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Avoiding Access Inequity Due to classification errors in zero-deforestation value chains: Coffee and the European union deforestation regulation

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ABSTRACT

European Union's Regulation 2023/115, commonly known as the European Union Deforestation Regulation (EUDR), promises to be a watershed event in global deforestation governance. A significant example of the hardening of soft law, spurred by major corporations committing to zero-deforestation supply chains, the EUDR is also a substantial wager on the efficacy of satellite-based remote sensing technologies for effective global forest governance. As remote sensing becomes more deeply embedded into global environmental governance, it is necessary to pay attention to the possibility that misclassification errors - mistaking one type of land cover for another - could become institutional errors with real consequences for those targeted by these initiatives. If compliant producers were to be excluded from zero-deforestation markets due to uncertainties resulting from misclassification errors, this would raise questions about the initiative's access equity. To develop recommendations for a strategy for avoiding this eventuality, we examine how classification errors could shape the EUDR's effects in the coffee sector. Coffee, a commodity predominantly cultivated for export by smallholders under tree shade, faces heightened susceptibility to the legislation, given the European market's significant influence on global consumption. Using ground-truth points collected in coffee-growing regions in Ethiopia and Tanzania, combined with other open datasets, we assess the rate at which five global land cover datasets identify coffee production as forest, finding high rates of misclassification in some geographies, particularly for shade-grown and agroforestry cultivation. Then, following a systematic review of remote sensing studies designed to detect the presence of coffee, we use quantile regression analysis to identify strategies that could be used to reduce classification accuracy for coffee to unproblematic rates. Based on these assessments, we argue that, even in a hard case like coffee, access inequities due to misclassification errors could be mitigated substantially by starting with a global dataset and then building regional, commodity-specific datasets. We suggest that finding ways to compensate and include smallholders, cooperatives, and other producer groups in a project of building monitoring datasets as a public good may be an appropriate strategy for the EUDR and similar zero-deforestation initiatives.

1. Introduction

Recent estimates suggest agricultural activities account for 61% to 83% of tropical deforestation (Pendrill et al., 2022), while agricultural exports, including cattle products, generate between 35 % and 48 % of tropical deforestation-related emissions (Pendrill et al., 2019). Responding to growing evidence that agricultural commodity trade plays an important role in habitat loss and climate change (Pendrill et al., 2019; Berman et al., 2023, Lambin and Furumo, 2023), civil society organizations and, more recently, governments, have exerted

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pressure on firms to rid their supply chains of products sourced from recently deforested lands (Lambin and Furumo, 2023). The European Union's Regulation 2023/115, commonly known as the European Union Deforestation Regulation (EUDR), is probably the most significant contemporary example. Firms seeking compliance with this regulation must meticulously document that selected materials in their supply chains do not derive from lands deforested after December 31, 2020.

The EUDR is one of a raft of sustainability regulations attempting to address social and environmental conditions of production along supply chains – building on earlier experiences in the UK, France, Germany, Norway, and the Netherlands. It comes alongside other EU initiatives, such as the 2023 Corporate Sustainability Reporting Directive and the 2024 Corporate Sustainability Due Diligence Directive. While the EUDR was scheduled to be fully implemented at the end of 2024, on October 2, 2024 the European Commission proposed a twelve-month delay. Following trilogue negotiations between the Commission, Parliament, and Council, full implementation has been postponed to the end of December 2025 for large operators and traders and the end of June 2026 for micro and small enterprises.[1]

While the EUDR signals a commendable ambition, analyses of other analogous, albeit voluntary, zero-deforestation initiatives have identified several key challenges. Examples include the moratorium major buyers agreed on purchases of soy from recently deforested lands in Brazil and efforts by large firms like Nestlé to construct traceable, deforestation-free supply chains for oil palm products (Austin et al., 2021; Garrett et al., 2019; Grabs et al., 2021; Lambin and Furumo, 2023; Lyons-White et al., 2020). These programs grapple with the key issue of balancing "access equity" - the fair and equitable opportunity for all producers to participate in zero-deforestation markets (Grabs et al., 2021) - with strict enforcement. Zero-deforestation schemes heavily reliant on market exclusion as their primary enforcement mechanism risk disproportionately blocking less adaptive producers - such as smallholders - from zero-deforestation markets. Even if those producers might access those markets initially (Cammelli et al., 2022), they may be unable to overcome the substantial transaction costs required to take part in zero-deforestation supply chains (Grabs et al., 2021), leading to access inequity.

Previous work has identified substantial technical and equity issues involved in tracing deforestation-driving commodities to their source (Bager and Lambin, 2022; Carodenuto, 2019; Gardner et al., 2019; Parra-Paitan et al., 2023). However, within the realm of zero-deforestation initiatives, limited attention has been directed towards the challenges of combining satellite-based monitoring with deforestation governance, a practice that is central to the EUDR and other zero-deforestation mechanisms. In short, any planetary-scale system tracking deforestation will make mistakes. If buyers are incentivized to exclude producers from zero-deforestation markets because of the uncertainty and risk such mistakes will generate, then land-cover classification errors could raise access equity risks. Smallholders may be challenged to appeal such decisions or to make themselves properly visible, even when organized in cooperatives. Ironically, exclusion due to from erroneous classification could force producers to switch to end-markets less sensitive to deforestation concerns, thus undermining the underlying spirit of anti-deforestation initiatives and related incentives.

Erroneous exclusion resulting from the limits of satellite technology should be considered explicitly in the institutional design of supply-chain governance initiatives. With careful institutional design, the potential risks can be substantially mitigated relatively cheaply, but those risks must be acknowledged and addressed directly. To illustrate this point, we examine a particularly hard case for satellite-facilitated supply chain governance. Though zero-deforestation efforts, including recent EU legislation, target several agricultural commodities (in the case of the EUDR, cocoa, coffee, palm oil, soy, rubber, wood and beef), we focus on coffee.

While coffee plays a relatively small role in driving tropical deforestation in the aggregate (Pendrill et al., 2022), it is disproportionately grown in conservation-priority areas (Hoang et al., 2023; Lambin and Furumo, 2023), and anticipated growth in global demand is driving further expansion (Treanor and Saunders, 2021). Coffee is a promising case for the EUDR's anti-deforestation strategy for two key reasons. First, very large shares of coffee production are exported to international markets, rather than being consumed domestically (Hoang et al., 2023; Lambin and Furumo, 2023). Second, the EU constitutes nearly half of total global coffee imports (Santiago, 2022; Treanor and Saunders, 2021). As a result, European firms are highly active in some key areas, such as Vietnam's Central Highlands, where the expansion of coffee cultivation contributes to forest loss (Pham et al., 2020). Yet coffee is also a challenging case. Much coffee production is under shade or other agroforestry systems. While such systems can support biodiversity and carbon sequestration (Jha et al., 2014; Lugo-Pérez et al., 2023; Sun et al., 2023), remotely sensed mapps have more difficulty distinguishing them from forest cover, as compared to pasturelands or open-field crops (Kelley et al., 2018a, 2018b; Maskell et al., 2021). These intricate dynamics are further complicated by the fact that an estimated 12.5 million smallholder coffee farms (Rushton, 2019) produce the majority of exports (though Brazil is a notable exception) (Zhunusova et al., 2022). Smallholders and cooperatives often have trouble meeting traceability demands due to the need for both technical equipment (e.g. GPS or blockchain-enabled devices) and a clear understanding of often complex or ambiguous legislative and corporate requirements (Santiago, 2022). Furthermore, some smallholders may object to being mapped and traced due to unclear tenure arrangements or other issues that place them in a legal gray zone. Some commentators have already suggested the EUDR could reduce smallholder coffee exports, particularly in Africa (Angel and Kurniawati, 2023; Keane et al., 2024).

