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Estimating forest extent across Mexico

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Supplementary material for this article is available online

Abstract

Information on forest extent and tree cover is required to evaluate the status of natural resources, conservation practices, and environmental policies. The challenge is that different forest definitions, remote sensing-based (RSB) products, and data availability can lead to discrepancies in reporting total forest area. Consequently, errors in forest extent can be propagated into forest biomass and carbon estimates. Here, we present a simple approach to compare forest extent estimates from seven regional and global land or tree cover RSB products at 30 m resolution across Mexico. We found substantial differences in forest extent estimates for Mexico, ranging from 387 607 km^2 to 675 239 km^2. These differences were dependent on the RSB product and forest definition used. Next, we compared these RSB products with two independent forest inventory datasets at national ($n = 26\,220$ plots) and local scales ($n = 754$ plots). The greatest accuracy among RSB products and forest inventory data was within the tropical moist forest (range 82%–95%), and the smallest was within the subtropical desert (range <10%–80%) and subtropical steppe ecological zones (range <10%–60%). We developed a forest extent agreement map by combining seven RSB products and identifying a consensus in their estimates. We found a forest area of 288 749 km^2 with high forest extent agreement, and 340 661 km^2 with medium forest extent agreement. The high-to-medium forest extent agreement of 629 410 km^2 is comparable to the official national estimate of 656 920 km^2. We found a high forest extent agreement across the Yucatan Peninsula and mountain areas in the Sierra Madre Oriental and Sierra Madre Occidental. The tropical dry forest and subtropical mountain system represent the two ecological zones with the highest areas of disagreement among RSB products. These findings show discrepancies in forest extent estimates across ecological zones in Mexico, where additional ground data and research are needed. Dataset available at https://doi.org/10.3334/ORNLDAAC/2320.

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 regulate the global carbon budget (IPCC 2019), and accurate assessments of global forest resources are critical for measuring progress in international efforts toward sustainable development, biodiversity conservation, and emissions reductions (Hansen *et al* 2013, Vargas *et al* 2017, FAO 2022). International efforts to monitor forests, 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 national reporting processes. In many instances, country-specific data depend heavily on remote sensing-based (RSB) forest cover maps to report statistics related to national and international commitments (FAO 2020). Therefore, RSB forest cover estimates are vital for national-to-regional measurement, reporting, and verification (MRV) systems.

Although RSB forest cover estimates are crucial for calculating local and global carbon budgets, several challenges arise when determining what constitutes a forest. The first challenge is ambiguity in the term 'forest' (FAO 2002). For example, Sexton *et al* (2016) found differences of up to 41.2 Gt C aboveground biomass within the tropics across forest cover estimates due primarily to different forest definitions among global RSB forest products. The 2020 FAO FRA remote sensing survey found differences of 16 180 000 km^2 in total global forest area estimates, which is equivalent to the total land area of Russia—mainly because of different definitions between RSB tree/forest cover and 'forest' land use (Castilla *et al* 2022, FAO 2022). Global institutions such as the FAO's FRA define 'forest' as primarily a land use feature, creating challenges using RSB products. For example, while RSB products might classify an agroforestry area with a 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 (FAO 2002, Sexton *et al* 2016), with studies showing that these different definitions have real-world implications on the measurement of forest area and carbon stock and their changes (e.g. degradation & deforestation) (Traub *et al* 2000, Fagan and DeFries 2009, Romijn *et al* 2012). 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 taller than 5 m (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 a tree height of 2–5 meters; with each country able to select their forest definition for national greenhouse gas inventories for reporting purposes.

A second challenge is the difficulty of collecting high-quality and consistent RSB data across forested ecosystems. These RSB products rely on cloud- and cloud shadow- free imagery to provide complete spatiotemporal coverage. Regions with extensive cloud cover often force product creators to stitch multiple years of imagery together to minimize cloud and cloud shadow contamination (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 can impact downstream RSB forest products (Zhu and Woodcock 2012, Wilson and Jetz 2016, Young *et al* 2017). Especially in high elevations and within the humid tropics, cloud cover substantially decreases the availability of clear-sky imagery during critical phenological stages (Hansen *et al* 2008, Wilson *et al* 2016). Also, the temporal compositing approaches using cloud-free and cloud shadow-free images from varying phenological stages can lead to unexpected systematic errors in forest products (Hüttich *et al* 2011). Given the importance of the tropics and subtropics in Earth's systems and their recent rapid changes due to natural and anthropogenic disturbance, it is critical to understand spatial and temporal changes in forest cover in these ecological zones.

The third challenge is the difficulty faced by end-users involved in MRV protocols, as they must interpret and choose from dozens of global and regional forest products with different methodologies. They need data with documented information about RSB products' errors and uncertainty for proper interpretation and, ideally, evaluations using country-specific forest information (such as national forest inventory data) of individual RSB products (Stehman and Foody 2019). Furthermore, multiple studies have reported that RSB products have moderate agreement among themselves (Fritz and See 2008, Song *et al* 2011, 2014, Sexton *et al* 2015, Feng *et al* 2016, FAO 2022), especially at finer spatial resolution (e.g. 30 m). Consequently, there is a need to identify consistency in forest definitions, agreement among RSB forest extent products (Sexton *et al* 2016), and ultimately increase the precision of new estimates (McRoberts *et al* 2016). National reporting of forest information to international institutions (i.e. FAO) often utilizes national forest inventories and regional or global RSB forest maps (FAO 2020, Gillerot *et al* 2021). Multiple RSB forest products are available and could reduce operating costs for measurements and reporting (FAO 2020). Therefore, the first steps are to evaluate product reliability with country-specific information and measure the agreement of multiple RSB forest products.

