Monitoring the Extent of Trees Outside of Forests in South Asia: Nature-based Solutions for Climate Change Mitigation

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Abstract

To reduce emissions of carbon and other greenhouse gases on a pathway that does not overshoot and keeps global average temperature increase to below 1.5° C, it shall be necessary to rely on nature-based solutions with atmospheric removals. Policies that focus solely on reducing deforestation will only lower future emissions. Without activities that create removals from carbon sequestration it will not be possible to balance residual emissions. On the other hand, activities that include regeneration or regrowth of tree biomass can be used to create net-zero emissions through carbon sequestration and atmospheric removals now. Although much attention has been focused on policy measures for natural forests, new methods with high resolution remote sensing and deep machine learning are enabling very high resolutions analysis of carbon individual tree canopies in landscapes with trees outside of forests (TOF). New allometric scaling models based on tree crowns at very high spatial resolution (<0.5m) can map large landscapes with millions of trees outside of forests. In addition to carbon removals, these landscapes are also important to livelihoods for millions of rural farmers and most TOF activities have the capacity to bring more countries into climate mitigation while also providing adaptation benefits. Here were present a multi-resolution, multi-sensor method that provides a way to measure carbon at the individual tree level in TOF landscapes in India. The results of this analysis show the effectiveness of VHR data compared to Sentinel-2 for applying tree crown canopy allometric scaling of carbon across large landscapes at the individual tree scale. At the same time a multi-sensor approach is demonstrated to have multiple advantages over a single sensor approach.

1.0 Introduction

Reducing Emissions from Deforestation and Degradation (REDD+) is an important component of international climate change agreements because it adds a pathway for mitigation through forest policy and management. Policies and measures for forests have great potential as mitigation options because they can be focused on both avoiding future emissions and increasing removals of atmospheric carbon. Thus, it is not surprising that forests receive considerable attention in the policy dialog on climate change mitigation, and thus an important focal point for new initiatives that promote private investment and capital flows in high biomass forest regions. New initiatives for high biomass forests include the Green Gigaton Challenge, Lowering Emissions by Accelerating Forest finance Coalition (LEAF), or the new Architecture for REDD+ Transactions (ART). Although proscriptions for forest actions include restoration of natural forests as a mechanism to remove carbon from the global atmosphere now, the main emphasis has been on reducing forest deforestation and degradation rates to avoid emissions in the future.

However, the problem with focusing policies only on reducing deforestation and its avoided emissions is that, to stabilize climate change below 1.5^{o} C increase in global temperature, there are few, if any, feasible emission reduction pathways that do not have residual emissions (Buck et al. 2023). In other words, most emissions pathways do not reduce emissions fast enough nor intensively enough to avoid an overshooting of the atmospheric carbon loading target level that averts a 1.5^{o} warming. Thus, many analyses conclude that a net-zero emissions strategy is needed (Bednar et al. 2021, Fuss et al. 2020), where residual emissions can be offset by activities that remove carbon from the atmosphere in tandem with activities aimed at reducing emissions. The concept of *global net zero* emissions is a way to describe balancing residual emissions of carbon dioxide with removals of carbon dioxide. Perhaps the best way to create carbon removals is through land-based activities that include enhancement of carbon sequestration in regrowing natural forests and in expanding the area and density of trees outside of forests (TOF).

Many non-forest landscapes, such as agricultural areas, have considerable tree cover, and much of these TOF lands are increasing biomass, representing important sinks for carbon sequestration (Akenyemi et al. 2021, Beckshäfer et al. 2017). The most important hotspots are TOF in agricultural landscapes in semi-arid tropical zones. South Asia is a particularly important region in this regard.

There is a growing array of demonstrated concepts, frameworks and working models related to landscape restoration that support the practical implementation of actions aimed at increasing TOF area and carbon stocks. These include farmer managed natural regeneration practices, the land degradation neutrality model, a wide variety of agroforestry systems, and other nature-based solution (NbS) options (Melo et al. 2021, Akinyemi et al. 2021, Lohbeck et al. 2020, Chomba et al. 2020, Griscom et al. 2017). Furthermore, most landscapes with a large presence of TOF are agricultural, where local communities and households are often economically depressed, financially poor, and heavily dependent on crop and tree-based resources for their livelihoods and income. Thus tree-based NbS mitigation interventions and policies are inherently livelihood strategies as well.

The deployment of actions focused on carbon removals in landscapes dominated by trees outside of forests depends on having accurate carbon measurement, monitoring, reporting and verification (MRV) methods and protocols. A key to scaling actions is an MRV system that covers large areas at scale, even while the spatial resolution of measurement would be the individual tree. With the increased availability of satellite remote sensing at the resolution <1m, and machine learning processing models that can segment individual trees from the landscape background, these MRV systems are possible (Skole et al. 2021, 2021b, Mugabowindekwe et al. 2023).

Most of the development of these tools have been focused on Africa, but the prospect for similar work in Asia is demonstrated in this paper. In this paper we describe a landscape approach that embraces TOF as an important element of climate change mitigation and adaptation, which can increase carbon removals from the atmosphere while providing enhanced livelihoods and multiple environmental co-benefits. The idea is worth serious consideration because the potential scale and magnitude of land area in South Asian rural treed land is extensive. Through strategic policy and economic development interventions, its TOF area and carbon could be increased and adopted by communities already using traditional TOF practices.

The idea is also important because TOF systems can have significant benefits for local communities through agroforestry and other tree-based production systems that bring higher economic returns to local livelihoods, as well as additional environmental co-benefits from land rehabilitation. For instance, multifunctional agriculture (Leakey 2017, Minang et al. 2015) has been demonstrated across South Asia to have social and environmental benefits that can improve welfare, especially when managed to include income generation activities. Including a focus on practices that increase income, or "land maxing" (Leakey 2020), extends the land-sparing and land-sharing frameworks in ways that directly benefit farmers, which in turn leads to further adoption and permanence of carbon in the landscape. For these reasons, and with the rapidly expanding capacity for robust measurements using Earth observation technologies, there is strength to the argument that REDD+ would benefit from expanding its current focus on land use change and forestry to a landscape approach that includes agriculture and other land uses (Smith et al. 2014).

2.0 Trees Outside of Forests and Climate Change Mitigation Policy

2.1 Policy Drivers for Evidence-based Natural Climate Solutions.

While new public-private partnerships are raising large capital investments for high biomass forests, including the Green Gigaton Challenge, Lowering Emissions by Accelerating Forest finance Coalition (LEAF), or the new Architecture for REDD+ Transactions (ART), greater inclusion of TOF would increase the relevancy and effectiveness of these investments because they create incentives for tree-based carbon removals in places and ways that matter to people and livelihoods, and thus better secure permanence and scale from these investments.

There is an urgent need for climate change actions applied across a range of landscapes, including more than high carbon density forests. One reason for including tree-based NbS, including TOF, in the overall portfolio of climate actions is that it strengthens policies and measures for both future emission reductions and current removals. A stronger TOF or other tree-based NbS focus would enhance meeting net-zero goals by adding landscapes which cover extensive areas in South Asia. These landscapes have potential for generating large atmospheric removals while directly contributing to adaptation measures and livelihood enhancements, and more stable income generation under climate stress conditions. In particular, an NbS or TOF-centered strategy would increase the number of participating countries beyond only those with high carbon forests. Many developing countries and South Asian countries already include actions involving TOF removals in their national plans, an emissions reduction category that surpasses the size of all other priority areas, including the energy sector. Agroforestry is specifically identified in more than 50% of all domestic Nationally Determined Contributions

(NDC). But for broadly based tree-centered NbS options to be more relevant to widespread adoption in policy frameworks, the current REDD+ and other forestry mitigation frameworks will need to be expanded to include agriculture and the AFoLU framework.

Tree-based systems are ubiquitous in the tropics, developing countries, and Asia in particular. They include both sparse treed ecosystems and a variety of tree-based production systems, such as agroforestry, ally cropping small-holder plantations, energy farms, shelterbelts, village or community woodlots, scattered individual trees and other woody perennial establishments in predominantly small holder agricultural landscapes. Tree-based systems provide important value chains from natural products and numerous indirect co-benefits for billions of people, including water retention, increased site fertility and productivity, food security, livestock fodder, energy from fuelwood and charcoal, direct incomes, conservation of biodiversity, and provision of timber and non-timber products. TOF systems enable smallholders to create a diversified portfolio of products other than annual crops alone, often with significantly higher economic value compared to annual crops. These TOF systems also sequester and store carbon and buffer against adverse impacts of climate change; increasingly TOF systems are an integral component of new strategies for climate-smart agriculture promoted by the government as well as non-government organizations and the Indian private sector.

2.2 Trees Outside of Forest and REDD+

Land Use, Land Use Change, and Forestry (LULUCF) has been the carbon inventory sector that covers emissions and removals of greenhouse gases resulting from direct human-caused land cover change and forestry activities. Methods and protocols for LULUCF have been specified by the Intergovernmental Panel on Climate Change (IPCC) and defined in decisions made by the Conference of the Parties in the United Nations Framework Convention on Climate Change. Largely, the REDD+ framework is LULUCF-focused. Although agriculture has been important to climate change mitigation efforts generally, the framework for Agriculture, Forestry and Other Land Uses (AFOLU) has not been prominent in the dialog on REDD+, even though Nationally Determined Contributions from many countries in Asia prominently feature tree-based activities in non-forest landscapes.

Figure 1 presents an idealized timeline for a parcel of forest or woodland, showing a range of land cover conditions and carbon stocking levels broadly representing the five REDD+ scope elements in forests (green-shaded end panels), with the inclusion of the AFOLU components in non-forest land (beige-shaded middle panel). The five scope elements of REDD are: conservation of carbon stocks, reduced emissions from deforestation, reduced emissions from degradation, sustainable forest management, and enhancements of carbon stocks. This figurative timeline begins with extant forest cover (conservation, avoided emissions) and transitions to forest management (sustainable forest management), followed by a period of forest degradation in which carbon stocks are depleted but the cover type remains forest. Using a definition of forest that includes cover fraction (e.g., greater than 10%), deforestation occurs when carbon stocks decline, converting to agriculture or non-forest degraded shrubland. Non-forest land contains trees outside of forests, including remnant trees, naturally occurring trees, agroforestry, other cultivated trees, small orchards and plantations, and trees managed for land or biomass restoration. Restocking of the landscape with trees through farmer-managed natural regeneration or forest landscape restoration may occur, and this establishes the last REDD+ scope element with the enhancements of carbon stocks. But all of these REDD+ scope elements apply to TOF landscapes just as much as to forests.

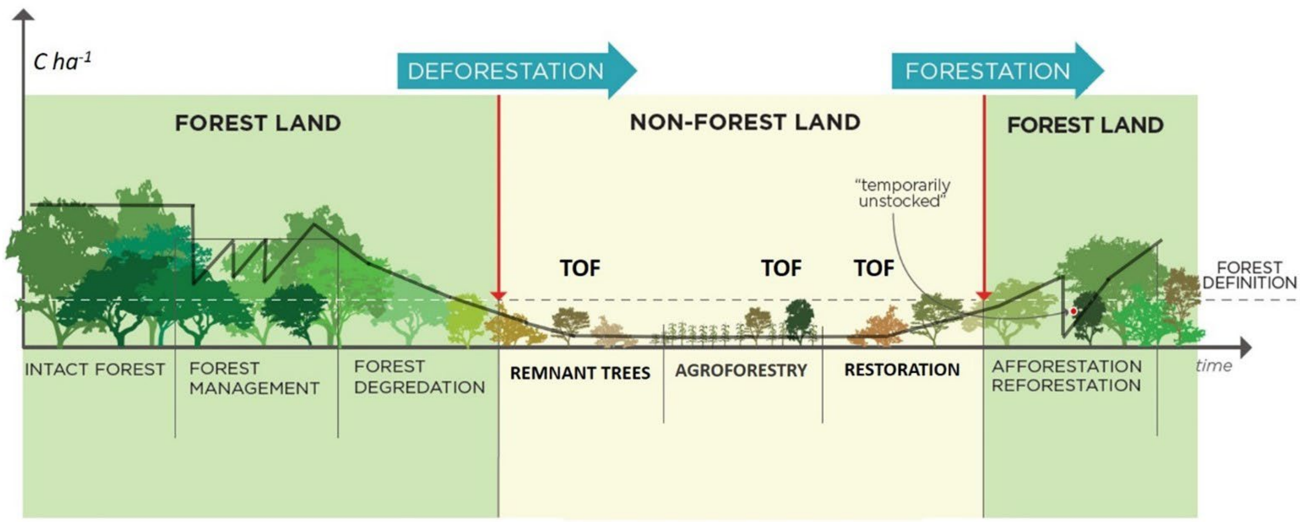

Figure 1. The scope elements of REDD+ and their relation to LULUCF and AFOLU. The green-shaded areas of the figurative timeline are current scope elements in the REDD+ framework. TOF systems are largely in agricultural landscapes outside of LULUCF. The relative carbon stocking is also shown, and although TOF carbon density is lower, the extent is large, and these landscapes are important for livelihoods and carbon sequestration efforts.

Trees outside forests include a variety of systems that present mitigation opportunities if included in REDD+ (Table 1). Functionally, they fulfill a range of emission reduction and removal functions; some help conserve carbon stocks in both biomass and soil organic matter, some sequester carbon from the atmosphere, and others reduce the pressure on forests by supplying alternative food, wood, or income sources such as community woodlots for fuelwood-based energy. All contribute to livelihoods and economic co-benefits, thus being potent approaches for capturing both mitigation and adaptation benefits at the same time through common interventions.

As a core element of the Paris Agreement (cf. Article 5), REDD+ has been implemented as a policy framework for large scale land-based mitigation. National REDD+ participation is voluntary and a flexible framework for reducing emissions as well as conservation and sustainable management of carbon stocks. To be consistent with the broader aims of the Paris Agreement, the REDD framework also includes adaptation and sustainable development actions, applicable across a range of countries rather than only those with high biomass forests. Targeting forested land alone will not be sufficient to achieve the blended goal that addresses mitigation, adaptation, and sustainable development. In this context, the “forgotten” biomass in REDD that is found in TOFs is a real gap in global actions to combat and adapt to climate change. A forest-only approach will miss opportunities for climate-smart land-based mitigation options in non-forest landscapes, where tree-based systems can increase carbon removals while also supporting nature-based adaptation and development.

Table 1 Examples of TOF systems and their potential contribution to REDD+		
Types of TOF	Examples	Potential for REDD+
Small holder Plantations	Linear planting, woodlots, ally planting, precious woods, pole woods, fuelwood farms	Increase removals, reduce emission by reducing pressure on forests
Orchards	Commodity trees, such as cashew, moringa, grewia, palm	Increasing removals
Scattered Individual Trees	Mango, Shea, Farmer managed regeneration, fertilizer trees such as Faidherbia, cordyla on farms	Conserving carbon, increasing removals
Agroforestry Complexes	Shade cropping, intercropping, Taungya	Increase removals, reduce emissions by reducing pressure on forest
Woodlots and Protected Blocks	Village forest areas, customary forests, sacred groves, fuelwood	Conserve carbon, increase removals, reduce emissions by reducing pressure on forests
Trees in Pastoral Zones	Silvopastoral	Conserve carbon, increase removals
Riparian Tree Covers	Gallery forests, buffer forests	Conserve carbon

2.3 Forest and Landscape Restoration through Agroforestry and Trees Outside of Forests

At a global scale, agriculture, forestry, and other land uses (AFOLU) account for approximately one-quarter of global net anthropogenic GHG emissions, mainly from agricultural production and deforestation (IPCC 2019). The overwhelming majority of global AFOLU-related GHG emissions come from a large number of developing countries with primarily rural or agricultural land base. In many of these countries in South Asia the rural landscapes contain scattered trees, either as remnants from forests and woodlands, or as established trees used that are part of a livelihood system (Dupar 2019). Many of these rural areas are also the poorest (Mbow et al. 2020). These landscapes with trees outside of forest are important to the international climate change mitigation policy community because they have great potential to be restored with tree-based systems such as agroforestry that provide carbon sequestration and livelihood and income benefits. International climate change policy measures are increasingly seeing TOF as natural climate solutions, specifically in emerging programs for Forest Landscape Restoration (FLR) such as AFR100, the African-wide contribution to the Bonn Challenge.

