Title: Boundary trees offer large carbon sequestration opportunities in Indian croplands

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Abstract

Agroforestry offers the promise of enhanced CO_2 sequestration, farmer income, climate resilience, and biodiversity, yet little is known about the current extent or future potential of specific agroforestry practices. We combine new datasets on 600 million trees and 146 million farm field boundaries across India to map the extent and potential of boundary plantations, a specific practice where farmers grow trees on field boundaries. To account for errors in machine learning predictions of both tree cover and field boundaries, we annotate >4000 high-resolution images and use prediction-powered inference to construct statistically valid confidence intervals. We find a national sequestration potential of 3.9 +/- 0.21 Gt of CO_2 for additional boundary trees in India cropland, with current adoption representing <15% of total potential. Many of the most promising states for future adoption are also among the poorest in India, suggesting synergies between climate and poverty goals.

Adding trees to agricultural land is often considered one of the most scalable and cost-effective opportunities for CO_2 removal[1]. Farmland trees also provide many other potential co-benefits, including food and fodder production, habitat for biodiversity, regulation of microclimate, and reductions in soil erosion[2]. These co-benefits have driven significant interest among farmers, scientists, policymakers, and businesses to increase adoption of agroforestry practices.

Recent studies have built on global remote sensing tree cover datasets to estimate the current adoption and future potential of agroforestry broadly [3–5]. For example, Chapman et al.[1] use a 30-meter woody tree cover product to estimate the potential additional CO_2 sequestration in each country by assuming the current median level of tree cover in each biome represents a realistic counterfactual level of CO_2 stocks in trees on farmland. Zomer et al. [6] use a global medium-resolution tree cover product and IPCC tier 1 estimates of CO_2 density to estimate current CO_2 stocks from agroforestry, with subsequent work [7] using these data to estimate potential CO_2 sequestration in various adoption scenarios. These studies generally point to a larger sequestration potential for agroforestry than almost all other natural climate solutions[4], though estimates vary widely. For example, Roe[4] estimates technical potential of 5-6 GT CO_2 $year^{-1}$ globally, Griscom estimates maximum potential of 1 $GTCO_2$ $year^{-1}$ globally, and Zomer estimate from 1.83 to 19 GT CO_2 total potential depending on the adoption scenario.

Several limitations of prior studies make it difficult to know with high confidence how much CO_2 agroforestry can sequester. First, estimates of potential largely depend on low-resolution (>30-meter) tree cover maps that miss many scattered trees in complex smallholder agricultural landscapes in the tropics[8], leading to underestimates of current tree cover and therefore overestimates of potential additional tree cover. Significant advances in methods and data for mapping trees at high resolution in agricultural land have been made using remote sensing satellite imagery, leading to the publication of national[9] and even continental-scale high-resolution maps[8] of trees in agricultural land, and these can be used to make more accurate estimates of current and potential tree cover. Second, estimates from previous work use machine learning generated predictions for remote sensing tree cover, but do not correct for machine learning prediction errors, which can lead to bias in the estimated potential. Recent approaches such as prediction-powered inference (PPI) enable the estimation of statistically valid confidence intervals from machine learning predictions[10,11], and these approaches should be used to calibrate estimates of potential tree cover based on machine learning predictions.

Third, whereas most studies consider the broad question of adding trees to agricultural land, often assuming all fields transition to median level of tree cover[7], understanding is needed at the level of specific agroforestry practices such as windbreaks, silvopasture, and riparian buffers[12]. Each practice is appropriate for different types of agricultural systems, crop species, and soil and climate conditions. For example, silvopasture is feasible in pasture lands and some crop lands where livestock are the primary source of income, while windbreaks are more common in croplands where crops are the primary income stream. Existing work estimating potential sequestration assumes that median levels of tree cover in each landscape represent the potential adoption scenario for agroforestry, ignoring the role of specific agroforestry practices. Each agroforestry practice is context-specific, so trying to estimate the adoption or potential of

farmland trees without understanding the specific practices in play can lead to misestimation of both current adoption and future potential of agroforestry.

According to prior estimates of CO_2 sequestration potential from agroforestry, India is among the countries with the largest total CO_2 sequestration potential[4]. Agroforestry has a history as a traditional agricultural practice in India spanning thousands of years, with a wide diversity of agroforestry practices in different regions of the country[13]. India was also the first country to implement a National Agroforestry Policy[14], so there is clear interest from policy makers on scaling the adoption of agroforestry. One policy called “Har Medh Par Ped,” translated as “trees on every field boundary,”[15] incentivized farmers across 20 states to add trees to crop-field boundaries. [916]This practice of adding trees to crop field boundaries is often referred to as windbreaks[12]. Importantly, windbreaks do not require taking land away from other crops while providing significant co-benefits to annual cropping systems including reduce wind damage, reduced soil erosion, microclimate moderation, providing fodder for livestock, additional income streams, and habitat for pollinators and other biodiversity. It therefore represents, in our view, one of the most scalable options among the agroforestry options.

