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TECHNICAL NOTE

MAPPING TREE PLANTATIONS WITH MULTISPECTRAL IMAGERY: PRELIMINARY RESULTS FOR SEVEN TROPICAL COUNTRIES

RACHAEL PETERSEN, DMITRY AKSENOV, ELENA ESIPOVA, ELIZABETH GOLDMAN, NANCY HARRIS, NATALIA KUKSINA, IRINA KURAKINA, TATIANA LOBODA, ALEXANDER MANISHA, SARAH SARGENT, VARADA SHEVADE

ABSTRACT

Tree plantations continue to expand worldwide to meet demand for timber, wood fiber, fruits, and vegetable oils such as palm oil. Many countries report national statistics on the area of land in plantations, but the extent and locations of these plantations are often not documented. New corporate commitments to eliminate deforestation from agricultural supply chains have led to increased demand for detailed spatial information on plantation dynamics. Recent advances in global land-cover mapping using Earth observation satellites offer a promising tool for mapping plantations. Several earlier efforts to use satellite imagery have yielded promising results. This study advances these efforts by mapping the location and extent of tree plantations in 2013 and 2014 in seven tropical countries (Brazil, Cambodia, Colombia, Indonesia, Liberia, Malaysia, Peru) through visual interpretation of moderate- and high-resolution satellite imagery and other ancillary spatial information. More than 45 million hectares of land in plantation systems were identified in these countries. Plantations varied in size (from less than 1 hectare to 145,000 hectares) and by type (large industrial to small and medium mosaics). Plantations mapped in Indonesia (24.3 million hectares) and Malaysia (10 million hectares) together constituted approximately 75 percent of the total mapped area. Indonesia with 12.8 percent and Malaysia with 30.2 percent also had the highest percentage of total land area in plantations. Finally, the percentage of total tree cover loss in 2013–14 within plantation boundaries was 44 percent in Indonesia and 65 percent in Malaysia. The plantation maps generated

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Technical notes document the research or analytical methodology underpinning a publication, interactive application, or tool.

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Transparent World

are important inputs to refine post-2014 estimates of tropical deforestation rates by differentiating between tree cover losses occurring within natural forests versus loss associated with plantation harvests.

INTRODUCTION

Planted forests (tree plantations) are composed of trees established through planting or seeding by human intervention, according to the Food and Agriculture Organization of the United Nations (FAO). They are a critical part of productive landscapes: they help support sustainable forest management, and serve a vital role in meeting the demand for timber products globally (Carle and Holmgren, 2008). With the global population predicted to reach 9.7 billion by 2050, they will continue to play an important role in meeting increased demand for forest products and agricultural commodities (United Nations, 2014). However, the productive functions of tree plantations must be weighed against the values of the natural forests they often replace; for example, tree plantations harbor less biodiversity (Savilaakso et al., 2014) and store less carbon than natural forests (Kho & Jepsen 2015).

Humans have established planted forests for millennia (FAO, 2010). However, trees are now being planted at an unprecedented scale and with vastly increased efficiency, driven by population growth and demand for forest products. Planted forest area increased by 66 percent—from 167.5 million hectares in 1990 to 277.9 million hectares in 2015—over the past 25 years and now accounts for 7 percent of the world's total forest area (FAO, 2015).

Knowing the locations of these plantations and monitoring their expansion is critical for policymakers and other stakeholders to balance increased food and timber production in the tropics with growing commitments to reduce emissions from deforestation. Although there are national area estimates for some types of planted forests, no global maps and few regional maps of tree plantations exist (Table 1). This is because of the difficulty of accurately distinguishing tree plantations from other vegetation, such as secondary forests, in remote sensing imagery. Data that differentiate tree cover loss and gain within mature, secondary forests from that within tree plantations is needed to better understand how tree plantations affect the biodiversity and carbon storage potential of the landscapes into which they expand.

The first globally consistent maps of annual tree cover change were published by Hansen et al. (2013) showing change between 2000 and 2012 by using freely available Landsat data from the U.S. Geological Survey. These data are updated annually and are available on the Global Forest Watch platform (www.globalforestwatch.org). On these maps, "tree cover" is any vegetation greater than 5 meters in height, which includes mature, secondary, and plantation forests. Scientists and environmental organizations have pointed out that these data fail to distinguish between loss and gain in natural forests and the change associated with plantation harvest cycles (Tropek et al., 2014; Rondonuwu 2014). The Tropek et al. study concluded that the definition of tree cover conflates vastly different land-use dynamics, such as the loss of primary and secondary forests with the harvesting of plantations, in measuring tree loss. Nor do these data differentiate natural forest regeneration from tree cover gain due to plantation growth (Le Maire, Dupuy, Nouvellon, Loos, and Hakamada, 2014).

The goal of this study is two-fold: (1) to create a better understanding of where and to what extent plantations constitute landscapes across seven tropical countries and (2) to estimate how much tree cover change identified by Hansen et al. falls within planted areas. Spatial data on the presence, extent, and type of tree plantations across the seven countries was used to address these issues. The seven countries were selected to offer a balance of tropical countries with a longer history of plantation systems (e.g., Indonesia and Malaysia) with those that are new frontiers of plantation expansion (e.g., Colombia, Liberia, and Peru).

While previous studies mapped plantations using remote sensing data (Table 1), this is the first study to distinguish multiple species and types (e.g., industrial, small-scale mosaics) of tree plantations across different geographies using a consistent methodological approach.

Notably, seven of the ten studies reviewed mapped only oil palm plantations, with five of the seven in Southeast Asia. Oil palm plantations—especially large-scale industrial operations—are visually distinct in satellite imagery due to their clean lines and the crown shapes of their trees. Promising efforts to map multiple plantation species include Fagan et al. (2015), who identified planted areas of six citrus fruit and timber species in Costa Rica with an accuracy of 88–89 percent, and Miettinen et al. (2012), who delineated pulp plantations in addition to oil palm in Peninsular Malaysia, Borneo, and Sumatra with a 90–94 percent accuracy. However, most previous studies have been limited to one country, or include only a single species (Table 1).

Information about land cover can be derived from satellite imagery in two ways: through visual interpretation or through semi-automated classification. Visual interpretation employs the expertise of humans to manually interpret and differentiate features on imagery. Semi-automated methods employ computer algorithms to assign each pixel in an image to a particular class. Most common are "supervised" approaches to semi-automated methods that first employ human expertise to identify example areas of each class to "train" automated models. Previous studies that mapped tree plantations through visual methods include Gunarso, Hartoyo, Agus, and Killeen, (2013) and Miettinen et al., (2012). Examples of semi-automated methods, used for example, to map homogenous oil palm, rubber, or eucalyptus tree plantations include Miettinen et al., (2012), Fagan et al., (2015), Gutiérrez-Veléz et al., (2015) and Le Maire et al., (2014). Notably, studies using visual methods achieved comparable accuracy to studies using supervised or unsupervised classification.

