Contrasting patterns of deforestation and reforestation in India's tropical dry woodlands

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Abstract

Tropical dry woodlands are key ecosystems for global biodiversity, carbon storage, and forest-based livelihoods in some of the poorest regions of the world. Many of these woodlands have been historically converted and degraded, and while recovery occurs in some areas, the pressure on remaining tropical dry woodlands remains high. Despite this, our understanding of spatial patterns of tropical dry woodland change is poor. Here, we reconstruct spatio-temporal dynamics of dry woodlands between 2014 to 2024 across India at 30-m resolution, a country with a long land-use history and widespread historical woodland decline, as well as large and active woodland restoration commitments. To better understand the geographic patterns of change, we conduct a spatial autocorrelation analysis of woodland losses and gains to compare decreases and increases of woodland cover inside and outside government administered lands. Our study reveals a gross gain of ~ 2.10 million hectare (Mha) compared with a loss of ~0.29 Mha of woodland. Within this net gain of 1.80 Mha, we find contrasting spatial patterns of woodland loss and gain. Government administered lands, where most of the country's native dry woodlands remain, experienced a loss of 0.17 Mha (58% of total loss). In contrast, outside government-administered lands, which are often human-dominated agricultural landscapes where active reforestation initiatives and forest plantations take place, tropical dry woodland area increased by around 0.78 Mha (37% of total gain). Our results highlight that regional or national-level woodland trends can mask important fine-scale deforestation and reforestation patterns with important implications for biodiversity, ecosystem services and rural livelihoods outcomes. As countries expand conservation and restoration efforts in the wake of the 30x30 agenda and other commitments, it is critical for monitoring efforts to capture the patterns of dry woodland change

at sufficient detail to inform policy making and spatial planning, and thus to support desired restoration outcomes.

Introduction

Global estimates suggest tropical dry woodlands cover around 1 to 1.2 billion hectares (Bha), accounting for roughly 40 percent of the world's tropical forests (FAO, 2019, Blackie et al. 2014). These dry woodlands are biodiversity-rich (Maestre et al. 2012) and store over 30% of the world's carbon (Hanan et al. 2021). They also support the livelihoods of many of the 1.6 billion people living in or close to forests (Newton et al. 2020) through fodder, wild food, charcoal, timber and other forest products, and provide agricultural commodities and timber to regional and global markets (Djoudi et al. 2015). Yet, despite their high social-ecological value, dry woodlands face growing threats from land-use changes as well as climate change intensifying fire regimes (Miles et al. 2006, Corona-Nunez et al. 2023). To address these challenges, many tropical countries have made global commitments to better protect and restore forests under various global agendas, including the 2022 Global Biodiversity Framework (30x30 agenda), the 2015 Paris Agreement, the 2014 New York Declaration of Forest 2014, and the 2011 Bonn Challenge. Implementing such commitments, however, requires information on the spatial patterns of these woodlands and how these are changing.

Despite high pressure on them, dry woodlands have received substantially less attention by research, policymaking and the wider public than their moist forest counterparts (Schroder et al. 2021, Buchadas et al. 2023). Although a few studies have highlighted dry woodland deforestation frontiers in Asia and Africa (Buchadas et al. 2022, Buchadas et al. 2023), there is limited understanding of more nuanced forest loss and gain patterns at national and regional scales. One reason for this limited understanding is varying and sometimes unclear definitions of what constitutes a dry woodland (Veldman et al. 2015, Pennington et al. 2018), making it difficult to compare across different assessments of dry woodland changes (e.g., from woodland to savannah or vice versa, Ratnam et al. 2011). As a result, there remains uncertainty in estimates of dry forest cover and how it is changing over space and time. For example, Bastin et al. (2017) estimate dry woodland cover to be around 1,156 million hectare (Mha) while Guirado et al. (2022) estimate it at around 1,283 Mha.

A second major limitation is that most dry woodland assessments only provide estimates of forest cover at a single point in time and do not inform on dry woodland changes over time. This limited longitudinal understanding is to a large extent driven by difficulties in reliably mapping dry woodland change, due to the high structural variation and complexity (e.g., more close versus more open dry woodlands, or higher versus lower share of tall trees) that characterizes these ecosystems. This complexity is challenging to adequately capture based on remote sensing against the context of high inter- and intra-annual phenological variation (Maura et al. 2012). As a result, research suggests that existing broad-scale and detailed forest change products, such as the Global Forest Watch dataset (Hansen et al. 2013) underestimate dry woodland extent (e.g., Tian et al. 2017), leading to an overestimation of the restoration potential in these woodlands (Fagan, 2020).

A region where the magnitude and spatial distribution of dry woodland losses and gains are particularly uncertain is India (Ratnam et al. 2011, Tian et al. 2017). Defined on the basis of low rainfall (average <1000mm per year), the country has one of the largest dry woodland extents globally - (Bastin et al. 2017), extending from the lower foothills of the Himalayas in the north to the semi-arid regions of western India and the Deccan Plateau in the south (Figure S1). This region includes a variety of forest types such dry deciduous forest, dry evergreen forest, open scrub, and savannas (Champion and Seth, 1968) as well as managed plantations, including Teak (*Tectona grandis*) and *Eucalyptus* species initiated during the colonial period (Guha 1983). India's dry woodlands are used by more than 70 million forest dependent people (GoI 2019). India's dry woodlands are also important tiger conservation landscapes in the Terai, central India, and the eastern Ghats region (Wikramanyake et al. 2011) and support a wide range of endangered and endemic birds and animals.

India's dry woodlands have been diminished through expanding land use, both historically and more recently (Reddy et al. 2016, Kalam et al. 2025). Restoring these woodlands has thus become a priority as part of India's national target to increase forest cover to 33% and to restore 26 Mha of woodlands by 2030 under the Bonn Challenge (GoI, 2019). India has already implemented restoration interventions in over 10 Mha of land since 2008 (Borah et al. 2018) and has ramped up tree planting efforts in recent years to meet its large international commitments (Fleischmann et al. 2020, Rana and Miller, 2021). As a result, the Forest Survey of India (FSI) reports an overall net gain of over 5 Mha over the last two decades (FSI, 2021). However, this aggregated statistics is likely to mask considerable gross changes (i.e., losses and gains) across the country. The spatial patterns of gross changes are not inferable as FSI forest-cover data are not publicly available. FSI has not consistently monitored whether losses and gains occur within or outside government owned forests and treats forest irrespective of land ownership (FSI, 2013). Furthermore, these numbers include forestry plantations and tree crop monocultures, suggesting there is a possibility that net woodland gain might still include native dry woodland loss.

India's dry woodlands have seen considerable loss in the 19th century, especially after 1995 (Kalam et al. 2025). There have been a few efforts to map vegetation cover in India (Roy et al. 2015a, Reddy et al. 2015), as well as decadal forest change estimates between 1985-2015 (Roy et al. 2015b), both derived from India's satellite IRS-Resourcesat. A more recent Landsat-based forest cover map was published for the year 2020 (Singh et al. 2021), but these datasets do not specifically map dry woodlands, are static and do not provide temporal information about dry woodland losses and gains for recent years.

Global landcover products like Hansen Global Forest Cover (Hansen et al. 2013), Alos Palsar Forest map (Shimada et al. 2014) does not specifically provide for dry woodland class nor their temporal change. We therefore continue to lack a robust, high-resolution assessments of dry woodland change in India particularly within government administered forest land where much of native dry woodlands are left.