Taking coffee as a case upon which to build recommendations for avoiding access inequity due to misclassification issues in zero-deforestation efforts more broadly, we address two key research questions. First, are plausible short-term error rates in global land-cover monitoring sufficient to generate access equity risks for producers? Second, if so, what strategies might help mitigate these risks?

The rest of this article is structured as follows: first, we begin with an overview of EUDR, its reliance on remote-sensing technologies, and why classification errors might lead to access inequity under its envisioned governance system. Next, we provide information on the methods we used to assess misclassification risks in the coffee sector. After presenting evidence from this assessment of the technical frontier for identifying coffee production locations using remote sensing, we discuss the governance implications resulting from the technical constraints we identify and how these might apply more broadly.

2. The European Union Deforestation Regulation

EU Regulation 2023/1115 formally came into force on 9 June 2023. Operators and traders were originally given 18 months and small and medium enterprises 24 months to comply with its requirements (European Commission, 2022; Abnett and Spring, 2022). However, this schedule has now been postponed by one year. Part of a wider trend of the hardening of soft law, especially concerning firm accountability (Berning and Sotirov, 2023; Gustafsson and Schilling-Vacaflor, 2023), the EUDR builds on zero-deforestation commitments that were made starting in the mid-2010s by a small but visible minority of large firms in major deforestation-linked sectors (Lambin and Furumo, 2023; Weather and Ellis, 2022). As interest in reducing European consumption's impacts on deforestation grew among governmental and civil society actors, firms in sectors where such commitments were becoming common

[1] Source: https://www.europarl.europa.eu/news/en/press-room/20241111IPR25340/eu-deforestation-law-parliament-wants-to-give-companies-one-more-year-to-comply, accessed on 18 December 2024.

sought legislation that could impose requirements on competitors and provide more legal certainty (Berning and Sotirov, 2024).

The EUDR identifies seven "deforestation-risk commodities" - "cattle, cocoa, coffee, oil palm, rubber, soya and wood" (Regulation 2023/1115, Art. 1, Section 1). Companies moving these commodities or their derivatives across external EU borders or placing them for sale on EU markets are obliged to fulfill due diligence requirements designed to guarantee deforestation-linked products are excluded from their supply chains. Importantly for commodities like coffee and cocoa, where agroforestry is common, the legislation defines deforestation broadly, as "the conversion of forest to agricultural use," including agroforestry (Regulation 2023/1115, Art. 2). Requirements vary according to the classification of individual countries of origin, which are categorized as "high", "standard", or "low" risk, though a "no risk" category might be included in the coming review period.

2.1. The EUDR and remote sensing

To meet their due diligence requirements, operators - that is, the firms or individuals importing or exporting affected products - are required to collect information on "the geolocation of all plots of land where the relevant commodities [...] were produced, as well as the date or time range of production" (Regulation 2023/1115, Art. 9, Section 1d). Locations are to be provided as precise latitude and longitude coordinates and, for plots larger than four hectares, should define polygons outlining the entire area (Regulation 2023/1115, Art. 2, Sec. 28). "[A]ny deforestation or forest degradation on the given plots of land shall automatically disqualify all relevant commodities and relevant products from those plots of land from being placed or made available on the market or exported" (Regulation 2023/1115, Art. 9). For the purposes of the regulation, "plots of land" are based on "real-estate property" (Regulation 2023/1115, Art. 2, Par. 27), suggesting forest clearance anywhere on a property, not just the production area, would constitute non-compliance. Non-compliant shipments (or income derived from them) may be confiscated, and non-compliant companies may be banned from the European market or fined up to 4 % of their total annual turnover in the market in question—a sum that could push smaller companies, especially trading houses, into bankruptcy and potentially affect exporting countries' foreign earnings.

To help implement these requirements, a preambulatory clause to the regulation called on the EU Observatory on Forests to develop a platform to support implementation efforts "as soon as possible" (Regulation 2023/1115, Pream. 31), outlining its desirable features as follows:

The EU Observatory should provide for land cover maps, including with time series since the cut-off date defined in this Regulation, and a range of classes allowing landscape composition to be examined. The EU Observatory should participate in the development of an early warning system combining research and monitoring capacity. As regards this Regulation, when technically feasible, the objective of the early warning system should be to be part of a platform that can assist the competent authorities, operators, traders and other relevant stakeholders and that can provide continuous monitoring and early notification of possible deforestation or forest degradation activities. (Regulation 2023/1115, Pream. 31)

A platform serving this function would need to combine two key capabilities. First, the regulation uses a cut-off date of December 31, 2020, considering any product grown on land identified as forest as of this date to be non-compliant (Regulation 2023/1115, Art. 3). The platform, therefore, requires a highly accurate global land-cover map at least as of the end of 2020. To serve this function, the EU Forest Observatory (2023a) launched the "global map of forest cover for the year 2020" which, while it "has no legal value per se [...] may serve as a tool to comply with the Regulation on deforestation-free supply chains." The Global Forest Cover 2020 dataset (Bourgoin, et al., 2024b) was constructed by combining several forest cover datasets to map a maximal forest extent using the EUDR's definition. The first version was released in 2023 (Bourgoin et al., 2023b), and an updated and improved version was released in late 2024 (Bourgoin, et al., 2024b).

Second, the system should reliably detect deforestation events in near real time. Because the EUDR defines deforestation as conversion to any agricultural use, including agroforestry, the platform should also distinguish primary or regenerating forests from agroforestry plots and identify conversion from forest to agroforestry on a regular basis. To help address this challenge, the EU Forest Observatory (2023b) provides a "global map of forest cover changes and their drivers," which identifies forest change following categories developed by Curtis, et al. (2018). This resource, however, is only a preliminary step toward the kind of early warning system envisioned in the legislation.

2.2. A neglected challenge to access equity: supply-chain exclusion via measurement error

Several assessments of zero-deforestation initiatives highlight the importance of reliable and precise geospatial technologies for effective monitoring. For example, Garrett, et al. (2019), argue that effective monitoring requires near-real-time validation of deforestation events. Austin, et al. (2021), similarly, suggest technical rigor (essentially, measurement validity), consistency, and accuracy in attributing responsibility for deforestation events are essential for the credibility of deforestation monitoring systems. However, firms engaged in zero-deforestation efforts may be overly optimistic about what technology can do. Reporting on interviews with company representatives involved in zero-deforestation work across several sectors and continents, Bager and Lambin (2022) note that 80 % of their sample companies use geospatial analysis, and especially Global Forest Watch Pro, as part of their mapping and monitoring efforts. Further, they characterize about half of their sample as expressing "techno-optimism," "believing that real-time satellite data will spell the end of deforestation" (Bager and Lambin, 2022, p. 10). This optimism is shared by some prominent value-chain actors, particularly in sectors like palm oil, where endeavors to enhance monitoring capabilities involve pursuing ever more sophisticated algorithms and higher-resolution satellite imagery (Gallemore, et al., 2022).

