QUANTIFYING UNCERTAINTY OF FOREST EXTENT ESTIMATES IN MEXICO BY COMPARING SATELLITE-DERIVED LAND AND TREE COVER PRODUCTS

by

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ABSTRACT

Information about forest extent and tree cover is needed to evaluate the status of natural resources, conservation practices and environmental policies. The challenge is that different forest definitions, remote sensing products, and data availability can lead to discrepancies in reporting forest area and ultimately forest carbon estimates. Here, I compared forest extent estimates from 7 regional and global land or tree cover products at 30 m resolution across mainland Mexico. Comparison results presented significant uncertainty in forest extent estimates for Mexico, ranging from 387,607 km2 to 675,239 km2 depending on which satellite-derived product and forest definition is utilized. Next, I compared these satellite-derived products with two independent forest inventory datasets at the national scale (n=21,167) and at the local scale (n=486). The highest agreement between satellite-derived products and forest inventory data is within the tropical moist forest, and the least agreement is within the subtropical steppe ecozones. I further developed a hybrid uncertainty product by combining the 7 forest extents to calculate forest likelihood. I identified a forest area of 340,661 km2 that has low agreement among satellite-derived products. The tropical dry forest and subtropical mountain system represented the two ecozones with the greatest amount of disagreement among satellite-derived products. These findings identify uncertainty surrounding forest extent estimates across ecozones in Mexico where additional ground data and research is needed.

Chapter 1

INTRODUCTION

Terrestrial ecosystems are estimated to remove around 31% of the annual carbon dioxide emissions from fossil fuel combustion (Friedlingstein et al., 2020). As part of terrestrial ecosystems, forests are crucial in regulating the global carbon budget (IPCC, 2019). Consequently, accurate assessments of global forest resources are critical to measuring progress on international efforts of sustainable development and emissions reductions (FAO, 2022; Hansen et al., 2013; Vargas et al., 2017). International efforts of forest monitoring, such as the Food and Agriculture Organization (FAO) Global Forest Resources Assessment (FRA) and the United Nations Collaborative Programme on Reducing Emissions from Deforestation and Degradation (REDD), rely on nationally led reporting processes. In many instances, national data rely partially on satellite-derived forest cover maps for reporting statistics related to national and international commitments (FAO, 2020). As such, satellite-derived forest cover estimates are vital information for international measurement, reporting, and verification (MRV) systems.

While satellite-derived forest cover estimates are critically important for calculating local and global carbon budgets, several challenges arise with determining what counts as forest. For example, Sexton et al. (2016) found differences of up to 41.2 Gt C globally across different satellite-derived forest estimates due primarily to differing forest definitions among the global forest products. The 2020 FAO FRA Remote Sensing Survey found differences of 16,180,000 km2 in total global forest area estimates - mainly because of different definitions between satellite-derived tree/forest cover and "forest" land use (FAO, 2022). Global institutions such as the Food and Agriculture Organization's Global FRA define "forest" as primarily a land use feature, whereas satellite sensors observe land cover. While satellite-derived products might classify an agroforestry area with high tree canopy cover (e.g., a palm oil production area) as "forest," the FAO would classify this same area as "agriculture" (FAO, 2020). Hundreds of different forest definitions exist globally (Sexton et al., 2016; FAO, 2002), with studies showing that these different definitions have real-world implications on the measurement of forest area, degradation, and carbon stock (Côte et al., 2018; Fagan and DeFries, 2009; Romijn et al., 2013; Traub et al., 2000). The FAO generally defines a forest as an area with more than 10% tree canopy cover that spans more than 0.5 ha and contains trees higher than 5 meters (FAO, 2000). The United Nations Framework Convention on Climate Change (UNFCCC) meanwhile defines forest as an area spanning 0.5 - 1 ha, 10-30% canopy cover, and with tree height of 2-5 meters - with each country able to pick their forest definition for national greenhouse gas inventories for reporting purposes.

A secondary challenge relates to difficulties in the collection of high-quality and consistent remote sensing data across forested ecosystems. Satellite-derived products rely on cloud-free imagery to provide complete coverage – and regions with typically high cloud occurrence can force product creators to stitch together multiple years' worth of imagery to reduce these gaps (Fagan and DeFries, 2009). Despite the best efforts to remove clouds and their shadows from imagery through temporal compositing, incomplete cloud and cloud shadow detection impact satellite-derived forest products (Wilson and Jetz, 2016; Young et al., 2017; Zhu and Woodcock, 2012). Especially in high elevations and within the humid tropics, cloud cover significantly decreases the availability of imagery during critical phenological stages (Hansen et al., 2008; Wilson and Jetz, 2016). In recent decades, the tropics and subtropics have accounted for around 94% of global deforestation – with most of this occurring in the tropics (FAO, 2020). Understanding spatial and temporal changes in forest cover in these ecological zones is critical, yet they present numerous challenges for remote sensing-derived forest products.

