WORLD RESOURCES INSTITUTE

TECHNICAL NOTE

ESTIMATING THE ROLE OF SEVEN COMMODITIES IN AGRICULTURE-LINKED DEFORESTATION: OIL PALM, SOY, CATTLE, WOOD FIBER, COCOA, COFFEE, AND RUBBER

ELIZABETH GOLDMAN, MIKAELA J. WEISSE, NANCY HARRIS, AND MARTINA SCHNEIDER

1. OVERVIEW

While agriculture is generally recognized to be a major driver of deforestation (e.g., Geist and Lambin 2002; Hosonuma et al. 2012; Curtis et al. 2018), few studies have attempted to estimate the role that particular commodities play in global deforestation, and even fewer have been spatially explicit. In this analysis, we estimate the extent to which seven commodities—oil palm, soy, cattle, plantation wood fiber, cocoa, coffee, and plantation rubber—are replacing forests, and map their impacts using the best available spatially explicit data. We report results for these seven commodities globally at the second administrative level (e.g., county, municipality, or other administrative subdivision, depending on the country), though the methods are flexible and could be applied to other commodities and geographic scales of analysis. To identify the specific commodities that have replaced forested land, we analyzed the overlap of current commodity extent with global annual tree cover loss from 2001 to 2018. We used recent, detailed crop and pasture maps for relevant regions and commodities where available, and supplemented them with coarser resolution global data where needed.

CONTENTS

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

Suggested Citation: Goldman, E., M.J. Weisse, N. Harris, and M. Schneider. 2020. "Estimating the Role of Seven Commodities in Agriculture-Linked Deforestation: Oil Palm, Soy, Cattle, Wood Fiber, Cocoa, Coffee, and Rubber." Technical Note. Washington, DC: World Resources Institute. Available online at: wri.org/publication/estimating-the-role-of-seven-commodities-in-agriculture-linked-deforestation.

2. DATA AND METHODS

Our approach for estimating direct deforestation impacts for the seven commodities of interest was to identify where the extent of each commodity overlaps spatially with annual tree cover loss data. To accommodate the fact that certain commodities of interest have a wealth of spatial data available for particular regions while others do not, we designed two methodological approaches. The first, more-detailed approach uses recent high-resolution spatial data on the extent of each commodity where available overlaid with previous tree cover loss. The second, coarser approach applies to those areas and commodities where detailed data are not available, and uses global, 10-kilometer-resolution datasets on the extent of each commodity to allocate tree cover loss to particular commodities. The two approaches are compared in Section 3.1 for commodities and regions where both coarse and detailed data are available.

2.1 Data

2.1.1 Deforestation data

We used the Hansen et al. (2013) tree cover extent and annual tree cover loss datasets to estimate deforestation between 2001 and 2018. We considered tree cover losses only in areas with at least 30 percent tree canopy cover for most analyses, as that matches the default statistics presented by Global Forest Watch. For the detailed soy and pasture analyses, we used a tree cover canopy density of 10 percent to better capture the conversion of less-dense woody vegetation in South American biomes such as the Chaco and Cerrado, which have faced widespread deforestation for commodity expansion. The tree cover loss dataset measures the first instance of complete removal of tree cover canopy at a 30-meter resolution for all woody vegetation over 5 meters in height.

We purposefully use the term "deforestation" throughout this analysis rather than "tree cover loss" as we assume that any former area of tree cover now occupied by one of the seven analyzed commodities represents a human-caused, permanent change in land use. The tree cover data do include tree plantations and agricultural tree crops, and some of the tree cover loss data used here may include harvesting cycles of plantations established as tree cover before the year 2000.[1] We mitigated the impact of plantation harvesting cycles where possible by excluding areas of known tree plantations as of the year 2000 (e.g., see the oil palm methods within Section 2.2.1). Overall, the harvesting of plantations made up only 8 percent of all tropical tree cover loss from 2013 to 2019.[2]

The coarse analysis also used the Curtis et al. (2018) dataset on tree cover loss by dominant driver to identify areas where agricultural activity is driving loss. The dataset assigns the dominant driver of tree cover loss from 2001 to 2018 at a 10-kilometer resolution using decision tree models, classifying tree cover loss occurring in each grid cell as either commodity-driven deforestation, shifting cultivation, forestry, wildfire, or urbanization. This analysis focuses on areas assigned to the commodity-driven deforestation class, which identifies areas of large-scale deforestation linked to commercial agricultural expansion, and areas assigned to the shifting agriculture class, which identifies temporary loss or permanent deforestation due to small- and medium-scale agriculture. The Curtis et al. (2018) dataset was updated from the original 2001–2015 time period to reflect additional loss and fire information for the years 2016–18 and now identifies the dominant driver of tree cover loss from 2001 to 2018.

2.1.2 Commodity extent data

We used several global crop extent datasets for the coarse approach, and many regional datasets for the detailed approach (summarized in Table 1).

The detailed analyses used a variety of best available spatially explicit datasets on the extent of soy, pasture, oil palm plantations, rubber plantations, and wood fiber plantations. All oil palm, rubber, and wood fiber data were extracted from the Spatial Database of Planted Trees (SDPT), which is a compilation of the best available spatially explicit plantation data (Harris et al. 2019). Except for oil palm, which has a global extent, all detailed datasets are limited in geographic scope and include only a subset of countries. This is particularly important for rubber and wood fiber, which have no available global spatial data to approximate outside of these areas using the coarse method. All detailed data sources are summarized in Table 1, including the original SDPT sources.

For the coarse approach covering those areas without detailed data, we used crop and pasture datasets from MapSPAM and EarthStat, respectively, to estimate the spatial distribution of each commodity of interest, with additional information from Gilbert et al. (2018) used to further filter pasture areas to those used specifically for cattle. The MapSPAM data are global, 10-kilometer-resolution maps of crop area for 42 crops in the year 2010 (Wood-Sichra et al. 2016). The data combine country and subnational reported production statistics, an agriculture land cover map and crop-specific suitability information, and biophysical limitations (based on climate, landscape, and soil conditions) into a model that identifies each crop's maximum potential, biophysically attainable crop yields, and suitable crops areas (IIASA and FAO 2012). The output is mapped with 10-kilometer grid cells of estimated area for each of the 42 crops, further broken into physical area and harvested area of irrigated high input, rainfed high input, rainfed low input, and rainfed subsistence crops. Subsistence farming is assumed to happen more intensively in areas with large rural populations, so rural population density from the Global Rural-Urban Mapping Project (GRUMPv1) helps to further identify subsistence farming (Balk et al. 2006).

The EarthStat pasture dataset similarly maps the proportion of pasture land extent at a 10-kilometer resolution using a combination of spatial data and national-level statistics for the year 2000 (Ramankutty et al. 2008). The data use the Food and Agriculture Organization of the United Nations' (FAO's) definition of pasture: land used permanently (five years or more) for herbaceous forage crops, either cultivated or growing wild. Agricultural inventory data from a variety of sources, including national statistics and FAO's FAOSTAT, were modeled onto Land Use/Land Cover maps of pasture derived from MODIS and SPOT Vegetation imagery. There are some known inconsistencies in the inventory data used, as some countries distinguish between grassland pasture and grazed land in their reporting, while most do not.

Gilbert et al. (2018) maps global livestock distribution from the year 2010 at a 10-kilometer resolution using subnational livestock distribution data. We used the dasymetric weighting version of the cattle density data, which disaggregates livestock census data based on weights derived from statistical models (instead of distributing them homogeneously) to minimize inclusion of pasture used for other grazing livestock, such as sheep or goats. Otherwise, we assumed clearing for pasture is linked to cattle, which can include the production of beef, dairy, and leather goods.

2.2 Methods

2.2.1 Detailed Approach Method

For commodities and regions where detailed spatially explicit extent data are available, we calculated tree cover loss within the latest available extent of the commodity using the following method:

1. **Assemble detailed and/or higher-resolution crop extent data**. See the oil palm, soy, wood fiber, and rubber sections below for more detail.
2. **Calculate forest area replaced by specific commodities**. Annual tree cover loss from 2001 to 2018 (Hansen et al. 2013) was calculated in the detailed commodity extent boundaries using a geodesic area method. Geodesic area calculations help account for area distortions that occur further away from the equator. All loss that occurred before the date of the commodity extent map was allocated to that commodity. Any loss that occurred after was not. Some of the results for recent years are less certain due to lags between the deforestation event and crop establishment or maturity—those areas are marked with dashed lines in the results (see Section 2.3). We also estimate the "direct" conversion of forests to oil palm and soy, which both have time series of extent, by limiting the number of years between loss and the commodity expansion (see the oil palm and soy sections below).
3. **Aggregate results to the second administrative level**. Report total forest area replaced by individual commodities at the second administrative level to allow for subnational, granular detail. Results can also be aggregated to the state/province, country, or global level as well, or viewed as individual 30-meter pixels.

OIL PALM

The detailed oil palm approach combined several datasets (see Table 1) to form a global oil palm plantation map. Oil palm plantation expansion datasets for various regions of Indonesia and Malaysia were combined to produce a comprehensive expansion map, in roughly five-year intervals, from 1990 to 2018. To create the expansion map, we began with Miettinen et al. (2016) industrial oil palm plantations on peat soils, then added plantations not already included,

Table 1 | **Datasets of Commodity Extent Used in This Analysis**

COARSE METHOD				
CROP	SOURCE	RESOLUTION	YEAR	SCALE
Cocoa, coffee, soy, oil palm	MapSPAM (Wood-Sichra et al. 2016)	10 kilometer	2010	Global
Pasture	EarthStat (Ramankutty et al. 2008)	10 kilometer	2000	Global
	Gilbert et al. 2018	10 kilometer	2010	Global
DETAILED METHOD				
CROP	SOURCE	RESOLUTION	YEAR	SCALE
Oil palm	Austin et al. 2017	Vector	1990, 1995, 2000, 2005, 2010, 2015	Indonesia
	Furumo and Aide 2017	250 meter	2014	Costa Rica, Ecuador, Guatemala, Mexico, Nicaragua, Panama, Venezuela
	Gaveau et al. 2014	Vector	1970, 1990, 1995, 2000, 2005, 2010, 2015	Sabah and Sarawak in Malaysia
	Gunarso et al. 2013	Vector	1990, 2000, 2005, 2010	Peninsular Malaysia
	Harris et al. 2019	Vector	2015	Dominican Republic, Gabon, Ghana, Ivory Coast, Madagascar, Nigeria, Sierra Leone, Solomon Islands, Sri Lanka, Thailand
	Miettinen et al. 2016	Vector	1990, 2000, 2007, 2010, 2015	Borneo, Peninsular Malaysia, Sumatra
	New Britain Palm Oil Ltd.[a]	Vector	2015	Papua New Guinea
	Orbital Insight 2018	2.5 meter	2017/2018	Cambodia, Colombia, Guatemala, Honduras, Indonesia, Liberia, Papua New Guinea, Peru, Malaysia
	Petersen et al. 2016	Vector	2013/2014	Brazil, Cambodia, Colombia, Indonesia, Liberia, Malaysia, Peru
	Roy et al. 2015	23.5 meter	2015	India
Soy	Song et al. in preparation	30 meter	2001–2018	South America
Pasture	LAPIG 2019	30 meter	2018	Brazil
Wood fiber	Atlas of Forest Resources of China[a]	1 kilometer	2004–08	China
	Government of Rwanda[a]	Vector	2008	Rwanda
	Government of Vietnam[a]	2.5 meter	2016	Vietnam
	Korean Forest Service[a]	Vector	Unknown	South Korea
	Ministry of Production and Labor[a]	30 meter	2013	Argentina
	Petersen et al. 2016	Vector	2013/2014	Brazil, Cambodia, Indonesia, Malaysia
	Roy et al. 2015	23.5 meter	2015	India
Rubber	Ministry of the Environment, Nature Conservation, and Sustainable Development[a]	Vector	2013	Democratic Republic of the Congo
	Ministry of Forestry and Wildlife and WRI[a]	Vector	Unknown	Cameroon
	Petersen et al. 2016	Vector	2013/2014	Brazil, Cambodia, Indonesia, Malaysia
	Roy et al. 2015	23.5 meter	2015	India