Here we aim to estimate how much CO_2 could be sequestered if farmers across India added trees to field boundaries. Leveraging high resolution datasets on tree cover[9] and field boundaries[16] that have recently been developed using satellite data and machine learning approaches, we estimate the current stock and potential additional CO_2 sequestration from increasing adoption of windbreaks in India.

Results

For both current and potential tree cover, we consider only areas within 3m of current field boundaries (see Figure 1). We estimate that existing Indian boundary trees have a total stock of 0.59 +/- 0.05 Gt CO_2 (Figure 2a), with additional potential from trees added to field boundaries of 3.92 +/- 0.21 Gt CO_2 (Figure 2b), using 95% confidence intervals in both cases. Large states like Maharashtra, Uttar Pradesh, Madhya Pradesh unsurprisingly contain both the largest current and potential CO_2 stocks.

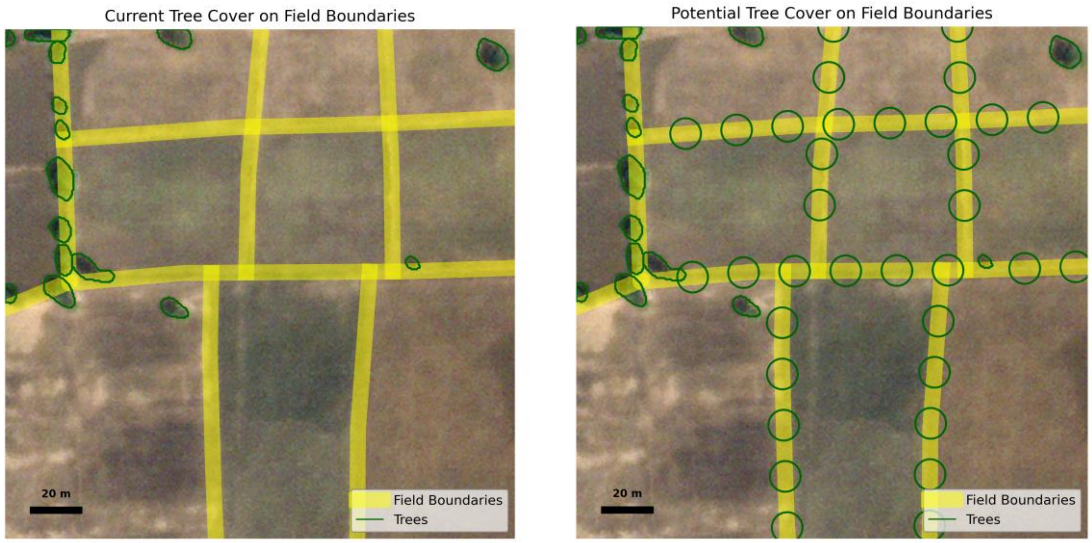

Figure 1: An Illustration of Border Tree Estimates. Example 200 x 200 meter satellite image with annotated field boundaries (yellow) and tree cover (green) for the current extent of adoption (left) and the potential from adding trees to boundaries without trees (right).

