Global Spatial Analysis to Identify and Characterize Wood Sourcing Regions

A Group Project submitted for the partial satisfaction of the requirements for the degree of
Master of Environmental Science and Management
for the Bren School of Environmental Science & Management

Amanda Chao, Mitchell Maier, Michael Millstein, Julia Paltseva

Faculty Advisor: Lee Hannah

Image: (TSC, 2015b).

BREN SCHOOL
ENVIRONMENTAL SCIENCE & MANAGEMENT
UNIVERSITY OF CALIFORNIA, SANTA BARBARA

THE SUSTAINABILITY CONSORTIUM

April 2016

Global Spatial Analysis to Identify and Characterize Wood Sourcing Regions

As authors of this Group Project report, we archive this report on the Bren School's website such that the results of our research are available for all to read. Our signatures on the document signify our joint responsibility to fulfill the archiving standards set by the Bren School of Environmental Science & Management.

Amanda Chao **Michael Millstein**

Mitchell Maier **Julia Paltseva**

The mission of the Bren School of Environmental Science & Management is to produce professionals with unrivaled training in environmental science and management who will devote their unique skills to the diagnosis, assessment, mitigation, prevention, and remedy of the environmental problems of today and the future. A guiding principal of the School is that the analysis of environmental problems requires quantitative training in more than one discipline and an awareness of the physical, biological, social, political, and economic consequences that arise from scientific or technological decisions.

The Group Project is required of all students in the Master of Environmental Science and Management (MESM) Program. The project is a year-long activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue. This Group Project Final Report is authored by MESM students and has been reviewed and approved by:

Lee Hannah

April 2016

ACKNOWLEDGMENTS

We would like to express our gratitude to the individuals and organizations that have made this thesis project possible.

We would like to thank our client, The Sustainability Consortium, particularly **Philip Curtis** and **Christy Slay**, and our academic advisor, **Lee Hannah**, for their guidance and support throughout this process and for providing the opportunity to work on this project.

We would also like to thank **Keila Hand** (World Wildlife Fund) and **Ben Best** (Bren School of Environmental Science & Management) for sharing insight and information that were instrumental to this project.

The faculty reviewers for our defense presentation, **John Melack** and **Matthew Potoski**, provided valuable feedback, and we are grateful for their input.

Finally, we would like to thank the **ACE Group** for providing funding support.

iii

ABSTRACT

The complex and global nature of wood product supply chains makes tracing products to their raw material sources nearly impossible, despite the desire of companies and external stakeholders to understand their influence on deforestation and other environmental and social issues. The Sustainability Consortium (TSC), a member organization committed to advancing product sustainability, has developed a Commodity Mapping Program that utilizes trade and procurement data to model supply flows and supports this information with geographic risk layers on relevant environmental and social impacts. TSC tasked this group with developing base maps to enable the Commodity Mapping Program to analyze global wood sourcing. Tree cover loss and gain data, provided by Hansen et al. (2013), in concert with Google Earth imagery, were used to identify global tree growing regions that are likely (tree farms) and not likely (palm plantations) to consistently supply wood. MODIS fire point data were also leveraged to determine forest lost to fire as a cause of deforestation that can be isolated from the influence of forest supply chains. The resulting base maps enable TSC to inform members on their wood commodity sourcing and the associated environmental and social impacts relative to other products and sourcing regions.

TABLE OF CONTENTS

EXECUTIVE SUMMARY

Deforestation threatens global wood product supply. Deforestation also threatens the many other services that forests provide, such as promoting biodiversity and sequestering carbon dioxide. In addition to deforestation, numerous environmental and social impacts, ranging from forced labor to water pollution, are linked to wood sourcing. Considering these risks, companies that produce wood products, as well as external stakeholders ranging from non-governmental organizations to customers, want to know whether a given product supply chain is tied to the aforementioned risk factors. Increasing supply chain knowledge also enables companies to identify opportunities to improve resource planning and allocation and increase efficiencies in their value chain, ultimately improving their bottom lines (WRI, 2015). However, complexities in forestry supply chains arising from convoluted processing and distribution, international regulatory inconsistencies, and the proprietary nature of supplier procurement data make it virtually impossible to trace a given product to its exact raw material source.

The Sustainability Consortium (TSC) is a member organization committed to enhancing the sustainability of consumer products (TSC, 2015a). To this end, TSC developed a Commodity Mapping Program, which models and maps trade flows using international trade data and company specific procurement data. TSC contextualizes its commodity mapping with geographic risk layers on relevant environmental and social impacts. Due to the complexities of wood product supply chains, wood supplier procurement data is often unavailable. Thus, to apply the Commodity Mapping Program to wood product origin and enable stakeholders to better understand the impacts associated with sourcing wood for specific products, spatial analysis was needed to identify where in the world wood is likely to be sourced at a fine scale. The global scope is crucial in order to encompass all of TSC's members and their supply chains, provide a global view, and to consider impacts of a given product or sourcing region relative to others. Fine resolution is also needed as impacts can vary drastically within a country or region.

This project leverages existing spatial datasets to generate global models and base maps that identify areas most and least likely to serve as consistent wood sources and characterizes these sourcing regions based on whether they are plantations or potential causes of deforestation on a 10km by 10km scale. Based on the assumption that plantations experience rapid cyclical harvest and regrowth in the same region, tree plantations that are most likely (tree farms) and least likely (palm plantations) to serve as consistent sources of wood commodity supplies were modeled using tree cover loss and gain data, provided by Hansen et al. (2013) and Google Earth imagery. The resulting base maps show the probability that any given 10km by 10km parcel of land contains a tree farm or palm plantation. MODIS fire points were then utilized to model where in the world forest is lost to fire as a cause of deforestation that can be isolated from the influence of forest supply chains. To identify potential wood sourcing areas that exhibit tree cover loss and partial or natural regrowth, rather than the accelerated regrowth indicative of plantations, tree cover loss associated with plantations and forest lost to fire could be subtracted from total tree

cover loss. These areas in which forests are cut and not regrown are more likely to be associated with land conversion, deforestation, and the associated social and environmental impacts.

The tree farm model proved to be particularly strong in its predictive capabilities, with tree cover gain serving as a reliable predictor of the presence of tree farms. The palm plantation model output does not appear to be overwhelmingly correlated with known oil palm concessions, and so additional available datasets may be necessary for accurate characterization of palm plantations. Furthermore, the fire model produced an oversampling of forest lost due to fire. This was anticipated as the MODIS fire points are unable to differentiate natural wildfire from controlled burns. However, the fire base map is able to identify specific fires including Santa Barbara's Zaca Fire of 2007. Ultimately, the models and base maps resulting from this project will increase the spatial accuracy of the Commodity Mapping Program as it applies to wood product sourcing and enable TSC members to better understand where the wood in their products is sourced and the associated environmental and social risks.

CLIENT INTRODUCTION

The Sustainability Consortium (TSC), the client of this project, is a global member organization dedicated to advancing the sustainability of consumer goods. It formed in 2009 in response to cross-industry stakeholder interest in collaborating to more accurately quantify and communicate the sustainability of products in response to increasing pressure and limited resources. TSC's over 100 members and partners represent an array of stakeholders, from manufacturers and retailers to non-governmental organizations and academics, who convene to construct science based decision making tools to address supply chain sustainability issues throughout product life cycles (TSC, 2015a).

TSC's portfolio of services, which exist to aid in the effective implementation of sustainable processes, products, and networks, are science based, stakeholder informed, and impact driven. One area in which TSC seeks to expand its offerings is in commodity mapping. TSC's Commodity Mapping Program identifies the geographies associated with product supply chain risks or hotspots. Hotspots are defined by TSC as a phase within a product's life cycle where significant social or environmental impacts occur. The tools developed by TSC incorporate procurement data and global trade data to model where a company's commodity supply could have originated, enabling companies to understand their supply chain risk exposure and identify where in the supply chain to focus sustainability efforts.

BACKGROUND

Global Forest Supply and Value

Earth's forests represent a vital resource from both economic and ecological perspectives. Covering over 31% of the earth's land area, forests are necessary for the regulation of atmospheric carbon dioxide and oxygen in the atmosphere (FAO, 2010). By removing carbon dioxide from the air and replacing it with oxygen as they photosynthesize, forests are necessary in containing the impacts of anthropogenic climate change associated with the release of carbon dioxide and other greenhouse gases. Further, forests provide necessary ecosystem services and harbor biodiversity by providing critical terrestrial habitats around the globe. Yet an estimated 13 million hectares of forest are lost every year to deforestation via land clearing for agriculture or urban development, unsustainable logging, and fire (FAO, 2010). As such, deforestation is a serious global problem due to its impact on climate change, biodiversity, and ecosystem services, among other socioeconomic considerations.

Forests also represent a vital economic resource, serving as the source for a host of commodities and materials used in the production of consumer goods. The United States alone produced between 12 and 14 million cubic feet of industrial roundwood (an aggregation of all categories of harvested wood for product categories except fuel) every year from 2003 to 2012 (U.S. Forest Service, 2016). As the population grows and global incomes rise, demand for forest resources will increase pressure on remaining forests.

Due to supply and reputational risks associated with unsustainable wood sourcing, many global brands have pledged zero net deforestation goals and demonstrated an interest in ensuring the sustainability of their forest sourcing. Considering the economic value and ecological significance of forests, stakeholder interest in information that could enable companies to better understand their forest supply and curtail deforestation comes as no surprise. However, complexities in the forestry supply chain, which encompasses a network of intermediary parties and processes that often involve multiple supply chains in many different countries, pose challenges to achieving this desired understanding (D'Amours, Rönnqvist, & Weintraub, 2008).

The wood product life cycle involves a complicated transfer of materials through a network of suppliers, dealers, buyers, manufacturers, distributors, and retailers (Anker-Rasch & Daviknes Sørgard, 2011). For example, the production of approximately 2.7 million tons of wood chips could involve a network of roughly 65 landowners, 600 suppliers, 120 sawmills, and 10 shipping operations (Nogueron & Laestadius, 2012). Since materials from various stages of a product's life cycle may flow between a number of facilities, it is generally not possible to determine the precise origins of wood product components.

The production of wood fiber involves a number of stakeholders including landowners, loggers, sawmills, dealers, and buyers. To further complicate matters, forest management and operational practices vary depending on whether the land is publicly or privately owned (D'Amours, Rönnqvist, & Weintraub, 2008). Typically, logs are harvested and transported to sawmills, where they are mixed together. Since companies often harvest wood in many different locations within a country, the mixing of logs prior to wood fiber production prevents the association of the fiber in a specific product to a specific region (WRI WBCSD, 2015). While vertically integrated companies that control both upstream and downstream processes tend to have less difficulty with traceability and are able to better manage their resources, the divergent nature of the forestry supply chain for non-vertically integrated companies provides an opportunity to improve the linkage between consumer products and their original raw materials (Anker-Rasch & Daviknes Sørgard, 2011). Additionally, the increasing prevalence of outsourcing in the U.S. has the effect of further disconnecting companies from their supply chains (WRI WBCSD, 2015).

Related to and in some cases resulting from these challenges, are the lack of data on plantation locations, forest ownership, planting rates, tree species, and yields from harvest, all of which are obstacles to supply chain understanding and transparency (Carle, Del Lungo, & Varmola, 2003). Compounding the limitations caused by the inherent complexities of the forestry supply chain is the proprietary nature of supplier data. For example, companies that compete against one another may jointly own sawmills. As such, the sharing of information regarding their individual suppliers may violate U.S. anticompetitive regulations (WRI WBCSD, 2015). In the U.S., information sharing in such a scenario may be considered by the Federal Trade Commission as horizontal conduct, which occurs when "competitors interact to such a degree that they are no longer acting independently, or when collaborating gives competitors the ability to wield market power together" (U.S. Federal Trade Commission, 2016).

Governance

In the United States, the Lacey Act, amended in 2008, encourages companies to improve supply chain management by requiring an import declaration stating the country of origin, species name of plants contained within a product, and the quantity and value of imports (GreenBlue, 2011). Through the imposition of penalties, including fines and jail time, the Lacey Act serves as a powerful deterrent for illegal logging and deforestation and has encouraged American companies to implement institutional changes and improve their relationships with their supply chains (WRI, 2009). Criticism of the Lacey Act centers on its acceptance of certain plant products for which the plant species or country of origin cannot be determined and lacking in terms of provision of a clear and supportive framework to guide compliance by importers and exporters (Rainforest Alliance, 2008).

On the global governance and collective action front, the ninth meeting of the Conference of the Parties in 2008 featured a call by the World Wildlife Fund (WWF) for countries and international organizations to pledge to zero net deforestation (ZND) by 2020 (WWF, 2009). Although WWF was successful in collecting signed commitments from 68 country delegates and creating awareness of deforestation, the ZND pledges were met with a number of inherent complications.

First, companies must have information regarding their supply chains as well as knowledge about potential environmental and social problems in different sourcing regions in order to meet ZND goals. While this is a positive indication that TSC's Commodity Mapping Program may be helpful for companies, these types of tools and data were not as readily available when companies committed to ZND. This lack of information may indicate that companies did not have an accurate idea of their contributions to deforestation or the challenges of pursuing ZND by 2020.

Second, ZND does not account for variations in forest type, quality, biodiversity, and ecosystem value (WWF, 2009). ZND adherence merely requires an equal area replacement of forests lost to clearance or conversion. As such, countries may still experience significant loss of natural forests and continue to contribute to climate change even if companies are pursuing ZND (Goering, 2013).