Note: [a.] More information about these datasets and their access is available in Harris et al. (2019).

but mapped by Austin et al. (2017), Gaveau et al. (2014), and Gunarso et al. (2013). To reduce double coverage, we used Austin et al. (2017) for Indonesia; Gaveau et al. (2014) for Sarawak and Sabah, Malaysia; and Gunarso et al. (2013) for Peninsular Malaysia. Data were included based on spatial coverage and recency. Finally, Petersen et al. (2016) and Orbital Insight data were also used in Indonesia and Malaysia to add plantations not covered in any of the above data, which include only industrial oil palm until 2015. Petersen et al. (2016) include small-to medium-size oil palm plantations, and Orbital Insight includes plantations through 2018.

Combining maps compounds commission errors associated with each map individually, but the total area of oil palm plantations among different maps for the same regions and years were generally consistent. Some portions of datasets were not included to avoid this issue (for example, Gaveau et al. [2014] also mapped plantations in Kalimantan, Indonesia, but they were not included because the data were already fully covered by Austin et al. [2017]). Coverage is also not complete through the entire time series for all regions, but this combined map is assumed to include the most comprehensive spatially explicit data available on oil palm expansion across Southeast Asia since the year 2000, and the most comprehensive spatially explicit global dataset when combined with all other sources (see Table 1).

The oil palm expansion map was then overlaid with the tree cover loss data as described above. Since the tree cover loss data used in this analysis may include plantation harvesting dynamics, we excluded areas of existing oil palm plantations from 2000 or earlier to reduce the likelihood of misclassifying oil palm harvest as forest loss. Only areas of tree cover loss prior to the oil palm plantations' establishment (as identified in the above datasets) were considered. For areas outside Indonesia and Malaysia, we assumed little oil palm plantation establishment prior to the year 2000 and allocated any loss in plantation boundaries to oil palm.

We also attributed direct conversion of forests to oil palm by analyzing loss in the four years prior to the date of a known new oil palm plantation, which is the time needed to confidently identify oil palm trees in imagery after planting (Austin et al. 2019). Oil palm plantations established more than four years after the loss event may have first experienced a different land use before becoming an oil palm plantation.

SOY AND PASTURE

For soy, we used a baseline year of 2000 and combined annual 30-meter soy data as mapped by Song et al. (in preparation) to produce a soy expansion map.[3] Any forest loss that occurred after 2000 and before the establishment of the soy in that pixel was considered forest replacement by soy. Because soy often replaces pasture land, we also estimated the area of forest directly converted to soy by analyzing any loss within three years of soy establishment.

Pasture extent was mapped by LAPIG for the year 2018 in Brazil (see Table 1) and all tree cover loss occurring between 2001 and 2018 that overlapped the pasture extent was attributed to pasture. Any forests replaced by pasture were assumed to be for cattle grazing, which can be for the production of beef, dairy, or leather goods.[4] Results are presented for cattle, and are derived from this assumption about pasture.

For both pasture and soy, we used a 10 percent tree canopy threshold to calculate tree cover loss statistics, rather than 30 percent. This was done to better capture loss in dry and woody savannah areas, such as the Cerrado and Chaco, which are often excluded when looking at tree canopy density with a 30 percent threshold but are important sourcing areas for these two commodities.

WOOD FIBER AND RUBBER

Maps of wood fiber and rubber plantations are available only for select countries (for rubber: Brazil, Cambodia, Cameroon, Democratic Republic of the Congo, India, Indonesia, and Malaysia; for wood fiber: Argentina, Brazil, Cambodia, China, India, Indonesia, Malaysia, Rwanda, South Korea, and Vietnam). These datasets are known to be incomplete. Countries included in the rubber plantation dataset account for only 40 percent of global rubber production, with Thailand, Vietnam, and China being important missing countries (FAO 2020). The wood fiber plantation dataset is also incomplete, but the most important missing countries that are important global sources of wood fiber production—the United States, Canada, and Sweden—have declined or remained consistent in their production of wood fiber over the past 20 years and are unlikely to have undergone recent land use changes to establish new wood fiber plantations (FAO 2020).

Importantly, this analysis considered forest replacement by only *plantations* of wood fiber and rubber, not any of these products that may be harvested from within existing forests. We did not attempt to estimate the impact on forests of selective logging, jungle rubber, or other forestry practices though these are also important and widespread in certain areas. Selective logging in particular causes widespread forest degradation in the tropics, and roads and infrastructure for logging can provide increased access to remote forest areas.

Unlike for oil palm and soy, determining the year wood fiber and rubber plantations were established is not possible because, to our knowledge, there are not multitemporal datasets for wood fiber and rubber plantation extent. Therefore, any tree cover loss occurring in these plantation areas prior to 2015, the latest year for which plantation data are available, was assumed to be these commodities replacing forests. This assumption may result in an overestimation of forests replaced by wood fiber and rubber plantations if tree cover loss was associated with plantation harvest dynamics rather than plantations replacing natural forests. While some of the individual country data are from before 2015, an analysis of loss attributed to before versus after the country's data creation year reveals that only 5 percent of rubber and wood fiber loss occurred after the creation year.

2.2.2 Coarse Approach Method

For commodities and areas where detailed data are not available, we relied on a coarse approach to allocate tree cover loss to different commodities based on the proportion of agricultural area they occupy within 10-kilometer grid cells (to match the resolution of the MapSPAM and EarthStat datasets). Results using the coarse approach are presented for cocoa, coffee, soy outside of South America, and pasture outside of Brazil. We also analyzed oil palm, soy in South America, and pasture in Brazil to compare the coarse and detailed approaches (see Section 3.1).

This allocation approach estimates deforestation based on three assumptions:

1. That all tree cover loss in the grid cell is due to agricultural expansion (approximated by the use of the Curtis et al. [2018] dataset)
2. That the proportion of loss related to a specific crop is the same as the proportion of that crop's physical area compared with the total area of all crops and pasture in the grid. For example, if 25 percent of a grid cell's agriculture area is soy, we assumed 25 percent of the replaced forests in that grid cell were replaced by soy. In reality, some or all of the soy area may occur on land that did not recently have forest or may have been established before our analysis period, but we have no way of knowing this based on the available coarse data.
3. That the proportion of that crop compared with other agricultural land has not significantly changed over time since the date for the crop data (2010 for MapSPAM, 2000 for EarthStat). For example, if 25 percent of a grid cell's agricultural area is soy based using MapSPAM data from 2010, we assumed no expansion or contraction of the proportion of soy extent through time and that 25 percent of the forest loss in every analysis year can be allocated to soy.

We used the following methods for the coarse approach:

1. **Filter tree cover loss to areas where agriculture is the dominant driver**. We included in the analysis only those 10-kilometer grid cells overlapping areas where commodity-driven deforestation and shifting agriculture were the dominant drivers of tree cover loss, as defined by the Curtis et al. (2018) dataset. This constrained the analysis to areas where crop agricultural production is the dominant driver of tree cover loss.
2. **Calculate total tree cover loss linked to agriculture**. Annual tree cover loss from 2001 to 2018 (Hansen et al. 2013) was calculated in each grid using a geodesic area method. Geodesic area calculations help account for area distortions that occur further away from the equator.
3. **Calculate the proportion of total agricultural land used for each commodity**. The total physical area of cocoa, arabica coffee, robusta coffee, and soy was derived from the MapSPAM data. We did not include any area of those crops that was considered "rainfed subsistence" given the focus on commodity production. The total physical area of pasture in each grid cell was derived from the EarthStat dataset. We also summed the total physical area of all crops and pasture for each cell using a combination of the MapSPAM and EarthStat data, and then divided the physical area of each crop by the total physical area to derive the proportion of the grid cell's agricultural land planted with that crop. Physical crop area, as opposed to harvested area, was used to estimate the total land occupied by each crop, and to avoid double counting areas with more than one crop harvest per year or undercounting crops that may not be completely harvested in a single year.

4. **Remove non-cattle-related pasture.** We identified pasture areas in the EarthStat map that had fewer than 100 head of cattle per 10-kilometer grid cell using Gilbert et al. (2018) and removed those areas from the calculation for pasture.
5. **Estimate the total agriculture-linked tree cover loss on land used for each commodity**. The annual tree cover loss in each grid cell (in hectares) was multiplied by the proportion of agricultural land used for each crop to estimate the area of forest replaced by that crop each year in each grid cell (Figure 1).
6. **Aggregate results to the second administrative level**. We report total forest area replaced by individual commodities at the municipality scale to allow for granular subnational detail if needed. Results can also be aggregated to the state/province, country, or global level or as individual 10-kilometer grid cells.

2.2.3 Combining results

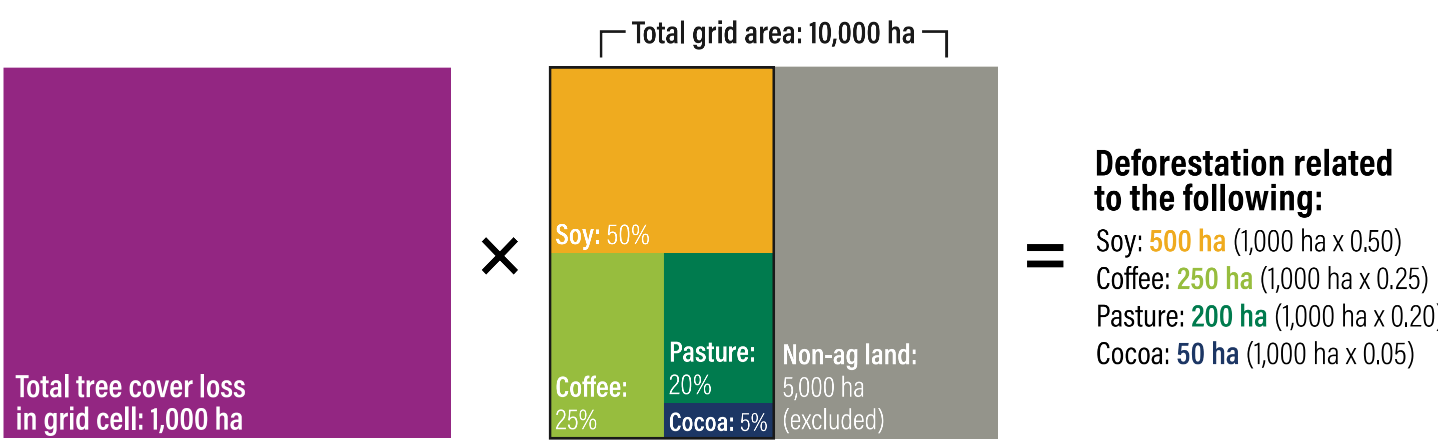
The results presented below use a combination of the detailed and coarse approaches. Where possible, we used results from the detailed approach, as we assume these are more accurate. Commodities and regions without detailed data are supplemented with data from the coarse approach. Table 2 shows which approach was used for which commodities.

The coarse approach was also performed for oil palm, South American soy, and Brazilian pasture to compare the detailed and coarse approaches (see Section 3.1), but is otherwise not presented as part of the results.

2.3 Accounting for production and other forms of lag

Our results cover the years 2001–2018 (with the exception of wood fiber and rubber, which have data available only through 2015). However, for each commodity, we assigned a "latest confident year" to our results, which identifies the latest year through which we are confident that the trend of forest replacement by that commodity is valid (Table 3). After this year, tree cover loss estimates for later years should be considered preliminary. This is because for some commodities, there is likely a time lag between the year in which deforestation occurs and the year that the commodity is established as part of the new agricultural land use. For example, oil palm trees do not reach maturity until at least three years after planting (Descals

Figure 1 | **Illustrative Example Outlining the Coarse Approach to Allocating Tree Cover Loss to Different Commodities in Areas without Detailed Maps**



Notes: This figure illustrates the "coarse" approach to allocating tree cover loss to commodities based on the proportion of the total agricultural area that they occupy within 10-kilometer grid cells. In this example, the total tree cover loss within a grid cell dominated by agricultural activity, as identified by Curtis et al. (2018), is calculated to be 1,000 hectares. The proportion of the area for each crop out of the total area of all crops and pasture is calculated and multiplied by the loss. In this example, soy represents half of the agricultural area in the cell, and so half of the total tree cover loss is allocated to soy. Ha stands for hectares, "ag" for agricultural.

Source: Authors.

et al. 2019), which can lead to an underestimation of forest replacement by oil palm in recent years because oil palm planted right after deforestation may not yet be large enough to appear in oil palm plantation extent data. Crop cycles may also result in a lag between deforestation and planting, such as for soy, which is generally planted only after two years of rice crops (Rudorff et al. 2012). Therefore, forest replacement by these commodities in later years may increase as the analysis is updated with new years of data.

Time lags in attributing deforestation can also occur due to land use change transitions that follow more complex trajectories than forest conversion to a single type of crop. For example, forests can be cleared first for pasture, sometimes for speculative purposes or to claim ownership of the land, and later transition from pasture into soy production. In Brazil, up to 80 percent of new cropland has been shown to expand into land that was previously pasture (Zalles et al. 2019). Those areas that have not yet transitioned may result in additional areas of specific crops replacing forests in future iterations of this analysis, or decreases in the case that the crop is replaced by something else. For oil palm and soy, where detailed time series data are available, we also estimate direct deforestation for those commodities, defined as when oil palm establishment occurs within four years of deforestation, or when soy establishment occurs within three years of deforestation. These cut-offs were chosen specifically to match other studies (e.g., Austin et al. 2019; Song et al. in preparation).

Table 2 | **Approach Used for Various Regions for Each of the Seven Analyzed Commodities**

COMMODITY	DETAILED APPROACH	COARSE APPROACH
Oil palm	Global	None
Soy	South America	Outside South America
Cattle	Brazil	Outside Brazil
Wood fiber	Argentina, Brazil, Cambodia, China, India, Indonesia, Malaysia, Rwanda, South Africa, and Vietnam	None
Cocoa	None	Global
Coffee	None	Global
Rubber	Brazil, Cambodia, Cameroon, Democratic Republic of the Congo, India, Indonesia, and Malaysia	None

Source: Authors.

Table 3 | **Latest Confident Year in Attributing Forest Replacement to Specific Commodities Due to Lag Times for Analyzed Commodities**

COMMODITY	LATEST CONFIDENT YEAR	RATIONALE
Oil palm	2015	Accounts for the three years needed for oil palm to reach maturity and be detected by latest available data (2018)
Soy	2016	Allows for two years of rice or other crops before the establishment of soy
Cattle	2016	Allows for potential lags and temporal mismatches between loss and pasture data
Wood fiber	2015	Cuts off data at latest available dataset
Cocoa	2018	Assumptions apply for all years, so including through the latest year of loss data
Coffee	2018	Assumptions apply for all years, so including through the latest year of loss data
Rubber	2015	Cuts off data at latest available dataset

Note: The "latest confident year" is the latest year through which we are confident that the trend of forest replacement by that commodity is valid.

Source: Authors.

3. RESULTS

Over the period 2001–2015, cattle, oil palm, soy, cocoa, coffee, wood fiber, and rubber accounted for 58 percent (71.6 million hectares) of all agriculture-linked deforestation (123 million hectares), as calculated by the Curtis et al. (2018) driver dataset. Of the seven commodities analyzed, cattle replaced the most forest by far (63 percent of all analyzed commodities)—pasture grazed by cattle occupies some 45.1 million hectares of land deforested between 2001 and 2015 (Table 4). Oil palm replaced the second-highest amount of forest (10.5 million hectares), followed by soy (8.2 million hectares), then cocoa, plantation rubber, plantation wood fiber, and coffee (each around 2 million hectares), though the analyses for rubber and wood fiber cover only select countries with plantations data likely resulting in an underestimation for those commodities. The remaining 42 percent of agriculture-linked tree cover loss includes small amounts of loss linked to a wide variety of other crops, as well as subsistence agriculture.

Year-on-year deforestation on land now occupied by cocoa and coffee increased over time, while that for oil palm, soy, rubber, and wood fiber has decreased in recent years, with little change over time for cattle (Figure 2). Geographic hot spots also varied widely for each commodity (Figure 3). Cattle had the widest geographic range of forest replacement, with hot spots in South America. Oil palm and soy were more geographically concentrated, with hot spots in Southeast Asia and South America, respectively. Cocoa and coffee were more geographically dispersed, although cocoa contributed to a higher proportion of total tree cover loss in West Africa.

3.1 Method Comparison

For those commodities and geographies where both global and detailed data are available (oil palm globally, soy in South America, and pasture in Brazil), the results of both approaches can be compared to examine how well the assumptions and data used in the coarse approach match the detailed results (Figure 4). The coarse approach underestimated the results from the detailed approach by 10 percent for oil palm and 40 percent for soy, but the two were very close for pasture (coarse approach 0.5 percent lower). The underestimation for soy and oil palm may be a result of the assumptions in the coarse method. If these commodities systematically account for a greater proportion of deforestation in each 10-kilometer grid cell than their proportion of agricultural lands, then there will be an underestimation. The temporal trend for detailed and coarse analyses largely matched throughout the time series, though this is not surprising given that both approaches use the same tree cover loss data. The oil palm results show a similar trend in 2001–2013, but diverge in 2014 and 2015. This is likely because decreases in oil palm plantation expansion after 2013 (similarly detected in Austin et al. [2019] and Gaveau et al. [2018]) would not be detected in the global MapSPAM data dating from 2010.

The relative consistency between the results using the two methods suggests that the coarse method can provide reasonable estimates of forest area replacement when detailed data are unavailable. However, the oil palm example in particular shows that changes in trends throughout the time series are not well captured by the coarse approach. Having multiple time steps of the coarse data from MapSPAM and EarthStat would likely help alleviate this problem.

Table 4 | **Total Forest Area Replaced by Analyzed Commodities, 2001–2015**

COMMODITY	DEFORESTATION (2001–2015, MHA)	DEFORESTATION (MHA/YEAR)
Cattle	45.1	3.0
Oil palm	10.5 (of which 6.2 was direct)[a]	0.7
Soy	8.2 (of which 3.9 was direct)[a]	0.5
Cocoa	2.3	0.2
Plantation rubber[b]	2.1	0.1
Coffee	1.9	0.1
Plantation wood fiber[c]	1.8	0.1
TOTAL	**71.9**	**4.8**

Notes: [a] Deforestation is considered "direct" when the commodity was established within four years (for oil palm) or three years (for soy) of the deforestation event. [b] Rubber data are available for Brazil, Cambodia, Cameroon, Democratic Republic of the Congo, India, Indonesia, and Malaysia. [c] Wood fiber data are available for Argentina, Brazil, Cambodia, China, India, Indonesia, Malaysia, Rwanda, South Korea, and Vietnam. Mha stands for million hectares. Totals may not sum due to rounding.

Source: Authors.

Figure 2A-H | **Year of Deforestation for Forest Areas Replaced by the Seven Commodities**

FIGURE 2A | FOREST AREA REPLACED BY THE SEVEN COMMODITIES

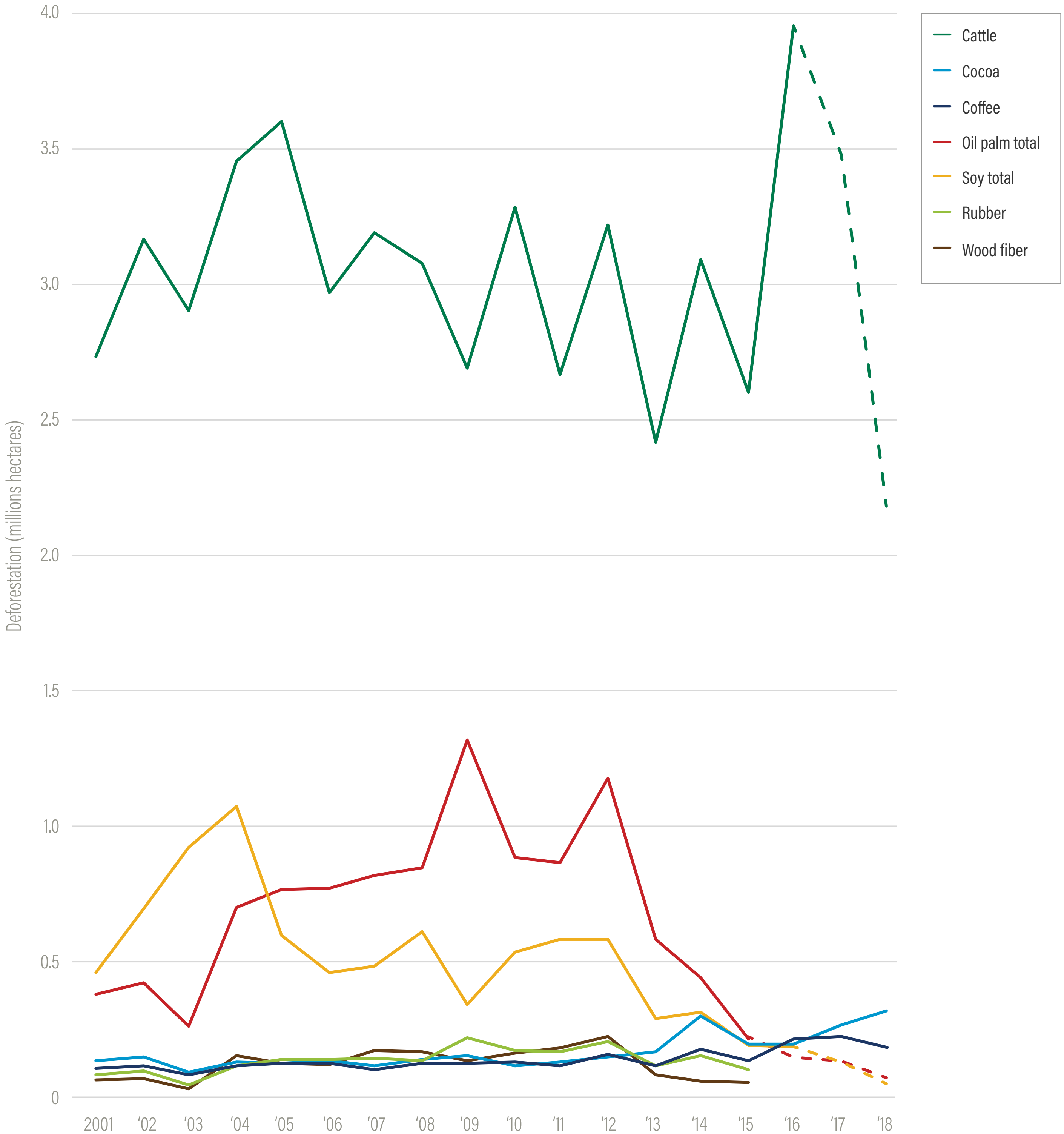


Figure 2A-H | **Year of Deforestation for Forest Areas Replaced by the Seven Commodities (Cont.)**

FIGURE 2B | FOREST AREA REPLACED BY OIL PALM

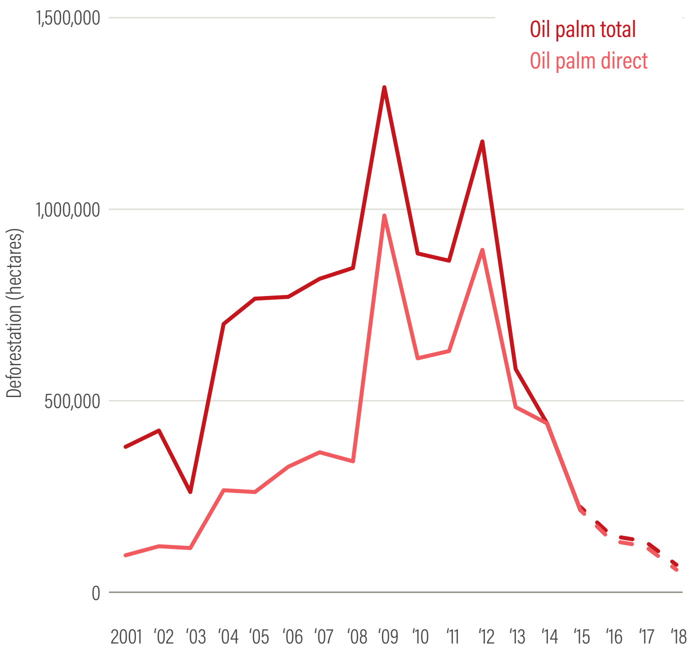


FIGURE 2C | FOREST AREA REPLACED BY SOY

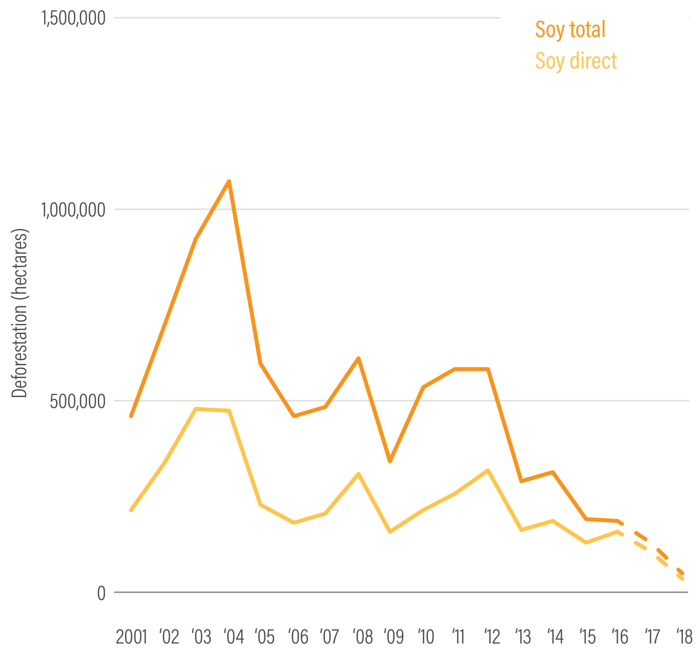


FIGURE 2D | FOREST AREA REPLACED BY CATTLE

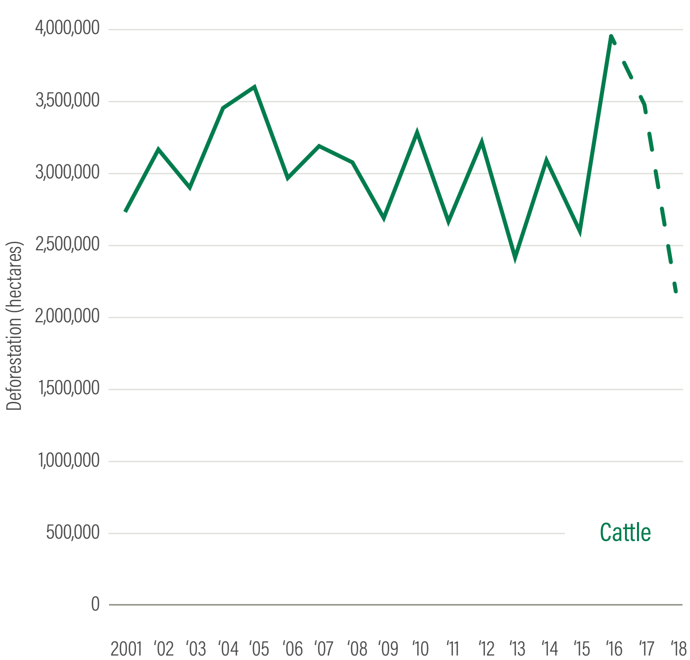


FIGURE 2E | FOREST AREA REPLACED BY WOOD FIBER

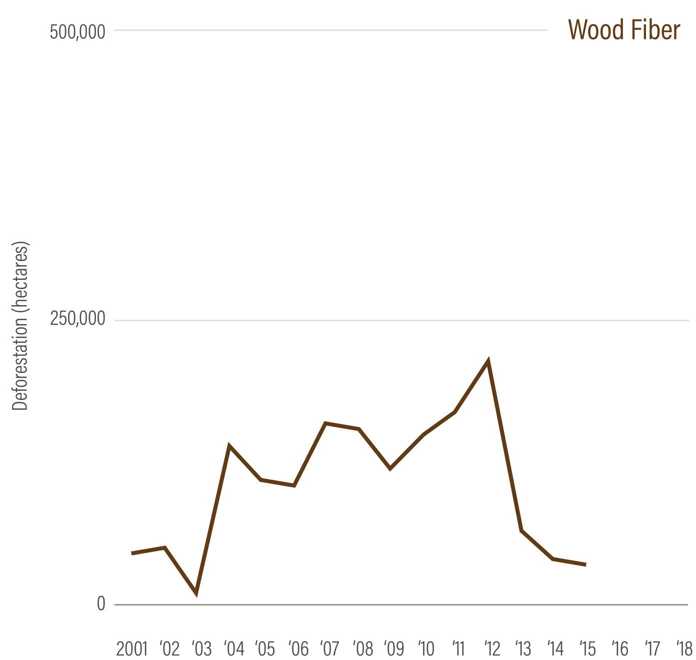


Figure 2A-H | Year of Deforestation for Forest Areas Replaced by the Seven Commodities (Cont.)

FIGURE 2F | FOREST AREA REPLACED BY COCOA

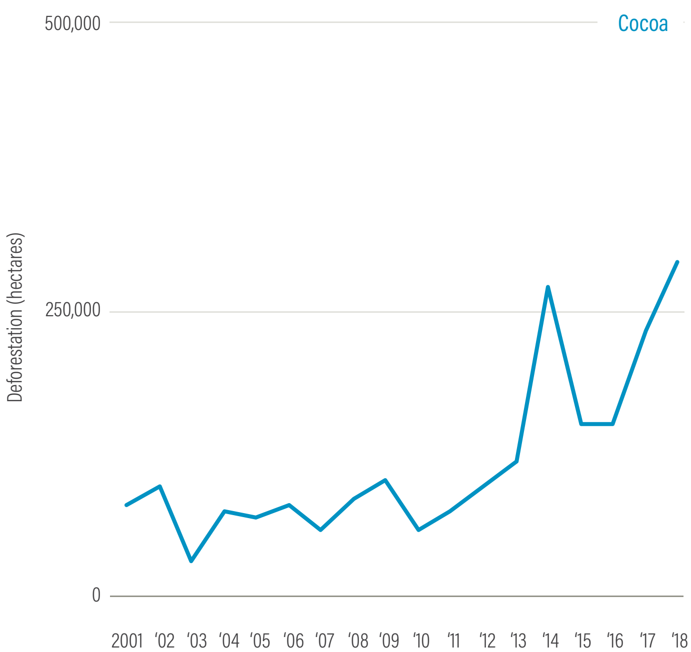


FIGURE 2G | FOREST AREA REPLACED BY COFFEE

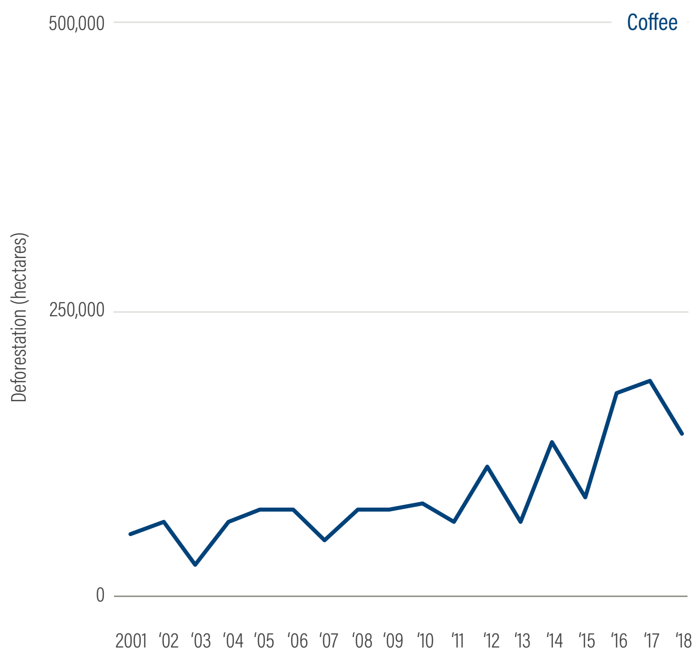
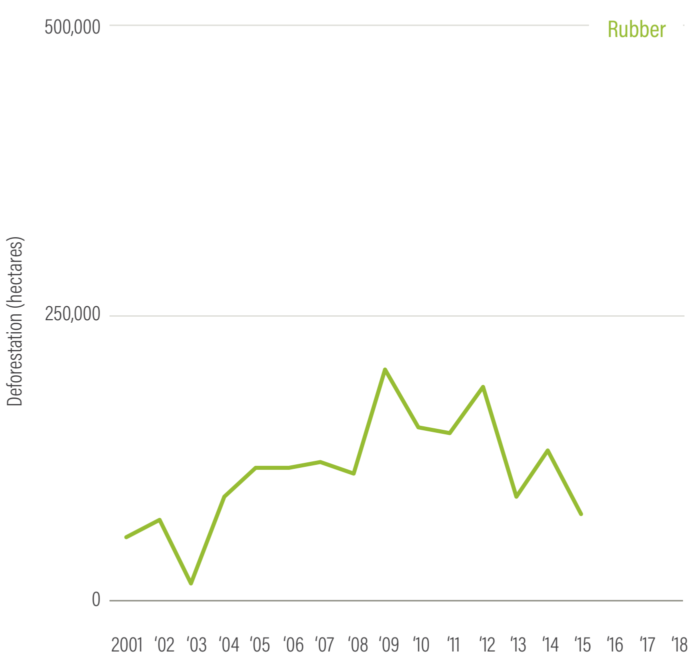


FIGURE 2H | FOREST AREA REPLACED BY RUBBER



Note: Dashed lines indicate preliminary numbers due to lags in linking tree cover loss to specific commodities (see Section 2.3 for details). Preliminary numbers are likely to increase as the analysis is updated with additional years of data. Deforestation is considered "direct" when the commodity was established within four years (for oil palm) or three years (for soy) of the deforestation event.

Source: Authors.

Figure 3A-E | **Forests Replaced by Five Analyzed Commodities from 2001 to 2015 per Second Administrative Level, Total Land Area (%)**

FIGURE 3A | PERCENT OF LAND WITH FORESTS REPLACED BY OIL PALM

FIGURE 3B | PERCENT OF LAND WITH FORESTS REPLACED BY SOY

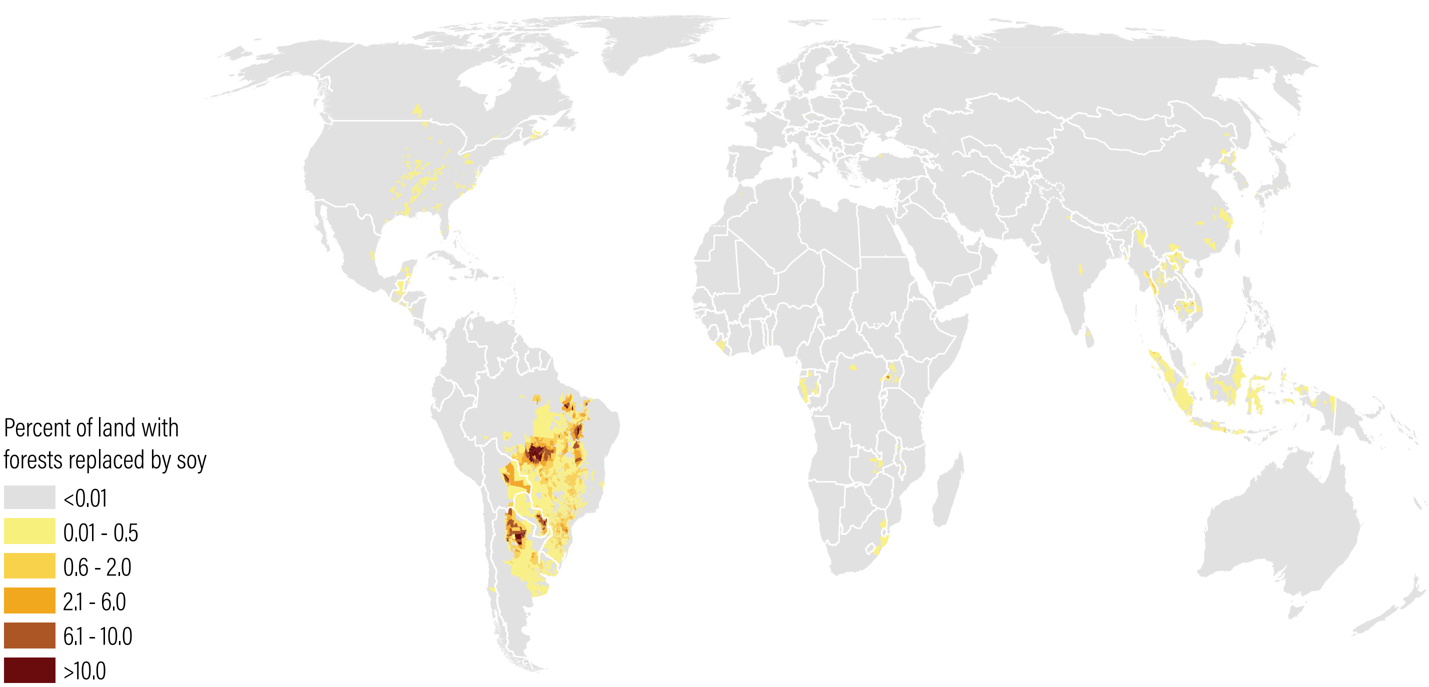


Figure 3A-E | **Forests Replaced by Five Analyzed Commodities from 2001 to 2015 per Second Administrative Level, Total Land Area (%) (Cont.)**

FIGURE 3C | PERCENT OF LAND WITH FORESTS REPLACED BY CATTLE

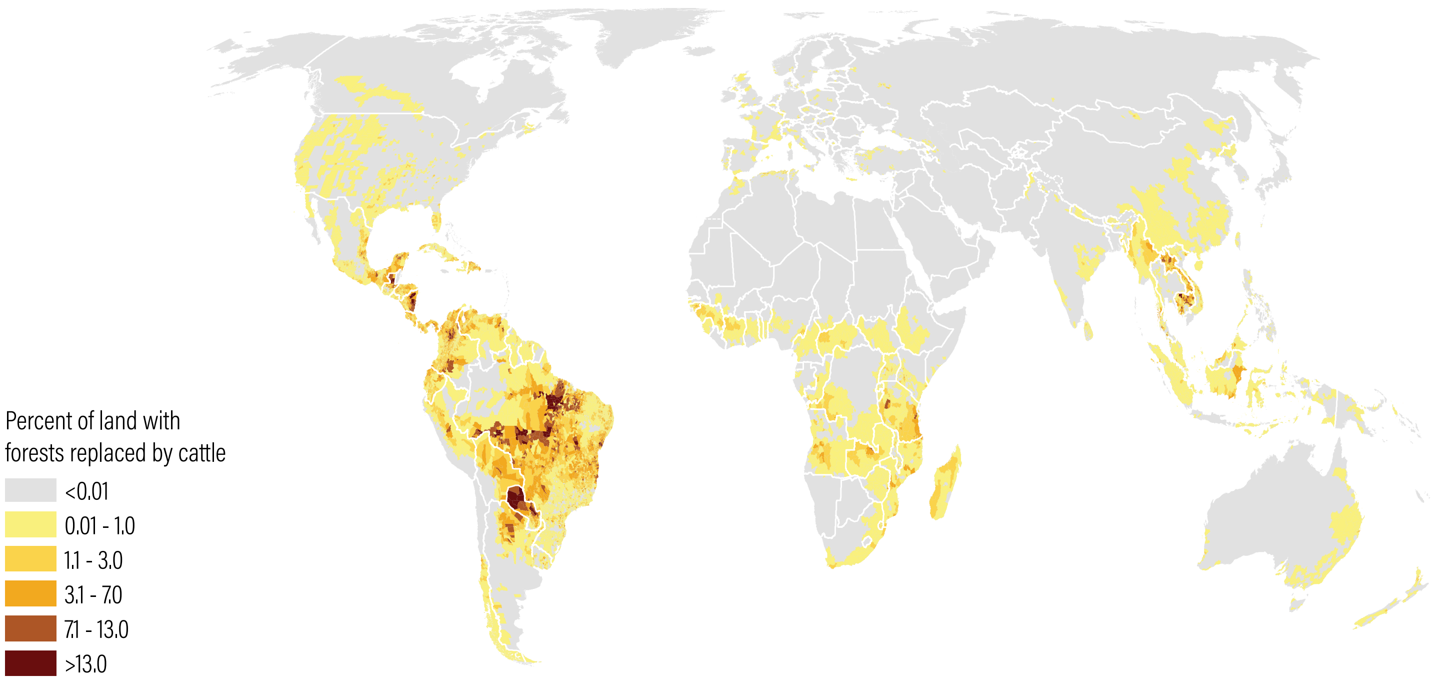


FIGURE 3D | PERCENT OF LAND WITH FORESTS REPLACED BY COCOA

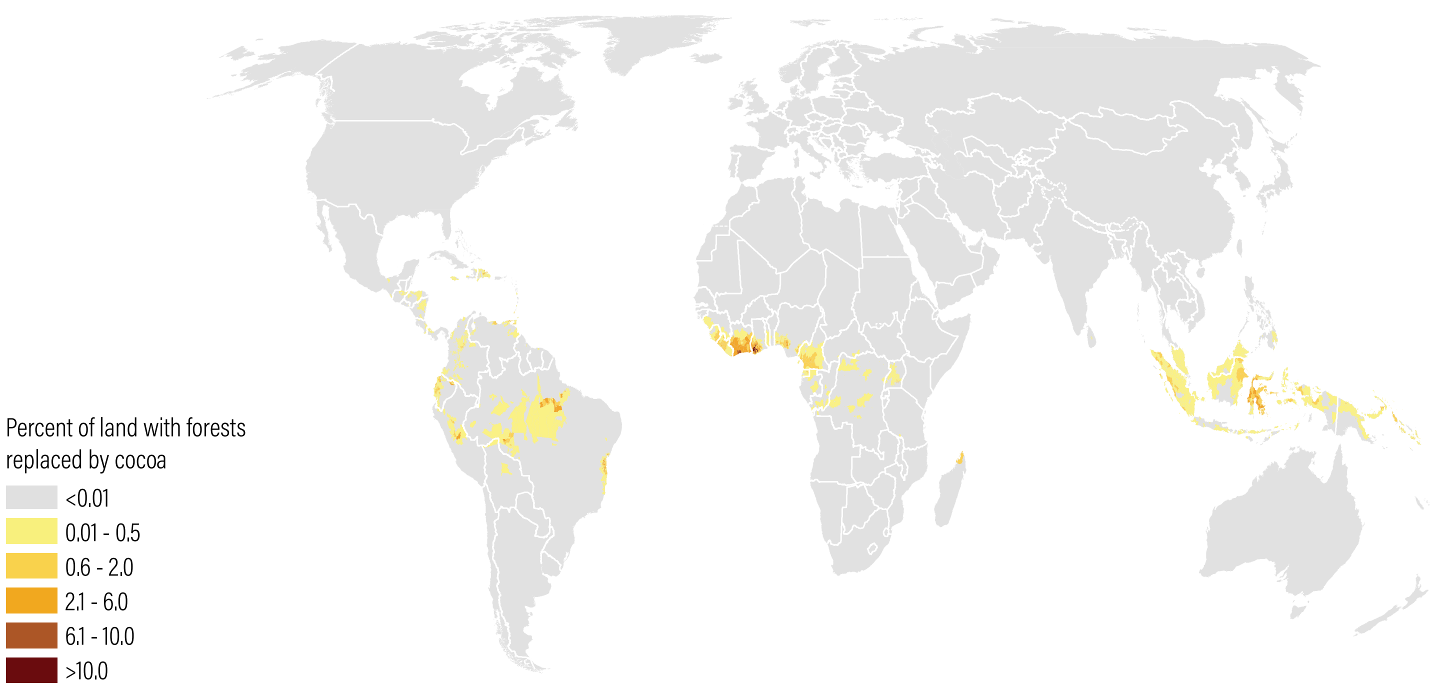
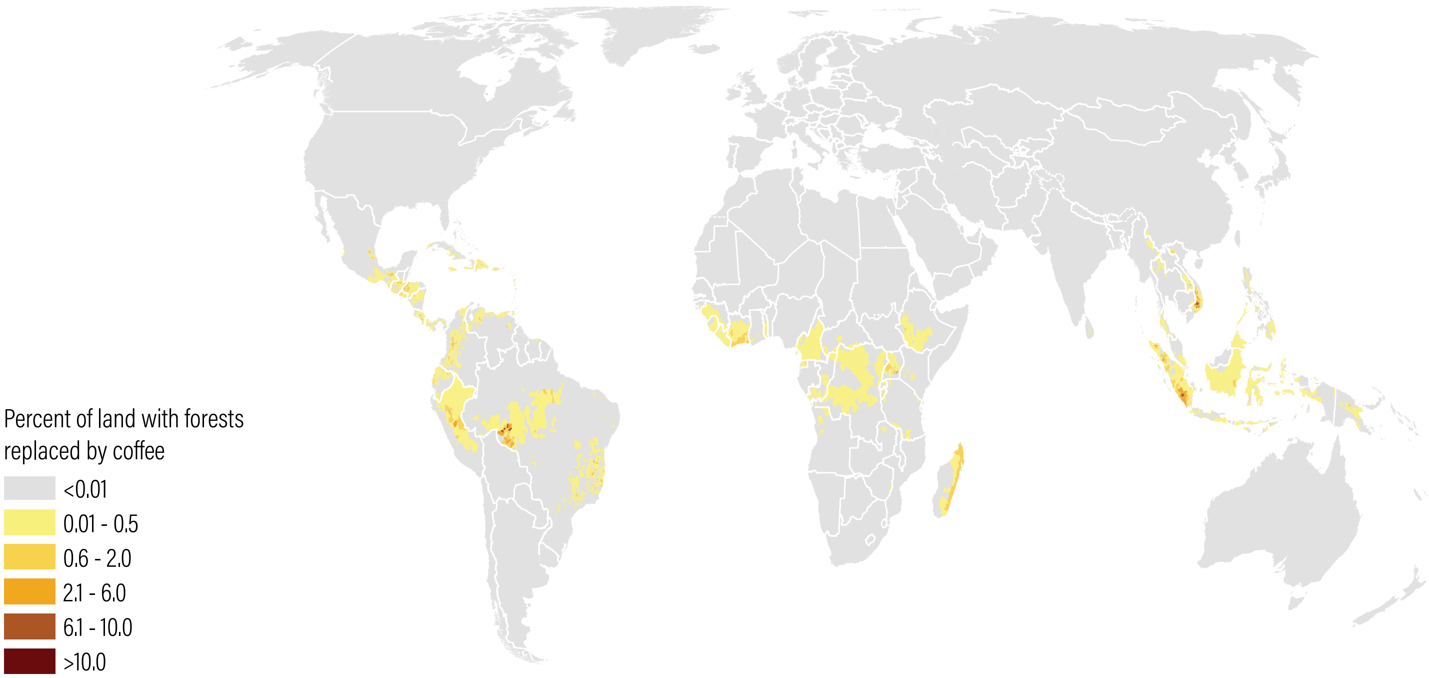


Figure 3A-E | **Forests Replaced by Five Analyzed Commodities from 2001 to 2015 per Second Administrative Level, Total Land Area (%) (Cont.)**

FIGURE 3E | PERCENT OF LAND WITH FORESTS REPLACED BY COFFEE



Note: Maps of forests replaced by wood fiber and rubber plantations are not included here due to the limited data available.

Source: Authors.

4. DISCUSSION

We see four main strengths to the approach presented in this study. First, it is a global approach that can provide estimates of forest replacement by commodities on a large scale with comparability across regions and individual commodities. Second, the approach is inherently spatial, allowing results to be disaggregated and visualized at multiple scales, even down to the 30-meter pixel level for the detailed results. Third, the detailed time series available for forest loss allows us to view trends over time for deforestation in land later occupied by the target commodities. Time series data for crops like soy and oil palm allow additional insight into places where commodity production may be more directly converting forests. And finally, the method is built for flexibility, with possibilities both to expand the analysis to additional commodities and to improve the estimates for the seven commodities as better and more updated spatial information becomes available.

4.1 Comparison with other studies

Results from this analysis can be compared to those of similar studies. Pendrill et al. (2019) also linked deforestation to specific commodities at a country scale and found that from 2005 to 2013, 5.5 million hectares per year could be attributed to expanding cropland, pastures, and plantations. For the same period, this analysis also found 5.5 million hectares per year of loss attributed to commodities; however, we included seven commodities and Pendrill et al. included all major crops, cattle, and forestry products. Pendrill et al. similarly identified cattle,

Figure 4A-C | **Comparison of Detailed and Coarse Method Results**

FIGURE 4A | GLOBAL FOREST AREA REPLACED BY OIL PALM, COMPARISON

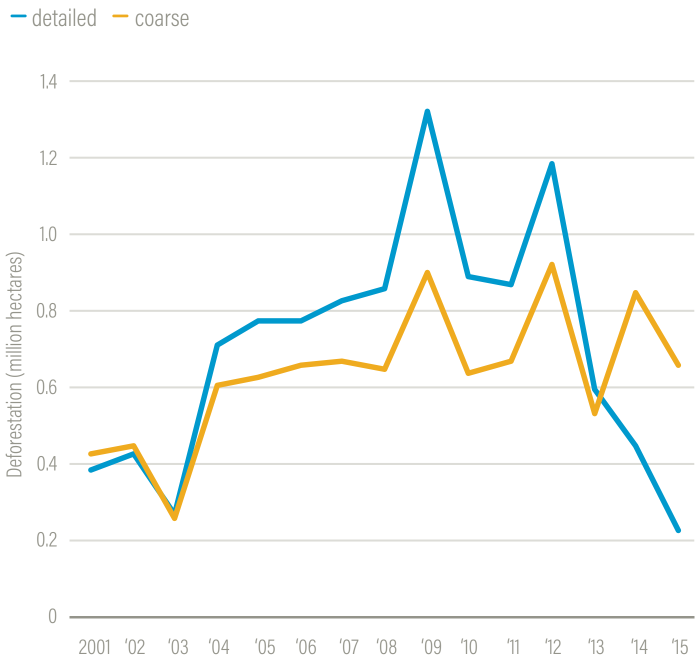


FIGURE 4B | SOUTH AMERICAN FOREST AREA REPLACED BY SOY, COMPARISON

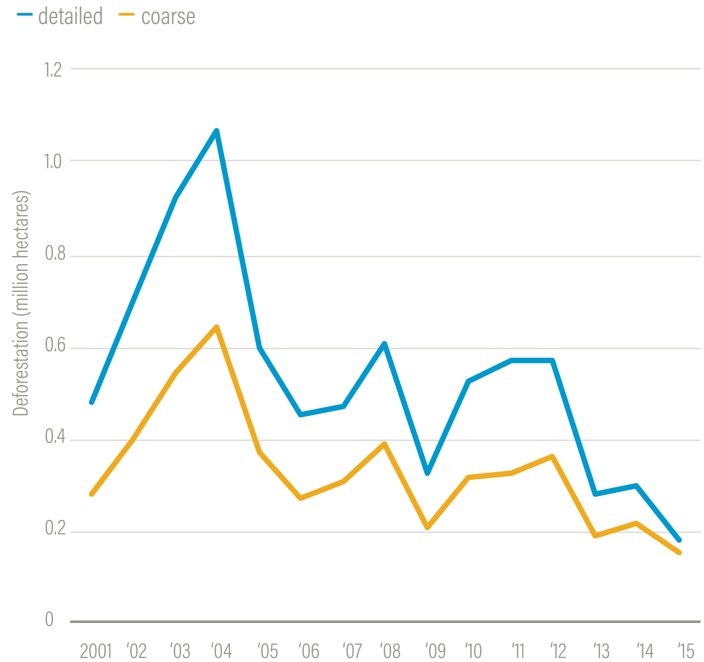
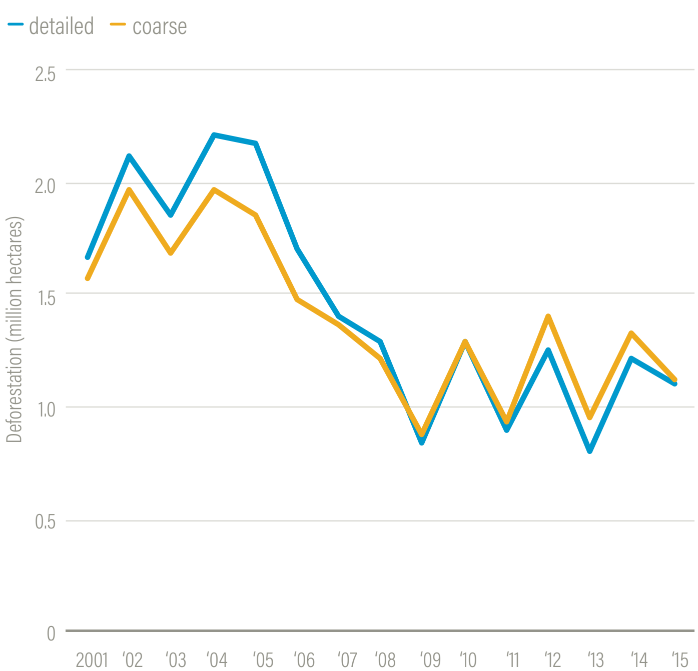


FIGURE 4C | BRAZILIAN FOREST AREA REPLACED BY PASTURE, COMPARISON



Note: "Detailed" refers to our more-detailed approach, which uses recent high-resolution spatial data on the extent of each commodity where available overlaid with previous tree cover loss. "Coarse" refers to our second approach, which applies to those areas and commodities where detailed data are not available, and uses global, 10-kilometer-resolution datasets on the extent of each commodity to allocate tree cover loss to particular commodities.

Source: Authors.

oil palm, and soybeans as commodities associated with a large share of commodity-related deforestation. But when comparing individual commodities, the results become more divergent. This study associated 36 percent more deforestation to cattle than Pendrill et al., likely because their analysis examined only where total pasture extent is expanding, whereas our analysis may also include areas where pasture has been displaced into forests. We also found only a quarter of the amount of deforestation associated with wood fiber that Pendrill et al. found, which could be explained because they included all forest plantations while this study included only plantations designated as wood fiber in Harris et al. (2019). Oil palm estimates were twice as high, and soy estimates were 23 percent higher than those in Pendrill et al. Their analysis incorporated many more crops and trade information, while our analysis includes more spatial detail with subnational-level results.

Several previous studies have attempted to quantify deforestation related to commodities in Southeast Asia. Austin et al. (2019) found that 2.1 million hectares of deforestation were caused by oil palm plantations in Indonesia between 2001 and 2016, compared with our estimate of 7.1 million hectares from 2001 to 2016. One major difference between the two analyses is that Austin et al. considered only the loss of primary forest, while this study accounts for all tree cover loss. If we limit our results to only primary forest areas as defined by Turubanova et al. (2018), we find only 2.6 million hectares of deforestation. Further, the Austin et al. paper considered the land use change only within four years of the deforestation event. When we apply the same constraint to attribute oil palm directly to deforestation, we find 1.7 million hectares of primary forest loss in Indonesia. Both results show similar trends in Indonesia, with a spike in deforestation for oil palm in 2009 and a marked decline after 2012. Austin et al. also quantified deforestation from timber plantations in Indonesia from 2001 to 2016 as 1.3 million hectares, compared with our estimate of 1.6 million hectares from 2001 to 2015. Similar differences related to the forest type and time period analyzed are at play here as well. Austin et al. likewise noted a spike in deforestation for timber plantations in 2012, though our data show a more dramatic decline in deforestation after that point, potentially related to the lag issues described in Section 2.

Gaveau et al. (2018) quantified the conversion of old-growth forests in Borneo to oil palm and pulpwood plantations as 3.1 million hectares from 2001 to 2017. Our analysis shows 2.0 million hectares of primary forest loss for pulpwood and oil palm conversion from 2001 to 2017, 1.6 million hectares when accounting only for direct oil palm conversion. Gaveau et al. also showed spikes in deforestation related to these commodities in 2009 and 2012, followed by a marked decline through 2017.

Other recent studies have attempted to quantify deforestation related to commodities in South America, particularly in Brazil. Tyukavina et al. (2017) found 20.3 million hectares of forest cover loss for pasture in the Brazilian Legal Amazon from 2001 to 2013. Our study finds only 13.8 million hectares for the same time period (for the Amazon biome in Brazil—a different boundary, but not different enough to account for the difference). Our analysis looks only at areas where pasture occurred in 2018, while Tyukavina et al. accounted only for the first disturbance. Thus, deforested areas where crops have eventually replaced pasture, a common practice in Brazil (e.g., Zalles et al. 2019), would be counted as forest loss for pasture by Tyukavina et al., but would not be included in our analysis if the pasture had already been replaced by crops before 2018. Both our study and Tyukavina et al. show a peak in forest replacement by pasture in the Brazilian Amazon from 2002 to 2005, followed by a rapid decline thereafter.

Trase (2020) also estimated annual pasture deforestation in Brazil and Paraguay, and soy deforestation in Argentina, Brazil, and Paraguay as part of its 2020 yearbook. They found 1.1 million hectares of pasture deforestation in 2015, which is equivalent to our estimate in 2015 (note that Trase used the same pasture extent data, but different data on forest change). In Paraguay, estimated pasture deforestation from 2014 to 2015 was 510 thousand hectares, compared with our estimate of 554 thousand hectares during the same time period. For Brazilian soy deforestation, Trase found 1.8 million hectares between 2006 and 2015, higher than our direct estimate of 1.2 million hectares over the same time period. The difference is likely due to the fact that Trase used different forest change data and considered soy deforestation to have occurred when soy was established within five years of the deforestation event, while our estimates consider three years of the deforestation event. Our soy estimate is similar to theirs for Paraguay with 7.4 thousand hectares in 2015 compared with their 7.0 thousand hectares. In Argentina, Trase estimated soy deforestation as 19 thousand hectares in 2016, compared with our estimate of 12 thousand in 2016.

4.2 Limitations

The analysis had several data limitations, including the following:

- **Detailed commodity maps are limited**. Our analysis is limited by the availability of commodity extent data. While the multiple time-step maps of oil palm (global), soy (South America), and pasture (Brazil) provide a wealth of information, publicly available detailed data for other commodities or outside of those extents are lacking. To our knowledge, there are not publicly available detailed maps at all for cocoa or coffee. For wood fiber and rubber plantations, these data exist only for select countries and miss some key production areas, and the differing sources of this information may result in inconsistencies across countries. Furthermore, future updates to this work will depend on timely updates to the existing detailed data.
- **Global coarse-resolution data on commodities have limitations.** Where detailed data do not exist, we relied on global coarse-resolution data, which are available only for single time points (2010 for MapSPAM, 2000 for EarthStat). This limitation necessitates a number of assumptions to estimate deforestation impacts, as outlined in Section 2. Most critically, we assumed that forest replacement by a commodity is proportional to that commodity's share of cropland in the year 2010 (2000 for pasture), which will result in underestimations of forest replacement for some commodities (e.g., if a commodity has significantly expanded in a grid cell since the date of the global data) and overestimations for others (e.g., if the commodity makes up a big share of the grid cell's cropland area but has remained constant since the date of the global data, while other commodities have expanded). In the absence of detailed, frequently updated data for all commodities, multiple timesteps of these global maps would go a long way toward improving our estimates, as we could better model the change in a commodity's extent within each grid cell over time. In particular, the mismatched dates of the pasture and crop data introduce a potential underestimation of forest replacement by pasture, and an overestimation of forest replacement by other crops. Further, these global datasets themselves are coarse modeled products based on nationally reported statistics, land cover/land use data derived from satellite imagery, and other biophysical parameters, each of which may contain errors or have inconsistent definitions and methodologies. Due to the dearth of global spatial information on croplands and pastures, neither MapSPAM nor EarthStat data have been validated, though the EarthStat team did perform an uncertainty analysis at a global level.
- **These data do not consistently capture complex land use change transitions.** The analyses presented here do not take into account the trajectory of land use change or the length of time between the deforestation event and the establishment of the commodity. Instead, in the case of the detailed analysis, we included all deforestation on areas that are currently occupied by that commodity, regardless of whether another land use was present in the interim (or whether that commodity will likely eventually be replaced by another). For oil palm and for soy, we do present estimates of direct conversion of forests to those commodities by limiting the time between the deforestation event and commodity establishment in the analysis, and hope to apply a similar logic to other commodities given detailed time series information. The analysis also does not account for indirect land use change (i.e., the target commodity displaces another commodity that may, in turn, expand into forested areas). Including indirect land use change could increase the amount of deforestation attributed to some commodities, especially for oil palm and soy, and decrease it for others.
- **In some areas, deforestation may be overestimated because not all forms of tree cover loss are deforestation.** All tree cover loss in an area later used for one of the target commodities was assumed to be deforestation, since replacing a forest with a crop represents a land use change. Historical

data from Indonesia and Malaysia were used to filter out historical oil palm plantations from the analysis to avoid counting old, unproductive oil palm trees being felled as tree cover loss. However, it is possible that some plantation dynamics in oil palm plantations outside Indonesia and Malaysia, or rubber and wood fiber plantations, are included in the figures and result in an overestimate of deforestation. Also, the felling of shade trees in existing cocoa farms might be counted as deforestation instead of a cocoa land management activity.

- **But in other areas, deforestation may be underestimated because some forms of deforestation are not captured as tree cover loss.** Not all land use changes related to commodity production may be detected as tree cover loss. For example, much of the production of cocoa and coffee occurs on very small farms (<1 hectare) that may potentially be missed by the Hansen et al. (2013) tree cover loss data, resulting in an underestimation of the area of forest replaced by these commodities. This analysis does not assess forest degradation. The analysis may also underestimate the conversion of dry forest and woody savannah areas like the Cerrado and Chaco, which are not always well represented in the Hansen et al. (2013) tree cover loss data due to their low canopy coverage. For the detailed soy and pasture analyses, we define tree cover as any woody vegetation with a minimum of 10 percent canopy cover (other analyses use 30 percent) to minimize this issue.
- **The combination of disparate datasets may result in errors and artifacts.** Each of the datasets used in this analysis has its own errors and uncertainties, which are compounded when they are combined. We do not quantitatively assess the accuracy or uncertainty of these estimates, but are committed to continuing to refine the data and analyses over time as better data become available.

ENDNOTES

1. This analysis uses the year 2000 as the baseline and only the first year of tree cover loss is included in the dataset. If a plantation was established before 2000, any harvest or clearing of older plantation trees may be picked up as tree cover loss. However, if an area was forest in 2000, then cut down and replaced by a plantation which was later harvested, only the first change (when the forest was cut down) would be captured as tree cover loss. Likewise, if there was no tree cover in the year 2000, then a plantation grew, which was then harvested, it would not be detected as tree cover loss because it was not included in the baseline year.

2. As calculated by overlapping the spatial extent of Harris et al. (2019) plantation boundaries and annual tree cover loss data.

3. While unpublished, Song et al. (in preparation) provides much higher spatial and temporal resolution soy data compared with any published data available for South America. We decided that in this instance, the improvements to this study's results from using this dataset outweighed the importance of using published data sources.

4. Cattle is a major driver of deforestation in Brazil, and data from Gilbert et al. (2018) confirm the dominant presence of cattle over other potential grazing livestock, such as sheep or goats.

REFERENCES

Austin, K.G., A. Mosnier, J. Pirker, I. McCallum, S. Fritz, and P.S. Kasibhatla. 2017. "Shifting Patterns of Oil Palm Driven Deforestation in Indonesia and Implications for Zero-Deforestation Commitments." *Land Use Policy* 69: 41–48. https://www.Sciencedirect.com/science/article/pii/S0264837717301552.

Austin, K.G., A. Schwantes, Y. Gu, and P.S. Kasibhatla. 2019. "What Causes Deforestation in Indonesia?" *Environmental Research Letters* 14 (2). https://iopscience.iop.org/article/10.1088/1748-9326/aaf6db.

Balk, D.L., U. Deichmann, G. Yetman, F. Pozzi, S.I. Hay, and A. Nelson. 2006. "Determining Global Population Distribution: Methods, Applications and Data." *Advances in Parasitology* 62: 119–56. https://doi.org/10.1016/S0065-308X(05)62004-0.

Curtis, P.G., C.M. Slay, N.L. Harris, A. Tyukavina, and M.C. Hansen. 2018. "Classifying Drivers of Global Forest Loss." *Science* 361 (6407): 1108–11. https://science.sciencemag.org/content/361/6407/1108.

Descals, A., Z. Szantoi, E. Meijaard, H. Sutikno, G. Rindanaa, and S. Wich. 2019. "Oil Palm (Elaeis guineensis) Mapping with Details: Smallholder versus Industrial Plantations and Their Extent in Riau, Sumatra." *Remote Sensing* 11 (21): 2590. https://doi.org/10.3390/rs11212590.

FAO (Food and Agriculture Organization of the United Nations). 2020. "Crops: Production Quantity." FAOSTAT Database, last updated June 15. Data from 2018. http://www.fao.org/faostat/en/#data/QC.

Furumo, P.R., and T.M. Aide. 2017. "Characterizing Commercial Oil Palm Expansion in Latin America: Land Use Change and Trade." *Environmental Research Letters* 12 (2): 024008. https://www.illegal-logging.info/sites/files/ chlogging/palmoillatinamericaIOP.pdf.

Gaveau, D.L., S. Sloan, E. Molidena, H. Yaen, D. Sheil, N.K. Abram, M. Ancrenaz, et al. 2014. "Four Decades of Forest Persistence, Clearance and Logging on Borneo." *PLOS ONE* 9 (7): e101654. https:// journals.plos.org/plosone/article?id=10.1371/journal.pone.0101654.

Gaveau, D.L.A., B. Locatelli, M.A. Salim, H. Yaen, P. Pacheco, and D. Sheil. 2018. "Rise and Fall of Forest Loss and Industrial Plantations in Borneo (2000–2017)." *Conservation Letters* 12 (3). https://conbio.onlinelibrary.wiley.com/doi/full/10.1111/conl.12622.

Geist, H.J., and E.F. Lambin. 2002. "What Drives Tropical Deforestation?" LUCC Report Series No. 4. https://www.pik-potsdam.de/members/cramer/teaching/0607/Geist_2001_LUCC_Report.pdf.

Gilbert, M., G. Nicolas, G. Cinardi, T. Van Boeckel, S. Vanwambeke, G. William Wint, and T. Robinson. 2018. "Global Distribution Data for Cattle, Buffaloes, Horses, Sheep, Goats, Pigs, Chickens and Ducks in 2010." *Scientific Data* 5: 180227. https://www.nature.com/articles/sdata2018227#f5.

Gunarso, P., M.E. Hartoyo, F. Agus, and T. Killeen. 2013. "Oil Palm and Land Use Change in Indonesia, Malaysia and Papua New Guinea." In *Reports from the Technical Panels of the 2nd Greenhouse Gas Working Group of the Roundtable on Sustainable Palm Oil (RSPO)*, edited by T.J. Killeen and J. Goon, 29–63. Kuala Lumpur: Roundtable on Sustainable Palm Oil.

Hansen, M.C., P.V. Potapov, R. Moore, M. Hancher, S.A.A. Turubanova, A. Tyukavina, D. Thau, et al. 2013. "High-Resolution Global Maps of 21st-Century Forest Cover Change." *Science* 342 (6160): 850–53. http://science.sciencemag. org/content/342/6160/850.

Harris, N.L., E.D. Goldman, and S. Gibbes. 2019. "Spatial Database of Planted Trees Version 1.0." Technical Note. Washington, DC: World Resources Institute. https://www.wri.org/publication/spatialdatabase-planted-trees.

Hosonuma, N., M. Herold, V. De Sy, R.S. De Fries, M. Brockhaus, L. Verchot, A. Angelsen, et al. 2012. "An Assessment of Deforestation and Forest Degradation Drivers in Developing Countries." *Environmental Research Letters* 7 (044009). https://doi.org/10.1088/1748-9326/7/4/044009.

IIASA and FAO (International Institute for Applied Systems Analysis and Food and Agriculture Organization of the United Nations). 2012. "Global Agro-ecological Zones (GAEZ v3.0)." Laxenburg, Austria: IIASA and FAO, Rome: FAO. http://www.fao.org/fileadmin/user_upload/gaez/docs/GAEZ_Model_Documentation.pdf.

LAPIG (Laboratório de Processamento de Imagens e Geoprocessamento; Image Processing and Geoprocessing Laboratory). 2019. "Pasture Area Brazil 2018." Accessed from Atlas Digital das Pastagens Brasileiras. https://www.lapig.iesa.ufg.br/lapig/index.php/produtos/atlas-digital-das-pastagens-brasileiras.

Miettinen, J., C. Shi, and S.C. Liew. 2016. "Land Cover Distribution in the Peatlands of Peninsular Malaysia, Sumatra, and Borneo in 2015 with Changes since 1990." *Global Ecology and Conservation* 6: 67–78.

Orbital Insight. 2018. "Oil Palm Plantations." More information available at https://blog.globalforestwatch.org/data-and-research/artificial-intelligence-helps-distinguish-the-forest-from-the-trees-part-1/.

Pendrill, F., U.M. Persson, J. Godar, and T. Kastner. 2019. "Deforestation Displaced: Trade in Forest-Risk Commodities and the Prospects for a Global Forest Transition." *Environmental Research Letters* 14 (5). https://iopscience.iop.org/article/10.1088/1748-9326/ab0d41.

Petersen, R., D. Aksenov, E. Goldman, S. Sargent, N. Harris, A. Manisha, E. Esipova, et al. 2016. "Mapping Tree Plantations with Multispectral Imagery: Preliminary Results for Seven Tropical Countries." Technical Note. Washington, DC: World Resources Institute. www.wri.org/publication/mappingtreeplantations.

Ramankutty, N., A. Evan, C. Monfreda, and J. Foley. 2008. "Farming the Planet: Geographic Distribution of Global Agricultural Lands in the Year 2000." *Global Biogeochemical Cycles* 22 (1). https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2007GB002952.

Roy, P.S., M.D. Behera, M.S.R. Murthy, A. Roy, S. Singh, S.P.S. Kushwaha, C.S. Jha, et al. 2015. "New Vegetation Type Map of India Prepared Using Satellite Remote Sensing: Comparison with Global Vegetation Maps and Utilities." *International Journal of Applied Earth Observation and Geoinformation* 39: 142–59.

Rudorff, B.F.T., M. Adami, J. Risso, D.A. de Aguiar, B. Pires, D. Amaral, L. Fabiani, et al. 2012. "Remote Sensing Images to Detect Soy Plantations in the Amazon Biome – The Soy Moratorium Initiative." *Sustainability* 4 (5): 1074–88. https://www.mdpi.com/2071-1050/4/5/1074/htm.

Song, X.P., M.C. Hansen, P.V. Potapov, B. Adusei, J. Pickering, M. Adami, A. Lima, et al. In Preparation. "Massive Soybean Expansion in South America since 2000 and Implications for Conservation."

Trase. 2020. "Trase Yearbook 2020: The State of Forest Risk Supply Chains." https://insights.trase.earth/yearbook/summary/.

Turubanova, S., P.V., Potapov, A. Tyukavina, and M.C. Hansen. 2018. "Ongoing Primary Forest Loss in Brazil, Democratic Republic of the Congo, and Indonesia." *Environmental Research Letters* 13 (7): 074028.

Tyukavina, A., M.C. Hansen, P.V. Potapov, S.V. Stehman, K. Smith-Rodriguez, C. Okpa, and R. Aguilar. 2017. "Types and Rates of Forest Disturbance in Brazilian Legal Amazon, 2000–2013." *Science Advances* 3 (4): e1601047. https://advances.sciencemag.org/content/3/4/e1601047.

Wood-Sichra, U., A.B. Joglekar, and L. You. 2016. "Spatial Production Allocation Model (SPAM) 2005: Technical Documentation." HarvestChoice Working Paper. Washington, DC: International Food Policy Research Institute (IFPRI) and St. Paul: International Science and Technology Practice and Policy (InSTePP) Center, University of Minnesota. http://ebrary.ifpri.org/utils/getfile/collection/p15738coll2/id/133503/filename/133714.pdf.

Zalles, V., M.C. Hansen, P.V. Potapov, S.V. Stehman, A. Tyukavina, A. Pickens, X. Song, et al. 2019. "Near Doubling of Brazil's Intensive Row Crop Area since 2000." *PNAS* 116 (2): 428–35.

ACKNOWLEDGMENTS

We are pleased to acknowledge the Tropical Forest Alliance, who commissioned and provided funding for this study. We would also like to acknowledge additional financial support from Norway's International Climate and Forest Initiative (NICFI) and the U.S. Agency for International Development (USAID).

This publication represents a first attempt by the Global Forest Watch (GFW) partnership to provide global information about the extent, location, and trends of forests replaced by specific commodities. We gratefully acknowledge the reviews and helpful comments of the individuals listed below who offered their time and expertise to the development and improvement of this product.

Reviewers

Justin Adams (Tropical Forest Alliance), Kemen Austin (RTI), Toby Gardner (TRASE), Craig Hansen (WRI), David Landholm (Climate Focus), Kevin Rabinovitch (Mars), Anne Rosenbarger (WRI), Ryan Sarsfield (WRI), Tim Searchinger (WRI), Francis Seymour (WRI), Christy Slay (The Sustainability Consortium), Fred Stolle (WRI), Gregory Taft (WRI), Rod Taylor (WRI), Katie Reytar (WRI), Arief Wijaya (WRI), Caroline Winchester (WRI), and Viviana Zalles Ballivian (University of Maryland)

TFA
TROPICAL FOREST ALLIANCE

ABOUT THE AUTHORS

Elizabeth Goldman is a GIS Research Manager for the Global Forest Watch program at WRI.
Contact: egoldman@wri.org

Mikaela Weisse is a Manager with the Global Forest Watch program at WRI.
Contact: mweisse@wri.org

Nancy Harris is the Research Strategy Director for the Forest Program at WRI.
Contact: nharris@wri.org

Martina Schneider is a GIS Research Analyst for the Global Forest Watch program at WRI.
Contact: mschneider@wri.org

ABOUT WRI

World Resources Institute is a global research organization that turns big ideas into action at the nexus of environment, economic opportunity, and human well-being.

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.

Maps are for illustrative purposes and do not imply the expression of any opinion on the part of WRI, concerning the legal status of any country or territory or concerning the delimitation of frontiers or boundaries.