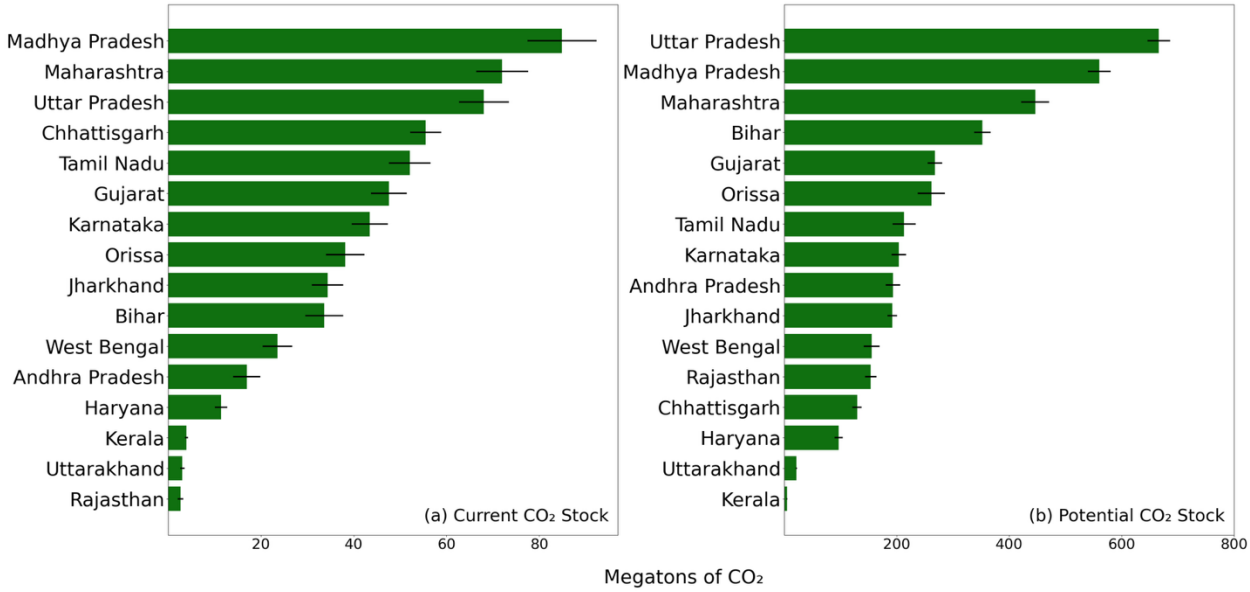

Figure 2: Current and Potential Total CO_2 Sequestration a) PPI-adjusted Current CO_2 Stock on Field Boundaries by state, with 95% confidence intervals. b) PPI-adjusted CO_2 Sequestration Potential by state, with 95% confidence intervals.

We also report estimates for the density of current (Figure 3a) and potential (Figure 3b) boundary tree CO_2 stocks to control for the size of different states. Kerala, Tamil Nadu, and Jharkhand contain the largest current density of CO_2 stocks, suggesting that both poor and rich states can have high boundary tree cover. However, the largest potential density is in poor states like Bihar, Jharkhand, and Uttarakhand, indicating significant potential for synergies between CO_2 sequestration and poverty alleviation(Table S1).

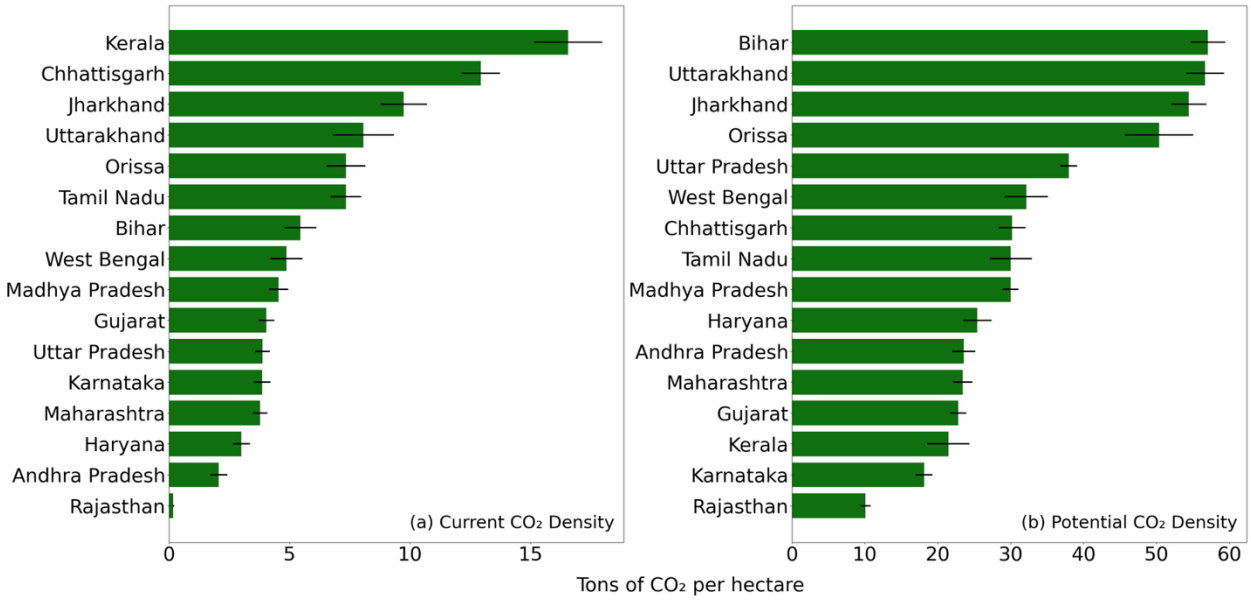

Figure 3a: Current and Potential CO_2 Densities a) PPI-adjusted Current CO_2 Stock Density on Field Boundaries by state, with 95% confidence intervals. b) PPI-adjusted CO_2 Sequestration Potential Density by state, with 95% confidence intervals.