End-users involved in MRV protocols are required to interpret or choose among dozens of global and regional forest products with differing methodologies. They need reliable data with associated uncertainty for proper interpretation and ideally, evaluations using country-specific forest information (such as national forest inventory data). One way to quantify such uncertainty is to understand the degree of agreement among various products. Other comparisons of several forest extent products exist to quantify uncertainty in this way - with results indicating only moderate agreement from product to product (FAO, 2022; Feng et al., 2016; Fritz and See, 2008; Sexton et al., 2015; Song et al., 2014, 2011). National reporting of forest information to international institutions often utilizes national forest inventory data products in addition to satellite-derived forest maps – such as information for forest degradation (FAO, 2020; Gillerot et al., 2021). Thus, there is also a need to quantify disagreement between satellite-derived products and national forest inventory data.

My main objective is to develop a hybrid forest cover product for mainland Mexico at 30 m resolution by combining information from 7 satellite-derived products. Mexico presents a unique case study due to multiple reasons. First, Mexico relies on utilizing remote-sensing forest cover products to complement MRV requirements as part of the United Nations REDD program (Gebhardt et al., 2014). Second, Mexico is one of the REDD participating countries with a long and established history of forest inventories (Gillerot et al., 2021), such as the National Forest and Soil Inventory (INFyS), which was also utilized in meeting MRV requirements (Vargas et al. 2017). Third, Mexico is a megadiverse country with large heterogeneity in climates, topography, ecosystems, and ecological zones (Koleff et al., 2018). Fourth, although there have been great efforts for reforestation, regeneration, and conservation of forests, there is still considerable pressure for deforestation and degradation (Burney et al., 2015). Hence, Mexico is a valuable testbed for efforts to quantify variability in satellite-derived products for carbon monitoring systems.

Here I tested the agreement between 7 satellite-derived forest cover products with ground information at the national and local scales. Then I developed a hybrid product from these 7 satellite-derived products to estimate forest cover uncertainty. I postulated the following interrelated questions: How well do regional and global forest cover products agree with inventory data across forests in Mexico? How do these products vary in estimating forest extents across Mexico? Considering the variability in product estimates, how much area has a high, medium, or low likelihood of being forested? The novelty of my study lies in my comparison of global and regional products to national forest inventory data used for reporting to international institutions in addition to deriving a hybrid forest cover product expressly for quantifying uncertainty across these products.

Chapter 2

METHODS

2.1 Satellite Derived Forest Extent Data

I selected 7 global, regional, and national forest and tree cover data products to extract information for Mexico. All data products were derived from high- and medium-resolution remotely sensed datasets (i.e., 10-30 m resolution) and represented the state of forest or tree cover from the years 2010 to 2020. These products were selected considering FAIR (i.e., findable, accessible, interoperable, and replicable) principles and to represent different methodological approaches. The original 7 products were developed by a wide range of sources and remote sensing data as detailed in Table 1.

Table 1: Land Cover & Tree Cover Product Overview

Product Name	**Spatial Resolution**	**Primary Remote Sensing Inputs**	**Citation**
European Space Agency 2020 Land Cover Map for Mexico (**ESA**)	10m	Sentinel-2A and 2B	ESA, 2020
Globeland30 2020 (**Globeland30)**	30m	Landsat 8, HJ-1, and GF-1	Jun et al., 2014
Commission for Environmental Cooperation 2015 Land Cover Map (**CEC**)	30m	RapidEye	CEC, 2020
Impact Observatory 2020 Land Cover Map (**IO**)	10m	Sentinel-2	Karra et al., 2021
NAIP Trained Mean Percent Cover Map (**NEX-TC**)	30m	Landsat 8 and NAIP	Park & Vargas, 2022
Global Land Analysis & Discovery Global 2010 Tree Cover (**Hansen-TC**)	30m	Landsat 7	Hansen et al., 2013
Global Forest Cover Change Tree Cover 30m Global (**GFCC-TC**)	30m	Landsat 5 and 7	Townshend, 2016

2.2 Validation Data

I used two independent datasets for the assessment of the 7 products. First, I used plot-level data from the Mexican government's Inventario Nacional Forestal y de Suelos (National Forest and Soil Inventory, or INFyS) from 2009-2014 (CONAFOR, 2014; Figure 1). INFyS comprises 26,220 plots distributed throughout the country and represents Mexico's primary input for forest-related land use categories as part of REDD

(UNFCCC 2022). At each location, the most recent year of data on tree cover density was used, and locations outside mainland Mexico were excluded from the analysis. Second, I used independent information for tree cover density for the Estado de México (i.e., Edomex) to test the 7 products at the state level (i.e., local scale). This information was collected using digital photography in 754 plots, as described previously (Salas-Aguilar et al., 2017). All datasets were projected to Albers Equal Area Conic North America.

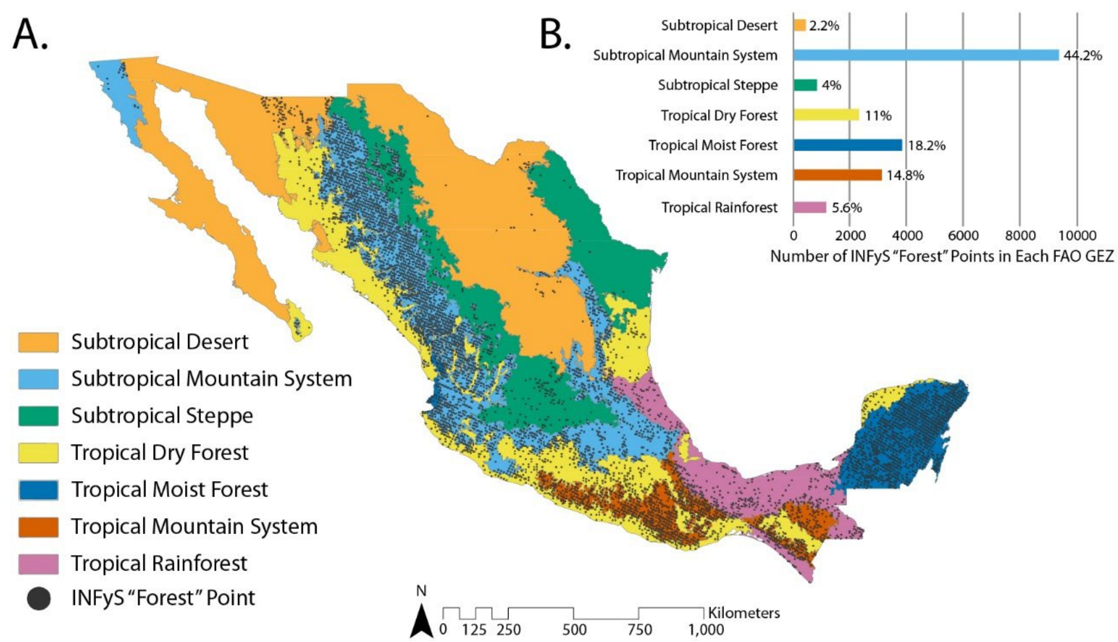

Figure 1: A. Distribution of FAO global ecological zones and B. INFyS ground data across Mexico. The tropical mountain system contains the highest number of INFyS forest plots per 1000 km2 (30.99 plots / 1000 km2), followed by the tropical moist forest (30.29 points / 1000 km2) and the subtropical mountain system (26.15 points / 1000 km2).

2.3 Data Analysis and Standardization

I used the FAO Global Ecological Zones (GEZ) for reporting forest statistics, validation results, and associated uncertainty (FAO, 2015). Mexico has 7 GEZs consisting of subtropical desert (29.5%), subtropical mountain system (18.4%), subtropical steppe (15.7%), tropical dry forest (17.2%), tropical moist forest (6.5%), tropical mountain system (5.2%), and tropical rain forest (7.4%) (Figure 1A). Each tree and land cover product was extracted for mainland Mexico and reprojected to Albers Equal Area Conic North America coordinate system. The ESA and IO products were resampled to a 30 m spatial resolution. To compare different product types at the pixel level, I recoded continuous data values in the percent tree cover products into categories (i.e., forest or no forest). For each land cover product, all reported forest types were combined to represent forest cover at the national scale. I defined a conservative 30% threshold for products reporting tree cover density to determine pixels of forest or no forest. In other words, pixels with >=30% cover were considered 'forest', and pixels with <30% cover were considered 'no forest'; this definition was applied to the validation data as well. This resulted in n=21,167 INFyS "forest" points (Figure 1) and n=486 points within Edomex from the digital photography-derived data. Previous studies have used different thresholds ranging from 10% to over 60% of tree cover density (Fernández-Montes de Oca et al., 2021; Romijn et al., 2013). I highlight that selecting such a threshold is a matter of current debate as discussed in the introduction section. There have been numerous calls for either establishing a single global forest definition or utilizing more robust ecological indicators, such as canopy height or biomass (FAO, 2002; Côte et al., 2018; Fagan and DeFries, 2009; Fernández-Montes de Oca et al., 2021; Romijn et al., 2013; Sexton et al., 2016). The selected 30% tree cover density threshold for this study represents the most conservative range in forest definition as per the United Nations

Framework Convention on Climate Change (UNFCCC). While I utilized a 30% threshold, I additionally produced results utilizing a 10% threshold to account for the impact of forest definition on findings.

2.4 Validation of Satellite Derived Forest Extent Products

I tested the agreement between each satellite-derived product and the corresponding INFyS locations for each FAO GEZ category. First, I calculated the number of locations where the INFyS and each satellite-derived product agreed on a "forest pixel." Then, I divided this number by the total INFyS locations (classified as a forest) within each GEZ to report the agreement as a percent. A similar approach was applied to calculate the agreement between each satellite-derived product and the ground data from both INFyS and Salas-Aguilar et al. (2017) within Edomex. Therefore, this approach allowed us to test the agreement for each of the 7 satellite-derived products at the national scale and to use an independent dataset for Edomex (i.e., state level).

2.5 Generation of a Hybrid Uncertainty Product for Forest Extent

A pixel-by-pixel comparison was undertaken to generate a map of forest likelihood across mainland Mexico. All 7 data products were stacked, and I tested the percent agreement among them for each pixel across Mexico. While I focused on how many products agreed within a pixel, I did not analyze which products agreed or disagreed with each pixel. This approach is comparable to the global forest vote map produced by

Sexton et al., 2016. I report three forest likelihood classes: high (85.71-100%; agreement between 6-7 products), medium (42.86-71.43%; agreement between 3-5 products), and low (14.29-28.57%; agreement between 1-2 products). Reporting uncertainty in the NASA Carbon Monitoring System is an ongoing challenge, and here I present a simple and practical way to summarize the results and facilitate application and decision-making.