Finally, there exist definitional incongruences regarding deforestation, which hinder understanding of deforestation and the advancement of best forest sourcing practices. The 2015 Global Forest Resource Assessment (FRA) by the Food and Agriculture Organization (FAO) defined deforestation as "the conversion of forest to other land use or the permanent reduction of the tree canopy cover below the minimum 10 percent threshold" (FAO, 2015). This can be thought of as the "long-term or permanent loss of forest cover" and implies that deforestation is characterized by transformation into another land use (FAO, 2015). Meanwhile WWF (2009) defines deforestation as "the conversion of forest to another land use or the long-term reduction of the tree canopy cover," including the "conversion of natural forest to tree plantations, agriculture, pasture, water reservoirs and urban areas but excludes timber production areas managed to ensure the forest regenerates after logging." These definitions of deforestation fail to protect areas of natural forest from many instances of one-time clearing, which can harm biodiversity and carbon sequestration ability as well (FAO, 2015).

ZND was subsequently amended to zero net deforestation and degradation (ZNDD). While the goal remains to achieve zero net forest loss by 2020, this new version accounts for forest quality and the protection of natural forests (WWF, 2016). Degradation encompasses the important components of forest health that were neglected by focusing on deforestation and is a crucial part of forest management. Degradation is defined by FRA, and similarly by WWF, as “changes within the forest, which negatively affect the structure or function of the stand or site, and thereby lower the capacity to supply products and/or services” (FAO, 2011; WWF, 2016a).

The Reducing Emissions from Deforestation and Forest Degradation program (REDD+) is an initiative created by the U.N. to facilitate collaboration between developing countries and international organizations to protect forests and reduce greenhouse gas emissions (WWF, 2016b). Much like ZNDD, REDD+ originally started as a program that focused on deforestation and neglected degradation. With the inclusion of degradation, the program offers funding to developing countries to incentivize the protection of forests and implement sustainability measures using a value system based on the amount of carbon stored in a forest (Rocchio, 2015). In order to use this method, accurate measures of forest cover along with a universal definition of a forest are needed.

The difficulty in managing degradation includes the limitation of monitoring forest changes via satellites (Putz & Redford, 2010). Forest degradation that occurs beneath canopy cover is not detectable by satellites with current technology. However, a larger challenge may, again, be the problem with definitions. There has yet to be an international standard for the definition of a forest or a tree. The U.N. recognizes over 800 definitions of forests. The U.N. Food and Agriculture Organization (FAO) created a broad classification guideline that includes minimum area, minimum tree cover, and minimum tree height with which countries are to establish their own threshold values (Lake & Baer, 2015). The 2015 FRA definition of a forest is more specific as it considers forests to be “land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use” (FAO, 2015).

Supply Chain Management Tools

Due to the global economic importance of the forestry industry, many tools and methods, such as TSC’s Commodity Mapping Program, exist to address the lack of transparency and traceability in wood product supply chains. These product offerings can generally be broken down into informational tools (based on mapping, survey responses, etc.) and attempts to physically track wood flows.

The World Resources Institute (WRI) Global Forest Watch program, along with over 40 other organizations, have partnered together to create the Global Forest Watch Commodities (GFW Commodities) program (WRI, 2016). GFW Commodities is an online platform that utilizes open source data and satellite data to provide businesses with information about deforestation in their supply chains. While GFW Commodities was created for the Roundtable on Sustainable Palm Oil (RSPO), it provides useful information regarding forest cover as well. Perhaps the most similar tool to TSC's Commodity Mapping Program is the Forest Analyzer, an interactive map that covers forest change (loss and gain), forest cover, forest fires, forest use, conservation, and logging concessions by country, region, and, even, for a user-drawn shape on the map. GFW Commodities is beneficial because it provides timely information in an accessible, interactive map. The drawback to this tool is that it is regionally limited, but new data are consistently being added on a global scale.

FAO's Global FRA offers an online tool called the Forest Land Use Data Explorer (FLUDE), which compiles primarily 2015 land use data, including agriculture and land use classifications, for the analysis of forest resource use (FAO, 2016). FLUDE uses information submitted by national governments to FAO as well as data from international organizations. FLUDE also uses remote sensing and Landsat data, in partnership with the European Commission Joint Research Centre (JRC) and remote sensing specialists around the world. The tool is organized by topic, which includes forest area and characteristics, disturbance and forest degradation, biodiversity and conservation, ecosystem services, and economics, and filter data, which include deforestation, planted forest, reforestation, and natural forest area change. The tool displays maps and charts relevant to the topic and filter data selected. While FLUDE is advantageous because of its interactive platform and the number of partnerships involved in the project, the tool lacks data over time as well as more region specific data.

The International Tropical Timber Organization (ITTO)'s Annual Review Statistics Database provides information regarding the production and trade of primary wood products (ITTO, 2014). This is accomplished using data from the Joint Forest Sector Questionnaire, which was formed through a partnership with Eurostat, the FAO Forestry Department, and the UN Economic Commissions for Europe (UNECE). The database incorporates trade data, tree species, price trends, and secondary wood products with questionnaire information to provide import and export quantity and value by country, wood type, and year. While this tool is helpful for trade information and analysis of resource flow, it is neither comprehensive nor spatially specific enough to help companies increase supply chain transparency.

The High Carbon Stock Approach Toolkit is the result of collaboration between The Steering Group, WWF, Greenpeace, Tropical Forest Trust, FPP, and plantation companies (Greenpeace Southeast Asia, 2014). The Toolkit provides a way to address deforestation via the identification of forests with high conservation value for land use planning. It uses Landsat data and GIS to classify land into the following six categories: high density forest, medium density forest, low density forest, young regenerating forest, scrub, and cleared land. While this tool is useful for identifying high value forests that should be protected and, consequently, where companies should not be sourcing from, it does not directly inform companies about their particular supply chains.

The Programme for the Endorsement of Forest Certification (PEFC) has an online platform called the Global Information Registry that tracks the trade of certified materials and allows certified suppliers to share information with downstream parties (PEFC international, 2016). This allows certified materials for solid wood and paper products to be traced along the supply chain. This is limited, however, because of its focus on certified wood and neglects to provide information for other sources of wood, which may restrict supplier options for companies and prevents companies from working on improvements with their current suppliers.

SmartSource is an online tool that allows access to supplier submitted information regarding the species, origin, and certification status of wood and fiber in a product. This tool is part of a Rainforest Alliance program and is used by retailers, importers, and manufacturers to manage supply chains for solid wood and paper products. String is another tool that allows all parties within the supply chain to request product information from their suppliers (WRI WBCSD, 2015). Similar to String, Forest Stewardship Council's (FSC) Online Claims Platform (OCP) allows all parties within the supply chain to access information and records for a product as it moves down the supply chain (FSC International, 2016). However, String and OCP are limited by the data that suppliers are willing to provide and the OCP only provides information regarding FSC certified solid wood and paper products.

In terms of approaches to physically track wood supply, electronic barcoding allows the tracking of timber in real time using barcodes and a data collecting software system that can report the GPS location as well as species of a tree (FSC International, 2016). This method provides information regarding each point of passage in the supply chain, but the technology is limited to solid wood or timber and requires commitment and organization amongst workers along the supply chain. Barcodes must be applied to standing trees, which remain on the stump after harvest, and corresponding barcodes must be added to felled logs. Manufacturers and retailers also use fiber analysis to categorize the type of tree used in paper products (WRI WBCSD, 2015). Fibers in paper samples may be used to verify whether the paper was made from hardwood or softwood species along with the pulping process, genus, and, in some cases, the species of the tree. While this method does not provide direct information regarding the origin of the wood fiber, it provides general information that can be used to deduce possible source regions. As such, companies have used this tool to demonstrate due care in consideration of the Lacey Act. (Grant, Nogueron,

& Hanson, 2011). Finally, DNA mapping entails the extraction of DNA from a population of trees to encapsulate genetic variation and comparing that to DNA from wood samples to verify their origins (WRI WBCSD, 2015). While this can only be used for solid wood, it is advantageous for random product sampling because it can be used for finished products. This tool may be used by forest managers, manufacturers, importers, and retailers, but is time and resource intensive.

While there are many approaches to improving supply chain transparency, the aforementioned tools for tracing wood supply are limited in one way or another by data availability constraints and scope. Upon completion, TSC's Forestry Commodity Mapping Program will be unique because it will show trends in global canopy cover over a comparatively long time span, from 2001-2013. Using this information, in conjunction with trade or company-specific sourcing data, will make it possible to deduce the location of tree farms and, consequently, potential wood sourcing regions. The addition of regional hotspot information will provide important context to tie potential sourcing regions with environmental and social risks. By providing a more comprehensive spatial and temporal view of the global forestry supply chain, the TSC Commodity Mapping Program can help companies better understand their current impacts and work with existing suppliers to improve supply chain sustainability rather than restricting companies to certified suppliers. To this end, companies are provided with information and resources to compare different sourcing regions and understand their supply chain impact relative to global trends. This provides companies with more information as well as more options for suppliers.

PROJECT SIGNIFICANCE

Forests represent a vital resource and provide countless services, including harboring biodiversity, helping to regulate the Earth's climate, and providing the commodity inputs for wood products. Companies that produce wood products and other stakeholders, including non-governmental organizations and consumers, have become increasingly aware of the threat of deforestation and numerous additional social and environmental issues associated with wood sourcing. However, the global, complex nature of wood product supply chains results in a lack of traceability and accessible high-quality information about wood sourcing regions. The subsequent lack of supply chain knowledge can inhibit companies from understanding the environmental risks or benefits associated with their product sourcing.

TSC's Commodity Mapping Program provides tools that address supply chain transparency and traceability issues by leveraging international trade data and applying company-specific procurement data (where available) to show companies and external stakeholders where in the world the commodity inputs to products are likely sourced. TSC also incorporates risk layers to show which geographies are prone to impacts such as deforestation, child labor, and water pollution. While TSC can use trade data and some basic sourcing knowledge to demonstrate the country where a product's commodity inputs are likely to originate, additional spatial analyses that identify sourcing regions on a finer scale must be included to demonstrate impacts that vary sub-nationally. Furthermore, company specific procurement data or regional analysis might pinpoint a company's supply source and the associated impacts, but the global scope of this project is needed to understand the benefits or risks from sourcing in a particular region relative to other regions.

This project enables the Commodity Mapping Program to begin to cover wood products by providing base maps that identify and characterize wood sourcing regions globally on a 10km by 10km scale. Specifically, it identifies plantations around the world that are most likely to serve as sources of entry for wood product supply chains (tree farms) and least likely (palm plantations), as well as deforested areas that are least likely to enter forest supply chains (forest lost to fire) on a consistent basis. The creation of these base maps provides valuable insights to exactly where wood is most and least likely to be sourced around the world and what characteristics describe these areas. This increases the spatial accuracy of the Commodity Mapping Program as it applies to wood products and will enable TSC members to better understand their wood product supply chains and the associated impacts based on where in the world the products are sourced and whether that sourcing originates from a plantation or deforestation.

Through the identification of plantations and forest fire and the associated tree cover loss, these models also show where tree cover loss occurs that is not related to either. This is a critical contribution of the project as it is in these areas, where tree cover is lost by processes other than fire and does not recover at rates consistent with plantations, that wood sourcing may pose the greatest risk of deforestation. Moving forward, TSC plans to integrate these areas of tree cover loss not identified as plantation or forest lost to fire with the plantation analysis to create a comprehensive global wood fiber production dataset. This dataset will inform its membership of the geographic significance of their wood sourcing in a comprehensive manner. By enabling TSC to provide its membership with enhanced global and cross-regional understanding of wood sourcing, this project plays a direct and significant role in equipping companies to better address the potential environmental and social risks associated with their sourcing, work towards internal and industry-wide commitments, and adhere to evolving regulations. This knowledge will also empower concerned customers and non-governmental organizations to hold these companies accountable. The new methodologies developed and utilized in this project may be applied in the future to further inform the Commodity Mapping Program as it relates to wood and other commodities.

PROJECT OBJECTIVES

The project aims to analyze global forest canopy change to identify and characterize wood sourcing regions to enable companies to better understand the origin of their wood products. The project helps to inform strategic wood sourcing for global brands by providing a series of mapping tools, which characterize wood sources that are consistent with plantations and deforestation.

Specifically, these tools:

1. Identify areas that are likely to be plantations, including both tree farms and palm.
2. Predict likely wood sourcing regions that are not classified as traditional tree farms.
3. Support the trade flow analysis of the larger Commodity Mapping Program.

METHODS

Guiding Logic

Spatial input data analyzed in this report highlight global forest change. Some of this canopy clearance enters wood supply chains on a recurring basis, some is periodically cleared, and some forested land is permanently cleared for purposes such as urbanization or agriculture. Wood can enter supply chains from one time clearing (deforestation) or from managed forest. Some cleared canopy, such as that lost to fire, may not enter supply chains at all.

Wood plantations, referred to as tree farms, represent a consistent point of entry into wood supply chains. In order to determine where in the world wood comes from, locations of tree farms must first be identified. These locations are predicted using the methodology described in the “Plantation Analysis” section.

Trees are also sourced from other regions that harbor different harvesting practices, such as natural regrowth or clear-cutting. When trees are harvested, the clearance is visualized as canopy loss. Some canopy is lost due to fire. Trees that burn are less likely to be entering wood supply chains. In order to delineate where else, besides tree farms, wood may be coming from, canopy lost to fire is subtracted from overall canopy loss. This output represents deforestation that cannot be attributed as lost to fire or occurring on plantations, so it could be entering supply chains. The locations of canopy lost to fire are visualized using the methodology described in the “Deforestation Analysis” section.