But even when GPS coordinates are available, misclassifying land cover maps derived from remotely sensed imagery remains problematic (Card, 1982; Curran and Hay, 1986; Curran and Williamson, 1985; Hord and Brooner, 1976; Hutchinson, 1982). Despite recent econometric advancements that mitigate classification errors' pernicious effects on statistical inference (Alix-Garcia and Millimet, 2023), misclassification remains virtually unavoidable when using remotely sensed data for land-cover monitoring. Generally speaking, classification errors arise from three sources: the data used to train classification algorithms in the first place (Elmes et al., 2020), mismeasurement on the part of the remote sensing device (Alix-Garcia and Millimet, 2023), and mistakes in classifying pixels of remotely sensed spectral data into discrete land-cover classes (Alix-Garcia and Millimet, 2023; Torchiana et al., 2022). Classification errors can be particularly pernicious because they are affected by geographic conditions, yielding different error rates across space, time, and land-cover classes (Alix-Garcia and Millimet, 2023; Nelson et al., 2021; Tamga et al., 2023; Torchiana et al., 2022;).

Misclassification errors could pose a straightforward problem for the EUDR: if plots that are in fact under production are inaccurately categorized as "forest" as of the regulation's baseline date, the producers in question may unjustly be excluded from the EU's deforestation-free market, or at the very least be saddled with the transaction costs of proving their innocence, despite actually complying with the regulation. This is a particularly significant problem for coffee and other tree crops, particularly in areas where coffee is grown under tree canopy, often being identified as forest in satellite-derived maps despite being under agroforestry production and, therefore, not forest according to EUDR (Regulation 2023/1115, Ch. 1, Art. 2, Par. 4). The data documentation for version 1 of the Global Forest Cover 2020 dataset (Bourgoin et al., 2023a), for instance, notes a tendency for the map to overestimate forest cover in cocoa production areas in West Africa and coffee production areas in Brazil and Vietnam.

We noted above that the EUDR's envisioned monitoring platform requires two capabilities: establishing baseline land cover and detecting forest conversions. While only the second capability involves detecting deforestation or degradation directly, the first may pose the highest risk to producers. This is because the EUDR incentivizes buyers to consider products from any plots they think may have experienced deforestation or degradation relative to the baseline of December 31, 2020, as technically non-compliant. If the baseline land-cover map is faulty, producers might later find themselves excluded for land conversion that took place before the cutoff date.

A strict reading of EUDR could entail that more producers are falsely thought to be in violation due to misclassifications in the baseline land-cover map than from mistakes in deforestation detection. This is because the loss of any randomly selected patch of forest in a heavily forested landscape is a statistically rare event. In contrast, the persistence of a forested patch in a heavily forested landscape is exceedingly common. Imagine, for example, that one algorithm for detecting deforestation had a relatively high false positive rate of 10 %. Because deforestation is a rare event, that algorithm might identify only ten deforestation events in the landscape in a given period, of which we might expect one to yield a false positive based on the algorithm's known error rate. Now imagine applying a land classification algorithm to identify forest cover in the same landscape. We know that the landscape is highly forested, so let us say this algorithm identifies 1000 pixels as forest. Even if the false positive rate for this algorithm were very low - say, 1 % - we would expect 10 of the 1000 identified forest pixels to be in fact non-forest, 10 times the total error we might find from the deforestation alert algorithm.

In short, because the presence of forest is a vastly more common circumstance than the presence of deforestation in any given time period, it is most likely that the overwhelming majority of classification errors in the first several years of a hypothetical deforestation monitoring platform's operation will come from the initial land-cover classification, rather than deforestation detection (provided that the deforestation detection algorithm is not based on simply comparing land-cover classifications over time). Indeed, because the number of pixels of land cover to be classified is so vast, even quite low error rates could result in numerous false indications of non-compliance with the corresponding zero-deforestation mandate. We explain how we assess these risks in the case of the EUDR's impacts on coffee in the following section.

3. Methods

Our methodological strategy is two-pronged: first, we identify whether or not short-to-medium-term forest misclassification rates are likely sufficient to cause access equity problems in the coffee sector under the EUDR; second, we delineate the technical strategies that can mitigate such inaccuracy. We discuss our approaches to addressing each research question in turn.

3.1. Research Question 1: Are plausible short-term error rates in global land-cover monitoring sufficient to generate access equity risks for producers?

As explained in the previous section, we believe the most likely access inequity risk coffee producers might face is the mistaken identification of their production area as forest in the EUDR baseline year. Firms compiling due diligence information in keeping with the legislation have two primary options for checking production locations in their supply base: 1) they could rely on extant global land-cover datasets, several of which are now available at a relatively high resolution of about 10 m; or 2) they could train their own models across their specific supply regions.

Estimating the risk of misclassification of coffee as forest in global datasets is a relatively straightforward matter – it entails taking known ground-truthed coffee production locations and investigating how they are classified in common global land-cover datasets. To accomplish this goal, we used data collected during fieldwork conducted in February-March, 2023, as part of a livelihoods study investigating coffee farmers' experiences dealing with climate change in Ethiopia and Tanzania. Field teams conducting a livelihoods survey in major coffee-producing regions in the two countries collected 2105 coffee production location points in Ethiopia and 3462 points in Tanzania, intending to use these points to train algorithms to map current and potential future coffee production locations and suitability. Survey sites were selected to cover the distribution of elevations and decadal changes in rainfall variability observed in the study regions. In Tanzania, sites were sampled from Mbinga, Rombo, Kyerwa, and Mbozi districts, while in Ethiopia, survey sites were sampled from Limu Seka, Ale, Yayu, Gera, and Goma districts of Jimma and Ilubabor zones.

We combined these data with additional groundtruth data on coffee production locations from several datasets, presented in Table 1, using Google Earth Engine to compute the rates at which these locations are identified as forest in four high-resolution global forest and land-cover datasets: Dynamic World (Brown et al., 2022), the European Space Agency's (ESA) WorldCover (Tsendbazar et al., 2022), ESRI's Global Land Cover (ESRI, 2023), and both versions of the Global Forest Cover 2020 dataset created by the EU Forest Observatory to support EUDR monitoring (Bourgoin et al., 2024b).

These datasets were selected because of their open availability and temporal proximity to the EUDR's December 31, 2020 cutoff date. Because these datasets were not collected with systematic validation in mind, and because some were collected two or three years before or after 2020, they should not be interpreted as constituting a representative assessment of the Global Forest Cover 2020 dataset. At the same time, we believe they permit evaluating the degree of misclassification risks.

To estimate the areas identified as coffee in the groundtruth samples that were classified as forests or tree cover in each of the five global land-cover datasets we consider, we constructed 10-meter buffers around all the point samples in Table 1, to approximate the native resolution of the global land-cover datasets. Using Google Earth Engine, we then computed the areas the buffer or polygons identified as trees or tree cover as of 2020 in the ESA WorldCover and ESRI Global Land Cover datasets, identified most frequently as under tree cover in the Dynamic World dataset from December 1 through 31, 2020, and identified as forest in the Global Forest Cover 2020 dataset, version 1 (Bourgoin et al., 2023b) and version 2 (Bourgoin et al., 2024b). We imported the results in R 4.3.0 (R Core Team, 2023) and converted the area estimates to a percentage of the total area of the polygon or buffer, capping the results at 100 % to allow for misalignment errors. Then, to estimate our uncertainty about the percentage of the area of groundtruth locations of different cultivation types shown in Table 1 identified as forest in the four global datasets, we constructed 1000 bootstrapped samples and calculated the median percentage of the areas of each of the samples in Table 1 identified as forest.

Examining the risks of misclassification in regional datasets is a bit more complicated. Because we are attempting to characterize the risks of falsely identifying a parcel as forested for whatever classification strategy a firm might select, we must allow for a range of potential misclassification rates. Furthermore, because the EUDR defines forests based on both land-cover type and spatial extent, we have to estimate the probability that a given misclassification rate results in a sufficiently large number of contiguous pixels misidentified as tree cover to count as a forest under the EUDR definition. For a coffee production area to be misclassified as forest in the baseline year, the misclassified pixels must be part of a contiguous forest area of at least 0.5 ha (Regulation 2023/1115, Art. 2, Par. 4). Mistaken identification of forested areas

Table 1
Datasets used in groundtruth validation.

