



LETTER

Existing land uses constrain climate change mitigation potential of forest restoration in India

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Abstract

Many countries have made ambitious pledges to increase forest areas to mitigate climate change. However, the availability of land to meet these goals is not well understood. Global studies indicate substantial potential, but do not account for local land-use and regional variation, crucial for policy making. Using India as a case study, we use a machine learning framework to define the bioclimatic envelope of forest cover and map this against current land-uses with varying suitability for restoration. We estimate the additional feasible area for restoration to be only 1.58 Mha, cumulatively sequestering 61.3 TgC, which is substantially less than estimates derived from global studies. However, we also find up to 14.67 Mha of opportunity for agroforestry in current agricultural land, delivering up to 98.1 TgC nationally. In the UN Decade of Restoration, we recommend developing forest restoration strategies that are compatible with existing land-uses, such as agroforestry, especially in countries that have large smallholder agriculture holdings.

KEYWORDS

agroforestry, climate change mitigation, forest restoration, India, natural climate solutions, reforestation, tree planting

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1 | INTRODUCTION

To limit global average temperature rise to 1.5°C, annual net emissions need to be 34 GtCO₂e lower than estimates accounting for current policies (United Nations, 2020). Previous research has highlighted restoration of forests as a key contribution to a net zero goal, sequestering carbon from the atmosphere (Griscom et al., 2017). Forest restoration seems to be a promising land-based option because of its relatively low costs, multiple cobenefits, and scalability (Brancalion & Holl, 2020). Griscom et al. (2017) estimated a maximum biophysical potential of reforestation globally to be 678 million hectares (Mha), yielding 2.8 PgCyr⁻¹ in annual mitigation. Using the same area estimates, Cook-Patton, Leavitt, et al. (2020) revised this estimate to 1.6 PgCyr⁻¹ of mitigation potential. Bastin et al. (2019) identified 4400 Mha of reforestation area available globally with a cumulative long-term mitigation potential of 205 PgC.

Such global studies are valuable in highlighting broad-scale patterns, driven by global-scale processes, but are limited in their ability to account for locally specific information in regions or countries, which can easily deviate from global estimates. Additionally, these global estimates can overestimate true potential due to inclusion of areas that are ecologically inappropriate for forest restoration, such as natural grasslands and savannas (Veldman et al., 2019), and inclusion (or limited exclusion) of agricultural and pasture lands where forest restoration may endanger future food security (Skidmore et al., 2019). If these caveats are overcome, it could lead to better-informed decision and policy making at the national and subnational scales (Cook-Patton, Gopalakrishna, et al., 2020).

Various countries have made national and international pledges to restore forests in order to limit global rise in temperatures (FAO, 2017). India has ambitious goals as part of its Nationally Determined Contribution to the Paris Agreement, which includes “additional (cumulative) carbon sink of 2.5–3 GtCO₂e by 2030” in the Land Use, Land Use Change and Forestry (LULUCF) category. To meet its international commitments, India aims to expand its forest cover area from 23% to 33% by 2030 (Pandve, 2009). However, there has been limited assessment of the feasibility of these targets and which regions are most appropriate to expand forest and tree cover area.

The only existing India-specific study estimated the opportunity for forest and tree cover restoration to be 138 Mha (Chaturvedi et al., 2018). The study employed a novel analysis that identified potential canopy densities in restorable areas. It also used information of carbon stocks of naturally regenerating forests by forest type for differ-

ent carbon pools, derived from extensive national carbon inventory data. However, this study was limited in that it did not consider natural disturbances (e.g., fire) that prevent ancient open ecosystems (i.e., less dense forests, grasslands, and savannah-forest mosaics) to reach their maximum potential of forest canopy density. Additionally, the analysis did not exclude croplands with less than 40% forest cover density, raising potential conflicts with food security.

In this study, we assess the potential of forest restoration to mitigate climate change by completing a spatially explicit mapping analysis of the feasible area of opportunity for forest restoration in all 28 Indian states (and six of eight Union Territories), hereby referred to as jurisdictions. We take advantage of a rich variety of India-specific datasets, including a 60 m vegetation classification map, with over 100 vegetation classes, forest cover canopy densities, and land uses and land covers (LULCs) (see full description of all datasets in Table S1). We expect reduced climate change mitigation opportunities mainly because of the complex regional variations in current LULCs, forest types, forest cover canopy densities, and associated carbon stocks that could naturally regenerate, that are unaccounted for in global studies. Consequently, we analyze the climate change mitigation potential of agroforestry at the national scale, here defined as systems and technologies, which include woody perennials, like trees, deliberately in agricultural cropland, in some form of spatial arrangement or on a temporal sequence (Dagar et al., 2014).

2 | METHODS

We define the feasible area of opportunity to be all land area that could sustain natural forests at biophysically appropriate forest canopy densities without compromising nonforest endemic ecosystems and without endangering food security. The resulting cumulative sequestration potential of the naturally regenerating forests is the climate change mitigation potential, hereby referred to as mitigation potential. First, we estimate the bioclimatic envelope of forest cover, and then map it against existing LULCs, excluding those that are unfeasible for forest restoration, resulting in the opportunity. Second, we determine the current LULC of the estimated opportunity by using published national datasets, validated by satellite imagery. Third, we estimate the mitigation potential. Lastly, we complete a national assessment of the maximum mitigation potential of agroforestry, focusing on agrosilvicultural systems (Dagar et al., 2014, Table S1 and Figure S1).