Data

This project calls on three major sources of spatial data: Hansen et al. (2013), MODIS, and Google Earth. Table 1 summarizes the individual datasets that were used.

Hansen/UMD/Global Forest Change Dataset

Hansen et al. (2013), at the University of Maryland's Department of Geographical Sciences, analyzed growing season Landsat 7 images using Google Earth Engine to produce global spatial data regarding forest extent and change from 2000 to 2013. The researchers define trees as vegetation taller than 5m in height. The study area excludes Antarctica and some Arctic islands. Only full canopy clearance is detected (e.g., selective understory logging is not identified as loss). The original global datasets have a spatial resolution of 1 arc-second per pixel, or roughly 30m by 30m at the equator (Hansen et al., 2013).

MODIS Fire Points

MODIS (Moderate Resolution Imaging Spectroradiometer) is a scientific instrument built by Santa Barbara Remote Sensing and launched by NASA. The Terra and Aqua satellites carry MODIS, and each satellite views the Earth's surface every 1 to 2 days. Fire data are sensed by MODIS and distributed by FIRMS (Fire Information for Resource Management System) – both are services run by NASA. The University of Maryland extracts and produces the actual data on active fire location (called source MCD14ML Fire Location Product, Collection 5, Version 1) (FIRMS, 2015). MODIS detects fires at a 1km by 1km resolution, with an active fire point representing the center of a 1km^2 pixel. That pixel may contain one or more fires. The MODIS data do not provide information on cloud cover or missing data. The dataset contains about 4 million fire points for each calendar year. Each fire point contains attributes presented in Table 2.

Google Earth

Google Earth is a global information system that renders a virtual globe by aggregating satellite imagery from different years. These analyses used Version 7.1.5.1557 and ran it on Microsoft Windows (6.1.7601.1). Google Earth presents imagery at a fine resolution, about 1m by 1m.

Table 1. Datasets used for spatial analyses.

Dataset	Dates	Definition	Encoded	Resolution	Source	Datum
Tree Cover	2000	Encodes canopy closure as percentage per grid cell	0-100: percentage tree cover per cell	1 arc-second per pixel	Hansen et al., 2013	WGS 1984
Gain	2000-2012	Identifies change from non-forest to forest entirely within study period	1: gain 0: no gain	1 arc-second per pixel	Hansen et al., 2013	WGS 1984
Loss	2000-2014	Identifies change from forest to non-forest state	1: loss 0: no loss	1 arc-second per pixel	Hansen et al., 2013	WGS 1984
Loss Year	2001-2013	Disaggregates Loss to annual time scale	0: no loss 1-13: year of loss, 2001 - 2013	1 arc-second per pixel	Hansen et al., 2013	WGS 1984
Fire Points	2001-2013; as requested	Active fire location	point dataset with table of attributes	1km x 1km	MODIS/NASA	WGS 1984
Oil Palm Concessions	NA	Displays areas (ha) in Cameroon, Republic of Congo, Indonesia, and Liberia that are "allocated by a government or other body for industrial-scale oil palm plantations…data may come from government agencies, NGOs, or other organizations and varies by date and data sources"	NA	NA	WRI Global Forest Watch, 2016: Cameroon (WRI); Indonesia (Ministry of Forestry); Liberia (Global Witness); Congo (WRI & Ministry of Agriculture)	WGS 1984

Table 2. MODIS fire point attributes (FIRMS, 2015).

Attribute	Description
Latitude	Center of 1km fire pixel but not necessarily the actual location of the fire as one or more fires can be detected within the 1km pixel.
Longitude	Center of 1km fire pixel but not necessarily the actual location of the fire as one or more fires can be detected within the 1km pixel.
Brightness	Brightness temperature of the fire pixel measured in Kelvin, using Channel 21/22.
Scan	The algorithm produces 1km fire pixels but MODIS pixels get bigger toward the edge of scan. Scan and track reflect actual pixel size.
Track	The algorithm produces 1km fire pixels but MODIS pixels get bigger toward the edge of scan. Scan and track reflect actual pixel size.
Acq_Date	Date of MODIS acquisition.
Acq_Time	Time of acquisition/overpass of the satellite (in UTC).
Satellite	A = Aqua and T = Terra.
Confidence	This value is based on a collection of intermediate algorithm quantities used in the detection process. It is intended to help users gauge the quality of individual hotspot/fire pixels. Confidence estimates range between 0 and 100% and are assigned one of the three fire classes (low-confidence fire, nominal-confidence fire, or high-confidence fire).
Version	Version identifies the collection (e.g. MODIS Collection 5) and the source of Level 1B data used to make the Level 2 product. The source for MCD14DL are near real-time data processed by LANCE FIRMS; this is indicated by .0 after the collection e.g. Version 5.0. MCD14ML are from MODAPS, these are standard/science quality data, processed by the University of Maryland (with a 3 month lag) and distributed by FIRMS; indicated by .1 after the collection e.g. Version 5.1.
Bright_T31	Brightness temperature of the fire pixel measured in Kelvin, using Channel 31.
FRP	Depicts the pixel-integrated fire radiative power in MW (megawatts).

Plantation Analysis

The Hansen dataset was used to predict areas of tree farms (sometimes referred to as tree plantations) and palm plantations globally. Data from these datasets were aggregated, compiled, and then input into a binary logistic model to predict existence of tree farms and palm plantations globally. Observed characteristics from global satellite imagery in Google Earth were used to build a binary dataset (existence, non-existence) for both tree farms and palm plantations. This dataset was then used as the dependent input variable to build a binary logistic regression model. The output of this model was two datasets that predict existence of tree farms and/or palm plantations. This component of the analysis uses tree loss, tree gain, and tree canopy cover spatial data from the Hansen dataset (Hansen et al., 2013) and global satellite imagery from Google Earth.

Methods

The datasets were initially aggregated to improve the processing speed and stability of the loss, gain, and tree canopy cover data. The aggregation process was performed in ArcGIS using the Block Statistics tool (solving for the mean value over an area of 10 pixels by 10 pixels, Figures 1 & 2). Note that an iteration model was used to iterate models globally over the original 504 tiles designated in the original Hansen data such as all resampling models (Figure 3). This iteration process was used when the size of outputs made the processing of a model unstable/unreliable. After iterating the resample process, the datasets were then projected to an equal-area projection to allow for area-based analyses. This process was performed in ArcGIS using the Project tool (Goode Homolosine projection, raster size of 250m by 250m; Figure 4). The datasets were then aggregated to a scale of 10km by 10km to allow for global modeling. This process was performed in ArcGIS using the Block Statistics tool (solving for the mean value over an area of 40 pixels by 40 pixels resulting in 10km by 10km averaged pixels; Figure 5).

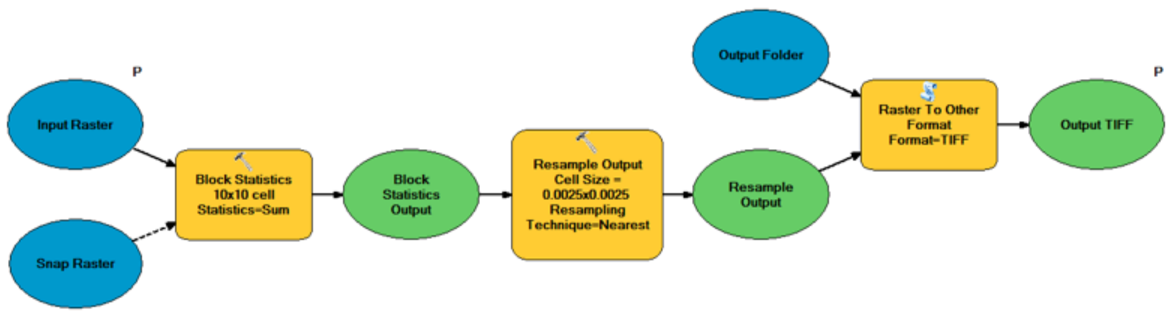

Figure 1. Resample to 0.0025 by 0.0025 degree cells. This model was used to resample/aggregate raster files from a resolution of 0.00025 by 0.00025 degree/cell to 0.0025 by 0.0025 degree/cell.

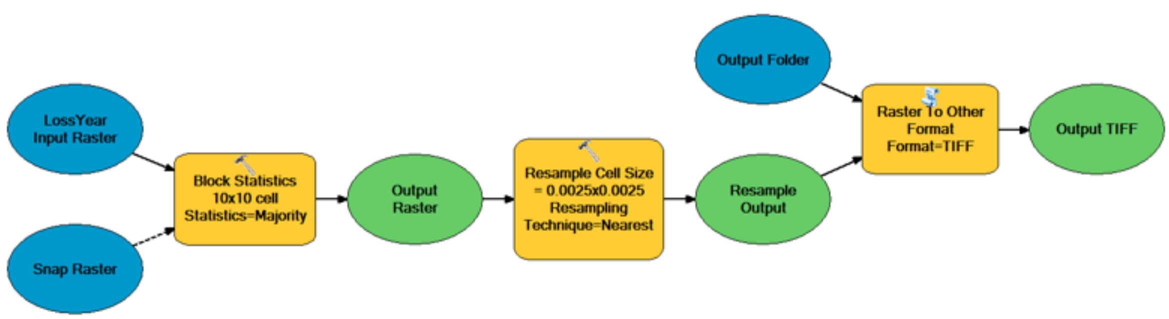

Figure 2. Resample to 0.0025 by 0.0025 degree cells for Loss Year. This model was used to resample/aggregate raster files from a resolution of 0.00025 by 0.00025 degrees/cell to 0.0025 by 0.0025 degrees/cell specifically for the Loss Year dataset (using a majority statistic over a sum statistic).

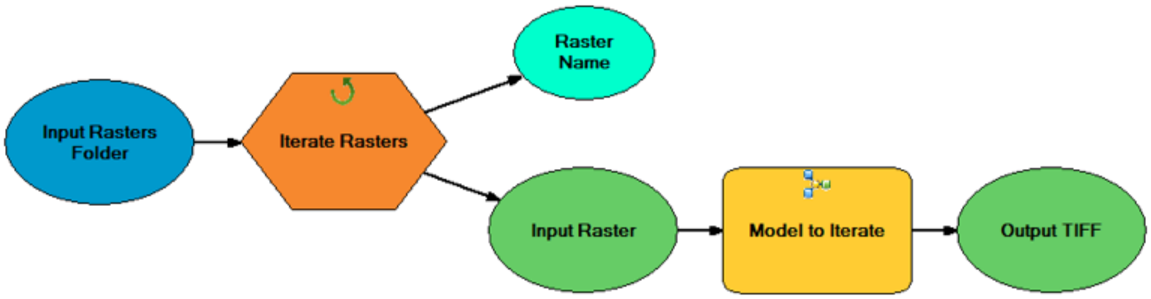

Figure 3. Iterate model. This model was used to iterate model processes over the 504 raster sections inherent in the Hansen dataset to allow for more reliable processing.

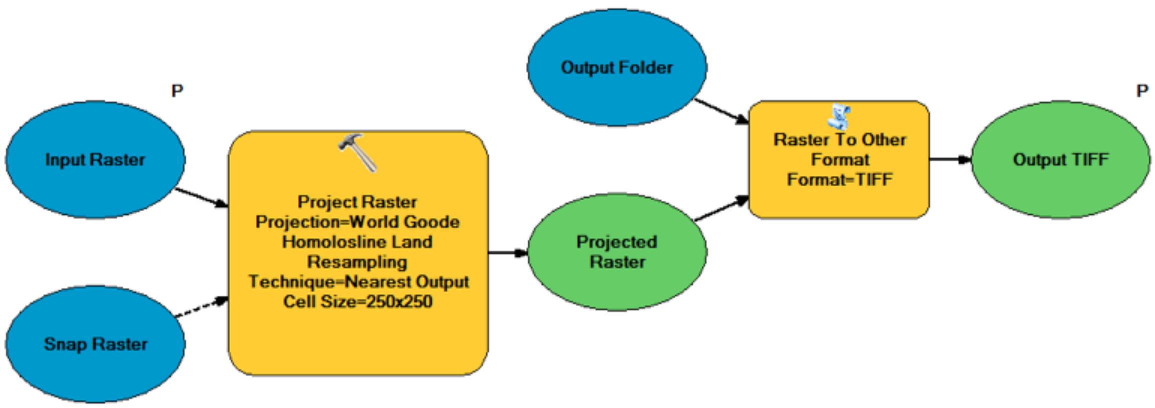

Figure 4. Project model. This model was used to project rasters into the World Goode Homolosine projection to allow for equal-area analysis.

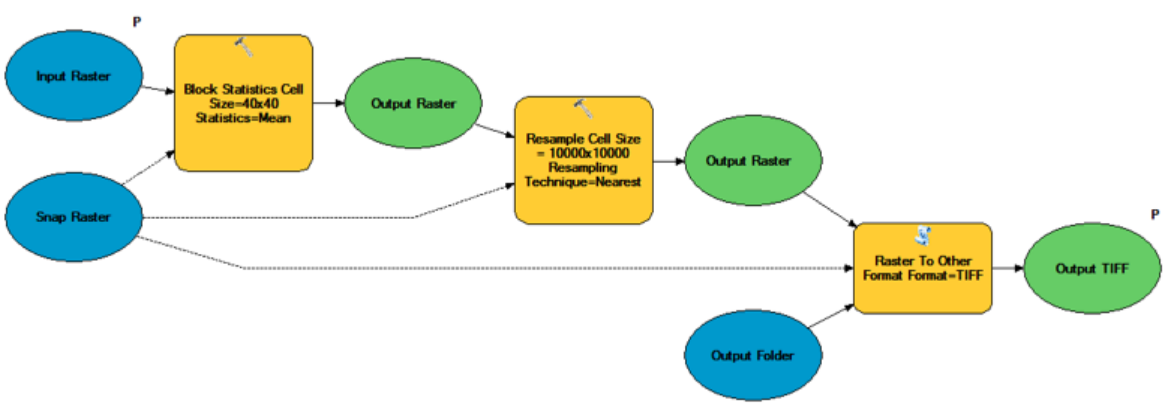

Figure 5. Resample to 10km by 10km cells. This model was used to resample/aggregate raster files from a resolution of 250m by 250m to 10km by 10km.