Chapter 3

RESULTS

3.1 Individual Product Evaluation at the National Scale

In general, all satellite-derived products had a higher agreement in ecozones with expected higher forest density (Figure 2). The largest agreement between the products and the INFyS data was across the Tropical Moist Forest, with a range of agreement from 81.6% (IO) to 94.7% (Hansen-TC). Products originally reporting tree cover density better agreed with INFyS data across the Tropical Rainforest (range of 82.8% - 91.8%) than land cover products (range of 63.3% - 76%). The Tropical Mountain System had a mixed agreement with a range between 60.2% (IO) and 88.3% (Globeland30).

Most land cover products (i.e., CEC, Globeland30, and ESA) had better agreement with INFyS than products originally reporting tree cover density (i.e., NEX-TC, Hansen-TC, and GFCC-TC) for ecological zones with expected low forest density. The CEC and ESA products agreed best with the INFyS data (50.9%-59.3%) in the sparsely forested Subtropical Steppe. In contrast, the products originally reporting tree cover density agreed between 5.9% (NEX-TC) and 18.3% (Hansen-TC) with INFyS data. The CEC had the highest agreement with INFyS data in the Subtropical Mountain System (84.5%), Tropical Dry Forest (74.5%), Subtropical Desert (76.3%), and Subtropical Steppe (59.3%). In comparison, products originally reporting tree cover density and the IO land cover product had challenges representing forest cover across these four ecozones (Figure 2).

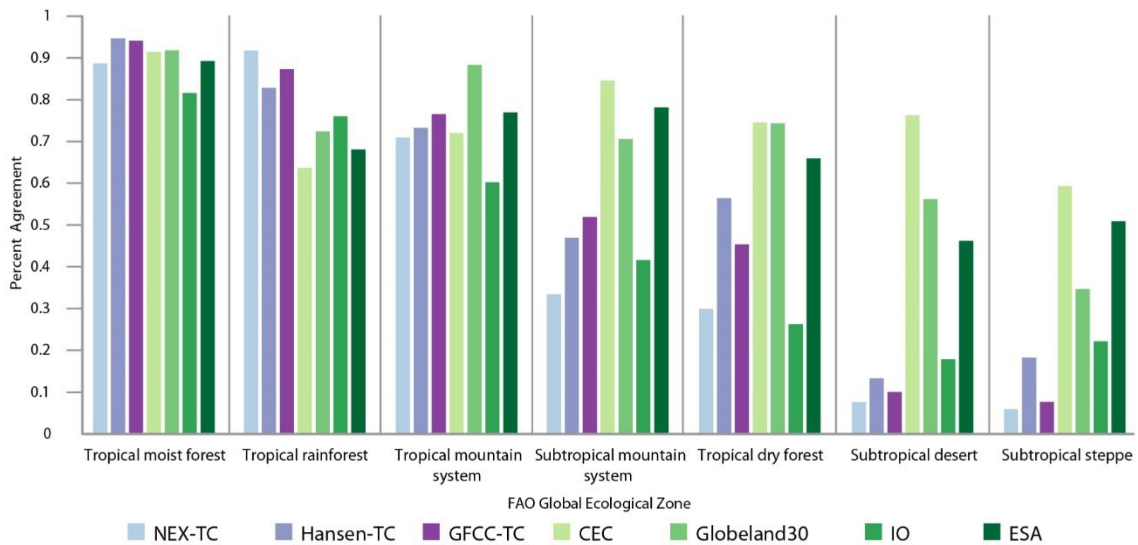

Figure 2: Forest agreement results of all 7 products within each global ecological zone. Products shown in shades of purple and labeled “TC” were derived using a 30% cover forest definition, while products shown in shades of green followed their own forest definitions.

The converted tree cover products (NEX-TC, Hansen-TC, and GFCC-TC) agreed better with the INFyS data using the 10% canopy threshold for defining a forest. Within the Tropical Dry Forest, Hansen-TC ranges from 56.4% agreement using the 30% canopy threshold definition, to 63% agreement with a 10% canopy threshold definition. GFCC and NEX-TC both see much larger ranges utilizing the 10% canopy threshold definition: GFCC varies from 45.4% to 95.3% agreement, while NEX-TC varies from 29.9% to

58.9% agreement. I clarify that these products already agree well within the higher forest density ecozones (using the 30% canopy threshold); therefore the improvements (using the 10% canopy threshold) mostly occur within the sparsely forested ecozones.

3.2 Individual Product Evaluation Within Edomex

I performed a complementary analysis of the 7 data products to estimate forest cover at the local scale. The Subtropical Mountain System is the dominant ecozone across Edomex. I found that Globeland30 and CEC agreed best with INFyS data (90% and 74%) while Globeland 30 and ESA agreed best with the Edomex data (93% and 94%) (Figure 3). Unlike at the national level, my findings did not indicate obvious differences in agreement between land cover and tree cover products with forest inventory data at the local level, however the 7 products had a higher agreement with the Edomex data than the INFyS data for the state.

