FOREST ECOLOGY

Classifying drivers of global forest loss

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Global maps of forest loss depict the scale and magnitude of forest disturbance, yet companies, governments, and nongovernmental organizations need to distinguish permanent conversion (i.e., deforestation) from temporary loss from forestry or wildfire. Using satellite imagery, we developed a forest loss classification model to determine a spatial attribution of forest disturbance to the dominant drivers of land cover and land use change over the period 2001 to 2015. Our results indicate that 27% of global forest loss can be attributed to deforestation through permanent land use change for commodity production. The remaining areas maintained the same land use over 15 years; in those areas, loss was attributed to forestry (26%), shifting agriculture (24%), and wildfire (23%). Despite corporate commitments, the rate of commodity-driven deforestation has not declined. To end deforestation, companies must eliminate 5 million hectares of conversion from supply chains each year.

Leaders of nearly 450 companies recently committed to zero deforestation in their supply chains by 2020 to meet consumer demand for deforestation-free products and to improve corporate social responsibility (*1*). Achieving these commitments requires transparency of complex supply chains for agricultural and forest products whose source locations are obscured by multiple aggregators and distributors (*2*). Large, multinational companies cannot determine the source of their supply beyond the location of their direct supplier, usually a distributor; this reduces the effectiveness of deforestation attribution and undermines a company's ability to take concrete action.

Companies, nongovernmental organizations, and governments are looking increasingly to data, maps, and tools to provide visibility on deforestation risk. Published maps of tree cover loss and gain derived from Landsat satellite observations (*3*) were a major step forward in consistent and transparent forest area change monitoring at a global scale. The launch of the online Global Forest Watch platform (*4*) extended the use and access of these data beyond the scientific community to include decision makers from governments, companies, and civil society organizations working to design and implement more effective forest policies.

However, the Hansen *et al.* dataset (*3*), updated annually on Global Forest Watch, does not distinguish permanent forest conversion associated with a change in land use [i.e., deforestation (*5*)] from other forms of forest disturbance that may be associated with subsequent regrowth (i.e., forestry, shifting cultivation, wildfire). This not only limits its utility for corporate decision-makers but also generates confusion when global forest cover change statistics derived from satellite imagery are compared directly against global land use change statistics as reported by governments in their national inventories (*6*). Deforestation involves the abrupt transition from land with trees to land without trees with no subsequent regrowth; loss of forest cover can also be associated with events such as wildfires, or with direct human-induced land use and land management practices such as clearcutting or selective logging, plantation forestry, smallholder agroforestry systems, or transitional subsistence farming due to shifting cultivation practices. As improvements in the spatial and temporal resolution of satellite imagery enable detection of smaller and more subtle changes to Earth's land surface relative to results from earlier monitoring efforts (*7*, *8*), more nuance is required in the attribution of global forest change dynamics.

Using high-resolution Google Earth imagery to visually classify nearly 5000 training sample cells, we developed a decision-tree model that predicts the most likely cause of forest disturbance at any 10 km × 10 km grid cell around the world since the year 2000 (*9*). Categories were assigned according to dominant disturbance type (Fig. 1), with each representing a different forest and land use dynamic: (i) commodity-driven deforestation, defined by the long-term, permanent conversion of forest and shrubland to a nonforest land use such as agriculture (including oil palm), mining, or energy infrastructure; (ii) shifting agriculture, defined as small- to medium-scale forest and shrubland conversion for agriculture that is later abandoned and followed by subsequent forest regrowth; (iii) forestry, defined as large-scale forestry operations occurring within managed forests and tree plantations with evidence of forest regrowth in subsequent years; (iv) wildfire, defined as large-scale forest loss resulting from the burning of forest vegetation with no visible human conversion or agricultural activity afterward; and (v) urbanization, defined as forest and shrubland

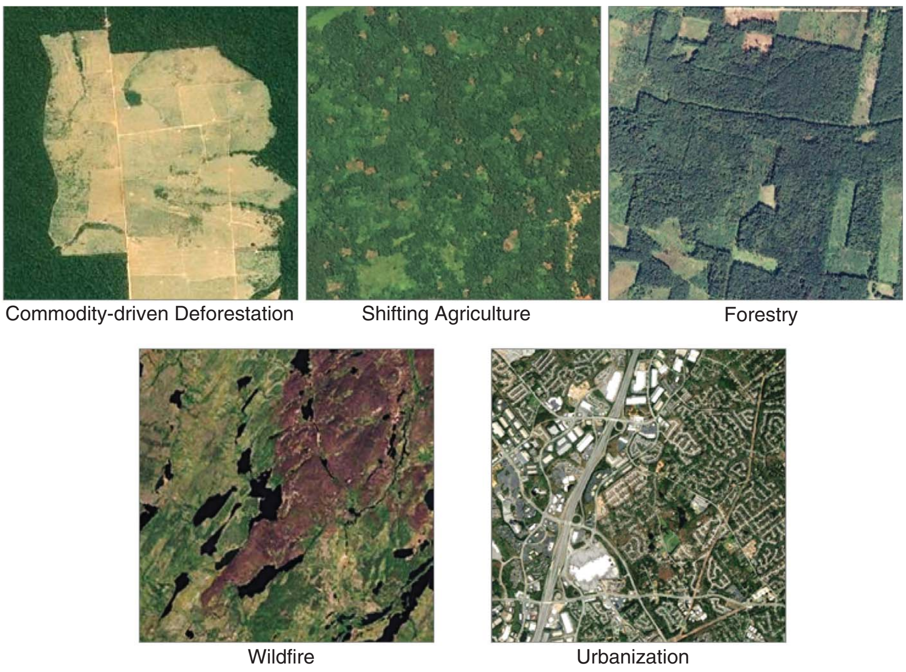

Fig. 1. Representative examples of Google Earth imagery used to train the forest loss classification model. See (*9*) for more examples of training imagery.

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conversion for the expansion and intensification of existing urban centers. Although urbanization is considered a form of deforestation, we included it as a separate class both to highlight the loss of forest in lands typically considered to be under urban use and because the set of actors responsible for clearing urban areas is distinct from those responsible for clearing forests for commodity production. We considered only direct drivers of forest disturbance, and we did not attempt to link these to underlying drivers such as demographic pressures or economic markets (*10*). A separate validation sample of 1565 randomly selected 10 × 10 grid cells was used to estimate map accuracy and proportions of the five disturbance types from the total forest disturbance area, both globally and by region.

Globally, 27 ± 5% of all forest disturbance between 2001 and 2015 was associated with commodity-driven deforestation (Table 1 and Fig. 2). The rate of deforestation remained steady across the 15-year period analyzed at approximately 5 Mha year^{-1} (Fig. 3A) with a geographic shift away from Brazil toward tropical forests elsewhere in Latin America and Southeast Asia (Fig. 3B). Beyond deforestation, forestry represented 26 ± 4% of total forest disturbance (Table 1), followed by shifting agriculture (24 ± 3%) and wildfire (23 ± 4%). An additional 0.6 ± 0.3% of forest loss was attributed to the intensification and expansion of urban centers. The driver attribution model's overall accuracy was 89%, with individual class accuracies ranging from 55% (urbanization) to 94% (deforestation) (table S4).

Drivers of forest loss varied regionally (Fig. 2). In temperate and boreal forests, forestry and wildfire were the dominant disturbance factors; in tropical regions, shifting agriculture and commodity-driven deforestation were preeminent. In the Southeast Asian countries of Indonesia and Malaysia, we identified widespread deforestation for agricultural expansion through visual evidence of oil palm plantations. Across Central and South America, forests were converted to row crop agriculture and cattle grazing lands. Shifting agriculture was the dominant driver in sub-Saharan Africa.

The forestry class in Fig. 2 explicitly maps sourcing regions for the global forest products industry. These are concentrated in North America, Europe, Russia, China, southern Brazil, Chile, South Africa, and Australia. Most forestry activities in South America, the United States, Europe, China, South Africa, and Australia showed signs of tree plantations, as evidenced by distinct rows of planted trees, whereas forestry activity in Canada and Russia contained predominantly large clearcuts without visibly distinct plantation rows (figs. S3 to S5). In Southeast Asia, most forestry activity took the form of low-intensity selective logging, especially on the island of Borneo. All forms of forestry were characterized by a dominant forest regrowth signal in the years following loss.

Wildfire was a dominant cause of forest disturbance in North America and Russia (Table 1 and Fig. 2). Wildfires in these regions were characterized by large areas of forest burned in a single year, then regenerating gradually over time (fig. S5). This driver was also differentiated from the others by the large disturbance size and low population density typically associated with wildfire events.

Other disturbances leading to forest loss (such as insect outbreaks, wind and ice storms, flooding, or rivers changing course) were not included in our model. However, only 1% of all model validation sample cells were attributed to a cause other than the five included in our analysis. We conclude that these other forms of disturbance are highly localized and temporally restricted phenomena.