Dataset	Source	Type	Obs.	Description
Brazil - JECAM	Jolivot, et al. (2021)	Polygon	37	Areas of coffee production collected as part of the Joint Experiment for Crop Assessment and Monitoring initiative, which used a standardized method for mapping sample crop areas in the tropics to serve as groundtruth for remote sensing applications
Brazil - LEM+	Oldoni, et al. (2021)	Polygon	19	Areas of coffee production collected as part of a large-scale mapping project of croplands in western Bahia state, Brazil, starting with field delineation from Sentinel−2 imagery, followed by two field visits
Ethiopia - Forest Coffee	Own data	Point	120	See main text.
Ethiopia - Garden Coffee	Own data	Point	169	See main text.
Ethiopia - Plantation Coffee	Own data	Point	59	See main text.
Ethiopia - Semi-Forest Coffee	Own data	Point	1757	See main text.
Kenya - JECAM	Jolivot et al. (2021)	Polygon	254	Polygons designating coffee production collected as part of the Joint Experiment for Crop Assessment and Monitoring initiative, which used a standardized method for mapping sample crop areas in the tropics to serve as groundtruth for remote sensing applications.
Tanzania - Arabica Region	Own data	Point	2676	See main text.
Tanzania - Robusta Region	Own data	Point	785	See main text.
Vietnam - Sun Coffee	Maskell, et al. (2021)	Point	102	Point locations indicating open-canopy grown plantation coffee, collected using Collect Earth based on pilot field observations
Vietnam - Intercropped Coffee	Maskell, et al. (2021)	Point	93	Point locations indicating intercropped coffee, collected using Collect Earth based on pilot field observations
Vietnam - New Coffee	Maskell, et al. (2021)	Point	91	Point locations indicating newly planted coffee, collected using Collect Earth based on pilot field observations
Uganda - FAO	FAO, (2021)	Point	59	Coffee plots identified first by a combination of raster data and field enumerators and then subjected to further cleaning and data quality control
United States - Hawaii	Perroy and Collier, (2021)	Polygon	710	Polygons showing coffee production locations produced by combining parcel and WorldView data, followed by site visit, workshop, and Google Earth verification to create a map of agricultural production in the state of Hawaii

could happen either because a 0.5-hectare area of contiguous pixels is misclassified or because misclassified pixels are contiguous to an existing and correctly classified forest.

To estimate these risks, we conducted simulations to identify what misclassification rates would be problematic. We can begin by describing the simplest case - one in which we assume that there is no forest on or adjacent to the plot. To simulate the risk of falsely identifying a site of coffee production as forest in this case, we modeled coffee plots as a square lattice of pixels, using the following procedure, where H is the size of the plot, in hectares, and P is bound between 0 and 1:

1. Construct a square lattice of pixels H hectares in size, assuming a 10-meter-resolution pixel.
2. For each pixel in the lattice, draw once from a random binomial distribution with the probability of a success set to P and the number of trials set to 1.
3. Remove all pixels for which Step 2 results in a 0.
4. Compute the size of the remaining sets of contiguous pixels.
5. Retain any contiguous sets of at least 50[2] pixels.
6. Compute the percentage of the plot area accounted for by the remaining pixels.

We conducted this simulation 10,000 times for every combination of H set to 1, 3, 5, and 10 and P set to 0.01 through 1, incrementing by 0.01. We used the igraph (Csardi and Nepusz, 2006) package in R 4.3.0 (R Core Team, 2023) to conduct most calculations for these analyses. In the more complicated case where the coffee plot borders on a forest, the simulation strategy is similar, except that in Step 5 in the sequence above we retained not only pixels that were part of 50-pixel contiguous groups but also any that were part of a contiguous group in which at least one pixel was in the lowermost row of the lattice (simulating a scenario in which the plot abuts a forest on one side).

The results of these simulations give us an estimated distribution of the percentage of pixels in a randomly selected plot that might be identified as forest according to the EUDR definition under each simulated combination of plot size and error rate. Using these estimates, we can identify at what misclassification rates regional maps could become problematic for EUDR purposes. By comparing these rates to the rates at which coffee locations are misclassified as forest in published literature, we can assess the risks to access equity that might accrue under a localized mapping strategy.

3.2. Research Question 2: What strategies might help mitigate misclassification risks?

Assuming that current misclassification rates may be problematic for access equity, perhaps technical strategies can reduce these rates to unproblematic levels. To investigate this possibility, we conducted a systematic literature search to identify the most successful approaches used in remote sensing and GIS literature to detect coffee production areas, with particular attention to shade-grown coffee. We then extracted information from all the classification attempts reported in these sources, building a dataset we used to estimate the association between different classification strategies and the accuracy they achieve in identifying coffee production locations. For clarity, Fig. 1 presents our

[2] Assuming a 10 m by 10 m resolution land-cover layer, 50 contiguous nodes would cover 0.5 ha.

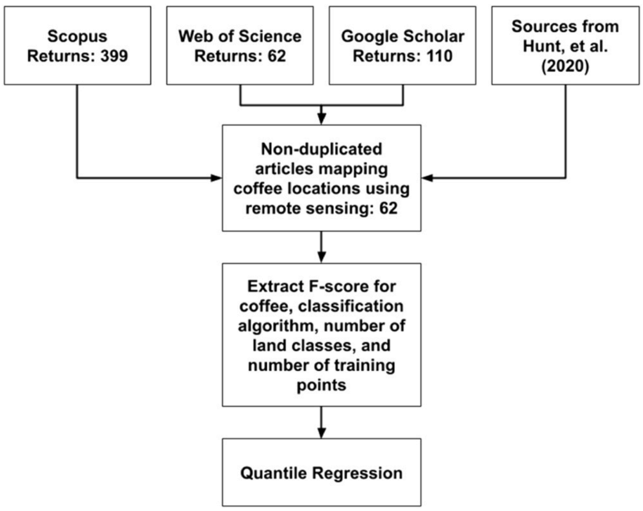

Fig. 1. Process used to address Research Question 2.

entire workflow.

Following PRISMA recommendations for scoping reviews (Tricco et al., 2018), we conducted a systematic search of literature using Scopus, Web of Science, and Google Scholar in November 2024. On each platform, we used the following search string: "coffee" AND ("satellite" OR "remote sensing"), restricting the search to the article abstracts for Scopus and Web of Science. Searches were conducted in English, but all returned sources were examined, regardless of their language of composition or publication date. Because Google Scholar does not allow for searches by abstract only, we advanced through the search pages, collecting potentially relevant returns as we did so until we had gone through 100 returns without finding a relevant source. This procedure resulted in an initial 62 sources from Web of Science, 399 sources from Scopus, and 110 from Google Scholar. We also gathered relevant sources Hunt et al. (2020a), (2020b) recent review of remote sensing applications in coffee. After filtering out duplicates and any articles that did not report specifically on efforts to map coffee locations using remote sensing technologies, 62 articles remained, which we used as our primary material for addressing our second research question.

Reading though these 62 articles, we collected data on their reported coffee classification attempts. First, as an approximate indicator of each approach's effectiveness at classifying coffee locations, we computed the F-score. Computed as the harmonic mean of the true positive and true negative rates for a given classification, the F-score provides a holistic measure of an algorithm's accuracy with respect to individual land-cover classes, like forest. It is readily computed from the most commonly reported accuracy metrics in the collected studies.