2.1 | Feasible area of opportunity

2.1.1 | Mapping of bioclimatic envelope of forest

We modeled the bioclimatic envelope of forest cover as a function of 12 edaphic, climatic, and topographical variables using the random forest algorithm (Supporting Information and Table S2). We used 11,116 GPS-gathered points of presences (unpublished from Roy et al., 2015) (Figure S2) of different forest types in each jurisdiction. These field data were collected based on a stratified random sample design, resulting in a 60 m resolution map of different vegetation types across India (including different types of forests and nonforest vegetation) (Table S1). We extracted 22,574 pseudoabsences (PsAb) or background sites as random points from areas with no current forest cover (Barbet-Massin et al., 2012) (Supporting Information, Figures S3 and S4). We used 10 random bootstrap sampled presences and PsAb (equally weighted), optimized with 700 trees and five predictors at each node using the *randomForest* R package (Liaw & Wiener, 2002). We calculated four accuracy metrics for each bootstrap and the ensemble model, which was used for the final prediction (Supporting Information, Figures S6 and S7). Additionally, we completed 10-fold nonspatial and spatial repeated cross validation (100 reps) of the ensemble model estimating the area under curve metric, as recent research has emphasized the importance of accounting for spatial autocorrelation to control for type I error rate inflation and ensure reliable validation statistics (Ploton et al., 2020). We estimated the bioclimatic envelope by setting the presence threshold to the mean of the predicted probabilities of 0.423 that allowed us to estimate the bioclimatic envelope of forests (Figure S7).

2.1.2 | Spatial exclusions of LULCs to estimate of opportunity

We excluded current ice/snow land cover that cannot be restored to forests, and wetlands due to different carbon accounting methodologies. We recognize that wetlands especially could provide considerable mitigation potential, but have dominant belowground processes, which are as or more important than aboveground vegetation, the latter being the focus of this study. We also excluded all current forests to meet the additionality benchmark, that is, mitigation that will occur with no forest restoration, assuming that these areas are not converted to another LULC. Additionally, we excluded all natural grasslands and woodlands, including savannahs, to protect native and endemic ecosystems. We then sequentially excluded national high-

ways, all agricultural lands, including irrigated cropland to secure food supply, and statutory towns, census towns, and villages (termed as settlements), resulting in our estimation of opportunity. We then estimated the area suitable for agroforestry within the same region as the bioclimatic envelope of forests after excluding ice/snow and wetlands, current forests, natural grasslands and woodlands, and national highways in irrigated and agricultural lands, which are classified as “villages” and “uninhabited.” Opportunity classified as current *jhum* (shifting cultivation) was included in opportunity for agroforestry to protect the livelihoods, food security, and cultures of people practicing *jhum*. We assumed no net change in food production from adoption of agroforestry in current cropland system. We deducted 25.31 Mha from the maximum opportunity for agroforestry (Dagar et al., 2014) to meet the additionality benchmark (see Supporting Information for further details about reasons for exclusions, Table S1 and Figure S1 for more details on the datasets, and the workflow of the analyses, respectively).

2.1.3 | Visual assessment of opportunity

We extracted the current LULC using Roy et al. (2015) for 560 random points in 28 jurisdictions (excluded Delhi and Tripura because of no opportunity). Additionally, we described the presence of forest cover and, where possible, the driver of absence of forest cover, such as presence of paths and agriculture, within a 60 m square buffer around each point, using Google Earth imagery at a 1:4500 scale. We did not distinguish between natural forests, plantations (e.g., timber), shade-grown coffee, and other tree-based land uses, as the imagery did not allow for this.

2.2 | Assessment of carbon stock

In each biogeographic zone and state, we allocated the dominant forest type and forest canopy density in the opportunity and assigned the associated carbon stocks for all pools, except for soil organic carbon, estimated from national forest inventory plots of naturally regenerating forests. Where opportunity could not clearly be assigned a dominant forest type or canopy cover density, we used a weighted average of the carbon stocks occurring in the biogeographic zone and state the opportunity was present in. Lastly, we used the mean net carbon sequestration potential of 6.68 MgCha⁻¹ (3.01–8.13 MgCha⁻¹) over the simulated period of 30 years from Dhayani et al. (2017) to calculate the additional mitigation potential of agrosilvicultural systems at the national scale (see Supporting Information for additional information and Table S1 for

details of datasets used). We reported the additional mitigation potential from forest restoration by aggregating the jurisdictions into six regions (Table S4) and reported the national-level mitigation potential of agroforestry separately.

All analyses were completed in R (R Core Team, 2020).

3 | RESULTS

We estimated the total forest bioclimatic envelope to be 101.0 Mha. Of this area of bioclimatic envelope, we sequentially excluded current ice/snow or wetlands (0.2%), existing forests (42.7%), natural grasslands, woodlands, and savannahs (1.3%), national highways (0.2%), irrigated croplands (17.1%), other agricultural lands (24.2%), and finally settlements (12.7%). We estimated 1.58 Mha of opportunity after all exclusions nationally (1.6% of the bioclimatic envelope). We estimated 39.9 Mha of agroforestry opportunity from the bioclimatic envelope in all agricultural lands, current *jhum*, and all croplands in “uninhabited” areas, of which 14.7 Mha corresponded to the additional opportunity for agroforestry. The biophysical envelope and opportunity varied widely by region and state (Figure 1 and Table S5). Chhattisgarh and Madhya Pradesh in central India had the highest opportunity of 0.26 Mha each, while Goa in western India and Mizoram in north-eastern India had the least opportunity of 0.002 Mha each and there was no opportunity remaining in Delhi and Tripura.

The dominant LULC of the opportunity of 1.58 Mha was degraded forests (33.2%) followed by scrub (28.8%). Visual inspection of opportunity showed a range of forest covers, including minimal forest cover due to agriculture, forests with open canopy cover and visible bare ground, no forest cover and visible bare ground, and scattered trees in small holding agriculture and settlement matrices (Figure 2, Figure S8, and Extended Figure 1).

At the national scale, we calculated 61.3 TgC mitigation potential across 1.58 Mha with variation across states and carbon pools (Figure 3 and Table S6). The central Indian states of Madhya Pradesh and Chhattisgarh had the highest mitigation potential of 12.6 and 10.9 TgC, respectively. Lastly, at the national scale, we estimated the maximum additional mitigation potential from agroforestry to be 98.1 TgC (44.2–119.6 TgC) over 14.67 Mha.

