities. If this entire area is available for tree plantations and converted to forests with low to high tree densities, Himachal Pradesh would have 31.54% (17,559 km^2) of its geographical area under forests. This would be the limit to tree-planting in the state.

However, we contend that even this tree planting potential can be difficult to realize on the ground as many available areas are located near village habitations and are being managed as grasslands by the local communities to meet grass requirements for their livestock. Moreover, the potential tree plantation area (2126 km^2) will be

Table 1
Percentage of suitability among included grid cells out of the total geographical area of the state (Highly Suitable >70 score, Medium Suitable >40 score and ≤ 70 score, Low suitability >0 and ≤ 40 score, Largely Unsuitable = 0 *score)*.

Proportion of rule/expert-based weightage	Proportion of ML weightage	Largely unsuitable (%)	Low suitability (%)	Medium suitability (%)	High suitability (%)
100	0	68.22	18.48	11.92	1.37
90	10	68.46	15.71	14.15	1.68
80	20	68.46	14.31	16.75	0.48
70	30	68.46	13.06	18.29	0.19
60	40	68.46	11.48	19.97	0.15
50	50	68.46	9.37	22.05	0.12
40	60	68.46	6.06	25.36	0.12
30	70	68.46	3.57	27.85	0.12
20	80	68.46	3.57	27.85	0.12
10	90	68.46	3.57	27.86	0.11
0	100	68.46	3.57	27.57	0.40

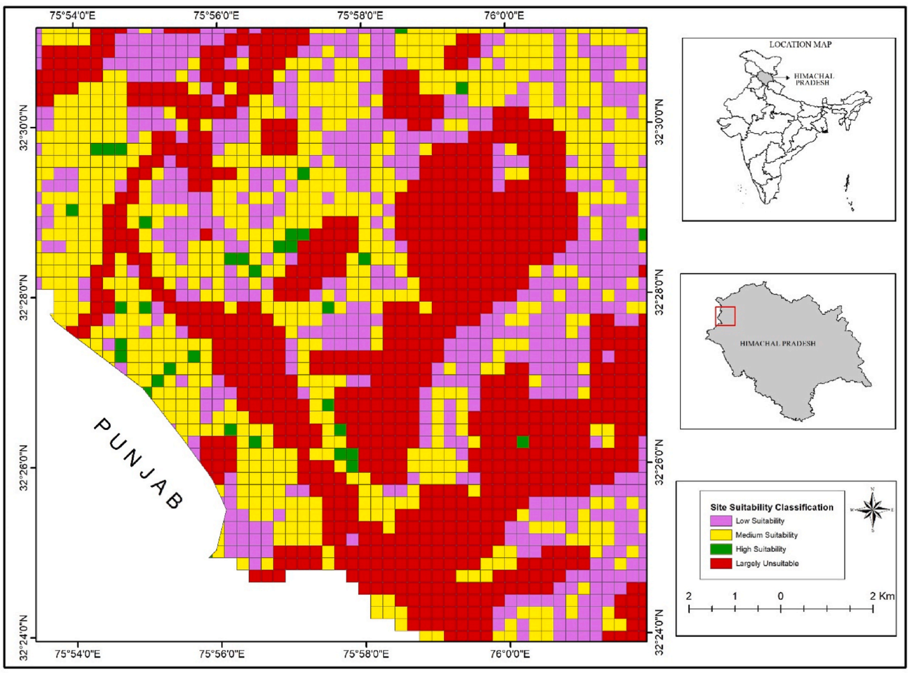


Fig. 3. Map showing site suitability details for the state of Himachal Pradesh for growing trees. Only a portion of the state is shown to display the site suitability classes.

considerably reduced when the current state of acreage under forest diversions (area diverted to other land uses such as roads, buildings and other infrastructure and power projects under Forest Conservation Act, 1980), encroachments (especially for agriculture and orchards), other community uses, and overlapping government and community tenure categories are taken into account.