This study represents an effort by NASA's carbon monitoring system (CMS) to engage with end-users and develop approaches to provide information and support decision-making (Hurtt *et al* 2022). Our main objective was to create a forest extent agreement map for mainland Mexico at 30 m resolution by combining data from multiple RSB products. This product was developed as part of a co-creation process with end-users (i.e. *Comisión Nacional Forestal* [CONAFOR] and *Programa Mexicano del Carbono* [PMC]) to evaluate the agreement of RSB products to classify forest extent across Mexico, provide insights for interpreting RSB information, and improve future designs of national forest inventories. Our approach is simple, replicable, and transferable to inform MRV initiatives. This study is based on evidence that assessing consensus among RSB products will help end-users (e.g. national forestry agencies) understand and utilize them more effectively (Sexton *et al* 2016).

Mexico presents a relevant case study with broad applicability to other countries within the tropics and subtropics. First, like many countries, Mexico utilizes RSB 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 *Inventario Nacional Forestal y de Suelos* (National Forest and Soil Inventory, or INFyS), which is used 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 substantial efforts for the 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 to develop simple, replicable, and transferable approaches to assess forest extent as part of MRV initiatives.

2. Methods

2.1. Data products

2.1.1. RSB forest extent products

We selected seven global, regional, and national forest and tree cover data products to estimate information for Mexico: ESA, Globeland30, CEC, IO, NEX-TC, Hansen-TC, and GFCC-TC (see details in table 1). All RSB products included fine- or medium-spatial resolution information (i.e. 10–30 m resolution) and represented the state of forest or tree cover from 2010 to 2020. We recognize that several other RSB products exist (Liu *et al* 2021), but we chose seven based on: (a) feedback from end-users in Mexico considering familiarity with the RSB products; (b) availability and FAIR (i.e. findable, accessible, interoperable, and replicable) data principles; and (c) selected products representing different methodological approaches from global to regional scales. The original seven products were developed from various sources and RSB data, as detailed in table 1.

2.1.2. Validation data

We used two independent datasets to assess the seven RSB products. Both datasets report canopy cover in percent and can be used to test different forest definitions (i.e. 10% and 30%). The first dataset represents plot-level data from the Mexican government's INFyS from 2009–2014 (Comisión Nacional Forestal (CONAFOR) 2021; 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). The most recent year of data on tree cover density was used at each location, and locations outside mainland Mexico were excluded from the analysis. A second independent dataset (hereafter referred to as Salas–Aguilar data) represents information for tree cover density for the *Estado de México* (i.e. Edomex) to test the seven products at the state level (i.e. local scale). This information was collected in 754 plots (1000 m^2 circular plots) using digital photography and a systematic sampling design described in detail elsewhere (Salas-Aguilar *et al* 2017). The 754 plots represent a systematic sampling covering various vegetation types, which included 12 different land uses in eight ecoregions of the Edomex (PMC 2015). All datasets were projected to Albers Equal Area Conic North America.

2.2. Data analysis

We used the FAO global ecological zones (GEZ; FAO 2015) for reporting forest statistics, validation results, and forest extent agreement information. Mexico has seven 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 1).

2.2.1. Data standardization

Each tree and land cover RSB product was extracted for mainland Mexico. The ESA and IO products (table 1) were resampled to a 30 m spatial resolution. To compare different product types at the pixel level, we recorded continuous data values in the percent tree cover products into categories (i.e. forest or non-forest). For each land cover product, all reported forest types were combined to represent forest cover at the national scale. We defined a 30% threshold for products reporting tree cover density to determine pixels of forest or non-forest. In other words, pixels with $\geqslant$30% cover were considered 'forest', and pixels with <30% cover were considered 'non-forest'. This definition was consistently applied to the validation point data, so points with $\geqslant$30% cover were considered 'forest points'. This resulted in $n = 21\,167$ INFyS 'forest' points (figure 1) and $n = 486$ points within Edomex from the Salas–Aguilar data. Previous studies have used different thresholds ranging from 10% to over 60% of tree cover density (Romijn *et al* 2012). We highlight that selecting such a threshold is a matter of current debate, as discussed in the introduction. While we focused our primary analyses and discussion on the 30% threshold, we additionally produced and discussed results using a 10% threshold to account for Mexico's latest forest definition used by the *Comision Nacional Forestal* (CONAFOR 2021).

Table 1. Remote sensing-based (RSB) forest products, spatial resolution, nominal year, and primary remote sensing inputs.