4 | DISCUSSION

4.1 | Forest restoration opportunity

Our estimates of opportunity and potential are substantially lower than those derived from global studies

(Table 1). We recognize that the criteria we have used to exclude LULCs that cannot be restored are strict. For example, by completely excluding all agricultural lands and irrigated lands, we do not account for opportunity and potential in agricultural lands that are invaded by exotic species. *Lantana*, an invasive species of growing prominence, has invaded the majority of India's pasture lands (13.2 Mha) in addition to forests and fallow lands (Negi et al., 2019). Clearance of these invaded lands to allow natural regeneration could lead to mitigation without compromising food supply. However, restoring forests across the majority of the bioclimatic envelope in India would require taking current cropland out of production, with potential impacts on food supply and livelihoods.

Also, our analyses indicate that different starting points of where forests could be sustained if restored, given bioclimatic conditions, might lead to different results of opportunity. Our resulting area of the bioclimatic envelope is comparable to that of Bastin et al. (2019) showing close congruence of potential areas, where natural forests can be restored in the absence of land use constraints. We recommend that future studies, about the area and location for forest restoration, thoroughly investigate the bioclimatic envelope of forests as the starting point.

We highlight the immense regional variation in opportunity and potential that remains unaccounted for in global studies, by primarily using national datasets that account for this variation in different LULCs, forest types, and forest cover canopy densities. Additionally, we strictly adhere to the constraints of additionality, food security, and protection of endemic and native ecosystems accounted for to a lesser extent by other studies. The highest potential is achievable in the central Indian states, which implies that restoration could be a priority climate change mitigation strategy in areas that have undergone historical deforestation, with consistent forest conversion for agriculture and mining activities (Reddy et al., 2016). The western Indian states have the least opportunity compounded by the least potential due to lower carbon stocks of local forest types (dominantly tropical thorn and dry deciduous forests from Reddy et al., 2015). Lastly, our results highlight that the high forest cover in the north-eastern states needs to be conserved via effective protection strategies for continued climate change mitigation and other ecosystem services, including habitat for biodiversity. However, our visual assessment suggests that opportunity classified as “degraded forests” and “scrub” needs further investigation considering the maximum bioclimatic forest canopy cover and biomass achievable at different successional stages, natural disturbances, such as herbivory and fires, and drivers of degradation (Ratnam et al., 2011).

Further fine-scale analyses could verify if forests could be sustained across the apparent bioclimatic envelope.

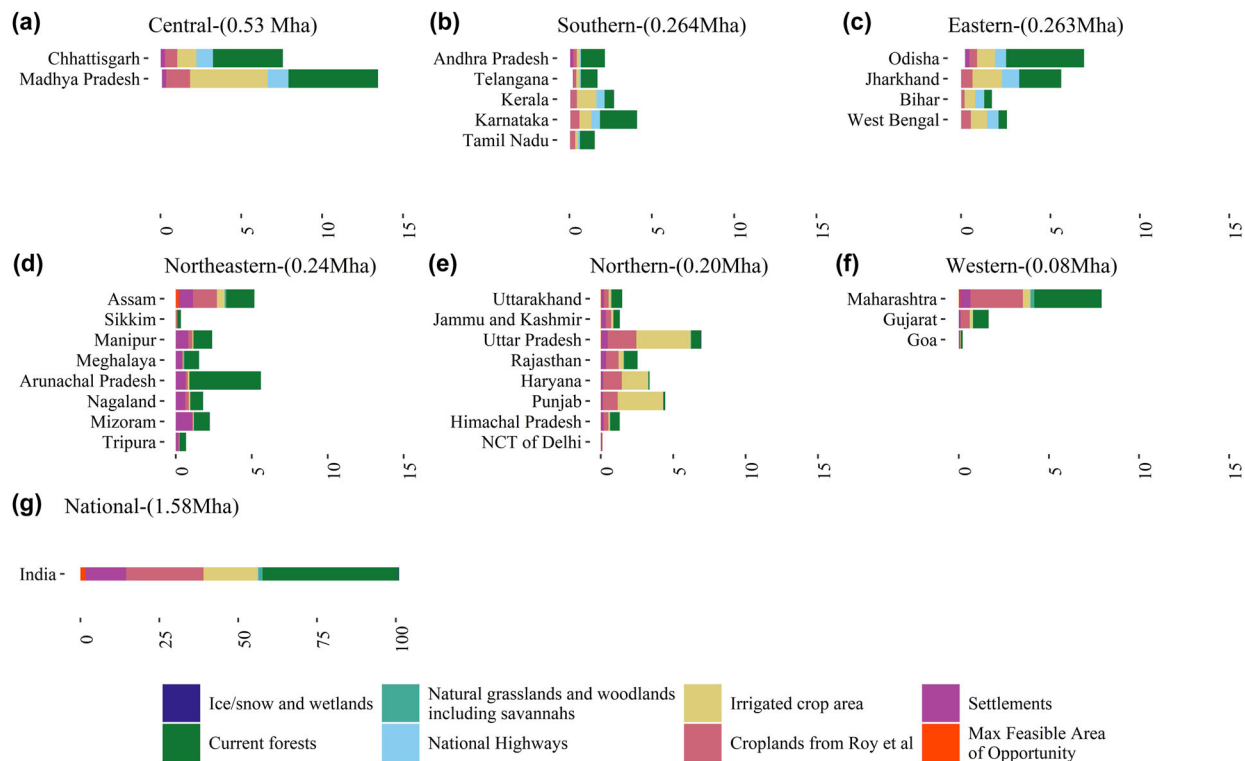


FIGURE 1 Opportunity (Mha) considering all LULCs that cannot be restored, by region (indicated in Figure 3 and listed in Table S3), arranged in decreasing order of total opportunity included in the title of each plot, left to right (a–f). Central states have the highest total opportunity of 0.53 Mha and western states have the least opportunity of 0.08 Mha. Within each plot, states are arranged in decreasing order of opportunity. Chhattisgarh has the highest opportunity of 0.26 Mha overall and within the central region, while Goa has the least opportunity of 0.002 Mha overall and in the western region. Delhi and Tripura have no opportunity remaining after accounting for all unrestorable LULCs. The size of each bar is the bioclimatic envelope of forest cover in that state (Mha), while the remaining colors indicate the area of different LULCs that cannot be restored and the feasible area of opportunity. National estimate of opportunity (Mha) of 1.58 Mha considering all LULCs that cannot be restored shown in (g), follows the same interpretation as the remaining figure with a different scale. See Table S5 for detailed estimates of opportunity for all jurisdictions