There are numerous features of a given land-cover classification attempt that might contribute to its F-Score, and we collected all available information on a selection of these for each coffee mapping attempt reported in the sampled articles. First, we recorded the satellite source used for the classification, grouping sources into those that were high (finer than 30 m by 30 m) and low resolution (30 m by 30 m or above). Second, we identified the type of algorithm used to perform the classification. We were particularly interested in comparing the two most commonly used algorithms, maximum likelihood estimation (MLE), long the standard approach, and random forests, an increasingly common strategy, particularly since the launch of Google Earth Engine. We therefore grouped the algorithms into three categories: MLE, Random Forests, and Other, a category encompassing numerous machine-learning strategies. Third, we recorded the total number of land classes targeted by the classification. Fourth, we collected the total number of training points used to make the classification.

Because all of these features may affect a classification's F-Score, it is necessary to model them simultaneously. A straightforward way to accomplish this is to estimate a regression model with an accuracy measure as the dependent variable. However, different classification strategies might affect both the mean expected accuracy of each classification attempt (the measure modeled in ordinary least squares regression) and the distribution of accuracy values we might reasonably expect under different conditions. Rather than basing our accuracy analysis on an ordinary least squares regression, which would only assess mean accuracy, we instead estimate a series of quantile regression models (Koenker and Hallock, 2001), which allows us to predict any selected quantile of the distribution of the dependent variable. Because the F-Score is bounded between 0 and 100, we logit transformed the score before modeling to minimize violations of regression assumptions, transforming the results back to the linear scale to ease interpretation. We estimated our quantile regression models using the quantreg (Koenker, 2022) package in R 4.3.0 (R Core Team, 2023).

4. Results

4.1. Research Question 1: Are plausible short-term error rates in global land-cover monitoring sufficient to generate access equity risks for producers?

To construct a plausible estimate of the rate at which coffee areas might be misclassified as forest in the types of databases stakeholders implementing the EUDR might rely on, we conducted preliminary validation analyses of five global land-cover datasets using the groundtruth datasets listed in Table 1. Fig. 2 presents the estimated percentage of each sampling area identified as under forest or tree cover, based on 1000 bootstrapped samples.

Consistent with the point made in Section 2 that misclassification rates can differ dramatically across geographic context, cropping types, and algorithms, we find substantial differences in the rates at which areas identified as coffee production in our groundtruth datasets are classified as under treecover or forest in the four global datasets we study. While these differences are partly attributable to differing land cover definitions - with datasets other than Global Forest Cover 2020 combining forests and plantations under "tree cover" - definitional differences alone cannot account for the degree of variation observed. Across the four datasets, ESA WorldCover identifies the largest share of the different geographies and coffee cropping types observed as forest, while ESRI Land Cover appears to be the least likely.

Despite that Global Forest Cover 2020 is designed to explicitly exclude plantations from the forest area, we nonetheless find coffee being identified as forest at relatively high rates in the Version 2 dataset in Hawaii, for semi-forest and (not surprisingly) forest coffee in Ethiopia, and in one of the Brazilian datasets. This is, however, a substantial improvement over Version 1 of the dataset, which substantially confused coffee areas with forest, an issue also observed in the official evaluation of the dataset (Bourgoin et al., 2023a). Intercropped and other shade-grown coffee production forms seem particularly likely to be identified as forest, even in the more accurate datasets. While some of this discrepancy is almost certainly accounted for by measurement error in the groundtruth datasets themselves - and some could also result from the fact that most of these datasets were assembled within two-to-three years around 2020, rather than in 2020 itself - it seems unlikely that these issues could account for all of the variation observed. Furthermore, the Global Forest Cover 2020 dataset is itself a patchwork of other global datasets assembled to map different relevant land covers, some of which have different resolutions or were collected at slightly different times (Bourgoin et al., 2024a). Any combination of these factors could account for some of the discrepancies we note.

If extant global land-cover datasets may not be adequate for all coffee geographies, it remains possible that mapping conducted over smaller areas could yield greater accuracy. When considering a possible bespoke regional coffee map that a firm might create for its own supply base, we

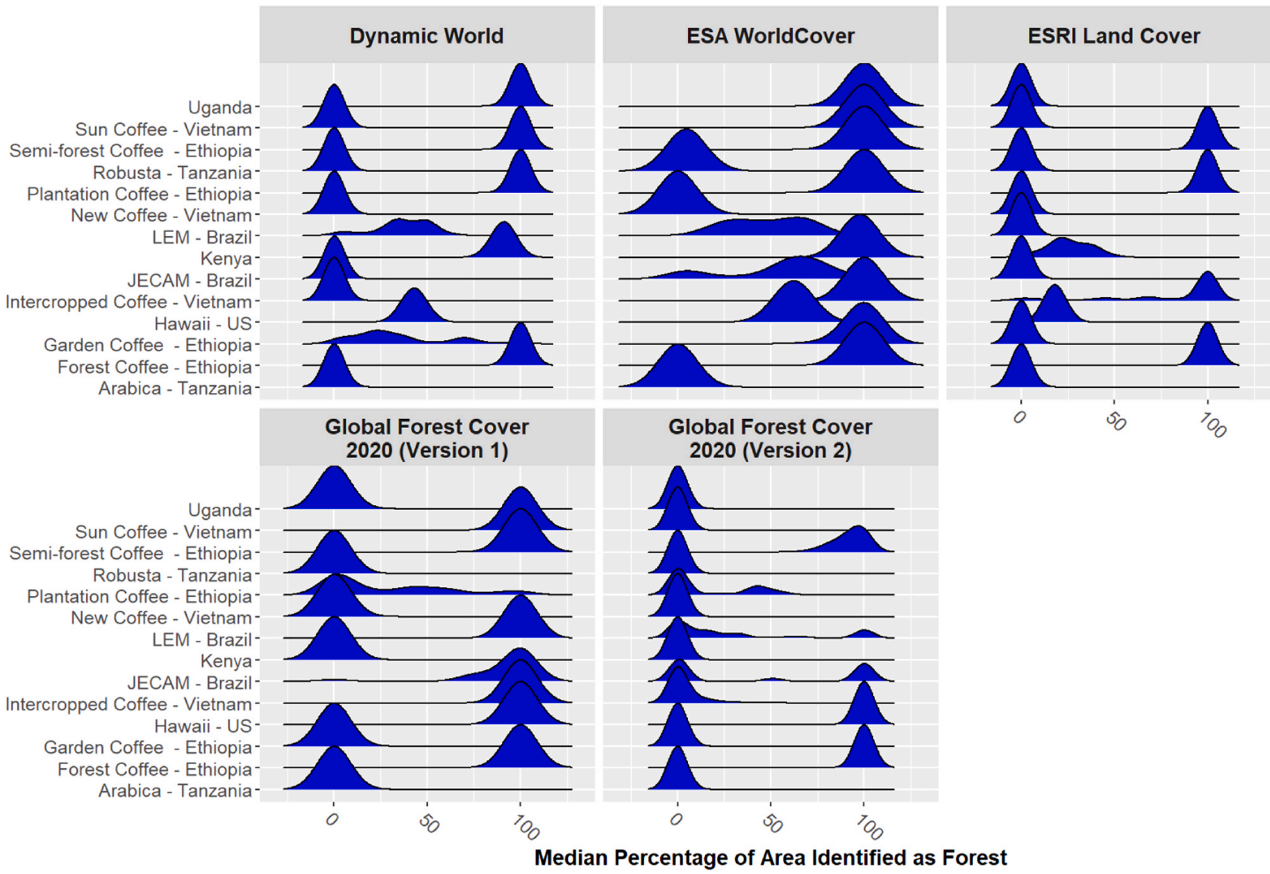

Fig. 2. Ridgeline plot showing distributions of the percentage of pixels covered by the groundtruth datasets listed in Table 1 identified as under tree cover or forest in the Dynamic World, ESA WorldCover, ESRI Global Land Cover, and Global Forest Cover 2020 datasets. Created using ggplot2 (Wickham, 2016) and ggridges (Wilke, 2023) packages in R.

must consider how misclassification at the pixel level could agglomerate into mistakes at the parcel level. Fig. 3 presents results from simulations of the connection between pixel-level misclassification rates and plot-level misclassification for plots of 1 and 3 ha in size (see Figure A1 in the Methods Appendix for results for 5 and 10 hectare plots, which are qualitatively similar). The simulations provide some good news: misclassification rates for a regional coffee map would need to be quite high to result in more than a small percentage of a given plot being identified as forest under the EUDR definition, even for plots adjacent to a forest area.