Product name	Spatial resolution	Nominal year	Primary remote sensing inputs	Citation
European Space Agency 2020 Land Cover Map for Mexico (**ESA**)	10 m	2020	Sentinel-2 A and 2B	Zanaga *et al* (2021)
Globeland30 2020 (**Globeland30**)	30 m	2020	Landsat 8, HJ-1, and GF-1	Chen *et al* (2015)
Commission for Environmental Cooperation 2015 Land Cover Map (**CEC**)	30 m	2015	RapidEye	CEC (2020)
Impact Observatory 2020 Land Cover Map (**IO**)	10 m	2020	Sentinel-2	Karra *et al* (2021)
NAIP Trained Mean Percent Cover Map (**NEX-TC**)	30 m	2017	Landsat 8 and NAIP	Park and Vargas (2022)
Global Land Analysis & Discovery Global 2010 Tree Cover (**Hansen-TC**)	30 m	2010	Landsat 7	Hansen *et al* (2013)
Global Forest Cover Change Tree Cover 30 m Global (**GFCC-TC**)	30 m	2010	Landsat 5 and 7	Townshend (2016)

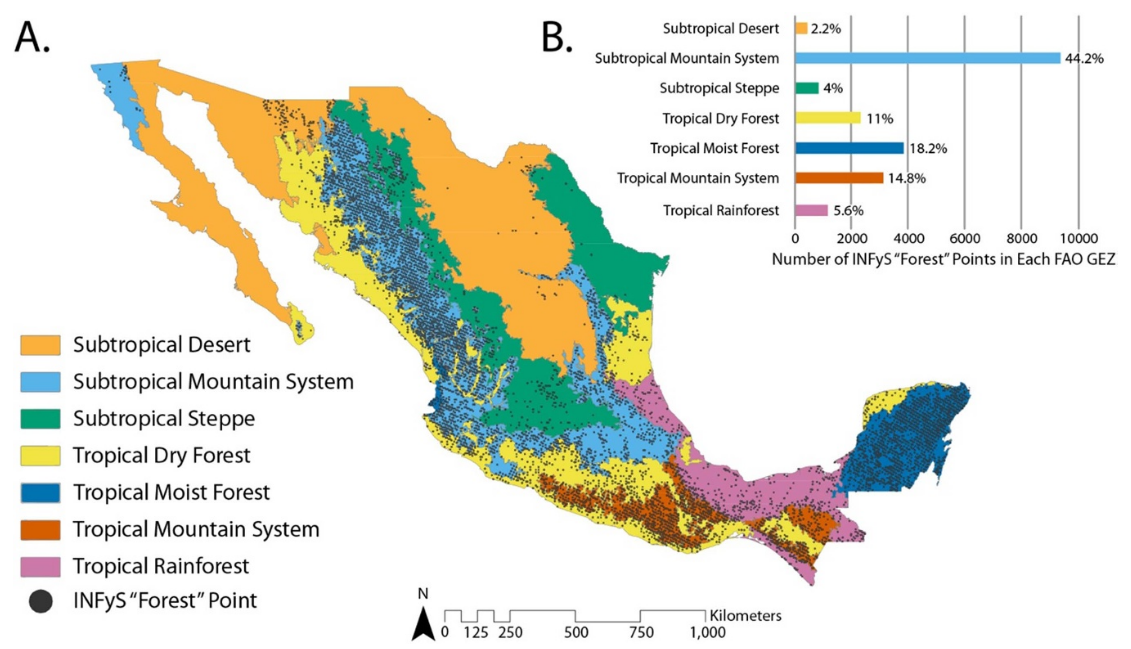

Figure 1. Distribution of FAO global ecological zones (A) and INFyS ground data across Mexico (B). The tropical mountain system contains the most INFyS forest plots per 1000 km^2 (∼31 plots/1000 km^2), followed by the tropical moist forest (∼30 points/1000 km^2) and the subtropical mountain system (∼26 points/1000 km^2) when using a 30% forest threshold.

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, Fagan and DeFries 2009, 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 UNFCCC. A methodological flow chart of processing steps for the seven RSB forest products is available in the supplementary materials (supplementary materials figure 1).

2.2.2. Validation of RSB forest extent products

We tested the accuracy of each RSB product at the national and local scales (i.e. at the Edomex). First, we identified the locations where the INFyS and each RSB product were the same in each 'forest' class. Then, we divided the number of locations showing agreement between the INFyS and RSB product by the total INFyS locations (classified as a forest) within each GEZ to report the accuracy as a percent. A similar approach was applied to calculate the accuracy between each RSB product and the information from the Salas–Aguilar data at the local scale (i.e. Edomex). If continuous RSB is available, future studies could use alternative methods for accuracy assessments. For example, it may be possible to calculate the mean of the differences between values for forest plots and RSB grid cells, as well as the sum of the squared differences between the values for these plots and cells. However, for this study, we analyzed various RSB products that contained both continuous and categorical data (as shown in table 1). Thus, we used the method described in section 2.2.2 to validate the chosen RSB products.

2.2.3. Generation of a forest extent agreement map
Using ArcGIS, a pixel-by-pixel comparison was undertaken to generate a map of forest extent agreement across mainland Mexico. All seven RSB data products were stacked, and we counted the number of categorical agreements for each pixel across Mexico. In other words, for each pixel, we calculated how many RSB products estimated that pixel to be forested. This approach is comparable to the global forest vote map produced by Sexton *et al* (2016) and the development of forest indicators that have defined 'places of agreement' for comparing multiple RSB products (Mondal *et al* 2020).

We report three forest agreement classes: high agreement (85.71%–100%; agreement between 6–7 products), medium agreement (42.86%–71.43%; agreement between 3–5 products), and low agreement (14.29%–28.57%; agreement between 1–2 products). We clarify that the medium forest agreement class represents the most extensive disagreement among the seven products because only 3–5 products agree on the classification. In other words, this category represents mixed classifications among the RSB products. In contrast, high forest agreement (6–7 products agree that there is a forested pixel) and low agreement (5–6 products agree that there is a non-forested pixel) represent consistency in the classification (i.e. ample agreement that it is a forested pixel for 'high agreement' or ample agreement that it is not a forested pixel for 'low agreement'). We highlight that reporting uncertainty in the NASA CMS is an ongoing challenge and active line of research. Here, we present a practical way to summarize the results categorically to facilitate application and decision-making, considering input from end-users and practitioners.