Furthermore, an additional dataset identifying the overlap in the tree loss and tree cover gain datasets was created. This dataset represents the percentage of loss and gain in an area that overlaps (e.g., a value of 100 indicates that there were equal amounts of loss and gain within the pixel; Figures 6 & 7). This overlap was calculated using the projected 250m by 250m tree loss and tree gain datasets and then aggregated using the Block Statistics tool (solving for the mean value over an area of 40 pixels by 40 pixels resulting in 10km by 10km averaged pixels). This tree loss/gain overlap dataset was created and utilized because of the underlying assumption that tree farms have much quicker regrowth rates than other tree management practices (i.e. natural forest or cleared land) due to active regrowth management. Additional datasets of the mean and maximum value of the surrounding 8 pixels (and the central pixel) for several datasets (tree loss, tree gain, and tree loss/gain overlap) were created in MATLAB to give more inputs on the tree statistic trends in an area. Furthermore, the tree cover data were used to normalize the tree loss and gain data. This normalization was used to transform the loss and gain data from statistics based on total area to statistics based on total tree cover. For example, before normalization a value of 50 in the loss dataset would indicate that there was a tree cover loss event in half of the total area within the 10km by 10km grid cell without any reference to the amount of initial tree cover in the cell. A value of 50% loss in a cell that is only covered by 50% tree cover is much more impactful than a value of 50% in a cell that has 100% tree cover. It is for this rationale that the normalization was employed.

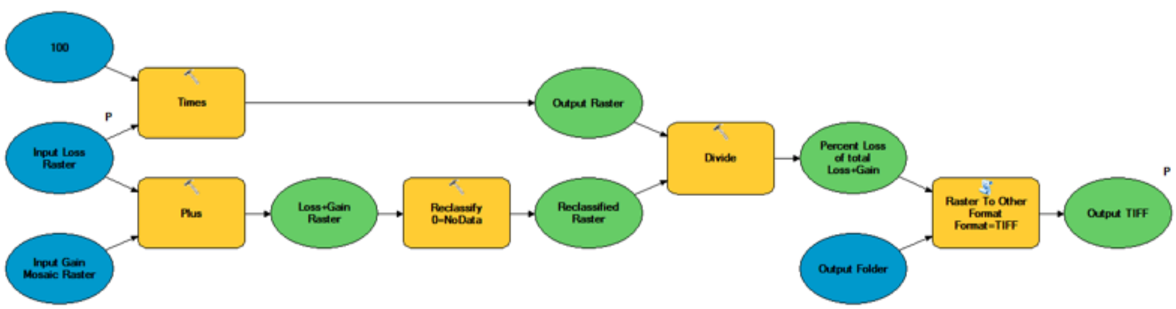

Figure 6. Loss Gain overlap statistic model. This model was used to calculate the loss gain overlap statistic. Output raster values represent the percentage of total tree cover loss and gain that was lost.

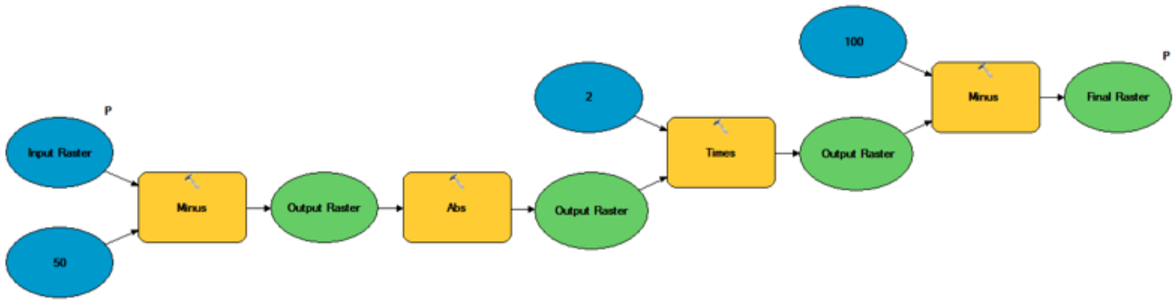

Figure 7. Recalculate Loss Gain overlap statistic. This model was used to recalculate the loss gain overlap statistic. Input raster values represent the percentage of total tree cover loss and gain that was lost. The output raster values represent the percentage of total loss and gain that was either lost or gained (e.g., a value of 100 indicates that areas of loss and gain are identical).

Next, a table of values (1=true, 0=false) was built using Google Earth imagery to analyze tree covers and the presence of tree farm visually. A true value was made if any amount of tree farm (and/or palm plantation) was observed within a particular block of a global 10km by 10km grid. The tree farm classification is defined as having clear rows of homogeneous trees with evidence of clearing by either the existence of cleared land within the grid or evidence of forest lost through historical imagery. The palm plantation classification is defined as having clear rows of homogenous palm trees, which can be identified by their fronds in Google Earth imagery where resolution is adequately high. If the resolution was low or identification was unclear in any region, the tested block was not included in the dataset to minimize error in the data.

This dataset of true/false Google Earth imagery values was then used as the dependent input variable in a binomial logistic regression model in MATLAB. The independent input variables were chosen from the tree loss, tree gain, and loss/gain overlap datasets. The output of this model was then implemented into an interactive map using the Leaflet library within RStudio (version 3.2.2).

Deforestation Analysis

This component of the project identifies where forest has been lost due to fire using the Hansen Loss Year and MODIS datasets. ArcGIS 10.3.1 was used for all spatial analyses. Confidence of fire occurrence was accounted for and areas of overlap of the two input datasets were identified on an annual scale. The areas of fire and canopy loss overlap represent the areas of forest loss that can be attributed to fire.

Approach Logic

The Loss Year dataset shows in which year a particular tree cover area was cleared. MODIS shows daily fire points. MODIS distinguishes low confidence fire as one that is below 30% confidence range (Giglio, 2010). To prevent the inclusion of any false alarms of fires occurrence, low-confidence fire points were removed from analysis. The analysis assumes that canopy clearance that overlaps with fire points in a given year likely resulted from the region being burned. Fire data exist as points in the centroid of 1km by 1km pixels, meaning that fire could have occurred anywhere within the given 1km^2 pixel. Burned area was categorized as any canopy loss that is within 1km of a fire point. Burn area extent was estimated by calculating the areas of contiguous Loss Year polygons.

Preparing Hansen Loss Year Dataset

The original Loss Year dataset pixel edge is 0.00025 decimal degrees. The raw dataset was resampled using Block Statistics (majority of 10 cells by 10 cells) to a pixel edge of 0.0025 decimal degrees (Figure 2). Blocks that had equal majorities came up as blank cells, so the team ran a Reclassify and subsequent Nibble step (Figure 8). The data were then projected to an equal area projection (Goode Homolosine) with a resolution of 250m by 250m (Figure 4).

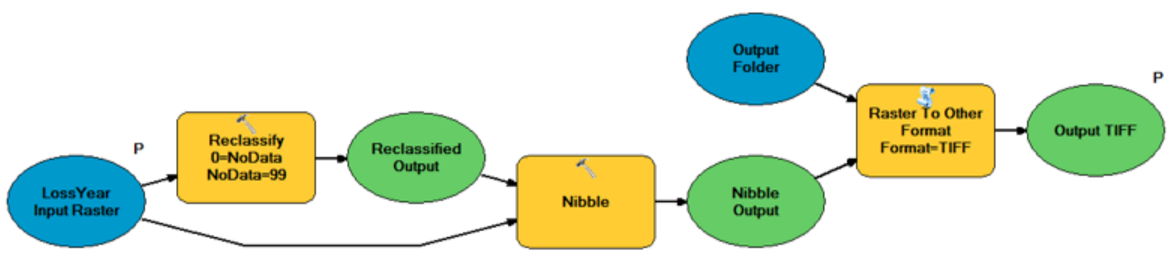

Figure 8. Nibble Loss Year model. This model was used to fill-in missing data points within the tree cover Loss Year 0.0025 by 0.0025 decimal degrees dataset that were caused from having equal amounts of loss from two years within an output cell in the aggregation model.

The Loss Year dataset is a raster with each cell coded as year of canopy clearance. It was broken up into annual rasters, which were then converted into polygons in order to select areas (in m^2) of canopy clearance (Figure 9).

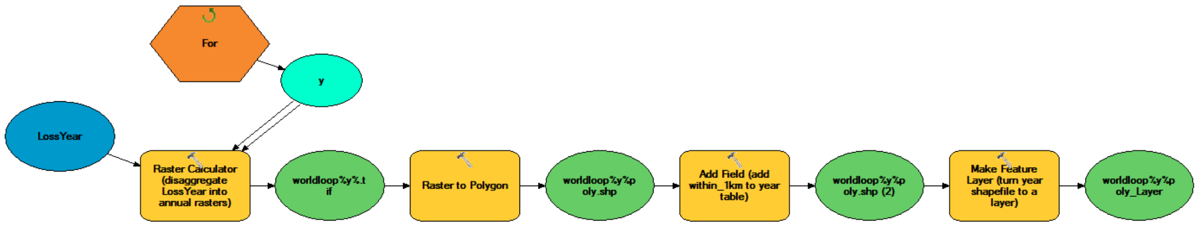

Figure 9. ArcGIS Model Builder sequence for Hansen Loss Year. First step of fire analysis, where the resampled and projected 250m by 250m Loss Year raster is broken up into polygons corresponding to years of canopy clearance ("y"), 2001-2013. The thirteen resulting polygons are created into feature layers with a column that represents whether the loss polygon was within 1km of a fire point.

Determining Burned Areas

The team developed a model to determine how much annual deforestation is due to fire (Figure 10). The input fire point files contain all fire detection confidence classes. In order to refine fire detection, the team made a layer out of only the nominal- and high-confidence fire points ($30 \leq C \leq 100$). The contiguous polygons of canopy loss that occurred within 1km of a corresponding annual confidence fire point were then selected and designated as lost due to fire in that year (Figure 11). The team then calculated areas (in m^2) of total annual canopy loss and annual canopy loss that can be attributed to fire. Finally, the analysis aggregated the annual total canopy loss polygons into one polygon showing global deforestation from 2001 to 2013 and aggregated the annual burned canopy regions into one burned canopy polygon by using "Selection -> Select by Location" in ArcGIS.

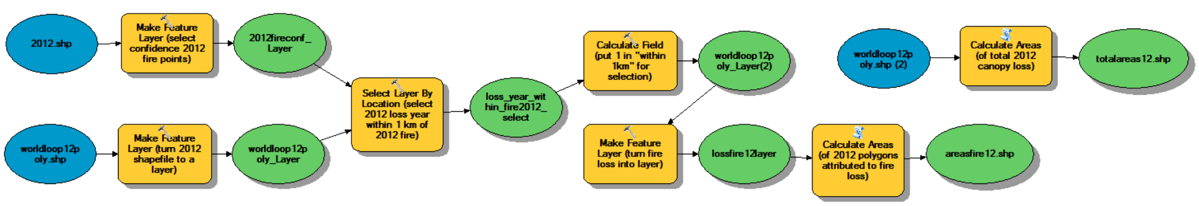

Figure 10. ArcGIS Model Builder sequence for calculating annual burned and total deforestation areas. Example sequence shown for 2012, where the area of canopy loss that occurs within 1km of a nominal- or high-confidence fire point and the total area of canopy loss are calculated.

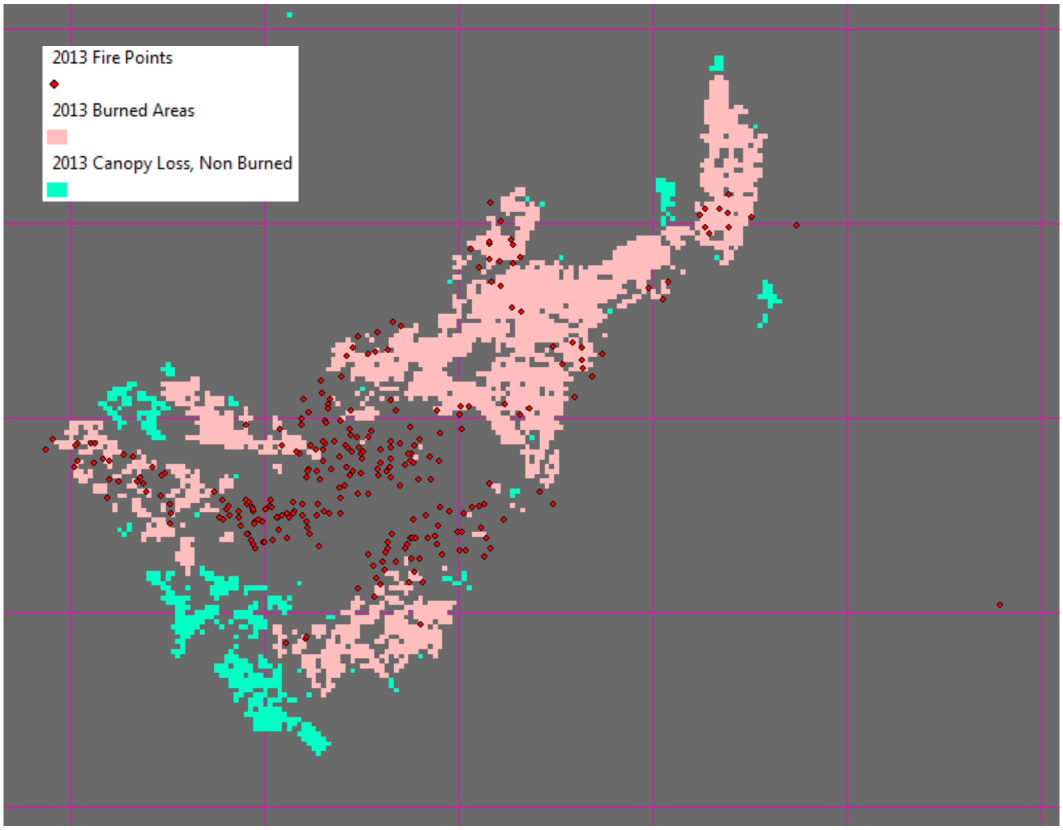

Figure 11. Representation of fire selection methodology, 2013. The purple background grid is 10km by 10km. The colored polygons represent areas of canopy loss in 2013. The red points represent centroids of $1km^2$ cells that contain at least one nominal- or high-confidence fire. The fire model selects the contiguous polygons that are within 1km of any red fire point and turns the polygons pink. The teal polygons represent canopy loss areas in 2013 that were not burned. Cell resolution: 250m by 250m.

