Ranking Priority Jurisdictions with Recent Deforestation for Specific Commodities

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Overview

In this analysis we focused on beef cattle, cocoa, palm oil, paper pulp, and soy with the aim to 1) identify the top producing jurisdictions by volume for regions supplying to the U.S. and globally, 2) rank priority jurisdictions with high levels of commodity-driven deforestation across endangered and vulnerable ecoregions. To identify the jurisdictions most likely to have produced commodities entering U.S. and global supply chains, we utilized a model that analyzes production regions using import and export statistics. For domestic production we utilized U.S. production statistics to identify states contributing a given commodity to the U.S. supply chain. To rank the priority jurisdictions for commodity-driven deforestation we created a new model incorporating commodity-driven deforestation, tree cover extent, crop production, and priority ecoregions.

Data and Methods

Identifying the Top Producing Jurisdictions

To identify the top producing regions globally we utilized TSC's Commodity Mapping Trade Network Model which utilizes import and export commodity data to identify source nations and then identifies the subnational production areas of each crop. This model identifies the proportion of a nations production of a commodity for export rather than domestic consumption. For supply chains originating in the U.S. only we did not utilize this model but used state production statistics directly. The datasets used to identify the top producing jurisdictions are listed in Table 1. Samples of the mapped output are found in Figures 1-2.

Table 1. Datasets used for crop production and sourcing

Global Data			
Crop	*Source*	*Resolution*	*Year*
cocoa, palm oil, soy	MapSPAM, Wood-Sichra et al. 2016	10-kilometer	2010
beef cattle	Robinson et al. 2014	5-kilometer	2007
beef cattle (pasture)	Ramankutty et al. 2008	10-kilometer	2000
cocoa, palm oil, soy, beef cattle, paper pulp	Food and Agriculture Organization (FAOSTAT)	Country	2017
National Data			
Crop	*Source*	*Resolution*	*Year*
Beef cattle	USDA	State	2020
	India Dept. of Animal Husbandry and Dairying	State/UT	2019
	Australian Bureau of Statistics	State	2019
	ABIEC	State	2018
Wood fiber (From WRI methodology)	Ministerio de Produccion y Trabajo	30-meter	2013
	Petersen et al. (2016)	Vector	2013/2014
	Atlas of Forest Resources of China (2010)	1-kilometer	2004-2008
	Roy et al. (2015)	23.5-meter	2015
	Government of Rwanda	Vector	2008
	Korean Forest Service	Vector	Unknown
	Government of Vietnam	2.5-meter	2016

Figure 1. Sample model output for top producing jurisdictions for global supply.