Despite the careful selection of bioclimatic variables to develop the envelope, large uncertainty remains, especially in areas that are currently almost completely forest-free (e.g., the north-west regions of Punjab and the Gangetic plain south of Nepal, which have a long history of agriculture). This could include comparisons with a historic baseline, such as precolonial forest cover in India, since areas where forests were present provide evidence that forests could still be sustained there. Also, we assumed that the newly regenerating forests will have the same composition and characteristics as current forests in the biogeographic zones of each state. However, future climate change will cause shifts in temperature and precipitation regimes, changing forest species community composition and dynamics (Scheiter et al., 2020), which we do not account for here. Scenario-based analyses for different climate change projections, including global vegetation models, will provide more insights into the composition and dynamics of regenerating forests (Kumar & Scheiter, 2019). Lastly, future work could assess how trends in cropland area associated with rural–urban migration

may affect future opportunities for forest restoration and agroforestry.

4.2 | Agroforestry opportunity

The higher opportunity and potential of agroforestry relative to forest restoration emphasizes the need for a diverse portfolio of strategies to mitigate climate change (Griscom et al., 2017). Additionally, the various benefits of agroforestry, including additional income source at the time of crop failure (Schroeder & Ladd, 1991), the creation of biodiversity corridors (Kremen & Merenlender, 2018), improved human health (Wolff et al., 2018), and national agroforestry policies, can accelerate the implementation of the agroforestry strategy.

The maximum potential of agroforestry estimated in our study, though coarse, highlights the complex reality, especially because we consider only agri-silvicultural systems. We can obtain more accurate estimates by accounting for other dominant agroforestry systems, such as

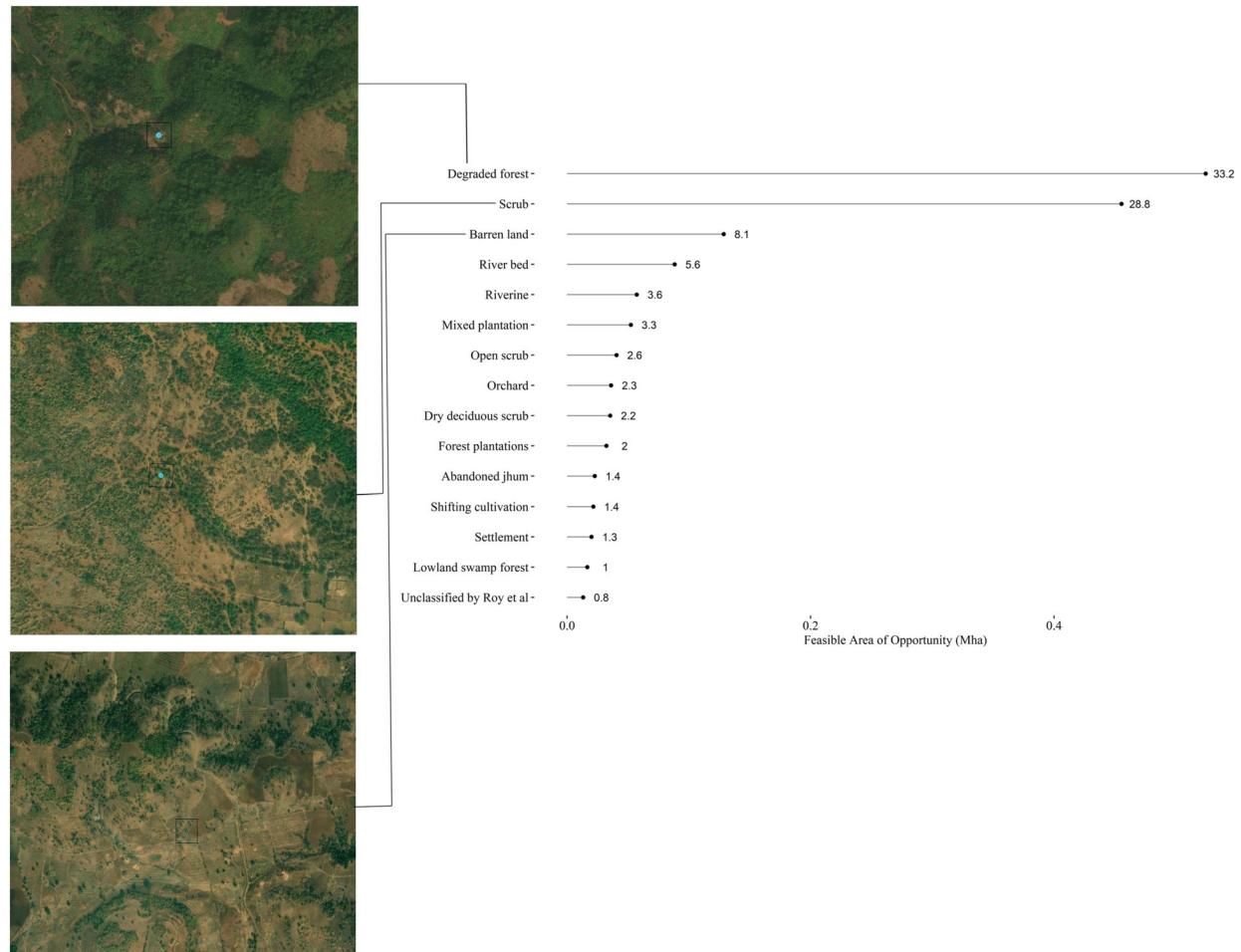


FIGURE 2 Assessment of current LULC of feasible area of opportunity. Proportion of top 15 current LULC classes (from Roy et al., 2015) accounting for 97.6% of the estimated 1.58 Mha opportune areas, where percentage is indicated by numbers at the end of each bar. 33.2% of opportune area was classified as degraded forests, 28.8% was classified as scrub, and 8.1% was classified as barren land. Examples of visual assessment of opportunity classified in the top three LULCs are shown in Meghalaya and Madhya Pradesh (top to bottom), where the teal dot is the centroid of the opportunity pixel and/or indicated by the black square (60 m side). See Figure S8 for more examples of visual assessment in remaining LULCs in other jurisdictions