The largely unsuitable category includes a high percentage of Non-Forest land area (84.8%) with very low proportion under OF (Open Forest), MDF (Moderately Dense Forest), or VDF (Very Dense Forest) (Table 2). These areas are also located at a very high elevation (3562 m, average), and further 412,868 grid cells have villages falling at 1 km or less, indicating the extent of the pressure of the local population on forest use. The very high percentage under Non-Forest land (NF) indicates the presence of rocky, snow-bound, alpine and sub-alpine pastures, croplands, and water reservoirs, which restrict any productive tree planting activity in the area.

On the other hand, areas with low suitability for tree planting have 58.42% area under Non-Forest, 20.3% under VDF, 12.37% under MDF, and 7% under OF (Table 2). These areas are located at an average elevation of 1651 m, and 332,166 grid cells have villages located at 1 km or less. Medium suitable areas have a high percentage under MDF (53%), followed by OF (23.38%), and then VDF (5.12%). The percentage under NF is low (5.12%), which indicates the presence of areas for planting trees. Such areas are located at an average elevation of 1541 m, and 275,110 grid cells have villages within 1 km or less. Lastly, areas with high suitability have a very high percentage of (76.56%), followed

Table 2
Descriptive on plantation site suitability classification in the state of Himachal Pradesh.

Suitability	Mean OF%	Mean MDF%	Mean VDF%	Mean NF%	Mean elevation in meters	Number of grid cells with village at 1 km or less
Largely Unsuitable	4.87%	4.36%	2.39%	84.80%	3562	412868
Low Suitability	7.00%	12.37%	20.30%	58.42%	1651	332166
Medium Suitability	25.38%	53.00%	5.12%	5.12%	1541	275110
High Suitability	76.56%	22.21%	0.15%	0.15%	1293	29158

by MDF (22.2%), and VDF (0.15%). Only 0.15% area falls under NF, which indicates high suitability of the area for planting trees (Table 2). These areas are located at a mean elevation of 1293 m and only 29,158 grid cells have villages located at 1 km or less.

Our results also show how the forest department is planting trees in largely unsuitable sites. Throughout the state of Himachal Pradesh, we found 25.4% of the total proposed tree plantations during the monsoon planting season of 2020 in largely unsuitable category ($n = 393$), 40.6% in areas with low suitability predictions (n = 627), 33.2% in areas with medium suitability ($n = 513$) and only 0.9% in areas with high suitability (n = 14). This is not a good distribution for approaching limits to tree planting. This trend may be due to several reasons. There is an overall absence of large patches of forests for planting trees across the state and, due to the target-driven approach of tree-planting programs and vested interests, forest rangers continue to select pockets where either tree planting is unnecessary due to high existing forest cover or there are poor site factors such as slope, elevation, soil quality, or other features (Fleischman, 2014; Ramprasad et al., 2020; Rana et al., 2022; Saxena, 1996).

Moreover, governments and donors usually evaluate the performance of forest rangers and other officials based on accountability systems that emphasize targets for the number of trees or areas under plantation (Fleischman, 2014). Such tree planting works are visible to external agencies for monitoring and evaluation and are therefore promoted at large scale with forest rangers and other forest officials, who in turn compete with one another to maximize the number of trees and area planted, even if suitable areas for growing trees are not available on the ground. Finally, poor institutional incentives, rewards, and punishment systems in the forest department encourage large-scale tree planting at the cost of local livelihoods, biodiversity, and tree cover. The vested economic interests of the forest rangers motivate them to prefer tree planting and soil conservation works over ANR, silviculture operations, effective fire and grazing management, or other forest improvement activities (Fleischman, 2014).

3.2. Initial deployment of e-plantation site assistant (ePSA) recommendation engine

Based on the above site suitability characteristics, we built the e-Plantation Site Assistant (ePSA) mobile app, a plantation site recommendation engine to assist forest rangers in selecting suitable sites for growing trees. A screenshot of ePSA is given in Fig. 4, showing different site suitability classes. Due to COVID-19, the there was a delay in launching the application, so only 201 out of about 1000 final users could test it on the ground. We do not believe, however, there is any systematic bias in this subset.