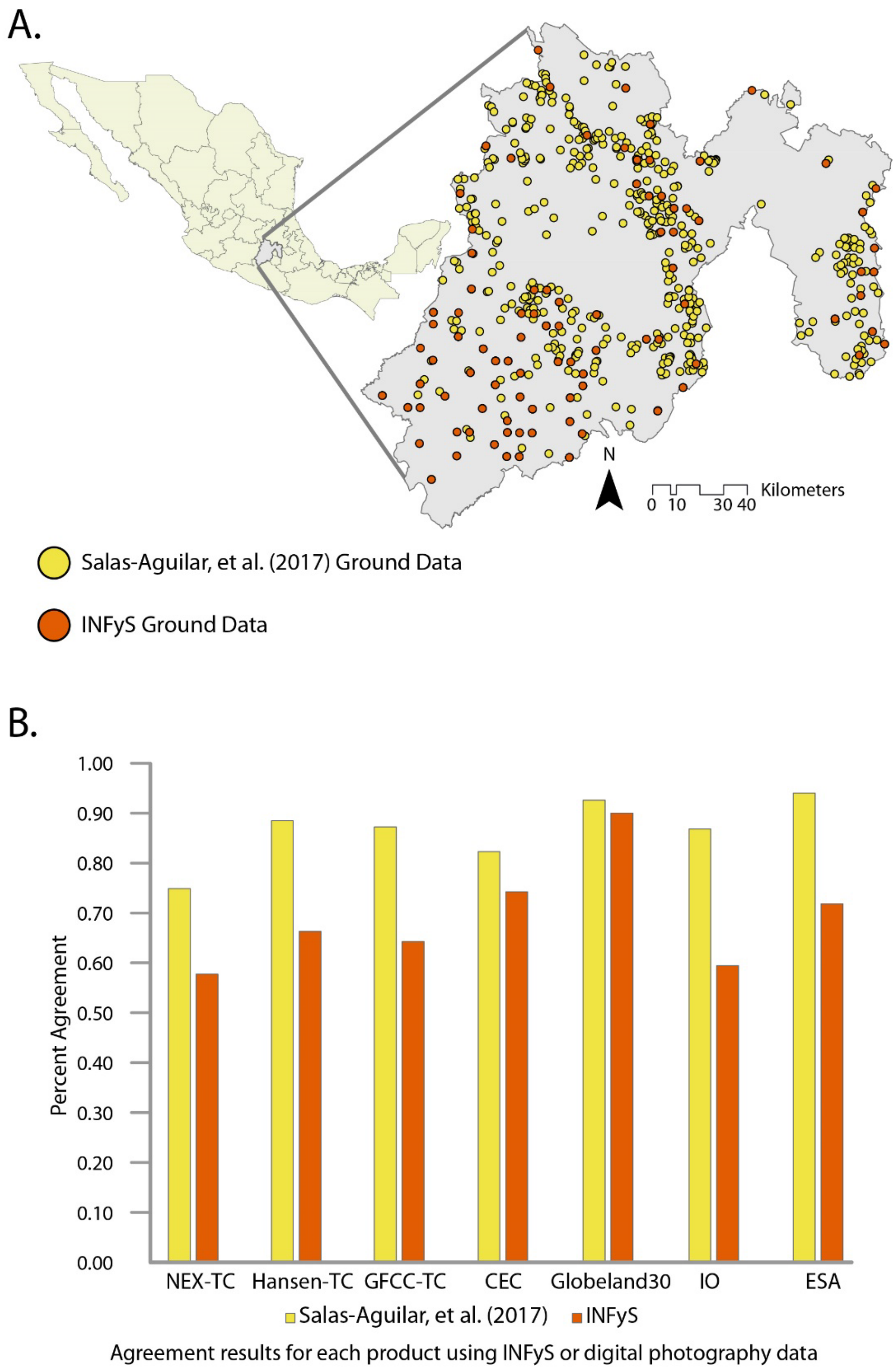

Figure 3: A. The distribution of INFyS (orange) and Salas-Aguilar, et al. 2017 (yellow) forest points within Edomex (Estado de México). B. Statewide agreement results for each product.

3.3 National Hybrid Forest Likelihood Map

The potential agreement among all 7 data products ranged from 14.29% (only one product identified a pixel as a forest) to 100% (all products identified a pixel as a forest; Figure 4). I found high agreement among the 7 products within regions such as the Yucatan Peninsula and mountain areas in the Sierra Madre Oriental (NE of Mexico) and Sierra Madre Occidental (Western Mexico) (Figure 4). As such, I categorized these areas within the high-likelihood class (Figure 5). In contrast, areas at the fringe of the Sierra Madre Oriental and Sierra Madre Occidental or the lowlands of Veracruz had a lower agreement among the 7 data products. The FAO FRA report for Mexico identified an area of 656,920 km2 as "forest" for 2020, while I found a range of 387,807 km2 (IO) - 675,395 km2 (ESA).