Table 1 | **Examples of Previous Studies that Used Remote Sensing to Map Tree Plantations**

STUDY	COUNTRY OR REGION	PLANTATIONS MAPPED	METHOD	IMAGERY	ACCURACY (PERCENT)
Fagan et al. 2015	Costa Rica	Five timber and one citrus species	Supervised (DT)	HyMap single date, Landsat multiyear (15m)	88–89
Gutiérrez-Vélez et al. 2013	Peru	Oil Palm–Industrial	Supervised (DT)	MODIS temporal, Landsat (30m–250m)	73–96
Nooni et al. 2014	Ghana	Oil palm	Supervised (MLC, SVM)	Landsat (30m)	89–93
Li and Fox 2012	Mainland Southeast Asia	Rubber	Supervised (MDC/KNN)	MODIS seasonal (250m)	83–94
Morel et al. 2011	Sabah, Malaysia	Oil Palm	Supervised (MLC)	ALOS PALSAR (30m)	77
Le Maire et al. 2014	Brazil	Eucalyptus	Supervised time series analysis and Segmentation/OBIA	MODIS seasonal, Landsat (30m–250m)	85
Koh et al. 2011	Malaysia and Sumatra	Oil palm (closed canopy)	Unsupervised cluster labeling & rule-based	MODIS, ALOS PALSAR (250m)	85–98
Gunarso et al. 2013	Indonesia, Malaysia, and Papua New Guinea	Oil palm–Industrial	Manual delineation	Landsat (30m)	N.A.
Miettinen et al. 2012	Peninsular Malaysia, Borneo, and Sumatra	Oil palm–Industrial	Manual delineation	Landsat, SPOT (10m–30m)	90–94
Carlson et al. 2013	Kalimantan	Oil palm	Segmentation/NN and delineation	Landsat (30m)	63–78

DT = Decision tree; MLC = Maximum-likelihood classifier; SVM = support vector machine; MDC/KNN = Mahalanobis distance classifier and K-Nearest Neighbor; SPOT = high-resolution satellite; ALOS PALSAR = L band microwave sensor aboard the ALOS satellite; Segmentation/NN = combination of spatial segmentation and spectral nearest-neighbor; Segmentation/OBIA = spatial segmentation and object-based image analysis methods

METHODS

Visual delineation was the primary method used to map plantations across seven tropical countries because it is an effective way to map heterogeneous plantation categories (different species and types) as a single class. The human eye can better detect landscape patterns and consider indirect indicators such as roads. We used semi-automated classification methods sparingly, as discussed below, because spectral characteristics of tree plantation reflectance patterns vary widely, and a number of other objects—such as secondary forests or clearings—can appear similar to tree plantations.

Definitions

The terms "plantations," "tree plantations," and "planted forest" are often used interchangeably. In this study we use the term "tree plantations"—sometimes shortened to "plantations"—throughout to indicate the biophysical presence of trees that are clearly planted and managed by humans. This is consistent with the FAO's definition of "planted forests" (FAO 2015), comprising "trees established through planting and/or deliberate seeding of native or introduced species." However, our definition includes tree species such as oil palm, coconut palm, citrus fruit trees, nut trees, and other agricultural trees not included in the FAO definition. In addition, we do not classify tree plantations according to their productive or protective functions, other than to approximate which species were planted in each area.

Our data include plantations of various types, ranging from large-scale industrial monoculture plantations to small mosaics where planted trees may be interspersed among other vegetation in a patchwork arrangement more typical of agroforestry systems. No minimum tree canopy cover or tree height was used to define plantations. Plantations in this study can have areas cleared that aren't yet planted, or areas where facilities, roads, or other infrastructure are present.

Areas delineated as "plantations" should therefore not be considered as total planted tree area of a certain plantation type. A percent estimation of tree coverage is indicated in the attribute data for both medium and small mosaic plantations to approximate the total area within the mosaic covered by planted trees. In addition, the classification system used has no strict relation to political or policy-based definitions; it should not be assumed that the mapping criteria used in this study directly relate to ownership or management systems.

Data Sources

The primary data source for the plantation mapping exercise was 30-meter Landsat source data from the U. S. Geological Survey due to its free online availability, large historical archive, and appropriate spatial resolution for regional mapping. We selected images from 2013 and 2014 because they were the most recent years available and so that we could have two years of data to find cloud-free images for multiple seasons. For visual interpretation, false-color composites were created using the red, near-infrared, and middle-infrared bands (channels 3, 4, and 5 of Landsat 5 and 7; and 4, 5, and 6 of Landsat 8). The red, near-infrared (NIR), and short-wave infrared (SWIR) bands are the most useful bands for plantation mapping (Nooni, Duker, Van Duren, Addae-Wireko, and Osei, 2014). In some cases, multiple image dates before the target year (2013–14) were required to detect and verify the presence of plantations (e.g., to identify clearcuts in a previous year). Unlike a single scene, the time series allowed for the visualization of seasonal changes and long-term dynamics, which are often critically important for the identification and delineation of tree plantations. We acquired the time series according to the following criteria:

- **CLOUDS:** The best available images and many additional scenes were combined to create maximum cloud-free coverage.
- **SEASONALITY:** Images from multiple seasons were selected, primarily from the most recent image year. Analysis of multiseason imagery was required to separate plantations from other land-cover types with similar spectral signals, such as secondary forests. Often cloud-free images were available only in the dry season, when it is more difficult to identify plantations. In these cases, images from multiple seasons were downloaded, despite partial cloud coverage. Where possible, two clear images were used, one from the dry season and one from the wet season.

Where available, Landsat imagery was supplemented with very-high-resolution (about 1 meter) imagery accessed from Google Maps, Bing Maps, and Digital Globe through its Open Landscape Partnership, which includes over 1.4 million square kilometers of submeter resolution imagery (www.openlandscape.info). Very-high-resolution images were used on a case-by-case basis to view the internal structure of plantations, including identifying the location of road networks and drainage systems, identifying tree species from the shape and density of tree crowns, measuring the share of plantation area in a given mosaic, and verifying the location of plantation boundaries. Approximately 3 percent of total land area in all of the countries was verified using very-high-resolution imagery.

The addition of ancillary georeferenced datasets helped identify areas where plantations were most and least likely to occur. These datasets include:

- **TREE COVER LOSS AND GAIN:** Areas where both loss and gain occurred over the 13-year period mapped by Hansen et al. (2013) were the most probable areas to check for plantations, especially large patches that could indicate areas of potential intensive forestry operations, plantation harvesting (or forest clearing), and regrowth. However, this dataset is not sufficient to identify plantations that were mature in 2000, and not harvested from 2000 to 2013 (rubber and oil palm plantations are typically on a 25–30 year rotation cycle).
- **INTACT FORESTS:** The Intact Forest Landscapes dataset (http://www.intactforests.org/) identifies the world's last remaining expanses of forested landscapes, larger than 50,000 hectares with no significant signs of human impact. This dataset was used to identify areas where plantations were less likely to be located. Intact forest areas were still examined to ensure that no recent clearing or plantations appeared in the most recent Landsat images.
- **CROWD-SOURCED IMAGES:** We used publicly available crowd-sourced field images, where available, which included georeferenced photos of land use taken by individuals on the ground. Sources of these images included Panoramino, which is accessible through Google Maps and Google Earth, and WikiMapia.