silvo-pastoralism (Chavan et al., 2015). Additionally, mitigation potential from agroforestry depends on various factors, such as the tree species planted, age of trees, geometry of planting, crop type, geographic location related to climatic conditions, soil health, and management practices (Dhayani et al., 2017). Further understanding of the fine spatial-scale interplay of these many factors will be needed to provide more accurate estimates of the total mitigation potential of agroforestry. Our mitigation potential is conservative, since some agroforestry may also be feasible outside the bioclimatic envelope of forests. We also acknowledge that the assumption of no change in food production when using land-sharing practices of agroforestry, compared to land-sparing practices of converting a portion of cropland to forests, is challengeable. We recommend further analyses to better characterize food production–climate change mitigation trade-offs from agroforestry. Lastly, we do not account for soil organic carbon pool

mainly due to lack of comprehensive data, which might have resulted in underestimates of potential, especially from agroforestry (Bossio et al., 2020).

4.3 | Climate policy implications

Our estimates of 61.3 TgC from forest restoration and 98.1 TgC (44.2–119.6 TgC) from agroforestry correspond to only 19.5–23.4% of India's LULUCF pledge to the Paris Agreement. India's National Action Plan for Climate Change (2008) includes the Green India Mission (GIM) that aims at protecting and restoring India's forest cover in response to climate change (Ravindranath & Murthy, 2010). However, a recent assessment indicated concerns about the targets and concluded that it is grossly underfunded (MoE-FCC, 2019). More importantly, the assessment pointed that afforestation, with non-native tree species, such as

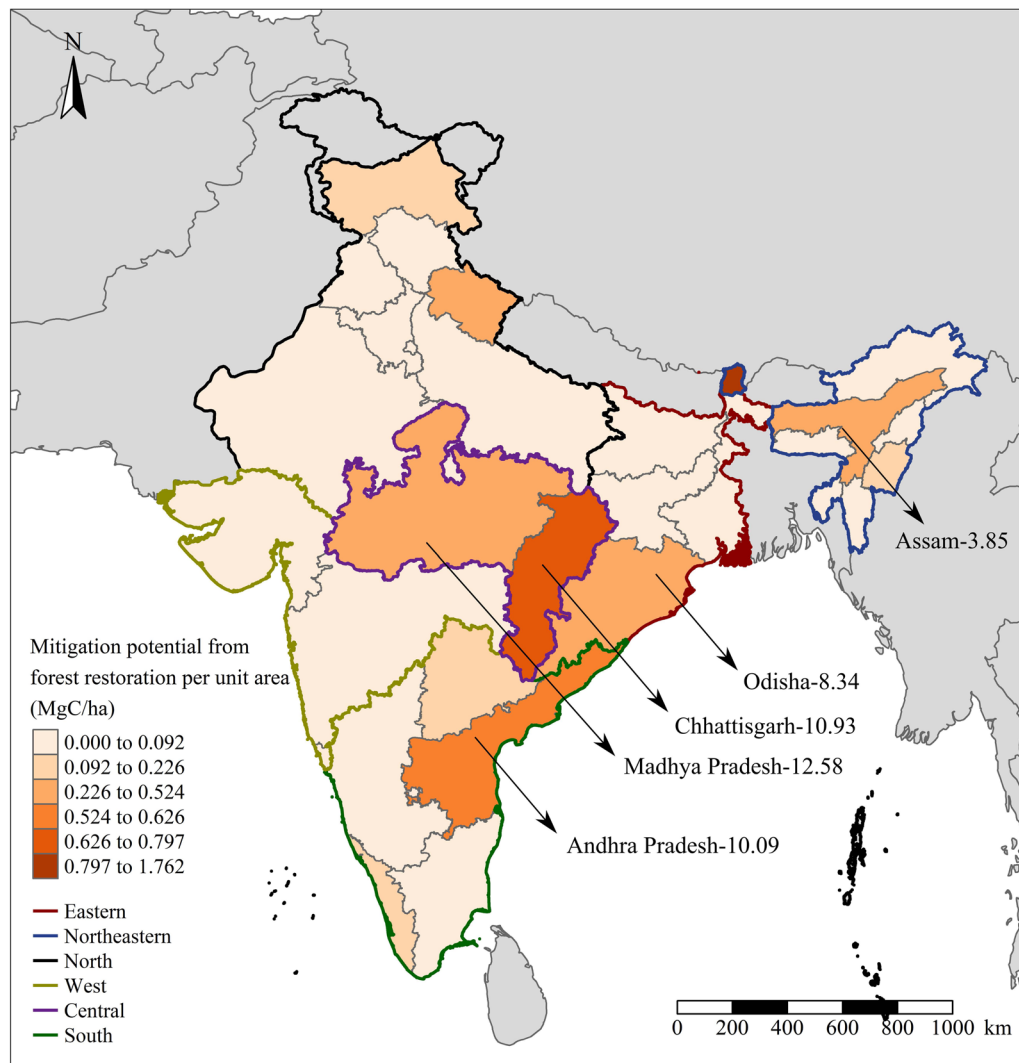


FIGURE 3 Mitigation potential of forest restoration normalized by total area of each state (MgC/ha) (no agroforestry). All areas in gray are not included in the analyses. Top five states with highest mitigation potential are indicated with units TgC. The highest potential is in the central Indian states of Madhya Pradesh and Chhattisgarh, totaling 23.5 TgC cumulative. See Table S6 for mitigation potential estimates of all jurisdictions

Eucalyptus, is the main strategy being employed, which is known to adversely affect biodiversity and will lead to overall reduced mitigation (Lewis et al., 2019; MoEFCC, 2019).

Our estimates of the potential from both forest restoration and agroforestry are only 17.5% of India's total GHG emissions in the year 2018 alone (total GHG emissions, including LUCF sector, is 912.8 TgC; World Resources Institute, 2021), highlighting the limited additional mitigation potential from forest restoration under current land uses. This finding underscores that forest restoration can only be one of many strategies fundamental to meet the goals of the Paris Agreement and that substantial greenhouse gas emission reductions will be needed by other sectors, most importantly energy (Anderson et al., 2019; Griscom et al., 2020).