A map of our estimates highlights that South India has a significantly higher current adoption rate of boundary tree practices than North India (Figure 4). In addition, adoption seems to be clustered in specific areas throughout the country, indicating that a farmer is more likely to have boundary trees if nearby to other farmers with this practice, perhaps because farmers learn from neighbors[17]. This clustering pattern appears at multiple scales and invites future qualitative work to understand why these areas have higher adoption rates of boundary trees.

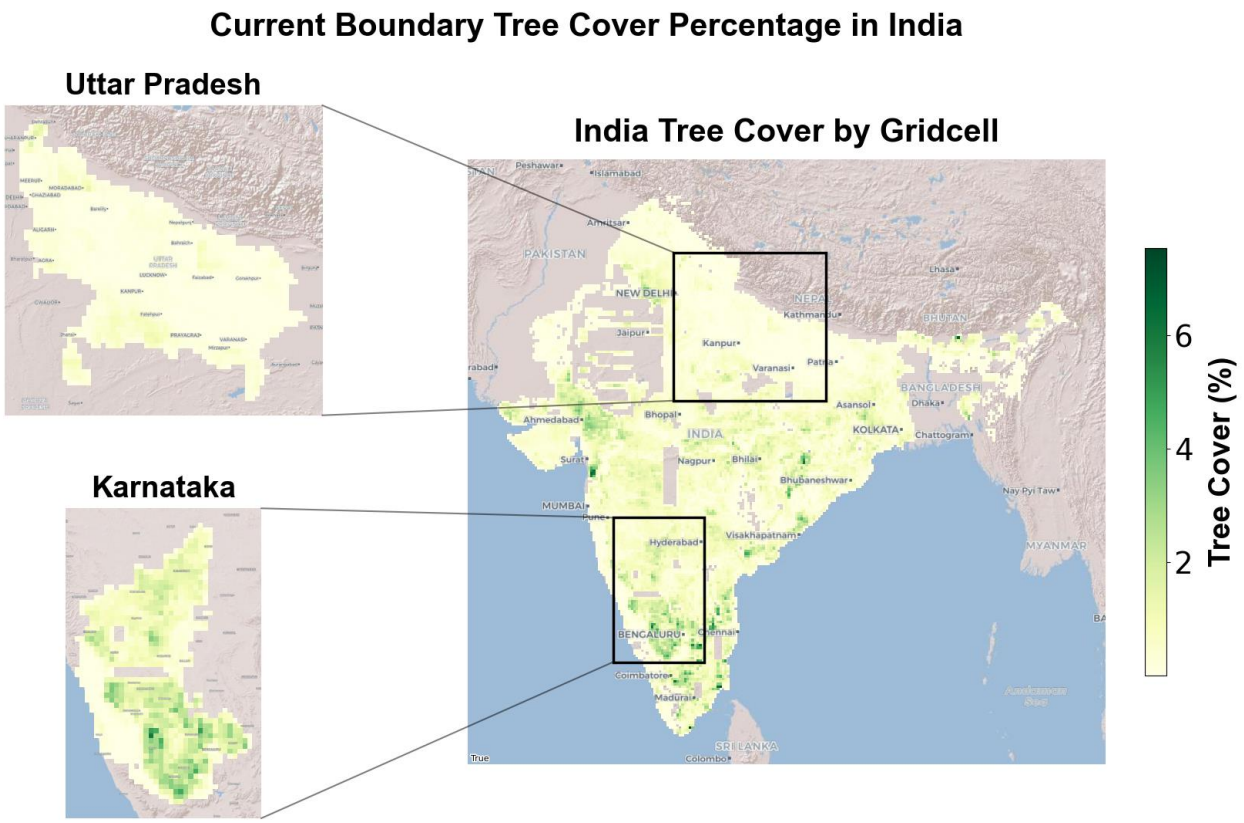

Figure 4: Map of Current Boundary Tree Cover in India. High adoption of this practice is clustered in specific areas, such as southern Karnataka.

We use our estimates of total potential CO_2 sequestration to construct scenarios of varying levels of adoption of boundary tree practices (25%,50%,75%) and varying levels of tree mortality (50%,70%,90%), following existing data on tree mortality in India (Figure 5). The level of adoption is the primary factor driving total potential CO_2 sequestration, even when tree mortality is 50%. We also observe that annual CO_2 sequestration only increases beyond 100 Mt after ~10 years in all scenarios, as trees take time to grow, and the majority of CO_2 sequestration will happen between 10 and 20 years after adoption. However, even in the most conservative scenarios of mortality and adoption, promoting boundary tree practices still leads to more than one Gt of CO_2 sequestration for the country of India.