Restoring tree cover in agricultural areas and reforesting degraded land are critical to ensure a sound natural resource base for development *and* to reduce emissions. The literature suggests that several AFOLU approaches offer significant potential for cost-effectively increasing carbon sequestration and reducing emissions, with a wide range of collateral conservation benefits

(Griscom et al. 2017). These include reducing loss of tree-based ecosystems or landscapes; reforesting and restoring forests and other landscapes with increasing biomass; improving forest, woodlot, plantation and agroforestry management; reducing the carbon footprint of food production through agroforestry; enhancing carbon sequestration in soils of croplands; sustainable intensification to reduce pressure for land use change; diversification of food systems; and addressing demand for unsustainable commodity production (Leakey 2020).

The utilization of trees on farms provides natural products and direct economic value to land managers as well as a range of indirect co-benefits, including water retention, increased site fertility and productivity, animal fodder, domestic energy from fuelwood and charcoal, biodiversity and more. TOF systems enable small holders to create a diversified portfolio of products other than annual crops alone, *often with significantly higher economic value compared to annual crops*, a claim we can explicitly test using our framework.

Although South Asia is an emerging urbanized, technical, and industrial economy, it is equally dependent on its natural capital in agriculture, forestry, and other natural resource sectors. Therefore, ultimately, evidence-based management of natural resources is integral to development, resilience, and self-reliance in South Asia. Degradation of agricultural, forests, and other land erodes the resource base, which can profoundly diminish economic development: it contributes to other environmental impacts and threats to human health, diminishes water quality and availability of water for human or ecosystem uses, reduces soil fertility and land productivity, increases species loss, and facilitates the spread of vector-borne and zoonotic diseases. In all countries of the region, the natural resource base plays an especially important role in the national economy, so the loss of natural capital can have particularly significant implications for development as well as global climate and environmental impact.

3.0 Study Site for a Case Study in India

3.1 Rationale for Analysis of TOF in South Asia.

This study quantitatively examines whether TOF in small holder agriculture landscapes of India is increasing. India provides an important and representative case study in South Asia, where we focus our analysis on methods for TOF detection and carbon measurement over landscapes and regions. India is an excellent place to develop a South Asia case study because of its large number of small holders and the government of India has long standing formalized management and policy priorities in small holder TOF systems (Fig.2).

A study by Schnell et al. (2015, 2015b) of TOF data from 6 countries showed a significant amount of carbon stored in TOF in neighboring Bangladesh, where TOF biomass was more than twice the total national forest biomass. Zomer et al. (2016) offers a first-order indication of the importance of this land use transition. They assess the role of trees on agricultural land and their significance for carbon sequestration at a global level, along with recent change trends. They report that in 2010, 43% of all agricultural land globally had at least 10% tree cover and that the area was increasing. Further, they estimated that trees contribute >75% of agricultural carbon stocks, increasing at somewhat less than 1% per year. Brazil, Indonesia, China and India had the largest increases in biomass carbon stored on agricultural land. Although carbon density is much lower in these land systems than, for instance, closed-canopy forests, these landscapes remain important because they cover significant areas of marginal and climate change-vulnerable land and are rural areas with high population densities of agriculturally dependent communities.

Figure 2. Trees outside of forests in India. Extensive landscapes with TOF occur across India in rural areas, supporting both carbon stocking and livelihoods, left. Three patterns of TOF in India agriculture landscapes, scattered, blocked, and linear, right.

3.2 Specific Study Site in a Hot Spot of Tree Cover Increases in Eastern India

Scientific and government reports are calling attention to a new trend in LCLUC in South Asia where biomass in tree cover is increasing in small holder agricultural landscapes outside national recorded forest areas (RFA). For instance, India's recent *State of the Forest Report* (FSI 2021), reports a national increase in forest area, with most of the increase attributed to TOF outside the RFA, mostly on individual small-holder's agricultural land. India estimates in 2017 indicate that the number of stems outside the RFA is as much as half of that in the RFA and increasing. In the state of Rajasthan for instance, forest cover inside the RFA declined by 103 km^2 since 2015, while tree cover outside the RFA increased by 569 km^2, resulting in an overall net increase of 466 km^2.

This study examines a specific region in India, where recent reports paint a picture of increasing TOF in open, semi-arid, predominantly agricultural lands outside of the formal reported forest areas (RFA). This region includes five large states: Andhra Pradesh, Telangana, Odisha, Karnataka, and Jharkhand. This region is also the most significant area of drylands in *tropical* Asia according to a recent important report in *Science* (Bastin et al. 2017). This is important because the region is large, significant to Asia, and includes both open forest and non-forest land.

Between 2017 and 2019, tree cover within the RFA declined slightly (-330 km2) while tree cover outside the RFA increased (4,306 km2). The trend has continued, such that between 2019 and 2021 tree cover within the RFA increased 31 km^2 while tree cover outside of the RFA increased 1,509 km^2 (FSI 2021). The states with the highest increase in tree cover were the focus of this study: Andhra Pradesh, Odisha, and Telangana. These three states account for more than 60% of the total increase in tree cover in the last decade (GoI 2021). Compared to total forest cover increases of 1,540 km^2 the increase in tree cover (TOF) was 721 km^2, but this estimate is somewhat uncertain because it includes considerable scattered individual trees, for which an area measurement may not adequately apply. It is important to begin measuring total canopy cover, and number of stems, but these estimates are not reported.

For the entire region of analysis we analyzed TOF mapping using Sentinel-2 data, while we provided a detailed analysis of TOF mapping using very high resolution data for a large sub-geographical landscape in Odisha.

4.0 New Methods for Direct Measurement of Trees Outside of Forests

4.1 Multi-Sensor Approaches Support Policy Requirements.

The international agreements arising from the 2015 Paris Conference of the Parties to the United Nations Framework Convention on Climate Change have brought forests into the framework for *mitigation* of GHG emissions. The Paris Agreements also address the role of forestry and agriculture in climate change *adaptation*. Forests, particularly closed tropical forest, have long been the focal point for land cover change monitoring and considerable progress has been made developing measurement and monitoring tools for these forest ecosystems (Hansen et al. 2013, Harris et al. 2021). Thus, most of the immediate international emphasis has been on developing robust measurements, reporting and verification (MRV) capacities for forests.

What has been missing until recently, is an equally aggressive technical development of methods for large scale measurements of TOF. To be included in climate change mitigation policy frameworks, new MRV capabilities are needed for four TOF feature-types: (*1*) trees in various configurations outside of forests in agricultural landscapes, (*2*) agroforestry systems specifically managed to combine perennial trees with annual crops, (*3*) tree plantations that have been planted for restoration or also commercial purpose, and (*4*) other isolated trees with low cover density not considered as forest or woodland, such as in urban areas. The most important application of TOF measurements is for landscape-wide mapping of Activity Data and Emissions Factors for National Forest Monitoring Systems (NFMS) supporting REDD+ program requirements. Most national inventories of the forest estate do not include trees outside forests, and thus national accounting is missing a substantial part of the woody resources of a country. In one example from a national assessment of all trees in Rwanda, it was found that 72% of the total tree cover and 50% of the national carbon stocks were in TOF (Mugabowindekwe et al. 2023).

Very high resolution large-area measurement capabilities are emerging across a wide spectrum of remote sensing platforms from medium resolution (10m, Sentinel-2) to high (3 m, Planet) and very high resolution (<1m, Worldview) products (Brandt et al. 2020, Beckschäfer et al. 2017, Schnell et al. 2015). Using medium resolution data from Landsat, Potapov et al. (*33*) showed how a continuous fields method could map increases in TOF cover, while forest cover was declining in Asia. A recent analysis (Skole et al. 2021) measured tree cover change in the African sparce woodlands, focusing on tree cover loss in TOF areas (customary forests, woodlots, village forest areas) using a spectral mixing model with Landsat data. We demonstrate in this paper how Sentinel-2 medium resolution data can detect TOF tree cover in India. These studies demonstrate that traditional medium satellite systems, which are locally calibrated, are generally capable of tracking tree cover changes of clusters of trees not forming forests. However, subpixel analysis of isolated individual trees continues to be challenging, and at medium resolution single trees remain hidden or are difficult to distinguish from the spectral signal of other vegetation types (Fig. 3).

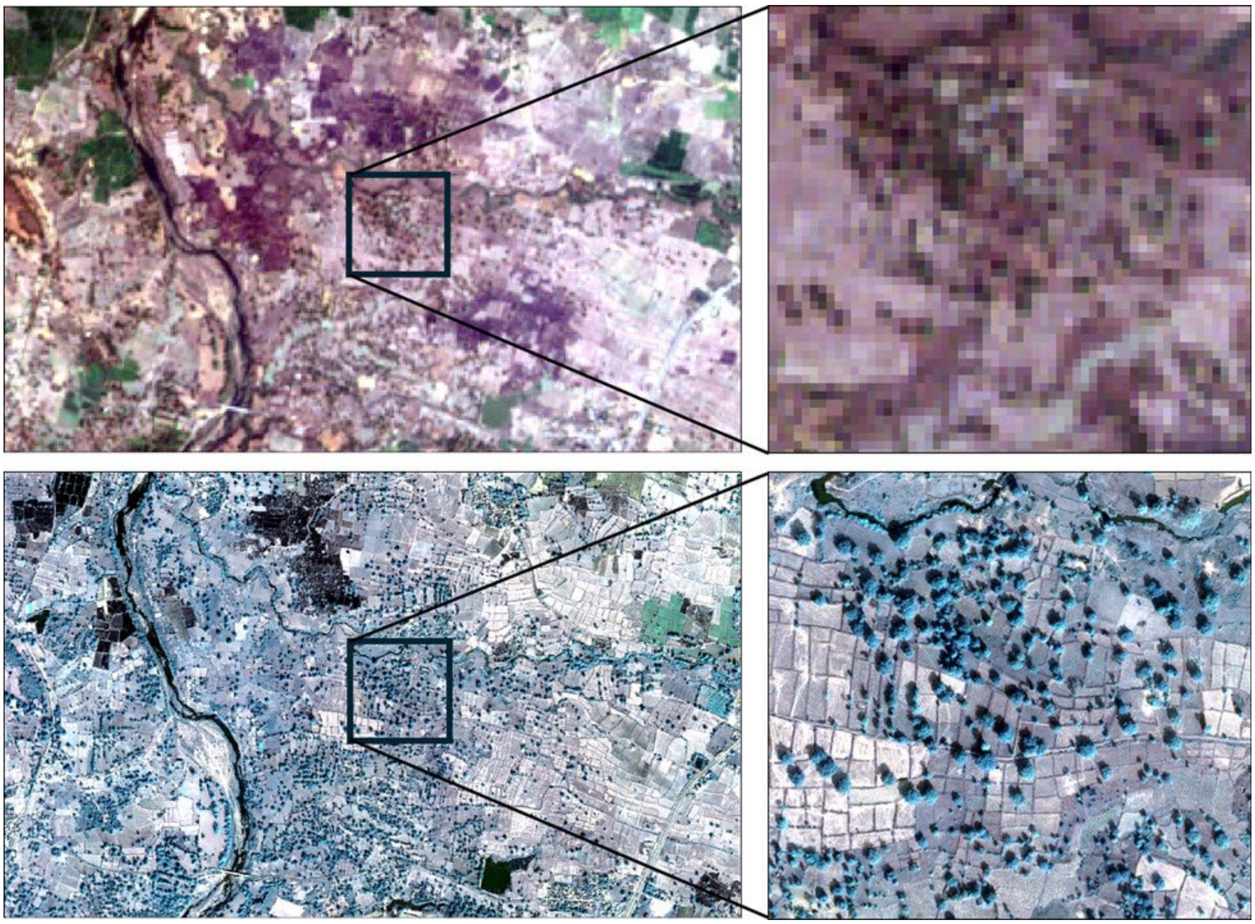

Figure 3. Invisible trees. The same area is shown for Sentinel-2 (10 m), top, and Maxar (0.5 m), bottom. Isolated trees which are challenging to distinguish from other vegetation types at 10 m are clearly visible at 0.5 m. Large landscape-wide data acquisition is available at 0.5m resolution, and can be processed with deep machine learning to extract allometric parameters at the individual tree level. Tree-level allometric scaling makes routine use standard local equations and inventory methods available to almost all countries' national programs. The area is an agroforestry landscape in India.

Use of VHR data has a long history of visual interpretation methods (Samasse et al. 2018, Kundhlande et al. 2017, Cotillon and Mathis 2017, Tappan et al. 2000), but these methods are often subjective and difficult to scale for larger areas. Recently, deep learning has emerged as a disruptive technology in different fields of object detection and is also increasingly used for analysis of satellite imagery. The principal of deep learning is that manual training teaches the artificial intelligence algorithm parameters that define the shape of a tree, which can then be automatically identified and mapped over millions of km² . Brandt et al. (2020) have demonstrated this approach by mapping the crown sizes of 1.8 billion isolated trees across 1.3 x 10^6 km^2 of the West African Sahara and Sahel. That study reported an unexpected high density of non-forest trees (13.4 trees per ha) in landscapes which had been considered pure desert or severely degraded. While the applied satellite images from Maxar at sub-meter resolution are relatively expensive, new micro-satellite constellations (e.g., from Planet Labs) provide cost efficient alternatives for mapping trees outside forests at unprecedented accuracy (Fig 3).

In the next sections, we present the results of new analyses of TOF using multi-scale satellite remote sensing data and machine learning processing. The examples demonstrate capacities for medium resolution data from Sentinel-2, which is capable of detecting both forests and TOF tree cover, compared to very high resolution data from MAXAR, which is capable of mapping individual tree crowns in TOF landscapes. The examples also present a new and novel approach to mapping individual tree carbon using combined satellite crown mapping and ground measurements to calibrate an allometric scaling model.

4.2 Method for Analysis of TOF Using Medium Resolution Data

We can generate maps of tree cover at 10m resolution for the entire state of Odisha in India using a machine learning algorithm and Sentinel-2 VNIR level 2 data. The 10m product is used to map forest tree cover and TOF areas. The machine learning framework produces an output layer of “hot pixels” that contain a measurable amount of TOF cover, along with its percent probability estimate produced by the machine learning model.

4.2.1 Data Preprocessing. We generated analysis-ready data from a Google Earth Engine Python API using applied to dataset available through the Google Earth Engine Sentinel-2 data catalog. We created cloud-free mosaics of Sentinel-2 imagery for the year 2022. We utilized the 10m resolution bands from the Sentinel-2 imagery. We split this data collection into large tiles of 189 x 189 km with the Google Earth Engine Export option. To produce a cloud-free dataset, we first produce a 12-month time series of images for the year 2022. To prepare this, all Sentinel-2 images with less than 30% cloud cover were selected and sorted month-wise. Clouds and cloud shadow masks were generated for each of the selected images in the full dataset. These masks were used to generate cloud-free individual images, where cloud gaps were filled by pixel contributions from the closest date image. For any remaining cloud or cloud shadow gaps in the monthly products, we filled these by interpolating between the images of the previous and next month where cloud-free data existed. Each month's median value was computed for all pixels across all VNIR bands. An annual product was generated from the cloud-free monthly mean products. The products were exported from Google Earth Engine as the analysis-ready data for use with a trained convolutional neural network.

4.2.2 Training Data Creation. Training sample data and sample areas were identified over large areas within each state. Samples identified tree cover in 10m resolution pixels using the high-probability data values in the 2020 Tropical Tree Cover data set published by WRI (Brandt et al. 2023). Each sample label pixel within a sample area was coded. The extent of samples and large areas enabled us to create a generalizable machine-learning model for mapping tree cover at 10 meters across a diverse landscape at the state scale. The sample labels and areas were organized into 256 x 256-pixel subsets and combined with collocated Sentinel-2 VNIR data created through the preprocessing steps.

4.2.3 Model Training. Sentinel-2 VNIR training sample data and labels are used as input to a deep neural network-based framework based on U-Net architecture. The U-Net is a fully convolutional network. The network consists of a contracting path and an expansive path, which gives it the u-shaped architecture. U-Net consists of an encoder for downsampling and a decoder for upsampling with skip connections. We made a model containing 31,110,497 trainable parameters.

Our model consists of a contracting encoder path to capture context and a symmetric expanding decoder path that enables precise localization. The encoder contains repeated application of two core operations: a conv block and max pooling downsampling. Each conv block consists of two 3 x 3 conv layers, each followed by BatchNorm and ReLU activation. The max pooling halves the spatial dimensions after each block. There are 5 encoder blocks, with a number of filters starting at 32 and doubling after each block. The decoder pathway mirrors the encoder, with corresponding conv blocks and upsampling instead of downsampling. Skip connections from the encoder blocks are concatenated to the decoder blocks to provide localization information. The bottleneck consists of a conv block between the encoder and decoder paths. The output layer is a 1 x 1 conv layer with sigmoid activation for pixel-wise prediction. Our model architecture takes 2560m x 2560m, 10m, annual cloud-free Sentinel-2 true color bands. The model was trained for 100 epochs with Adam optimizer using TensorFlow 2.14.0 and Nvidia T4 GPUs with a batch size of 16 on Google Colab.

***4.3.4. Data Prediction*.** The application of the pre-trained deep neural network model is completed on 256 x 256 10-meter pixels data tiles of three bands of preprocessed Sentinel-2 VNIR data. Each data tile is padded with values of 0 for processing and then unpadded for a final product. This reduces prediction errors at the tile edges. Processed tiles are mosaiced and clipped to the state boundary.

The model output predicts the presence of tree cover in each 10-m pixel area. The model output is a map of probability values from 0 – 100 for the presence of tree cover. We use a threshold of probability greater than or equal to 40 to determine tree cover extent. To map areas of forest and non-forest, we aggregate the 10-m tree cover product to 70 x 70m (0.49 ha). All 70 x 70m grid cells with 10m pixels greater than or equal to a model probability of 70 are mapped as Forest Areas. All other 70 x 70m grid cells are Non-Forest Areas. Within the non-forest areas we then map all 10-m tree cover pixels the meet the >= 40 probability threshold as TOF.

4.4 Method for Analysis of TOF Using Very High Resolution Data

An individual tree crown TOF dataset was generated employing a machine-learning model trained on Very-High Resolution (VHR) Images obtained through NASA's Commercial Smallsat Data Acquisition (CSDA) program. This initiative, spearheaded by NASA's Earth Science Division (ESD), aims to identify, assess, and procure commercial small-satellite (smallsat) data that aligns with NASA's Earth science research and application objectives. The initial VHR images had a 2m spatial resolution, but was subsequently pan-sharpened to 0.5 meters. Training labels for the model were crafted by manually delineating polygons of individual tree location and crown polygon.

4.4.1 Data Preprocessing. The high-resolution images were sourced from various satellites participating in the Commercial Smallsat Data Acquisition (CSDA) program. Predominantly, data was obtained from MAXAR satellites, specifically WorldView-2, WorldView-3, and GeoEye-1. These satellites offered images with resolutions ranging from 1.5 meters to 2 meters. To initiate the preprocessing, we prioritize selecting images with optimal visibility, minimizing cloud cover. Upon procurement, the next step involves ortho-rectifying the data. Ortho-rectification eliminates distortions caused by sensor tilt and topographic relief, ensuring each point on the images is accurately represented as if captured directly below the sensor.

Following ortho-rectification, we subset the bands to Near Infrared (NIR), Red, and Green bands. This selection is driven by substantial variation in chlorophyll exhibited by the NIR band, with the Red and Green bands providing complementary information. The Blue band is omitted due to its tendency to introduce noise in the form of haze uncertainty.

The subsequent step involves pan-sharpening the image. Pan-sharpening combines high-resolution details from a panchromatic band with lower-resolution color information from other bands, typically visible bands. We employ the NNDiffuse Pan Sharpening algorithm, utilizing nearest neighbor diffusion. This process enhances the spatial resolution of multispectral images by diffusing higher-resolution information from the panchromatic image. The algorithm leverages nearest-neighbor relationships to seamlessly blend details from the panchromatic image into corresponding multispectral bands, resulting in a pan-sharpened image characterized by improved clarity and detail. At this stage, we have an ortho-rectified, pan-sharpened image with NIR, Red, and Green bands.

4.4.2 Training Data Creation. The generation of our training dataset involves a manual process where training labels are meticulously crafted by outlining polygons around individual tree crowns. To ensure the model's generalization across diverse landscapes within the target area, we initiate the process by selecting a 200-meter x 200-meter sample area. This strategic selection encompasses various land types, aiming to create a model capable of addressing the complexities of the intended application area.

Within this chosen sample area, polygons are drawn around trees found in different settings such as villages, farmlands, and forests. The assessment of the appropriateness of these polygons, and their accuracy, is conducted using Very-High-Resolution (VHR) data as a backdrop in ArcGIS. This meticulous validation process ensures the quality and precision of the training labels. Subsequently, the sample area and corresponding sample label bands are stacked onto our preprocessed image. This results in an image containing five bands: ortho-rectified and pan-sharpened Near Infrared (NIR), ortho-rectified and pan-sharpened Red, ortho-rectified and pan-sharpened Green, Sample Areas, and Sample Labels.

The next step involves breaking down each dataset into smaller samples of dimensions 128 pixels x 128 pixels. These smaller samples consist of three-band images as features, accompanied by manually drawn polygons serving as labels. To enhance the robustness of the training dataset, any features or labels with null or none values are systematically removed from the training samples. This meticulous process of training dataset creation ensures that the model is equipped with comprehensive and accurate information, facilitating effective learning and application across diverse landscapes within the specified target area.

4.4.3 Model Training. The training process involved generating a probability prediction for tree extent using a model trained with ortho-rectified, pan-sharpened images as features and manually drawn polygons as labels. The chosen deep learning model is the Residual Network (ResNet), a framework specifically designed to facilitate the training of networks with greater depth than previously employed models.

In the realm of deep learning, the use of more layers in neural networks is intended to reduce error rates. However, as the number of layers increases, a common challenge known as the Vanishing or Exploding gradient emerges. This issue causes the gradient to either diminish significantly or become excessively large, resulting in increased training and test error rates. ResNet mitigates this problem through the incorporation of skip connections, a technique proposed by He et al. (2016). The specific ResNet model chosen for this machine-learning application is ResNet-50, characterized by 50 layers, encompassing both convolutional and fully connected layers. The model architecture processes 64-meter x 64-meter VHR images with a resolution of 0.5 meters. The training was conducted on an AMD 20 GPU provided by Michigan State University's High-Performance Computing Clusters.

4.4.4 Model Prediction. Tree prediction and mapping was accomplished using a pre-trained model tailored for the specified area. The pre-trained model operated on ortho-rectified, pan-sharpened, three-band VHR images which are split into 128 pixels x 128 pixels. Notably, during the observation phase, it was identified that the pre-trained model tends to generate "fuzzy" predictions along the borders. To resolve this issue, we employed the application of image flipping, which entails predicting each tile three times on different axes. The mean of these flipped predictions was calculated to remove undesired fuzziness around the borders of the predictions. Following prediction, individual predictions were seamlessly mosaiced and clipped to conform to the defined boundary areas.

4.5 Method for Individual Tree Carbon Mapping Using

The preparation of high resolution maps of TOF at the individual tree crown level enables the preparation of individual tree carbon maps across very large landscapes and geographic areas. The advantage of having an individual tree crown map is that allometric scaling can be appropriately used to estimate biomass and carbon. Many approaches to biomass mapping of tree cover using remote sensing rely on data that is so coarse that generalized tree canopy cover forms the basis of biomass estimation. Allometric scaling requires the use of an individual tree structural parameter. Moreover, with individual parameters, there is a wide range of allometric models (equations) available to account for landscape or tree-type-specific differences. Even with canopy cover models calibrated against sample plot data, often no finer resolution than 50m, nonlinearities can introduce error. However, most allometric equations are based on tree stem diameter or tree height and when using the height structural parameter, the stem diameter is also required. That presents a problem for remote sensing because stem diameter cannot be measured with satellite observations. However, we produce a novel method for allometric scaling in which ground calibration is used to produce an estimate of stem diameter through a measurement of tree crown diameter or area. Individual tree Crown Projected Area (CPA) is the primary output of our VHR data machine learning model.

We used the method described in Skole et al. (2021) and Mugabowindekwe et al. (2023). The method requires ground collection of tree data in model calibration sites in Odisha. The sampling scheme was based on having two large model landscapes, one in northern Odisha and one in southern Odisha, covering approximately 10,000 km^2. Within each model landscape, we identified 10 test sites each of 10km-by-10km square. In each test site, a random selection of 5 1 ha sample plots was made. The number of sample plots was determined by an a priori estimation of the required number to acquire measurements on 500 trees.

Within a test site plot, we deployed a field inventory to collect individual tree data on crown areas, standard allometric parameters (cf. diameter at breast height and crown projected area), species and landscape descriptions, and tree location information co-registered to the tree map products. A sample frame inventory was deployed using standard operating procedures for forest carbon inventories (Walker et al. 2012). Allometric measurements from field plots were used to estimate diameter at breast height (DBH) from crown projected area (CPA) using linear ordinary least squares regression. The estimated DBH was used as an input parameter in the standard, local allometric equation to estimate tree biomass. The aim of estimating DBH from remote sensing, rather than directly estimating carbon, is so our approach is compatible with national forest inventory practices in the Senegal that routinely use tree and forest inventories from existing allometric equations.

Using ground-collected data on individual tree stem diameter, tree canopy diameter, and tree canopy projected area, an ordinary least squares linear regression was estimated from the field-measured sample tree data. This produces a simple model to estimate DBH from remote sensing CPA which is produced by the VHR machine-learning model. The estimated DBH was used with a standard allometric equation based on DBH, in this case using the IPCC default tropical dry allometric equation. The estimation of stem diameter from crown parameters was based on an OLS regression of 1,415 sample trees, shown in Figure 4 and Table 2.

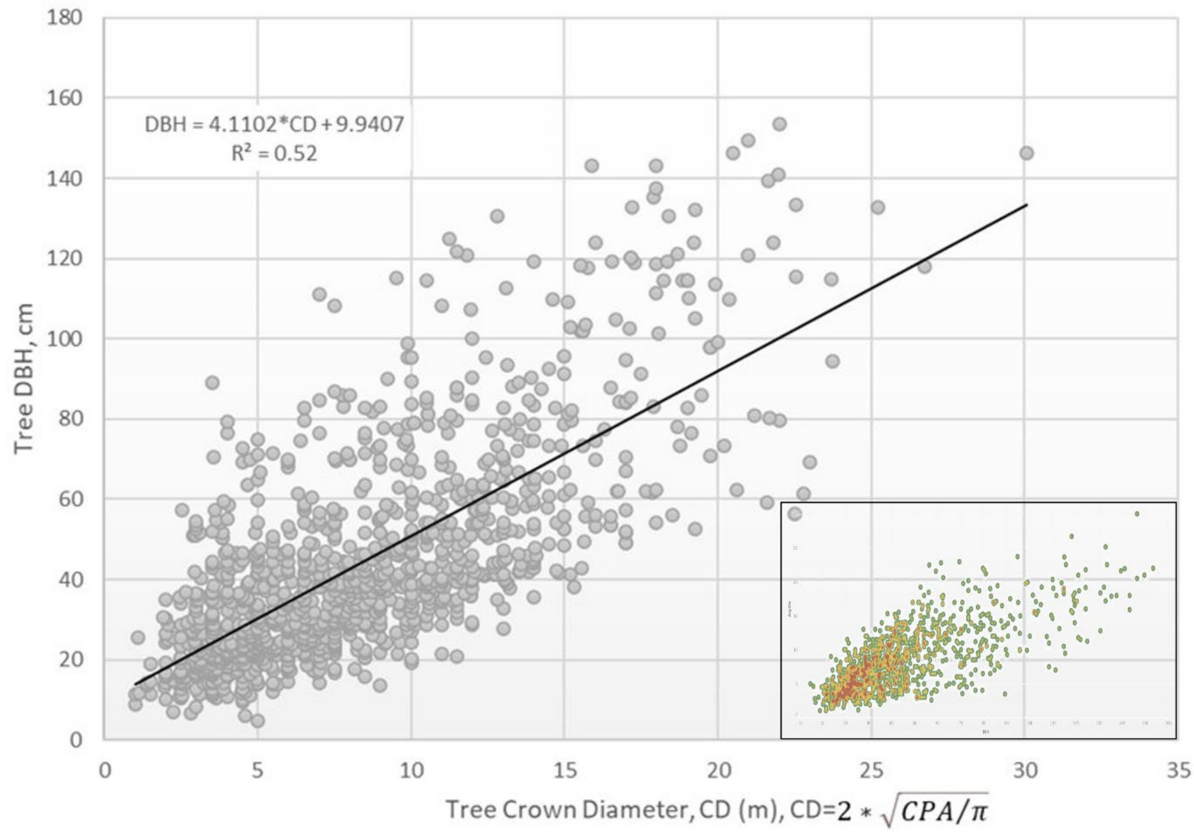

Figure 4. Results from 1 ha field sample plots, which estimate an OLS model to predict tree stem diameters from remote sensing observations of CPA.

Table 2. Model equations to estimate stem diameter and tree carbon

Tree crown diameter, CD (m)	$\mathrm{CD} = 2 * \sqrt{CPA/\pi}$
Estimated DBH, cm	DBH = 4.1101 * CD + 9.9407
Aboveground Biomass, kg	AGB = 34.4703 - 8.0671 * D + 0.6589 * D^2
Belowground Biomass, kg	BGB = AGB * 0.26
Whole tree carbon stock, kg	C = AGB + BGB

5.0 Results and Discussion

5.1 Tree Cover with Sentinel-2 10m Data.

With Sentinel-2 data the model predicts tree cover regardless of forest or TOF. To separate forest and TOF cover areas using the Sentinel-2 processing, we used an aggregate contiguity analysis based on the widely used definition of a forest as having complete tree cover over a contiguous area of 0.5 ha. A 70m x 70m grid was overlaid on the Sentinel-2 product, which are 10m resolution pixels that have been predicted by the model to be tree cover areas (to contain detectable tree cover). Each pixel in the model prediction dataset as a probability estimate is attached, and all pixels with ≥40% are considered to have tree cover (of unknown subpixel quantity). Our aggregate contiguity test for forest areas examines all pixels within a 70m x 70m grid cell with a ≥70% probability. When all pixels meet the test, the grid cell is considered forest and all model prediction pixels in the grid cell are considered forest pixels. All other model-predicted pixels are non-forest or TOF. The TOF pixels are those not classified as forests with a probability estimate greater than 40%. The approach results in some minor inclusion or exclusion errors, but generally along forest edges.

Table 3 presents area estimates of forest tree cover, trees outside of forest cover, and non-treed land cover in the three states of Odisha, Telangana, and Andhra Pradesh, broken into forest and TOF classes. These states are three of the five major states where the national Forest Survey of India has reported notable increases in tree cover. In Odisha, there is more tree cover area in TOF than forest. In Odisha, 43% of the land has no detectable tree cover, while 34% and 23% are areas of TOF and forest, respectively. Inspection of the data for other states shows that forest cover is greater than TOF cover, but the cover associated with TOF is in all cases surprisingly large. However, it is important to note cautiously that while the total tree cover area for forest based on VHR mapping may well reflect actual crown cover areas, the estimates from Sentinel 10m resolution data consider the entire pixel area and are thus overestimates.

Table 3. Sentinel-2 based prediction of tree cover in Forest and TOF landscapes (km^2)

Indian State	**Forest**	**ToF**	**FSI Forest**	**FSI TOF**	**Non-For/No ToF**	**Total Area**
Odisha	35,130	53,327	52,156	29,474	67,611	156,069
Telangana	19,688	14,548	21,214	8,214	77,908	112,144
Andhra Pradesh	37,658	22,121	29,784	14,903	100,345	160,124
	Forest (%)	**ToF (%)**			**Non-For/No ToF (%)**	
Odisha	23%	34%			43%	
Telangana	18%	13%			69%	
Andhra Pradesh	24%	14%			63%	

5.2 Comparison with Official Inventory Estimates.

The mapping using Sentinel-2 data covers three entire states, while the VHR analysis only covers a large test area. Therefore, we can compare the Sentinel-2 10 m resolution deep learning model of forest and TOF areas to the latest release of the Indian report on the State of the Forests (FSI 2021), and these are shown in Table 3. With perhaps one exception for the state of Andhra Pradesh, it appears that the FSI analysis overestimates forest cover and underestimates TOF cover compared to our analysis. For Andhra Pradesh the FSI estimates underestimate forest cover compared to our analysis. Because of definitional differences between how FSI computes forest cover versus tree cover vs TOF we have combined both the

FSI tree cover and TOF for our comparison. If one only considers our TOF estimates compared only to the FSI TOF estimates, we conclude that the official estimates are under reporting the area in TOF *senso stricto* by as much as 200-300%.

5.3 Tree Cover with VHR 0.5m Data.

Using VHR data the machine learning model can predict the crown polygon, and hence map the tree-object and derive precise estimates of individual tree canopies, deriving an allometric parameter of the crown projected area (CPA). At a spatial resolution of 0.5m, the mapping is object-based and is a precise estimate of crown cover area, and when summed a precise area estimate of tree cover (Fig 5). Table 4 presents the results of the VHR analysis for a 5468 km^2 test area in Odisha state and a direct comparison with results from Sentinel-2 analysis above. The total VHR tree cover measured as total tree crown area is 1470 km^2, compared to the tree cover of 2902 km^2 from Sentinel-2 analysis, which is a 198% overestimate by Sentinel-2. It is difficult to directly compare the two sensors' estimates in a contingency matrix due to pixel resolution differences. If we examine only the improved accuracy of the VHR model but we observe that the Sentinel-2 detection of forest results in 125 km^2 of co-mission, that is, areas not detected as any kind of tree cover at all with VHR. The commission error of TOF areas is 1454 km^2. In this test landscape, the majority of the tree-cover is in TOF compared to forest. It is important to note that because the VHR machine learning model is derived at the 0.5 m resolution, it is a direct measurement of canopy cover on an individual tree basis over the entire landscape.

Figure 5. Results of the VHR data machine learning model, and the crown based allometric scaling model. The raw VHR data is shown on the right, while the individual tree carbon mapping is shown on the left with color coding from low carbon (light tones) to high carbon quantities (darker blue tones).

Table 4. Results of VHR Analysis, Compared to Sentinel (km2)		
Detection class	**Sentinel Model**	**VHR Model**
Forest	571	445
ToF	2,331	1,025
No Trees	2,566	3,998
TOTAL	*5,468*	*5,468*

5.4 Analysis of Carbon Stocks in TOF Using Tree Crown Allometric Scaling.

We used the VHR mapping product in conjunction with the derived allometric scaling model from the ground calibration to estimate carbon stocks in TOF trees and trees in forests and for the landscape as a whole. The VHR model works extremely well in this part of the world with an abundance of TOF cases. The results are shown in Table 5. The total number of stems in the study area was 33.93 x 10^6 including 11.95 x 10^6 in forest and 57.49 x 10^6 in TOF. This proportion of trees in the study site was not the same as in the state of Odisha, so to evaluate these results in the context of the entire state the forest tree count was doubled. The results suggest that 48% of all trees are in TOF, which for most inventories has not been evaluated. This is a relatively large number compared to forests.

Individual tree carbon estimates were based on the allometric equation in Table 2. Total carbon in the test area was 9.72 x 10^6 tC, including 2.58 x 106 in forests and 7.13 x 106 in TOF, or 73% in TOF areas. To evaluate the carbon representative of the state the forest estimate was scaled to the proportional distribution between forest and TOF for the state, which results to suggest that 58% of the carbon is in TOF systems (Fig. 5).

The results clearly show that there is a large proportion of trees in TOF and their contribution to carbon stocks is also high. The results suggest that while tree counts are higher for forest areas in total, carbon stocks are higher in TOF areas in total, perhaps as a result of having fewer but larger trees. Also, although carbon density is almost 3-fold higher in forest land than TOF landscapes, the considerably larger area of land with TOF results in more carbon.

Table 5. Summary of VHR mapping of individual trees and carbon stocks.

VHR Data	Stems	Stems Adjusted	Fraction	tC	tC ha^{-1}	tC Adjusted	Fraction	Area (ha)
Study Area	33,934,724	45,889,372	1.00	9,716,135	18	12,298,494	1.00	546,812
Forest	11,954,648	23,909,296	0.52	2,582,359	45	5,164,718	0.42	57,070
TOF	21,980,076	21,980,076	0.48	7,133,776	15	7,133,776	0.58	489,742

5.5 Multi-resolution Observations for Detection, Crown Mapping and Allometric Carbon Scaling of Individual Trees.

The analysis suggests an approach to mapping TOF where basic allometric scaling can be applied to estimate carbon stocks across large areas and landscapes at the individual tree level. Although methods using machine-learning applied to medium resolution data, such as the 10m Sentinel-2 can be suitable for detection of a wide range of tree clusters and some large individual trees, they require an alternative approach to estimate carbon because standard local allometric equations use individual tree parameters. On the other hand, the use of methods using deep machine-learning with VHR satellite data can be calibrated to produce a canopy-based allometric scaling model to estimate parameters such as DBH. Thus, the large area mapping can be combined with standard and local allometric scaling equations suitable for specific project areas or national carbon inventories.

The results here are consistent with a growing body of literature regarding individual tree crown mapping using VHR remote sensing (Brandt et al. 2020, Reiner et al. 2023) and application to carbon stock estimates (Mugabowindekwe et al. 2023). There remain some important challenges. Most notable is the problem when more than one tree crown overlaps with a neighboring tree crown, and by extension the mapping of individual trees in forests. This analysis did detect clusters of TOF trees and attempted to map forests at the tree level. The approach may be improved by merging a cover-based method for closed canopy mapping, where carbon stocks are assigned to cover types using Sentinel-2, merged with this VHR method where carbon stocks are assigned to trees outside of the closed canopy areas. Another improvement could be made by adding height data, especially if it were derived from the same VHR data. A good example of this has been reported by Tolan et al. (2024).

This analysis produced different carbon stocks and carbon densities for individual trees and clusters of trees growing together, including patches that might be considered under the definition of forests. Generally, the open grown individual trees have higher carbon stocks. This could be accurate and reasonable as a result of farmer promotion or management of these trees, where large trees are protected particularly for their size and stature as production trees or for other utility, while clusters of trees tend to be open canopy natural or remnant trees which include understories. Further, there is some evidence that across these landscapes large individual trees are being harvested preferentially (Brandt et al. 2023). However, the method we use for assigning carbon stocks to clusters of trees could bias the result toward mean values, which would be lower than the open grown individual trees which could represent maximum sizes in the overall size class distribution.

6.0 Conclusions.

6.1 Application to Policy Needs for Monitoring.

The conventional wisdom for more than two decades has been to see LCLUC in Asia through a lens of agricultural expansion and concomitant loss of natural ecosystems. Moreover, land degradation is viewed as a dominant characteristic of agricultural land use in Asia. Arguably this model has been important and relevant to understanding global climate change and the carbon cycle as well as other global-scale land science processes. However, when viewed against this backdrop we often overlook how significant an increase in tree cover in small holder agricultural landscapes is to our understanding of carbon sequestration, drivers of LCLUC, and the needs of policy and development communities. The TOF question is central to understanding where and how natural ecosystem conversion trends and land degradation are being, *or can be*, reversed – with significant benefits to small-holders' livelihoods and their land productivity.

Heretofore it has been difficult to bring measurement and monitoring of TOF landscapes into the policy setting due to a lack of methods and tools. Indeed, there have been very few examples of TOF estimates of carbon over large landscapes, or with enough spatial resolution to meet carbon project requirements. The results of this analysis in India suggest that it is possible to deploy monitoring of TOF carbon to support REDD+ programs and projects, as well as forest and landscape restoration actions, such as the Bonn Challenge or AFR100. The significance of having measurement and monitoring capabilities for TOF lies in its utility for measuring carbon sequestration and doing so in rural landscapes that are important to livelihoods.

6.2 An Argument for Increased Consideration of Trees Outside Forests.

The World Agroforestry Center often notes that the "future of trees is on farms". This catchphrase reflects that while forests worldwide are being converted and degraded, *tree cover* outside of forests may be increasing at a rapid pace, *especially in developing countries and in semi-arid agricultural landscapes*. It also reflects the growing expert opinion that there are more opportunities for planting trees in non-forested areas than in dense tree cover areas. Further, the number of trees that can be planted on agricultural land without compromising food security is very high, especially when integrated with the farming system.

South Asian agricultural landscapes are traditionally known for their use of tree systems to capture a range of ecosystem functions and as a source of food, fiber, and energy. Many of the farming practices in South Asia are tree-based systems that combine trees with land management practices for food and animal production. Across India, tree-based systems have proven suitable for smallholder farmers and low-income households, because the range of practices offer a source of livelihoods and a basis for local economies (Nair 1993). In India, various forms of agroforestry have developed across a range of environmental, social, and economic contexts, resulting in a diversity of types Mbow et al. 2020, Mbow et al. 2014)

In contrast to forests, areas of non-forest tree cover are often not included in the national assessments of tree resources, even if the cover density is high. Consequently, data about this carbon resource are rare, and information that is available is typically fragmented across the range of institutions and stakeholders that deal with one or more of the various TOF types. For example, smallholder plantations, woodlots, and agroforestry often align with separate national agencies or institutions for forestry, energy, and agriculture, respectively. National climate change mitigation and adaptation programs often focus on forests without considering the impact of TOF carbon sequestration or their co-benefits related to land productivity and biodiversity.

A global survey (Zomer et al. 2016) found that in 2010 almost half of all agricultural land had considerable tree cover and that the area was increasing. This analysis suggests that from global tree cover in agricultural land was 10% or perhaps higher, and from 2000 to 2010, there was a 2% increase. These systems could constitute an extremely large area of tree cover that is additional to what is formally classified as 'forest'. Although the biomass density is low compared to forests, the large area and increasing stocks make these places quantitatively important for carbon sequestration. An important study across three continents of TOF data from 6 countries (Schnell et al. 2015) showed a significant amount of carbon stored in TOF systems. Trees may contribute >75% of agricultural carbon stocks and are increasing at 1% per year, which on a global basis may be storing an additional 740 Mg CO_2 per year (Zomer et al. 2016).

6.3 Rethinking the REDD Framework in a Broader Context.

Currently, REDD+ is formulated mainly around the LULUCF framework, which is limited to the application of REDD within forests (Figure 1) and international attention is beginning to re-focus on reducing emissions from deforestation in closed canopy tropical forests, such as the new initiative for Architecture for REDD+ Transactions (ART/TREES), and emphasizes avoided emissions in high carbon density closed forest ecosystems. We argue that there is an urgent need for climate change mitigation actions that are applied across a range of landscapes, including more than these high carbon density forests, and include carbon removals. Furthermore, with increasing interest in linking climate change mitigation and adaptation, policies and measures are needed that have direct social, economic and livelihood co-benefits. Bringing a strong TOF focus into REDD+ would expand the framework to landscapes that cover extensive areas in Africa, having the potential for generating large atmospheric removals while also directly contributing to adaptation measures and livelihood enhancements. This strategy would increase the number of participating countries beyond those with high carbon density forests, including those many countries in Africa with relatively low forest emissions. More than half of South Asian countries have expressed interest in agroforestry as part of their REDD+ strategies (Minang et al. 2014). Furthermore, evidence suggests that many farmers already manage for and promote TOF, so there is a ready link to scale through activities that leverage traditional knowledge. There is a compelling case to expand the current framework to one centered on AFOLU, agriculture, forestry, and other land uses.

Many countries include removals-based actions involving TOF in their reporting on Nationally Determined Contributions. LULUCF and agriculture mitigation targets are included in 73% of all NDCs submitted so far (UNFCCC 2021), which surpasses all other priority areas including in the energy sector. Countries with LULUCF actions are more likely to favor removals-based activities over avoided emissions, with reforestation and agroforestry being identified in more than 50% of all domestic LULUCF and agriculture mitigation activities. Yet, strictly speaking, REDD+ and NDC reporting are different components of the international agreements under UNFCCC. Thus, an expanded AFOLU approach brings NDC and REDD+ closer together programmatically and would improve the coordination between the forestry and agriculture sectors in national programs. It would also improve cross-agency and inter-institutional coordination of mitigation and adaptation programs.

Important initiatives such as the Bonn Challenge recognize the value of forest landscape restoration to climate change mitigation and adaptation. It also highlights the importance of removals, even in ecosystems and landscapes that have low carbon densities. New calls for increasing investments and actions with tree-based systems are being registered. New technical concepts such as multifunctional agriculture (Leakey 2017), land-maxing (Leakey 2020) multifunctional landscapes (Mbow et al. 2021, Cockburn et al. 2019) and farmer-managed natural regeneration (Lohbeck et al. 2020) are promoted in the peer literature, alongside increasing evidence that farmers promote these systems if barriers are removed or there are strong pathways to capture the ecosystem services values. At the same time, new measurement methods using earth observing systems are quickly being deployed. These new monitoring tools have capabilities to measure fine resolution objects at the scale of individual trees, while simultaneously being applied across expansive geographic extent. These measurement and monitoring tools have opened a window of opportunity to expand the existing REDD+ framework to include trees outside of forests, which in turn can create the enabling environment for large-scale climate-smart investments in natural climate solutions.

6.4 Nature-Based Components of Net-Zero Goals.

Effective emissions reductions are at the core of organizational responses to climate change through direct emissions abatement. Most financial institutions (FI) have started to focus on net-zero as the guiding concept for climate mitigation. However, a lack of consistent principles, definitions, metrics, and evidence of effective strategies to meet net-zero targets limits the ability of FIs to support the reduction of emissions in the real economy that is needed to stabilize temperatures at 1.5°C above pre-industrial levels. There are two basic fundamentals underlying net-zero goals:

1) Set science-based goals and targets that are aimed at reducing emissions to mitigate a 1.5^{o} C rise in global temperatures by selecting pathways without overshoot that primarily focus on emission abatements.
2) Residual emissions can be neutralized by implementing or financing activities that permanently remove an equivalent amount of atmospheric carbon, which can be NBS activities.

The salient points are threefold. First, there is widespread agreement that full zero emissions targets are not likely to be realistic if adhering to a pathway that achieves global temperature mitigation soon and without overshooting at scale under realistic cost. Second, the best, if not the only, strategy for immediate and complementary removals is through NBS, principally tree-based NBS, because other NBS (of NCS) are future-focused avoided emissions. Third, to achieve permanence, or best ensure maximum likelihood for permanence, activities systems would be tied closely to livelihoods and other economic or income valuations and sustainability, in which most NBS activities are situated along with multiple co-benefits (cf. biodiversity).

Current thinking on how to implement net-zero in this context stipulates that companies cannot purchase carbon credits as a replacement for actual emissions reductions through the value chain, i.e. offsetting emissions. However, activities or investments outside the value chain are recommended to support societal net-zero goals and to address residual emissions through evidence-based NBS-carbon activities. *To do this, it is necessary to know what activities are real and impactful, and how to measure and report against disclosures or goals.*

6.5 From Net Zero to Disclosure.

While the net-zero framework is guiding progressive and voluntary business strategies for firms, regulations are also evolving quickly in North America, Europe, and Asia. While some of the new or proposed rules and regulations have a singular focus on climate change issues, others address sustainability more broadly. For instance, the US Securities and Exchange Commission is set to finalize new rules for climate disclosures that, as proposed, focus on the oversight of climate-related risks, the financial impacts of severe weather events and greenhouse gas emissions.

For investors who have committed to supporting the goal of net zero emissions by 2050 or sooner by joining the Net Zero Asset Managers Initiative, the Paris-aligned Investor Asset Owner Commitment, and the Net Zero Asset Owners Alliance, this draft rule is absolutely critical. Without clear and comparable climate disclosures from companies, investors cannot evaluate climate risks for individual holdings or make plans to address the systemic risks of climate change across their portfolios and the real economy.

The bottleneck will likely be in the NBS-carbon components of reporting because they are more difficult and not well known to traditional accounting firms or organizations, let alone participating firms and financial institutions. Thus, measurement, reporting, and verification using science-based standards, practices, and protocols for carbon in NBS applications needs rapid development.

6.6 High Integrity Measurements Based on Earth Observations

For mitigation policy to be effective, there will need to be an increased level of climate finance made available from a range of donors and private sector actors. Although emerging initiatives such as LEAF Coalition are mobilizing public funds for NbS actions in the REDD+ space, it has become clear to many observers that it will not be enough. Private sector financing will also be required, but before that happens at a global scale, investors are increasingly needing high integrity measurements. Although ground-based measurements will be needed, the deployment of new precision and global scale measurements will need to come from Earth Observations. The kinds of results demonstrated in this study suggest that increasingly large area assessments of carbon stocks and stock changes with very high resolution consistent with the use of allometric scaling and NbS types of systems will be possible. Twining the technical means for measurement from the science community with new-standard setting initiatives such as the Integrity Council for Voluntary Carbon Markets (ICVCM) and the Voluntary Carbon Markets Integrity Initiative (VCMI) by leveraging programs such as the Global Observations of Forest Cover (GOFC) program will increase confidence and raise the level of discussion from carbon literacy to carbon intelligence.

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