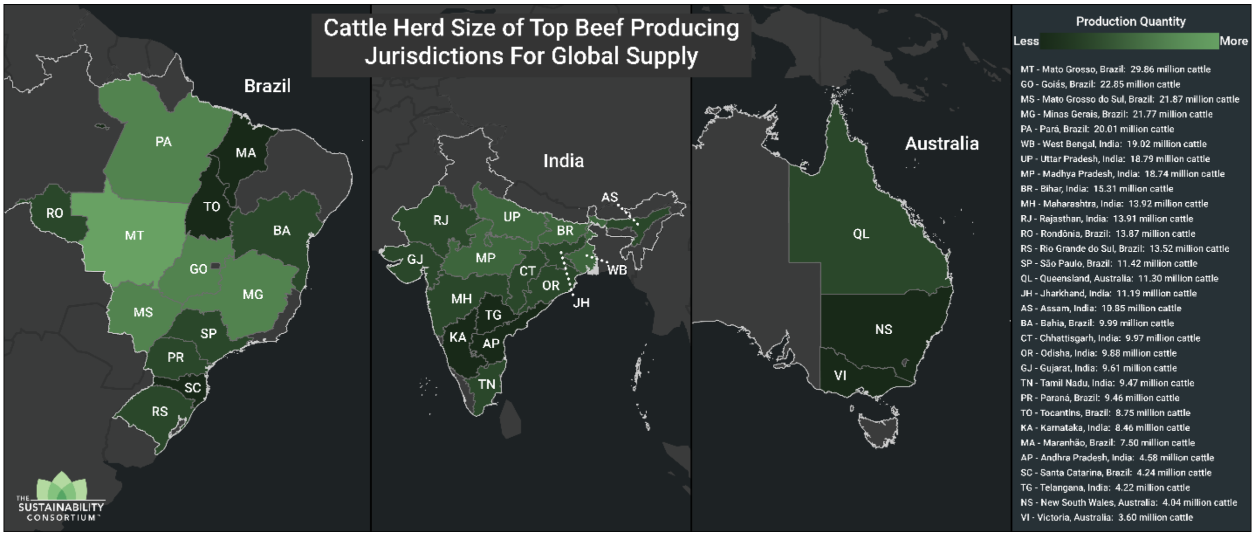
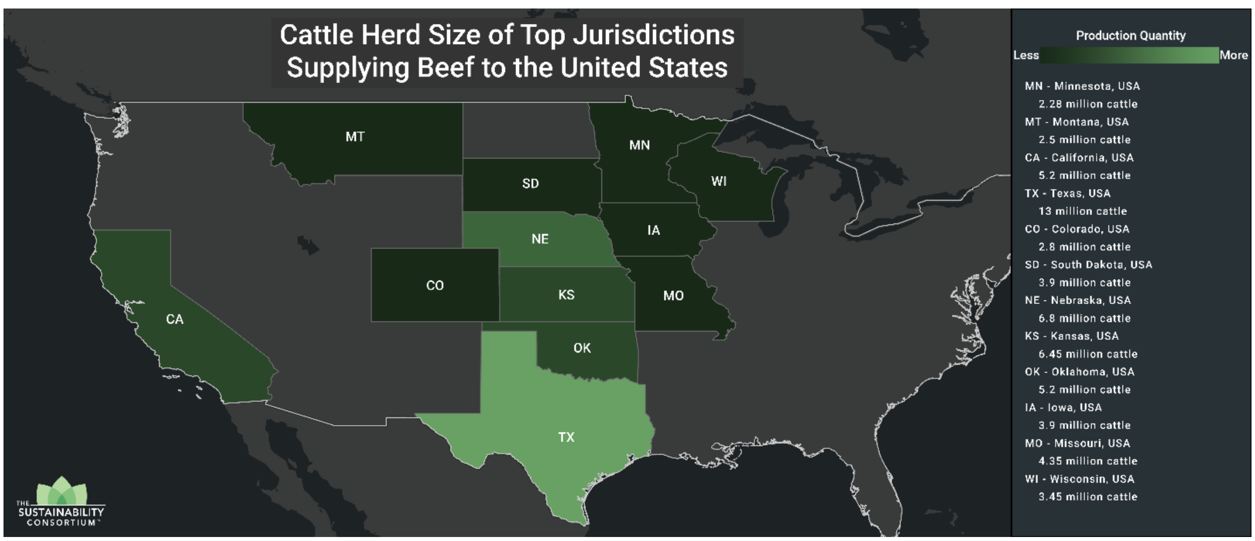


Figure 2. Sample model output for top producing jurisdictions for the U.S. supply.



Ranking priority jurisdictions with recent deforestation

Allocating Deforestation to Production of Commodities

To allocate deforestation globally to expansion of commodity production, we utilized a model developed by the World Resources Institute for the Tropical Forest Alliance (TFA). This model first narrows its scope to all locations classified in the Curtis et. al. 2018 model as either commodity driven deforestation or shifting agriculture. These two classes represent the portion of that model's output that relates to commodity production, excluding forest loss related to forestry, wildfire and urban expansion.

Within each of these locations, data from the MapSPAM dataset on crop production is used to allocate portions of each grid cell to the production of 42 different crops and crop-type categories. This dataset is combined with the Pasture dataset produced by Earthstat. This results in 43 different area measurements for each grid cell in the model that represent the land area predicted to be used in the cultivation of the given crop. For each grid cell, these 43 measurements can then be summed for an estimate of the total crop area for that cell. Using that sum, one can then calculate the portion of each cell's total cropland used to produce a given crop by dividing the area allocated to the crop by the total cropland for that cell.

As these cells have all been classified as having forest loss with commodity production in some form as the dominant cause, the assumption is made that all the forest loss observed in that cell should be allocated to commodity expansion. Without any globally consistent information on crop expansion rates, this is simply done proportionally to each crop's share of the total cropland in each cell. For example: A cell with 500ha of soybean cultivation, 250ha of palm oil cultivation and 250ha of pasture would have a total cropland value of 1000ha, with 50% of cropland being soy, 25% palm oil and 25% being pasture. If this cell experienced 100ha of deforestation over the observed period, 50ha would be associated with soybean expansion, 25ha with palm oil expansion, and 25ha with pasture expansion. More detailed methods will be available soon at https://www.globalforestwatch.org/

Ecoregional Scoring for Deforestation

With deforestation allocated to each crop, the next step is calculating an ecoregional score for each jurisdiction (first level administrative unit) globally. This score is designed to quantify the value of intervention in this jurisdiction in relation to how much rare biodiversity is at risk from the jurisdiction's deforestation. In order to define rare biodiversity, the World Wildlife Fund's Global 200 Priority Ecoregions dataset is used, which identifies the terrestrial ecoregions with the most unique and irreplaceable flora and fauna. Out of this global dataset, all of the forest-type ecoregions are selected which also have a classification of either 'Endangered' or 'Vulnerable'. It is with this subset of endangered/vulnerable priority forest ecoregions that the ecoregional scores are calculated.