RESULTS AND DISCUSSION

Plantation Analysis

The results of the logistic regression for the tree farm model show a significant relationship between tree cover gain and prevalence of tree farm (p-value < 0.001; Table 3). This relationship is well understood as tree gain in tree farms is a distinguishing factor of this type of forest/tree management practice over others (such as transformation into agriculture or natural regeneration of forest). The other two input factors (tree loss and loss/gain overlap) did not show the same statistical significance. However, loss of tree cover and loss/gain overlap certainly occur on global tree farms. Therefore, these datasets were not eliminated despite the lower statistical significance.

For the tree loss data, there are many other forest events that can occur other than the cutting on a tree farm that could result in tree cover loss. Accordingly, it is not surprising that loss alone is not a great predictor of tree farm, as it is not a unique characteristic of tree farms. However, it does help to identify tree farms in relation to forest that does not experience any or little loss and for that reason is still viable within the model. The low significance of loss/gain overlap is surprising. A major characteristic of tree farm management is the loss and subsequent (and relatively rapid) regain of tree cover. This loss and gain pattern differentiates the management style from others. Accordingly, the low significance does not preclude the data from the model but indicates that some modifications may need to be made on the sampling of the data. Currently the loss/gain overlap data were compiled at the 0.0025 by 0.0025 degree/pixel resolution and then aggregated to 10km by 10km. Changing the compilation resolution may allow for a better representation of tree/loss overlap and allow for a more statistically robust model. A sensitivity analysis may allow for better understanding on how sampling of loss/gain overlap will affect the final model output.

Overall, the logistic model appears to perform reasonably well. Of the 43 inputted true values, 22 values were predicted above 80%, and 30 values were predicted above 50% (Figure 12). This indicates that 70% of the inputted values were correctly predicted above 50% but 30% were not correctly predicted. Identification and analysis of non-identified regions in the future will allow for a better understanding of limitations of the model and allow for better inputs to improve the model. Furthermore, additional testing data points through satellite imagery may help improve the overall reliability of the output as additional sample points are input into the regression model. It is important to note that it is possible that managed forests where natural regrowth occurs after timber harvest (e.g., United States national forest land) are likely to be predicted as farm within the tree farm model if tree gain is high enough (due to the positive factor gain has on the logistic model output).

Table 3. Tree farm regression results. Results of logistic regression for tree farm existence (true/false) using tree loss average, tree gain average, and loss/gain overlap average predictor variables.

	Estimate	SE	tStat	p-value
(Intercept)	-2.489	0.435	-5.719	< 0.001
L	-0.020	0.024	-0.855	0.392
G	0.208	0.051	4.102	< 0.001
L/G	0.021	0.028	0.755	0.450
160 observations	156 error degrees of freedom			
p-value < 0.001				

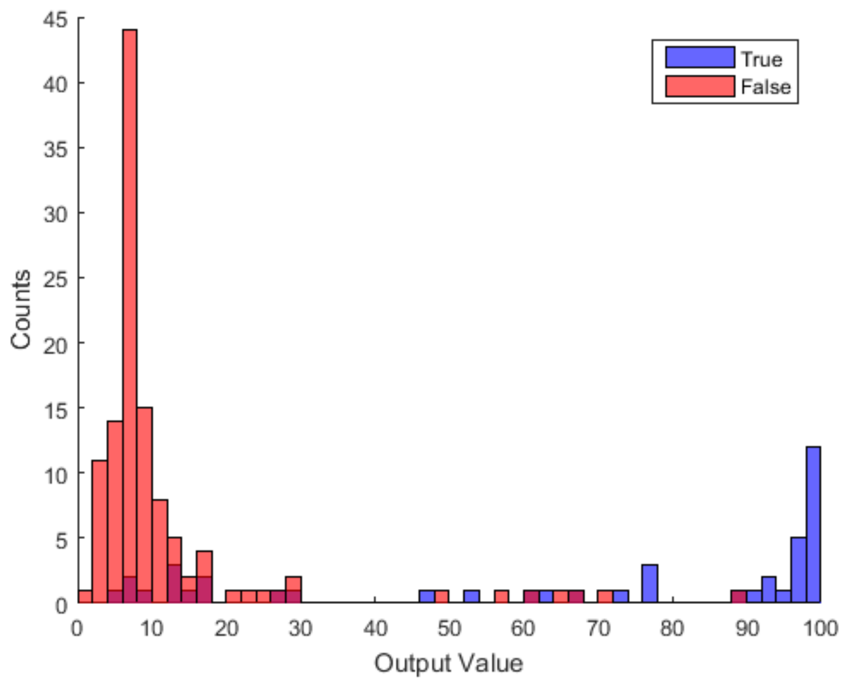

Figure 12. Tree farm model results. Results of tree farm model output showing the model prediction values for inputted validated (blue=true, red=false) data.

Unfortunately, the palm plantation model did not perform as well as the tree farm model. The goal of the palm model was to identify areas of palm plantations as it was expected that palm plantations might be falsely identified as tree farms in the tree farm model where significant growth of oil palm occurs (due to the nature of gain as a significant factor within the logistic farm regression). Palm plantations need to be identified, as these plantations produce a different commodity crop (palm oil) and do not represent areas that contribute greatly to forest product supply chains. Therefore, palm plantations identified as tree farms create false understanding about the amount of forest products originating from those regions.

Table 4. Palm plantation regression results. Results of logistic regression for palm farm existence (true, false) using tree loss maximum, tree gain maximum, and loss/gain overlap maximum average predictor variables.

	Estimate	SE	tStat	p-value
(Intercept)	-2.948	0.413	-7.135	< 0.001
L	0.004	0.003	1.239	0.215
G	-0.001	0.010	-0.067	0.947
L/G	0.053	0.013	3.994	< 0.001
199 observations	195 error degrees of freedom			
p-value < 0.001				

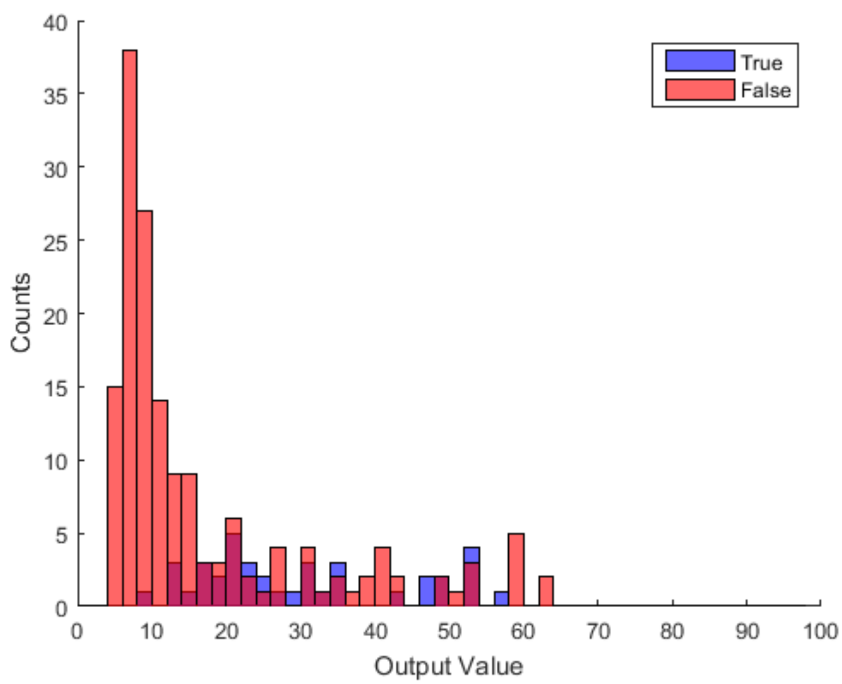

Figure 13. Palm plantation model results. Results of palm plantation model output showing the model prediction values for inputted validated (blue=true, red=false) data.

In the logistic regression for palm plantations, loss/gain is highly significant (p-value < 0.001; Table 4). This high significance likely results from the pattern of forest clearing being immediately replanted with fast growing oil palm. Unfortunately, this significance does not result in a model that appears to accurately predict palm plantations (Figure 13). Additional inputs and analyses are needed to rectify the output of this model before it can be relied upon with any certainty. If no adjustments or additional datasets are available that can substantially improve this model, it may be possible to substitute this model with datasets of designated palm plantations that are already available (e.g., oil palm concession datasets; Table 1).

Tree Farm Classification

All dataset outputs were combined into a single interactive document using the Leaflet package in RStudio. This output allows for dynamic exploration and investigation of the full global datasets in an easily transferable and readable way. The primary dataset in the final output is the farm model (Figure 14). The data is coded as circles in the map area. The circles correspond to information about the surrounding 10km by 10km cell around the circle center. Colors of the circles indicate the model prediction of tree farms within the area (red corresponds to high probability and green corresponds to low probability of tree farm location). The size of the circles indicates the amount of loss that has occurred in the cell according to the Hansen data. Large circles indicate higher amounts of tree cover loss. With this symbology, information about both type of management as well as amount of production can be surmised. Accordingly, this understanding should allow for the ability to identify highly productive tree farm regions. Similar symbology is also used in the palm plantation model.

One region of high tree farm concentration is the southeastern corner of the United States (Figure 15). However, some of the most revealing information in this global tree farm dataset comes from examination of smaller areas identified as tree farms because the model typically has low probabilities for tree farms within national forests and parkland. For example, the model predicts large amounts of tree farm activity around the Okefenokee National Wildlife Refuge, but it does not seem to predict much farming extending into the refuge. On the other hand, in the neighboring Osceola National Forest, although seemingly reduced compared to nearby land, tree farms are predicted to extend into the park. By looking at global imagery within an interactive interface inside the Osceola National Forest, this prevalence can be confirmed (Figure 16). This type of tree farm prevalence may not be known by a user before exploring the model, so this type of identification is indicative of the manner in which local timber harvesting understanding may be gained from using this model.

Another highly predicted area of tree farms is the western coasts of the United States and Canada (Figure 17). However, these areas may show a limitation to the precision of classification of tree management style using this model. These areas likely represent locations of high timber production, but the management in these areas also likely differs from that of the southeastern United States. From global imagery, clearing and regrowth can be seen in many of these areas, but the forests are not divided and sectioned into homogenous rows as is evident in tree farms in the southeastern United States or elsewhere (Figure 16 & 17). In these forests, the trees are likely cleared and replanted, but are not as vigorously managed as they would be on a designated tree farm. Understanding and better incorporating these differences is a challenge moving forward with this model.