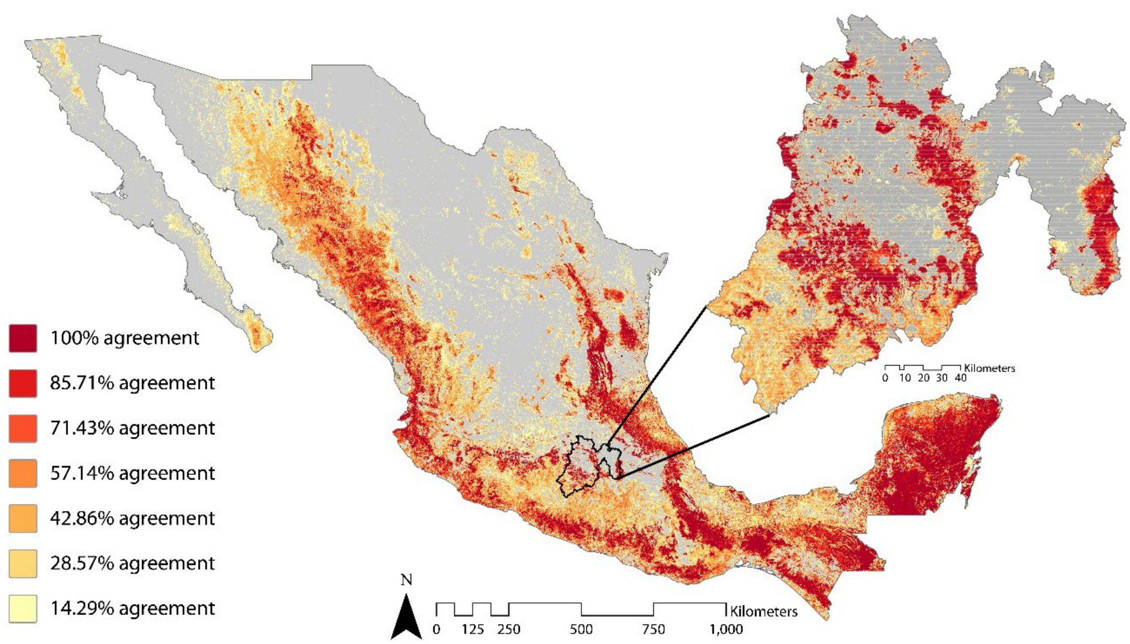

Figure 4: A. Hybrid uncertainty map showing the percent agreement among the 7 products across mainland Mexico. The percentage represents how many products identified each pixel as being forested. B. Closeup of Edomex.

I found that an area of 1,021,794 km^2 was identified as forest by at least one satellite-derived product at the national scale. Within this area, 26% (288,749 km2) was classified as high forest likelihood, 33.34% (340,661 km2) as moderate forest likelihood, and 38.4% (392,383 km2) as low forest likelihood (Figure 5).

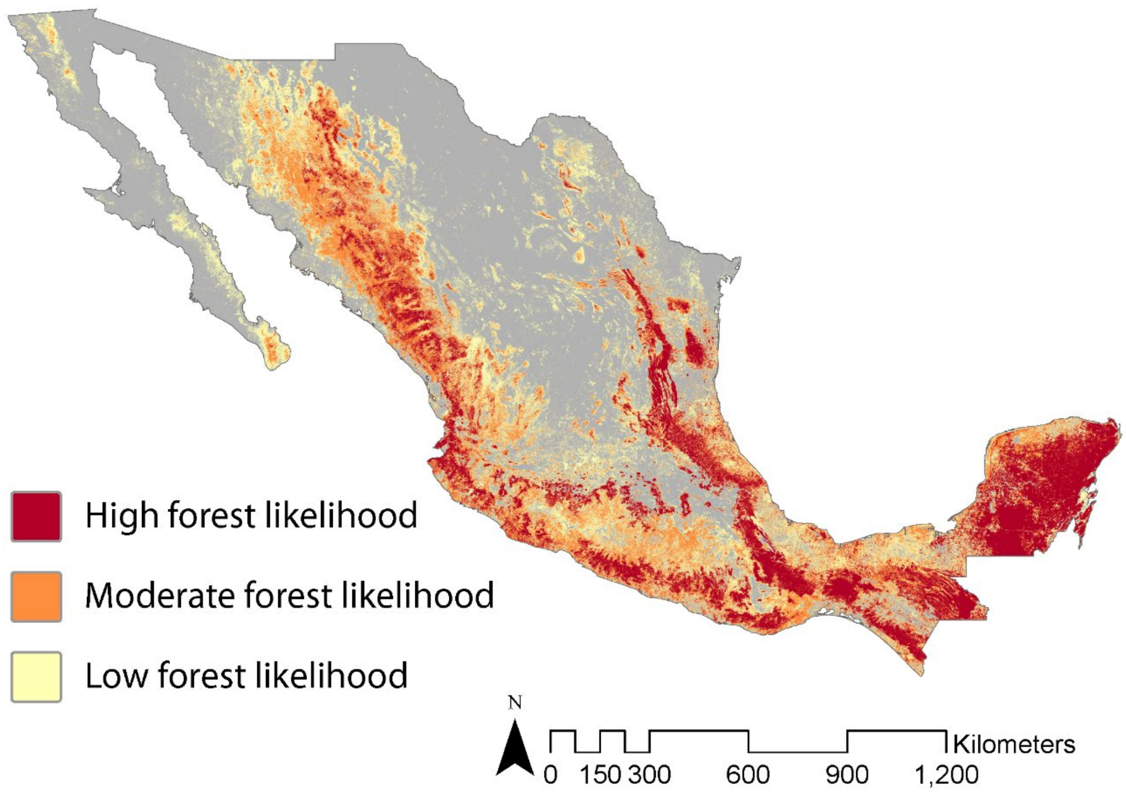

Figure 5: 3 class forest likelihood map derived from hybrid forest likelihood map. High forest likelihood is the area identified as forested by 6 or 7 products, moderate forest likelihood is the area identified as forested by 3-5 products, and low forest likelihood is the area identified as forested by only 1 or 2 products.