Our results are consistent with other recent findings that global estimates of forest restoration tend to overestimate climate change mitigation potential in tropical countries with large agricultural holdings. Zeng et al. (2020) showed that although there is 121 Mha of degraded land available for reforestation for climate change mitigation in Southeast Asia, only 0.3–18% of it is feasible when considering on-the-ground financial, land use, and operational constraints. Our finding also mirrors the results of Griscom et al. (2020), who estimate that reforestation is only a minor component of the total mitigation potential in countries with large agricultural land use footprints and other dominant nonforest ecosystems like grasslands and savannahs. Like Griscom et al. (2020), we find that integrating agroforestry in agricultural lands is likely to be an effective and alternative strategy to

TABLE 1 Comparison of estimates of feasible area of opportunity and mitigation potential estimated in this study against India-specific estimates from global studies

Study reference	Estimates for India specifically from respective reference		Reasons for discrepancies
	Area of opportunity as defined in the respective reference	Mitigation potential as defined in the respective reference	
This study	1.58 Mha forest restoration opportunity 14.67 Mha agroforestry opportunity	61.3 TgC forest restoration potential 98.1 TgC (44.2–119.6 TgC) agroforestry potential	
Griscom et al. (2017)	33.16 Mha	519 TgCO ₂ eyr ⁻¹ (141.67 TgCyr ⁻¹)	<p>Reliance on ecoregional maps to define biophysical potential of forest systems versus our use of GPS gathered field points of forest cover to develop biophysical envelope as the starting point is one reason for our area estimates being lower. Additionally, the use of various global datasets to exclude LULCs, such as agricultural lands and current forests, versus the use of national datasets in this study that show regional variation could explain the lower area estimates of this study.</p> <p>Additionally, our cumulative estimates of mitigation potential are lower than Griscom et al. (2017), as we use refined and fine resolution carbon stocks data from an extensive Indian national inventory as opposed to from the literature.</p> <p>Our cumulative mitigation potential is not comparable with Cook-Patton, Leavitt et al. (2020), as they calculate annual increase in stocks from natural regeneration. However, we highlight that Cook-Patton, Leavitt et al. (2020) extracted over 10,000 data points from the literature, none of which are from India and used over 60 environmental predictors in the same machine learning framework as us, without accounting for spatial autocorrelation between environmental predictors.</p>
Cook-Patton, Leavitt et al. (2020)	33.16 Mha	106.9 TgCyr ⁻¹	
Bastin et al. (2019)	9.93 Mha	Mitigation potential estimated at biome level and hence unavailable for India specifically	Though their biophysical envelope of 98.72 Mha is close to our estimates of 101.0 Mha, they do not exclude native and endemic savannahs, grasslands, and woodlands to estimate reforestation opportunity, making our estimates of potential area lower.
Brancalion et al. (2019) and Strassburg et al. (2020)	No estimates of area available and incomparable to our study	No estimates of mitigation potential available and incomparable to our study	The primary goal of both studies is spatial prioritization/optimization analyses when considering a variety of ecosystem services, and not just climate change mitigation potential, hence, making the results incomparable with that of our study. Also, the area estimates of both studies use completely different criteria for exclusion of land uses and land cover. For example, Strassburg et al. (2020) estimate opportune areas as areas that have natural forest cover but have been converted to agricultural lands and propose restoration of these areas back to natural forests, raising the important point of endangerment of food supply.

(Continues)

TABLE 1 (Continued)

Study reference	Estimates for India specifically from respective reference		Reasons for discrepancies
Busch et al. (2019)	No estimates of area available and incomparable to our study	191 MtCO ₂ e between 2020 and 2050 at \$20/tCO ₂ e	Estimates from reforestation in marginal agricultural lands, primarily based on economic analyses of opportunity costs, while in our study, we completely exclude all agricultural lands to secure food supply.
Chaturvedi et al. (2018)	17.98 Mha “protection” strategy 33.6 Mha “wide-restoration” strategy	No estimates of mitigation potential available for comparison	There are differences in conceptual groupings of area of opportunity. However, methodologically, Chaturvedi et al. (2018) exclude a variety of LULCs from India’s total land mass as the starting point resulting in higher estimates relative to our study that uses a bioclimatic envelope as the starting point.
Chapman et al. (2020)	No estimates of area available for comparison	72.73 TgC	Our estimates of agroforestry are higher because of the use of different datasets of aboveground biomass, crop, and pasturelands (we do not distinguish pasturelands separately) and the thresholds in Chapman et al. (2020) that define additional potential gain in crop and pasturelands.
Chaturvedi et al. (2018)	87.22 Mha “mosaic-restoration” strategy	No estimates of mitigation potential available for comparison	The relatively higher estimates of mosaic restoration strategy are due to inclusion of all croplands with less than 40% forest canopy cover, while we exclude all croplands and irrigated lands for food security.

Note: Our estimates of mitigation potential are cumulative carbon stocks that would naturally regenerate in the opportunity, while some of the studies included provide a rate of carbon stock accumulation, not allowing for direct comparison.

restoration of closed canopy forests. In this respect, our case study of India has parallels to many African countries like Chad, Sudan, Somalia, and Kenya (Griscom et al., 2020).

Moving ahead, we recommend further research to investigate not only the total area available for forest restoration and agroforestry, but also social and cultural dimensions like forest governance and land tenure issues because of historical and current land use legacies, and other factors associated with the political economy of specific forest restoration schemes. This information will be crucial for prioritization of different states and regions for implementation and monitoring activities (Le et al., 2012; Lele & Menon, 2014). This information will also help prioritize policies, enable financial resources, and guide on-the-ground implementation activities in the upcoming UN Decade of Restoration.

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CONFLICT OF INTERESTS

The authors declare no conflict of interests.

AUTHOR'S CONTRIBUTIONS

Conceptualization—TG; data acquisition—PSR and PKJ; methodology—TG, GL, DB, and JAG; formal analysis—TG; investigation—TG and GL; writing original draft—TG; writing review and edition—TG, GL, DB, JAG, PSR, PKJ, and YM; visualization—TG; supervision—YM.