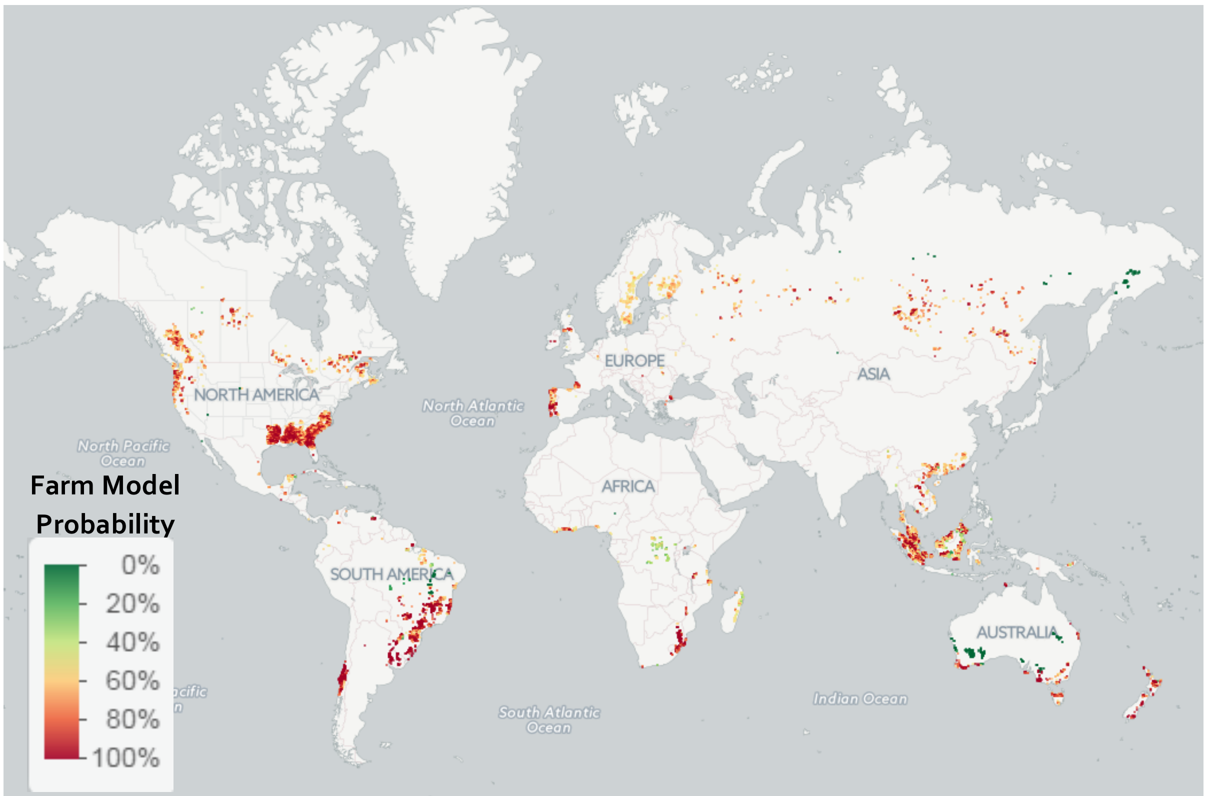

Figure 14. Tree farm model global output. Global output of tree farm prediction with red areas indicating high probability of tree farms and green areas indicating low probability. Note: in this iteration, only areas that have values of tree loss greater than 10% and model predictions for either the tree farm or palm plantation model greater than 50% are included to limit the size of the dataset and focus on timber producing hotspots.

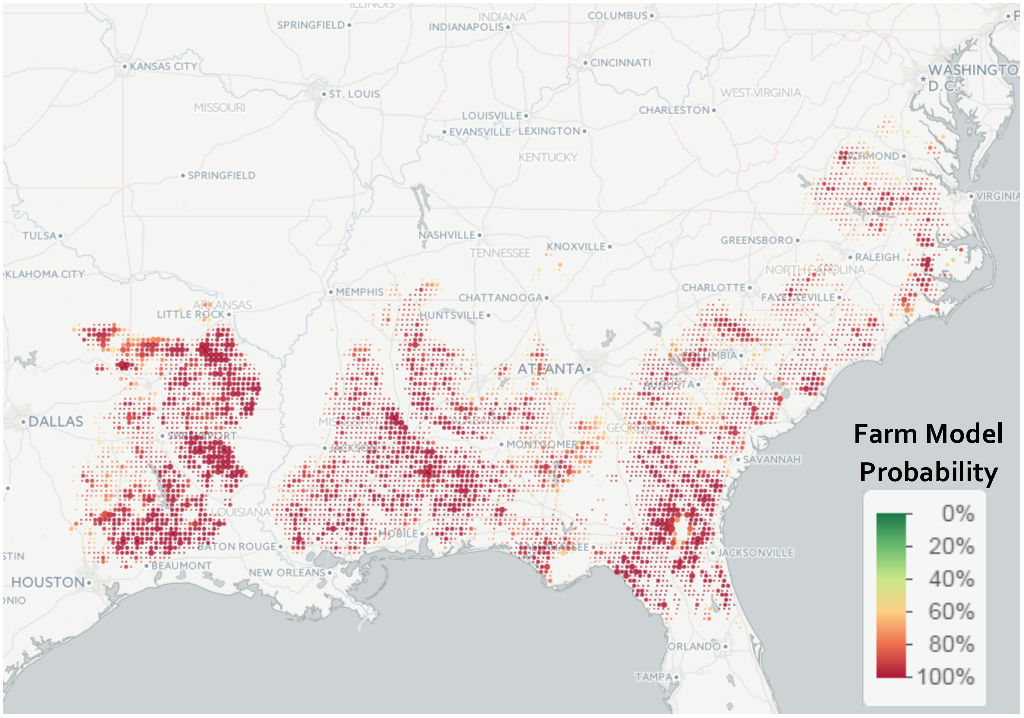

Figure 15. Tree farm model output for southeastern United States. Circle colors indicate probability of tree farm (red = high; green = low). The model predicts large amounts of tree farms within the area.

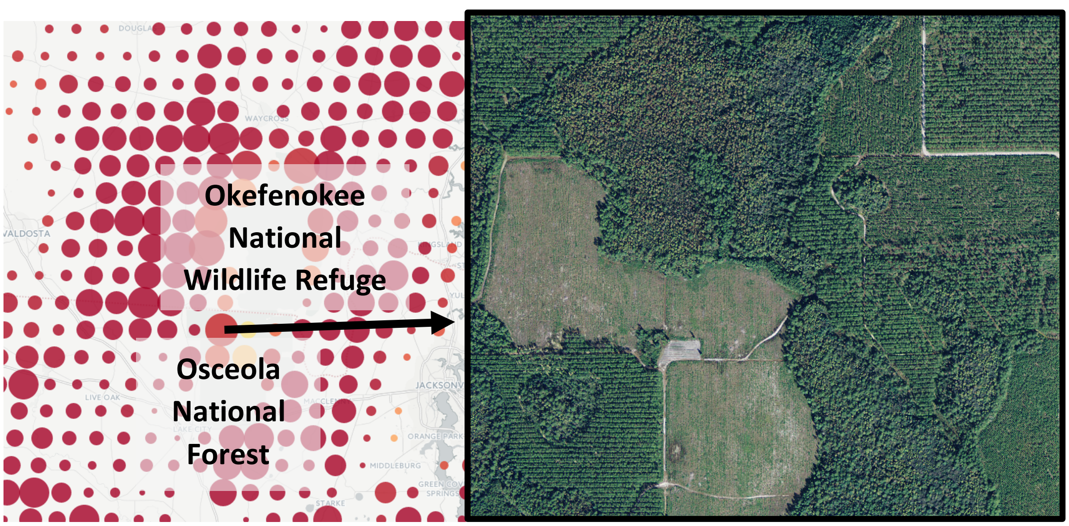

Figure 16. Tree farm model output of the Okefenokee National Wildlife Refuge and the Osceola National Forest. Circle colors indicate probability of tree farm (red = high; green = low). Tree farms are predicted to a lesser degree inside the refuge and national forest land, though some tree farms extend into the Osceola National Forest. The prevalence of tree farms can be verified by global imagery (right).

Figure 17. Tree farm model output of western United States and Canada. Circle colors indicate probability of tree farm (red = high; green = low). The western coasts of the United States and Canada show high probabilities of tree farms, verified by global imagery (right).

Brazilian Farm Correlation with Global Forest Watch Data

WRI Global Forest Watch recently published a dataset for a select number of countries detailing the existence of tree plantations (Peterson et al., 2016; WRI GFW, 2016). The methodology for determining tree plantation locations involved prescreening for tree farm areas using the Hansen et al. (2013) Global Forest Change Dataset and then processing plantation areas manually using high-resolution satellite imagery. Due to the less automated process with a smaller processing extent, it is likely that the precision of this dataset is fairly high. Accordingly, the new WRI dataset allows for an excellent opportunity to examine the precision of the tree farm logistic model developed in this report. To examine this precision, the data from WRI were aggregated by farm area coverage (with farm area designated as either wood fiber or recently cleared areas within the dataset). These data were aggregated to the 10km by 10km grid scale used in the processing of the tree farm logistic model, and then the two datasets were compared. Visually, there is clear overlap between the two datasets (Figure 18). Both datasets demonstrate large areas of tree farm in southeastern Brazil with only smaller areas elsewhere. Furthermore, the correlation between the datasets is fairly high, though it greatly depends on whether areas of low tree cover loss are included in the calculation (Figure 19). When all areas are included, the correlation (between tree farm probability and tree farm prevalence) is around 0.58. However, when only areas experiencing greater than 25% tree cover loss are included, the correlation is nearly 0.85. This dependency indicates that the logistic model may not be as accurate when low levels of tree loss occur. However, the model goal was to determine areas of large wood fiber contributions, which the comparison with an alternate dataset verifies.

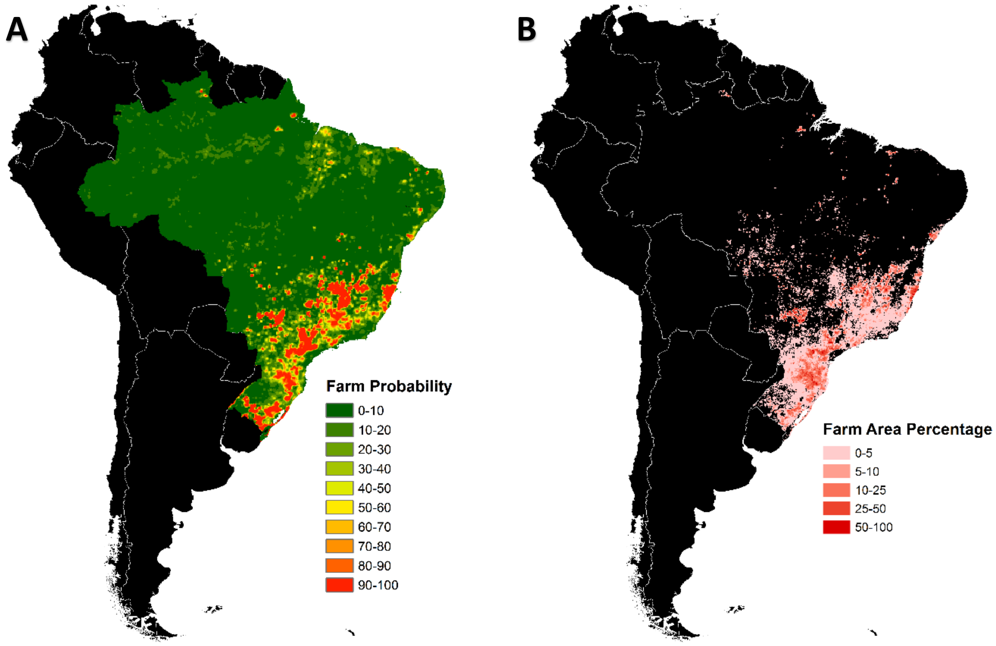

Figure 18. Tree farm model vs. Global Forest Watch plantation data. Inset A demonstrates the probability of tree farms as predicted by the tree farm logistic model. Inset B demonstrates the percentage of area cover of tree farms aggregated from Global Forest Watch data.

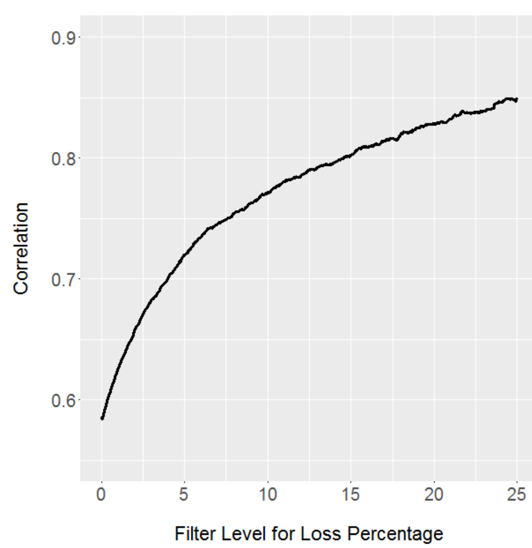

Figure 19. Correlation between tree farm model and Global Forest Watch plantation data as a function of Loss Percentage. Correlation between the logistic tree farm model and the Global Forest Watch plantation data as a function of tree loss. The logistic tree model data were filtered so that only 10km by 10km grid cells with a tree cover loss value greater than each given x-value were used in the correlation computation.

Palm Plantation Classification

Analyzing the palm plantation output in the context of the full global model allows for additional understanding about the quality of the model. Indonesia is a particularly important area for palm plantations as there are large and growing concentrations of these plantations in this part of the world. In this model, the goal is to limit the false identification of palm plantations as tree farms that may lead to inaccurate information about the locations of timber harvesting. Unfortunately, within the model, palm plantations may lead to inflated values for tree farm probability. The interactive interface allows for investigation into the areas where such false identification is occurring. For example, in Indonesia, many areas of tree farm are identified in areas that have been designated for oil palm concessions (Figure 20). Unfortunately, examining the overlap between the palm model output and oil palm concession areas, there does not appear to be a great correlation (Figure 21). It is important to note that oil palm concession do not necessarily indicate the actual presence of palm plantation nor exclude the presence of tree farms. Concessions simply indicate areas designated for planting oil palm, which may occur in the future. Therefore, it is not expected that the palm model would perfectly overlay oil palm concession locations. However, due to the low statistical performance of the palm model, oil palm concession locations may be the best indicator of palm plantations at this time.