Here, we map the spatial patterns of loss and gain of India's dry woodlands for the period 2014 to 2024 and analyse the patterns of loss and gain within and outside government administered forest land. To do so, we developed an annual dry woodland cover time-series based on Landsat imagery using machine learning algorithms in Google Earth Engine. We use government administered forest boundaries to study the loss and gain of native woodlands., providing insights about the net loss of native dry woodlands and gain from plantations outside of forest land.

Methodology

Landsat Image Processing. To map dry woodland dynamics, we used all Landsat 8 (Level 2, Collection 2, Tier 1) surface reflectance imagery for the period 2014 to 2024. We first pre-processed images using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm and masked out clouds and cloud shadows using CFMask (Zhu and Woodcock 2012, Dwyer et al 2018). We chose not to include Landsat imageries prior to 2014 because Landsat 7 images are impacted by scan line errors. Next, for each Landsat image, we selected six raw spectral bands as well as eight spectral indices commonly used for forest detection (Storey et al. 2016, Clark, 2020; Pflugmacher et al. 2019): Enhanced Vegetation Index (EVI); Normalized Difference Moisture Index (NDMI); Normalized Difference Water Index (NDWI); Normalized Burnt Ratio (NBR); Modified Soil Adjusted Vegetation Index (MSAVI); Tasseled Cap Brightness (TCB); Tasseled Cap Greenness (TCG); and Tasseled Cap Wetness (TCW).

For each band and index, we calculated a set of spectral temporal metrics (STMs) for each pixel in each year, specifically the mean, median, standard deviation and the 10^{th}, 50^{th}, and 90^{th} percentiles. STMs have been shown to be useful for mapping tropical dry woodland change elsewhere (Baumann et al. 2018, Baumann et al. 2022). Image compositing to generate STMs was conducted using all available imagery in the period June to December. This period was selected as dry woodlands in India are largely composed of dry deciduous trees (Champion and Seth, 1968) that shed their leaves during early summer (January to May). In these months it is therefore difficult to detect differences in spectral signatures between forest and non-forest land (Figure S2). In contrast, in June to December the dry woodland vegetation has higher leaf area and chlorophyll, which helps spectral indices distinguish between land cover classes (Ambika et al. 2016, Higginbottom et al. 2023).

To account for impacts of inter-annual weather variability on vegetation signatures, total annual precipitation from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) as an additional metric (Funk et al. 2015) as spatial and temporal variability in rainfall impact vegetation spectral metrics in tropical dry forests (Souza et al. 2016). We also include latitude and longitude as additional predictors to account for location specific spectral signatures of woodland non-woodland class (Hengl et al. 2018). In total, we generated 73 predictors as inputs to our forest classification model (5 STMs for each of 14 bands and indices, times five, plus precipitation, latitude, and longitude metrics).

Training data. We used very high resolution (VHR) imagery from Google Earth to generate training data for our forest classification model. We first digitised polygons distributed across our study area for two broad land-cover classes: (i) non dry woodlands, including buildings, water bodies, barren land and other land without trees; and (ii) dry woodlands, including native forests, other woody vegetation, and dense tree plantations on farms where tree canopy cover was greater than 10% per hectare. This threshold choice is commonly used to characterize dry woodlands (e.g., Buchadas et al. 2023) and is in line with both the Indian government (FSI, 2019) and UN FAO (FAO, 2020).

When digitising training polygons, we sought to capture the diversity of conditions that are reflected in our two land-cover classes. We ensured our sampling polygons varied in sizes (between 100X100m to max 250X250m) and included forested areas with both dense and open tree cover, along with plantations (see Figure S3). Tree plantations of species like Eucalyptus, Teak, and Poplar were included in the woodland class as their spectral signatures are similar to native woodlands (Altamirano et al. 2020). We chose to include agroforestry, consisting of scattered trees on farms, in the non-forest class for our analysis, as these scattered trees do not meet our minimum 10% tree canopy definition. We ensured that we digitised a similar extent of dry woodland (1651 polygons) and non-woodland polygons (794 polygons).

From these polygons, we extracted 1800 randomly selected training points without replacement for seven years: 2015, 2017, 2018, 2019, 2020, 2022 and 2024. We included an additional 1187 points for both forest and non-forest classes across these seven years to cover areas in our study region where we did not have enough training points (SI figure S4A). We did so to appropriately capture inter-annual variation in spectral signatures (e.g., caused by rainfall variations) between years. We thus collected a total of 14887 training points, yielding a total of 5080 (34%) in dry woodland areas and 9807 (66%) non-woodland areas.

Classification and post-processing. To generate dry woodland maps for each year, we used a Random Forest classification. Random Forest models are a regression-tree-based machine-learning tool that predict the probability of a pixel being assigned to a certain class and are widely used in vegetation and land-cover classifications (Hansen et al. 2013, Higginbottom et al. 2023) because they typically outperform other classifiers, require relatively small training data sets, and are interoperable (Rodriquez-Galiona et al. 2012).

We trained our Random Forest model to predict woodland and non-woodland using our entire training dataset. To identify the best hyperparameter setting for the Random Forest model, we used Bayesian optimization approach that provides a best possible combination of different hyperparameters: *numberOfTrees*, *variablesPerSplit*, *minLeafPopulation*, *maxNodes* based on evaluating the RMSE for different combination. Bayesian optimisation has shown higher classification accuracy of Random Forest models (e.g., Zhang et al.2021). The Bayesian optimization using the training data was performed in Python (Code made available in Github). The model output from the Bayesian optimisation was further subjected to minor tuning of the hyperparameters and manual evaluation of accuracy as Bayesian optimisation could still have out of bag error, as it validates the accuracy using part of the training data itself. The model that had the best accuracy was finally used for classifying the annual time-series maps and had the final model parameters numberOfTrees=2000, variablesPerSplit=15, minLeafPopulation=20, maxNodes=100, and seed=1.

All land-cover maps contain some degree of uncertainty. Therefore, it is important to limit the degree of pseudo-change in land-cover change analyses due to randomly distributed misclassified pixels in individual years. To address this, we followed Ding et al. (2022) to remove spatial and temporal misclassification. First, we used a 3x3 majority filter to eliminate single woodland pixels located outside woodland areas, which likely represent misclassifications. Second, we developed a temporal correction algorithm to reclassify non-woodland pixels to woodland if these pixels were classified as woodland in the prior and subsequent years.

Map accuracy and area estimation. We followed best practices as set out by Olofsson et al. (2014) to evaluate our woodland maps. Our number of validation points is based on the observation that our estimated forest class was around 10% of our total study area, an expected user's accuracy (Ui) at 0.7, and a target standard error of 0.01, resulting in an estimated 2100 validation points required (Table S1). As suggested by Olofsson et al. 2014, the number of points for each class and year were decided based on minimum sample requirements. We estimated 1620 points as minimum required for a good validation for each year in the time series, and this was divided into 120 forest points and 1500 non-forest points. Thus, a total of 17820 points were validated across 11 years (2014-2024) (SI Figure S4B).From this data we then calculated an error matrix as well as bias-corrected user's, producer's and overall accuracies (see Table S2). We also estimated the standard error and 95% confidence intervals as outlined in Olofsson et al. (2014).

Estimating dry woodland change. We estimated net woodland loss and gain for the period 2014 to 2024. A pixel was classified as loss if it was identified as woodland in all the first three years and as non-woodland all the last three years (2022–2024). Conversely, a pixel was classified as woodland gain if it was non-woodland in the first three years and woodland in the final three years. We took a three-year time window as it provided a more robust and conservative estimate of both woodland losses and gains as opposed to using the first year and last year of the timeseries for change analysis.

We also evaluated the accuracy, area estimates and confidence interval of our resulting loss and gain map. To do so, we used 60 random points for each of the forest loss and gain class as well as the no-change class to generate an error matrix for forest loss and gain (Stehman, 2009). To better understand and visualize the spatial patterns of woodland loss and gain, we divided our study area into 20-km grid cells and estimated global and local indicators of spatial association (LISA) based on Moran's (Anselin, 1995, Bivand and Wong, 2018) using the "spdep" package in *R*.

Comparing woodland loss and gain inside and outside government lands. To better understand the spatial patterns of forest loss and gain inside and outside government-managed areas, we used government-forest boundaries derived from toposheets (Figure S5) published in year 2009 by the Survey of India in its website. We generated district-level data (n = 328) on loss and gain inside and outside government lands and ran a series of linear regressions. Out of 376 districts, we only included districts with more than 10 hectares (ha) of dry woodlands in 2014, leaving a final set of 328 districts in 17 states. Our first set of regressions took the form:

$$Y_i = \beta_0 + \beta_1 Loc_i + \beta_2 baseline_i + \beta_3 state_k + \in_i$$

where Y_i represents dry woodland loss or gain (ha) in district i, β_o is the intercept; $\beta_1 Loc_i$ is a binary location variable indicating whether losses or gains are occurring inside (Loc = 1) or outside (Loc = 0) government areas in district i; $baseline_i$ is the amount of dry woodland in 2014; and $state_k$ represents state-level fixed effects. To examine whether dry woodland losses and gains inside or outside government areas vary by state, we also ran a set of regressions with state-level interaction effects:

$$Y_i = \beta_0 + \beta_1 Loc_i + \beta_2 baseline_i + \beta_3 state_k + \beta_4 (Loc_i \times state_k) + \in_i$$

where $\beta_4 (Loc_i \times state_k)$ represents the interaction term capturing how the effect of location differs depending on the state. The reference state in our regressions was Andhra Pradesh.

Results

Our Random Forest model was able to accurately map woodland cover across India's dry forest region. Our annual maps had a mean unbiased overall accuracy of 0.93 (Table S2), with overall accuracy exceeding 0.84 in all years. At the class level, we also obtain consistently high bias-adjusted producer's and user's accuracies in all years, with values for woodland and non-woodland classes ranging from 0.89 to 0.96 and 0.81 to 0.94, respectively, across annual maps (Table S3).

In 2014, at the start of our study period, bias-adjusted dry woodland extent was 14.86 Mha (SE=0.58), equivalent to 7.6% of our study area (Figure 1, Table S4). By 2024, dry woodland area was an estimated 17.94 Mha (SE=0.54). Between 2014 to 2024, we estimate bias adjusted loss to be 0.27 Mha (SE=0.01) and the bias adjusted gain to be 1.79 Mha (SE=0.09).

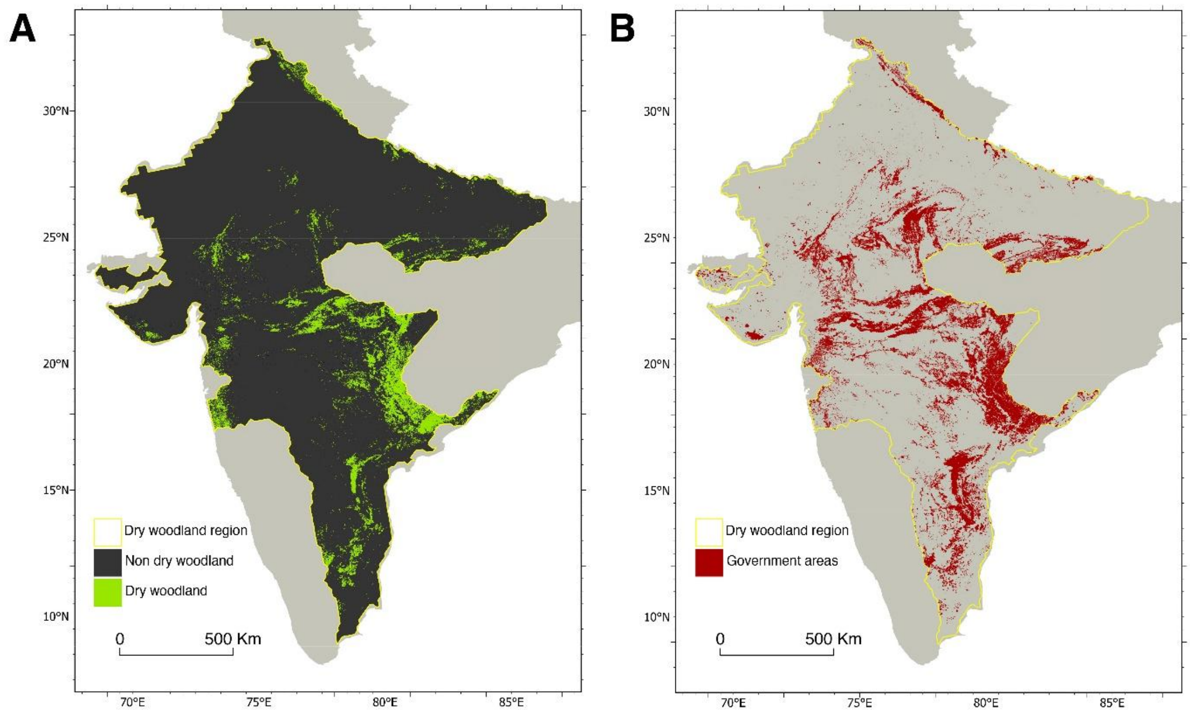

Figure 1: *Forest cover in India's dryland biome in 2014 (A) and government managed forest lands derived from digitized toposheets (B).*

Of the 14.86 Mha of dry woodland cover in 2014, only 12.54 Mha was within government land with the remaining 2.32 Mha located outside government land. The total area of government forest land as per the Survey of India digital boundaries was 30.27 Mha about of which 17.91 Mha was not mapped as forest. These areas could be degraded forests or open grasslands and savannahs. For example, in Rajasthan, which is a semi-arid region, our government forest land estimate is 3.2 Mha whereas FSI estimates only 1.6 Mha of forest cover (FSI, 2021).

We estimate that, within government lands, there has been a loss of dry woodland area of around 0.17 Mha (58%) in comparison to a loss outside government forest of 0.12 Mha between 2014 and 2024. Similarly, forest gains were also greater within government lands (1.32 Mha) than non-government lands (0.78 Mha) (Figure 2A, B and C).).

Differences in forest gain and loss between government and non-government lands are statistically significant (loss coefficient = -5873, SE = 1280 and p<0.0001; gain coefficient =11210, SE= 7063, p< 0.0001, Supplementary Table S6). We also found significant location and state interaction effects (Figure 3) that suggest substantial state-level variation in dry woodland losses and gains within and outside government forests with respect to baseline forests. State-level heterogeneity was particularly prominent for a few states, with Rajasthan showing high gains within government lands and Maharashtra, Madhya Pradesh and Himachal Pradesh showing significant losses within government lands (Figure 3, Table S8).

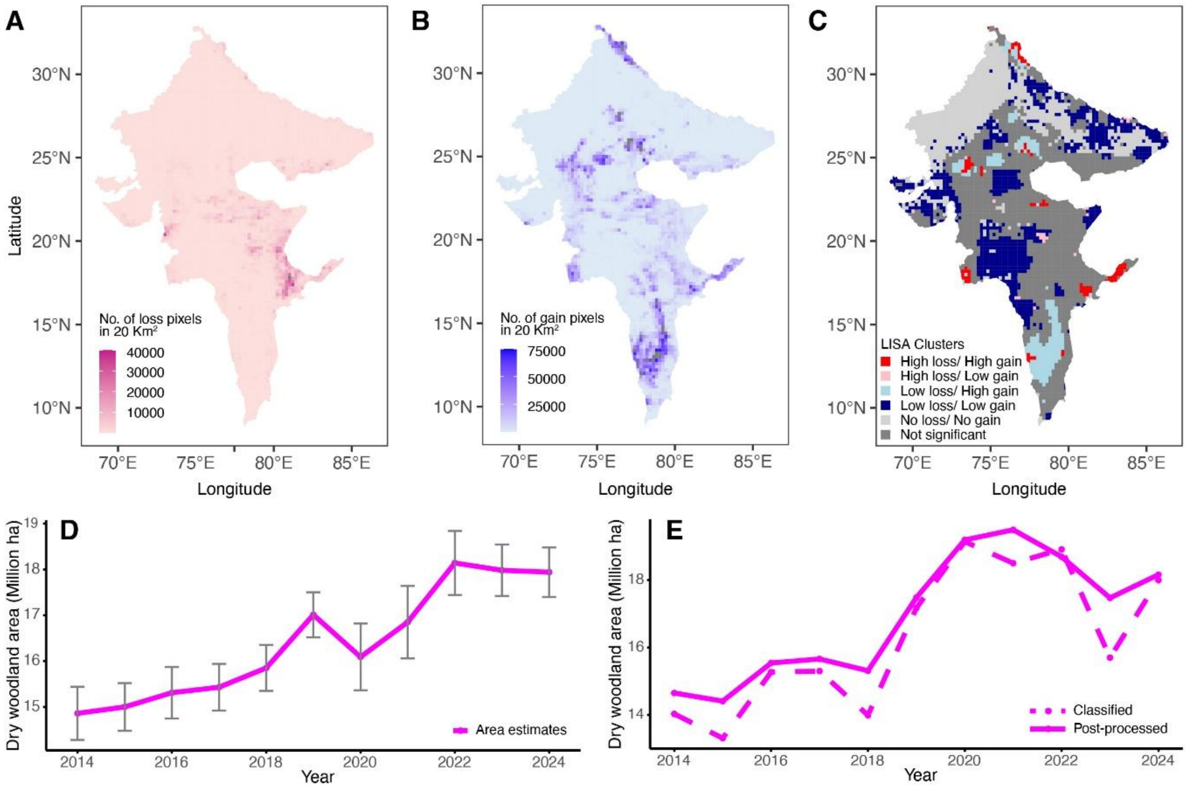

Figure 2. *Post-processed locations of dry woodland loss (A) and gain (B); Spatial association between dry woodland loss and gain (C); Area estimates for dry woodlands with error bars representing the 95% confidence intervals generated from the error matrix of the classified map (D); Area under classified image is derived from the Random Forest classification model, and the post processed image is result of applying spatial and temporal correction to the classified map (E). For figures (A)(B) and (C) 30m pixel-level estimates have been aggregated into 20km^2 grids for visualization purposes.*

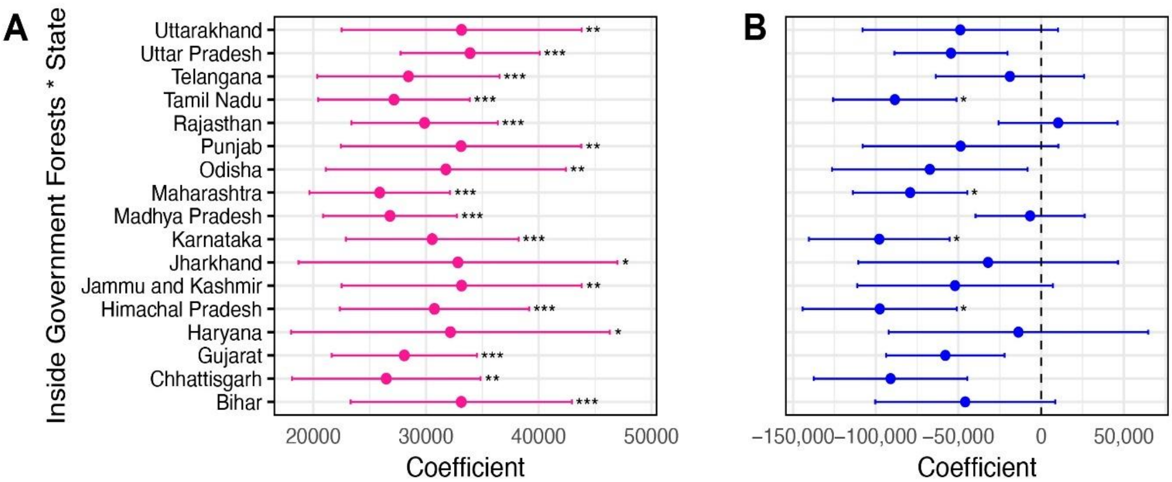

Figure 3. *Location (inside or outside government lands) and state-level interaction term coefficients for gains (blue points) and losses (magenta points) demonstrating substantial*

variation in location effects between different states (the reference state is Andhra Pradesh). Error bars represent standard errors (= p<0.05; ** = p < 0.01, *** = p < 0.0001).*

Overall, patterns of loss and gain were spatially associated (Moran's I= 0.51, p <0.0001, Figure S6). However, we found significant spatial variation of dry woodland losses and gains in some regions (Figure 2C). Dry woodland gains predominantly occurred in the states of Andhra Pradesh, Gujarat, Rajasthan and Madhya Pradesh, while losses were largest in the states of Andhra Pradesh, Telangana, Madhya Pradesh and Maharashtra (Figure 2A, 2B). We also found clear hotspots of both high loss and high gain in the states of Maharashtra and Andhra Pradesh and hotspots of both low loss and high gain in the states of Rajasthan and Madhya Pradesh (Figure 2C).

Locally, both the states of Andhra Pradesh and Telangana show contrasting loss and gain patterns. Dry woodland loss within government land was about 17,900 ha and 32,600 ha for Andhra Pradesh and Telangana, respectively. Similarly, gains outside government land were about 166,200 ha and 54,100 ha for Andhra Pradesh and Telangana, respectively. We also found large dry woodland gains in the semi-arid state of Rajasthan, with around 207,000 ha of gain occurring within government land and 45,300 ha of gain occurring outside of government land. Since, India's dry woodland region covers only parts of the states of Himachal Pradesh, Uttarakhand and Jharkhand, their losses and gains were very small. When compared to baseline (2014) dry woodland cover, we found that Andhra Pradesh, Gujarat, Maharashtra, Telangana, Jharkhand, and Odisha lost around one to three percent of their dry-land forest within government land. Similarly, a few states gained substantial amounts of dry woodland relative to baseline: Andhra Pradesh (44%), Haryana (181%), Gujarat (30%), Karnataka (123%), Rajasthan (66%) and Telangana (54%).

Discussion

India's dry woodlands cover three-fifth of the country's land area and are central to its forest restoration commitments. Yet, we lack detailed information about how dry woodland areas are changing spatially and temporally. Information about dry woodland area losses and gains is critical for restoration policy and practice. Our analysis of India's dry woodlands allows us to make two key contributions to our understanding of dry woodland changes in the region. First, we are able to produce the first independent, rigorously validated annual time-series of dry woodlands for India, covering the period 2014-2024. Our data are available freely in Google Earth Engine (link), providing detailed insights on the spatio-temporal patterns of dry woodland change across India. Second, our analysis of where losses and gains occurred, including within and outside government areas, allows us to better understand contrasting deforestation and reforestation frontiers at national and subnational levels.

Our forest-cover estimates of 14.86 Mha are substantially higher than publicly available global forest cover change products for India's dry forest biome. Previous datasets have estimated ~9.6 million hectares of dry woodland for 2014 using the high-resolution global forest cover data from Hansen et al. (2013) at a tree canopy threshold of 10%, and ~13.11 million hectares estimated in 2015 using Copernicus Global Dynamic Land Cover data (Buchhorn et al. 2020). Our maps also have substantially higher overall accuracy than other (global) forest-cover products. The user's accuracy and producer's accuracy for our classified image for 2014 was 0.89 and 0.91, respectively while the user accuracy and producer accuracy for Hansen's forest cover data for year 2014 using the same validation points used in our analysis was 0.71 and 0.52, respectively. Similarly, the user accuracy and producer accuracy for our classified image for 2015 was 0.90 and 0.94, respectively while the user accuracy and producer accuracy for the Copernicus Global Dynamic Land Cover data for 2015 was 0.88 and 0.64, respectively. Furthermore, our user and producer accuracy was 0.85 and 1 for dry woodland gain respectively, and 0.91 and 1 for dry woodland loss, respectively. These accuracies are high when compared to the loss and gain accuracies from other drylands regions, including from savannas (Feng et al. 2016). Together, these results build trust in our maps and highlights the importance of developing independent, regional forest cover mapping approaches to support monitoring and evaluation and complement larger scale regional and global scale assessments of the state of the world's forests (Tulbure et al. 2021).

Although we find substantial dry woodland gains outside of government-administered lands, many of the observed gains are likely due to large-scale timber and tree-crop plantations. For example, in the state of Gujarat, where we see 49,230 ha of woodland gains outside government areas, a report by the Coconut Development Board in 2023 highlights over 26,000 ha of coconut plantations in the state (GoI, 2023a). In the state Andhra Pradesh, where we estimate gains of over 99,000 ha, the National Mission on Edible Oil, has increased palm oil plantations from 27,514 hectares in 2005 to over 184,640 ha in 2022 (GoI, 2024). Similarly, we find that Maharashtra and Gujarat have woodland gains exceeding 50,000 ha outside government lands. The International Timber Trade Organisation have noted that these two states, as well as Andhra Pradesh and Rajasthan, have significantly increased their production of timber from trees on farms to meet the growing timber requirement in India (Kant and Nautiyal, 2021).

A key limitation of our analysis thus is that it is unable to distinguish between natural regeneration and tree-cover gains driven by plantations like Eucalyptus, Teak and palm on farmlands. Developing longitudinal remote-sensing products that are able to distinguish between different types of forest-cover remains a key research frontier with important implications for the monitoring and evaluation of forest restoration efforts (Chiarucchi and Piovesan, 2020, Kuemmerle et al. 2013). There have been a few recent developments helping to distinguish plantations like rubber and eucalyptus from natural forests (e.g., Lesiv et al. 2022, Wang et al. 2023, and platforms like Global Forest Watch have started to also include and differentiate forest plantations). However, accurate mapping products that distinguish natural forests and plantations continue to be an important area of development for monitoring forest landscape restoration. Nonetheless, our spatial association analysis highlights clear hotspots of high dry woodland losses and gains particularly in Rajasthan and Andhra Pradesh, that should be studied in greater detail to understand what is driving changes in these regions, which can derive useful lessons for managing dry woodlands.

Our time series analysis shows that dry woodland cover has increased from an estimated 14.86 Mha in 2014 to 17.94 Mha in 2024. However, the gross gain (2.10 Mha) masks substantial gross forest loss (0.29 Mha). Our estimated loss of 0.17 Mha of forest within government land is close to the Government of India's own records of forest loss of 0.17 Mha in the dry woodland states (GoI, 2025). India's forest survey also reports a continual increase in forest cover in the states with dry woodlands from 42.67 Mha in 1987 to 47.46 Mha in 2023 (FSI, 2023). However, in the absence of spatial data available from the Forest Survey of India, it is unfortunately currently not possible to make direct comparisons with our analysis since the aggregated government data also includes other forest types. While our analysis focuses on a contemporary time-series of eleven years, our model can be readily extended to future years to support continuous monitoring of India's dry woodlands, and relies solely on open data (e.g., data from the Landsat archive and Google Earth Imagery) and analysis platforms (e.g., Google Earth Engine) further supporting reproduction and extension of dry woodland mapping.

Our results also point towards varying spatial patterns of loss and gain in India's dry woodlands, with substantial increases in aggregate forest cover after 2018. Similar variations in loss and gain patterns have been shown in other regions, including in Latin America (Redo et al. 2012) and Southeast Asia (Meyfroidt et al.2014). Importantly, we find that most losses continue to occur inside government administered areas, which host much of the country's remaining natural forests. These losses therefore likely have significant implications for carbon storage, forest-dependent livelihoods and biodiversity. Dry woodland gains within government administered forest lands are likely driven by increased restoration and afforestation efforts to achieve India's (natural) forest cover targets under schemes like the Green India Mission, the Compensatory Afforestation Fund and the National Afforestation Programme (Borah et al. 2018, MoEF, 2023). The ecological success and integrity of these restoration efforts remains to be explored, but India's dryland reforestation frontiers are unlikely to offset the environmental degradation caused by the country's dry woodland deforestation frontiers.

Forest loss and gain studies in many countries have regularly pointed to the need to disentangle net losses and gains, especially in natural and planted forests (Sloan et al. 2019). Countries reporting to global biodiversity and restoration targets, including the new Global Biodiversity Framework and other commitments, often resort to monitoring forest cover alone and thus inadequately report progress against forest integrity goals and targets (Pillay et al. 2024). Our study demonstrates why monitoring deforestation and reforestation jointly, and at high spatial detail is an important part for monitoring efforts linked to global biodiversity and restoration agendas.

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Supplementary figures and tables

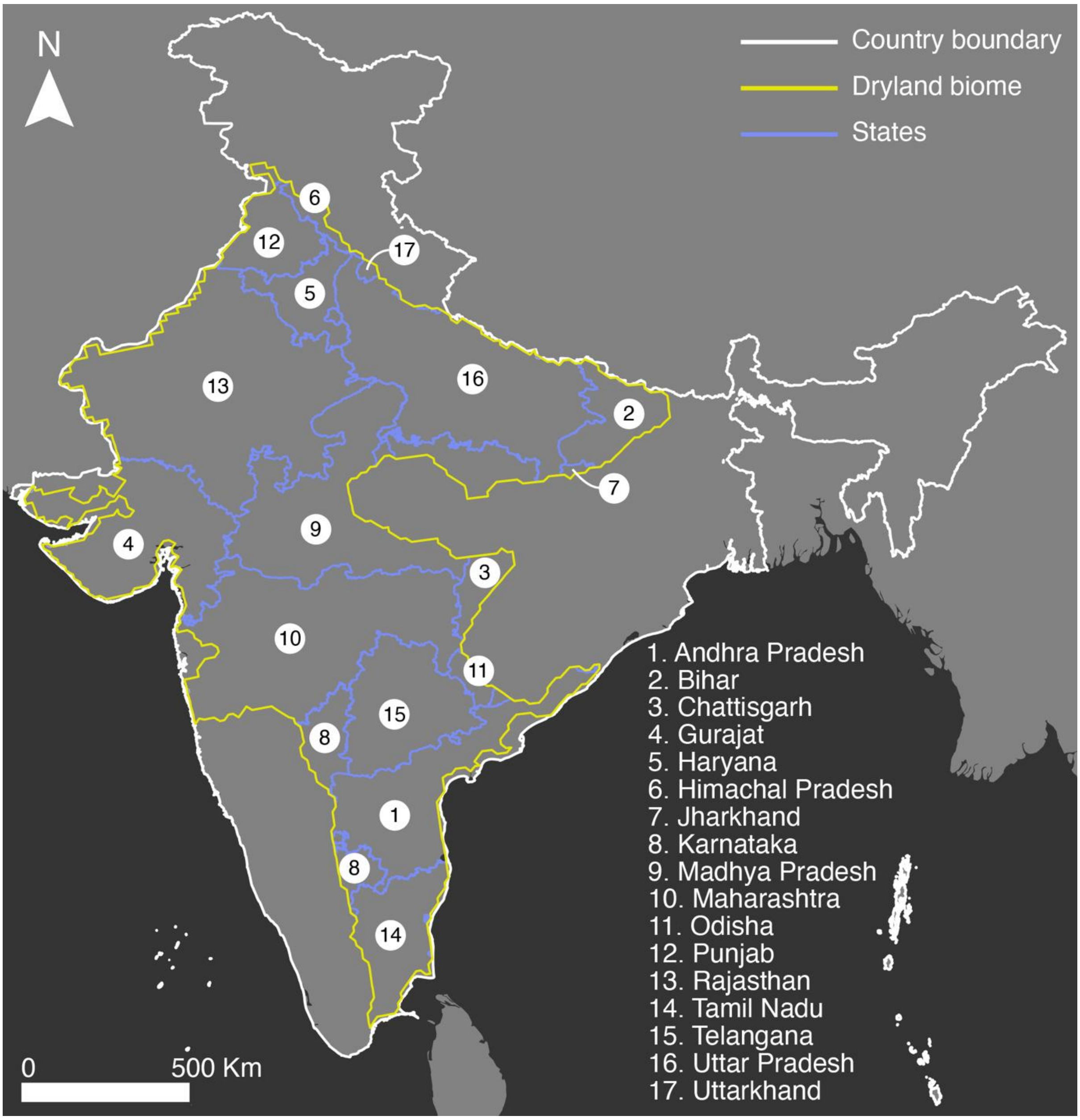

Figure S1. Map of India, including the dry woodland region and study states within it.

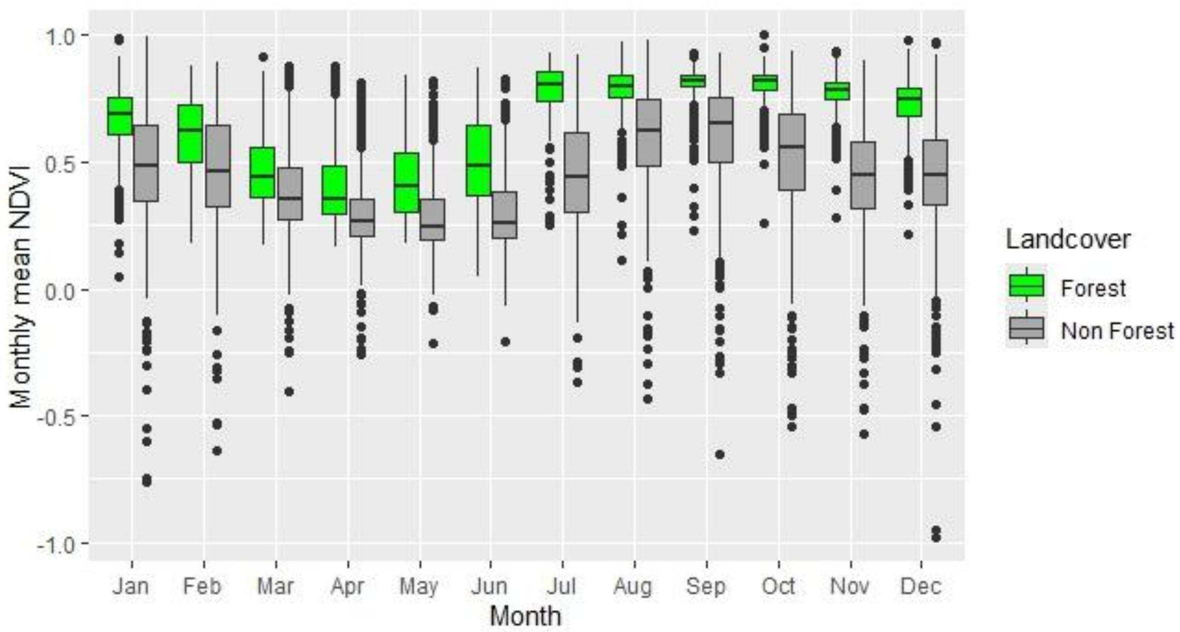

Figure S2: Monthly mean NDVI of Forest and non-Forest pixels for the year 2022.

Figure S3. Polygons used to extract training data points in different types dryland forest landscapes, including dense forest (a), open forests (b), tree plantations on farms (c).

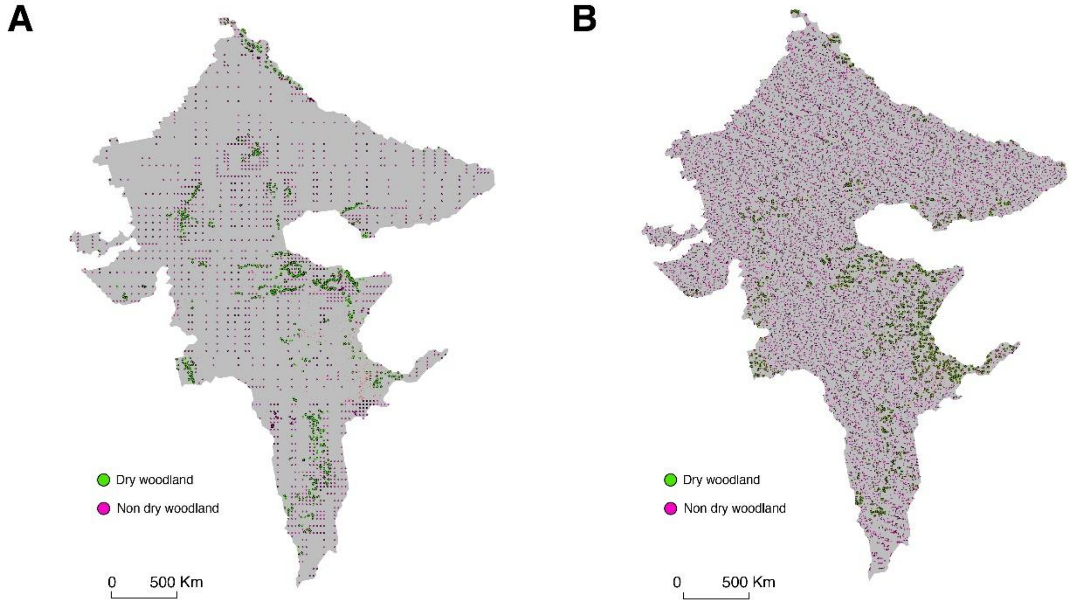

Figure S4. Distribution of 14887 training data points (dry woodland - 5080 points) and distribution of 17820 validation points (dry woodland - 1320 points).

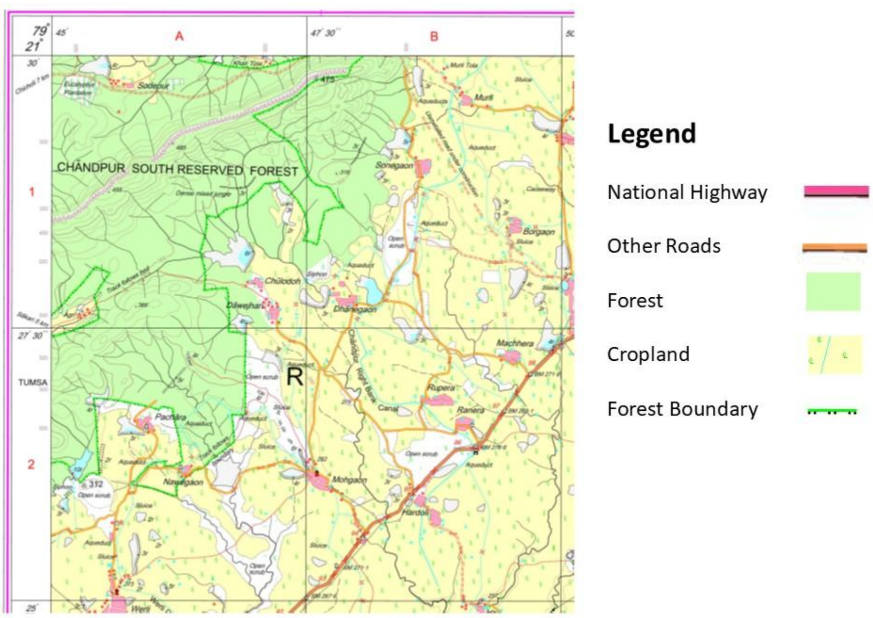

Figure S5: A sample of Survey of India toposheet used to digitize forest boundaries taken from Bhandara district, Maharashtra.

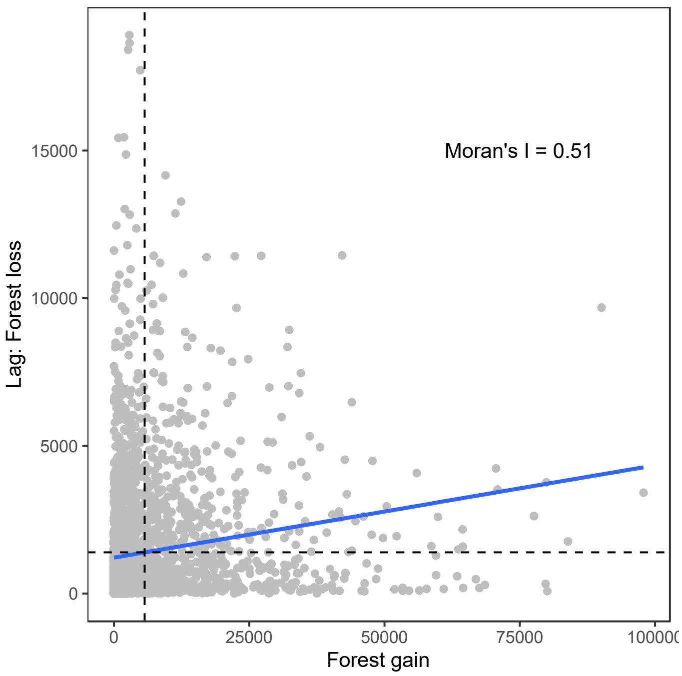

Figure S6. Spatial association of forest loss and gain

Table S1: Estimated number of accuracy assessment points

	Area M ha	% Area (wi)	Ui	Si	si X wi	Share of point
Non Forest	174.67	0.9	0.7	0.4582	0.41238	209.9
Forest	19.15	0.1	0.7	0.4582	0.04582	23.32
TOTAL	193.82				0.46	
			n= sum(siXwi)^2/O(S)		2099.90	233

Table S2: User, Producer and Overall accuracy for Forest and non-Forest class for years 2014-2022

	Forest		Non forest		
Year	User	Producer	User	Producer	Overall Accuracy
2014	0.89	0.91	0.99	0.99	0.98
2015	0.90	0.94	0.99	0.99	0.98
2016	0.91	0.91	0.99	0.99	0.99
2017	0.92	0.93	0.99	0.99	0.99
2018	0.95	0.91	0.99	0.99	0.99
2019	0.93	0.95	0.99	0.99	0.94
2020	0.81	0.95	0.99	0.98	0.86
2021	0.81	0.91	0.99	0.98	0.84
2022	0.88	0.88	0.99	0.99	0.87
2023	0.94	0.89	0.99	0.99	0.91
2024	0.91	0.94	0.99	0.99	0.92

Table S3: Bias adjusted user and producer accuracy

	Forest		Non forest	
Accuracy	User	Producer	User	Producer
2014	0.91	0.89	0.99	0.99
2015	0.94	0.90	0.99	0.99
2016	0.91	0.92	0.99	0.99
2017	0.92	0.93	0.99	0.99
2018	0.95	0.91	0.99	0.99
2019	0.93	0.96	0.99	0.99
2020	0.81	0.96	0.99	0.98
2021	0.81	0.93	0.99	0.98
2022	0.88	0.91	0.99	0.99
2023	0.94	0.91	0.99	0.99
2024	0.92	0.95	0.99	0.99

Table S4: Area in million ha for classified map, post processed and bias adjusted area estimates with standard error

Year	Classified	Post processed	Area estimates	Standard error	Confidence Interval
2014	14.03	14.65	14.86	0.58	1.14
2015	13.31	14.41	15.00	0.52	1.02
2016	15.27	15.54	15.31	0.56	1.10
2017	15.30	15.66	15.43	0.51	1.00
2018	13.99	15.31	15.85	0.50	0.98
2019	17.17	17.48	17.01	0.49	0.96
2020	19.14	19.19	16.09	0.73	1.43
2021	18.50	19.49	16.85	0.79	1.55
2022	18.91	18.69	18.14	0.70	1.37
2023	15.70	17.47	17.98	0.56	1.10
2024	18.00	18.16	17.94	0.54	1.06

TableS5 : Area estimates of woodland loss and gain

	Loss	**Gain**
Area based on time series analysis	0.29	2.10
Bias adjusted estimates	0.27	1.79
Standard error	0.01	0.09
Confidence Interval	±0.02	±0.18

Table S6 : Regression results estimating loss and gain as a function of location, baseline forest cover and State.

		Loss			Gain			
	Estimate	SE	t value	Pr(>|t|)	Estimate	SE	t value	Pr(>|t|)
(Intercept)	4909	2740	1.79	0.074	155100	15120	10.26	< 2e-16
Location: Inside	-5873	1280	-4.59	0.000	11210	7063	1.59	< 2e-16
Bihar	-2850	5011	-0.57	0.570	-154600	27640	-5.59	0.113
Chhattisgarh	4404	4257	1.03	0.302	-176400	23490	-7.51	0.000
Gujarat	928.60	3309	0.28	0.779	-142800	18250	-7.82	0.000
Haryana	-2764	7222	-0.38	0.702	-129400	39840	-3.25	0.000
Himachal Pradesh	-4105	4278	-0.96	0.338	-104200	23600	-4.42	0.001
Jammu and Kashmir	-2107	5453	-0.39	0.699	-138500	30080	-4.61	0.000
Jharkhand	-2330	7221	-0.32	0.747	-146200	39830	-3.67	0.000
Karnataka	-1743	3928	-0.44	0.658	-103500	21670	-4.77	0.000
Madhya Pradesh	-2491	3043	-0.82	0.414	-120700	16790	-7.19	0.000
Maharashtra	-1638	3183	-0.52	0.607	-142700	17560	-8.13	0.000
Odisha	559.10	5441	0.10	0.918	-156500	30020	-5.21	0.000
Punjab	-2778	5452	-0.51	0.611	-139100	30070	-4.63	0.000
Rajasthan	-2943	3334	-0.88	0.378	-106300	18390	-5.78	0.000
Tamil Nadu	-4776	3445	-1.39	0.166	-101500	19000	-5.34	0.000
Telangana	17090	4109	4.16	00	-79130	22670	-3.49	0.000
Uttar Pradesh	-2002	3175	-0.63	0.529	-155800	17520	-8.89	0.001
Uttarakhand	-2233	5444	-0.41	0.682	-156000	30030	-5.19	< 2e-16
Baseline	0.02	0	21.42	< 2e-16	0.03	0	6.53	0.000

Table S7 : Regression results estimating loss and gain location and state interaction effects.

Coefficients:		Loss				Gain		
	Estimate	SE	t value	Pr(>|t|)	Estimate	SE	t value	Pr(>|t|)
(Intercept)	18300	3655	5.01	0.000	133100	20280	6.56	0.000
Location: Inside	-33830	5227	-6.47	0.000	57770	29010	1.99	0.047
Bihar	-18960	6919	-2.74	0.006	-132500	38400	-3.45	0.001
Chhattisgarh	-8932	5907	-1.51	0.131	-130700	32780	-3.99	0.000
Gujarat	-12620	4531	-2.79	0.006	-114800	25140	-4.57	0.000
Haryana	-18290	9986	-1.83	0.068	-123700	55420	-2.23	0.026
Himachal Pradesh	-19100	5906	-3.23	0.001	-56190	32770	-1.71	0.087
Jammu and Kashmir	-18130	7519	-2.41	0.016	-113600	41720	-2.72	0.007
Jharkhand	-18200	9986	-1.82	0.069	-131300	55420	-2.37	0.018
Karnataka	-16480	5388	-3.06	0.002	-55640	29900	-1.86	0.063
Madhya Pradesh	-15590	4202	-3.71	0.000	-118000	23320	-5.06	0.000
Maharashtra	-14430	4411	-3.27	0.001	-103500	24480	-4.23	0.000
Odisha	-14860	7517	-1.98	0.049	-123800	41720	-2.97	0.003
Punjab	-18780	7518	-2.50	0.013	-115900	41720	-2.78	0.006
Rajasthan	-17390	4566	-3.81	0.000	-112400	25340	-4.44	0.000
Tamil Nadu	-17920	4735	-3.79	0.000	-58160	26270	-2.21	0.027
Telangana	2759	5701	0.48	0.629	-69440	31640	-2.20	0.029
Uttar Pradesh	-18420	4329	-4.25	0.000	-129600	24020	-5.40	0.000
Uttarakhand	-18310	7519	-2.44	0.015	-132600	41730	-3.18	0.002
Baseline	0.02	0.00	21.65	< 2e-16	0.03	0	5.98	0.000
Location:Bihar	33130	9803	3.38	0.001	-45900	54400	-0.84	0.399
Location:Chhattisgarh	26480	8367	3.16	0.002	-91050	46430	-1.96	0.051
Location:Gujarat	28080	6443	4.36	0.000	-57920	35750	-1.62	0.106
Location:Haryana	32170	14140	2.28	0.023	-13750	78470	-0.18	0.861
Location:Himachal Pradesh	30750	8399	3.66	0.000	-97560	46610	-2.09	0.037
Location:Jammu and Kashmir	33160	10660	3.11	0.002	-52070	59160	-0.88	0.379
Location:Jharkhand	32830	14140	2.32	0.021	-32110	78460	-0.41	0.683
Location:Karnataka	30550	7661	3.99	0.000	-97880	42520	-2.30	0.022
Location:Madhya Pradesh	26810	5940	4.51	0.000	-6695	32960	-0.20	0.839
Location:Maharashtra	25890	6242	4.15	0.000	-79180	34640	-2.29	0.023
Location:Odisha	31760	10650	2.98	0.003	-67310	59100	-1.14	0.255
Location:Punjab	33110	10660	3.11	0.002	-48690	59160	-0.82	0.411
Location:Rajasthan	29870	6486	4.61	0.000	10260	35990	0.29	0.776
Location:Tamil Nadu	27160	6720	4.04	0.000	-88440	37290	-2.37	0.018
Location:Telangana	28440	8081	3.52	0.000	-18910	44840	-0.42	0.673
Location:Uttar Pradesh	33910	6165	5.50	0.000	-54520	34210	-1.59	0.112
Location:Uttarakhand	33150	10650	3.11	0.002	-48890	59090	-0.83	0.408

Table S8: State wise forest loss and gain- area in ha

States	Forest within govt. land 2014	Loss	Gain	Forest outside govt. land 2014	Loss	Gain	% Loss in govt land	% Loss outside govt land	% Gain in govt land	% Gain outside govt land
Andhra Pradesh	1746421	17882.01	269610.8	377462.16	29210.76	166157.7	1.02	0.08	15.44	44.02
Bihar	138295.4	1892.79	8037.18	114025.14	1645.38	2431.44	1.37	0.01	5.81	2.13
Chhattisgarh	1277181	24573.06	13240.8	110522.43	8699.76	4756.41	1.92	0.08	1.04	4.30
Gujarat	475555.5	8489.61	51278.58	143054.37	14869.53	43245.09	1.79	0.10	10.78	30.23
Haryana	18773.28	23.58	11320.47	1192.5	20.34	2169.72	0.13	0.02	60.30	181.95
Himachal Pradesh	207375	953.01	31332.96	223148.52	3433.77	61038	0.46	0.02	15.11	27.35
Jammu and Kashmir	23550.66	242.1	9702.72	10102.41	242.46	7280.73	1.03	0.02	41.20	72.07
Jharkhand	23839.74	265.32	5686.02	620.1	27.81	348.93	1.11	0.04	23.85	56.27
Karnataka	83062.44	75.51	38988.09	63168.84	2996.19	77852.16	0.09	0.05	46.94	123.24
Madhya Pradesh	2745221	33929.46	317822.6	189189.27	13168.98	59263.02	1.24	0.07	11.58	31.32
Maharashtra	2559338	35669.25	92265.21	590895.27	20380.14	91477.44	1.39	0.03	3.61	15.48
Odisha	99952.11	2259.27	2646.72	24723.54	1609.74	3717	2.26	0.07	2.65	15.03
Punjab	28411.02	66.33	11387.34	13723.02	73.71	6967.71	0.23	0.01	40.08	50.77
Rajasthan	520521.6	2964.6	206970.9	68068.35	3026.43	45275.4	0.57	0.04	39.76	66.51
Tamil Nadu	616799.6	376.2	91474.47	147743.55	3490.65	136789	0.06	0.02	14.83	92.59
Telangana	1370572	32566.77	124265.6	98883.81	17938.62	54089.46	2.38	0.18	9.07	54.70
Uttar Pradesh	332014.1	5829.48	30765.96	96417.18	1541.79	15804.36	1.76	0.02	9.27	16.39
Uttarakhand	93063.6	1370.43	5482.35	3794.13	59.04	291.87	1.47	0.02	5.89	7.69
Total	12359947	169428.8	1322279	2276734.59	122435.1	778955.5	1.37	0.053	10.70	34.21