Visual Delineation Methods

After image stacks were compiled, we applied an auxiliary rectangular grid to the seven countries to ensure thorough inspection of each scene. For on-screen visual interpretation, Landsat images were displayed with a working scale from 1:25,000 to 1:100,000. We divided images using a grid of 20 x 20 kilometers for less densely planted countries, such as Colombia, and a 10 x 10 kilometer grid for more densely planted areas, such as Malaysia. All images were prescreened for the presence of plantations by visually scanning and marking any plantations. The tree cover loss and gain data (Hansen et al., 2013) helped to locate plantation clusters. Images containing plantations were assigned to technicians for visual delineation. Plantation areas were digitized from these images using ESRI ArcGIS Desktop software. Visual delineation includes the following steps:

Preprocessing

1. Select and download image
2. Select image bands and adjust histogram

Prescreening

1. Screen image for presence of plantations using tree cover loss and gain data (Hansen et al., 2013)

Delineation

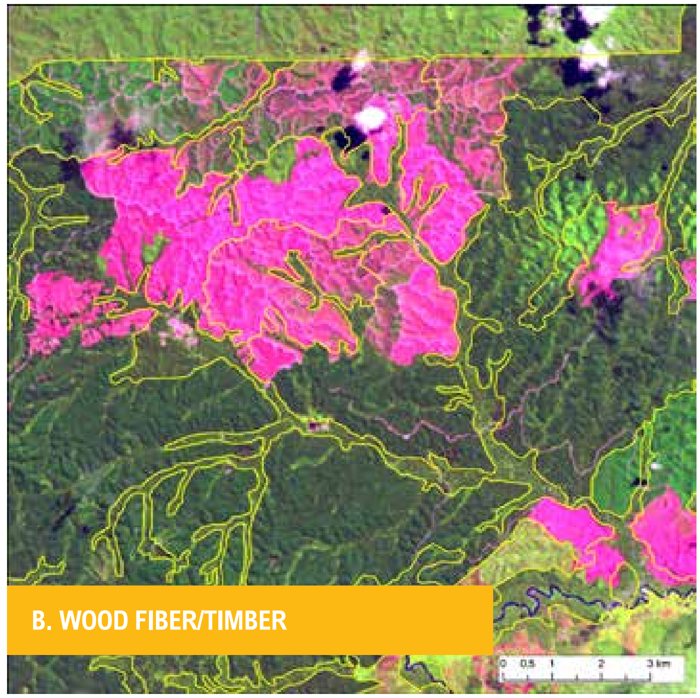
1. Delineate plantation polygons in ArcGIS

Quality Control

1. Check species compositions using field verification points and very-high-resolution imagery
2. Check polygon topology
3. Manually review attribute table for errors

Texture, shape, color, and size of features were the primary factors used for visual delineation of plantation areas. For example, the shape and sharpness of plantation boundaries were important characteristics for identifying large plantations (Figure 1A). Many plantations, particularly those in flat areas, have angular shapes with straight distinctive boundaries. Otherwise, plantation boundaries often follow natural boundaries such as river banks, lakes, wetlands, and mountain ranges (Figure 1B). The color of plantations also appeared brighter than surrounding forests in the imagery.

Figure 1 | **(A) Delineation (Yellow Outline) of Industrial Rubber Plantations, Depicting Angles of Boundaries (B) Delineation of Wood Fiber/Timber Plantations that Follow Topography**



Source: World Resources Institute and Transparent World

Homogenous plantations (usually large industrial plantations) exhibit uniform and low-contrast visual patterns due to the unified height and density of tree crown cover (Figure 2A). Such unified canopy structure creates a regular, mottled texture on the image surface.

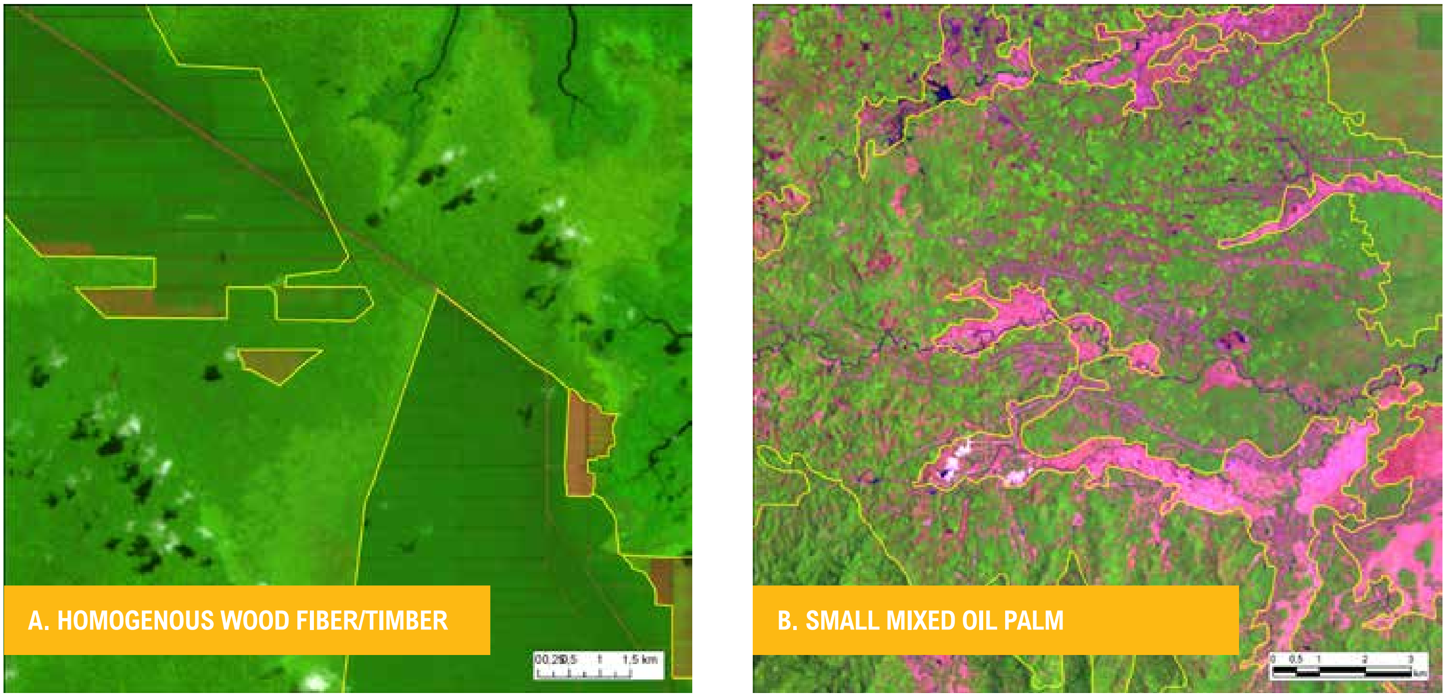
Areas cleared for plantations appear distinct from logging and agriculture in tropical countries on satellite imagery. They generally have larger plot sizes than agriculture and are located near other plantation clusters. New clearings for plantations always include clearcut areas with a completely removed tree canopy and angular or landscape-defined boundaries similar to other established plantations in the area. Small plantations include a visible internal structure: patches of plantations with different ages and mixes of species and sizes with smaller patches of secondary forests, croplands, and other land uses (Figure 2B).

Nearby roads, as well as roads within plantations, often serve as an indirect indicator of plantations by providing context and suggesting management of an area. Roads to timber logging sites in the tropics are usually overgrown with vegetation, whereas plantation roads are usually well maintained. Road conditions were assessed across multiple years using Landsat time series. A network—often a grid—of roads may also exist inside a plantation.