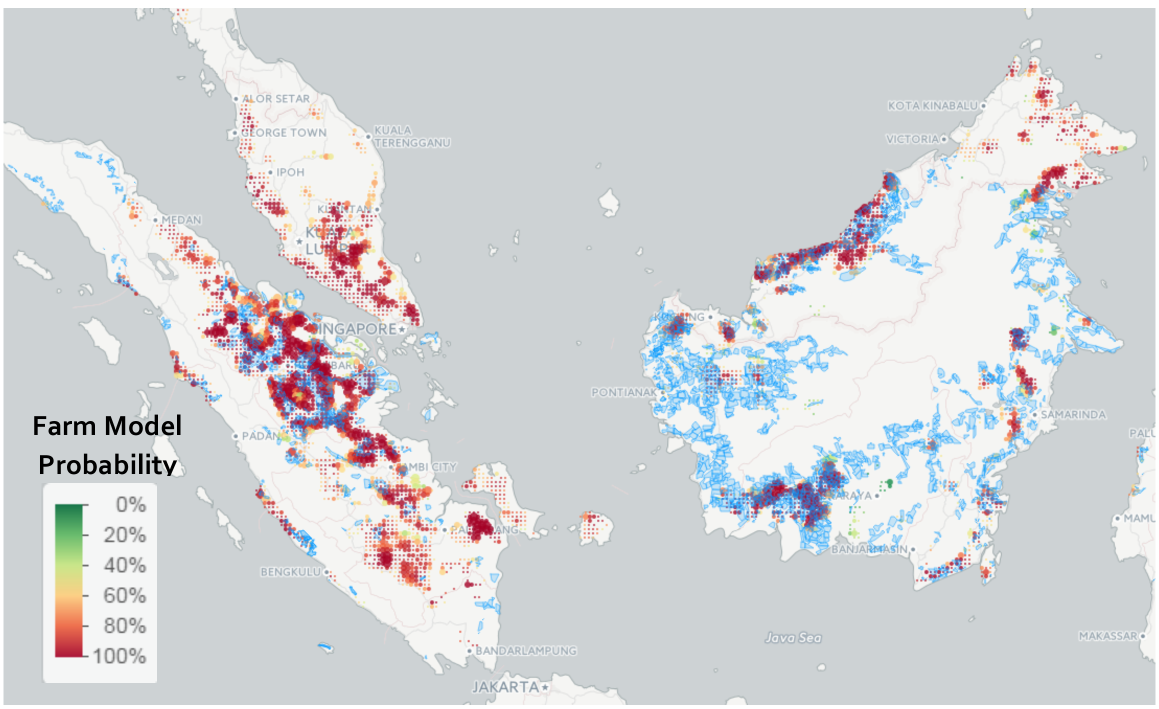

Figure 20. Indonesia tree farm probabilities and oil palm concessions. Areas of overlap between high tree farm probabilities as indicated by the tree farm model (red circles) and oil palm concession locations from Global Forest Watch data (blue outlined areas) indicate high risk areas for falsely predicting palm plantations as tree farms.

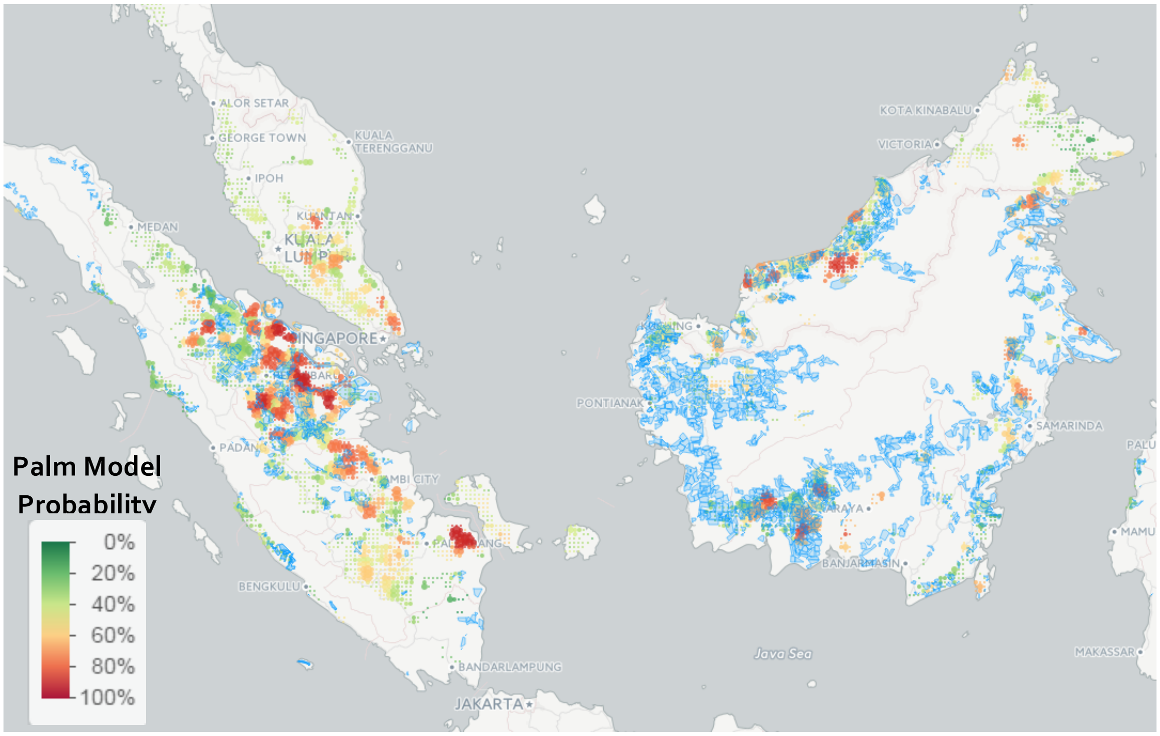

Figure 21. Indonesia palm plantation probabilities and oil palm concessions. Areas of overlap (or lack thereof) between high palm plantation probabilities as indicated by the palm plantation model (red circles) and oil palm concession locations from Global Forest Watch data (blue outlined areas) indicate possibly weak prediction capabilities of the palm plantation model.

Deforestation Analysis

Deforestation occurs outside the scope of tree farms. Regions that are not likely to be tree farms, but still experience great canopy loss, could possibly be contributing to supply chains (Figure 22). Some of the deforestation in these regions may be caused by fire. Maps of canopy burned by fire were created in order to determine where deforestation is very unlikely to be entering supply chains. Once fire loss is accounted for, the remaining deforestation patterns reveal wood sourcing regions with practices that differ from a tree farm.

Thirteen global maps of annual canopy lost to fire in 2001-2013 were constructed (Figure 23). Closer visualization of regions of known, large wildfires, such as the Zaca Fire in Santa Barbara County in 2007, verify the methodology used to identify fire burn areas (Figure 24). Areas of annual deforestation and the proportion of annual deforestation that was caused by fire were calculated (Figure 25). Annual burned regions were then aggregated into a map of all canopy clearance caused by fire over the entire time period (Figure 26).

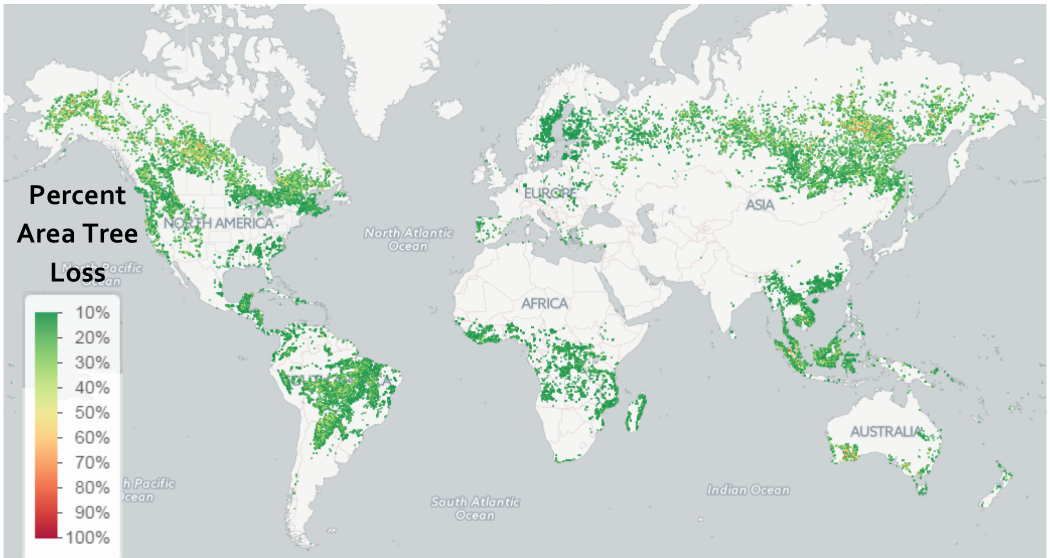

Figure 22. Tree loss not highly predicted as tree farm. Areas of tree loss greater than 10% where the tree farm model probability was 50% or lower.

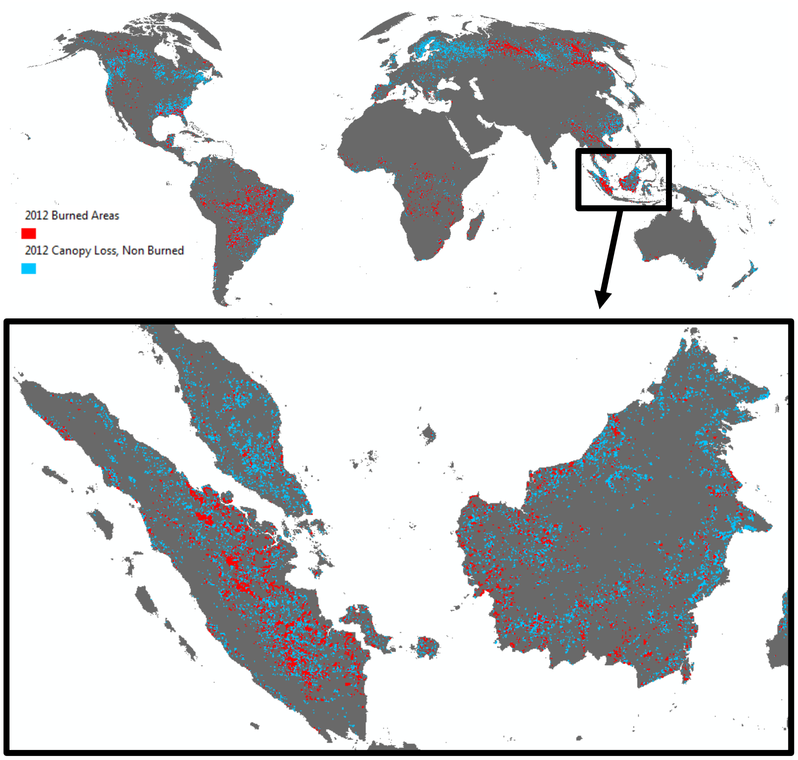

Figure 23. Global canopy loss in 2012. Red areas are trees that burned. Blue areas represent deforestation not caused by fire. Inset reveals closer view of the islands of Sumatra and Borneo. Cell resolution: 250m by 250m. Projection: Goode Homolosine.

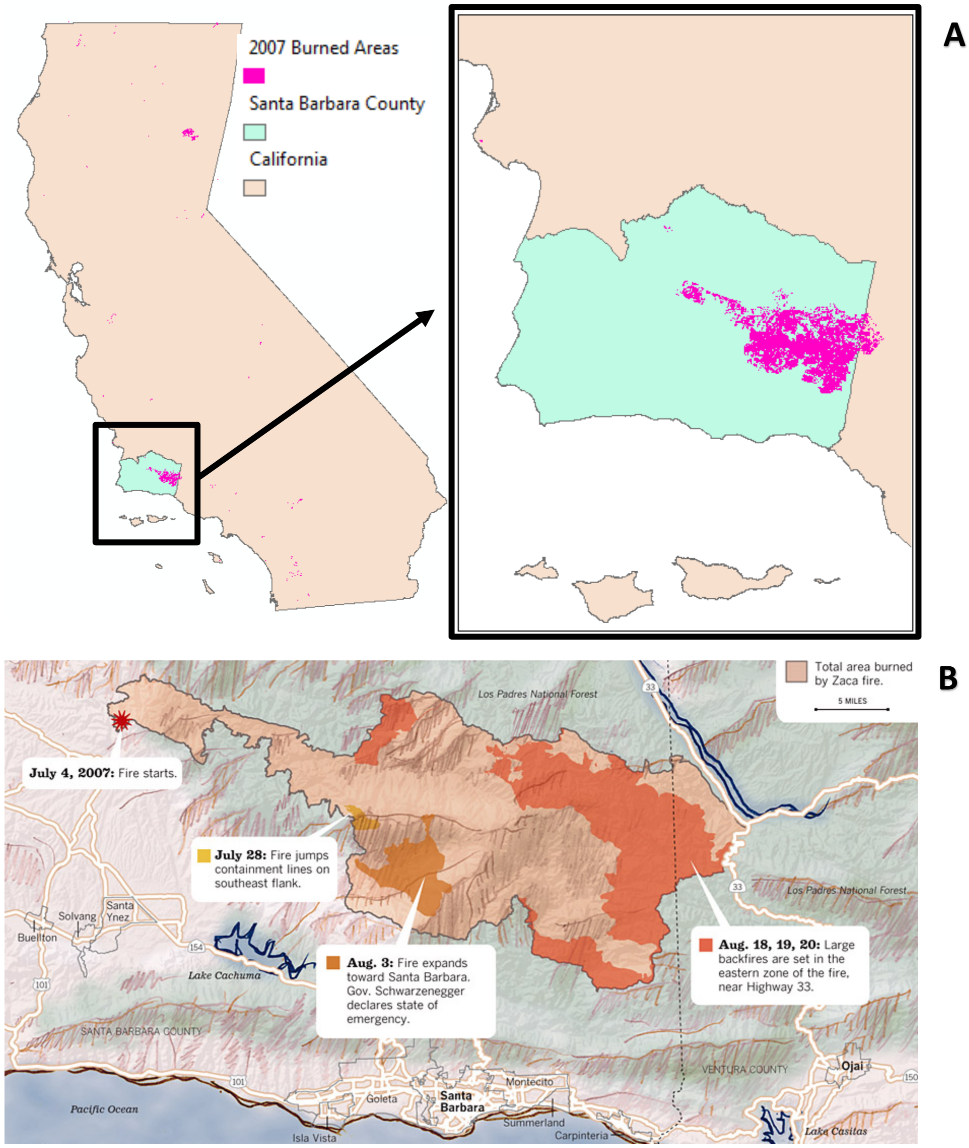

Figure 24. Burned canopy in California, 2007. A: Purple areas represent canopy that was lost to fire in 2007. The inset reveals burned canopy resulting from the Zaca Fire in Santa Barbara County. Cell resolution: 250m by 250m. Projection: Goode Homolosine. B: Verification of actual Zaca Fire extent from the Los Angeles Times (Boxall & Cart, 2008).