Forest loss due to urbanization represented a small fraction (0.6 ± 0.3%) of total loss. More than two-thirds of this loss occurred in the eastern United States, and the remainder was associated with expanding cities in China, Brazil, Indonesia, and Australia, as well as considerable low-density expansion across sub-Saharan Africa.

Regional class accuracies (tables S5 and S6) reflect the extent to which our model could distinguish differences in regional land use and land management patterns. Confusion among classes occurred when spatial land use patterns in a region were not sufficiently distinct from one another or when there were too few areas of a given class within a region to be adequately represented in a training sample. For example, forestry was associated with a distinct set of spatial patterns in North America, and thus the producer's accuracy (i.e., absence of errors of omission) was high (96%) for this class and region, whereas forestry in Southeast Asia showed less distinct patterns of tree harvesting and regrowth, resulting in a lower producer's accuracy (78%) for this class and region (table S6). Forest plantations in Southeast Asia contained patterns of loss and regrowth similar to those seen with the expansion of new agricultural oil palm plantations categorized within the commodity-driven deforestation class. This was particularly true for small-scale palm plantations that are planted and grown at roughly the same spatial and temporal scale as short-rotation wood fiber plantations (fig. S3). In sub-Saharan Africa, shifting agriculture is a widespread driver of forest disturbance (Fig. 2). Spatial patterns that distinguish this class include small size of clearings; the presence, timing, size, pattern, and location of human-induced fire; and the eventual regeneration of forest vegetation to a degraded secondary state. However, spatial patterns of commodity-driven deforestation in this region appear almost identical to shifting agriculture, but without the distinctive regrowth signal (fig. S6). The similarity in spatial patterns between

Table 1. Disaggregation of global and regional tree cover loss by driver for the period 2001 to 2015. Map-based estimates are based on Global Forest Watch data (*3*) and a driver of tree cover loss from the current study. Sample-based estimates are based on the validation sample of 1565 randomly selected 10 × 10 grid cells from the current study. Uncertainty of sample-based estimates represents a 95% confidence interval.

	Map-based estimates							Sample-based estimates				
	Hansen *et al.* (*3*)		Current study: Driver of tree cover loss					Current study: Driver of tree cover loss				
Region	**Tree cover loss (Mha, 2001–2015)**	**Tree cover loss (% of global total, 2001–2015)**	**Deforestation**	**Shifting agriculture**	**Forestry**	**Wildfire**	**Urbanization**	**Deforestation**	**Shifting agriculture**	**Forestry**	**Wildfire**	**Urbanization**
North America	70	21%	1%	<1%	56%	40%	2%	2 ± 1%	1 ± 1%	48 ± 11%	48 ± 11%	1 ± 1%
Latin America	78	25%	56%	31%	13%	1%	<1%	64 ± 8%	24 ± 7%	9 ± 3%	<1 ± <1%	<1 ± <1%
Europe	15	5%	None	<1%	99%	1%	None	None	<1 ± <1%	95 ± 5%	5 ± 5%	None
Africa	39	13%	4%	92%	4%	<1%	<1%	2 ± 1%	93 ± 3%	4 ± 2%	<1 ± <1%	1 ± 2%
Russia/China/South Asia	64	20%	<1%	<1%	41%	58%	<1%	2 ± 2%	1 ± 1%	38 ± 12%	59 ± 12%	<1 ± <1%
Southeast Asia	39	13%	78%	9%	13%	<1%	<1%	61 ± 13%	20 ± 10%	14 ± 6%	2 ± 6%	<1 ± <1%
Australia/Oceania	10	3%	7%	10%	29%	53%	1%	8 ± 6%	10 ± 4%	19 ± 9%	62 ± 14%	1 ± <1%
Global	**314**	**100%**	**25%**	**21%**	**31%**	**22%**	**<1%**	**27 ± 5%**	**24 ± 3%**	**26 ± 4%**	**23 ± 4%**	**1 ± <1%**

these two classes resulted in low model accuracy for the commodity-driven deforestation class in Africa; much of the commodity-driven deforestation was misclassified as shifting agriculture (table S6). In northern forests, particularly Russia, there are locations where wildfires spread through previously logged areas or where logging occurred after a fire event (fig. S5). In these cases, attributing a single driver to such areas proved difficult because patterns indicative of multiple drivers were present in the same cell, albeit in different years within the time period analyzed (2001–2015).

The global scope of our analysis was designed to assist corporations in identifying wood fiber source regions and regions of deforestation due to commodity agriculture. Although we accurately mapped dominant classes of forest disturbance globally, opportunities remain to disaggregate landscapes further at regional and local scales. For example, we did not map changes in forest condition through time in landscapes dominated by shifting agriculture; further differentiation of primary from secondary forest clearing within this land-use class could improve our understanding of the differences between deforestation and degradation impacts (*11*). Differentiating key drivers such as row crops from pasturelands in South America, or tree plantations from disturbed natural forests in Southeast Asia (*12*), would allow for more specific supply chain analyses to identify corporate risk and responsibility from commodity-driven deforestation.

Our methodology serves as a hybrid between the accuracy and statistically unbiased estimates achieved through a sample-based approach, as favored by academic researchers (*13*, *14*), and the spatial comprehensiveness of a wall-to-wall mapping approach (*3*) preferred by a wider variety of practitioners and forest stakeholders. The results identify where deforestation is occurring; perhaps as important, they show where forest loss is not deforestation. For most regions and drivers, the map output can be used directly to quantify the proportion of forest loss caused by each driver, because map-based estimates fall within the confidence intervals of sample-based estimates (table S7). Wildfire was associated with nearly one-fourth of the world's forest loss; this type of loss is not likely to be reduced easily through management intervention. In contrast, deforestation across Central and South America, Africa, and Southeast Asia should be the geographic focus of corporate

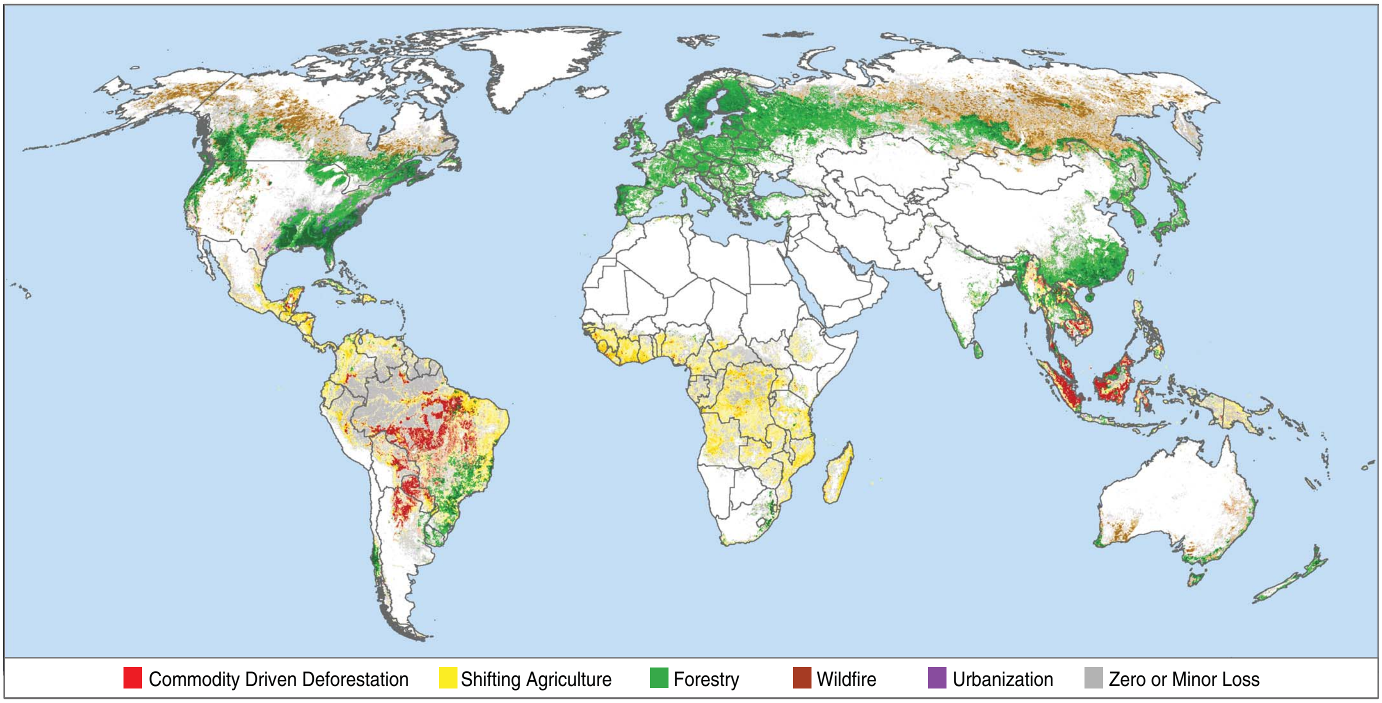

Fig. 2. Primary drivers of forest cover loss for the period 2001 to 2015. Darker color intensity indicates greater total quantity of forest cover loss.

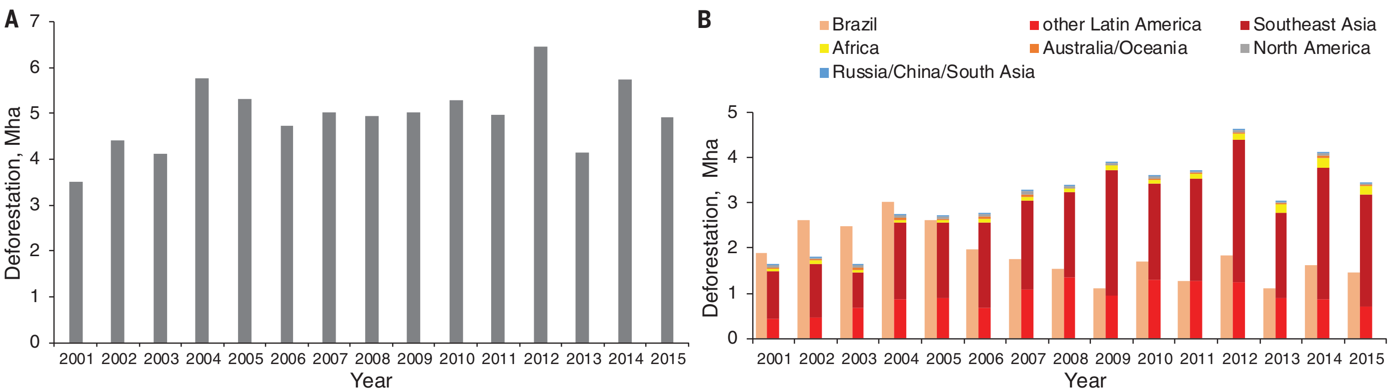

Fig. 3. Annual deforestation rates. (**A**) Annual worldwide tree cover loss from commodity-driven deforestation between 2001 and 2015. (**B**) Comparison of annual commodity-driven deforestation in Brazil and the rest of the world between 2001 and 2015.

efforts to eliminate deforestation from supply chains, as well as international policies designed to reduce greenhouse gas emissions from deforestation and forest degradation (*15*).

Our results indicate that policies designed to achieve zero-deforestation commitments are not being adopted or implemented at the pace needed to meet 2020 goals (Fig. 3). In regions dominated by forestry, felled trees enter wood and fiber supply chains including paper, packaging, and forest products. These areas should not be included in the monitoring of zero-deforestation commitments because they are not undergoing deforestation, as defined by a change in land use that prevents subsequent forest regrowth. Instead, companies and governments can use Fig. 2 as a wood fiber sourcing map to target priority areas for certification efforts and supply chain traceability. Identifying regions dominated by shifting agriculture may be important for identifying the extent to which this land use contributes to forest degradation, and for food supply chains where sourcing from smallholder farmers is often a priority, but where slash-and-burn practices may be leading to undesirable impacts and corporate risk. Finally, our analysis contributes to a more informed discussion about forest conservation, restoration, and management options globally by providing an enhanced experience for the more than 2 million users of the Global Forest Watch platform to understand what is driving forest change around the world, thus preventing a common misperception that any tree cover loss shown on the map represents deforestation (*16*).

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SUPPLEMENTARY MATERIALS

www.sciencemag.org/content/361/6407/1108/suppl/DC1
Materials and Methods
Figs. S1 to S10
Tables S1 to S7
Data S1 to S4
References (*17*–*30*)

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Mapping global deforestation patterns
Forest loss is being driven by various factors, including commodity production, forestry, agriculture, wildfire, and urbanization. Curtis *et al.* used high-resolution Google Earth imagery to map and classify global forest loss since 2001. Just over a quarter of global forest loss is due to deforestation through permanent land use change for the production of commodities, including beef, soy, palm oil, and wood fiber. Despite regional differences and efforts by governments, conservationists, and corporations to stem the losses, the overall rate of commodity-driven deforestation has not declined since 2001.
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