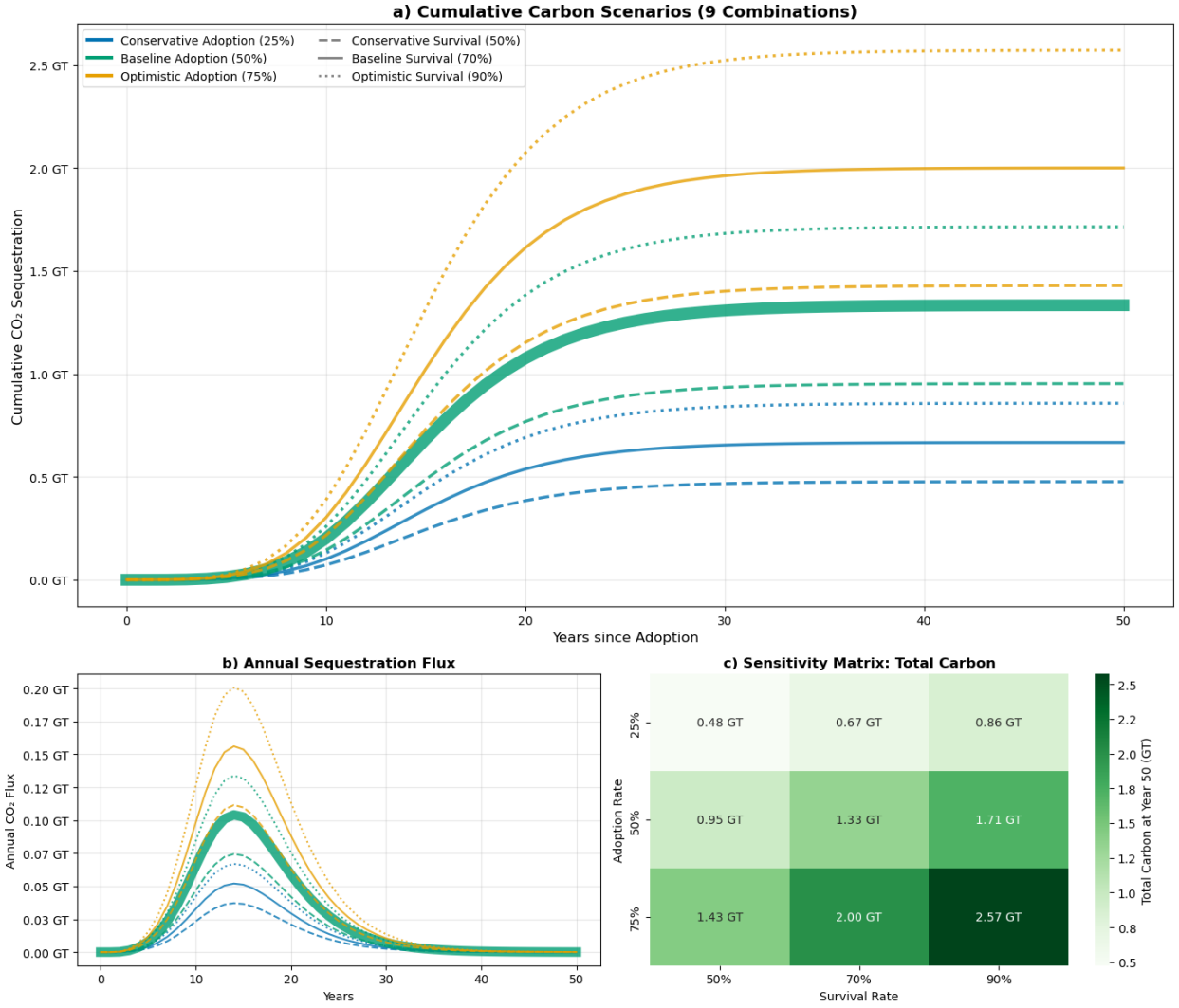

Figure 5: Cumulative and annual carbon sequestration in various adoption scenarios. Under varying adoption scenarios (25%, 50%, 75%) and varying tree mortality scenarios (50%, 70%, 90%) we report a) Cumulative CO_2 Sequestration Scenarios over over Time, b) Annual sequestration flux, and c) Total CO_2 sequestration Sensitivity Matrix to these varying scenarios

Discussion

Our analysis reveals that boundary plantations in India represent a substantial natural climate solution that is currently largely untapped. By integrating high-resolution remote sensing with rigorous statistical correction, we estimate a technical potential for additional carbon sequestration of 3.9 +/- 0.21 Gt CO_2. This value is roughly equivalent to 1.4 years of India's total greenhouse gas emissions, or nearly 11 years of the country's transportation sector emissions[18]. These findings align with the upper range of estimates for agroforestry potential in India from previous global studies but offer a crucial refinement: by focusing specifically on field boundaries, we demonstrate that gigaton-scale removal is possible without competing with food crops for land. This distinguishes boundary trees from other land-intensive mitigation strategies,

such as afforestation or block plantations, making them uniquely viable for India's land-constrained, smallholder-dominated agricultural system.