A phone survey was conducted in September 2020 and forest officials were asked to explain whether site suitability recommendations matched field realities. Our user study to assess the usefulness of ePSA surveyed 30 out of these 201 users (15%) via a random sample. Note that a sample of 30 is much larger than most studies in human-computer interaction, where the average sample size is 12 (Caine, 2016). Using standard statistical methods for survey-based research, a sample size of 30 out of 201 has an 11% margin of error at the 80% confidence level. Adequate care was taken not to bias the user study findings due to the position of the first author, and we believe there is no such bias in the responses of the forest officials concerning their feedback about ePSA. While interviewing, the identity of the first author was not disclosed to forest officials. Moreover, no interviewed official works directly under the first author.

Only 4 officials disagreed with the recommendations of the ePSA, whereas 26 officials fully agreed with the suggestions made by the recommendation engine. That is, 86.67% of the officials were satisfied with recommendations, showing high reliability of the site suitability and recommendation engine for growing trees. Given our constraints in obtaining empirical data on the quality of suitability prediction generated and the fact we used expert feedback to confirm ePSA quality, it will be fruitful to revisit this study in the future to evaluate the progress of tree growth in recommended areas on the ground. Note that tree growth itself does take several years.

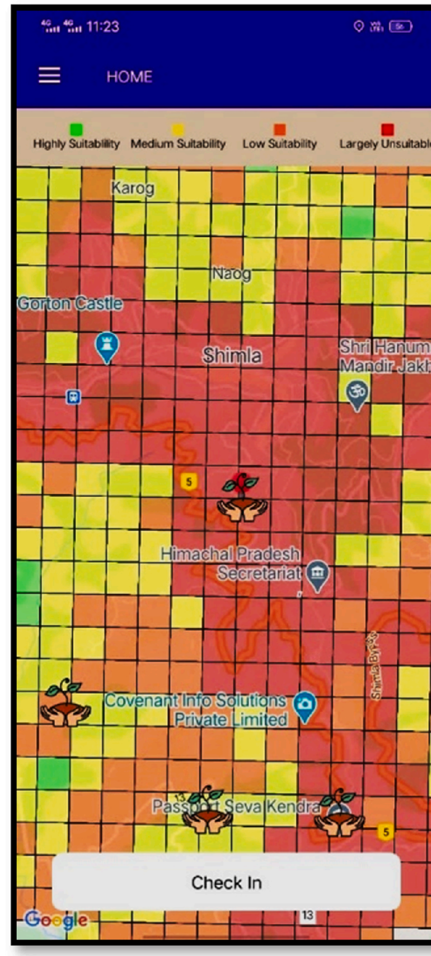


Fig. 4. ePSA mobile app showing site suitability classes.

Notably, our user study (carried out using standard methodology for such research in the human-computer interaction (HCI) literature and not just unstructured anecdotes) indicates that it was not just the information provision through ePSA that was useful, but also the site-suitability assessments. In particular, forest officials in 11 sites shifted to new locations for planting trees based on the ePSA recommendations. This is a significant fraction, given the level of professional prestige that Forest Service officers enjoy in India, and given the well-known phenomenon that people in high-prestige professions (such as doctors, judges, and astronauts) are most likely to assert their own judgements ahead of machine-recommended assessment (see e.g. Neil Armstrong landing on the moon by joystick rather than autopilot, as described by Mindell (2011)).

3.3. Limitations

Our approach has some limitations. First, satellite data may miss some important social-ecological dynamics due to the choice of specific spatial and temporal resolutions, incompatibility in various spatial layers, and radiometric corrections. For example, a stunted Chir Pine (*Pinus roxburghii*) vegetation due to local biophysical constraints may appear to be a patch of scrubland or areas with scarce trees, which the algorithm may suggest as a potential patch for plantation. Second, despite the usefulness of the machine learning models in learning and drawing inferences from patterns in data and making site suitability predictions, they still are not capable to provide causal inference-based insights limiting the broader utility of prediction-based inferences (Mullainathan and Spiess, 2017; Rana and Miller, 2019; Rana and Varshney, 2020). For example, regular diversion of forestland to non-forestry uses such as constructing roads, dams, and buildings, salvage tree removal by state forest corporation, and forest loss due to wildfires, floods, and diseases require continual updating of site suitability classification to make it more dynamic and suited to local field realities. Finally, ePSA needs to be further tested on the ground to evaluate its performance under diverse settings and iteratively improved.

4. Conclusion

Our findings show that there are limits to tree planting programs as a natural climate solution in the state of Himachal Pradesh, India. Out of the total geographical area of the state, 68.46% is unsuitable to grow trees, 15.70% has low suitability, and 14.14% has medium suitability due to critical biophysical, edaphic and socio-economic factors. Only a small percentage of the area in the state of Himachal Pradesh has high suitability (1.68%) where trees (1100 trees per hectare) can be planted. We also found continual high percentage of tree planting in places where there is a high likelihood of plantation failure and wastage due their poor site quality, in turn perhaps due to vested interests of forest officials (Rana et al., 2022).

Under limited field testing and validation, we also show the potential utility of using e-Plantation Site assistant recommendation engine in assisting forest rangers in selecting the right locations for growing trees based on site suitability considerations. Overall, our paper suggests the utility of combining remote sensing data, theoretical and field expert-knowledge, and machine learning models in the form of algorithm fusion from the AI safety literature (Kshetry and Varshney, 2019) in dealing with complex social-ecological problems such as selecting suitable sites for planting trees.

This finding has some important implications for the tree-based restoration objectives of the state and country, and are relevant to similar developing country contexts. First, state and national governments should adjust their plantation targets as per the field site suitability conditions and higher expectations from tree-based natural climate solution should be properly curtailed due to land use, financial, and operational constraints (Gopalakrishna et al., 2022; Rana et al., 2022; Zeng et al., 2020). For example, site suitability assessments should be conducted for all states to adjust India's Nationally Determined Contributions to take field site suitability conditions into account. Moreover, instead of setting ambitious goals such as achieving forest cover in 66% of the geographical area of Himalayan states, tree planting targets should be made based on how much suitable area is available to grow trees as per the site suitability classification. For example, we found that Himachal Pradesh can only achieve 31.54% forest cover (or less due to encroachments, forest conversion to other land uses, etc.) due to socio-ecological and biophysical limits. Though there is a need for further validation of the plantation site assistant recommendation system (smartphone app), its use across India and in several other similar country contexts can not only help identify the most suitable sites for growing trees while promoting transparency, but also can save a tremendous amount of money that can be diverted to other important socio-economic challenges or alternative climate mitigation strategies (Rana et al., 2022).

Second, there is a need to amend current plantation norms and strategies to obtain long-term success of tree-based restoration programs. For example, tree planting programs and norms are imposed by higher-ups uniformly across diverse country contexts without carrying out a prior site assessment and diagnostic to design such programs as per local site requirements based on existing vegetation, resource use, and site factors (Fleischman, 2014; Rana et al., 2022; Rana and Miller, 2021). Instead of focusing on targets, tree-planting based natural climate solutions should support community-designed site-specific interventions to ensure triple outcomes: enhanced biodiversity, carbon storage, and improved livelihoods. In many such places, a higher focus on assisted natural regeneration (ANR) rather than planting trees can be more effective and efficient to protect local biodiversity and reduce waste of financial resources (Crouzeilles et al., 2020; Duguma et al., 2020). Effective participation of local communities in site/species selection and empowering them to take ownership of these plantations through community forest rights can ensure long-term success of tree plantations in terms of benefiting livelihoods, carbon storage, and biodiversity conservation (Rana and Miller, 2021).

In sum, shifting the focus from extensive target-based tree-planting to protecting forest ecosystem goods and services, supporting forest-based livelihoods, prioritizing assisted natural regeneration, and promoting broadleaved species seems the most appropriate future direction for the India and other developing countries with similar contexts while adopting tree-restoration based natural climate solutions. In this context, site suitability assessments and site recommendation engine can play an important role in prioritizing suitable areas for growing trees to minimize waste, maximize co-benefits, and otherwise evaluate such tree planting activities. The practical utility of site suitability-based recommendations indicates its promising use in largely similar contexts of other developing countries that are also witnessing similar large-scale industrial or small-scale public tree planting programs and can help avoid massive waste on tree planting programs with little contribution to carbon storage and local livelihoods, by staying within fundamental limits of tree planting.

CRediT authorship contribution statement

Pushpendra Rana: conceived of the study, designed the, Formal analysis, Data curation, Writing – original draft. **Lav Varshney:** provided critical analytical insights, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data is open access.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.135566.

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