The forest agreement map can be downloaded from the ORNL distributed active archive center for biogeochemical dynamics (Braden *et al* 2023).

3. Results

3.1. Evaluation of RSB products against forest inventory data

3.1.1. National scale
All RSB products generally had greater accuracy in ecological zones with expected higher forest density (figure 2). The greatest accuracy of RSB products was across the tropical moist forest, ranging from 81.6% (IO) to 94.7% (Hansen-TC). The RSB products initially reporting tree cover density (NEX-TC, Hansen-TC, and GFCC-TC) had greater accuracy across the tropical rainforest (82.8%–91.8%) than land cover products (ESA, Globeland30, CEC, and IO) (63.3%–76%). The accuracy of RSB products was mixed across the tropical mountain system, ranging between 60.2% (IO) and 88.3% (Globeland30).

Most land cover products (i.e. CEC, Globeland30, and ESA) had greater accuracy than products initially 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 had greater accuracy (50.9%–59.3%) in the sparsely forested subtropical steppe. In contrast, the products initially reporting tree cover density had an accuracy between 5.9% (NEX-TC) and 18.3% (Hansen-TC). The CEC had the greatest accuracy in the subtropical mountain system (84.5%), tropical dry forest (74.5%), subtropical desert (76.3%), and subtropical steppe (59.3%). In comparison, products that initially reported tree cover density and the IO land cover product had lower accuracy across these four ecological zones (figure 2).

The converted tree cover products (NEX-TC, Hansen-TC, and GFCC-TC) had greater accuracy using the 10% canopy threshold for defining a forest. Within the tropical dry forest, Hansen-TC varied from 56.4% (using the 30% canopy threshold definition) to 63% accuracy (10% canopy threshold definition). GFCC and NEX-TC had more extensive ranges when using the 10% canopy threshold definition: GFCC varied from 45.4% to 95.3%, while NEX-TC varied from 29.9% to 58.9%. We clarify that these products, using the 30% canopy threshold, had greater accuracy in ecological zones represented with higher forest density; therefore, the improvements in accuracy (using the 10% canopy threshold) mainly occur within ecological zones that are sparsely forested.

3.1.2. Local scale
We performed a complementary analysis to evaluate the accuracy of each RSB product at the local scale using Salas–Aguilar data (i.e. within Edomex). The subtropical mountain system is the dominant ecological zone across Edomex. We found that Globeland30 and CEC had the greatest accuracy with

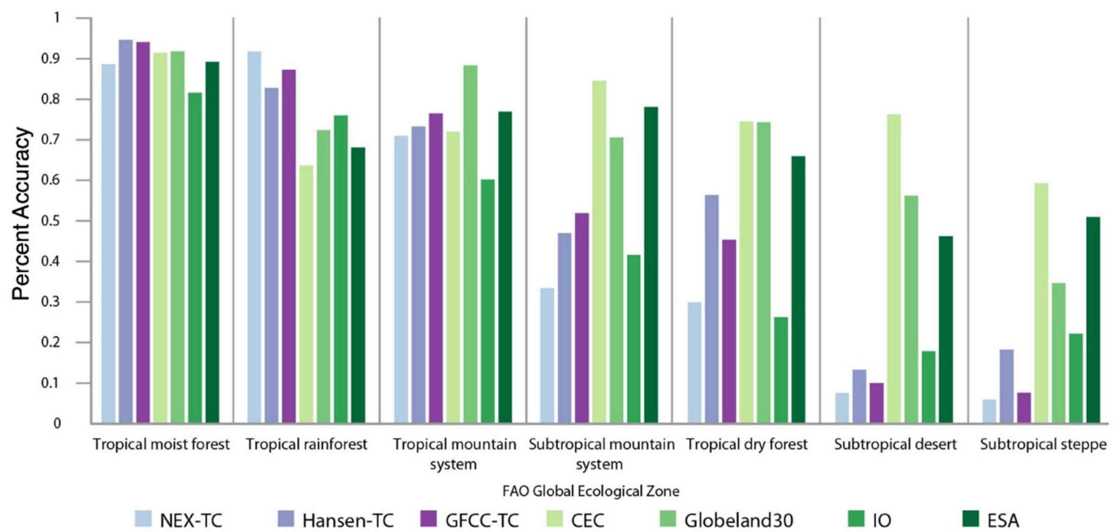

Figure 2. Accuracy results of all seven products within each global ecological zone. Products shown in shades of purple and labeled 'TC' were produced using a 30% cover forest definition, while products in shades of green followed independent forest definitions.