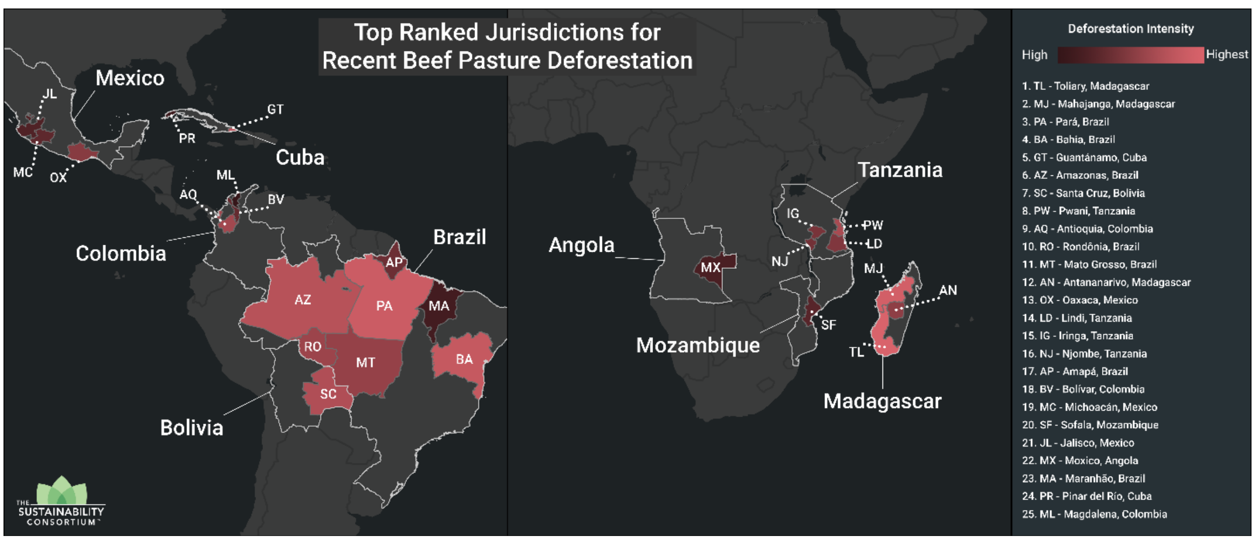
Within each jurisdiction, the quantity of its deforestation that occurs within these priority forest ecoregions is identified. For each priority ecoregion that contains deforestation from a given jurisdiction, the percentage of that ecoregion's total tree cover extent circa 2000 that was deforested between 2014-2018 within that jurisdiction is calculated. This recent five- year period was used as a proxy to indicate potential future deforestation risk. For example: if jurisdiction A has 100ha of deforestation within ecoregion B and 200ha of deforestation in ecoregion C, and ecoregion B had 1,000 ha of tree cover in 2000 while ecoregion C had 5,000ha, then jurisdiction A has deforested 10% of ecoregion B and 4% of ecoregion C. These scores are taken as decimals and added together at the jurisdiction level, giving jurisdiction A an ecoregional score of 0.14. Scores were then sorted from highest to lowest to identify the top 25 jurisdictions for interventions per commodity.

Note that some forest ecoregions may have experienced high levels of deforestation but were not included in this analysis if they were not listed as endangered or vulnerable and included in the Priority 200 Ecoregions list.

Table 2. Datasets used to for deforestation ranking

Global Data			
Title	*Source*	*Resolution*	*Year*
Priority 200 Ecoregions (forested regions classified as 'critical or endangered' or 'vulnerable' only)	Olson, D.M., and E. Dinerstein 2000	ecoregion	N/A
Drivers of Global Forest Loss	Curtis et al. 2018 (updated)	10km	2014-2018
Tree Cover	Hansen et al. 2013 (updated)	30m	2000

Figure 3. Sample model output ranking jurisdictions with high levels of commodity-driven deforestation across threatened and endangered ecoregions for global supply.



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