Figure 6 shows the distribution of the likelihood of forest extent for each ecological zone. The Subtropical Steppe and Subtropical Desert are predominantly within the low forest likelihood class. The Tropical Moist Forest comprised the highest number of pixels within the high forest likelihood class, with an area representing 86,443 km2. This represents nearly 30% of all the pixels identified as high forest likelihood. The likelihood distribution of the Tropical Mountain System is skewed towards high forest likelihood, with over 50% of its area identified as high forest likelihood. The likelihood of forest extent is relatively equally distributed across the Tropical Rainforest. For Tropical Dry Forest and Subtropical Mountain System most pixels are classified as moderate forest likelihood, thus representing ecozones with greater uncertainty (Figure 6).

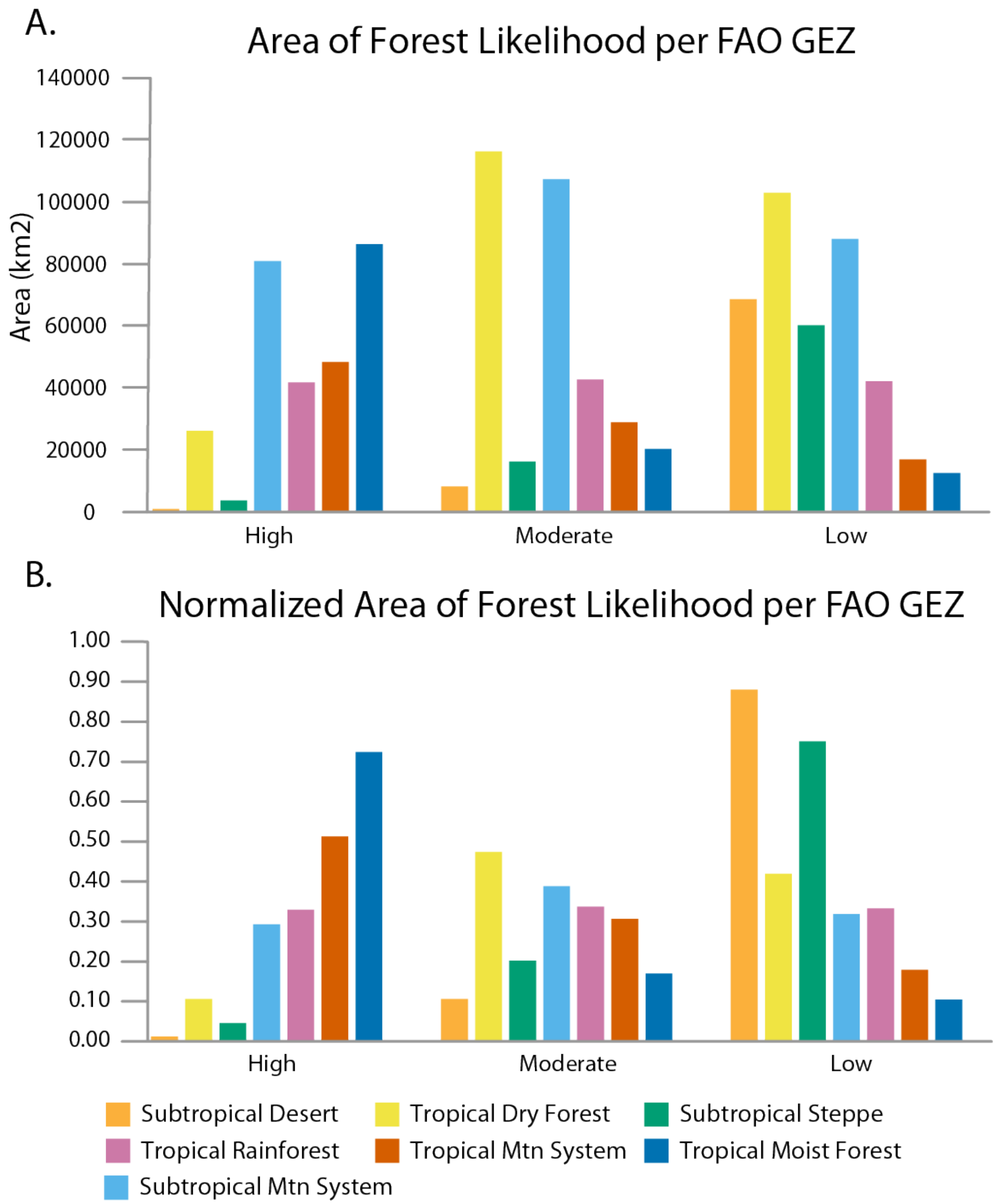

Figure 6: A. Area of forest likelihood within each Food and Agriculture Organization Global Ecological Zone. B. Normalized area of forest likelihood for Food and Agriculture Organization Global Ecological Zone.

Chapter 4

DISCUSSION

I found a considerable range in degree of agreement between satellite-derived forest products and forest inventory data in Mexico. While agreement was highest with INFyS data in densely forested ecozones (i.e., tropical moist forest), agreement generally dropped in more sparsely forested ecozones such as the subtropics. This may indicate difficulties in satellite-derived products' abilities to identify open forests in Mexico, particularly percent tree cover products. However, the agreement of percent tree cover products with INFyS over the sparsely forested ecozones was greatly improved when a more liberal forest definition (10%) was applied. In alignment with previous research, this finding indicates that selected forest definition can greatly impact forest extent estimates (Sexton et al., 2016; FAO, 2022; Côte et al., 2018; Fagan and DeFries, 2009; Romijn et al., 2013; Traub et al., 2000). Still, a decline in agreement with INFyS data is observed across most products and utilizing both forest definitions within these regions, suggesting a reason beyond forest definition for the observed decline. At the local level I observed major differences in product agreement with the two forest inventory datasets available in Edomex (Figure 3B). I postulate that different methodologies and sampling designs between the INFyS and digital photography-derived forest inventories are possible explanations for the degree of difference observed. The different results in

Edomex (Figure 3B) highlights the critical need for balanced sampling locations when conducting forest inventories. Overall, satellite-derived forest products varied greatly in their agreement with forest inventory data depending on ecological zone.

I identified forest likelihood in Mexico based on the number of times an area was identified as being forested by the 7 products. The moderate forest likelihood class (Figure 5) represents the highest degree of disagreement among the 7 products and takes up an area equivalent to over half of the FAO's estimate of total forest area in Mexico (XX sq. km). Thus, I have low certainty/agreement about the forest status of a very large area based on satellite-derived estimates. End-users located within this area (predominantly within the subtropical mountain system and tropical dry forest) might reconsider relying solely on satellite-derived forest products for decision making. Considering the degree of disagreement among products, additional research to improve satellite-derived product consistency would be valuable within these areas. The collection of additional ground-based forest observations within this area could also help forest product creators to generate more accurate products.

Researchers and end-users are utilizing the increasing volume of satellite-derived forest products for environmental decision making and MRV efforts. Thus, it is critical for them to identify the degree of uncertainty in satellite-derived products within their area of use before selecting a product and deciding how to utilize it (Brown et al., 2017; Justice et al., 2000; Morisette et al., 2002). My hybrid uncertainty map (Figure 4, Figure 5) represents one way for end-users to identify regions of uncertainty in forest extent estimates in Mexico. Here, I relate uncertainty to the degree of agreement among the forest products for each pixel. I identified a large range of total forest extent estimates across the 7 satellite-derived products, corroborating prior research in Mexico that has found similarly substantive differences in forest extent estimates (Gebhardt et al., 2014). Due to this large variation, end-users in areas inconsistently identified as forested by the independent forest products (i.e., lowlands of Veracruz) must be cautious in utilizing any one product. In other regions with more certainty/agreement (i.e., Yucatán Peninsula), users can utilize a range of satellite-derived forest products with more confidence. My hybrid map can facilitate understanding of the associated uncertainty of utilizing these products in Mexico.

Significant debate is ongoing regarding the use of various forest definitions, or the appropriateness of simple percent tree cover definitions as utilized here (Côte et al., 2018; Fagan and DeFries, 2009; Fernández-Montes de Oca et al., 2021; Romijn et al., 2013; Sexton et al., 2016). My use of a 30% threshold to identify forest/non-forest binaries of tree cover introduces one limitation of my research. As discussed, when utilizing a more liberal 10% threshold when validating the products with INFyS data I observed improved agreement in tree cover products and inventory data. Here, I only report results for the hybrid uncertainty and forest likelihood map utilizing the 30% threshold due to overestimation of forest area associated with a 10% threshold applied to these products (FAO, 2022). My threshold may result in some underestimation of forest area within the tree cover products, which could explain the lower total forest area identified by these products and lower agreement with ground data. Additionally, it is important to note that several of the products are no longer in their native format due to the application of the forest definition (percent tree cover products, forest inventory products) and upscaling to 30 m resolution (IO and ESA). Results might differ for these products in their native format and resolution. The issues of forest definition and upscaling for data standardization are inevitable limitations of such a comparison of so many independent datasets.

In conclusion, I compared 7 satellite-derived land and tree cover products within mainland Mexico in order to identify the range of forest extent estimates. When compared to Mexico's national forest inventory data, I found a general decline in agreement from the tropics to the subtropics. This identifies regions where satellite-derived products disagree most with Mexico's official forest data (especially within the subtropical desert and subtropical steppe). I also developed a hybrid uncertainty map comparing forest extent across the 7 products that found a significant range of total forest estimates for Mexico. My findings suggest that end-users of these satellite-derived forest products must carefully consider the impact of utilizing one product over another, as results will vary considerably from product to product. Product decision is less impactful within certain high-agreement regions in Mexico, such as the Yucatán Peninsula. End-users within the tropical dry forest and subtropical mountain system ecozones are the most likely to be impacted by the differences among products. More research and ground data within these ecozones might help improve consistency among newly generated products, reducing this impact.

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