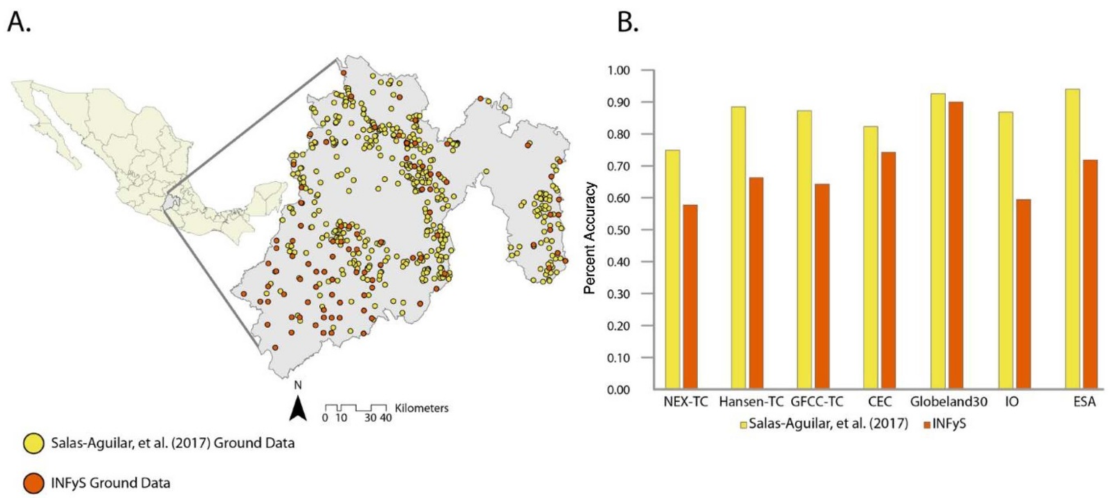

Figure 3. The distribution of INFyS (orange) and Salas–Aguilar *et al* (2017) (yellow) forest points within Edomex (Estado de México; (A)). Statewide agreement results for each product (B).

the INFyS data (90% and 74%, respectively), while Globeland 30 and ESA had the greatest accuracy with the Edomex data (93% and 94%, respectively) (figure 3(B)). In contrast with the national scale, our results did not indicate apparent differences in accuracy between land cover and tree cover products with forest inventory data at the local scale; however, the seven products had a greater agreement with the Salas–Aguilar data than the INFyS data at this scale.

3.1.3. National forest extent agreement map

The agreement among all seven data products ranged from 14.3% (when only one product identified a pixel as a forest) to 100% (when all products identified a pixel as a forest) and was evaluated for each one of the >2.1 million pixels to create the agreement map (figure 4). We found extensive agreement among the seven products within regions such as the Yucatan Peninsula and mountain areas in the Sierra Madre Oriental (Northeastern Mexico) and Sierra Madre Occidental (Western Mexico) (figure 4). As such, we categorized these areas within the high forest agreement 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 medium or low agreement among the seven data products.

We found that an area of 1021 794 km^2 was estimated to be forested by at least one RSB product at the national scale. Within this area, 26% (288 749 km^2) was classified as high forest agreement, 33.34% (340 661 km^2) as medium agreement, and 38.4% (392 383 km^2) as low agreement (figure 5).

The official national estimate for Mexico identified an area of 656 920 km^2 as forest (FAO 2022). Individually, the seven products produced a range of

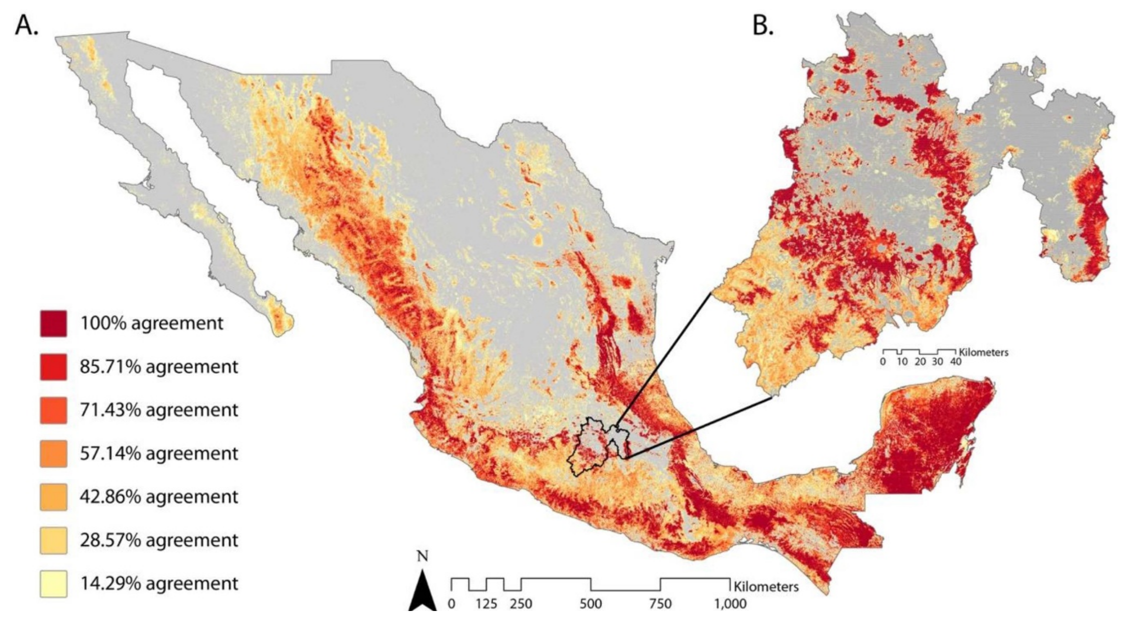

Figure 4. Forest extent agreement map showing the percent agreement across the seven products (A). The percentage represents how many products identified each pixel as being forested. An enlarged representation of Edomex (Estado de México) for the forest extent agreement map (B).

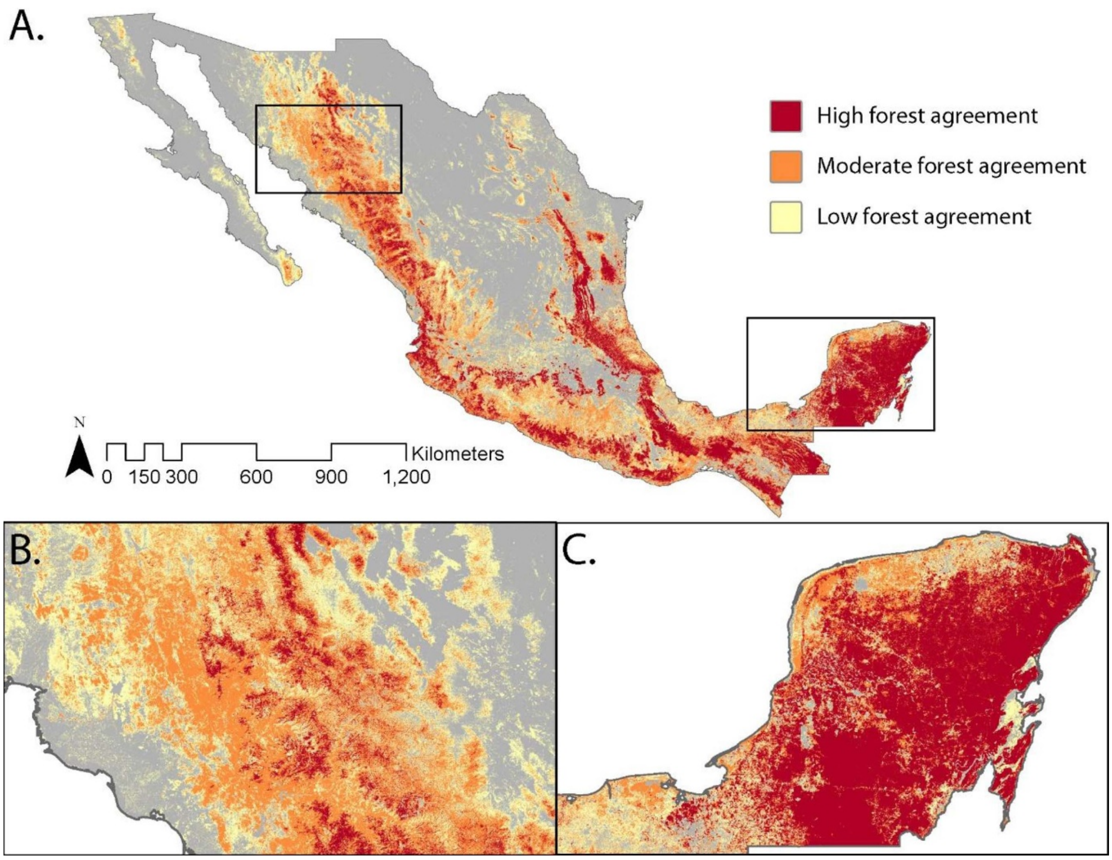

Figure 5. Categorical forest agreement map produced from the forest extent agreement map in figure 4(A). A high forest agreement is an area identified as forest by 6 or 7 products, a medium agreement is identified as forest by 3–5 products, and a low agreement is identified as forest by only 1 or 2 products. An enlarged representation of an area of medium forest agreement in the northern range of the Sierra Madre Occidental (B), and of high forest agreement in the Yucatán Peninsula (C).

estimates, with a minimum of 387 807 km^2 identified as forest (IO) and a maximum of 675 395 km^2 identified as forest (ESA). The high and medium agreement classes represent pixels identified as forested the most frequently by RSB products. When adding the area of these two classes, we found a

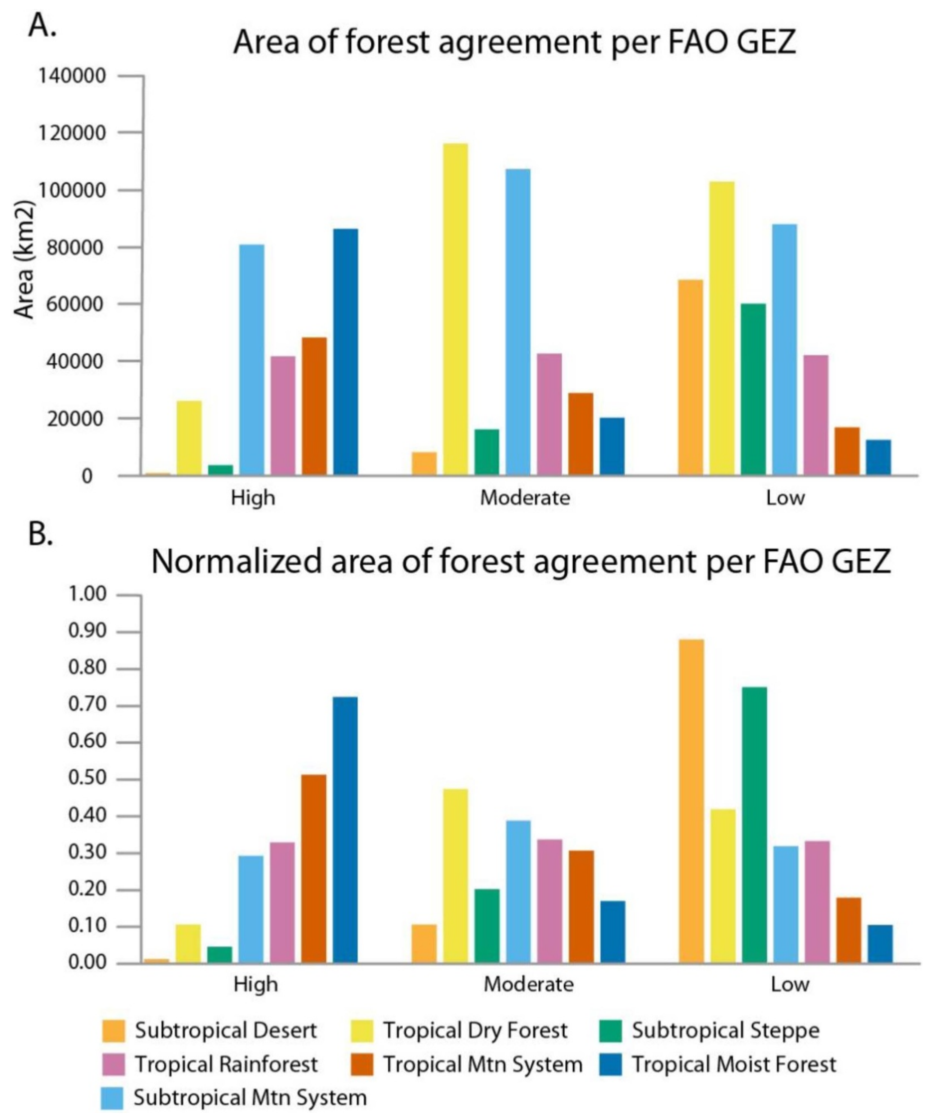

Figure 6. Area of forest agreement within each food and agriculture organization global ecological zone (A). Normalized area of forest agreement for food and agriculture organization global ecological zone (B).

forest area of 629 410 km^2, around 4% off the official estimate.

Figure 6 shows the distribution of forest agreement for each ecological zone. The subtropical steppe and subtropical desert were predominantly within the low agreement class. The tropical moist forest comprised the highest number of pixels within the high forest agreement class, with an area of 86 443 km^2. Figure 6 indicates that nearly 30% of all the pixels identified as forested in Mexico were within the high forest agreement class, representing a substantial area with most or all products agreeing that the pixels were forested. The distribution of the tropical mountain system was skewed towards high forest agreement, with over 50% of its area identified as such. Forest agreement was relatively equally distributed across the tropical rainforest. Most pixels were classified as medium forest agreement for tropical dry forests and subtropical mountain systems, thus representing ecological zones with greater product discrepancy (figure 6).

4. Discussion

We found a considerable range in degree of accuracy between RSB forest products and forest inventory data across Mexico. While accuracy was greater with INFyS data in densely forested ecological zones (i.e. tropical moist forest), accuracy generally decreased in more sparsely forested ecological zones across the subtropics. This may indicate a limited capability of the RSB products to correctly classify open forest ecosystems as forests across Mexico, particularly for percent tree cover products. It may also be influenced by the INFyS methodological design, which utilizes different distances between plots within other regions (i.e. distances between plots in forests of 5 × 5 km, semi-arid zones of

10×10 km, and arid zones of 20×20 km). However, the accuracy of percent tree cover products with INFyS over the sparsely forested ecological zones was greatly improved when a more relaxed forest definition (10%) was applied (supplementary materials figure 2). Our approach to using these different forest definition thresholds on RSB products aligns with previous findings on how RSB product forest definition can greatly affect national forest extent estimates (Traub *et al* 2000, Fagan and DeFries 2009, Romijn *et al* 2013, Sexton *et al* 2016, FAO 2022). While our findings align with these results, we further classified agreement (among RSB products) and accuracy (for national or local forest inventory data) down to the ecological zone level, providing additional insights at a finer scale than other global comparisons. It is worth noting that applying different forest definitions for semi-arid and arid zones decreased accuracy for most RSB products. This emphasizes that forest structure (Shugart *et al* 2010), sampling design (Stehman *et al* 2011), and ground measurement techniques (Korhonen *et al* 2006) influence the relationship between RSB products and ground information beyond a definition of forest cover. This finding is more prominent at the local level, where we observed a better RSB product agreement with the Edomex forest inventory than with INFyS (figure 3(B)).

We postulate that different methodologies between the INFyS and the Salas–Aguilar data could be the reason behind discrepancies in our results within the Edomex region. The INFyS data are distributed systematically throughout the country with plot density relating to specific regions (e.g. semi-arid). In contrast, the Salas–Aguilar data come from a systematic sampling across Edomex's vegetation types and likely better represents vegetation succession and degradation across the region (Programa Mexicano del Carbono (PMC) 2015, Salas–Aguilar *et al* 2017). The different results in the Edomex region (figure 3(B)) highlight the need for considering probability density distributions of parameters of interest (e.g. height, diameter, canopy cover) and the spatial dependency of this information for improving the optimization of inventories (Vargas and Le 2023). The differing methodologies for data collection on the ground (e.g. digital photography versus transect approach) and differing spatial distributions likely further contribute to these differences. Finally, we recognize that RSB products have different nominal years (table 1), complicating validation with forest inventories conducted at different times. Still, we did not observe a consistent, systematic error in accuracy regarding the RSB products and their nominal time. Tested RSB products varied greatly in their accuracy with forest inventory data depending on the ecological zone. Thus, forest structure should also be considered when estimating tree cover at the plot level and interpreting RSB products.