Fig. 4 shows a histogram of the rates at which coffee locations were misidentified as forest in the 12 sources found through our systematic review that provided sufficient information for this value to be calculated. While the evidence here is unfortunately quite limited, it does give cause for optimism. In no case did we find an example in our sources of a regional or local remotely sensed coffee map where coffee was confused for forest at anywhere near the rates at which our simulations suggest misclassification risks might occur. This suggests that current technologies are likely sufficient to mitigate misclassification risks in regions where global datasets are unreliable.

4.2. Research Question 2: What technical tools might help mitigate misclassification risks?

One way to mitigate the misclassification risks described in the previous section would be simply to have even more accurate classification systems. Fig. 4 presents predictions from a series of quantile regressions predicting the F-score, a simple measure of overall classification accuracy, for individual attempts to map coffee production locations reported in the literature sample described in Section 3.2. Coefficient estimates are presented in Figure A4 in the Methods Appendix.

Fig. 4 suggests that newer machine-learning algorithms tend to outperform MLE for coffee classification, though there is no systematic difference between random forests and other types of machine-learning models (which compose the bulk of the “other” category). Nevertheless, given its relative simplicity and lower computational requirements relative to more advanced deep learning classification techniques like convolutional neural networks, its overall performance would seem to make random forests an attractive technique. The turn towards machine-learning classification strategies (see Supplemental Information), therefore, bodes well for increased accuracy in coffee production area detection.

We also find an important result for land classes. As might be expected, additional land classes are associated with slightly lower F-Scores at lower percentiles, but their drag on performance is less pronounced at higher accuracies. This is potentially good news, as it suggests that, if an algorithm performs reasonably well, a moderate number of land cover classes may not substantially decrease accuracy in coffee location prediction.

The type of classification algorithm employed also clearly correlates with classification accuracy. As Fig. 4 demonstrates, non-MLE classification algorithms are generally associated with higher accuracy than MLE approaches across most percentiles. However, the difference is only statistically significant for Random Forest approaches at the 80th percentile and above (Fig. 5).

Some additional good news is that we observe no systematic differences in accuracy between lower and higher-resolution datasets. While we might be inclined to think that higher-resolution datasets would always tend to have greater accuracy, it is really better to think of them as

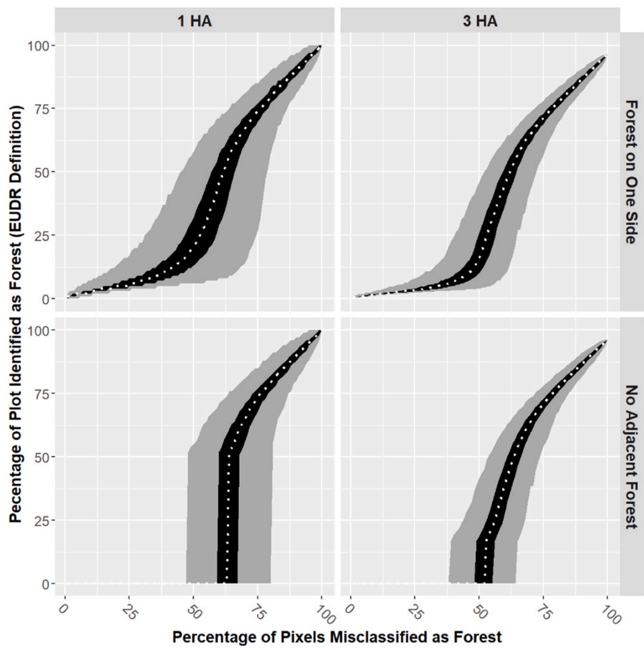

Fig. 3. Distributions of simulated percentages of plot areas misidentified as forest across the range of possible pixel-level misclassification rates. Gray envelopes denote the range of 99 % of the simulated values for each combination of plot size, forest adjacency, and misclassification rate. Black envelopes denote the range of the middle 50 % of simulated values for the condition. Because the EUDR definition requires forests to be at least 0.5 ha in size, the rate of forest identification for a single-hectare plot without adjacent forest is zero until the misclassification rate hits 50 %. Because the results for 5 and 10 hectare plots are qualitatively similar to these, we present them in Fig. A1 in the Methods Appendix for presentational purposes.

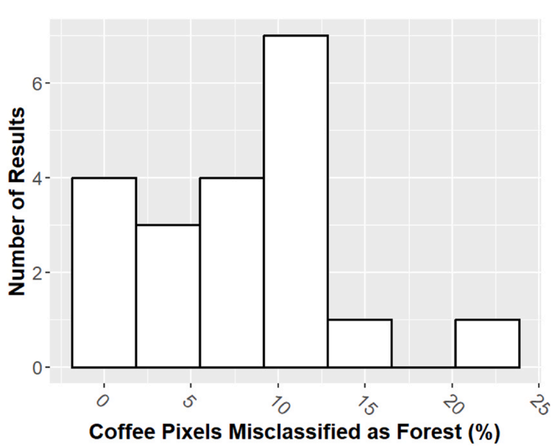

Fig. 4. Histogram denoting the range of rates at which coffee was misclassified as forest in the articles collected through the systematic literature described in Section 3.2. Unfortunately, calculating these values requires complete classification matrices, which articles frequently omit (Morales-Barquero, et al., 2019), meaning only 12 articles from the literature search provided sufficient information to compute these rates. Based on a *t*-test of their F-scores, classification results for which this information is reported do not have accuracy rates distinguishable from those in articles for which this information is unavailable ($t = -1.7$, $df = 26.4$, $p = 0.1$).

having higher precision. That is, high-resolution datasets may be better able to detect smaller forest changes, but this comes at the cost of needing to accurately predict a multiplicatively larger number of pixels (a 30-meter by 30-meter resolution pixel, for example, would cover 9 10-meter by 10-meter pixels, meaning there is potentially more measured variation to classify). Similarly, we do not find that classifications using very many (i.e., 5000 +) training points are substantially more accurate than those operating in the hundreds.

5. Discussion: Avoiding Access Inequities Due to Measurement Errors in Zero-Deforestation Coffee Value Chains

The results reported in the previous section are not intended to be definitive. Rather, they highlight that misclassifications pose predictable risks for implementing the EUDR or similar zero-deforestation legislation. If the rate of false-positive indications of non-compliance is sufficiently high, government officials and firms must decide whether and how to shrug off or respond to a potential “tsunami of false alerts” (Arjen Vrielink, qtd. in Kumar, 2023).