Semi-Automatic Methods Used in Brazil

For Brazil, a semi-automatic spectral-based classification method was used to map some timber and wood fiber plantation species (e.g., pine, eucalyptus, and acacia). These species exhibit a widespread and distinctive spectral reflection. The same method was used to map clearings for plantations in Brazil, which are also distinctive due to the spectral reflection of bare ground. Brazil has a high proportion of timber and wood fiber plantation species that are spectrally distinctive, thus semi-automated methods were used to save time where these methods had a high rate of success.

Figure 2 | **(A) Delineation of Homogenous Wood Fiber/Timber Plantations**
(B) Delineation of Small Mixed Oil Palm Plantations



Source: World Resources Institute and Transparent World

Preprocessing steps included manual cloud masking. No atmospheric correction was made, and any atmospheric contamination was taken into account through training point selection. The classification model used the neural networks training algorithm (Kohonen's self-organizing maps) within ScanEx's NeRIS software (Kohonen, 2001). This algorithm has been used successfully to classify forest carbon stocks, agriculture, and ecosystem types (Stümer, Kenter, and Köhl, 2010; Kussul et al., 2015; Pérez-Hoyos, Martínez, García-Haro, Moreno, and Gilabert, 2014).

A mask of nonforest unchanged area was made to separate clearings and agriculture areas. The mask was produced by including all area with 0 percent tree cover in the Tree Cover 2000 dataset (Hansen et al., 2013). All gain and loss areas from 2001–13 (Hansen et al., 2013) were removed to identify older changes. In this way, the mask removed croplands, pastures, and other areas converted for agricultural purposes. The remaining area was vectorized for post processing.

Post-processing steps smoothed polygon boundaries and eliminated polygon areas below 1 hectare. Majority filter and smooth polygon tools from ArcGIS were applied to reduce speckle and rough polygon edges that result from raster to polygon conversion. The final plantation polygons were manually assigned species classifications based on field observations, as described below. Some obvious mistakes produced by the neural networks algorithm were also corrected manually. Semi-automatic methods included the following steps:

Preprocessing

1. Select and download image
2. Select image bands and adjust histogram
3. Mask clouds manually

Classification

1. Collect samples (30–50 per image)
2. Train neural networks with samples
3. Classify image with trained neural networks

Post processing

1. Run majority filter to remove speckle
2. Convert raster to vector
3. Run smooth polygon tool to remove rough edges from vector polygons

Quality Control

1. Use tree cover loss and gain data (Hansen et al., 2013) to check for missing plantations
2. Manually adjust polygons with incorrect classifications
3. Check species compositions using field verification points and very-high-resolution imagery
4. Check polygon topology
5. Manually review attribute table for errors

Classification Types

Each plantation area identified in the study was classified into one of the following categories:

1. **LARGE INDUSTRIAL PLANTATION:** Contiguous plantation with area larger than 100 hectares. Often many plantations are located close together forming clusters of tens of thousands of hectares. These clusters may contain small settlements or other nonplantation areas (below 100 hectares).
2. **MID-SIZE PLANTATION:** Mosaic of smaller plantation areas embedded within areas of clearing, logging, croplands, secondary forests, settlements, and industrial activity. Defined using three criteria: (a) the area of the individual patches of the mosaic are more than 10 hectares and less than or equal to 100 hectares; (b) plantations in the mosaic comprise at least 50 percent of the mosaic landscape; and (c) total area of the mosaic greater than 100 hectares.
3. **SMALL PLANTATION:** Mosaic of smaller plantations embedded within areas of other land uses, such as clearing, logging, croplands, settlements, industrial activity, and secondary forests. Defined using two criteria: (a) the area of the individual patches of the mosaic is less than or equal to 10 hectares; (b) plantations in the mosaic comprise at least 50 percent of the mosaic landscape. These patches are often considered to be "gardens" or "agroforestry" by local inhabitants.
4. **RECENT CLEARING FOR NEW PLANTATIONS:** Defined by senescent vegetation or bare ground, sometimes with a distinctive internal road network that suggests future plantation development. Generally located next to planted areas and have spatial patterns similar to other plantations in the region. If located in hilly or mountainous areas, usually shaped in terraces on slopes.

Field Verification

Field validation points were collected and used for classification corrections and for distinguishing individual species within plantations. They were particularly helpful in mapping small mosaic plantations and correcting mistakes in species identification from satellite imagery.

Field surveys were carried out in Brazil, Indonesia, and Malaysia to collect ground points indicating the presence of a plantation/forest, type of plantation, planted tree species, and other information. Field points were limited to a 1-kilometer buffer from roads so that they could be easily reached or seen (Figure 3). Points were selected to cover the maximum variability and diversity of the following parameters:

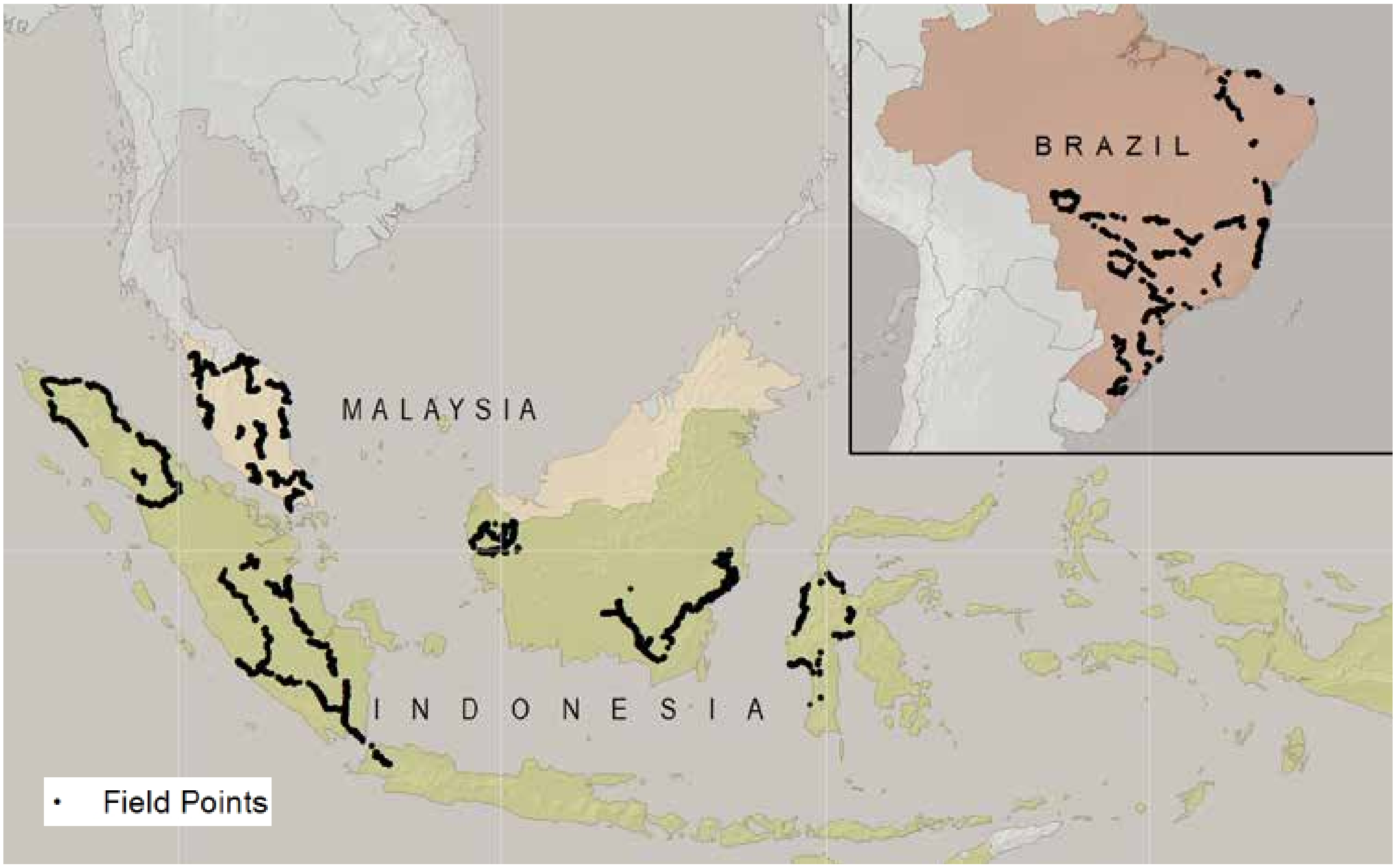
- Patterns in plantation area
- Planted tree species and combinations of species
- Plantation age and the periods in their rotation cycles
- Climatic and terrain conditions

We collected over 7,800 points: 1,150 in Brazil, over 5,600 in Indonesia, and over 1,100 in Malaysia (Figure 4). Descriptions include a plantation type, age, planted species, and an estimated canopy density, canopy height, treeline interval, and other characteristics.

RESULTS

We mapped 45.8 million hectares of tree plantations across seven countries using 2013 and 2014 data. This number does not represent total planted area, but the total mapped area of all plantation types, including mosaics. Approximately 75 percent of the total area mapped was located in Indonesia and Malaysia (Table 2).

Figure 3 | **Field Verification Points**



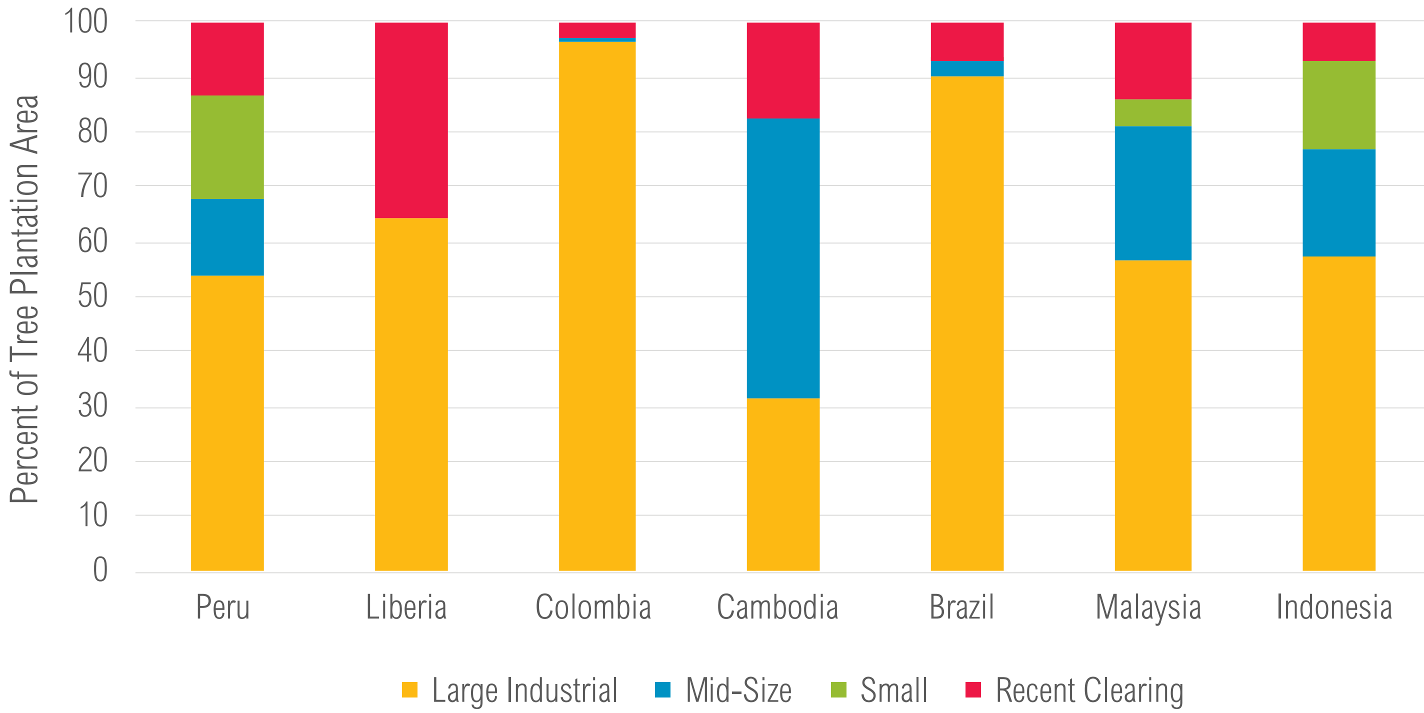
Source: World Resources Institute and Transparent World

Table 2 | **Total Area of Tree Plantations Mapped in Seven Tropical Countries, 2013-14**

COUNTRY	PLANTATION AREA (000 HECTARES)	TOTAL LAND AREA (000 HECTARES)	PERCENT LAND AREA IN PLANTATIONS
Peru	103.8	130,080.6	0.1
Liberia	145.6	9,654.8	1.5
Colombia	498.6	114,403.8	0.4
Cambodia	914.6	18,245.7	5.0
Brazil	9,522.8	855,188.4	1.1
Malaysia	10,010.8	33,142.6	30.2
Indonesia	24,600.0	190,227.9	12.9
TOTAL	**45,796.2**	**1,350,943.8**	**3.4**

Source: World Resources Institute and Transparent World

Figure 5 | **Distribution of Plantation Types by Country, 2013-14**



Source: World Resources Institute and Transparent World

Distribution by Plantation Type

Colombia had the largest proportion of its plantation area in large industrial plantations (95 percent), followed by Brazil (86 percent). Liberia had the highest proportion (35 percent) of plantations recently cleared for planting, but not yet fully planted. Cambodia was the only country with more area (51 percent) in mid-sized plantations than in large industrial plantations (32 percent). Malaysia and Indonesia had similar distributions of plantation types, with the majority (57 percent) of their plantation areas in large industrial plantations, followed by mid-size plantations (25 percent and 19 percent respectively) and small mosaic plantations (5 percent and 16 percent respectively) (Figure 5). The plantation area of each country in different size plantations is shown in Table 3.

Distribution by Plantation Species

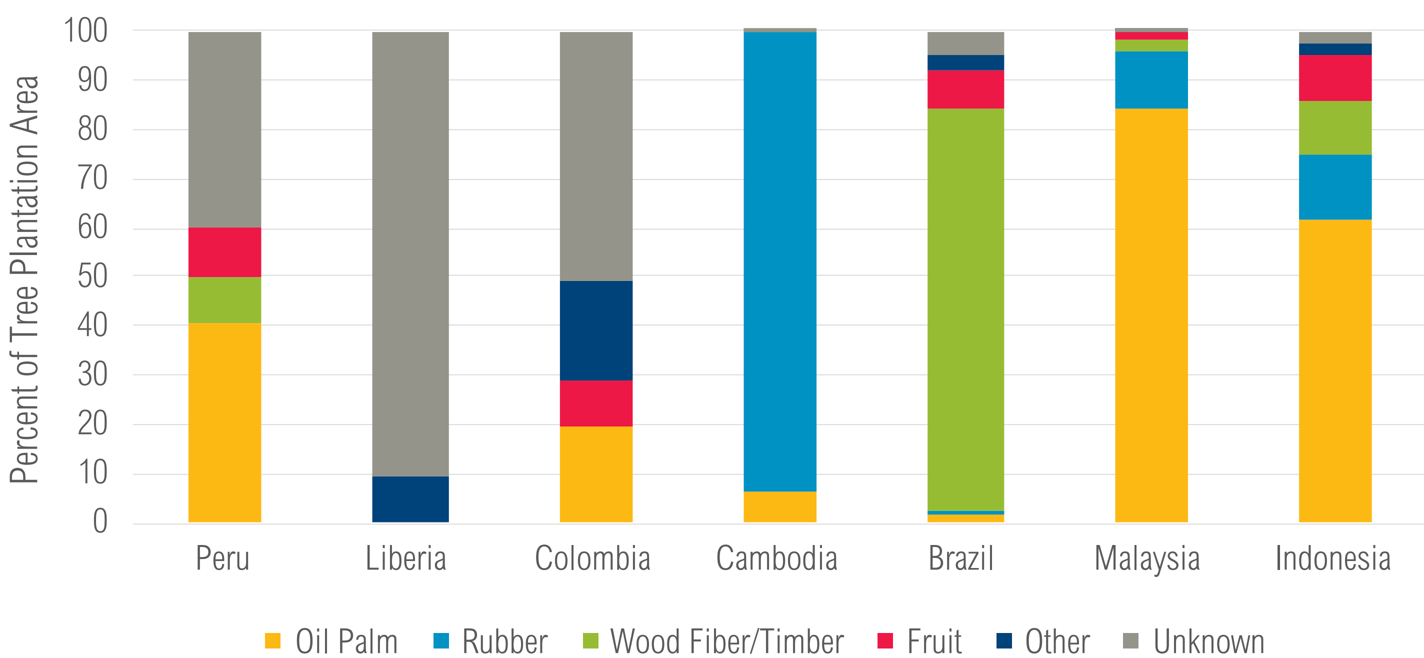
Plantations in Brazil, Cambodia, Indonesia, and Malaysia were dominated by monoculture systems. More than 80 percent of plantations in Brazil were planted with wood fiber and timber species, particularly *Acacia sp.* (Figure 6). In Cambodia, 94 percent of all mapped plantation areas were classified as rubber. In Malaysia and Indonesia, 84 percent and 62 percent of all mapped plantations were oil palm (monoculture or mixed), respectively. Oil palm was also prevalent in Latin American countries, representing 40 percent of the plantation area in Peru and 20 percent in Colombia. In Brazil the percentage of oil palm planted was much lower (1.4 percent), but the total area planted (122,900 hectares) was similar to the area planted in Peru and Colombia combined (142,900 hectares) (Table 4). In Liberia, a lack of very-high-resolution imagery, no field verification visits, and a large proportion of newly established plantations prevented species identification; 91 percent of the plantation area in Liberia was of unknown species.

Table 3 | **Distribution of Plantation Types by Country, 2013-14**

COUNTRY	LARGE INDUSTRIAL PLANTATIONS	MID-SIZE PLANTATIONS	SMALL PLANTATIONS	RECENT CLEARING FOR PLANTING	TOTAL AREA
	AREA (000 HECTARES)				
Peru	56	14	20	14	104
Liberia	94	0	0	52	146
Colombia	481	3	0	16	499
Cambodia	290	462	0	162	915
Brazil	8,563	291	19	650	9,523
Malaysia	5,659	2,477	487	1,388	10,011
Indonesia	14,122	4,741	3,929	1,808	24,600
TOTAL	**29,265**	**7,988**	**4,455**	**4,088**	**45,796**

Source: World Resources Institute and Transparent World

Figure 6 | **Percent of Tree Plantation Species by Country, 2013-14**



Source: World Resources Institute and Transparent World

Table 4 | **Area of Tree Plantation Species Mapped, 2013-14**

COUNTRY	OIL PALM	OIL PALM MIX	RUBBER	RUBBER MIX	WOOD	WOOD MIX	FRUIT	FRUIT MIX	OTHER	OTHER MIX	UNKNOWN	TOTAL
AREA (000 HECTARES)												
Peru	36	0	0	0	9	0	9	0	0	0	36	90
Liberia	0	0	0	0	0	0	0	0	9	0	86	94
Colombia	95	0	0	0	0	0	44	0	98	0	246	483
Cambodia	16	32	703	0	.2	0	0	0	0	0	1	753
Brazil	123	0	57	0	7,317	0	660	0	0	286	430	8,873
Malaysia	5,348	1,919	418	629	158	0	79	36	0	34	4	8,623
Indonesia	11,721	2,440	839	2,050	2,227	339	1,199	954	36	421	600	22,826
TOTAL	**17,338**	**4,391**	**2,018**	**2,679**	**9,712**	**339**	**1,990**	**989**	**142**	**740**	**1,403**	**41,742**

Source: World Resources Institute and Transparent World

Tree Cover Loss Within vs. Outside Plantations

As discussed earlier, current satellite-based monitoring systems cannot differentiate between natural forest conversion and tree plantation harvesting. Our efforts to map tree plantations were intended to provide contextual information to better understand when tree cover loss is occurring within plantations versus outside (in natural forests, with potentially bigger impacts on biodiversity).

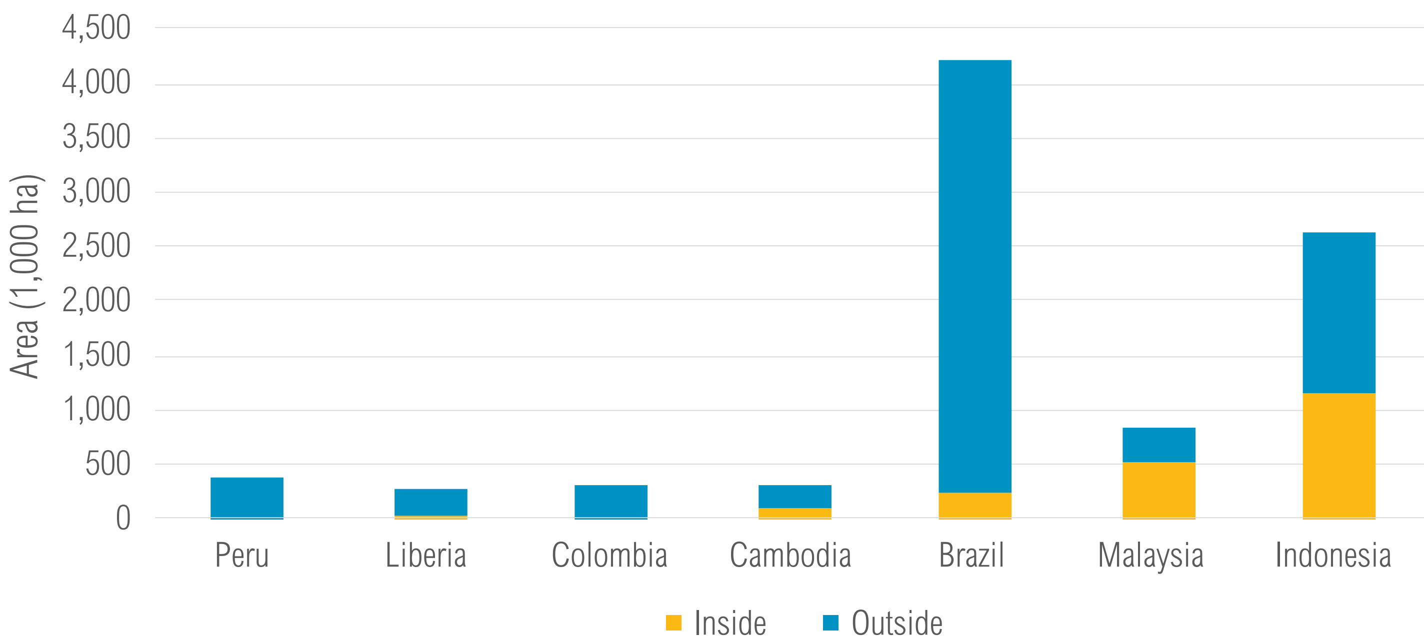
We calculated the total area of tree cover loss within vs. outside mapped plantation boundaries for the years 2013 and 2014 to match the years of the plantation data. Less than 10 percent of total tree cover loss in 2013 and 2014 occurred within plantation areas in Brazil, Peru, Colombia, and Liberia (Figure 7). In contrast, Malaysia and Indonesia had a much higher percentage of tree cover loss within mapped plantation boundaries (65 percent and 44 percent, respectively).

Accuracy Assessment

Researchers at the University of Maryland (Varada Shevade, Tatiana Loboda) conducted an independent accuracy assessment on the plantation boundaries for peninsular Malaysia. The assessment was a double-blind study using stratified, random, and nonadjacent sampling with very-high-resolution (30 centimeter) imagery from Digital Globe from the years 2013 to early 2015. The accuracy assessment covered only the presence/absence of plantations. We did not attempt to validate the map at the species level or assess the contours of individual polygons mapped. Sarawak and Sabah were not included in this assessment.

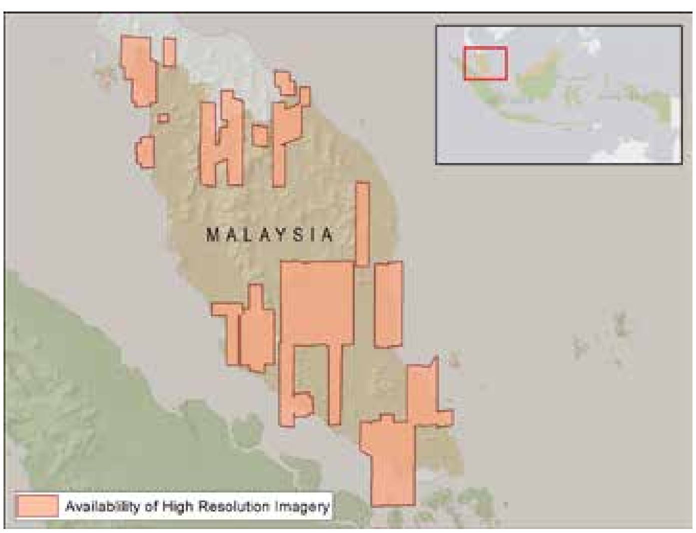
We created 1,000 stratified random points: 500 points within the plantation class and 500 points within the nonplantation class. Points were limited to the area where very-high-resolution (VHR) imagery was available (Figure 8). The points were spaced at a minimum of 100 meters away from each other to minimize the impact of adjacency on map accuracy assessment and 30 meters away from

Figure 7 | **Area of Tree Cover Loss Inside and Outside Plantation, by Country, 2013-14**



Note: Loss figures were calculated using a 30 percent minimum for tree cover canopy density.
Source: World Resources Institute and Transparent World

Figure 8 | **Available VHR Imagery for Peninsular Malaysia**



Source: World Resources Institute and Transparent World

the boundary of the plantations to allow for subpixel uncertainty in the boundary placement. VHR imagery was inspected and each point was assigned as either "plantation" or "nonplantation."

The resulting overall accuracy for peninsular Malaysia was 86.7 percent (Table 5). Producer's accuracy for the plantation class was 93.86 percent, while the user's accuracy was 78.87 percent.

Area proportions (Table 6) provide adjusted area estimates for plantation and nonplantation areas (Olofsson et al., 2014). The 95 percent confidence interval for plantation area in peninsular Malaysia is ± 284,584 hectares, meaning that based on the accuracy assessment, we can be 95 percent confident that the plantation area in peninsular Malaysia is between 4,547,893 and 5,117,060 hectares. Confidence intervals are calculated by determining the standard error of the plantation class area proportion and applying that value to the total area.

Table 5 | **Sample Data Error Matrix for Plantation Points Mapped in Peninsular Malaysia**

		REFERENCE			
		PLANTATION	NONPLANTATION	TOTAL	USER'S ACCURACY (%)
Classification	Plantation	321	86	407	78.87
	Nonplantation	21	379	400	94.75
	Total	342	465	807	
	Producer's Accuracy (%)	93.86	81.51		
	OVERALL (%)				**86.7**

Source: World Resources Institute and Transparent World

Table 6 | **Area Proportion Error Matrix for Plantations Mapped in Peninsular Malaysia**

		REFERENCE			
		PLANTATION	NONPLANTATION	TOTAL	AREA (HA)
Classification	Plantation	0.334	0.089	0.424	4,832,477
	Nonplantation	0.030	0.546	0.576	8,432,987
	TOTAL	**0.364**	**0.636**	**1.000**	**13,265,464**

Source: World Resources Institute and Transparent World

Considering the wider scope of this mapping exercise (multiple plantation species and types), the estimated accuracy of mapped plantations in peninsular Malaysia is comparable to previous studies. For example, Nooni et al. (2014) calculated an overall accuracy of 71.9 percent for their maximum likelihood classifier method used to map oil palm in Ghana; Fagan et al. (2015) estimated an overall accuracy of 88.5 percent for the multispectral model used to map tree plantations in Costa Rica.

Accuracy assessments for the remaining six countries in this study are under development. This technical note will be updated with the results from these assessments when they are available in early 2016.

DISCUSSION

In this study based on 2013 and 2014 data, we mapped 45.8 million hectares of tree plantations across seven countries, or an area slightly larger than the state of California.

The greatest plantation area, both in absolute and percentage terms, was in Indonesia and Malaysia (24.6 million hectares or 12.9 percent and 10 million hectares or 30.2 percent of land area, respectively). These two countries also had the greatest proportion of total tree cover loss in 2013–14 within plantation boundaries (55 percent and 65 percent respectively). This suggests that much of the tree cover loss detected by the University of Maryland Google data in these two countries is not deforestation (permanent conversion of forest to nonforest land) but rather the harvesting of tree plantations. However, more detailed investigation of satellite imagery would be required to determine if the loss was in fact due to harvesting of plantations planted before 2000, or if the loss represents recent clearing of natural forests to make way for plantations.

Less than 10 percent of total tree cover loss detected in 2013–14 occurred within plantation areas in Brazil, Peru, Colombia, and Liberia. This indicates that the majority of tree cover loss detected in these countries is likely loss of natural forests. Additional contextual datasets, such as primary forest maps, can help better understand the land-use-change dynamics outside plantations.

Limitations

While these data represent the best available maps of all tree plantations across multiple countries, key limitations include:

- **EXPANSION RATES.** This dataset provides a valuable snapshot of land composed of plantations, but does not indicate rates of expansion. While several other studies (Carlson et al., 2012; Gunarso et al., 2013; Gutiérrez-Vélez et al., 2013; Koh, Miettinen, Liew, and Ghazoul, 2011; Miettinen et al., 2012) used historical imagery to quantify the expansion of plantations, we did not attempt to map the change in areas covered by plantations over time.
- **UNMAPPED DETAIL IN MOSAIC PLANTATIONS.** It was not possible to delineate individual planted areas within small and medium mosaics. These boundaries indicate our best effort to map landscapes in which more than 50 percent of area is covered by tree plantations. It is thus not possible to identify if tree cover changes within mosaic type plantations are occurring within or outside planted areas. The percent planted indicated in the attribute data represents the best approximation of the analysts.
- **LABOR-INTENSIVE METHODS.** As discussed earlier, no fully automated classification systems currently exist to reliably differentiate natural from plantation forests of all species at scale. While the approach of this study (visual delineation) may not be as systematic as desired, it does account for the reality of complex landscapes that do not exhibit distinct boundaries between one land cover category and the next.
- **POTENTIAL FOR DEFINITION CONFUSION.** The remote-sensing-based definitions used to classify plantations by type could be mistaken for policy definitions relating to ownership and management. These maps should not be considered as proxies for which plantation areas are owned or managed by smallholders versus large industrial companies, as we were able to indicate only the size of polygons and did not determine the entities managing them.

Limitations of the accuracy assessment include:

- **USE OF POINTS FOR VALIDATION.** Validation points that fall on or adjacent to infrastructure present within plantation boundaries, such as roads or buildings, may have been assigned to the nonplantation class during validation.
- **MOSAIC PLANTATION DEFINITION.** The definition which includes areas with at least 50 percent plantation area, but can also include other land uses. A validation point could have fallen on a nonplantation land use within a mosaic and been assigned as the nonplantation class during validation. Mosaic plantations make up 30 percent of plantations mapped in Malaysia and this type class may have contributed to lower accuracy numbers.
- **SPECIES AND TYPE CATEGORY ASSESSMENT.** The accuracies of the species and type categories were not assessed. These attributes also represent best approximations by analysts and should not be used for official purposes. The species-type classifications are likely most reliable in countries where field data were collected (Indonesia, Malaysia, and Brazil). Smaller areas within mosaic plantations cannot be attributed to any particular species; rather, the dataset identifies only the presence of a species within the general area.

The maintenance of this dataset is particularly important to understand how tree plantations expand and contract in each of these tropical countries. Future tree cover change within the mapped plantation areas indicates tree harvesting, replanting, or land-use change; tree cover loss outside these areas could indicate loss of natural forests, as well as harvesting of newly-established plantations. Given the time-intensive nature of visual delineation, it is unlikely that these maps will be reproduced often without an advanced automated algorithm. Further research is needed to identify unique spectral signatures and/or automated methodologies that can reduce the time and cost of updating and expanding the datasets.

In addition to frequent updates, we would also ideally extend coverage of plantation boundaries to other countries to better understand the dynamics of tree cover loss across the globe. Testing of automated methodologies would need a regional focus to determine the best methods for different areas. Finally, the availability of more high-resolution imagery from various sources would allow greater certainty and specificity of species and type classifications.

CONCLUSION

In this study, we mapped tree plantations across seven tropical countries using satellite imagery captured in 2013 and 2014. These maps advance existing efforts to differentiate land use by identifying multiple plantation types, their extents and species. However, this is the first study to map multiple species across multiple countries, and to examine tree cover loss inside and outside of those plantations using a consistent approach.

These maps could be useful in several policy applications, including:

1. Refining estimates of carbon emissions from tropical deforestation
2. Monitoring commodity supplier activity
3. Overlaying plantation boundaries with legal concession boundaries to assess compliance
4. Land-use planning to determine where production is best suited and where natural forest should remain or be restored

These data represent a critical advance toward better differentiation between loss and regeneration of natural forests from tree plantation harvesting cycles. Accurate maps of tree plantations, combined with global tree cover change products, can help these countries monitor future plantation activity, and assess the efficacy of policy mechanisms to guide the expansion of industrial tree plantations into nonforest ecosystems. This will become more important as tropical countries balance the need for increased food, fuel, and fiber production with the need to reduce greenhouse gas emissions from land-use-change.

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Alexander Zudkin, GIS specialist, Greenpeace Russia

ABOUT THE AUTHORS

Rachael Petersen is a Research Analyst with Global Forest Watch at the World Resources Institute, USA.
Contact: RPetersen@wri.org

Dmitry Aksenov is Director General of Transparent World, Russia.
Contact: picea2k@gmail.com

Elena Esipova is Head of the Land Cover Thematic Interpretation Department at Transparent World, Russia.
Contact: lemna.minuta@gmail.com

Elizabeth Goldman is a Research Analyst with Global Forest Watch at the World Resources Institute, USA.
Contact: EGoldman@wri.org

Nancy Harris is Research Manager with Global Forest Watch at the World Resources Institute, USA.
Contact: NHarris@wri.org

Natalia Kuksina is Deputy Head of the Land Cover Thematic Interpretation Department at Transparent World, Russia
Contact: nkuksina@gmail.com

Irina Kurakina is a Lead Specialist at Transparent World, Russia
Contact: ezovitova@gmail.com

Tatiana Loboda is an Associate Professor in the Department of Geographical Sciences of the University of Maryland at College Park.
Contact: loboda@umd.edu

Alexander Manisha is Head of the Land-Use Monitoring Department at Transparent World, Russia.
Contact: Alexander.manisha@gmail.com

Sarah Sargent is a Research Analyst with Global Forest Watch at the World Resources Institute, USA.
Contact: SSargent@wri.org

Varada Shevade is a PhD student in the Department of Geographical Sciences of the University of Maryland at College Park.
Contact: vshevade@umd.edu

ABOUT WRI

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Our Challenge
Natural resources are at the foundation of economic opportunity and human well-being. But today, we are depleting Earth's resources at rates that are not sustainable, endangering economies and people's lives. People depend on clean water, fertile land, healthy forests, and a stable climate. Livable cities and clean energy are essential for a sustainable planet. We must address these urgent, global challenges this decade.

Our Vision
We envision an equitable and prosperous planet driven by the wise management of natural resources. We aspire to create a world where the actions of government, business, and communities combine to eliminate poverty and sustain the natural environment for all people.

Our Approach
COUNT IT
We start with data. We conduct independent research and draw on the latest technology to develop new insights and recommendations. Our rigorous analysis identifies risks, unveils opportunities, and informs smart strategies. We focus our efforts on influential and emerging economies where the future of sustainability will be determined.

CHANGE IT
We use our research to influence government policies, business strategies, and civil society action. We test projects with communities, companies, and government agencies to build a strong evidence base. Then, we work with partners to deliver change on the ground that alleviates poverty and strengthens society. We hold ourselves accountable to ensure our outcomes will be bold and enduring.

SCALE IT
We don't think small. Once tested, we work with partners to adopt and expand our efforts regionally and globally. We engage with decision-makers to carry out our ideas and elevate our impact. We measure success through government and business actions that improve people's lives and sustain a healthy environment.