DATA AVAILABILITY STATEMENT

Data of presences of different vegetation types were acquired under a Memorandum of Understanding with Dr. P. S. Roy and Dr. P. S. Joshi. Map of forest canopy cover densities was acquired under a Memorandum of Understanding with the Forest Survey of India. Remaining data are freely available and listed in Table S1. Bioclimatic envelope of forests developed in this study is

available on Zenodo <https://zenodo.org/record/5789318#.YbywFlmnxaQ> (<https://doi.org/10.5281/zenodo.5789318>).

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REFERENCES

- Anderson, C. M., DeFries, R. S., Litterman, R., Matson, P. A., Nepstad, D. C., Pacala, S., ..., & Field, C. B. (2019). Natural climate solutions are not enough. *Science*, 363(6430), 933–934. <https://doi.org/10.1126/science.aaw2741>
- Barbet-Massin, M., Jiguet, F., Albert, C. H., & Thuiller, W. (2012). Selecting pseudo-absences for species distribution models: How, where and how many? *Methods in Ecology and Evolution*, 3(2), 327–338. <https://doi.org/10.1111/j.2041-210X.2011.00172.x>
- Bastin, J.-F., Finegold, Y., Garcia, C., Mollicone, D., Rezende, M., Routh, D., ..., & Crowther, T. W. (2019). The global tree restoration potential. *Science*, 365(6448), 76–79. <https://doi.org/10.1126/science.aax0848>
- Bossio, D. A., Cook-Patton, S. C., Ellis, P. W., Fargione, J., Sanderman, J., Smith, P., ..., & Griscom, B. W. (2020). The role of soil carbon in natural climate solutions. *Nature Sustainability*, 3(5), 391–398. <https://doi.org/10.1038/s41893-020-0491-z>
- Brancalion, P. H. S., & Holl, K. D. (2020). Guidance for successful tree planting initiatives. *Journal of Applied Ecology*, 57, 2349–2361. <https://doi.org/10.1111/1365-2664.13725>
- Brancalion, P. H. S., Niamir, A., Broadbent, E., Crouzeilles, R., Barros, F. S. M., Zambrano, A. M. A., ..., & Chazdon, R. L. (2019). Global restoration opportunities in tropical rainforest landscapes. *Science Advances*, 5(7), eaav3223. <https://doi.org/10.1126/sciadv.aav3223>
- Busch, J., Engelmann, J., Cook-Patton, S. C., Griscom, B. W., Kroeger, T., Possingham, H., & Shyamsundar, P. (2019). Potential for low-cost carbon dioxide removal through tropical reforestation. *Nature Climate Change*, 9(6), 463–466. <https://doi.org/10.1038/s41558-019-0485-x>
- Chapman, M., Walker, W. S., Cook-Patton, S. C., Ellis, P. W., Farina, M., Griscom, B. W., & Baccini, A. (2020). Large climate mitigation potential from adding trees to agricultural lands. *Global Change Biology*, 26(8), 4357–4365. <https://doi.org/10.1111/gcb.15121>
- Chaturvedi, R., Duraisami, M., Jayahari, K. M., Kanchana, C. B., Singh, R., Segarin, S., & Rajagopal, P. (2018). *Restoration Opportunities Atlas of India*. World Resources Institute.
- Chavan, S. B., Keerthika, A., Dhyani, S. K., Handa, A. K., Newaj, R., & Rajarajan, K. (2015). National Agroforestry Policy in India: a low hanging fruit. *Current Science*, 108(10), 1826–1834. https://www.jstor.org/stable/24905606?seq=1#metadata_info_tab_contents
- Cook-Patton, S. C., Gopalakrishna, T., Daigneault, A., Leavitt, S. M., Platt, J., Scull, S. M., ..., Fargione, J. E. (2020). Lower cost and more feasible options to restore forest cover in the contiguous United States for climate mitigation. *One Earth*, 3(6), 739–752. <https://doi.org/10.1016/j.oneear.2020.11.013>
- Cook-Patton, S. C., Leavitt, S. M., Gibbs, D., Harris, N. L., Lister, K., Anderson-Teixeira, K. J., ..., & Griscom, B. W. (2020). Mapping carbon accumulation potential from global natural forest regrowth. *Nature*, 585(7826), 545–550. <https://doi.org/10.1038/s41586-020-2686-x>
- Dagar, J. C., Singh, A. K., & Arunachalam, A. (2014). Introduction. In J. C. Dagar, A. K. Singh & A. Arunachalam (Eds.), *Agroforestry systems in India: Livelihood security & ecosystem services* (pp. 1–20).
- Dhayani, A. S., Handa, A., Newaj, R., Chavan, S., Alam, B., ..., Gunasekaran, S. (2017). Estimating carbon sequestration potential of existing agroforestry systems in India. *Agroforestry Systems*, 91(6), 1101–1118. <https://doi.org/10.1007/s10457-016-9986-z>
- FAO. (2017). From reference levels to results reporting: REDD+ under the UNFCCC. Retrieved from <http://www.fao.org/3/CA0176EN/ca0176en.pdf>
- Griscom, B. W., Adams, J., Ellis, P. W., Houghton, R. A., Lomax, G., Miteva, D. A., ..., Fargione, J. (2017). Natural climate solutions. *Proceedings of the National Academy of Sciences of the United States of America*, 114(44), 11645–11650. <https://doi.org/10.1073/pnas.1710465114>
- Griscom, B. W., Busch, J., Cook-Patton, S. C., Ellis, P. W., Funk, J., Leavitt, S. M., ..., Worthington, T. (2020). National mitigation potential from natural climate solutions in the tropics. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 375(1794). <https://doi.org/10.1098/rstb.2019.0126>
- Kremen, C., & Merenlender, A. M. (2018). Landscapes that work for biodiversity and people. *Science*, 362(6412), eaau6020. <https://doi.org/10.1126/science.aau6020>
- Kumar, D., & Scheiter, S. (2019). Biome diversity in South Asia — How can we improve vegetation models to understand global change impact at regional level? *Science of the Total Environment*, 671, 1001–1016. <https://doi.org/10.1016/j.scitotenv.2019.03.251>
- Le, H. D., Smith, C., Herbohn, J., & Harrison, S. (2012). More than just trees: Assessing reforestation success in tropical developing countries. *Journal of Rural Studies*, 28, 5–19. <https://doi.org/10.1016/j.jrurstud.2011.07.006>
- Lele, S., & Menon, A. (2014). *Democratizing forest governance in India*. Oxford University Press.
- Lewis, S. L., Wheeler, C. E., Mitchard, E. T. A., & Koch, A. (2019). Restoring natural forests is the best way to remove atmospheric carbon. *Nature*, 568(7750), 25–28. <https://doi.org/10.1038/d41586-019-01026-8>
- Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. *R News*, 2(3), 18–22. <https://cran.r-project.org/doc/Rnews/>
- MoEFCC. (2019). *Performance of the National Action Plan on Climate Change (NAPCC) Committee on Estimates (2018–2019)*. Retrieved from <https://www2.gov.bc.ca/gov/content/governments/organizational-structure/ministries-organizations/ministries/environment-climate-change>
- Negi, G. C. S., Sharma, S., Vishvakarma, S. C. R., Samant, S. S., Maikhuri, R. K., Prasad, R. C., & Palni, L. M. S. (2019). Ecology and use of *Lantana camara* in India. *Botanical Review*, 85(2), 109–130. <https://doi.org/10.1007/s12229-019-09209-8>
- Pandve, H. (2009). India's national action plan on climate change. *Indian Journal of Occupational and Environmental Medicine*, 13, 17–19. <https://doi.org/10.4103/0019-5278.50718>
- Ploton, P., Mortier, F., Réjou-Méchain, M., Barbier, N., Picard, N., Rossi, V., ..., Péliissier, R. (2020). Spatial validation reveals poor predictive performance of large-scale ecological mapping models. *Nature Communications*, 11(1), 1–11. <https://doi.org/10.1038/s41467-020-18321-y>

- R Core Team. (2020). *R: A language and environment for statistical computing*. Vienna, Austria. Retrieved from <https://www.r-project.org/>
- Ratnam, J., Bond, W. J., Fensham, R. J., Hoffmann, W. A., Archibald, S., Lehmann, C. E. R., ..., Sankaran, M. (2011). When is a “forest” a savanna, and why does it matter? *Global Ecology and Biogeography*, 20(5), 653–660. <https://doi.org/10.1111/j.1466-8238.2010.00634.x>
- Ravindranath, N. H., & Murthy, I. K. (2010). Greening India Mission. *Current Science*, 99, 444–449. <https://doi.org/10.2307/24109567>
- Reddy, C. S., Jha, C. S., Diwakar, P. G., & Dadhwal, V. K. (2015). Nationwide classification of forest types of India using remote sensing and GIS. *Environmental Monitoring and Assessment*, 187(12), 777. <https://doi.org/10.1007/s10661-015-4990-8>
- Reddy, C. S., Jha, C. S., Dadhwal, V. K., Hari Krishna, P., Vazeed Pasha, S., Satish, K. V., ..., Diwakar, P. G. (2016). Quantification and monitoring of deforestation in India over eight decades (1930–2013). *Biodiversity and Conservation*, 25(1), 93–116. <https://doi.org/10.1007/s10531-015-1033-2>
- Roy, P. S., Behera, M. D., Murthy, M. S. R., Roy, A., Singh, S., Kushwaha, S. P. S., ..., Ramachandran, R. M. (2015). New vegetation type map of India prepared using satellite remote sensing: Comparison with global vegetation maps and utilities. *International Journal of Applied Earth Observation and Geoinformation*, 39, 142–159. <https://doi.org/10.1016/j.jag.2015.03.003>
- Scheiter, S., Kumar, D., Corlett, R. T., Gaillard, C., Langan, L., Lapuz, R. S., ..., Tomlinson, K. W. (2020). Climate change promotes transitions to tall evergreen vegetation in tropical Asia. *Global Change Biology*, 26(9), 5106–5124. <https://doi.org/10.1111/gcb.15217>
- Schroeder, P., & Ladd, L. (1991). Slowing the increase of atmospheric carbon dioxide: A biological approach. *Climatic Change*, 19(3), 283–290. <https://doi.org/10.1007/BF00140167>
- Skidmore, A. K., Wang, T., de Bie, K., & Pilesjö, P. (2019). Comment on “The global tree restoration potential.” *Science*, 366(6469). <https://doi.org/10.1126/science.aaz0111>
- Strassburg, B. B. N., Iribarrem, A., & Beyer, H. L. (2020). Global priority areas for ecosystem restoration. *Nature*, 586, 724–729. <https://doi.org/10.1038/s41586-020-2784-9>
- United Nations. (2020). *Emissions Gap Report 2020*. 1–102. Retrieved from <https://www.unenvironment.org/interactive/emissions-gap-report/2019/>
- Veldman, J. W., Aleman, J. C., Alvarado, S. T., Michael Anderson, T., Archibald, S., Bond, W. J., ..., Zaloumis, N. P. (2019). Comment on “The global tree restoration potential.” *Science*, 366. <https://doi.org/10.1126/science.aay7976>
- Wolff, N. H., Masuda, Y. J., Meijaard, E., Wells, J. A., & Game, E. T. (2018). Impacts of tropical deforestation on local temperature and human well-being perceptions. *Global Environmental Change*, 52, 181–189. <https://doi.org/10.1016/j.gloenvcha.2018.07.004>
- World Resources Institute. (2021). Historical GHG emissions. Climate Watch. Retrieved from <https://www.climatewatchdata.org/ghg-emissions>
- Zeng, Y., Sarira, T. V., Carrasco, L. R., Chong, K. Y., Friess, D. A., Lee, J. S. H., ..., Koh, L. P. (2020). Economic and social constraints on reforestation for climate mitigation in Southeast Asia. *Nature Climate Change*, 10(9), 842–844. <https://doi.org/10.1038/s41558-020-0856-3>

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