While such an outcome is certainly possible, our analysis suggests it could be avoided at relatively low cost, even for a “hard case” like coffee. As argued in Section 2.2, the most likely source of such a “tsunami” would come from establishing a reliable baseline forest map rather than deforestation detection. Evaluating the baseline map using widely dispersed groundtruth points can help identify areas where the global layer is unreliable for particular commodity types. As noted in the results section, our analysis of the Global Forest Cover 2020 version 1 dataset corresponds quite well with the results of the EU Forest Observatory’s self-evaluation (Bourgoin et al., 2023a).

After identifying areas where the global baseline map underperforms, it would be possible to generate regional maps of the specific commodity, which could then be used independently or else combined with the global baseline map, a strategy the EU Forest Observatory already adopted to address misidentification of plantation forests and oil palm plantations as forests under the EUDR definition (Bourgoin et al., 2023a). The accuracy metrics reported in the literature using remote sensing techniques to map coffee cultivation areas indicate that using advanced classification algorithms, amassing an appropriate number of training points, and being modest in the number of land classes to be predicted can certainly help limit the worst rates of misclassification. The good news from our simulations is that we only need to avoid the worst cases - error rates above 50 %. Our evidence suggests that for regions and cultivation types where a global dataset confuses the targetted commodity for forest at unacceptable rates, conducting classifications at a regional scale would eliminate most issues.

A critical issue here involves who would bear the burden of proof of establishing an accurate account for baseline forest cover in the case of uncertainty. Generating high-quality regional maps requires appropriate ground-truthed datasets, which also require detailed knowledge of local cropping practices.

Functional regional-scale maps in coffee-growing areas could be developed piecemeal, with firms first responsible for the burden of proof in mapping their own supply bases. However, this approach could disenfranchise producers by situating firms as the key arbiters. Furthermore, there are questions about whether firms alone can build teams and expertise that can properly represent producers and ensure equitable compliance. Alternatively, a coalition of firms, perhaps alongside civil society organizations like the World Resources Institute or governmental organizations like the Food and Agriculture Organization or the EU Commission, could develop a resource collaboratively, similarly to the way firms and civil society organizations developed collective tools for zero-deforestation in the palm oil sector (Jespersen, et al., 2024).

Conversely, a participatory approach to the collection of validation data and forest monitoring could be necessary to generate the quality data needed for a monitoring system to operate efficiently and equitably affected communities themselves to define the monitoring objectives (Danielsen et al., 2022). Such an approach could help mitigate the EUDR’s current orientation - producing knowledge for downstream stakeholders, who are positioned as key actors and gatekeepers (Verhaeghe and Ramcilovic-Suominen, 2024). Participatory mapping

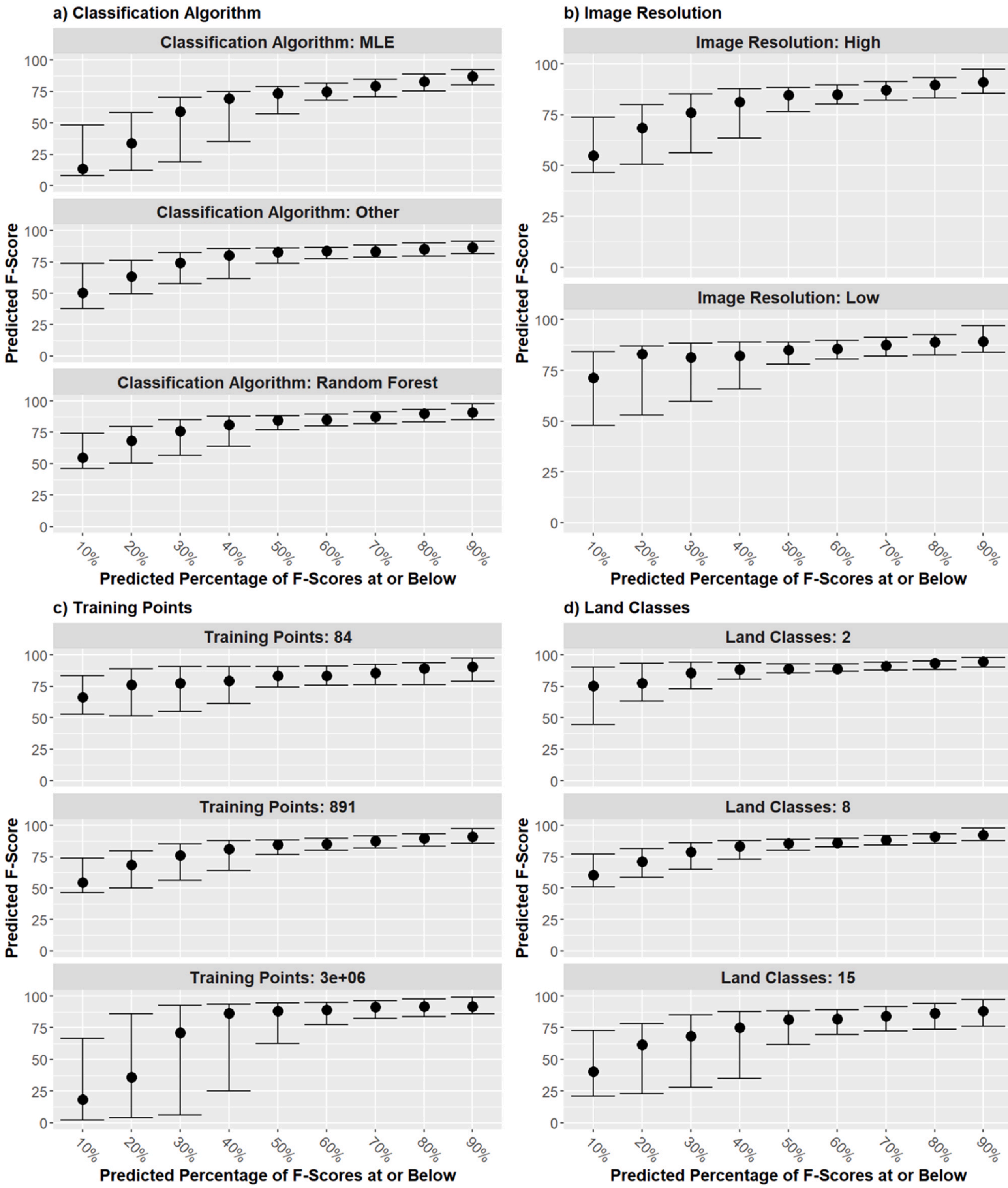

Fig. 5. Predictions from quantile regression models of selected percentiles of F-Scores for coffee land-cover classification, based on data characteristics and algorithms used for classification. Dots show the predicted F-Score at selected percentiles. Whiskers show bootstrapped 95 % confidence intervals for the predictions. Predictions are shown for all values of discrete variables and minimum, median, and maximum values of continuous variables used in the models. When not serving as the plotted prediction variable, Classification Algorithm is set to Random Forest, Image Resolution is set to High, Training Points are set to 850, and Land Classes are set to 10. N = 133.

tools, such as the Earth Defenders Toolkit,[3] designed to operate in areas without Internet connectivity, allow communities to control what they map, what data they share, and how. These seem preferable to systems where actors more downstream in the supply chain are given the task of assessing compliance.