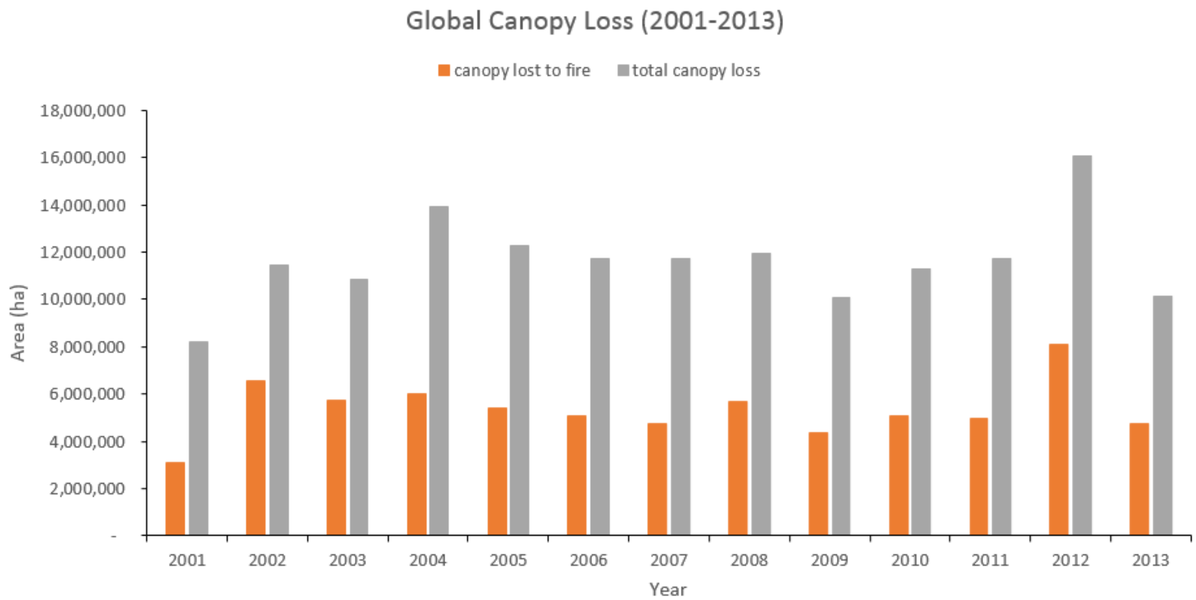

Figure 25. Areas (hectares) of annual global deforestation, 2001-2013. Canopy lost to fire is determined using nominal- and high-confidence fire points from the corresponding year of tree cover loss.

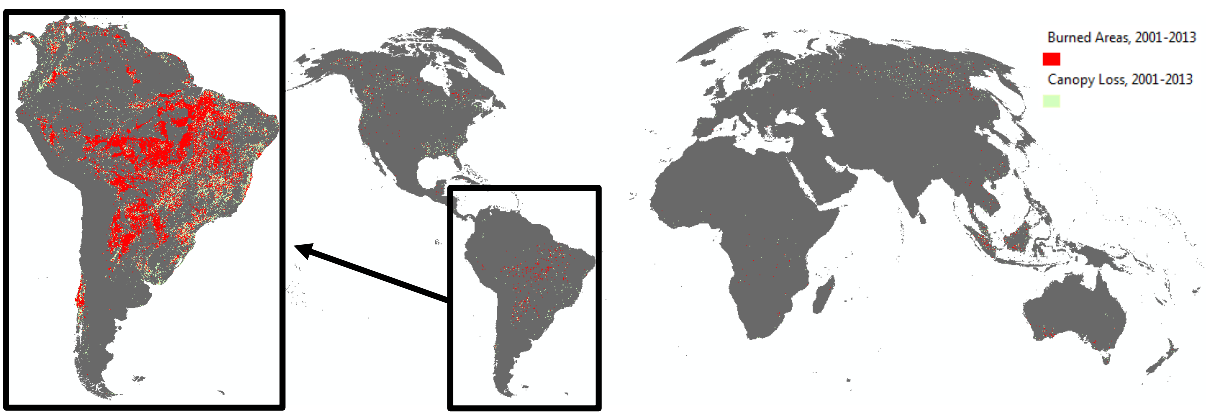

Figure 26. Aggregate global canopy loss, 2001-2013. Red areas are trees that burned between 2001 and 2013. Green areas represent deforestation not caused by fire. Inset reveals closer view of South America. Cell resolution: 250m by 250m. Projection: Goode Homolosine.

The maps created in this analysis visually confirm annual deforestation on a global and regional scale. The methodology identifies which forests are being lost due to fire. Conversely, it also identifies potential areas of wood extraction, as these regions of canopy loss cannot be explained by fire (Figure 26).

This study calculates the extent of annual global canopy clearance as a range between 8 and 16 million hectares (Figure 25). The current analysis estimates that about half of annual deforestation results from fire. Events of known wildfires, such as the Zaca Fire, reveal large patches of canopy that were lost to fire (Figure 24). These deforestation events do not contribute to known logging practices, so the maps visually confirm that the methods developed in this study can identify burned canopy. Regions that practice slash-and-burn land clearance, such as the Amazon, also reveal the resulting deforestation patterns via this satellite analysis (Figure 26).

However, there are some limitations to this study. The extent of fire that leads to deforestation is currently being oversampled due to the nature of the model design in ArcGIS and format of input data. If a single fire point is within 1km of a large canopy loss polygon (Figure 11), the entire contiguous polygon is flagged as a burned area. The MODIS data do not distinguish between manmade and wildfires. Fire Radiative Power (FRP) is a fire point attribute that was considered as a distinguishing characteristic, but a literature review did not identify any wildfire-specific FRP ranges. This leaves the possibility of a small flame (ex: campfire) selecting a large clearance area, when in reality the region is being cut, or the flame did not cause canopy clearance. The temporal aspects of canopy loss (annual) and fire points (daily) do not align entirely. This does not account for a scenario where wood is harvested first, and the region is burned afterwards.

Nonetheless, it is reasonable to conclude that some annual deforestation occurs from fires that burn through regions. The aggregate global map (Figure 26) shows fire prone areas (red), from which wood is likely not entering supply chains. It also shows areas of canopy clearance that cannot be attributed to fire occurring within that time frame (green), therefore the cleared wood must be going somewhere. The nature of the input satellite imagery is not fine grained enough to distinguish selective logging, nor can it identify a forest that has been replanted with another wood type (such as virgin rainforest replaced with *Acacia sp.*).

The results from the fire analysis must be incorporated into the tree farm classification model to determine which *proportion* of tree cover has been lost to fire between 2001 and 2013 within any given 10km by 10km world grid cell. Then, the proportion of an area that is lost to fire can be used as an independent predictor variable that a particular region is a tree farm or an oil palm plantation.

CONCLUSIONS

This analysis represents an initial step in the evaluation of a larger global forest product model. The goal of this classification dataset is to identify regions of tree loss that are due to tree farm activities. Due to the commercial nature of tree farms, the canopy loss identified and characterized in this report is likely to result in commercial forest products. This report concludes that layering canopy cover loss and gain data can predict with consistency the likelihood of a given area of canopy cover corresponding with a tree farm. By subtracting the likely plantation areas and forest lost to fire from total forest loss, the methodology developed in this report can also reasonably predict where wood is sourced from non-plantation sources. Ultimately, both the plantation and non-plantation results will be incorporated into TSC's tools and provide the foundation on which TSC plans to build a comprehensive global wood sourcing model. TSC's Commodity Mapping Program, as it is applied for its Paper, Pulp and Forestry Working Group, will be unique upon completion because it will show trends in global canopy cover over a comparatively long time span, from 2001-2013. The base maps developed in this report are important steps that enable inter-regional analysis of wood product supply chains to predict the relative impacts of specific sourcing regions and products.

REFERENCES

Anker-Rasch, T-L., & Daviknes Sørgard, S. (2011). Green supply chain management: a study of green supply chain management within the pulp and paper industry. *Norwegian School of Economics and Business Administration.* Web. Accessed 06 Jan 2016.

Boxall, B., & Cart, J. (2008, July 27). As Wildfire Get Wilder, the Costs of Fighting Them are Untamed. *Los Angeles Times*. Web. Accessed 27 Jan 2016.

Carle, J., Del Lungo, A., & Varmola, M. (2003). The need for improved forest plantation data. *XII World Forestry Congress.*

D'Amours, S., Rönnqvist, M., & Weintraub, A. (2008). Using operational research for supply chain planning in the forest products industry. *INFOR: Information Systems and Operational Research*, *46*(4), 265-281.

Fire Information for Resource Management System (FIRMS). (2015). FIRMS MODIS Fire Archive Download. *NASA Earth Data*. Web. Accessed 02 Nov 2015.

Food and Agriculture Organization of the United Nations (FAO). (2010). World Deforestation Decreases, but Remains Alarming in Many Countries. *FAO News Article*. Web. Accessed 08 Jan 2016.

Food and Agriculture Organization of the United Nations (FAO). (2011). Assessing Forest Degradation: Towards the Development of Globally Applicable Guidelines. Working paper. Vol. 177.

Food and Agriculture Organization of the United Nations (FAO). (2015). FRA 2015 Terms and Definitions. Working paper. Vol. 180.

Food and Agriculture Organization of the United Nations (FAO). (2016). Global Forest Resources Assessments. Web. Accessed 04 Jan 2016.

Goering, L. (2013). 'Zero Net Deforestation' Goals May Harm Natural Forest - Experts. *Thomson Reuters Foundation News*. Web. Accessed 04 Jan 2016.

GreenBlue. (2011). Paper Life Cycle: The Rising Costs of Illegal Logging. Web. Accessed 04 Jan 2016.

Greenpeace Southeast Asia. (2014). Steering Group Established to Oversee the High Carbon Stock (HCS) Approach for Implementing 'No Deforestation' Commitments. *Greenpeace*. Web. Accessed 04 Jan 2016.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., ... & Townshend, J.R.G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science, 342*, 850–53.

Lake, S., & Baer, E. (2015). What Does It Really Mean When a Company Commits to 'Zero Deforestation'? *World Resources Institute*. Web. Accessed 04 Jan 2016.

Nogueron, R., & Laestadius, L. (2012). Sustainable Procurement of Wood and Paper-Based Products: Version 3. *World Resources Institute*. Web. Accessed 04 Feb 2016.

Peterson, R., Aksenov, D., Espipova, E., Goldman, E., Harris, N., Kuksina, N., ... & Shevade, V. (2016). Mapping Tree Plantations with Multispectral Imagery: Preliminary Results for Seven Tropical Countries. *World Resource Institute: Technical Note*.

Programme for the Endorsement of Forest Certification (PEFC International). (2016). Who We Are. Web. Accessed 12 Feb 2016.

Putz, F.E., & Redford, K.H. (2010). The Importance of Defining 'Forest': Tropical Forest Degradation, Deforestation, Long-term Phase Shifts, and Further Transitions. *Biotropica, 42*(1), 10-20.

Rainforest Alliance. (2008). The Lacey Act Amendment: What Does It Mean to Your Business? *Rainforest Alliance for Business*. Web. Accessed 04 Jan 2016.

The International Tropical Timber Organization (ITTO). (2014). The Annual Review Statistical Database. Web. Accessed 04 Feb 2016.

The Sustainability Consortium. (2015a). The Sustainability Consortium: Transforming the consumer goods industry to deliver more sustainable consumer products. Web. Accessed 15 Feb 2016.

The Sustainability Consortium. (2015b). TSC Paper Primer. Web. Accessed 15 Feb 2016.

U.S. Federal Trade Commission. (2016). Anticompetitive Practices. Web. Accessed 06 Jan 2016.

U.S. Forest Service. (2016). Total US Industrial Roundwood Production from 2003 to 2012 (in million cubic feet). *U.S. Department of Agriculture.* Accessed 16 Feb 2016.

World Resources Institute (WRI). (2009). Fact Sheet: Are You Ready for the Lacey Act? Web. Accessed 04 Jan 2016.

World Resources Institute (WRI). (2016). GFW Commodities. Web. Accessed 04 Jan 2016.

World Resources Institute (WRI) Global Forest Watch (GFW). (2016). Oil palm concessions (select countries). *Open Data Portal*. Accessed 12 Jan 2016.

World Resources Institute (WRI) & World Business Council for Sustainable Development (WBCSD). (2015). Tools for Increasing Transparency in Supply Chains. *Sustainable Forest Products*. Web. Accessed 04 Jan 2016.

World Wildlife Fund (WWF). (2009). Zero Net Deforestation by 2020. *Issue brief.* Web. Accessed 11 Feb 2016.

World Wildlife Fund (WWF). (2016a). Deforestation. *WWF Global*. Web. Accessed 04 Jan 2016.

World Wildlife Fund (WWF). (2016b). Forests. Web. Accessed 04 Feb 2016.