Methodologically, we present a scalable framework for converting "imperfect" big data into "policy-grade" evidence. As satellite imagery and machine learning models become ubiquitous, the risk of propagating prediction errors into policy decisions grows. Our application of PPI[11] highlights the danger of relying on raw machine learning outputs alone. Without the PPI rectifier, standard approaches would have underestimated the current CO_2 stock on field boundaries (by 65%) and overestimated the potential CO_2 sequestration on field boundaries (by 59%), leading to biased overestimates of future potential. By pairing massive but noisy satellite datasets with small, high-quality "gold standard" samples, we show that it is possible to produce statistically valid confidence intervals at national scales. This approach can be readily applied to map other climate-smart practices, such as cover cropping, tillage reduction, or water conservation structures anywhere in the world where high-resolution training data is scarce but determining accurate adoption rates is critical.

Geographically, our results point to a geographic roadmap for intervention. While states in South India currently exhibit higher adoption rates, the greatest *potential* for additional sequestration lies in the northern and eastern plains, particularly in states like Chhattisgarh, Bihar, and Jharkhand. These regions are characterized by lower current tree densities but high biophysical suitability for agroforestry. Crucially, these are also some of India's most economically vulnerable states. Prioritizing these areas for schemes like "Har Medh Par Ped" could deliver a "triple win": sequestering carbon, enhancing climate resilience against heatwaves and erosion, and providing new income streams from timber and fodder for low-income farmers.

Finally, while this study establishes the biophysical potential of boundary trees, realizing this potential requires addressing the socio-economic dimensions of adoption. Our biophysical maps show where trees can grow, but they do not explain why they are absent. Future research should prioritize understanding the barriers preventing farmers in high-potential regions from planting trees—whether it be insecure land tenure, lack of access to quality saplings, or concerns over competition with crops. Furthermore, our carbon estimates assume survival rates based on typical growth curves, yet actual sequestration will depend heavily on species selection and long-term tree management. Integrating these high-resolution spatial estimates with on-the-ground socio-economic surveys will be essential for designing incentives that ensure planted trees survive to maturity, transforming this massive theoretical potential into a permanent climate reality.

Methods

To estimate the current extent and additional potential of adding trees to field boundaries for India, we combine two recently released national-scale high-resolution data products for India: a dataset on field boundaries released by Wang et al.[19], and a dataset on tree cover released by Brandt et al.[9]. Both datasets were derived from applying machine learning models to very high-resolution satellite data to generate smallholder field-scale geospatial data products. Although they represent the best available data, they contain sufficient errors to necessitate explicit adjustment in our analysis, which we achieve using prediction-powered inference (described below).

Data

Smallholder Field Boundaries

Wang et al.[19] train a machine learning model to predict field boundaries from both Airbus 1.5-meter imagery and Planetscope 4.8-meter imagery. They performed manual annotation on high-resolution satellite imagery of >10,000 fields sampled from France and India to train and evaluate their model, achieving IoU of 0.86 in India. Here we developed an India wide dataset of field boundaries by applying this model to 1.5 meter imagery from airbus across India, generating 146 million field boundaries. There were issues with airbus imagery in some regions, so some regions have been ignored, largely concentrated in Northwest India, and these gaps are visible in Figure 4.

Farmland Tree Cover

Brandt et al.[9] train a machine learning model to predict pixel-level tree cover from Planetscope 3-meter imagery, enabling them to achieve near individual tree-level spatial resolution for tree cover. Again, they use manual annotations of high-resolution satellite imagery to train and evaluate their model achieving an F1-score of 0.65.

Other data sources

To focus only on fields that represent cropland, we use the ESRI LULC 10-meter land cover map to filter out non-cropland pixels, which has 90.2% precision in detecting cropland on a biome-stratified dataset for the world. We also leave out states with an area smaller than 30,000 square km. as their contribution to the national CO_2 sequestration potential is negligible to the total potential.

Estimating Current and Potential Boundary Tree CO_2 Sequestration

To estimate the current extent and future potential CO_2 sequestration from adding trees to field boundaries, we estimate both the current area of field boundaries and the area of boundary trees at the state-level for 17 states of India, leaving out small states.