While there are reasons to worry about the EUDR's implications for smallholders, Li (2024) points out that it could also bring much-needed

[3] See https://www.earthdefenderstoolkit.com

transparency to sectors like oil palm production and benefit smallholders, who are less likely to cause deforestation than large corporate operations. Enabling producers - particularly smallholders, farmer associations, and cooperative unions - to easily and rapidly correct misclassifications on their land - and, ideally, be compensated for doing so - would help mitigate some access inequity risks. Furthermore, it could facilitate better respecting indigenous groups' data sovereignty. Proper resources would be needed to compensate local data collectors for their efforts, and a participatory approach could also provide an opportunity to better involve smallholders in the governance process. To the extent that any monitoring system supporting the EUDR could be considered a public good, compensating communities for the value of the data they generate, which would be essential to such a platform's functioning, would be in the EU's interest.

6. Conclusion

The EUDR could be a potential watershed moment in global anti-deforestation efforts, with remote sensing technologies possibly providing new techniques for more equitable global governance (Bager and Lambin, 2022). In this article, however, we have demonstrated how current remote sensing technologies, while very powerful, nevertheless could produce sufficiently high classification errors to pose risks of access inequity to some coffee producers. Fortunately, it is possible to combine global and regional mapping efforts to reduce classification errors to a level that would be manageable, even for particularly hard-to-map commodities like coffee. While current technology can mitigate the risks that misclassification errors generate access inequities, participatory mapping, and providing producers with a free, readily accessible, effective, and efficient grievance mechanism are also essential for securing this outcome.

To be clear, the analysis conducted here only suggests possibilities. Relying on already existing datasets and collecting evidence from a systematic literature review sheds light on possible strategies for mitigating access inequities due to misclassification errors in systems supporting zero-deforestation efforts. Still, a thorough assessment would benefit from a globally representative, purposely created dataset and a carefully crafted experimental protocol for assessing the performance of different algorithms with different data sources, in different geographies, and with different numbers of training points. We hope, nevertheless, that the evidence presented here suggests such efforts may be warranted, at the very least for sectors like coffee and cocoa, where risks of misclassification errors could be particularly high.

Declaration of Competing Interest

none

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.landusepol.2025.107609.

References

Abnett, K., & Spring, J. (2022). *EU agrees law preventing import of goods linked to deforestation*. Reuters. ⟨https://www.reuters.com/business/environment/eu-agrees-law-preventing-import-goods-linked-deforestation-2022-12-06/⟩.

Alix-Garcia, J., Millimet, D., 2023. Remotely incorrect? Accounting for nonclassical measurement error in satellite data on deforestation. J. Assoc. Environ. Resour. Econ. 10 (5), 1335–1367.

Angel, M., & Kurniawati, D. (2023). Coffee firms turning away from Africa as EU deforestation law looms. *Reuters*, 19 December. ⟨https://www.reuters.com/markets/commodities/coffee-firms-turning-away-africa-eu-deforestation-law-looms-2023-12-19/⟩.

Austin, K.G., Heilmayr, R., Benedict, J.J., Burns, D.N., Eggen, M., Grantham, H., Greenbury, A., Hill, J.K., Jenkins, C.N., Luskin, M.S., Manurung, T., Rasmussen, L.V., Rosoman, G., Rudorff, B., Satar, M., Smith, C., Carlson, K.M., 2021. Mapping and monitoring zero-deforestation commitments. BioScience 71 (10), 1079–1090.

Bager, S.L., Lambin, E.F., 2022. How do companies implement their zero-deforestation commitments. J. Clean. Prod. 375, 134056.

Berman, N., Couttenier, M., Leblois, A., Soubeyran, R., 2023. Crop prices and deforestation in the tropics. J. Environ. Econ. Manag. 119, 102819.

Berning, L., Sotirov, M., 2023. Hardening corporate accountability in commodity supply chains under the European Union Deforestation Regulation. Regul. Gov. ⟨https://onlinelibrary.wiley.com/doi/pdf/10.1111/rego.12540⟩.

Berning, L., Sotirov, M., 2024. The coalitional politics of the European Union Regulation on deforestation-free products. For. Policy Econ. 148, 103102. https://doi.org/10.1016/j.forpol.2023.103102.

Bourgoin, C., Ameztoy, I., Verhegghen, A., Carboni, S., Colditz, R.R., & Achard, F. (2023a). Global first cover 2020 - Data access. Brussels: European Commission, EU Science Hub. ⟨https://forobs.jrc.ec.europa.eu/GFC⟩.

Bourgoin, C., Ameztoy, I., Verhegghen, A., Carboni, S., Colditz, R., & Achard, F. (2023b). Global map of forest cover 2020 - version 1 [deprecated]. European Commission, Joint Research Centre. ⟨http://data.europa.eu/89h/10d1b337-b7d1-4938-a048-686c8185b290⟩.

Bourgoin, C., Ameztoy, I., Verhegghen, A., Desclée, B., Carboni, S., Bastin, J., Beuchle, R., Brink, A., Defourny, P., Delhez, B., Fritz, S., Gond, V., Herold, M., Lamarche, C., Mansuy, N., Mollicone, D., Oom, D., Peedell, S., San-Miguel, J., Colditz, R. and Achard, F. (2024a). Mapping global forest cover of the year 2020 to support the EU Regulation on Deforestation-free Supply Chains. Luxembourg: Publications Office of the European Union. doi:10.2760/262532, JRC136960.

Bourgoin, C., Verhegghen, A., Degreve, L., Ameztoy, I., Carboni, S., Colditz, R., & Achard, F. (2024b): Global map of forest cover 2020 - version 2. European Commission, Joint Research Centre. ⟨http://data.europa.eu/89h/e554d6fb-6340-45d5-9309-332337e5bc26⟩.

Brown, C.F., Brumby, S.P., Guzder-Williams, B., Birch, T., Hyde, S.B., Mazzariello, J., Czerwinski, W., Pasquarella, V.J., Haertel, R., Ilyushchenko, S., Schwehr, K., Weisse, M., Stolle, F., Hanson, C., Guinan, O., Moore, R., Tait, A.M., 2022. DynamicWorld, near real-time global 10m land use land cover mapping. Sci. Data 9, 215. https://doi.org/10.1038/s41597-022-01307-4.

Cammelli, F., Levy, S.A., Grabs, J., Valentim, J.F., Garrett, R.D., 2022. Effectiveness-equity tradeoffs in enforcing exclusionary supply chain policies: Lessons from the Amazonian cattle sector. J. Clean. Prod. 332, 130031.

Card, D.H., 1982. Using known map category marginal frequencies to improve estimates of thematic map accuracy. Photogramm. Eng. Remote Sens. 48 (3), 431–439.

Carodenuto, S., 2019. Governance of zero deforestation cocoa in West Africa: New forms of public-private interaction. Environ. Policy Gov. 29, 55–66.

R. Core Team. (2023). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ⟨https://www.R-project.org/⟩.

Csardi, G., Nepusz, T., 2006. The igraph software package for complex network research. *InterJournal*. Complex Syst. 1695 (5), 1–9.

Curran, P.J., Hay, A.M., 1986. The importance of measurement error for certain procedures in remote sensing at optical wavelengths. Photogramm. Eng. Remote Sens. 52 (2), 229–241.

Curran, P.J., Williamson, D., 1985. The accuracy of ground data used in remote-sensing investigations. Int. J. Remote Sens. 6 (10), 1637–1651.

Curtis, P.G., Slay, C.M., Harris, N.L., Tyukavina, A., Hansen, M.C., 2018. Classifying drivers of global forest loss. Science 361 (6407), 1108–1111. https://doi.org/10.1126/science.aau3445.

Danielsen, F., Eicken, H., Funder, M., Johnson, N., Lee, O., Theilade, I., Argyriou, D., Burgess, N.D., 2022. Community monitoring of natural resource systems and the environment. Annu. Rev. Environ. Resour. 47, 637–670.

Elmes, A., Alemohammad, H., