COSA Committee On Sustainability Assessment | AIDDATA A Research Lab at William & Mary

# Assessment of Deforestation Detection Solutions to Support EUDR Compliance in Honduras

Report

September 2026

# Contact Information

Committee on Sustainability Assessment, thecosa.org
Audra Wilson-Max
Communications Director
aw@thecosa.org

AidData, aiddata.org
Alex Wooley
Director of Partnerships and Communications
awooley@aiddata.org

## Citation

Committee on Sustainability Assessment and AidData. 2026. *Assessment of Deforestation Detection Solutions to Support EUDR Compliance in Honduras.* Committee on Sustainability Assessment and AidData at William & Mary.

## About the Organizations

**The Committee on Sustainability Assessment (COSA)** is a non-profit that advances smart metrics and technology to improve data collection and decision-making for sustainability. COSA works with more than 100 partner institutions around the globe, and has been engaged with organizations such as GIZ, FAO, Forest Data Partnership, CIAT, Rainforest Alliance through the Digital Innovations in Agricultural Supply Chains Alliance (DIASCA) program, specifically focusing on forest monitoring and EUDR. COSA has also partnered with the EU and GIZ to co-facilitate EUDR Learning Communities in Central America and Africa, and with the Gates Foundation to assess the effectiveness of early-action initiatives for EUDR compliance in Honduras. As part of the Gates Foundation grant, COSA is also supporting the Ethiopia Coffee Association with training and the implementation of socioeconomic and geospatial data collection for EUDR compliance, in collaboration with AidData and Bopinc.

COSA's work with Earth Observation aligns closely with its broader focus on Agile Data Collection—approaches designed to generate rapid, actionable insights for timely decision-making, including in response to detected deforestation events. Agile Data deploys SMART metrics through short, cost-effective surveys administered at flexible frequencies. These can be paired with context-appropriate field technologies such as IVR, mobile apps, or chatbots that use human or artificial intelligence to automate data validation, analysis, and user feedback. When combined with Earth Observation, Agile Data enables more accurate, real-time information flows and supports iterative, shared learning—moving beyond traditional compliance-oriented, ex post monitoring systems. Together, these agile and satellite-based approaches strengthen adaptive management and improve the outcomes of investments and interventions.

**AidData** is a research and innovation laboratory based at William & Mary, a leading research university located in Williamsburg, Virginia. Since its inception 15 years ago, AidData has worked with dozens of international partners to develop innovative datasets and generate insights in previously underexplored areas. AidData is a recognized leader in geospatial impact evaluations (GIEs): Over the last ten years, AidData has led a wide-ranging, global effort to use causal inference tools and subnationally georeferenced data to measure program impacts.

GIE methods are especially useful and cost-effective in under-evaluated sectors and settings where measuring outcomes over space and time is challenging. AidData has deployed GIEs in a variety of analyses of deforestation and broader environmental impacts in Brazil, Cambodia, Mali, Nepal and across the globe. Earth observation approaches form a core backbone of much of this work, creating powerful observations for forest conditions, agricultural productivity, and environmental conditions, among other key outcomes. AidData also uses artificial intelligence and machine learning tools to build next-generation development outcome measures of crop productivity, food security, and local resilience to climate change. Finally, AidData’s free spatial data integration and extraction tool, GeoQuery, lowers the barriers to geospatial analysis by helping users more easily measure local conditions in data-poor environments.

## Acknowledgements

This report was prepared by Goodman, S., Serfilippi, E., BenYishay, A., Hall, J., Mendoza, J., de Los Rios, C., and Calfat, S. The authors would like to begin by thanking the Gates Foundation, under the leadership of Richard Caldwell, for funding this assessment and for its continued support and guidance throughout the work. We are also grateful to the individuals and organizations listed below for their time, openness, and collaboration. In particular, we thank those who participated in interviews and shared practical insights on how their solutions have been implemented for EUDR compliance, those who provided geolocation datasets that enabled comparative analysis, and partners who facilitated access to farmers within their supply chains.

**EUDR Learning Community for Central America**
- Daniel Dubon, Promecafe
- Christian Fedlmeier, GIZ
- Anna Kuehnel, GIZ

**International Coffee Organization**
- Hannelore Beerdlandt, ICO

**IHCAFE**
- Napoleon Matute
- Sonia Buezo

**Instituto de Conservación Forestal**
- José A. Romero

**University of Maryland**
- Matt Hansen

**European Forest Institute / OpenForis Ground**
- Frederic Baron

**Food and Agriculture Organization (FAO) / OpenForis Ground**
- Jonas Spekker

**Early Action Initiatives and Deforestation Detection Providers**

Solidaridad, RGC, and Café Ventura
- Edward Moncada

- Maria Duran
- Lurvin Ventura
- Juan Carlos Salguero
- Alexis Aguirre
- Angela Pelaez
- Andrés Acevedo

Cohonducafe

- Wendy Arely Gonzalez Ordonez
- Hugo Benjamin Avila Hernandez
- Terence Fuschich
- Manuel Eduardo Sosa Sosa
- Sania Alvarenga Santiago

COCAOL, CLAC, and Satelligence

- Felix Asdrubal Sanchez Ruiz
- João Mattos
- Nanne Tolsma

Enveritas

- Carlos Ortiz Pérez

We also extend our sincere thanks to the farmers who opened their farms and shared their time and experiences, helping us ground this work in field realities and strengthen the relevance of our findings.

## Acronyms

| | |
|---|---|
| API | Application Programming Interface |
| CA | Central America |
| COSA | Committee on Sustainability Assessment |
| EAI | Early Action Initiative |
| EC JRC | European Commission Join Research Centre |
| EFI | European Forest Institute |
| EO | Earth Observation |
| ESA | European Space Agency |
| EU | European Union |
| EUDR | European Union Deforestation Regulation |
| GIS | Global Positioning System |
| GIZ | Deutsche Gesellschaft für Internationale Zusammenarbeit (German Society for International Cooperation) |
| GNSS | Global Navigation Satellite System |
| GPS | Global Positioning System |
| IHCAFE | Instituto Hondureño del Café (Honduran Coffee Institute) |
| LiDAR | Light Detection and Ranging |
| NIR | Near-Infrared |
| RGB | Red, Green, Blue |
| RS | Remote Sensing |
| SSP | Small-scale Producer |
| SWIR | Short-Wavelength Infrared |
| TMF | Tropical Moist Forest |
| USDA | United States Department of Agriculture |
| USGS | United States Geological Survey |
| VHR | Very High Resolution |

# Table of Contents

# Executive Summary

The European Union Deforestation Regulation (EUDR) seeks to curb global deforestation by requiring importers of key commodities—including coffee, palm oil, and beef—to demonstrate that products were not produced on land that was recently deforested. Verifying compliance at the plot level poses significant operational challenges, particularly when relying on a combination of farmer-reported information and remotely sensed data, both of which may contain measurement error.

In support of these objectives, COSA partnered with AidData, a recognized leader in geospatial impact evaluations, to assess the accuracy, cost-effectiveness, and inclusiveness of using Earth Observation (EO) data and traceability systems for EUDR compliance among coffee producers in Central America. Using a standardized analytical framework applied across three Early Action Initiatives (EAIs),[1] this study examines how different approaches to farm georeferencing, EO data acquisition and processing, and related methodological choices affect compliance outcomes. Rather than evaluating individual EAIs or compliance solutions in isolation, the analysis draws conclusions by identifying common patterns and contrasts across initiatives.

The study integrates benchmark-quality geospatial plot boundaries, multiple deforestation detection approaches, very high-resolution satellite imagery, drone-based validation, and a nationally representative socioeconomic survey of Honduran coffee farmers. Together, these data provide a comprehensive empirical assessment of the practical opportunities, limitations, and trade-offs involved in implementing the EUDR deforestation-free requirements at the plot level.

Results indicate that plot boundary precision—often assumed to be a major constraint for EUDR compliance—has a relatively limited influence on deforestation detection outcomes compared to other sources of variation. This finding suggests that lower-cost, lower-precision tools can be fit for purpose for boundary delineation, with important implications for reducing compliance costs and barriers to participation. In contrast, deforestation detection methodologies themselves are the primary source of disagreement across providers. No single plot was consistently classified as deforested by all providers, and agreement on positive detections was generally low. Coarser-resolution imagery tends to

[1] Early Action Initiatives (EAIs) are pilot, early-stage efforts by public, private, or multi-stakeholder actors to test and operationalize EUDR compliance approaches ahead of full enforcement. They explore different combinations of georeferencing, Earth Observation data, deforestation risk assessment, and traceability methods to assess cost, accuracy, scalability, and inclusion—particularly for smallholders.

increase sensitivity but also raises the risk of false positives, while finer-resolution imagery reduces error but may fail to detect marginal or ambiguous cases.

Interpretation is further complicated by the distinction between tree loss and EUDR-defined deforestation, particularly in shade-grown coffee systems where canopy dynamics may reflect routine farm management rather than land-use change. Limited temporal availability of high-resolution imagery—especially around the EUDR cutoff date—also constrains certainty in plot-level compliance determinations.

Socioeconomic findings underscore the importance of designing compliance systems that are not only technically robust but also inclusive. While overall deforestation rates in the sample were low, farmers demonstrated limited awareness of the EUDR, and alignment between farmer-reported tree removal, provider classifications, and expert image interpretation was often weak. Systematic differences between EAI and non-EAI farmers, as well as discrepancies in self-reported land size, highlight potential biases that decision makers must consider to ensure that compliance responsibilities and risks are distributed equitably across producers.

Overall, the study confirms that while modern deforestation-detection tools are powerful, they are not infallible. Effective EUDR implementation will require calibrated tolerance for uncertainty, multi-layered validation approaches (including targeted use of high-resolution imagery and field verification), sustained capacity building, and clear communication with producers—particularly smallholders, who are least equipped to navigate complex data requirements.

The findings from Central America provide a foundation for scaling EUDR compliance frameworks to more complex geographies and commodities. Parallel work in Ethiopia and the potential application to other sectors further underscore the broader relevance of these insights. As the EUDR matures, continued learning, cross-provider calibration, transparent documentation, and adaptive system design will be essential to achieving regulatory objectives while avoiding unintended adverse impacts on smallholders and environmentally sustainable production systems.

# 1. Introduction

The European Union has embraced a regulation (EU Deforestation Regulation - EUDR) to restrain the negative impact of the EU market on global deforestation and the degradation of forests worldwide. Before introducing certain products to the EU market or exporting them, operators that first place the product in the EU markets will be required to submit a due diligence statement that will be reviewed by the competent authority in the port of entry. The purpose of this requirement is to guarantee that goods entering the EU market have not been obtained from lands or territories where forest degradation or deforestation has occurred since 31 December 2020[2] and that their production complies with local legislation of producing countries. These goods currently include: beef, cocoa, coffee, palm oil, rubber, soy and wood.

Documenting that each unit of the covered goods has been grown on land that has not been deforested is a complex undertaking. Traceability of each unit to the plot of land where the commodities were produced is necessary to demonstrate that there is no deforestation on a specific location. Geographic information linking products to the plot of land is already used by part of the industry and a number of certification organizations. However, traceability to the farm is far from ubiquitous, and furthermore, obtaining credible confirmation that the plot of land was not recently deforested is challenging at such scales.

Ground-based information (e.g., photographs in the field with linked geotags and time stamps) or remotely sensed data (e.g., satellite and airborne imagery) may be used to verify if the geolocation of declared commodities and products is linked to deforestation. However, each of these approaches are likely to incur residual uncertainty or measurement error, whether from the ground-based observations, satellite-based sensors, or other parts of the process. More costly and/or complex versions of these approaches (e.g. higher sampling frequency or higher resolution satellite imagery) may yield higher accuracy but also incur much higher costs and potentially exclude some smaller producers from export markets. Thus, assessing which approaches can cost-effectively provide reliable confirmation that commodities are “deforestation-free” is essential.

The EUDR does not prescribe a specific protocol for demonstrating compliance through the due diligence statement. In response, a series of high-profile pilot efforts—known as Early Action Initiatives (EAIs are essentially independent consortiums of organizations, including

[2] The EUDR was supposed to be applied to products landing in the EU on or after January 1, 2025, with an associated window for monitoring beginning on December 31, 2020. The legislation has since been postponed for one year due to implementation delays.

certifiers, governmental entities, traders, producers, and service providers, etc.) in Central America (EAIs) have been testing different approaches. Through a Gates Foundation grant, COSA and AidData partnered to support the Central American EUDR EAI Learning Community in assessing the effectiveness of leading EUDR compliance solutions currently being deployed or made available to supply-chain actors and that are in use by the EAIs. As part of this effort, the partnership developed a standardized benchmark to evaluate the accuracy, effectiveness, and inclusion implications of using Earth Observation (EO) data for EUDR compliance. The study focused on EAIs led by coffee producers, traders, and government entities, as well as a range of deforestation-assessment providers intended to reflect the diversity of emerging EUDR solutions.

This report presents the findings of that study, carried out within the Central American EUDR EAI Learning Community. Honduras emerged as one of the most well-represented countries, with numerous partnerships between EAIs and deforestation-detection providers that illustrate the broader landscape of EO tools and approaches available for EUDR compliance. As a result, the study focused primarily on activities in Honduras, while ensuring that the resulting insights are applicable to other geographies and commodities worldwide.

The analysis drew on multiple EAIs and deforestation-assessment providers but did not aim to directly compare them individually. Instead, it identified cross-cutting patterns and trends by pooling commonalities across initiatives. Using a standardized assessment framework, the study examined how different approaches to geo-referencing farm sites, acquiring and processing EO data, conducting ground-truthing, and carrying out other components of EUDR compliance affect cost, accuracy, and inclusion.

The resulting guidance is intended to equip organizations with the information needed to make operational decisions that support effective, inclusive, and compliant EUDR implementation.

The combined objectives of this research were to:

1. **Develop a standardized benchmark model** using high-quality data for collecting farm-location information and assessing deforestation.
2. **Identify cost-efficient approaches**, relative to the benchmark, that meet EUDR requirements while safeguarding the inclusion of smallholders and cooperatives.
3. **Examine unintended consequences** associated with different approaches to EUDR compliance, improving overall understanding of the compliance landscape.

4. **Identify shared challenges and potential synergies** across EUDR compliance efforts that could be supported by EU-funded and other programs in Honduras and Ethiopia.

The following sections describe the methodology used in this study, covering sample selection, ground data collection, deforestation-detection approaches, satellite and drone imagery validation, and the analytical framework used to assess deforestation accuracy. The results section presents the findings from the deforestation-detection analysis and explores how socioeconomic conditions identified in farmer surveys relate to plot characteristics, deforestation outcomes, and other EUDR-relevant aspects of agricultural land use. Finally, the discussion section examines key challenges and opportunities identified throughout the study, their implications for ongoing EUDR compliance efforts, and potential directions for community engagement and future research.

# 2. Methodology

## 2.1 Overview

The variety of approaches for EUDR compliance emerging through the EAIs in Central America are important sources of innovation to meet the challenge of efficiently ensuring that imported commodities are "deforestation-free." However, all approaches are likely to yield some residual uncertainty or measurement error, whether from satellite-based sensors, data processing, farm boundaries collection, statistical models, or other factors. One of the overarching challenges is therefore to assess the accuracy and effectiveness of these approaches, using a standardized benchmark, and to understand the potential real-world implications of errors.

Although benchmark quality data collection, analysis, and validation may not be feasible at scale, it can provide a practical comparison point for more realistic approaches by highlighting the accuracy levels that are feasible when using the highest quality data. Alternative methods—reflecting those implemented by an EAI for full data collection or derived from the benchmark data to simulate real world error—can then be compared to the benchmark to assess their relative accuracy and effectiveness. Benchmark quality data is intended to reflect the highest quality options available[3] for each of the key dimensions

[3] The selected tools, data, or methods for the benchmark may be surpassed by alternatives but are beyond what any practical solution would leverage. For instance, in practice most plot data will be collected with cell phone GPS or basic consumer GPS devices that cost less than a few hundred dollars and may be accurate up to a few meters. The benchmark quality data will use a dedicated sub-meter accuracy GNSS receiver that costs approximately $3000 USD. High end surveying equipment can achieve millimeter accuracy and can cost tens of thousands of dollars.

necessary for EUDR compliance: primarily plot boundary collection and deforestation assessment.

The benchmark data utilized in the study will include components associated with farm plot boundary collection and satellite imagery-based deforestation detection. To obtain farm plot boundaries for the benchmark, we utilize farm visits by trained enumerators with dedicated high end GPS devices walking the perimeter of each farm plot alongside the farmer, resulting in precise polygons defining the farmed areas. Similarly, satellite imagery analysis of deforestation will be based on expert human evaluation of sub-meter resolution commercial imagery, including satellite image tasking when needed, and optical and LiDAR drone site visits for extremely granular validation of site conditions.

To establish the benchmark and evaluate a range of comparison approaches, we select coffee farmers in Honduras from a small subset of EAIs out of all EAIs currently underway,[4] as well as a nationwide group of farmers not in an EAI.[5] The overall selection of farmers is intended to reflect a diverse mix of both geographies within Honduras and the EAIs selected. In addition to the approaches and deforestation detection providers utilized by the selected EAIs, we also incorporate three additional approaches for deforestation detection (total of six) available for EUDR compliance.

For each selected EAI, as well as the non-EAI group of farmers, we:

1. Randomly sample a set of farm plots from those included in the EAI (or non-EAI group) that will be used for the assessment.
2. Obtain benchmark quality data for the sample through site visits to conduct farmer socioeconomic surveys and collect plot boundaries.
3. Simulate a range of lower quality data collection approaches using the benchmark boundary data (e.g., simplifying boundary polygons, point vs polygon).
4. Run all boundary permutations through the six deforestation detection providers workflows.
5. Use submeter satellite imagery to visually review all plots which had disagreements among the deforestation provider assessments, as well as a subset of sites with full agreement.
6. Visit a final subset of sites with optical and LiDaR drones for granular validation.

[4] At the time the study began, 18 EAIs were at varying stages of implementation in the Central American learning community and were considered for inclusion in the study.

[5] Non EAI farmers were randomly selected from the IHCAFE national coffee registry. This registry contains information on 97277 coffee farmers relative to the 2022/2023 coffee production year.

The differences between the approaches used by the deforestation detection providers, as well as mechanisms introduced into the study, include multiple dimensions of potential measurement error, including plot boundary precision, satellite imagery availability and quality (i.e., spatial and temporal resolution), as well as the accuracy of the deforestation detection approach. These sources of potential error are evaluated within the context of the EAI or non-EAI group, geographic distribution, as well as a range of related categories derived from the farmer survey. Exploring the effectiveness of methods based on plot size or gender, for example, is critical to ensuring that data and compliance requirements/practices being associated with and developed for with EUDR do not lead to marginalization or even exclusion of smallholder farmers or other vulnerable populations from export market participation.

The ultimate aim of the methodology is to enable identification of the most effective approaches for accurately assessing deforestation relative to the benchmark that are also as inclusive (i.e., accessible both practically and financially) as possible. By evaluating how precision in each dimension of data impacts the accuracy of the deforestation assessment, the necessary time and financial resources required to collect plot boundaries or purchase satellite imagery can be minimized. The remainder of this section will focus on detailing each of the elements involved in the associated methodology.

## 2.2 Sample Selection

### 2.2.1 Overall Sample

The selection of sites for analysis is based on two tracks of work. The first leverages coffee farm plots identified through participation in early action initiatives (EAIs). The second is based on a sample of non-EAI plots within the broader area of the EAIs. A total sample of approximately 1500 farmers is initially selected covering 12 out of the 15 coffee growing departments in Honduras. The sample is proportionally divided into 750 EAIs households, along with 750 non-EAI households randomly selected from IHCAFE 2022/2023 coffee registry. The rationale of having two groups of farmers (EAI versus non-EAI) is based on the need to understand the representativeness of the EAI farmer's sample at a national level.

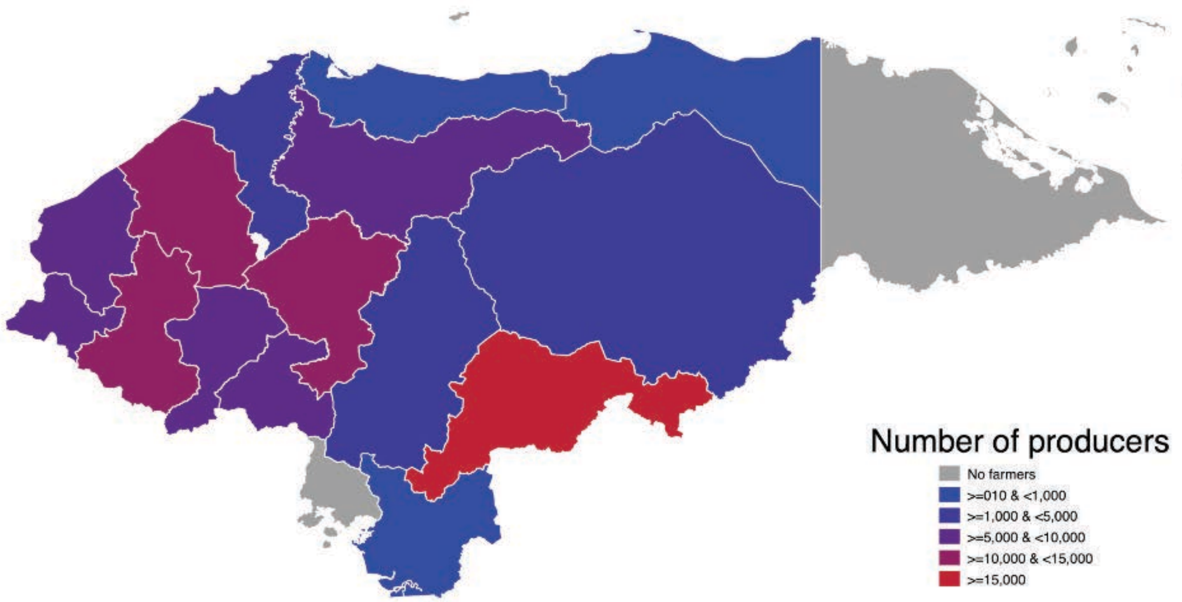
### 2.2.2 Early Action Initiative (EAI) Selection

The EAIs community of practice accounts for 28 EAIs, mostly placed in Honduras. In agreement with the community of practice, COSA and AidData initially shortlisted 9 EAIs based on the location (Honduras) and basic information available on deforestation tools, and polygons detection methods. A final subsample of the EAIs is then selected to reflect a diverse geographic range and associated EUDR compliance tools in use. A sub-sample of farmers are then selected from each EAI's farmers list using a stratified random sampling to estimate a proportion, accounting for gender and land size (i.e. strata). Each selected EAI shared farmer's information and farmer's plot level data associated with its initiative.

#### 2.2.3 Non EAI Selection

Around 750 additional producers are selected as an additional group from a nationally representative sample across the country. The list of farmers was based on the IHCAFE national coffee registry, which contains information on 97,277 coffee farmers relative to the 2022/2023 coffee production year. Each of these 97,277 farmers belong to one of the 15 coffee producing departments in Honduras. The registry accounts for 226 municipalities associated with the 15 departments and 15,836 villages (69 villages per municipality on average). Figure 2.1 shows the number of producers per department in the registry.

**Figure 2.1. IHCAFE 2022/2023: Coffee producers by department in IHCAFE registry**




The IHCAFE coffee registry is used to draw a nationally representative sample of farmers proportional to the number of farmers living in each of a set of selected villages. While IHCAFE can provide detailed statistics on the distribution and characteristics of farmers in the list, they cannot share individual farmer information. To implement an effective stratified sample using this data, several steps are taken prior to generating a new listing of individual farmers based on village visits.

The first step of this sampling strategy is to consider 12 out of the 15 departments in Honduras. The departments excluded from the sample are Atlantida, Choluteca and Colon. According to the IHCAFE coffee registry for 2022/2023, the excluded departments account for only 0.39% of coffee, and they were not covered by any of the selected EAIs. The second step is to proportionally select 50 municipalities in each of the selected departments. The selection of the municipalities per department is proportional to the number of producers in each department. The third step is to stratify the villages of the 50 selected municipalities into high, medium and low populated villages and select four each of the high, medium, and low populated villages.

The fourth step is to sample 12 farmers in each high populated village, 8 in each medium and 3 in each low populated village. Once the villages are selected, a listing of farmers in each of the selected villages must be created since IHCAFE cannot share individual coffee farmer level data from which a sample could be drawn. The listing is created through local village visits and is then used to draw a random sample according to the above sampling strategy.

## 2.3 Ground Data Collection

Based on the farmer sample derived from the EAI and non-EAI listings, a small team of 11 in-country personnel, including a field manager, are deployed to visit each farm and conduct a survey and record plot boundaries. The field team is equipped with dedicated GPS devices and tablets with survey software and GPS collection software (Figure 2.2).

**Figure 2.2. Farmer survey using tablet (L), and location data collection using EOS Arrow with tablet (R)**

*Photos by COSA, used with permission*

The GPS devices utilized are [EOS Arrow 100+](EOS Arrow 100+) submeter GNSS receivers. The Arrow receivers are capable of submeter precision when recording locations, and drastically exceed typical smartphone based or basic consumer level GPS device performance. While more advanced and even more precise systems exist for commercial surveying, the Arrow device is sufficiently more precise than devices likely to be used for boundary collection to be suitable for use as a benchmark. Location and survey data collection is managed using Samsung A9+ tablets with SurveyCTO software installed.

### 2.3.1 Training

The field team is provided with a detailed training on the use of the GPS equipment and data collection protocols. Training materials are shared with the field team for initial review and testing in advance of an in-person training and pilot. A preliminary training is used to identify any critical gaps or issues and conduct data collection tests prior to the final in-person training at the start of the field work session. The in-person training is conducted over five days and includes two days of "classroom" review of the survey, hardware, and technical collection protocols, as well as two days of field pilots at local coffee farms. The final day of the training is used to review, answer questions, and make final refinements to the survey and protocols.

### 2.3.2 Farmer Surveys / *Socioeconomic Survey*

The initial component of field data collection involved gathering information from the farmer who owns or manages each plot (household head). This information consists of farmer-reported metrics as well as a range of general control variables. Farmers are surveyed at their plot or home. Farmers were asked to report information about the random plot for which plot boundaries have been taken and about the overall plots.

Types of information collected from farmers during the survey includes:

- Basic socio-demographic characteristics such as sex, age, number of household members, level of education, productive and durable assets owned, and experience in coffee farming.
- Farm characteristics such as total and coffee land size, land ownership.
- Description of selected plot land use such as type of cultivated coffee, coverage of trees/vegetation vs coffee plants, steepness of the plot; and coffee plot characteristics such as estimated number of coffee trees in plot, distance between trees, coffee trees density, age of coffee trees, type of pruning.
- Production of coffee in the selected plot and total coffee production.
- Exposure to shocks and stressors in the last 5 years, and capacity to cope with shocks.
- Deforestation and land use change measures such as trees added, removed, or lost over the past 5 years; and land and coffee land added and/or removed from cultivation in the last 5 years.

### 2.3.3 Plot Boundaries

A single plot owned or managed by the farmer is randomly selected during the survey component of the field work. The enumerator and farmer then travel to the identified plot to conduct the remainder of the data collection.

Primary data collection at farm plots involves a combination of boundary traces, observations made by the field team, and photographs. Boundary traces are performed using the high accuracy EOS Arrow 100 GNSS receiver paired to a survey tablet and GIS software/app. Photographs are collected using the survey tablet, as are additional observations and the associated point location of specific observations (e.g., signs of deforestation). All data collected at a plot is paired with a farmer record tied to the previously conducted survey.

The boundary traces are collected during a plot walk in which a member of the field team is accompanied by the plot owner/manager. The plot is explored prior to beginning the recording to avoid errors during the final boundary trace. Additional data collection on the plot includes a general picture of the plot and observations made on the plot. Significant observations enumerators may make include signs of deforestation, non-agricultural sections of forest, cleared land, coffee plants, and shade trees.

### 2.3.4 Drone data collection

Separate from the primary field data collection team, a specialized partner subsequently visits a subset of sites to collect drone data to facilitate validation. The drones collect a combination of optical and LiDAR data. Drone based optical imagery provides high precision and very high resolution (10cm) imagery directly associated with sampled plots. Drone LiDAR imagery provides precise canopy height and coverage insight of plots. The combination of optical and LiDAR imagery enables improved deforestation validation of ground-based data collection and other deforestation assessment approaches being evaluated. The subset of sites considered for drone data collection are based on a combination of disagreement on deforestation status across the deforestation detection methods being evaluated, as well as geographic and EAI coverage.

## 2.4 Deforestation Detection

A range of deforestation detection methods are available in support of EUDR compliance. Deforestation detection primarily relies on one or more sources of satellite imagery and an algorithm capable of identifying signs of deforestation within an image (or between images at multiple points in time). Common sources of satellite imagery at the European Space Agency's Sentinel series as well as the USGS Landsat series. Both Sentinel and Landsat imagery are free and publicly available and provide moderate resolution (10m and 30m respectively). Imagery available from Landsat and Sentinel are used in widely established deforestation monitoring approaches such as Global Forest Watch have been a cornerstone of deforestation efforts for many years.

Alternatively, commercial satellite imagery products are available at much finer resolutions (3m down to submeter). Landsat and Sentinel can have much broader spectral ranges, enabling the potential for more refined monitoring of changes in vegetation or other characteristics, while commercial imagery may only include visible (red, green, blue) and near infrared (NIR) bands. Historical coverage and revisit frequency also varies significantly across imagery. Some commercial imagery can also be accessed for free through programs such as NICFI. A brief overview of some of the more commonly used satellite imagery for deforestation detection is included in Table 2.1.

**Table 2.1. Overview of commonly used satellite imagery for deforestation detection**

| Source | Name | Resolution | Bands | Revisit | Available since 2020? |
|---|---|---|---|---|---|
| USGS | Landsat 8 | 30m | RGB + NIR + SWIR + Thermal + Cirrus | 16 days global coverage | Yes, globally |
| ESA | Sentinel 2 | 10-60m (band dependent) | RGB + NIR + SWIR + coastal | ~5 days global coverage | Yes, globally |
| Planet | Planetscope | 3-4m | RBG+NIR before Aug 2021, and additional multispectral bands since | Near daily global coverage | Yes, globally |
| Planet | SkySat | submeter | RBG+NIR | No guaranteed revisit | Location dependent |
| ESA/Vantor [6] | Worldview 3 | submeter | RGB+NIR at finest resolution, additional multispectral bands at coarser resolution | No guaranteed revisit | Location dependent |

Similar to imagery options, there are a wide range of techniques for detecting deforestation. Finer resolution imagery can be paired with computer vision techniques to detect individual tree loss and other changes to landscapes. Spectral bands and composite indices can be used to detect vegetation and spectral patterns associated with trees, as well as train machine learning algorithms such as random forests. Beyond the broader class of algorithms used, the specific data processing, models, parameters, training data and related decisions can have considerable impacts on the effectiveness of a particular deforestation detection implementation.

While approaches and providers may share many similarities, the underlying methodology leaves ample room for disparity in the final deforestation assessments that are produced. Often, the particular disparities between approaches revolve around edge cases or situations less prominent in the training data used to produce the model. For instance, training data for locations where there is not deforestation are abundant and relatively easier to computationally identify (i.e., consistent tree cover) whereas deforestation can take many forms and may require nuanced interpretation.

A critical element to assess these differences between deforestation detection providers is the confusion matrix. A confusion matrix defines the number of instances of true positives

[6] Maxar was rebranded as Vantor in 2025.

(accurately detecting deforestation), false positives (detecting deforestation where there was none), true negatives (accurately detecting no deforestation), and false negatives (detecting no deforestation where there actually was deforestation). Although an objective and infallible ground truth of deforestation does not exist, to facilitate comparison the providers are assessed based on agreement/disagreement among themselves, as well as using high resolution imagery and drone data to provide a reliable and explainable "ground truth" of deforestation status to use for validation and to generate confusion matrixes.

### 2.4.1 Boundary Error Simulation

The benchmark plot boundary is collected using advanced handheld GPS devices (EOS Arrow 100+) at a high level of precision while carefully navigating the extent of the plot. In addition, imagery assisted review and manual correction are conducted during post-processing to improve plot boundaries and reduce errors or erroneous points when possible or needed. The resulting output is effectively the ideal representation of the plot boundary. To simulate less precise methods of plot boundary/location data collection, additional permutations of the boundary are created by artificially introducing error into the benchmark plot data. A range of error simulations are used to reflect different types of potential data collection formats and sources of error. The error simulations focus on two main approaches: 1) introducing error into the boundary trace, or 2) deriving a single point representation of the plot (such as is specified by EUDR for plots under 4ha).

Simulating errors to the boundary trace is intended to reflect a combination of walking incorrect boundary paths when collecting data as well as using less precise GPS devices. Less precise GPS devices are simulated by randomly jittering vertices of the benchmark polygon. Human error in pathing is simulated by making semi-random adjustments to the benchmark polygon such as buffering / contracting or simplifying the vertices of the polygon to reflect "cutting corners" when walking the plot.

The use of simple point / coordinate information rather than boundary trace polygons is explored by generating points within the benchmark boundary trace polygon. Generated points may reflect the centroid or randomly locations within the polygon. Buffers based on the generated points are also evaluated in order to assess the possibility of using buffers for deforestation detection under some EUDR compliance approaches.

Figure 2.3 illustrates the variety of permutations generated. The permutations include 1) three levels of traditional geometric simplification using the Douglas-Peucker algorithm; 2) three levels of coordinate quantization; 3) three levels of coordinate jittering; 4) 10 meter positive and negative buffers of the original boundary, as well as convex hull of the boundary; 5) points reflecting the centroid, jittered centroid, representative point (i.e., a "centroid" guaranteed to be within the geometric boundaries), and three randomized points within the boundary; 6) a buffer of the point permutations to match the area of the original boundary; 7) a buffer of the point permutations to result in a 4 ha area.

**Figure 2.3. Example of plot boundary permutations (uuid 058b5716-3a36-49a4-94a7-17ac7d56439a)**

**(A) Simplification** **(B) Quantization** **(C) Jitter**

**(D) Buffers and convex hull example (centroid)** **(E) Points and area buffers** **(F) 4ha buffer**

### 2.4.2 Provider Assessments

Since the announcement of EUDR, several companies and organizations have developed tools for automating the detection of deforestation on farmland, with the intent to provide their services to those requiring EUDR compliance certification. Since in-person surveys can be expensive, and the EUDR definition of deforestation involves a five-year time period, computer-aided analysis of historical satellite imagery promises to speed up the process of proving compliance, as well as making it cheaper.

To support engagement with the study and avoid impacting ongoing development efforts of individual deforestation detection providers, the study does not identify/label the providers who participate. Relevant aggregate level characteristics of the providers, such as the general class of algorithm used or imagery source, may be included in the analysis (e.g., if imagery resolution consistently impacts accuracy).

The study includes deforestation assessment from six deforestation detection providers, including two public products, listed in Table 2.2. Each provider assesses the full sample of plot boundaries and boundary permutations[7] and provides results indicating whether there was deforestation detected at each plot. The distinctions between deforestation detection approaches aim to emphasize underlying data sources and classes of methods rather than providers or proprietary modifications of established methods.

**Table 2.2. Deforestation assessment providers included in study**

| **Deforestation tool*** | **Associated EAI** |
|---|---|
| Solidaridad | Solidaridad + RGC + Café Ventura |
| Trade in Space | Cohonducafe |
| Satelligence | Clac/Cocoal |
| Enveritas | - |
| Whisp | - |
| UMD GLAD | - |

Based on the specific provider methodology, the features are either given directly to the provider to be run assessed, submitted through a provider dashboard for automated assessment, assessed utilizing an API, or evaluated locally based on deforestation data layers shared by the provider. The specific outputs of the deforestation assessments from providers come in various forms based on their unique approaches. While some providers

[7] Two of the six providers were only able to run deforestation assessments on the core/true boundaries and did not test the additional permutations.

generate binary “deforested” / “not deforested” metrics, others provide risk assessments (e.g., high, medium, low), or otherwise multi-faceted assessments.

All provider assessment results which are not binary are cross walked to create the most realistic/probable binary result to enable compatible comparisons across the providers. In cases where interpretation of risk categories or other factors could produce variable outcomes, both were tested and the one that ultimately produced fewer false positives/negatives was included in the findings.

### 2.4.3 High-resolution Satellite Imagery Analysis

Given the inherent likelihood for disagreement on deforestation status across providers, an independent measure of deforestation is critical for evaluation. While the field work at each farm included both enumerator observations as well as farmer reported information related to deforestation, the enumerators 1) are not experts in identifying deforestation, and 2) only have visibility on the current state of the plot. In addition, farmer reported information is subject to the farmer’s ability, awareness, and willingness to recall/disclose information related to deforestation over the past five years.

Satellite imagery can be an effective tool for assessing historical conditions using both algorithmic approaches (i.e., how the deforestation detection providers generate assessments) as well as through manual/human visual assessment. While algorithms can leverage relatively coarse resolution imagery to identify spectral trends and patterns indicative of deforestation, human interpretation is generally more limited to very fine/high resolution images where specific features (e.g., trees) can be identified. As a result, satellite imagery such as Landsat (30m), Sentinel (10m), and even Planetscope (4m) provide limited value for visual human analysis (Figure 2.4).

**Figure 2.4. Comparison of 30m Landsat imagery (top left), 10m Sentinel 2 imagery (top right), 4m Planetscope imagery (bottom left, Vantor 2025), and 30cm WorldView 3 imagery (bottom right, Vantor 2025).**

Commercial satellite imagery products available in submeter resolution (as fine as 15cm with post processing) enable much easier and more reliable visual interpretation (Figure 2.4). Historical coverage of submeter resolution imagery can vary drastically based on location and specific satellite platforms but are increasingly available as the number of satellites and imagery catalogs grow. Contemporary coverage can be similarly limited but can be acquired by custom tasking of satellites to collect new images. Submeter resolution imagery can present computational challenges due to the scale of the data relative to coarser resolution products but is increasingly possible by leveraging cloud computing resources. More practically, submeter imagery and custom satellite tasking can require significant financial resources to purchase. Although use of submeter imagery at scale for operational purposes tied to EUDR may not be feasible for most organizations, it can serve as an effective "ground truth" or benchmark for the study.

When available, submeter imagery is used to review all plots for which there is any disagreement among the deforestation detection providers regarding the deforestation status over the past five years. Imagery is also reviewed for plots where the farmer survey indicates the possibility of deforestation or tree removal. In addition, a random selection of sites where there is full agreement are also reviewed using submeter imagery to identify potential false positives/negatives impacting all approaches.

Visual inspection of plots, utilizing imagery as close to January 1, 2021, and December 31, 2025, as possible, will be used to classify the status of each plot. Possible status classification, described further in Table 2.3, are: “uncertain”, “no change”, “unlikely deforestation”, “minor tree loss”, “major tree loss”, “potential deforestation”, and “likely deforestation.”

**Table 2.3. Classification categories and descriptions used for visual imagery inspection**

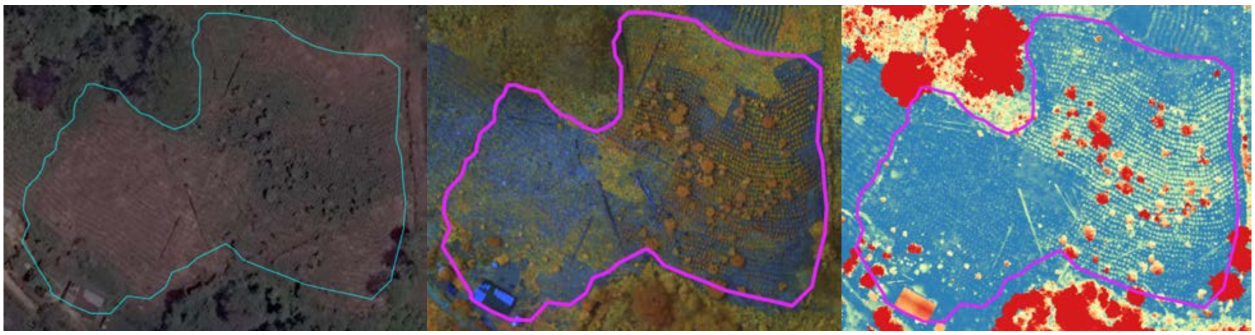
| Classification | Description |
|---|---|
| Uncertain | Imagery sufficiently close to the start date was not available, or available imagery was not of sufficient quality (e.g., due to cloud coverage) to determine the change status of the plot. |
| No change | There were no observable changes within the plot. |
| Unlikely deforestation | There may have been some changes within the plot or ambiguity in imagery, but it is unlikely to be associated with deforestation. |
| Minor tree loss | There was an observable loss of a small number of trees (typically less than 3 to 5 overall, often spread out) but are not signs of deforestation. This may reflect natural tree loss, necessary pruning/removal of trees for plot health, or scenarios where a small number of trees are otherwise removed from plots already being used for agriculture. |
| Major tree loss | There was an observable loss of a moderate number of trees (typically at least 3 to 5 overall and often spread out but occasionally in patches) but are not signs of deforestation. This may reflect natural tree loss (e.g., pest or fire, necessary pruning/removal of trees for plot health, or scenarios where a moderate number of trees are otherwise removed from plots already being used for agriculture. |
| Potential deforestation | There was sufficient removal of trees in areas that may not have been previously used for agriculture to consider deforestation may have occurred. This classification is used when it is possible the plot was used for agriculture, but it is difficult to confirm through imagery (e.g., dense canopy coverage). |
| Likely deforestation | There was a clear removal of trees followed by agricultural development on plots that were unlikely to have had previous agricultural usage. This classification is used when the temporal coverage of imagery, and visibility of the plot (i.e., through canopy) to determine that no signs of prior agriculture can be observed. |

### 2.4.4 Drone Imagery Validation

Separate from the primary field data collection team, we subsequently revisited a subset of sites to collect drone data using a combination of optical and LiDAR sensors to facilitate validation. Drone based optical imagery provides high precision and very high-resolution imagery (10cm resolution) directly associated with sampled plots. Drone LiDAR imagery provides precise canopy height and coverage insight of plots. The combination of optical and LiDAR imagery facilitates improved deforestation validation of both the ground-based data collection and the deforestation detection approaches (example of imagery shown in Figure 2.5).

Due to the extensive time and costs involved with collecting drone data, it is only possible to visit a relatively small number of sites with the drones. A sample of sites are selected that reflect a combination of 1) geographical coverage, 2) EAI (and non EAI) association, and 3) type/level of disagreement among the providers on the deforestation status of the plot. An initial sample of approximately 50 plots are prepared, with the aim of visiting at least 30 plots.

**Figure 2.5. Comparison of 30cm commercial satellite imagery from Vantor (L), 10cm optical imagery (M), and LiDAR drone imagery (R)**



## 2.5 Socioeconomic Data Analysis

The study incorporates a socioeconomic data collection component to complement the geospatial and deforestation detection analyses. This component is designed to document the characteristics of coffee producing households, their production systems and their recent experiences with land use and agricultural management. The socioeconomic information serves two purposes. First, it provides a descriptive foundation for understanding the conditions under which farmers operate. Second, it enables an examination of how these conditions relate to variation in plot characteristics, land use decisions and the accuracy of deforestation assessments.

The survey instrument was administered during the field visits and was closely integrated with the collection of benchmark plot boundaries. Enumerators conducted interviews with farmers to gather information on demographic characteristics, household composition, education and experience in coffee cultivation. The survey also collected detailed information on land size, number of plots, coffee area, shade management, planting density and the age structure of the coffee trees. These variables support a systematic characterization of production systems across the sample, including differences between EAI and non EAI farmers and across departments.

Additional modules captured information on production and management practices, including yields, pruning methods, fertilizer use and the prevalence of newly planted, replanted or replaced trees. These indicators allow the study to distinguish routine management from changes that may resemble land use conversion. The survey also documented the shocks experienced by households since 2021, their severity and the strategies used to recover. These measures help contextualize the stability of production systems and the potential pressures that may influence land expansion or contraction.

All socioeconomic information was linked to the high precision plot boundaries collected in the field. This integration enables subsequent statistical analysis that examines how socioeconomic characteristics correlate with plot conditions and with patterns of agreement or disagreement among deforestation detection approaches. The objective of incorporating the socioeconomic component is therefore to provide a comprehensive account of the context in which compliance with the EUDR is expected to occur. Understanding these conditions is essential for assessing whether different monitoring approaches are likely to be inclusive and whether certain types of farmers may face greater challenges in demonstrating compliance.

# 3. Results

## 3.1 Boundary Data

Based on the nine EAIs within the Central American learning community that were active in Honduras, three were selected based on progress at the time the study began, data availability, and diversity of geographic coverage and compliance approaches. In addition to the selected EAIs, the IHCAFE coffee registry was used to supplement the sample with more nationally representative coverage. An initial selection of 750 farmers was made from the EAIs, and 750 from IHCAFE, with additional replacement samples selected when possible.

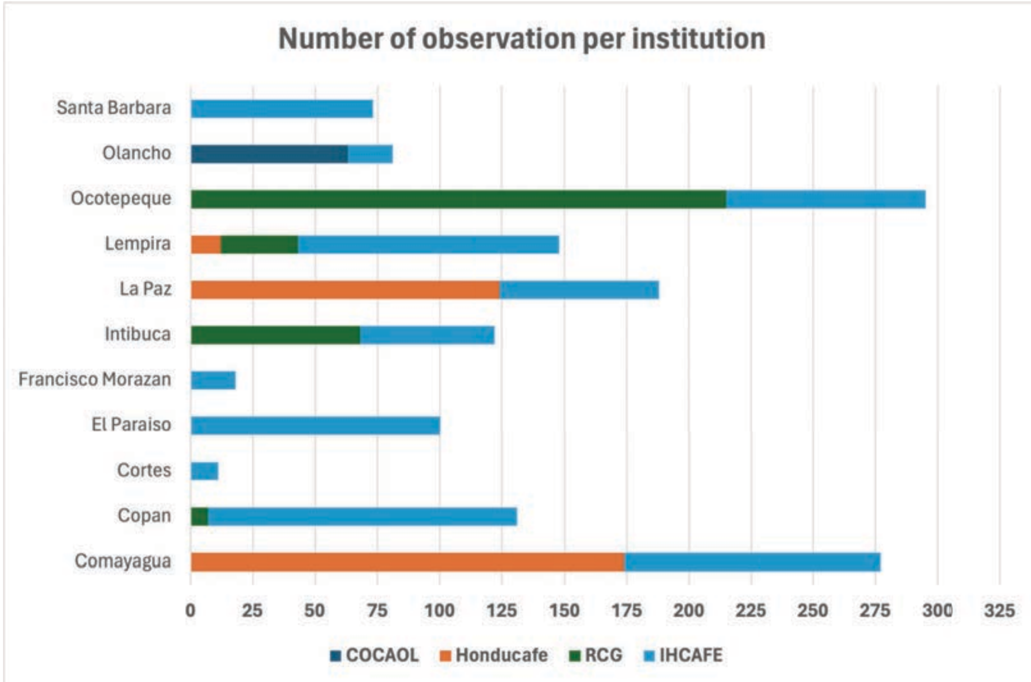
Field work—including listing creation, farmer surveys, and plot boundary collection—was conducted between September 2024 and January 2025 considering the harvesting season going from December 2023 to March 2024. Enumerators were ultimately able to visit 750 farmers from the non-EAI listing, and 694 from the EAIs. Table 3.1 presents the final list of EAIs selected for the study and the breakdown of the final sample sizes.

**Table 3.1. EAIs selected for the study**

| EAI/Group | EAI Size | Farmer's Department | Sample Size |
|---|---|---|---|
| **Solidaridad + RGC + Café Ventura** | 1600 | Intibucá, Ocotepeque, Lempira, Copán | 321 |
| **Cohonducafe** | 1500 | Comayagua, La Paz, Lempira | 310 |
| **Clac/Cocoal** | 72 | Olancho | 63 |
| **IHCAFE** | 97,277 | 12/15 coffee departments | 750 |

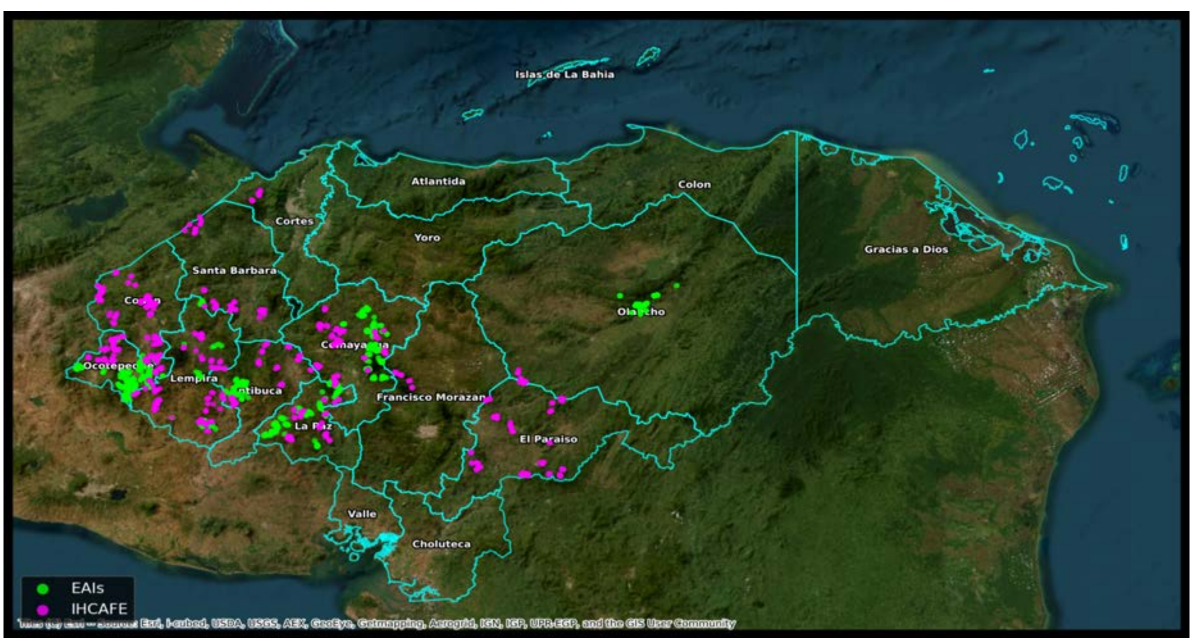
The most represented departments are Ocotepeque (around 20.43% of the sample, 72.88% EAI and 27.12% non-EAI), Comayagua (around 19.18% of the sample, 62.82% EAI and 37.18% non-EAI), and La Paz (around 13.02% of the sample, 65.96% EAI and 34.04% non-EAI), as shown in Figure 3.1.

**Figure 3.1. Respondents by department and EAIs/non EAIs**




The raw boundary data collected was reviewed, cleaned to resolve any geometry issues or other anomalies (e.g., crossing lines, slivers). Figure 3.2 shows the locations of the 1444 plots visited from the sample of EAI and non-EAI farmers across Honduras.

**Figure 3.2. Selected plot locations**



A total of 46,208 features were included in the final set of data to be utilized in the study, based on the cleaned 1444 plot boundaries. The additional permutations reflect a range of user or device errors which could impact the precision of the data collection as detailed in the Methodology. All features were provided with unique identifiers that could be used to associate them with the underlying farmer survey and original boundary for later comparison.

## 3.2 Farmer Survey

In this section we include the results from key portions of the farmer survey which directly inform or contextualize the broader findings. The topics include sociodemographic, knowledge of the EUDR, as well as farmer reported land use and land change. Results from additional sections of the farmer survey on topics such as coffee production, fertilizer usage, and shocks are included in the appendices.

### 3.2.1 Sociodemographic

Across the sample, a majority of the respondents were men (78%, 1130 out of 1444). The proportion of male and female farmers in the sample is in line with IHCAFE (2022/2023) National Coffee Registry in which males represent 76% of the coffee producers, females 23%, and companies 1%. There were no significant differences between male and female socio-demographic characteristics except that males have more years of experience in coffee cultivation than females on average (20.8 years for males and 16.9 years for females), and females are more likely to own a smartphone. Notably though, when comparing the EAI and non-EAI subsets of the sample, we found many significant (based on t-tests) differences in many socio-demographic characteristics, although most are minor differences, as described in Table 3.2.

**Table 3.2. Overall socio-demographics**

| | | Total | Non-EAI | EAI | *t-test p-value EAI versus non-EAI* | *t-test p-value Male versus Female* |
|---|---|---|---|---|---|---|
| **Gender (%)** | **Female** | 21.75 | 18.4 | 25.36 | *0.0013* | - |
| | **Male** | 78.25 | 81.6 | 74.64 | | |
| **Age** | | 51.07 | 52.57 | 49.38 | *0.000* | *0.1974* |
| **Age Group (%)** | **Young (15-24)** | 0.88 | 0.41 | 1.41 | *0.0506* | *0.3273* |
| | **Adult (25-50)** | 46.88 | 42.05 | 52.34 | *0.0001* | *0.4125* |
| | **Senior (50+)** | 52.24 | 57.54 | 46.25 | *0.0000* | *0.3164* |
| **Schooling (%)** | **No education** | 5.06 | 6 | 4.03 | *0.0886* | *0.1560* |
| | **Primary** | 75.21 | 80.67 | 69.31 | *0.0000* | *0.6417* |
| | **Secondary** | 10.66 | 8.4 | 13.11 | *0.0037* | *0.9198* |
| | **Technical** | 1.59 | 0.8 | 2.45 | *0.0123* | *0.6102* |
| | **Bachelor** | 1.45 | 0.8 | 2.16 | *0.0309* | *0.0181* |
| | **Higher Education** | 6.02 | 3.33 | 8.93 | *0.000* | *0.1733* |
| **Years of education** | | 5.98 | 5.23 | 6.79 | *0.0208* | *0.000* |
| **Household size** | | 4.29 | 4.39 | 4.17 | *0.0113* | *0.1093* |
| **Years of experience** | | 19.97 | 20.77 | 19.06 | *0.003* | *0.000* |
| **Certified coffee** | | 22.85 | 5.6 | 41.49 | *0.000* | *0.343* |
| **Membership in a PO** | | 54.19 | 39.5 | 70.23 | *0.000* | *0.5418* |
| **Smartphone ownership** | | 54.63 | 49.34 | 60.06 | *0.0001* | *0.0692* |
| **Wealth Index** | | 0.1827 | 0.184 | 0.1812 | *0.5936* | *0.0333* |

The average age of the households was 51 years of age, with non-EAI farmers significantly older than those in the EAI sample. The youngest households aged 15-24 represented only 0.88% of the population and most of the youngest households were found in the municipality of Comayagua. The senior households aged 50+ represented more than half the sample 52% (41.57% EAI and 58.43% non-EAI) and most of them were found in

Comayagua (19.38% of the senior households) and in Ocotepeque (18.26% of the senior households). If we further disaggregate the age, we observe that 16% are older than 65 years and 12.33% are less than 35 years old. Regarding education, 75.21% of households have primary education, and 10% have secondary education, while only 5% of the population did not complete any education. Additionally, the EAI subset of the sample had more years of education than the non-EAI subset. The average household size is 4.2 members, with the EAI showing slightly larger households than the non-EAI. In general, 54% of participants have a smartphone while 31.2% have only a feature phone, while the remaining 14.18% only have basic phones. Based on the assets listed in the Demographic Health Survey for Honduras (2011-2012) as a proxy for wealth, we register a low asset-based wealth level for most of the sample. Notably though, the vast majority of the sample owned land (95.9%), and only 4.1% rented (or have land and rented additional land).

### 3.2.2 EUDR Knowledge

Overall, the data indicate that while familiarity with the EUDR is generally low (Table 3.3), EAI areas tend to show slightly higher levels of awareness, particularly in the intermediate and higher familiarity categories, whereas Non-EAI areas show a higher concentration of respondents with no familiarity at all. Familiarity with the EUDR is low for both women and men, and the data show no statistically significant differences between the two groups across any response category.

**Table 3.3. Familiarity with EUDR among respondents**

| How familiar are you with the European Union's legislation on deforestation-free products (EUDR)? | | | | |
|---|---|---|---|---|
| | **EAI** | **Non-EAI** | **Total** | **t-test p-value** |
| **None** | 25.6% | 32.9% | 29.4% | 0.0024 |
| **Little** | 49.0% | 51.6% | 50.3% | 0.3222 |
| **Some** | 19.3% | 13.7% | 16.4% | 0.0042 |
| **Quite a bit** | 5.9% | 1.7% | 3.7% | 0 |
| **A lot** | 0.1% | 0.0% | 0.1% | 0.2987 |

### 3.2.3 Land Use

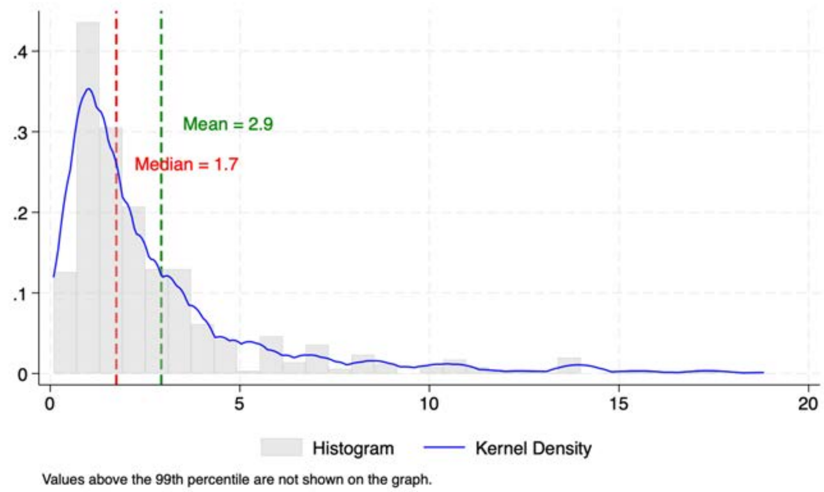
Farmers in our sample have a total land size of 3.8 hectares on average, as shown in Table 3.4, with 3.62 hectares for the EAI and 3.98 hectares for the non-EAI, with significant difference in total land size only between male and female (p-value=0.000)

**Table 3.4. Land size**

| | EAI | Non-EAI | Total | t-test p-value |
|---|---|---|---|---|
| **Total land (ha)** | 3.62 | 3.98 | 3.80 | 0.41 |
| Female | 2.36 | 2.27 | 2.32 | 0.000 |
| Male | 4.06 | 4.37 | 4.22 | |
| **Total coffee area (ha)** | 3.04 | 2.82 | 2.92 | 0.23 |
| Female | 2.15 | 2.10 | 2.12 | 0.000 |
| Male | 3.35 | 2.99 | 3.15 | |
| **Coffee area on the random plot (ha)** | 1.35 | 1.10 | 1.22 | 0.000 |
| Female | 1.16 | 0.95 | 1.07 | 0.007 |
| Male | 1.42 | 1.14 | 1.27 | |

Farmers allocate most of their land to coffee. On average the area allocated to coffee cultivation is around 2.92 hectares (2.82 hectares for the EAI and 3.04 hectares for the non-EAI groups) which represents 92% of the total farm area. Female farmers have on average 2.12 coffee hectares while male have 3.15 coffee hectares. The significant differences between male and female observed for total land size are also confirmed for the coffee land (p-value== 0.000). The specific plot that was randomly selected for the study has an average size of 1.35 hectares for the EAI and 1.1 hectares for the non-EAI, with a statistical difference between EAI and non-EAI (p-value of 0.000). While the average random plot size for females is 1.06 and for males is 1.26, with a p-value of 0.007 (Table 8). The distribution of coffee land does not show a big variation, and it follows a right skewed distribution (Figure 3.3). The results are confirmed both for the EAI and the non-EAI groups.

**Figure 3.3. Coffee land distribution**




Following the classification of farmers presented in the IHCAFE 2022/2023 national report, and considering the total land size, 86.77% of our farmers can be classified as small farmers, while 12.53% medium and 0.68% large farmers. The results are confirmed even considering coffee land size in Table 3.5.[8] The proportions in our sample are in line with the proportions at national level at which there are 90% small, 8.6% medium and 0.4% large.

In general, small coffee farmers are located in Cortes, La Paz, Santa Barbara and Francisco Morazan. Farmers declare having 2.2 coffee plots (2.08 EAI and 2.22 non EAI). With non-EAI groups having a statistically higher number of coffee plots than farmers in the EAI group. No significant differences have been registered in the number of plots with respect to farmer gender.

[8] Small farmers are the ones with an extension of land equal or lower than 6.97 hectares, medium with land bigger than 6.97 hectares and lower or equal to 34.86 hectares, and large with more than 34.86 hectares (IHCAFE, 2022/2023).

**Table 3.5. Type of farmers and land size (in ha)**

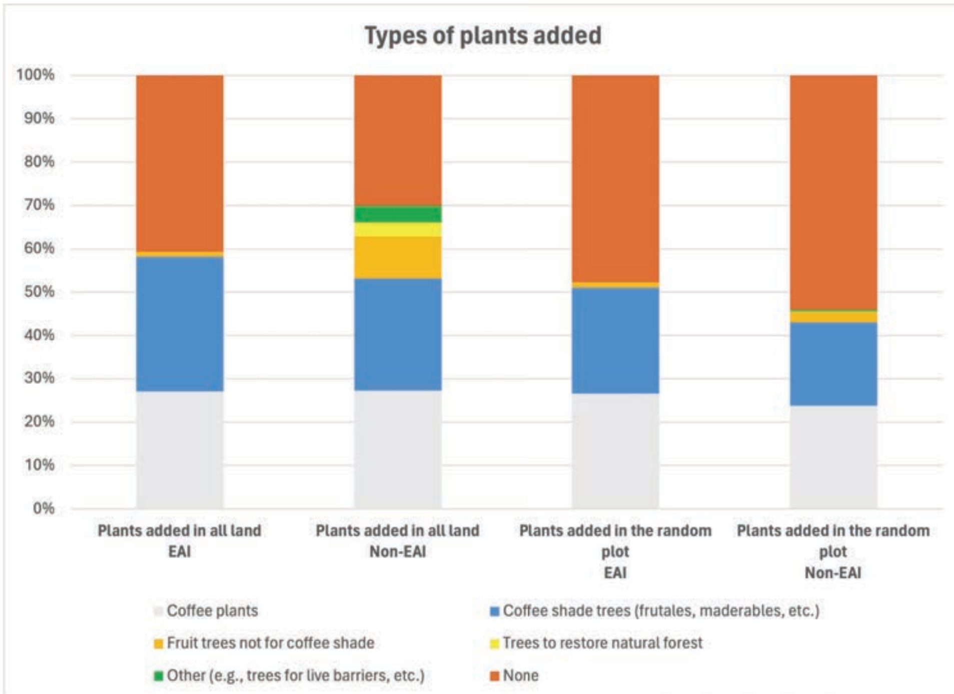
| | EAI | | Non-EAI | | Total | | | |
|---|---|---|---|---|---|---|---|---|
| | **All land** | **Coffee land** | **All land** | **Coffee land** | **All land** | **Coffe e land** | ***T-test (total land)*** | ***T-test (coffee land)*** |
| **Small <= 6.97%** | 86.6 | 89.19 | 86.93 | 90.40 | 86.77 | 89.82 | *0.8517* | *0.4489* |
| **Medium >6.97 and <=34.86 %** | 13.11 | 10.81 | 12 | 9.60 | 12.53 | 10.18 | *0.5239* | *0.4489* |
| **Large >34.86%** | 0.29 | 0 | 1.07 | 0 | 0.69 | 0 | *0.0748* | . |

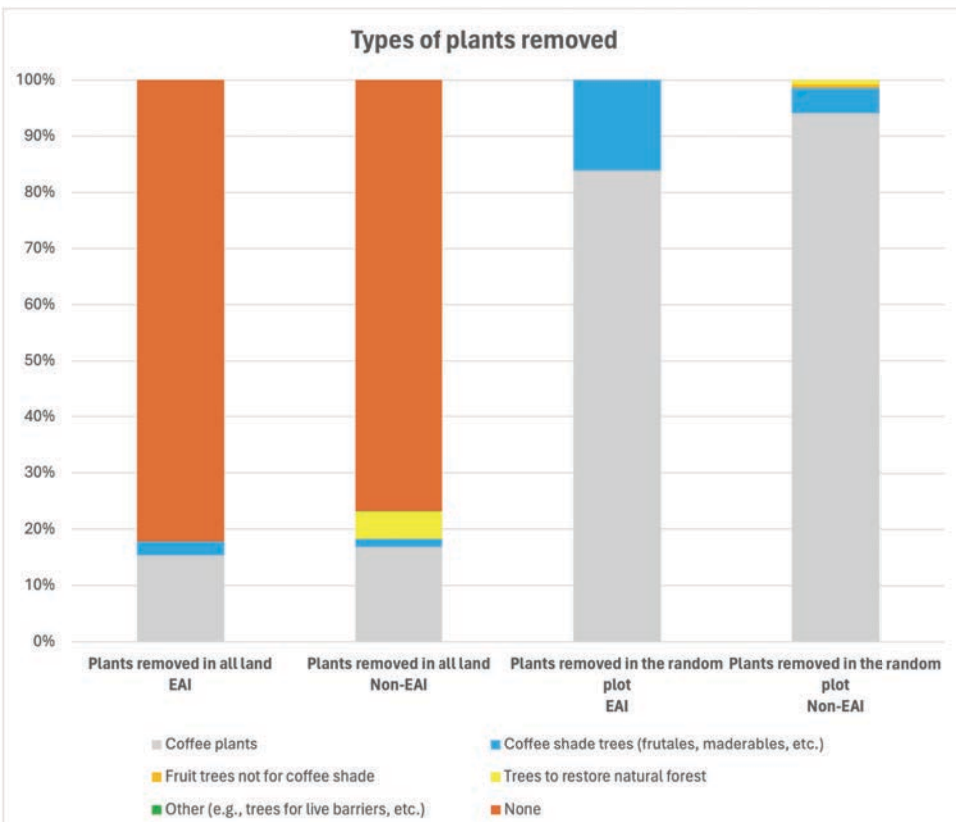
### 3.2.4 Land Change

Considering all land, since 2021 (i.e. in the last 5 years), 47.87% of farmers did not plant any new trees. For the remaining, around 58% of the farmers declared to have added primarily coffee plants (29%) and coffee shade trees (29%). When asked about the removal of trees, we did not observe any responses indicating deforestation occurring in the last five years. Most of the farmers declared to not have removed any trees (81%), and the remaining removed primarily coffee trees (17%). For both the addition and removal of trees, similar patterns were observed for the total productive units and the random plot (Figure 3.4).

A small subset of farmers indicated that they had increased or decreased their productive land since 2021 (<5%). Land size increases average just over 1ha while decreases were slightly lower but close to 1 ha as well. Land size increases were associated with reduction in the area of other crops, purchasing / acquiring / inheriting land, reducing fallow land, or reducing grass areas, and were not indicative of deforestation. A similarly small subset of farmers (<7%) experience a loss of coffee of shade trees due to pests or disease. Farmers who did deal with pests or disease saw non-trivial (>20%) losses of coffee or shade trees. Additional details on the farmer responses associated with potential deforestation is included in the Appendices.

**Figure 3.4. Type of plants added (top) and removed (bottom)**



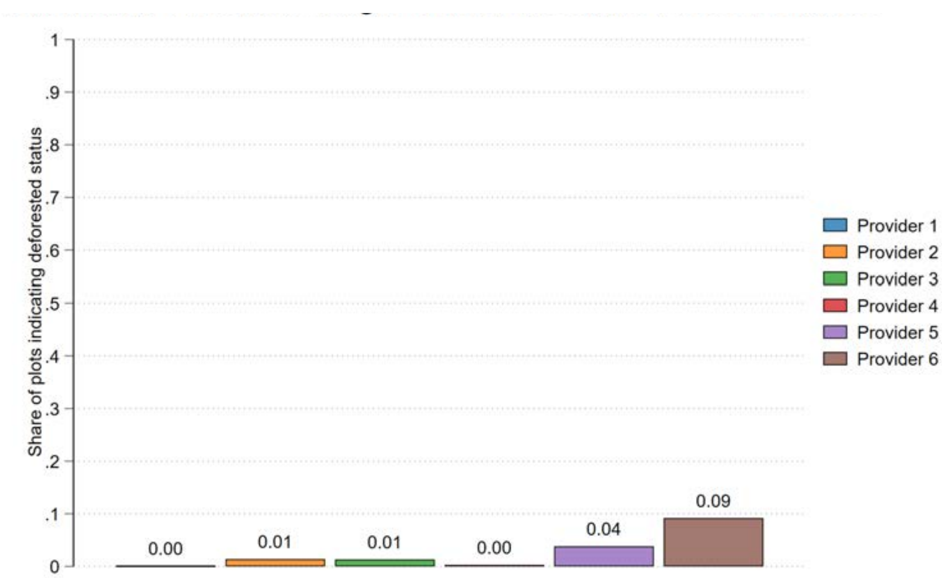



## 3.3 Deforestation Detection

Across all plots (including all permutations) there was full agreement by six providers that no deforestation had occurred between the start of 2021 and the end of 2025[9] for over 80% of the plots in the study. The agreement rates associated with no deforestation are also consistent with the self-reported deforestation and land use change measures captured during the farmer surveys, in which 81% reported that they had not removed any trees in the past five years. The remaining farmers primarily reported removing coffee trees (17%).

There were no plots—based on the true boundary or any permutations—where all providers agreed deforestation had occurred. In other words, for the 20% of plots on which at least one provider indicated deforestation, there was variation in how many providers agreed. Overall, the share of plots which were assessed to have deforestation by any of the providers was relatively low, as seen in Figure 3.5. A comparison of the deforestation detection rates across providers reveals a considerable amount of variation between the providers (Figure 3.6). Individual provider detection ranged from as few as one plot (<0.1%) to 132 plots (>9%).

**Figure 3.5. Share of plots for which each provider detected deforestation**

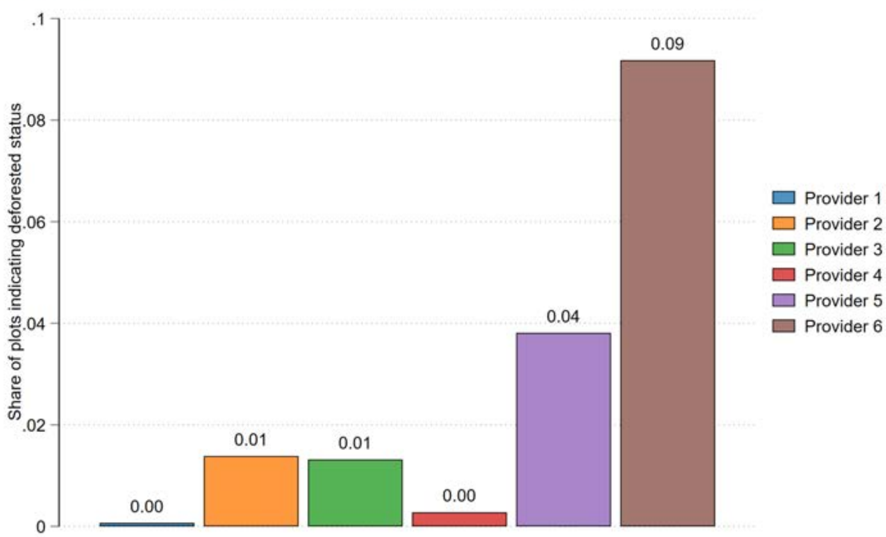



*Note: This graph is provided in scale to illustrate the overall low rate of deforestation detection across the sample.*

---

[9] At the time the study was conducted, in the middle of 2025, EUDR was set to go into effect on January 1, 2026. As a result, deforestation was assessed from the start of the planned window (January 1, 2021) through 2025 as late as possible. Actual end dates for the assessment varied based on imagery availability but was typically June-August 2025.

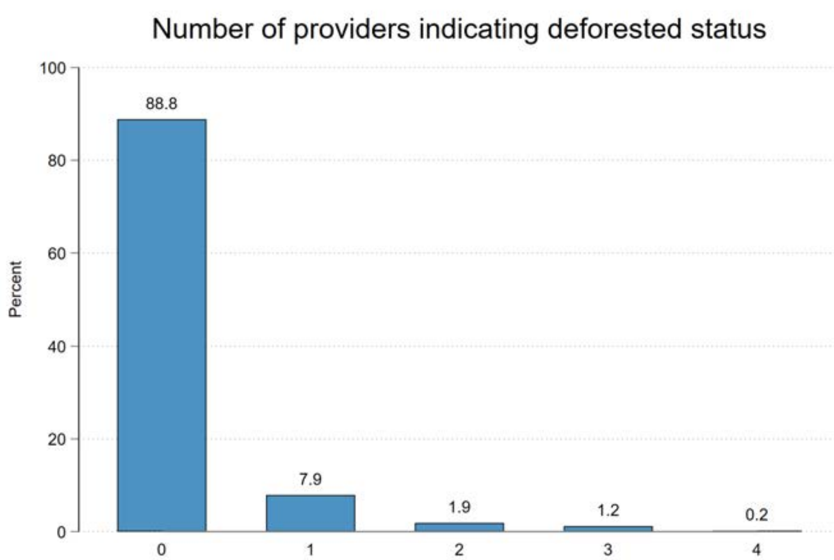
**Figure 3.6. The share of plots for which each provider detected deforestation**




*Note: This graph is zoomed in to illustrate the variability in deforestation detection rates across providers.*

In cases where at least one provider detected deforestation on a plot (based on the true plot boundary) there was frequent disagreement among providers. Of the 162 cases where deforestation was detected in the true boundary by any provider (11.2% of all plots), 114 had detections by only a single provider. For only 48 cases was deforestation detected by two or more providers (Figure 3.7).

**Figure 3.7. Plots (% of plots on y-axis) broken down by the number of providers which detected deforestation within the boundary (count of providers detecting deforestation on x-axis). Based on the benchmark boundary trace.**



### 3.3.1 Comparison with Satellite Imagery

We address the heterogeneity of deforestation detection across providers by utilizing visual inspection of very high resolution (VHR) imagery to establish a more reliable "truth" metric for evaluating the accuracy of the providers and providing additional insight into plot conditions and changes. Imagery was reviewed for 315 plots where at least one provider detected deforestation or where the farmer survey indicated the possibility of deforestation or tree removal. Table 3.6 describes the resulting classification of the plots included in the 315 plots included in the visual analysis. We also reviewed an additional ~300 plots where all providers agreed there was no deforestation to explore the potential of false negatives. Only 2 of these plots indicated any potential of deforestation having occurred.

**Table 3.6. Result of expert VHR imagery classification by category**

| **Visual imagery inspection classification** | **Count** |
|---|---|
| Uncertain | 3 |
| No change | 188 |
| Unlikely deforestation | 52 |
| Minor tree loss | 49 |
| Major tree loss | 4 |
| Potential deforestation | 17 |
| Likely deforestation | 2 |
| *Total* | *315* |

Figure 3.8 provides an example of a 0.36 ha plot classified as having "minor tree loss" using VHR imagery, but one provider detected deforestation. Imagery from 2020 shows clear signs of agriculture within the plot, ruling out deforestation based on the EUDR criteria. However, optical and LiDAR imagery from 2025 do indicate that a few trees in the central region of the plot were removed. The loss of trees may be why one provider detected deforestation for this plot despite the VHR imagery review ultimately determining this did not meet the EUDR deforestation criteria.

**Figure 3.8. Left: Imagery from 2020 (© 2025 Vantor, from Google Earth) showing agriculture throughout the plot interspersed with trees and vegetation. Middle: Drone imagery from 2025 visualized using a false color composite of Red, Red Edge, and Near Infrared bands which reveals that some trees were removed in the center of the plot. Right: LiDAR imagery from 2025 (blue is ground, yellow is smaller vegetation such as coffee, red is tree canopy) which confirms the finding from the optical drone imagery.**

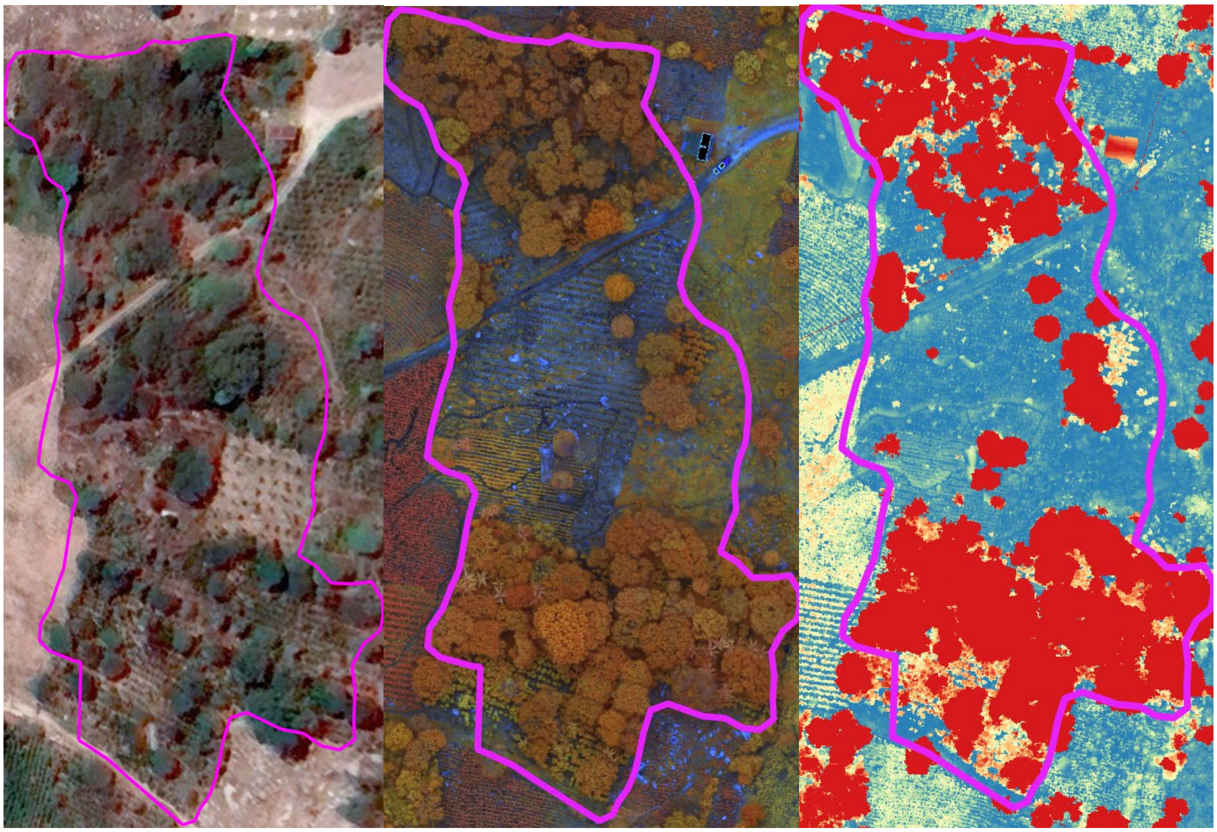
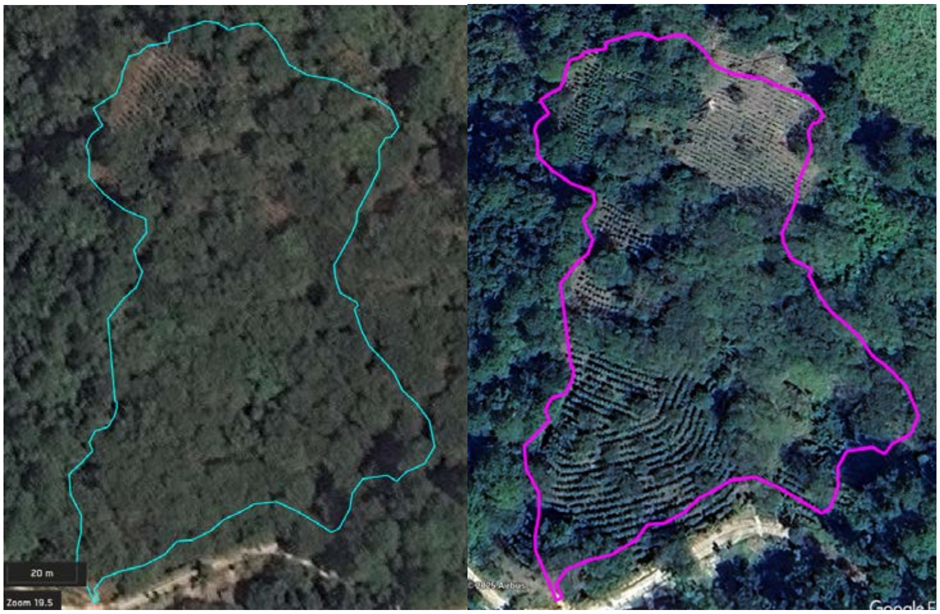


Figure 3.9 illustrates a 1 ha plot classified as having "major tree loss" which was detected as deforestation by one provider. Agriculture can be seen in the top half of this plot in 2020 with dense canopy coverage throughout the lower section of the plot making it difficult to confirm the presence of agriculture. In the 2025 image it appears that many trees have since been removed in the NE and SW portions of the plot. Given the clear loss of a considerable number of trees, but the presence of agriculture in the 2020 image, this was classified as major tree loss rather than deforestation.

**Figure 3.9. Left: Imagery from 2020 (Ⓒ 2025 Vantor) showing agriculture throughout the plot interspersed with trees and vegetation. Right: Imagery from 2025 (Ⓒ 2025 Airbus, from Google Earth) showing**

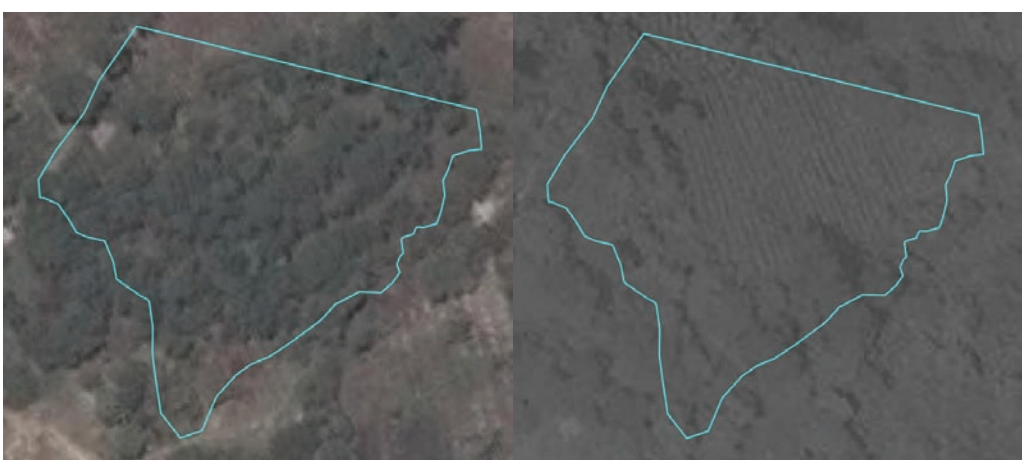


The classification of "unlikely deforestation" was used in instances where there were significant changes within the plot that were not clearly tied to agricultural land use and may have been why one or more providers detected deforestation on the plot. Figure 3.10 shows imagery of a 0.5 ha plot that has clear agriculture present in the earlier image. In the later image, it can be seen that land has been cleared of trees in the NW for developing a new structure and a road, and in the south land was cleared of trees but does not appear to have been used yet. While the presence of agriculture throughout the plot in 2018 rules out the potential of deforestation under the EUDR, even without agriculture present the available imagery would not be conclusive evidence of deforestation due to the dates of the only available imagery. It is possible that the tree removal observed took place after 2018 but before the EUDR start date in 2021. Challenges related to the temporal coverage of satellite imagery will be revisited in the Discussion section.

**Figure 3.10. Left: Imagery from 2018 (© 2025 CNES / Airbus, from Google Earth) showing agriculture throughout the plot interspersed with trees and vegetation. Right: Imagery from 2023 (© 2025 CNES / Airbus, from Google Earth) showing trees having been cleared in the NW and South.**

A site where multiple providers detected deforestation was a 0.40 ha plot which was classified as “potential deforestation” after VHR imagery review (Figure 3.11). The available VHR imagery was slightly blurry, complicating the assessment, but it appears that a large section of the plot with trees in 2021 was replaced with agriculture by 2025. However, based on the imagery it is too difficult to determine whether there was agriculture present on the plot in 2021. As a result of the uncertainty around land use and the removal of a significant area of trees, this was classified as potential deforestation.

**Figure 3.11. Left: Imagery from 2021 (© 2025 Vantor). Right: Imagery from 2025 (© 2025 Vantor).**



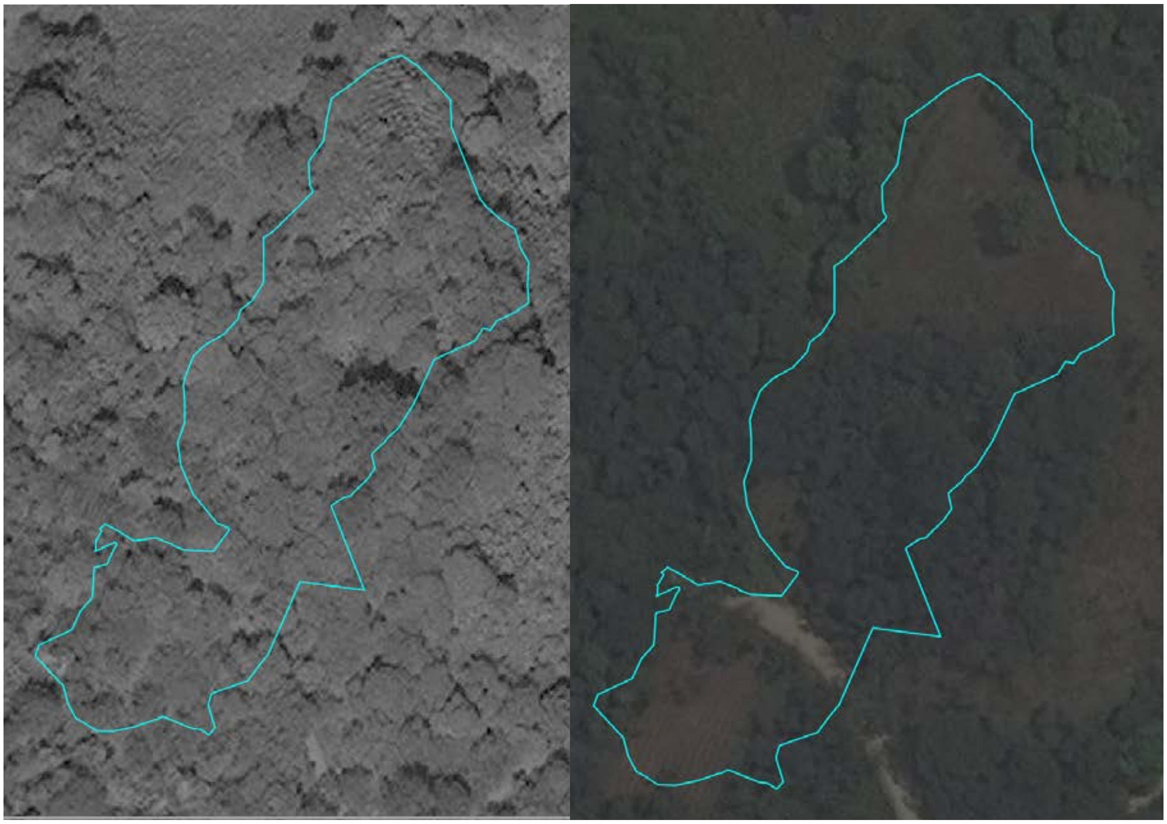
A classification of “likely deforestation” was used for plots where the strongest case for deforestation could be made. The 0.9 ha plot shown in Figure 3.12 showed no signs of agricultural use in VHR imagery from 2021 and had been largely cleared and replaced with agriculture by 2025. The size of the forested area in 2021, the extent of the tree removal, and the implementation of agriculture (with none visible in the earlier image) makes this one of the most likely candidates for deforestation based on the EUDR criteria. The classification of “likely deforestation” is used rather than “deforestation” as even in such cases it is not possible from satellite imagery alone to determine whether there were any crops or agroforestry land use beneath the tree canopy in 2021. The challenges such scenarios present, and this particular example, will be explored further in the Discussion section.

**Figure 3.12. Left: Imagery from 2021 (ⓒ 2025 CNES/Airbus, from Google Earth). Right: Imagery from 2025 (ⓒ 2025 Vantor).**

Lastly, classifications of “uncertain” were used in rare cases (3 total) where no sufficient quality imagery was available to perform a reasonable analysis, and classifications of “no change” were used when no meaningful change was observed on the plot”.

The two cases of possible false negatives identified were classified as “potential deforestation” as they were not conclusive. The 0.9 ha plot in Figure 3.13 did have agriculture present in the Northern section in 2020 where some additional trees were removed, but the Southern section, where no agriculture was observed, had been significantly cleared of trees by 2025. The presence of agriculture within the plot and the less than ideal quality of the imagery makes this example inconclusive.

**Figure 3.13. Left: Imagery from 2020 (© 2025 Vantor). Right: Imagery from 2025 (© 2025 Vantor).**



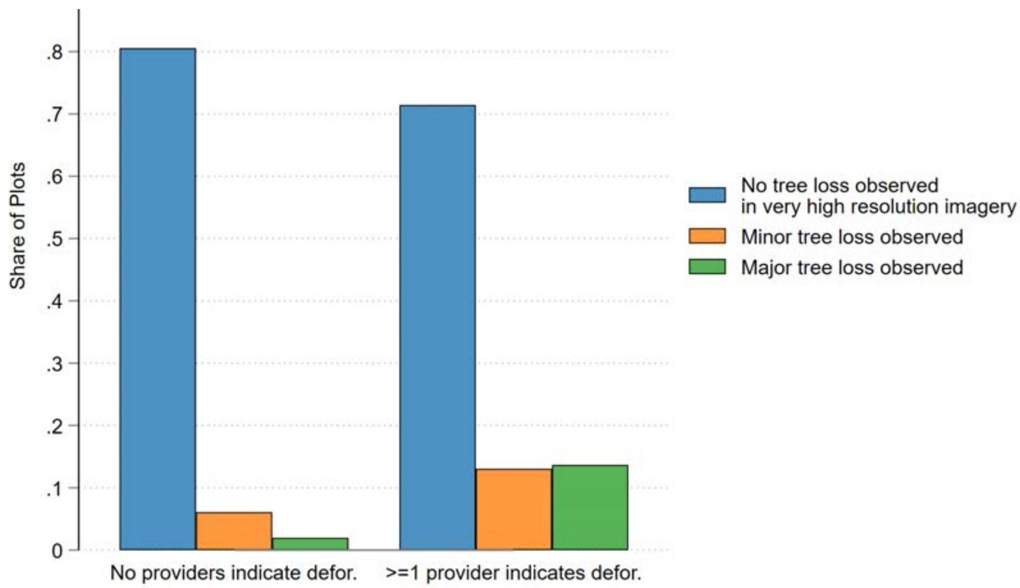
Similarly, the 0.7 ha plot in Figure 3.14 showed a noticeable clearing of land along the northern boundary and extending beyond the plot. Given the proximity to the boundary, and a lack of clarity on whether agriculture was present on the site prior to the clearing, this was also inconclusive.

**Figure 3.14. Left: Imagery from 2023 (ⓒ 2025 Airbus, from Google Earth). Right: Imagery from 2025 (ⓒ 2025 Vantor).**

To facilitate further analysis, the imagery classification was grouped into three categories. Unlikely deforestation was merged with no change into "no tree loss"; potential deforestation and likely deforestation were merged into major tree loss; minor tree loss remained alone. The visual classifications were then compared to the provider classifications. Overall rates of agreement between visual inspection and the providers were reasonable but still varied substantially across providers.

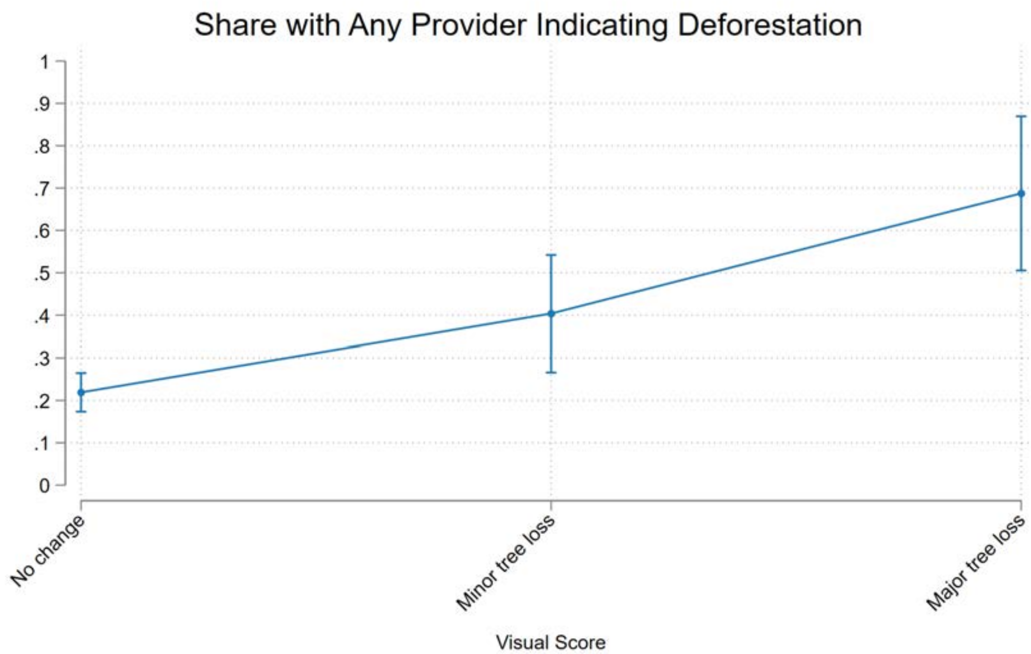
The graph in Figure 3.15 shows the share of plots classified by visual inspection as having (1) no tree loss, (2) minor tree loss, or (3) major tree loss, broken down by whether any providers indicated deforested status for the plot. Among plots which no providers indicated were deforested, no tree loss was observed through visual inspection in 80% of cases. Major tree loss was rarely observed on such plots (i.e., in fewer than 5% of cases). For plots on which at least one provider indicated deforestation, some (minor or major) tree loss was observed in only 30% of cases (although these were much more likely to be "major" rather than "minor" losses compared to plots where no provider indicated deforested status).

**Figure 3.15. Comparison of results from VHR imagery assessment based on whether any provider detected deforestation at the same plot.**



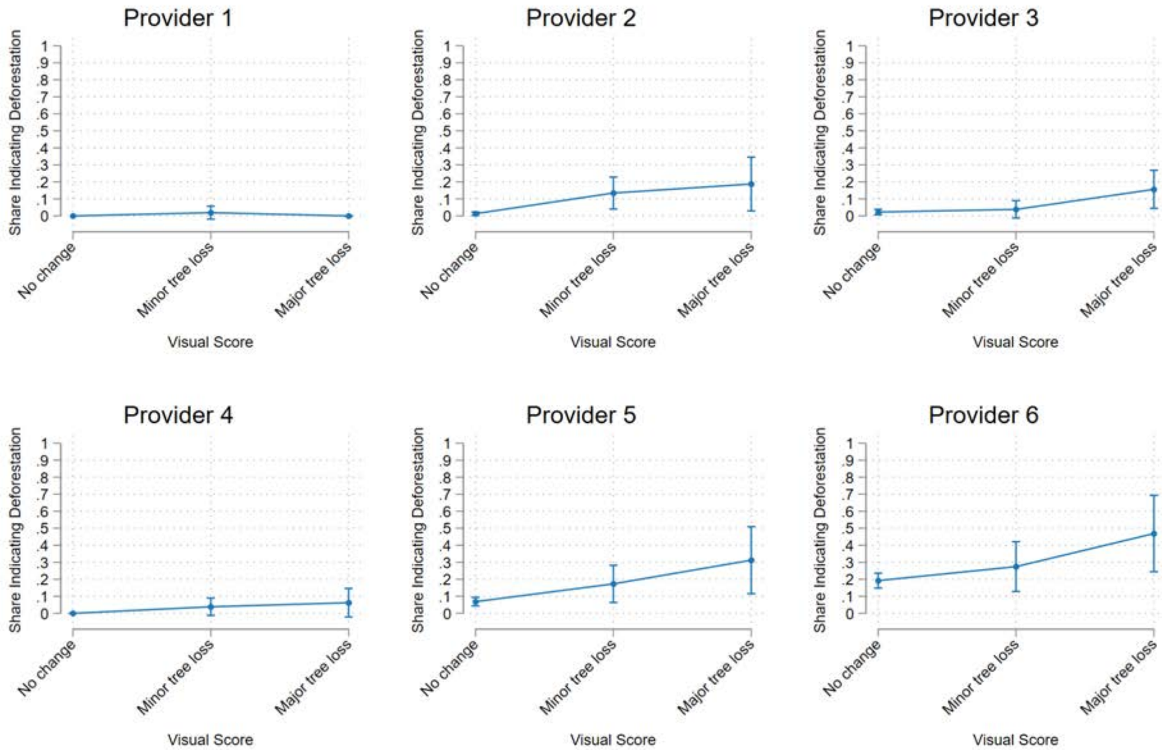

The results of provider and visual assessment can also be interpreted by examining the frequency at which providers reported deforestation for each category of tree loss observed during visual analysis. The graph in Figure 3.16 shows the share of plots with at least one provider indicating deforested status, broken down by categories of tree loss observed using VHR imagery. Half of plots on which major tree loss was observed also had at least one provider indicating deforested status, significantly higher than the 20% rate among plots with only minor tree loss or no change.

**Figure 3.16. Frequency at which providers reported deforestation for each category of tree loss observed during visual analysis**




Substantially more variation is revealed when the same interpretation is applied based on individual providers. Figure 3.17 shows the share of plots for which each provider indicated deforested status, broken down by the tree loss category observed using VHR imagery.

**Figure 3.17. Share of plots for which each provider indicated deforested status, broken down by the tree loss category observed using VHR imagery.**

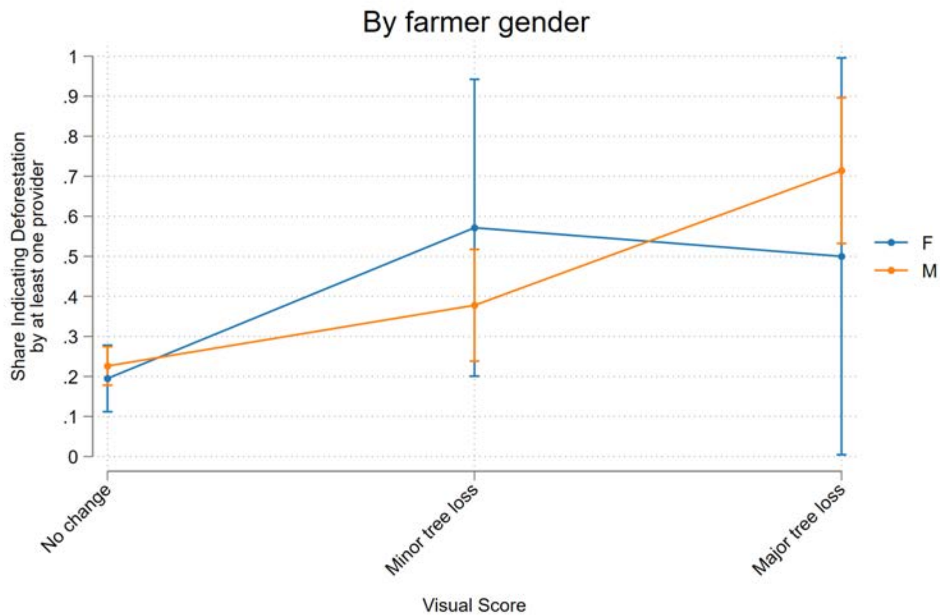



### 3.3.2 Agreement Rates Across Covariates

Agreement between the visual imagery analysis and the providers was also explored based on five covariates derived from either the farmer survey associated with each plot or relevant geospatial characteristics of the plot. The covariates include farmer gender, plot size, EAI participations, population density, and average plot slope.

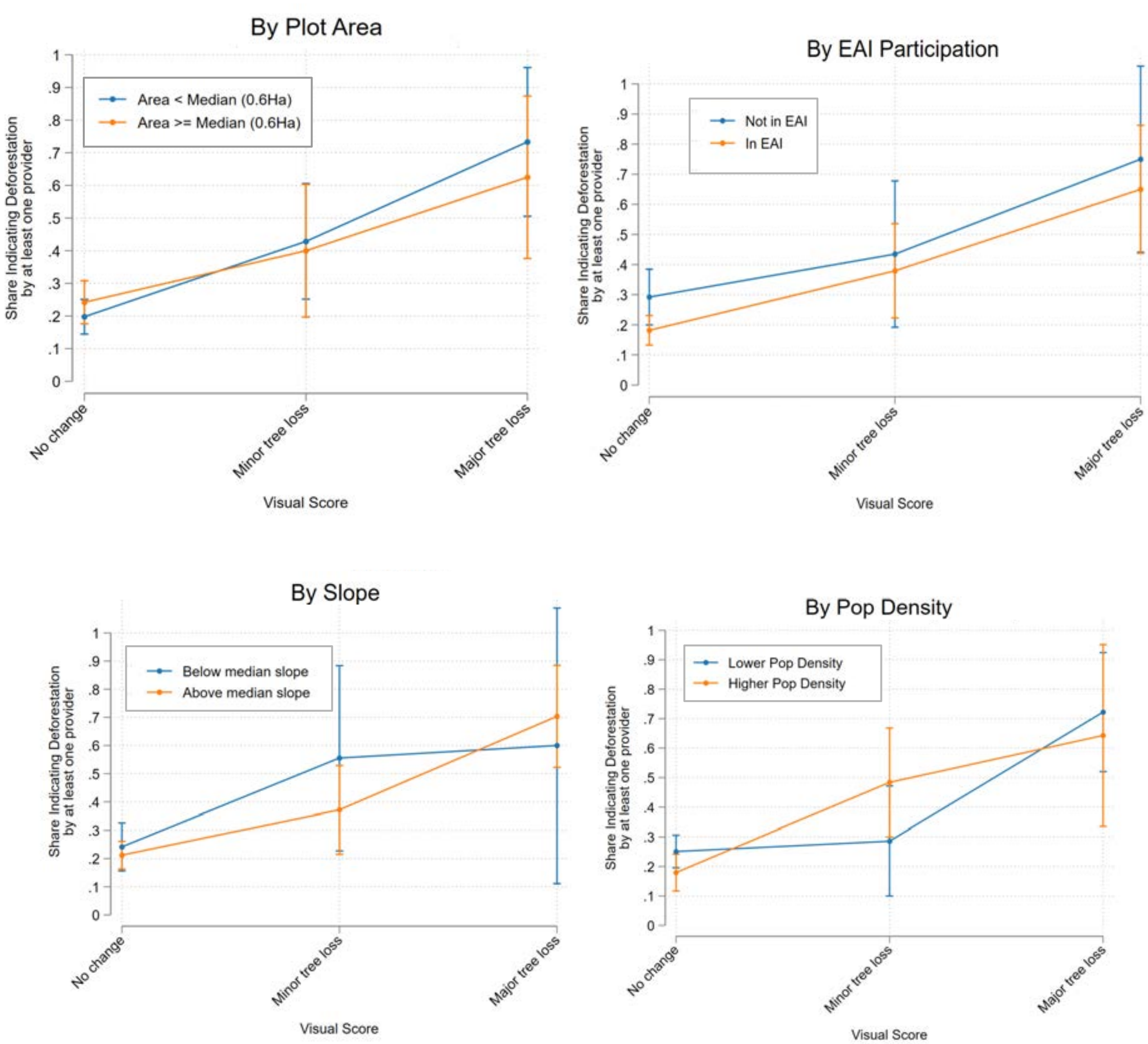
Figure 3.18 shows agreement rates by farmer gender. The findings reveal some offsetting differences in the rates at which providers classify plots farmed by men and women as deforested (even for plots our team categorized as exhibiting minor tree loss or greater). For example, 58% of female-farmed plots on which minor tree loss was observed were classified as deforested by at least one provider, compared to only 38% of male-farmed plots on which minor tree loss was observed. Conversely, 70% of male-farmed plots on which *major* tree loss was observed were classified as deforested by at least one provider, while 50% of female-farmed plots were. However, the relatively small samples within each gender-by-tree-loss-category mean it is not possible to statistically distinguish these gendered differences. Moreover, the offsetting directions suggest that the overall relationship between gender and detection accuracy is not clear.

**Figure 3.18. Agreement rates between provider deforestation detection and VHR imagery assessment, broken down by gender.**




We also consider whether the relationship between provider detection and our visual inspection holds across plot size, plot slope, population density in the surrounding area, and each farmer's participation in an EAI (or not). As seen in Figure 3.19, we find quite similar relationships between provider detection and visual inspection across subsamples of all of these characteristics. In other words, the agreement between providers and VHR imagery inspection does not appear to depend on the plot area or slope, nor on nearby population density or the farmer's participation in an EAI.

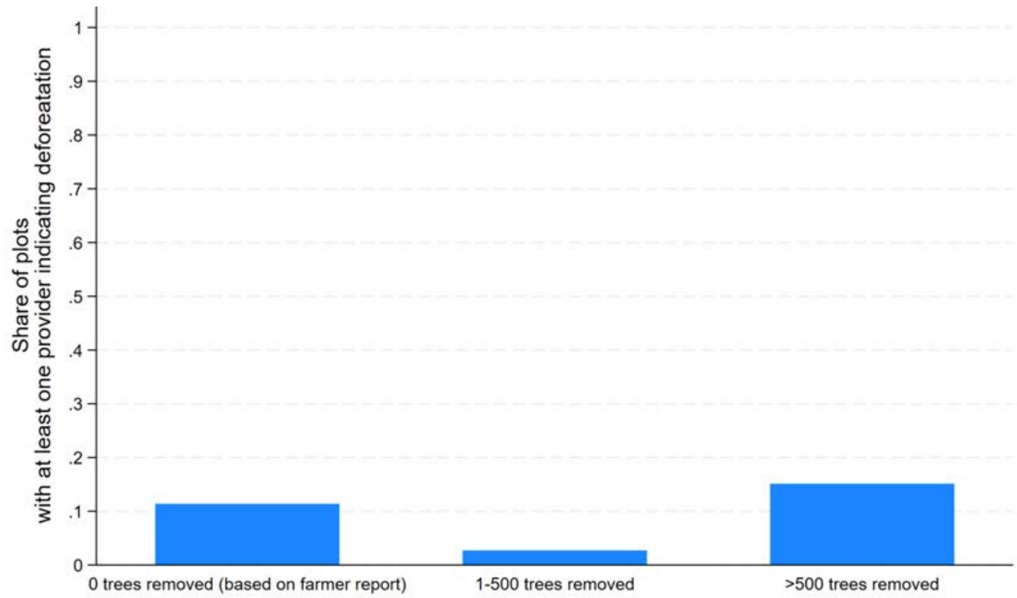
**Figure 3.19. Provider and VHR imagery assessment agreement rates broken down by four covariates: plot area (top left), EAI participation (top right), slope (bottom left) and population density (bottom right).**




### 3.3.3 Agreement with Farmer-reported Tree Removal

We also assess the extent to which plots where providers indicated potential deforestation correspond with those for which farmers reported recent tree removal (either of coffee or shade trees). In total, 12% of farmers reported removing at least one tree from the selected plot during the preceding five years, with half (6%) reporting removing more than 500 (largely coffee) trees. However, as we show in Figure 3.20, the overlap between the provider-indicated deforestation and farmer-reported tree removal is relatively limited. For plots where farmers report removing a large number of trees (>500), providers indicate deforestation for 16% of cases. This is somewhat higher than those for which farmers reported no tree removal (11%), but still far from the majority of cases. Moreover, for plots where farmers reported more limited tree removal (1-500 trees, 6% of plots), providers only rarely indicated deforestation (<5% of cases).

**Figure 3.20. Agreement between Farmer-reported Tree Removal and Provider-indicated Deforestation**



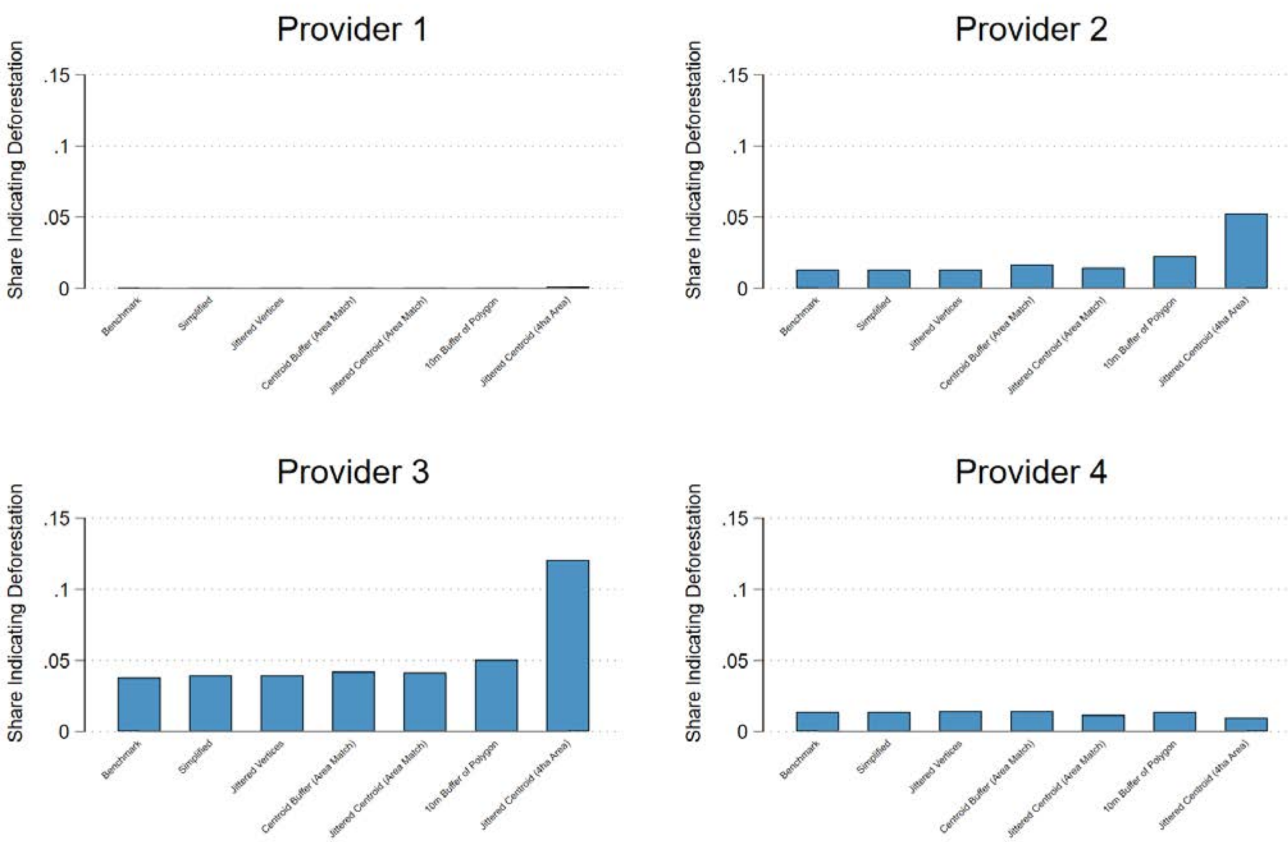

### 3.3.4 Influence of Boundary Precision

The 30 additional boundary permutations were assessed by the providers to determine the role of boundary precision in accurately detecting deforestation on farm plots. Permutations reflect variable precision intended to simulate a mixture of both human and device error.

Figure 3.14 plots the share of plots indicating deforested status under permutation groups for the four providers that assessed all plot permutations. The permutations were aggregated into six groups, in addition to the true benchmark plot boundary. The groups are 1) using geometric simplification, 2) jittering vertices, 3) buffering the centroid or near centroid points based on actual plot area, 4) buffering random points based on actual plot area, 5) using the convex hull or buffer of plot, and 6) buffering based on 4ha area. Overall, the feature permutations had relatively little impact on the deforestation assessment in most cases (Figure 3.21).

Simplification, jittering, convex hull and simple buffering were largely consistent with the assessment of the benchmark. Buffering points based on the true area resulted in slightly increased rates of deforestation. The largest difference was associated with the 4 ha point buffers, which more than doubles the deforestation rates for multiple providers. However, this permutation is also the least realistic one, because it imposes much larger plot sizes than typical, and the providers' assessments thus more frequently reflect deforestation outside the true plot boundaries that is erroneously assigned to the plot when using this permutation. In general, the results indicate that plot boundary precision is not likely to be a major source of error or concern in most of the assessments.

**Figure 3.21. The share of plots indicating deforested status based on permutation grouping for the four providers that assessed all plot permutations**




# 4. Discussion

The forthcoming implementation of the EUDR has prompted the development of numerous compliance solutions, leveraging geospatial data and earth observation to detect deforestation at the individual plot level. Despite the broader field of deforestation monitoring benefitting from both a mature body of research and continual advancements, the implementation of these methods for large scale regulatory compliance introduces many practical challenges. The scale and specificity defined by the EUDR—requiring compliance at the individual plot level—along with the potential consequences of compliance failure have reframed traditionally academic measures of the accuracy and precision of deforestation detection methods as factors with the potential to critically impact the livelihoods of farmers. The research presented in this study aimed to contextualize and evaluate the current range of EUDR compliance approaches—including both plot boundary data collection and earth observation-based deforestation detection—to better understand what level of accuracy and precision is both possible and needed to inclusively support deforestation monitoring at the plot level.

A range of approaches for plot boundary data collection and deforestation detections were assessed by establishing a high-quality benchmark for comparison. The benchmark leverages data, tools, and methods that exceed what is feasible for operational implementation at scale in terms of cost, time, and quality. Boundary data is collected with dedicated GNSS receivers capable of mapping locations with sub-meter accuracy, while deforestation detection incorporates a mixture of sub-meter resolution satellite imagery, optical and LiDAR drone imagery, and expert visual assessment. By comparing existing approaches with the benchmark, it is possible to contextualize realistic levels of deforestation detection accuracy and inform both decision making processes by exporters and other organizations developing compliance workflows, as well as policy makers considering the potential impact of EUDR outcomes of smallholder farmers and other potential vulnerable populations.

## 4.1 Challenges

### 4.1.1 Boundary Precision

One notable source of variation between EUDR compliance efforts is driven by the need for individual plot locations. Honduras has over 100,000 coffee farms[10] and other countries such as Ethiopia can have millions of coffee farms[11], a majority of which are smallholders. While a large number of these farms fall under the 4ha EUDR requirement for collecting plot boundary polygons, even ensuring each plot has an accurate GPS point is a substantial undertaking. Collecting hundreds of thousands to millions of points or polygons entails large scale data protocols, training procedures, and quality assurance with numerous opportunities for errors. Regardless of the specific operational approach for collecting data at scale, two of the primary sources of error when collecting GPS data (point or polygon)

[10] https://coffeehunter.com/our-origins/honduras/

[11] https://www.sciencedirect.com/science/article/pii/S2666154325000663

are user and device error. An erroneous GPS point due to poor signal on a consumer smartphone or an enumerator failing to walk the correct plot boundary can ultimately impact the deforestation assessment for the plot and may result in exclusion from the EU market for farmers.

By permuting the precise benchmark polygons collected for the study, we were able to simulate a range of user and device errors. The permutations reflect different levels and types of error in each category using different geometric modifications such as simplification, jittering, random points, and buffering. The findings revealed that permutations reflecting typical user errors such as walking the approximate boundary but cutting corners or wandering around terrain has relatively little impact on deforestation assessments. Permutations reflecting moderate device error, such as erratic placement of GPS points along the walked path, also had limited impact on the assessment. Even when reducing the benchmark to a single point (centroid or random) and buffering based on the actual plot area, there were relatively minor changes to the deforestation assessment. The only major differences occurred when reducing the benchmark to a single point and then buffering to produce a 4-ha area. While this is not a prescribed practice under any known EUDR compliance solutions, it reflects the use of an oversized buffer that has the potential to occur if an approach were to use fixed buffer sizes to approximate the area of plots under 4 ha. The resulting features showed much higher rates of deforestation detections compared to the benchmark boundary or other permutations (i.e., more false positives).

A limiting factor in the evaluation of the permutations is the relatively low overall rates of deforestation around the plots included in the study. In other countries where deforestation may be more prevalent or proximate to coffee plots, it is possible that a comparable study would indicate a greater impact when utilizing varying permutations. While there is still the possibility of individual cases where deforestation detection using a boundary produced with user or device error could meaningfully alter the findings, such situations would appear to be relatively uncommon in Honduras. The findings indicate that high precision (i.e., submeter accuracy) devices are likely not needed in Honduras, but efforts should be made to 1) ensure points are within the plot for plots <4ha and ideally collect a reasonable estimate of the plot size, and 2) walk a reasonable approximation of the plot boundary for plots >4ha at a slow pace to allow the device to record sufficient points. 3) For any size plot, it is always critical to verify a good GPS signal before collecting data.

Quality assurance and review of plot location data is also essential and is ideally conducted in near real time with data collection to enable revisiting plots where data correction may be needed. Examples of quality assurance checks that be done include:

- Check plot does not overlap with other plots or is a duplicate of an existing plot
- Check plot does not overlap with water bodies or other illogical land cover types. This could be done using a regional or even global land cover classification layer.
- Check for extreme irregularities such as the plot going into another country, extremely large area, or spikes in the boundary.
- Check for geometry errors in plot boundary polygons such as self-intersections. These may be automatically correctable but may reflect larger issues.

The European Forest institute provides more details on suggested checks and best practices in the November 2025 Due Diligence in practice report.

### 4.1.2 Deforestation Detection

Another major source of variation between EUDR compliance efforts is the deforestation detection approach utilized. Deforestation detection approaches can leverage one or more sources of satellite imagery, and even drone or aerial imagery for fine tuning and validating models when needed. At least four notable types of imagery are actively being utilized for EUDR compliance, including Landsat, Sentinel, Planetscope, and commercial sub-meter imagery. In addition to the underlying imagery source(s) used, workflows for training and implementing deforestation detection have the potential for nearly infinite unique variations. Factors which impact the final performance of a deforestation detection approach include, but are not limited to, 1) the specific subset of imagery used for training, 2) the quality of the training data labels, 3) data preparation and processing, 4) the model and model parameters used, and 5) the training and validation procedures.

We limited the direct comparisons of specific methodological elements or approaches in the study findings due to 1) there being too many potential variables (e.g., imagery combinations, models, training protocols) to provide insights that would be consistent across all applications (e.g., “imagery source X will always outperform Y”), and 2) to avoid biasing ongoing development of EUDR compliance solutions. However, the broader findings and trends revealed throughout the evaluation can provide insight into the practical implementation of deforestation detection solutions for EUDR compliance and allow relevant stakeholders and decision makers to make informed decisions when organizing a compliance solution that meets their needs.

One of the most prominent findings from the analysis was the lack of agreement on where deforestation was detected across providers. While providers did agree that the majority of sites (80%) did not have deforestation, there were no sites where all providers agreed deforestation had occurred. The lack of agreement among providers is a reflection of the impact that different data, training, and related choices used by each provider (described above) can have on the final deforestation detection results. A number of high-level trends surfaced when evaluating the results. Providers which used coarser resolution imagery had significantly higher rates of deforestation detection. The associated approaches may be more likely to catch less distinct cases of deforestation, but also much more likely to generate false positives. In contrast, providers leveraged finer resolution imagery may miss borderline or potential deforestation but achieve greater accuracy due to far fewer false positives.

A critical factor impacting all deforestation detection models being used to assess shade grown coffee is the distinction between tree loss and actual deforestation as defined by the EUDR. Deforestation detection approaches have historically been trained to identify tree loss, with some additional specificity for forested area and tree height in some instances. However, under the EUDR definitions, sites that have previously been established for agroforestry are not considered for potential deforestation. As a result, the removal of shade trees (in the case of coffee plantations) may be detected as deforestation by some models but does not reflect actual deforestation under the EUDR.

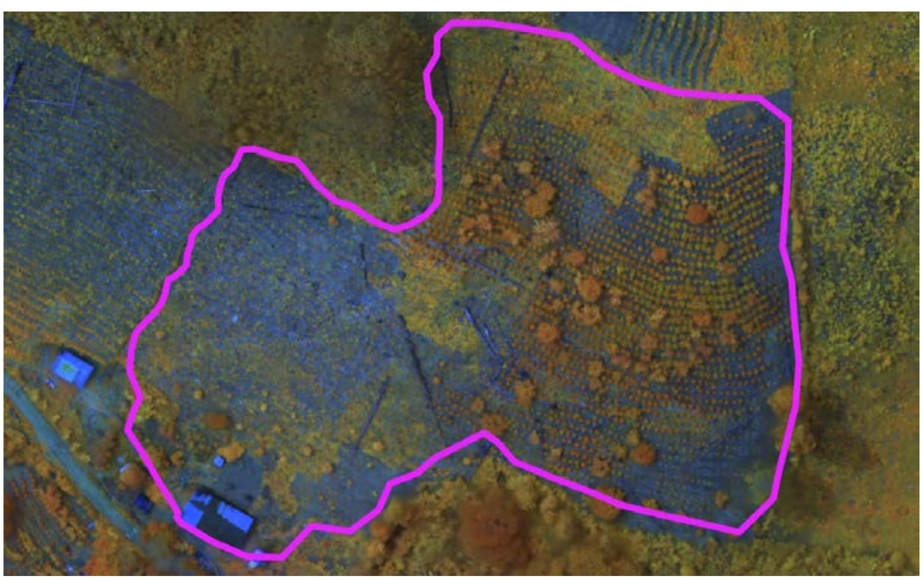
Approaches using either finer resolution imagery capable of identifying crops within plots or incorporating additional data layers on agricultural land use can be more effective at eliminating false positives related to tree loss on agroforestry sites. Even with deforestation detection tailored to coffee or other agroforestry land uses, eliminating false positives is a difficult task. Expert review of VHR imagery resulted in zero sites in the study where deforestation could be conclusively identified. A small number of sites had likely deforestation, and a number had the potential for deforestation. Yet even leveraging nearly ideal imagery and extensive expert review, it was not possible using satellite imagery alone to determine whether there may have been existing agroforestry / coffee on sites which had very clear tree loss.

The example shown in Figure 4.1 is one of the most notable cases for deforestation observed in the study. Imagery from early 2021 shows a stand of trees within the plot running from NW to SE. The trees cover roughly more than half of the plot, which is just under 1ha overall. The areas to the SW and NE within the plot are largely clear aside from irregular small vegetation but do not have any visible signs of coffee or other agricultural usage. Subsequent imagery from the later half of 2025 reveals there has been considerable change within the plot. The tree stand has been severely reduced, with little canopy remaining. There are however signs of some trees, perhaps pruned, still standing. The previously and newly cleared areas now show visible signs of agriculture, with rows of planting covering nearly the entire plot.

**Figure 4.1. Left: Imagery from 2021 (© 2025 CNES/Airbus, from Google Earth) showing tree canopy running across most of plot from NW to SE, with no agriculture visible. Right: Imagery from 2025 (© 2025 Vantor) showing significantly fewer trees and clear signs of agriculture throughout plot.**

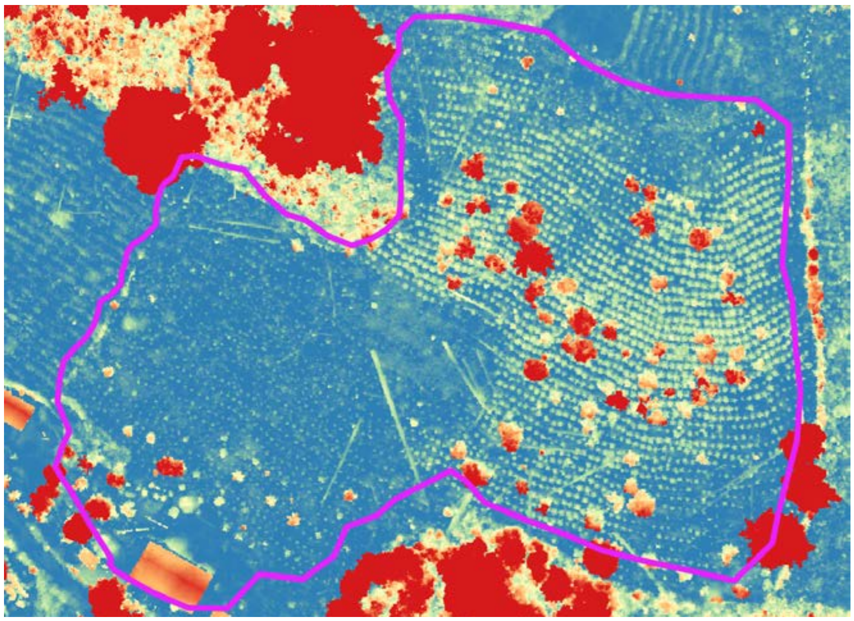
Drone imagery from the later half of 2025 viewed using bands for a false color composite (Red, Red Edge, and Near Infrared) provides a detailed look at the plot distinguishing live growth from the ground and other features (Figure 4.2). Within the image it is possible to see felled timber, individual coffee plants, surrounding vegetation, and the remaining trees.

**Figure 4.2. Drone imagery from 2025 viewed using false color composite of the red, red edge, and near infrared bands.**



Additional LiDAR imagery (Figure 4.3) provided details on the height of the plants across the plot. Some variation within coffee plants is observed, with plants in the western half averaging about 0.5 meters and plants in the eastern half averaging about 1 meter—potentially indicating when they were planted between 2021 and 2025. More notably, the remaining trees within the plot are under 5 meters tall, while trees adjacent to the cleared area outside the plot are generally over 10 meters tall.

**Figure 4.3. LiDAR imagery from 2025 indicating height of features. Ground level is blue, coffee plants are yellow-green (0.5-1.5m), and trees are orange/red (3-30+ meters).**



Despite the clear evidence of change within the plot and the removal or reduction of trees, it is difficult to confirm there was not any coffee being grown under the canopy of the trees in 2021. In this case, there would be a need for the farmer, exporter, or other responsible organization to provide documentation that could prove the land did have coffee being grown or was otherwise being used for agroforestry as of or prior to 2021 in order to be compliant with the EUDR. This example is reflective of the broader difficulty of conclusive deforestation detection for shade grown coffee, as it will effectively always require additional documentation to determine the original status of the land beneath dense canopy.

The necessity of additional documentation to disprove potential false positives could result in considerable additional use of resources (time for farmers/exporters to find appropriate documentation, time for Competent Authorities to review and validate, etc.) being used to support EUDR compliance. Although documentation may be necessary in certain circumstances, it may be possible to reduce the number of occurrences by targeting critical forested areas.

The European Commission's Joint Research Centre produces a range of Tropical Moist Forest (TMF) products based on Landsat that tracks the extent, degradation and deforestation, as well as regrowth of TMFs. TMFs are one of the most critical forest systems around the world that are fundamental to biodiversity, carbon sequestration, medicine, and more. Using the TMF layer from 2020, we found that only 128 out 1444 sites (8.9%) in the study had an TMF within the plot, while only 48 sites (3.3%) had 20% or greater overlap with TMF.

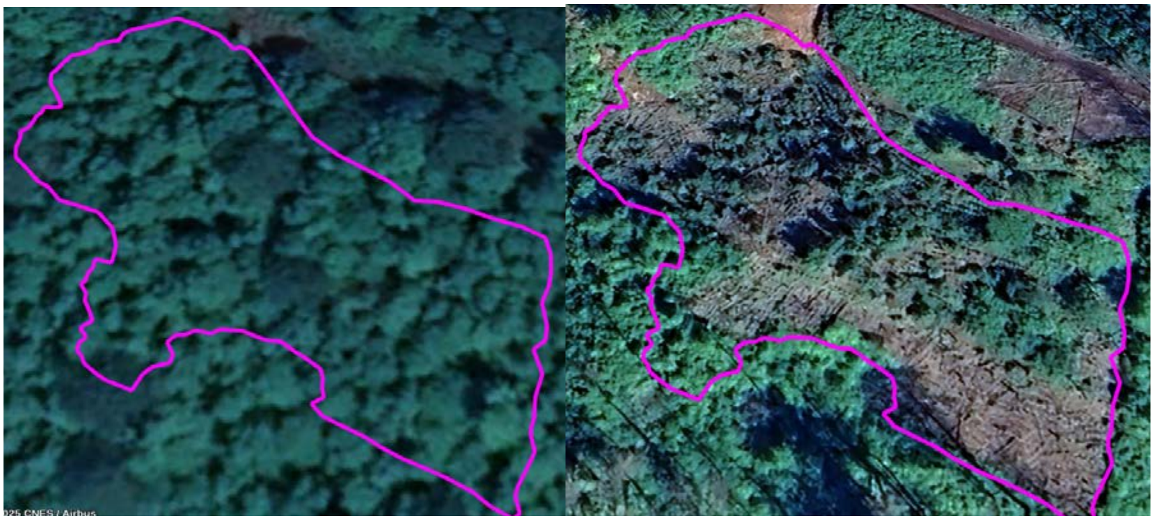
Incorporating other country specific data layers on forest status or agricultural land may enable further elimination of plots requiring review and validation and is also recommended by the EFI in their *Due Diligence in practice* report. The EU JRC TMF products as well as similar datasets are being used by some deforestation detection providers but can also be incorporated into due diligence statements produced by exporters to address provider-identified deforestation, or as subsequent validation steps by Competent Authorities to minimize additional requests for data/documentation from farmers.

The example introduced in Figure 4.4 reflects many false positives that can easily be ruled out due to existing agriculture or agroforestry within the plot and very minor overlap with TMF. Despite the initial apparent differences between the images, which can likely be attributed to the sun angle and sensor differences, there is relatively little change within the plot between 2021 and 2025. There is agriculture present throughout the plot in 2021, and no clear signs of tree loss regardless within the plot. Some tree loss is visible outside the plot however, which may be the reason why deforestation was detected by three providers in the study. The relatively high agreement among providers is evidence of the importance of validation, and the limitation of purely computation approaches in some instances where manual review could quickly determine deforestation had not occurred within the plot.

**Figure 4.4. Left: Imagery from 2021 (Ⓒ 2025 Airbus, from Google Earth) showing rows of crops throughout the plot, interspersed with trees. Right: Imagery from 2025 (Ⓒ 2025 Vantor) showing similar conditions inside the plot, but some tree loss outside the plot.**


Another factor which can make it difficult to be conclusive about deforestation status is the availability of imagery at specific points in time. Figure 4.5 shows a plot where submeter resolution imagery was only available in 2019 and 2023. Compared to the dense canopy seen in 2019, there was considerable tree removal by 2023. However, due to the lack of imagery between 2019 and 2023, it is not possible to determine whether the tree removal took place before or after January 1, 2021. If imagery from 2020 showed the trees had already been removed, the plot would likely be in compliance with the EUDR. However, if imagery from 2021 showed there was still dense canopy coverage, it would then depend on the farmer to provide evidence they were using the land beneath the canopy for agroforestry. Based on the available imagery alone, this case would likely also depend on documentation.

**Figure 4.5. Left: Imagery from 2019 (© 2025 CNES/Airbus, from Google Earth) showing dense canopy cover. Right: Imagery from 2023 (© 2025 CNES/Airbus, from Google Earth) showing significant clearing of the plot.**



Overall, modern deforestation detection methods perform very well yet are not infallible. The effectiveness of approaches relies not only on the training of the underlying model, but also on the implementation and usage in an actual deforestation detection workflow. Determining the specific objectives, risk tolerance, capacity for validation in a workflow will enable selecting the appropriate model or models and related steps to incorporate. Ultimately, no approach will produce 100% accurate results and so procedures for validation and quality assurance are critical to develop. It is also worth noting that EUDR compliance solutions, related efforts, and underlying deforestation detection methodologies are continually evolving and improving over time.

The findings and considerations highlighted in this study are intended to provide insight into broader applications of deforestation detection but are inherently reflective of the sample utilized. The same had fairly low overall deforestation rates which is intertwined with the nature of shade grown coffee in Honduras. Applications evaluating deforestation for other commodities or in other geographies may have unique considerations which supplement, alter, or even contradict the specific insights derived from this study. The findings from this study should be utilized as insights for developing an approach that suits an organization’s needs or for considering how policy and compliance protocols can be adapted to balance reducing deforestation with the limitations of modern deforestation detection approaches.

## 4.2 Farmer Surveys and Socioeconomic Considerations

In addition to generating primary ground-truth data on plot locations and boundaries, the plot visits created an opportunity to collect complementary information directly from farmers on plot conditions, management practices, land-use history, and relevant socioeconomic factors. The resulting farmer survey produced a rich dataset that: (1) supports the validation and contextualization of deforestation-risk assessments and satellite-based observations; (2) provides insights into farmer behavior and decision-making processes; and (3) enables analysis of trends and characteristics across the broader sample that may influence deforestation dynamics and related practices.

### 4.2.1 Sampling and Inclusivity

Analysis of the EAI sample in comparison with a nationally representative (non-EAI) sample indicates that farmers selected to participate in the EAI are predominantly cooperative members, have received at least one certification, and tend to be more productive and resilient. This suggests that the EAI selection process may have underrepresented more marginalized and non-associated farmers.

In terms of gender representativeness, however, the EAI sample is relatively inclusive: women account for 25% of coffee farmers in the EAI sample, compared to a national average of 23% female coffee farmers (IHCAFE National Coffee Registry 2022/2023).

Additional relevant findings on the differences between the EAI and non-EAI samples involved the reported coffee yield and resilience to shocks. We utilized a regression analysis to explore which sociodemographic characteristics had the greatest impact on reported yields. Consistent with the overall inclusivity of the sample, gender was not found to be a significant determinant of yield. Instead, the primary factors influencing yield were farmer age, EAI membership, and household wealth levels. In addition, EAI member farmers—particularly men—demonstrated greater resilience and a stronger capacity to recover from shocks (e.g., drought, flooding, disease, or illness) experienced since 2021. Further details on resilience and yield are presented in the Appendices.

Given that the EAIs included in the study reflect different EUDR compliance approaches and geographic contexts, their level of inclusivity is not, in itself, a concern. To account for the more limited scope of the EAIs, a non-EAI comparison group was intentionally designed to be nationally representative. However, as findings are disseminated or policy and investment decisions are made based on the EAI results, it will be important for decision makers to carefully consider the differences between the EAI samples and a nationally representative population of farmers, and the implications these differences may have for interpretation and scaling.

#### 4.2.2 Measured versus Reported Land Size

To assess potential bias between farmer self-reported land area and measurements derived from full GPS plot boundaries, benchmark polygon-based land size estimates were compared with land size figures reported during farmer interviews. The analysis reveals a positive association between plot size and the discrepancy between GPS-based and self-reported measurements. Specifically, the magnitude of the discrepancy increases with farm size: larger farms tend to underreport their land area, while smaller farms tend to overstate the size of their landholdings.

These results are consistent with the findings of Carletto et al. (2013) among maize producers in Uganda and have important implications for yield estimation.[12] When smallholders overreport land size and larger farmers underreport their holdings, yield estimates become systematically distorted appearing artificially lower for small farms and higher for larger ones. The discrepancy between GPS-based and self-reported land size measurements decreases when controlling for EAI membership, suggesting that EAI farmers are more likely to report land area accurately. This may reflect prior training received by EAI members on land measurement or their previous exposure to plot boundary mapping exercises. More broadly, these findings underscore that farmer-reported data are not always fully accurate, a point that becomes particularly salient when interpreting self-reported metrics related to deforestation, as discussed in the following sections. Additional details on the comparison of measured versus self-reported land size can be found in the tables in the Appendices.

#### 4.2.3 Deforestation

The overall low rates of deforestation detected in the study sample are encouraging particularly in light of the limited awareness of the EUDR revealed by the farmer survey. More than half of the farmers in the sample declared to know little about EUDR (50.3%), while a further 29.4% indicated no knowledge at all. The results suggest that gender does not play a significant role in shaping awareness or understanding of the EUDR. Both women and men show similarly low levels of familiarity, with responses concentrated in the "None" and "Little" categories. Notably, non-EAI farmers demonstrate a greater lack of EUDR

[12] Calogero Carletto, Sara Savastano, Alberto Zezza, Fact or artifact: The impact of measurement errors on the farm size–productivity relationship, Journal of Development Economics, Volume 103, 2013, Pages 254-261, ISSN 0304-3878, https://doi.org/10.1016/j.jdeveco.2013.03.004.

awareness than EAI participants, which may reflect information-sharing and outreach efforts associated with the organizations coordinating the EAIs.

One of the most important components of the farmer survey focused on land use and land-use change, including questions related to deforestation, the removal of coffee plants or shade trees, or expansion of agricultural land. While no responses were indicative of deforestation, a number of farmers did report removal of coffee plants and shade trees. As shown earlier, the results reveal limited alignment between farmer-reported removal and deforestation detections identified by service providers. Similarly, in many cases, expert review of very high–resolution (VHR) imagery was unable to detect evidence corresponding to the self-reported removals.

**Figure 4.6. Top: Imagery from 2019 (© 2025 Vantor) showing trees throughout plot with signs of agriculture throughout. Bottom: Imagery from 2025 (© 2025 Vantor) showing similar conditions and no noticeable removal of trees.**

As an illustrative example, for the plot shown in Figure 4.6, the farmer reported the removal of 600 shade trees; however, no visual evidence of significant change is apparent within the plot. The observed discrepancy may stem from survey-related errors—such as incorrect recording by the enumerator or the farmer recalling information for a different plot—or from inherent limitations in satellite-based detection. While the removal of several hundred trees would typically be expected to be detectable, possible explanations include regrowth of fast-growing shade species or the thinning of small, under-canopy trees that may not be visible in imagery. Given the relatively small proportion of farmers reporting any tree removal, and the even smaller share reporting substantial removal, the sample size was insufficient to explore the underlying drivers of these discrepancies in greater depth.

## 4.3 Parallel and Future Work

### 4.3.1 Related Work in Ethiopia

Ethiopia is the world's largest coffee producer by volume, with approximately 95% of production coming from smallholder farmers[13] and an estimated 30% of exports (2022/23)[14] destined for the European Union. In early 2025, COSA and AidData, in collaboration with Bopinc, launched a project aimed at strengthening the capacity of local organizations—specifically the Ethiopian Coffee Association (ECA)—to provide EUDR-related services to its members, supporting their compliance with current and future regulations while reinforcing ECA's value, sustainability, and relevance to the sector.

As part of the project, ECA enumerators were trained in high-quality survey data collection as well as geospatial data capture using smartphone-based tools with built-in GPS functionality. Field implementation generated critical insights to inform the pricing and design of a sustainable business model, developed jointly with ECA, to enable the continued delivery of these services. In parallel, systems were established within ECA to ensure that collected data can be securely stored, managed, and shared for export requirements and EUDR compliance, in line with data governance best practices.

This work builds on lessons learned from the original work in Honduras, operationalizing proven survey methodologies and technologies at scale. The project's findings directly contribute to Ethiopia's EUDR readiness and provide practical input for the ongoing refinement of EUDR data collection approaches.

### 4.3.2 Applications Involving Other Geographies or Commodities

Monitoring deforestation of coffee in Central America, where it is predominantly shade grown, presents several challenges as explored throughout this report. In particular, it can be challenging to map clear plot boundaries in areas of dense vegetation and canopy, and

---

[13] *Strategies to improve the quantity and quality of export coffee in Ethiopia, a look at multiple opportunities* (Muhie, 2021)

[14] Ethiopian Coffee and Tea Authority (2024). National Action Plan for the Implementation of Compliance Measures on EUDR.

it can also be difficult to confirm whether areas suspected of deforestation were previously used for agriculture (due to limited visibility beneath the canopy). Coffee grown in other geographies which have sparser canopy coverage or use sun-grown approaches may require less effort to monitor and result in clearer assessments.

Factors influencing deforestation detection on coffee farms across different geographies are also relevant when considering deforestation detection of other commodities covered by the EUDR (rubber, palm oil, cocoa, soy, wood, cattle). While rubber and cocoa plants are often grown under some canopy as part of agroforestry systems, similar to coffee, soy and palm oil trees typically require full sun. Timber comes from a range of trees, but it is less common to harvest understory trees as they are usually smaller. While monitoring cattle directly using satellite imagery presents unique challenges, the conversion of land for grazing or related land uses and associated deforestation is more straightforward to identify.

The fundamental approaches for data collection and deforestation detection will largely be similar across commodities and geographies, but it will be essential to consider the unique conditions associated with each and how approaches will need to be adapted to maintain sufficient accuracy while avoiding unintended side effects. In some instances, the particulars of specific geographies and commodities may lead to opportunities for improving EUDR compliance. In the case of crops which tend to be grown in full sun on uniform fields it may not only be possible to more reliably assess deforestation, but even potentially leveraged machine learning to identify plot boundaries and thus reduce the time and costs associated with boundary data collection. Other factors that could influence deforestation detection and associated compliance efforts include: the extent of mature forests; satellite imagery coverage; crop phenologies and ability to detect from satellite imagery; agricultural practices; proximity to urban development. Ultimately, the unique considerations for each country and commodity should be carefully considered when adapting generalized strategies for EUDR compliance.

# 5. Conclusion

This study provides an assessment of the practical challenges, limitations, and opportunities associated with implementing compliance solutions for the EUDR at the plot level. By integrating benchmark-quality geospatial data, multiple deforestation-detection approaches, very high-resolution imagery, drone-based validation, and a nationally representative socioeconomic survey of Honduran coffee farmers, the research establishes a baseline for evaluating both technical performance and real-world implications of emerging compliance solutions.

Across all components of the analysis, several themes emerge. First, boundary precision—while often assumed to be a critical constraint—has limited influence on deforestation detection relative to other sources of variation. Most geometric perturbations intended to model real world sources of error had limited impact on deforestation classifications, with only unrealistically large plot buffer scenarios being a notable exception. This finding suggests that low-cost, lower-precision data collection equipment is suitable for work related to deforestation detection, and that investments in extremely high-precision plot boundary collection may have diminishing returns relative to other aspects of compliance workflow design.

Second, deforestation detection itself remains the main driver of disagreement across providers. No single plot was identified as deforested by all six providers, and other levels of agreement on positive detections was generally low. Coarser-resolution imagery tends to increase sensitivity but at the cost of false positives, while finer-resolution imagery reduces error but may miss marginal or ambiguous cases. The distinction between tree loss and EUDR-defined deforestation further complicates assessments, particularly in shade-grown coffee systems where canopy dynamics are complex and sometimes indistinguishable from routine farm management. Limited temporal coverage of high-resolution imagery, especially around the regulatory cutoff date, also restricts certainty about compliance for some plots.

Third, socioeconomic patterns underscore the importance of designing compliance systems that are both technically sound and inclusive. While deforestation rates across the overall sample were low, farmers demonstrated limited awareness of the EUDR, and alignment between farmer-reported tree removal, provider classifications, and expert image interpretation was often weak. Discrepancies in self-reported land size, as well as systematic differences between EAI and non-EAI farmers, highlight potential biases that decision makers must consider if compliance responsibilities are to be distributed equitably. The results also reinforce the need for validation procedures, capacity building, and clear communication channels to ensure that smallholders—who are least equipped to navigate complex data requirements—are not disproportionately exposed to compliance risks.

Overall, the study confirms that while modern deforestation detection tools are powerful, they are not infallible. Effective EUDR implementation will require calibrated tolerance for uncertainty, multi-layered validation (including targeted use of high-resolution imagery and field verification), and careful alignment of provider methodologies with both regulatory expectations and local agronomic realities. The findings point to a critical opportunity: compliance systems that balance detection accuracy, operational feasibility, and farmer inclusion can reduce administrative burden while safeguarding livelihoods and improving confidence in supply-chain due diligence.

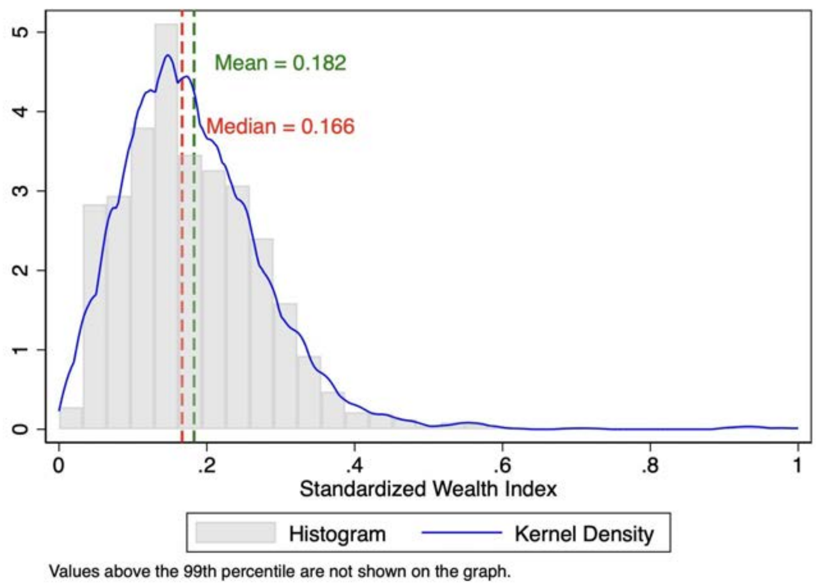
Looking ahead, the insights gained from the study in Honduras offer a foundation for scaling compliance frameworks in additional geographies and for other commodities, where deforestation patterns and operational considerations may differ. The parallel work in Ethiopia and the potential application to other sectors underscore the broader relevance of these findings. As the EUDR matures, continued learning, cross-provider calibration, transparent documentation, and adaptive system design will be essential for ensuring that regulatory objectives are met without unintended adverse impacts on smallholders and environmentally sustainable production systems.

# 6. Appendices

## A1. Asset Wealth Index

With reference to the wealth status, the assets listed in the Demographic Health Survey for Honduras (2011-2012) have been used as a proxy for wealth. We register a low asset wealth level for most of the sample, on average equal to 0.182, Figure A1.

**Figure A1. Asset Wealth Index**




We register no significant difference between the EAI and the non-EAI group in terms of asset wealth (Table A1), but males are slightly wealthier than female respondents (Table A2).

**Table A1. Asset Wealth Quintiles by EAI/non-EAI**

| | EAI | Non-EAI | Total | T-test |
|---|---|---|---|---|
| Wealth index | 0.1812 | 0.184 | 0.1827 | 0.5936 |
| Poorest quintile N=301 | 0.0684 | 0.0681 | 0.0682 | |
| Fourth N=277 | 0.1260 | 0.1276 | 0.1267 | |
| Third N=291 | 0.1696 | 0.1697 | 0.1696 | |
| Second N=287 | 0.2230 | 0.2198 | 0.2211 | |
| Richest quintile N=288 | 0.3263 | 0.3365 | 0.3310 | |

**Table A2. Asset Wealth Quintiles by Sex**

| | Female | Male | Total | T-test |
|---|---|---|---|---|
| Wealth index | 0.1719 | 0.1857 | 0.1827 | 0.0333 |
| Poorest | 0.0711 | 0.0673 | 0.0682 | |
| Fourth | 0.1268 | 0.1268 | 0.1268 | |
| Third | 0.1683 | 0.1700 | 0.1697 | |
| Second | 0.2187 | 0.2218 | 0.2212 | |
| Richest | 0.3307 | 0.3311 | 0.3311 | |

## A2. Resilience and Shocks

There were 44.53% (643/1444) of households that faced at least one shock since 2021 (EUDR cutoff date: 31/12/2020), Figure A2. The most common shocks reported were:

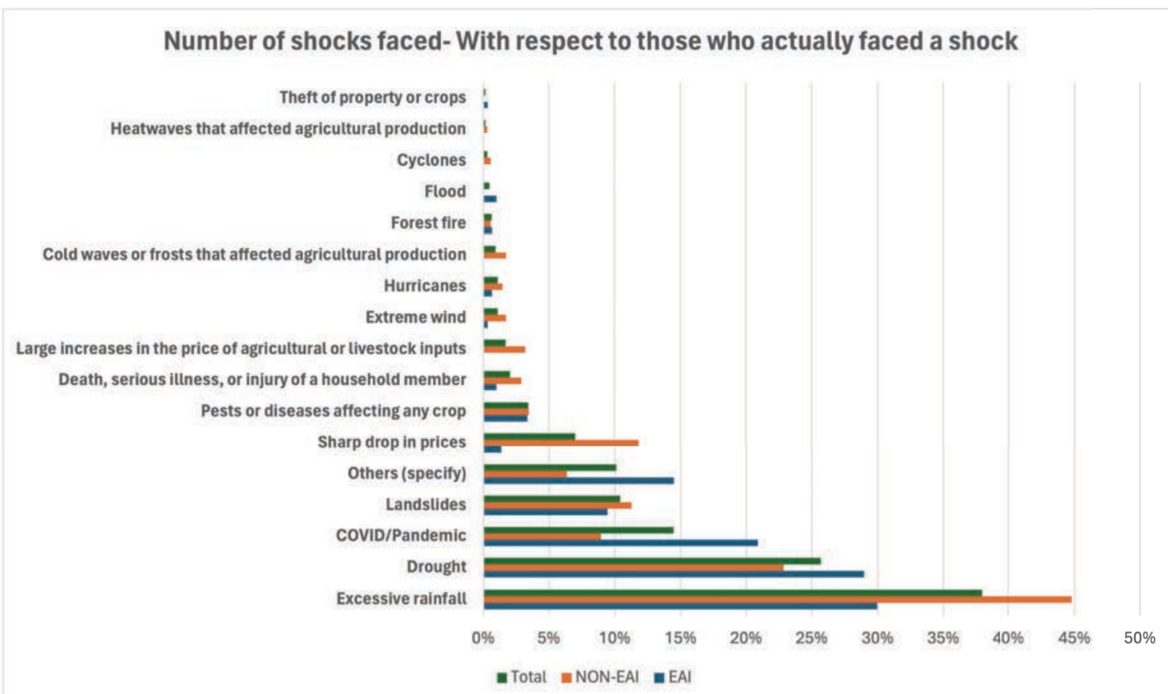
1. Excessive rains (37.95%, 244/643)
2. Droughts (25.66%, 165/643)

3. COVID/Pandemics (14.46%, 93/643)
4. Landslides (10.42%, 67/643)

On average, households faced 1.17 shocks (considering those who face any shock, and it would be 0.5235 for the complete sample) shocks since 2021 with excessive rains (37.53%) having the highest average frequency of 4.2 times. The average severity of shocks was 2.92 in a scale between 1 (less intense with almost no impact) to 5 (impact stronger than ever) and the average recovery ability was 2.88 in a scale between 1 (not affected significatively) and 5 (did not recover at all).

We found a significant difference between the EAI and the non EAI with the Non-EAI group facing slightly more shocks than the EAI group (p-value= 0.0291), with higher severity (p-value 0.000), but showing a higher recovery ability (Figure A2). We found no difference between the male and female in the number of shocks faced (p-value=0.8460), in mean shock severity (p = 0.5611), and in the recovery ability (p = 0.1015).

**Figure A2. Number of shocks faced (with respect to those who actually faced a shock)**



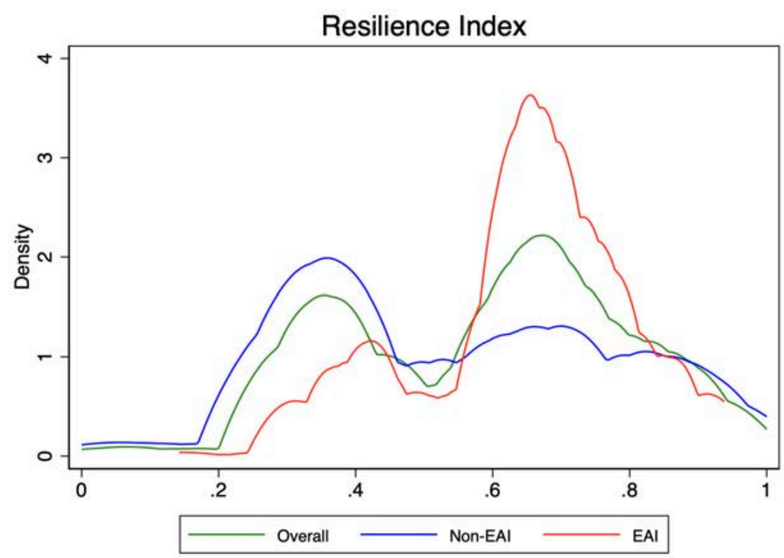

The average standardized resilience index (based on IFAD Ability to Recover Index[15]) for those who faced a shock was 0.5881 which indicates a moderate level of resilience on a scale

[15] The Resilience Ability to Recover Index is a resilience measure adopted by IFAD (2015). The Ability to Recover Index is easily measured through a self-assessment of a farmer's perceived ability to recover from shocks. The Ability

between 0 (no resilience) and 1 (fully resilient). However, the bimodal distribution of the resilience index shows that farmers are clearly divided in two groups, the ones with high resilience, with a peak at around 0.637, and the one with low resilience with a peak at around 0.315. The non-EAI group seems to be less resilient than the EAI group (p-value = 0.0000) and men are as much resilient as women (p-value = 0.1111) (Figure A3). Further, the plot of the distribution clearly shows that the majority of the EAI group belongs to the second pick of the distribution, the one with higher resilience.

Households implemented different coping strategies to shocks, mostly detrimental coping strategies such as the use of savings (60%) and reduction of food consumption (18.5%) together with the reduction of non-essential goods (28.5%).

**Figure A3. Resilience Index**




to Recover (ATR) index is the mean value of respondents' responses across all shocks experienced. The incidence of experience of each shock is a variable equal to one if the shock was experienced, and zero otherwise. To ensure comparability between recovery ability of households with different exposure to shocks, IFAD computes the Corrected Ability to Recover Index (ATR corrected). In practice IFAD, first computes the Shock Exposure that is a weighted average of the incidence of experience of each shock (a variable equal to one if it was experienced and zero otherwise), multiplied by the perceived severity of the shock. Then, it computes the Shock Exposure Corrected to create a measure of the ability to recover that assumes that households' perceptions of shock exposure are the same and thus are comparable across them. Finally, using the calculated values of ATR and the estimated coefficient, the corrected Ability to Recover index is calculated.

Sources: https://www.ifad.org/documents/38714170/40193941/htdn_climate_resilience.pdf/fd0b42b0-3fc1-41e2-bd45-c66506fa5004
https://www.ifad.org/documents/38714170/39318582/Measuring+IFAD%E2%80%99s+impact.pdf/36c251f1-854e-42de-8990-773728abe1f7?t=1540911311000

## A3. Coffee Trees

On average farmers maintain 13,763 coffee trees in the total coffee area (Figure A4). This corresponds to 4756 trees per hectare (Table A2). In the random plot farmers have 4989 trees on average, which represents 36% of the total number of coffee trees, and 4515.637 coffee trees per hectare (Table A3).

**Figure A4. Distribution of coffee trees in the total coffee area**

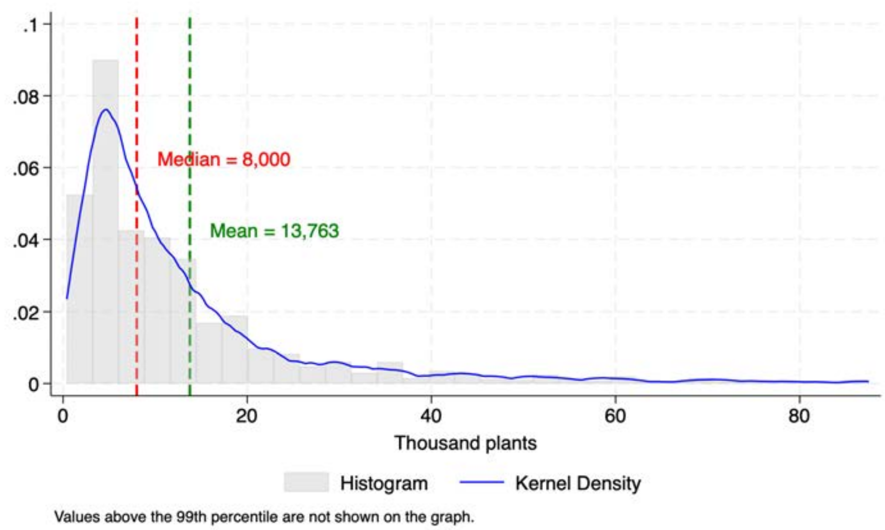



**Table A3. Coffee trees by EAI/Non-EAI**

| | EAI | Non-EAI | Total | T-test |
|---|---|---|---|---|
| Trees in total coffee land | 14335 | 13234 | 13763 | 0.2189 |
| Trees per hectare (all coffee land) | 4779 | 4735 | 4756 | 0.2777 |
| Trees in random plot land | 5513 | 4505 | 4989 | 0.0001 |
| Trees per hectare (random plot) | 4505 | 4525 | 4515 | 0.8286 |

In the random plot, most coffee trees are planted at intervals of 1.5 by 1.5 meters (58.3%) , but 18% of farmers use a lower distance than the recommended one corresponding to 0.8 meters, Table A4.

**Table A4. Coffee trees density, by EAI/Non-EAI (random plot)**

| Average planting distance between each plant | EAI % | Non-EAI % | Total % | T-test |
|---|---|---|---|---|
| 2 meters | 10.23 | 17.47 | 13.99 | 0.0001 |
| 1.5 meters | 63.26 | 53.73 | 58.31 | 0.0002 |
| 0.8 meters | 15.56 | 20 | 17.87 | 0.0278 |
| Other | 10.95 | 8.8 | 9.83 | 0.1705 |

The same pattern is confirmed looking at the tree density by sex and by department. Trees are mostly cultivated in a gentle slope, but 21% of the farmers reported having trees in steep land. In the random plot, around 91.8% of coffee trees are currently in production, while the remainder have been replanted (3%), have recently been replaced (2.8) or have been added (2.2%), as described in Table A5.

**Table A5. Productive coffee trees (random plot)**

| Percentage of coffee trees | EAI | Non-EAI | Total |
|---|---|---|---|
| Productive Trees | 92.1% | 91.6% | 91.8% |
| Replanted Trees | 3.8% | 2.4% | 3.0% |
| Replaced Trees | 2.1% | 3.5% | 2.8% |
| New Trees | 2.0% | 2.5% | 2.3% |

In the random plot, on the one hand, 87.5% of total coffee trees are in the most productive range (3-15 years) as shown in Table A6. On the other hand, old coffee trees (30 years or older) represent only 0.2% of the total coffee trees. These percentages are statistically the same when considering EAI versus non-EAI. This also holds when considering sex. The most common type of pruning on the random plot is "coppicing, root or top pruning" (40%), followed by sanitary pruning (29.6%) and light pruning (23.4%).

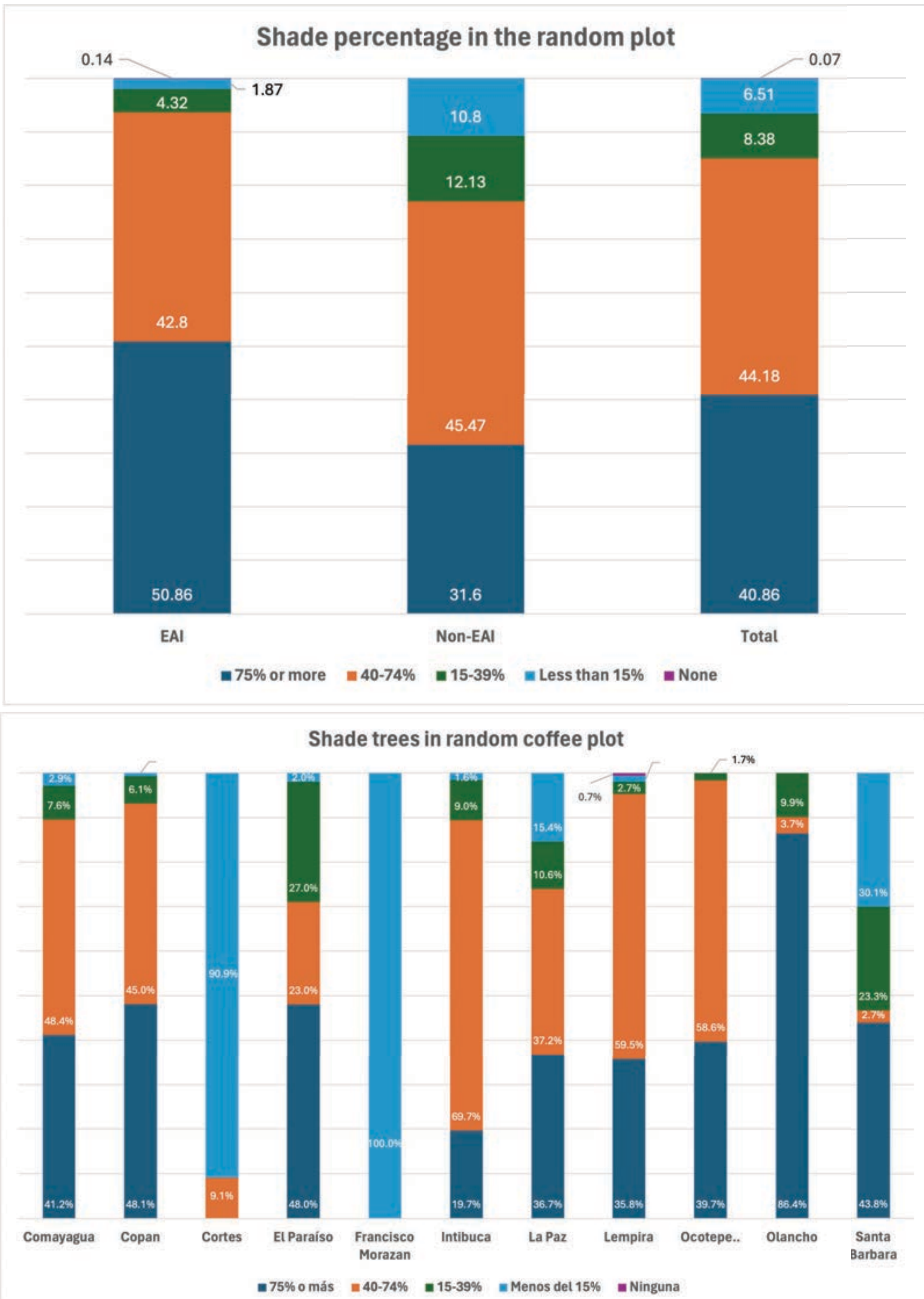
**Table A6. Coffee trees age (random plot)**

| Percentage of coffee trees by their age range | EAI % | Non-EAI % | Total % |
|---|---|---|---|
| 0 - 2 | 3.8 | 4.0 | 3.9 |
| 3 - 9 | 50.3 | 50.0 | 50.1 |
| 10 - 15 | 38.0 | 36.8 | 37.4 |
| 16 - 30 | 7.6 | 8.9 | 8.3 |
| Over 30 | 0.2 | 0.2 | 0.2 |

In the selected random plot, shade -grown coffee is a widespread practice in Honduras. Approximately 40% of the farmers declared to have over 75% of the shaded coffee land, while 44% had between 40 and 75%, while the remaining 8% declared between 15-39% and 6% less than 15% (see the top chart of Figure A5 below).

Interestingly there are two departments in which shade-grown coffee is not appearing to be a common practice, this department is San Francisco Morazan and Cortes which are also the departments that are hosting the smallest producers (see the bottom chart of Figure A5 below).

**Figure A5. Percentage of coffee shaded land by EAI and Non-EAI and by department (random plot)**



## A4. Intercropping

Intercropping is a common agricultural practice among coffee producers in Honduras. According to the data, approximately 44% of the producers reported that 50% or more of their coffee-growing land is intercropped, while around 41% have between 25% and 49% of their land under intercropping practices. A smaller portion, about 9.5%, reported intercropping in only 10–24% of their land, and roughly 6% practiced intercropping in less than 10% of their area (Figure A6) In line with patterns seen for other sustainable practices, there are departments such as Francisco Morazán and Cortés where intercropping is hardly practiced. In Cortés, for instance, 91% of producers report less than 10% intercropping, and in Francisco Morazán, 89% fall into that same category, Figure A7. These two departments are also characterized by a high concentration of very small-scale producers, which may explain the limited use of this practice.

**Figure A6. Intercropping by EAI (random plot)**

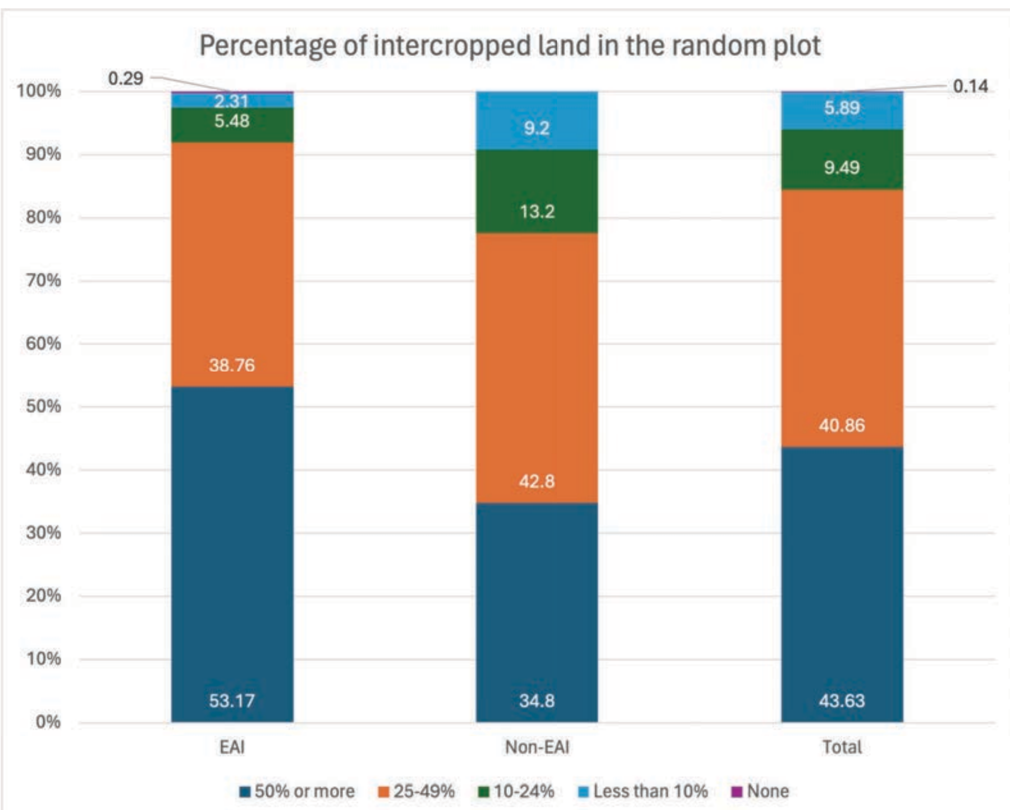
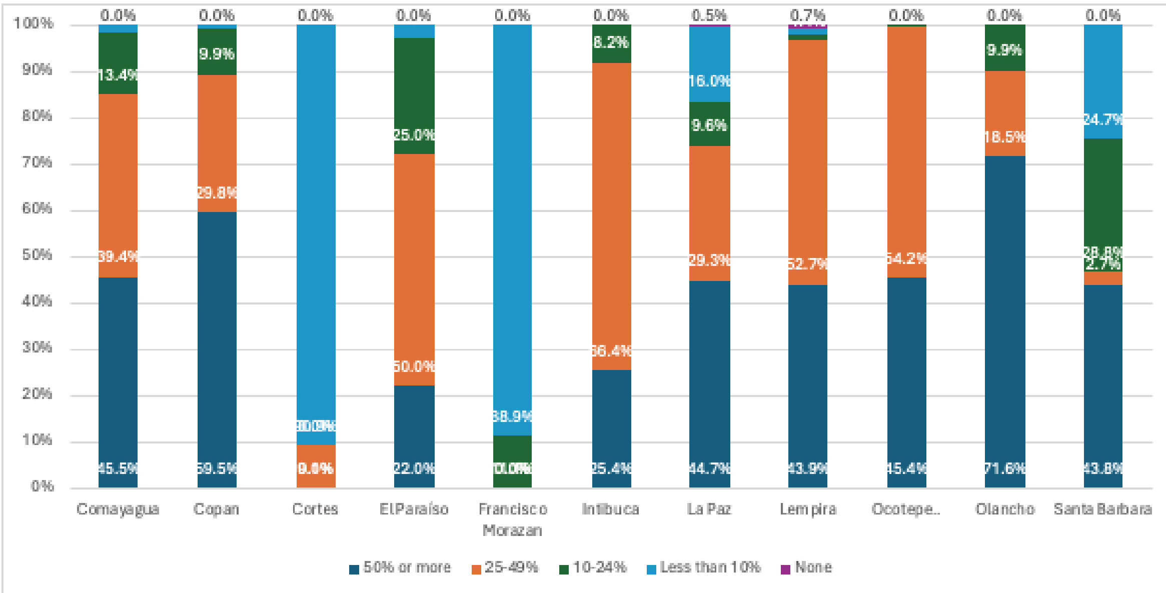


**Figure A7. Intercropping by department (random plot)**




## A5. Fertilizer Use and Agriculture Practices

The use of organic fertilizer is a widespread practice both in the EAI (72.8%) and in the Non-EAI (97.4%), but the use of chemical fertilizers is common especially between the EAI (52.1% versus 18.6%), Table A7.

**Table A7. Soil fertility management practices**

| | EAI | Non-EAI | Total | T-test |
|---|---|---|---|---|
| Organic fertilizer use | 72.8% | 97.4% | 85.6% | 0.0000 |
| Chemical fertilizer use | 52.1% | 18.6% | 34.7% | 0.0000 |
| Mulching use | 22.5% | 44.4% | 33.9% | 0.0000 |
| Pesticide use | 21.8% | 26.9% | 24.4% | 0.0222 |
| Nitrogen fixing use | 53.9% | 60.4% | 57.3% | 0.0125 |

For those who use organic or chemical fertilizers, the majority follows their knowledge of the nutrient coffee needs both in the EAI and the Non-EAI (41.6%), but 26% of the Non-EAI and 29.4% of the EAI follow the professional advice or the recommendation of the region.

**Table A8. Good agricultural practices**

| How was the appropriate amount of fertilizer determined? | EAI | Non-EAI | Total | T-test |
|---|---|---|---|---|
| Applied as much fertilizer as possible, even if it wasn't enough | 30.5% | 30.4% | 30.4% | 0.9459 |
| Applied fertilizer based on their knowledge of the nutrients coffee needs | 40.1% | 43.1% | 41.6% | 0.2642 |
| Applied fertilizer based on general recommendations for the region or for coffee in general | 11.6% | 21.6% | 16.8% | 0.0000 |
| Applied fertilizer based on a professional assessment of the soil and the coffee plantation's needs | 17.8% | 4.7% | 11.0% | 0.0000 |
| Other, specify | 0.0% | 0.3% | 0.2% | 0.1743 |

## A6. Coffee Production

### A6.1 Production per Hectare

In the sample we have 1444 farmers. The ones reporting coffee production in all productive land are 94% of the sample (N= 1357).[16] Considering all productive land, the average kilograms of cherry coffee produced per hectare is 4404 with a median of 4251 Kg per hectare (see Figure A8, top). Focusing on the random plot, the farmers reporting production in the random plot are 93% of the sample (N= 1350).[17] The production of the random plot

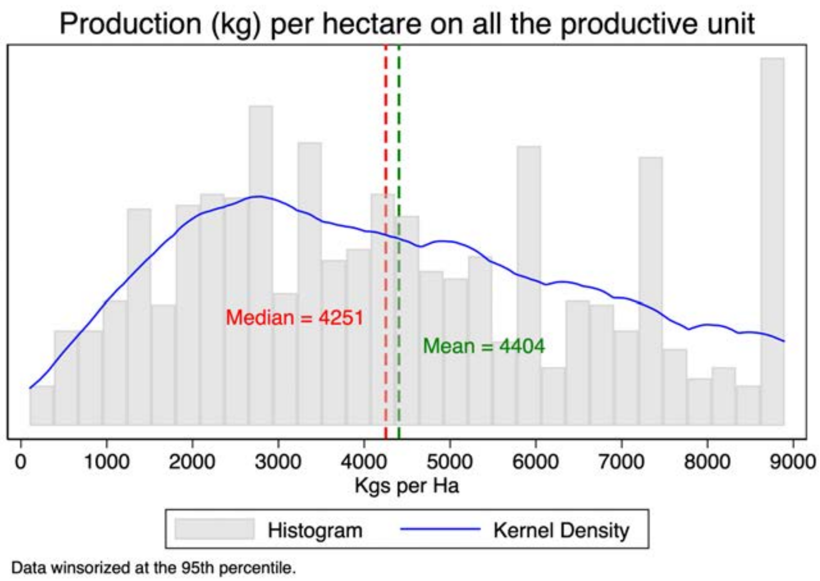
---

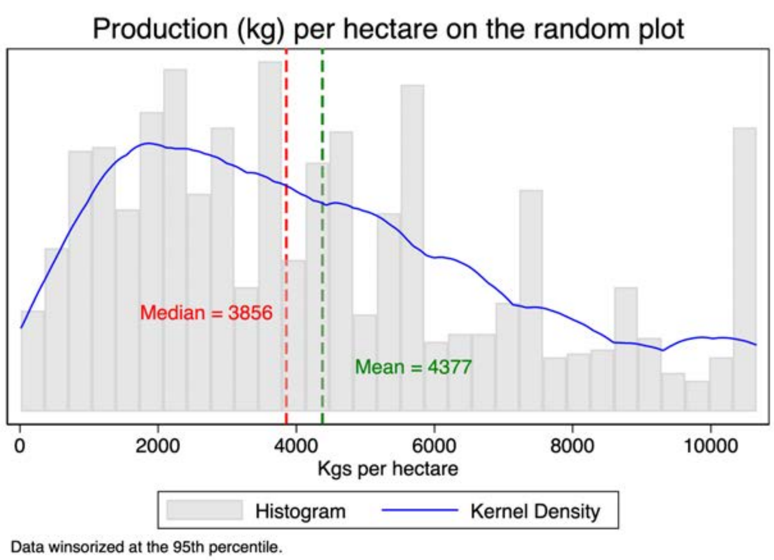
[16] There are 1,444 observations with available data for area and number of trees. The only variable that contains zeros or missing values is production for which there are 47 having zero production and 40 cases have missing production data.

[17] Production per productive coffee plant is missing in 99 cases out of 1,444. A closer look at these 99 cases shows different situations. There are 26 cases where farmers report no productive trees and no production in the random plot. Therefore, we can consider these farmers to have zero production due to the unproductive trees. In 68 cases, there is a positive share of productive trees, but no production is reported in the random plot, so we consider these farmers with missing production. In the remaining 5 cases, production is reported despite indicating zero productive trees, so we consider that these farmers made a mistake in reporting the productive trees, but we cannot compute the share of productive trees for them.

represents 90% of the total production per hectare. In particular, the average kilograms of fresh cherry produced per hectare is 4680.8 kg with a median of 3856.1 Kg per hectare (see Figure A8, bottom).

**Figure A8. Distribution of productivity Kg fresh cherry**



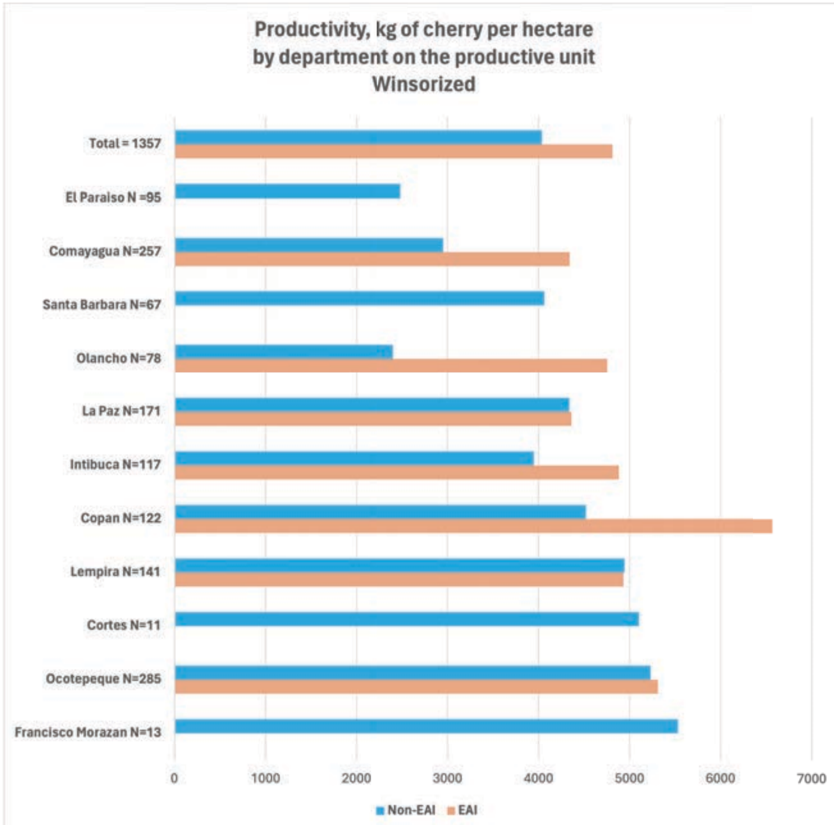

The production per hectare does not significantly differ by sex: males show 4437 Kg/ha and 4407kg/ha in all productive land and in the random plot, respectively, while females 4286 Kg/ha and 4296 Kg/ha in all productive land and in the random plot, respectively. The EAI (4811 kg/ha) has significatively higher yields than the non-EAI (4036 kg/ha) with a p-value equal to 0.000. The same holds for the random plot: EAI 4808 and non-EAI 3995 with a p-value equal to 0.000.

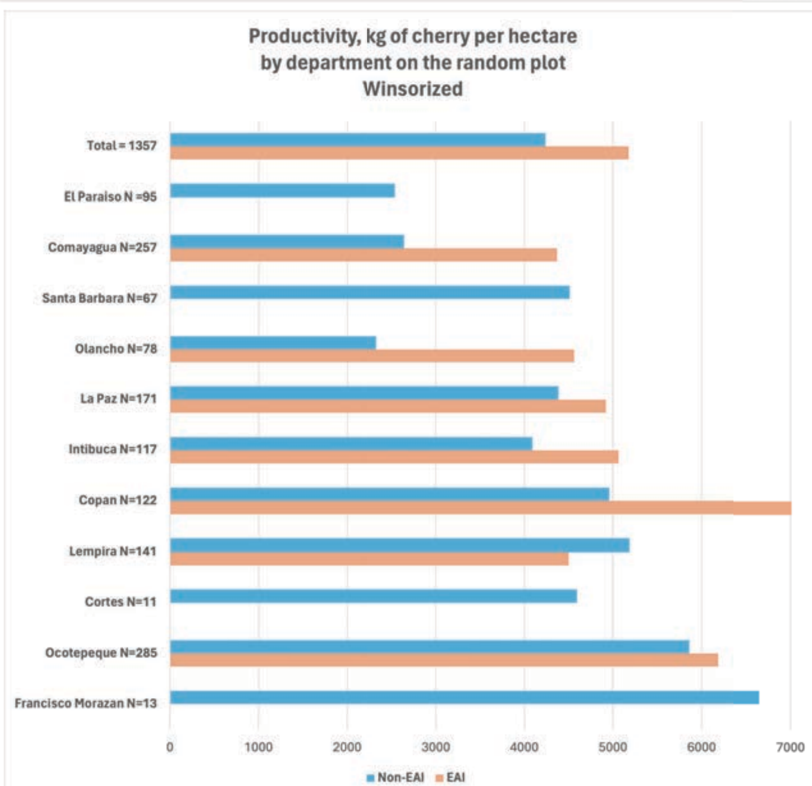
The yield (i.e. Kg of fresh cherry in all productive unit) varies by region, Francisco Morazán (5532 Kg/ha), Ocotepeque (5288 Kg/ha) and Cortes (5100 Kg/ha) lead the top three positions on production per hectare with over 5000 Kg/ha, while Comayagua (3788 Kg/ha) and El Paraíso (2481 Kg/ha) are the least productive regions. Interestingly, two of the departments with higher productivity like Cortes and Francisco Morazan are the ones with smaller farm size (see Figure A9 below).

Figure A9 reports values for Kg fresh cherry per hectare in all productive units by departments, and by EAI and non-EAI. On average, the Kg fresh cherry per hectare in 2023/2024 (4447.8) look lower than the ones recorded by IHCAFE for 2022/2023 (5812.2) and this decrease in productivity is in line with USDA (2024) that registers a contraction of 24% in productivity between the two seasons. In this case, the difference between the overall average and the IHCAFE record is a reduction of 30% with respect to IHCAFE ).[18]

18 https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=Coffee%20Annual_Tegucigalpa_Honduras_HO2024-0002.pdf

**Figure A9. Distribution of Kg fresh cherry per hectares by department**



### A6.2 Production per Coffee Plant

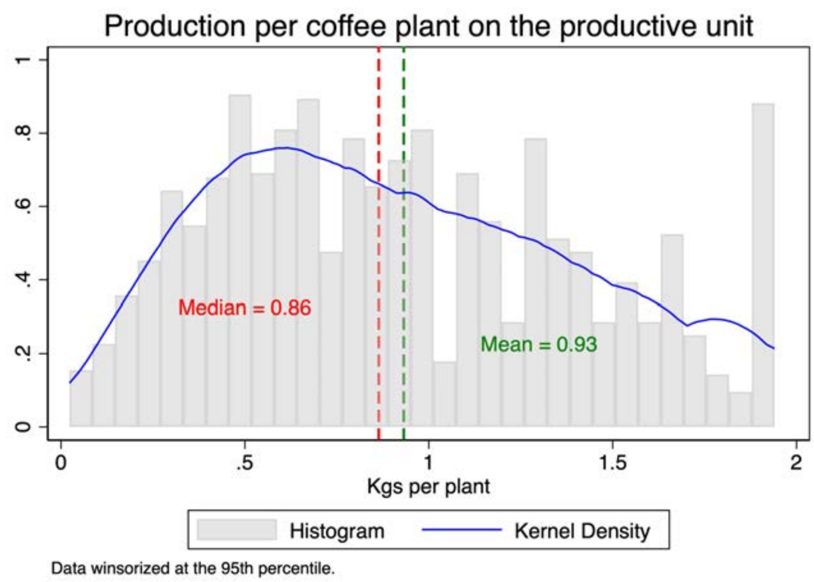
If we consider the production per coffee plant in all productive units, the distribution looks right skewed and on average farmers achieve a productivity rate of 0.93 Kg of fresh cherries per coffee tree, considering all the plots (see the top chart of Figure A10 below).[19] Further, in the random plot, the coffee distribution per plant shows a mean of 0.99 kg with a median of 0.91 kg (see the bottom chart of Figure A10 below).[20]

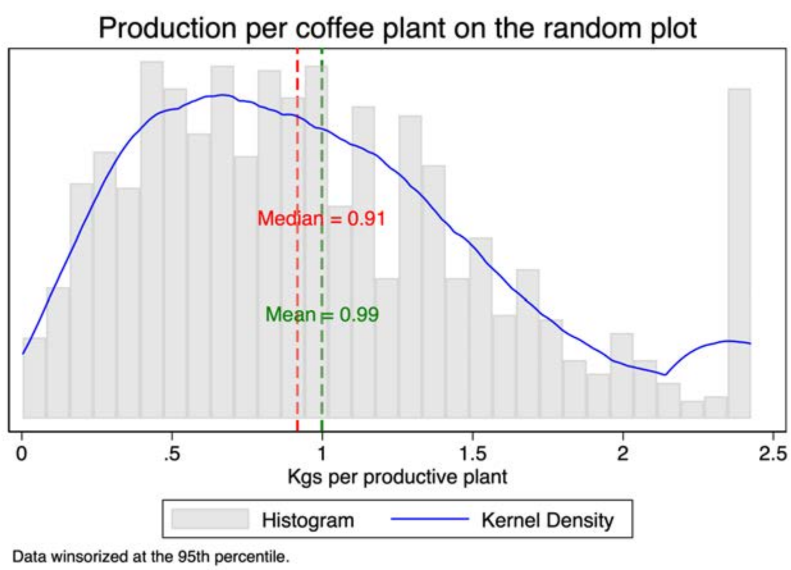
Both in all productive units and in the random plot, the EAI shows higher production than the non-EAI, with 1.01 Kg of fresh cherries per plant for the EAI (1.19 in case of the random plot) and 0.85 (0.99 in case of the random plot) for the non-EAI. We did not notice any difference between sex both in the case of the full productive unit (0.93 for males and 0.91 for females) and in the case of only the random plot (male 1.09 for males and 1.05 for females).

[19] A productive coffee plant is one that has not been resown, replanted, or recently added (productive plant is usually above than 2 years). Production per productive coffee plant is missing for the overall productive unit since we did not ask this question.

[20] In the random plot, the coffee distribution per productive plant shows a mean of 1.08 kg with a median of 0.994 kg.

**Figure A10. Distribution of production per coffee plant (kg fresh cherry per plant)**




### A6.3 Determinants of Productivity

A simple ordinary least squares model (OLS) was employed to assess some determinants of productivity (Table A9). Model A estimates the average coffee production per hectare (Kg Fresh Cherries per hectare) with clustered standard errors at municipality level and winsorized data. Model B estimates the same equation but simply changes the dependent variable into Kg Fresh Cherries per plant. Model C uses quantile regression to re-estimate Model B with winsorized data. Variables used as controls in the analysis are departments, farmer’s characteristics such as, sex and age, wealth indicators, number of shocks faced in the last 5 years, coffee area, good agricultural practices, certification, and EAI membership. Factors that matter the most for higher productivity seem to be wealth, organic fertilizer use, participation in a certification program and being in the EAI group.

**Table A9. Yield and its determinant**

| | A<br>OLS<br>y=Kg fresh cherry per hectare | B<br>OLS<br>y=Kg Fresh cherry per plant | C<br>Quantile Regression<br>y=Kg fresh cherry per plant |
|---|---|---|---|
| Sex = Male | 93.52 | .0148 | .0300 |
| | (141.5) | (.03) | (.0402) |
| Age | -8.994* | -.00180* | -.00240** |
| | (4.514) | (.001) | (.00112) |
| Number of HH members | 57.07 | .0112 | .0127 |
| | (42.88) | (.00908) | (.0127) |
| Wealth index | 2762.6** | .752*** | 1.204*** |
| | (1088) | (.255) | (.291) |
| Number of shocks faced since January 2021 | -121.1 | -.0362** | -.0436** |
| | (84.85) | (.0172) | (.0221) |
| Total coffee area, hectares | -10.49 | -.000732 | -.00402 |
| | (17.85) | (.00427) | (.00685) |
| Use of chemical fertilizer | 383.8** | .0741** | .105** |
| | (166.8) | (.0351) | (.0528) |
| Use of organic fertilizer | 560.7*** | .110*** | .103** |
| | (161.4) | (.0339) | (.0454) |
| Use of pesticides | -120.0 | -.0326 | -.0623 |
| | (158.2 ) | (.0347) | (.0506) |
| Certification | 501.3 | .0939 | .0877 |

| | | | |
|---|---|---|---|
| | (301.4) | (.066) | (.0917) |
| Non-EAI=1 | -456.3** | -0.101*** | -.134** |
| | (181.6) | (.0349) | (.0545) |
| Department Dummies | YES | YES | YES |
| Cluster S.E. | YES | YES | YES |
| N | 1357 | 1357 | 1357 |
| R2 | 0.15 | 0.13 | 0.12 |

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

## A7. Survey Indicators of Potential Deforestation

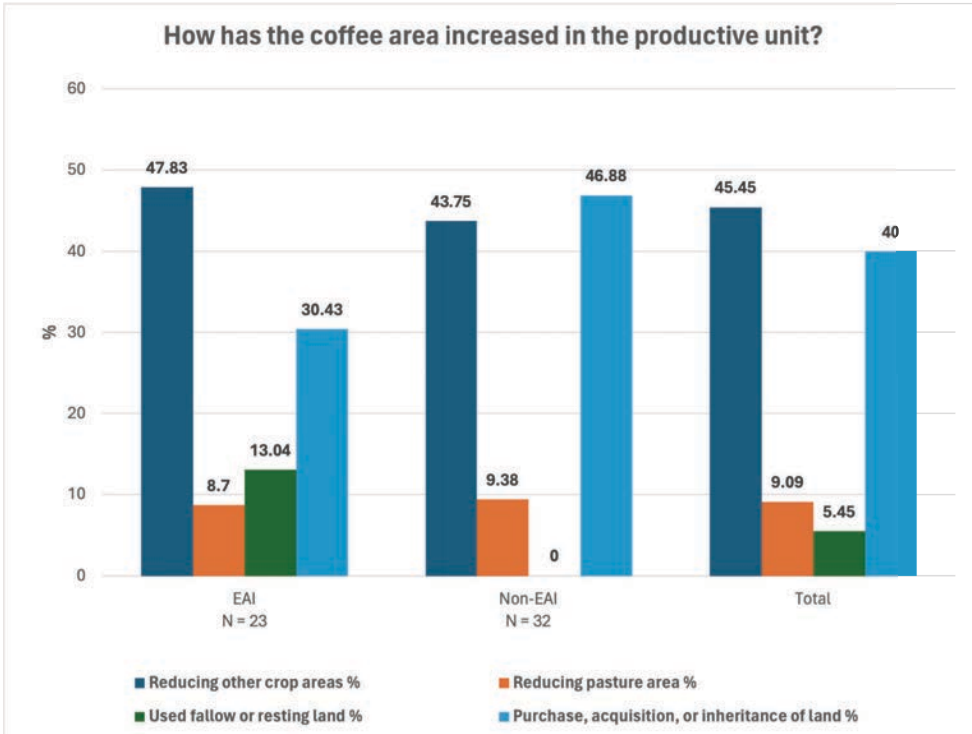
We also have asked farmers whether they have changed the land use both in random plots and in all productive land since 2021. Most of them (95.59%) declared to have not changed the land use both looking at all productive units and at the random plot, Figure A11.[21] Looking at all productive units, the ones answering to have increased it (3.91% on average, 3.4% EAI and 4.4% Non EAI) reported an average increase of 1.15 hectares (1.01 EAI and 1.25 non-EAI), and the ones answering they decreased it reported an average decrease of 1.12 hectares (0.98 EAI and 1.24 non-EAI). Around 0.14% of Non-EAI reported to not know the answer to this question. Looking at the random plot, the ones answering to have increased it (3% on average, 2% EAI and 4 % Non- EAI) reported an average increase of 1.20 hectares (0.90 EAI and 1.33 non-EAI), and the ones answering they decreased it (0.84% on average, 0.59% EAI and 1.09% non-EAI) reported an average decrease of 1.07 hectares (1.04 EAI and 1.08 non-EAI). Around 0.29% of EAI farmers declared to not know the answer for the random plot.

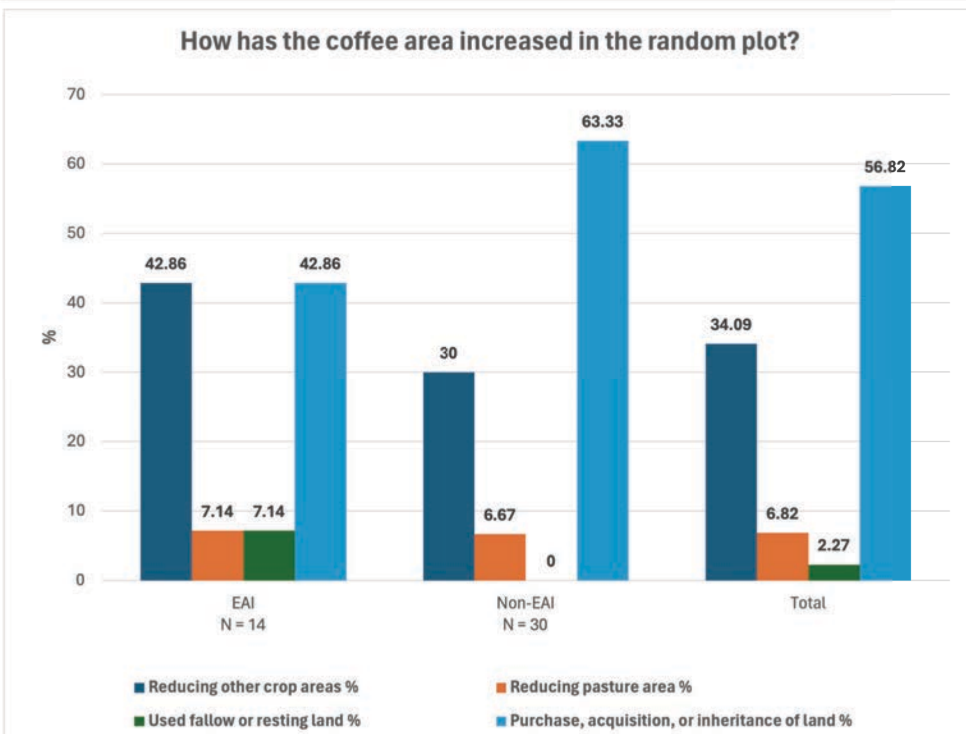
[21] In the overall productive unit, the area was mainly changed through inheritance or successions (54%) and purchased without formal titles (29.17).

**Figure A11. Land use change**


Out of the 3.91% farmers (N=95) who increased their coffee area in the productive unit, 45.45% (N=25) reduced the area of other crops, 40% (N=22) bought, acquired, or inherited the land, 5.45% (N=3) reduced fallow land, and 9.09% (N=5) reduced grass areas, Figure A12 left. Therefore, there were no signals of deforestation. Similar patterns are observed for the coffee area in the random plot, Figure A12 right.

**Figure A12. How coffee area has been increased**

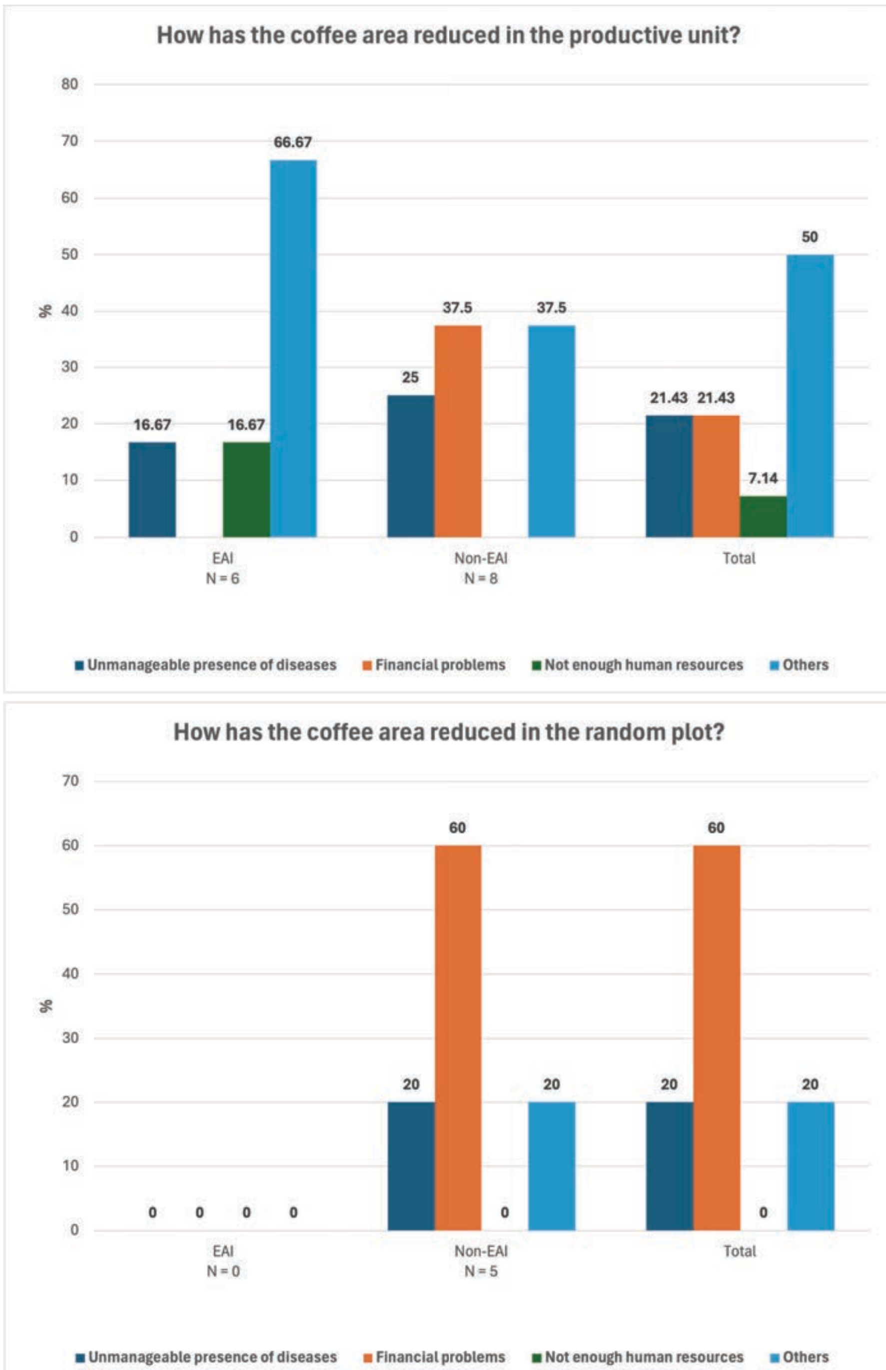



In the analysis of the reduction of the coffee area both in the random plot (N=12) and in the overall productive unit (N=14), the main reasons reported by the farmers were related to

"Other reasons" than the ones listed. The other reasons listed for the random plot were left as inheritance (N=3), landslides (N=1), and left the business (N=1); similar reasons have been registered for the overall productive unit: left as inheritance (N=3), due to landslides (N=2) , difficulty in access land (N=1) and left the business (N=1).

**Figure A13. How coffee area has been reduced**



Further, we asked farmers whether they have cut or burned coffee plants due to pest disease or whether pests and disease caused losses in shade coffee trees in the random plot, Table A10 and Table A11. In both cases we observe that most of the farmers did not face any problems related to pests and disease both for coffee (92.94%) and for shade trees (92.73%). In both cases there is a 6.65% and 6.72% who faced those issues. Pests and disease cause the loss of around 23% of the coffee trees or shade trees for the farmers who faced the issue.

**Table A10. Cut or burn due to pest and disease (random plot)**

| **Do you cut and burn coffee plants that have had severe pest infestations on the random plot?** | **EAI** | **Non-EAI** | **Total** |
|---|---|---|---|
| No | 88 | 97.07 | 92.94 |
| Yes | 11.24 | 2.4 | 6.65 |
| I do not know | 0.29 | 0.53 | 0.42 |
| Share of plants cut or burned due to severe pests on the random plot since January 2021 | 26.3 | 9.4 | 23.1 |

***Table A11. Loss in shade trees due to pests and disease***

| **Did pests and diseases cause the loss of shade trees, fruit trees, timber trees, etc.?** | **EAI** | **Non-EAI** | **Total** |
|---|---|---|---|
| No | 92 | 93.6 | 92.73 |
| Yes | 8.07 | 5.47 | 6.72 |
| I do not know | 0.14 | 0.93 | 0.55 |
| Share of shade, fruit, timber trees, etc. (other than coffee) lost due to pests or diseases on the random plot since January 2021 | 17.1 | 32.0 | 23.5 |

## A8. Self-reported Land Size and Polygon-level Data

We run an OLS estimation where our dependent variable is represented by a plot size specific difference between the GPS and the self-reported measure. The controls used in this regression include a set of characteristics of the household head (age, education, and gender) to proxy respondents' characteristics that are deemed to influence the ability to accurately report land size. We also include plot size, and its squared term, to test whether the relationship observed in the descriptive analysis holds in a multivariate framework, and a dummy reflecting whether the self-reported land variable is a round number, to capture the impact of rounding. Topography will also affect land estimates by farmers, as steep plots may be more likely to be subject to measurement error, therefore we included it in the estimation. The results of the estimation of the model are reported in Table A12.

The data show a positive association between plot size and the difference between GPS and self-reported land measurements in levels. This discrepancy increases with plot size: farmers with larger plots tend to under-report, while small farms tend to over-state the size of their landholdings.

**Table A12. Self-reported land size versus polygon level data**

| **Variable** | Coefficient | Std. Error |
|---|---|---|
| Plot size (GPS) | .248*** | .046 |
| Plot size (GPS) squared | .015** | .006 |
| Total farm area | -.046*** | .005 |
| Dummy: Round in Self-Report | -.206*** | .048 |
| Number of coffee plots | .046** | .022 |
| Dummy: Plot is steep | -.101* | .058 |
| Head's gender (male) | .006 | .055 |
| Head's age | -.003* | .002 |
| Head's education level | -.034 | .024 |
| Dummy: Plot selection error | -3.077*** | .208 |

| | | |
|---|---|---|
| Constant | -.077 | |
| R-squared | .317 | |
| N | 1362 | |

* Significant at 10%; ** significant at 5%; *** significant at 1%