Computing current extent of field boundaries

We convert the predicted field boundary polylines to polygons by adding a 3-meter buffer. For each state, we compute the sum of the areas of these buffered polygons to estimate the total area of field boundaries, representing the total potential area for adding trees to field boundaries.

Computing current extent of boundary tree cover

We take the 3-meter tree cover raster from Brandt et al.[9] and identify all pixels with both 1) tree cover confidence greater than a threshold of 0.5 and 2) a 3-meter radius field boundary overlapping with the pixel. We then sum all such pixels to compute the total area of boundary tree cover.

Correcting for Errors in ML-derived products for field boundaries and tree cover

Because ML-derived predictions are always imperfect, both the field boundaries and tree cover products contain errors which can bias estimates of the current extent of boundary tree cover.

To account for these errors, we leveraged the prediction-powered inference ++ framework[10], an approach for generating statistically valid confidence intervals for a parameter of interest using ML-derived predictions. This process requires having a gold-standard dataset in which the ground truth values of the quantity of interest are present alongside the ML-derived predictions. This paired dataset of ground truth values the ML predictions enables one to compute a rectifier and a standard deviation, following the algorithm from PPI, shown below.

Input: labeled data (X, Y), unlabeled features $\tilde{X}$, predictor f, error level $\alpha \in (0, 1)$

1: $\widehat{\theta^{\mathrm{PP}}} \leftarrow \widetilde{\theta^{f}} - \hat{\Delta} := \frac{1}{N}\sum_{i=1}^{N} f(\widetilde{X}_i) - \frac{1}{n}\sum_{i=1}^{n}(f(X_i) - Y_i)$ ▷ prediction-powered estimator

2: $\hat{\sigma}_f^2 \leftarrow \frac{1}{N}\sum_{i=1}^{N}\left(f(\widetilde{X}_i) - \widetilde{\theta^{f}}\right)^2$ ▷ empirical variance of imputed estimate

3: $\hat{\sigma}_{f-Y}^2 \leftarrow \frac{1}{n}\sum_{i=1}^{n}\left(f(X_i) - Y_i - \hat{\Delta}\right)^2$ ▷ empirical variance of empirical rectifier

4: $w_\alpha \leftarrow z_{1-\frac{\alpha}{2}}\sqrt{\frac{\hat{\sigma}_{f-Y}^2}{n} + \frac{\hat{\sigma}_f^2}{N}}$ ▷ normal approximation

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Output: prediction-powered confidence set $\mathrm{C}_\alpha^{\mathrm{PP}} = \left(\widehat{\theta^{\mathrm{PP}}} \pm w_\alpha\right)$

Constructing groundtruth annotations for tree cover and field boundaries.
To construct our gold-standard set, we leverage high-resolution 50-cm Planet Skysat images to annotate both individual tree crowns and field boundaries (Figure 1). This resolution is more than sufficient to accurately resolve field boundaries and individual tree crowns. Specifically, we trained an annotator to label all tree crowns and boundary polylines for 200 200 m x 200 m images for every state in India, totaling more than 4000 annotated images. To ensure high-quality, we perform double annotation for 200 images from across India and measure inter-annotator agreement, achieving IOU of 89%.

Using groundtruth images and state-level estimates to construct PPI intervals for each state
Given our annotated set of skysat images, we compute the predicted tree cover and boundary areas for these images using the same data products described above, which yields paired groundtruth and predicted values for boundary tree cover and boundary area in each satellite image. If we treat boundary area, boundary tree cover, and potential additional boundary tree cover within a 200 m x 200 m square as our parameters of interest within the PPI framework, we can use our 200 paired values of Y ("ground truth) and Yhat (predicted values) for each parameter to construct a statistically valid confidence interval . We then multiply the point estimates and upper and lower bounds for the densities by the number of 200 m x 200 m squares in the whole state to convert our estimates to total values for the whole state.

Computing Potential CO_2 *Sequestration from Boundary Trees*
To convert our tree cover area estimates to CO_2 stocks requires estimates of CO2 density. Panwar et al.[20] conducted a comprehensive review of CO_2 densities in agroforestry systems in different regions and practices of India. As expected, the CO_2 densities are higher in wetter biomes than in dryer biomes. Because we do not have CO_2 densities for every region in India,

we make the simplifying assumption that CO_2 density linearly increases with the amount of rainfall within an observed range, and we use the minimum and maximum CO2 densities found in this study to define this range in both CO_2 density and rainfall. We use block plantation CO2 densities because we are only considering the area on which there are trees rather than the whole farm. We compute average CO_2 densities for each state using average annual rainfall. Specifically, we set the range of CO_2 density to be between 52 tons ha^{-1} and 139 tons ha^{-1} which are the lowest and highest CO_2 densities in block plantations that occur in the driest and wettest parts of India respectively[20]. The CO2 densities are shown in Supplementary Figure 1, averaging close to 100 tons ha^{-1}, which is similar to the CO_2 densities used in Roe et al.[4] and Griscom et al. for similar regions. To construct confidence intervals of current and potential CO_2 sequestration from boundary trees, we simply multiply the point estimate and standard deviations by the CO_2 densities for that state.

Forecasting CO_2 Sequestration Under Various Adoption and Mortality Scenarios

Given our estimate of total potential CO_2 sequestration, we constructed different scenarios to forecast realistic CO_2 sequestration over time while varying levels of adoption and levels of tree mortality. We assume that tree growth follows the Chapman-Richard growth function[20] below, where B_max is the maximum CO_2 a tree can hold which we derive from our total potential calculation, k is the growth rate which we set at 0.25, and m is the lag phase during which tree growth is fairly slow .

$$B_t = B_{max} \cdot (1 - e^{-k \cdot t})^m$$

We use a value of m = 3 , which is a common value for fast growing agroforestry tree species and assume adoption follows the Bass Diffusion model with a logistic S curve below. A_max is the maximum potential adoption rate, which we vary over a conservative, baseline, and optimistic scenario of 25%, 50%, and 75%, and we assume the adoption period is 15 years, after which the farmers who would adopt border trees have already done so. We also account for tree mortality with conservative, baseline, and optimistic scenarios of 50%, 70%, and 90%.[21]

$$A(t) = \frac{A_{max}}{1 + e^{-c(t - t_{mid})}}$$

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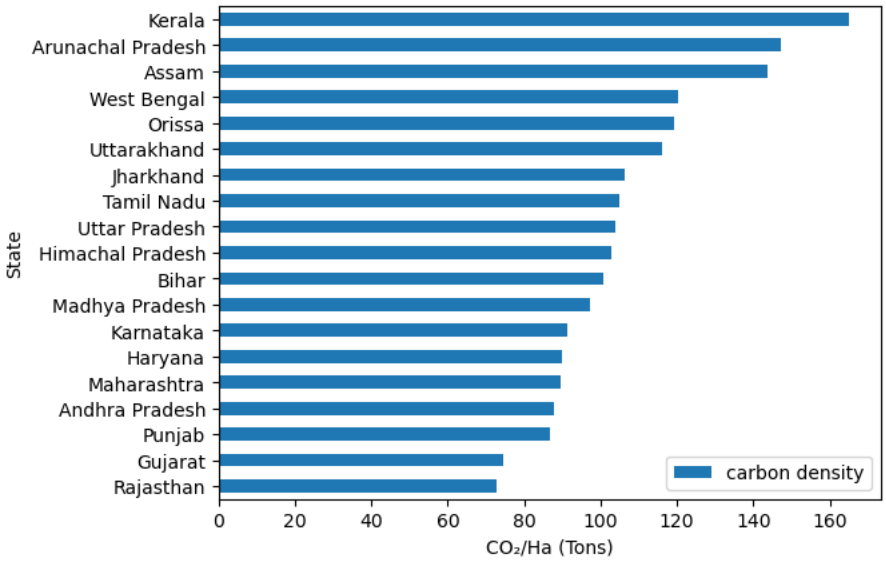
Supplements

State	Per Capita Income (Nominal USD)	Current Boundary Tree Carbon	Potential Boundary Tree Carbon
Karnataka	$4,445	15.46	72.45
Haryana	$4,372	12.03	101.81
Tamil Nadu	$4,269	29.37	120.06
Gujarat	$4,069	16.19	91.22
Maharashtra	$3,858	15.13	93.8
Kerala	$3,837	66.23	85.8
Uttarakhand	$3,572	32.27	226.74
Andhra Pradesh	$3,264	8.27	94.3
Rajasthan	$2,264	0.7	40.36
West Bengal	$2,188	19.48	128.62
Odisha	$2,166	29.39	201.5
Madhya Pradesh	$1,889	18.19	120
Chhattisgarh	$1,799	51.77	120.79
Jharkhand	$1,400	38.95	217.79
Uttar Pradesh	$1,298	15.53	151.97
Bihar	$807	21.82	228.27

Supplementary Table 1: Per-capita GDP by state (from Reserve Bank of India Handbook of Statistics on Indian States) along with boundary tree cover density estimates from this study. [22]



Supplementary Figure 1: Carbon densities assigned for each state which we estimate using existing evidence on carbon sequestration of agroforestry of various biomes in India along with the rainfall level for each state.

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