We identified forest extent agreement in Mexico based on the number of counts a pixel was identified as a forest by overlapping seven RSB products. Considering information about places of agreement when comparing multiple RSB products could guide the collection of additional ground-based forest observations and provide insights for further validation of RSB products. We highlight that the medium forest agreement class (340 661 km^2) represents an area equivalent to over half of the official national assessment of the total forest area in Mexico (656 920 km^2). This is relevant because this category represents the most extensive degree of disagreement among the seven products, highlighting the challenges confronted by fine-resolution RSB products (Liu *et al* 2021). We propose that areas within this medium forest agreement class (i.e. subtropical mountain system and tropical dry forest) must be the focus of detailed analyses for MRV as they will need more than RSB forest products for decision-making.

A better understanding of the degree of difference between RSB products also benefits the global community because Mexico is prominently covered by tropical forests, with the FAO (2020) FRA identifying the tropics as representing over 90% of global deforestation from 2010–2020 (FAO 2020). Mexico is facing pressure for deforestation and is largely covered by the ecological zone that is experiencing the fastest rate of global deforestation, but Mexico is also one of only a handful of countries within this ecological zone with an established history of forest inventories that allow accuracy assessments and direct comparisons to RSB forest products as was undertaken here.

We found a high agreement among all RSB products and high accuracy with INFyS within the tropical moist forest. On the other hand, nearly half of the tropical dry forest fell into the moderate agreement class, which indicates disagreement between RSB products regarding forest status. In this ecological zone, the choice of RSB products must be considered carefully due to the possibly vastly different estimates among RSB products in this area. Notably, the CEC and Globeland30 products had higher accuracy within this ecological zone (i.e. tropical dry forest) when utilizing the INFyS forest inventory data. We recognize that further research is required for developing products to detect forest changes, describe the associated uncertainty (Rodriguez–Veiga *et al* 2016), and develop approaches to increase the precision of those products (McRoberts *et al* 2016).

We note that our intent was not to predict forest status without error or suggest an approach for reporting official forest extent at the international level. It is possible that the differences we found are due to map errors and other random effects rather than actual differences on the ground. However, by partnering with end-users (CONAFOR), this study

(a) presents a simple and replicable approach to assess various RSB forest products and (b) underscores the significance of a co-creation process in customizing the analysis and forest extent agreement map production to meet end-users requirements. This approach can be applied to other countries or regions worldwide, and it follows the principle that assessing consensus among RSB products can help end-users (such as national forestry agencies) understand and utilize them more effectively (Sexton *et al* 2016).

Ongoing discussions exist regarding the use of various forest definitions, including the appropriateness of simple percent tree cover definitions as utilized in this study (Fagan and DeFries 2009, Romijn *et al* 2013, Sexton *et al* 2016). We argue that using a 30% threshold to estimate forest/non-forest binaries of tree cover is an appropriate approach for Mexico because it does not disproportionately underestimate the official national forest extent. Our result of the high-to-medium forest agreement extent of 629 410 km^2 is only 4% smaller than the official national estimate of 656 920 km^2 (FAO 2022). A more relaxed 10% threshold improved agreement between RSB products and inventory data. However, only three (i.e. tree cover products) out of seven RSB products were influenced by this definition (supplementary materials figure 2). A 10% threshold could arguably overestimate forest area, but plot-level measurements of percent canopy cover should also be standardized and improved across Mexico. We highlight that our harmonization resulted in reformatting information from percent tree cover to a binary category and upscaling to 30 m resolution (i.e. for IO and ESA). Arguably, results might differ for these products in their native format and resolution, and future product-specific studies could be performed, especially across areas of medium forest agreement. Given the disparities in data availability and forest definitions, it is also imperative to incorporate regional and local data in evaluating RSB products and to cater to end-users needs in the co-creation process. Finally, we emphasize that it is essential to recognize the ongoing challenges to achieve consensus for a forest definition, the implications for upscaling and data harmonization, and reporting uncertainty in CMS products (Hurtt *et al* 2022).

5. Conclusion

This study compared seven RSB land and tree cover products with a resolution of 30 meters within Mexico to estimate the range of forest extent agreements. Identifying discrepancies in RSB products, and selecting a forest definition, is critical before selecting a product and deciding how to use it. Our forest extent agreement map represents a simple and replicable method for summarizing and evaluating information highlighting regions with different forest agreement categories based on RSB products that can be applied worldwide.

When compared against Mexico's national forest inventory data, we found a general decline in the accuracy of RSB products from the tropics to the subtropics. Our analysis identified regions where RSB products disagree with Mexico's official forest data, particularly within the subtropical desert and steppe.

We developed a forest extent agreement map comparing forest extent across the seven RSB products and found a substantial range of total forest extent for Mexico. Our findings suggest that end-users of these RSB forest products must carefully consider the impact of using one product over another, as results will vary considerably across heterogeneous landscapes such as Mexico. We identified regions of high forest agreement across RSB products, including the Yucatán Peninsula and mountain areas in the Sierra Madre Oriental and Sierra Madre Occidental. In contrast, tropical dry forest and subtropical mountain system ecological zones have the most prominent challenges for agreement among RSB products.

We propose that more research and ground data within these challenging ecological zones will reduce discrepancies in validating RSB products, improve forest monitoring efforts, and define forest extent across Mexico. Our study highlights the significance of the co-creation process with end-users in evaluating RSB products using regionally collected independent data and reflecting their unique needs.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.3334/ORNLDAAC/2320.

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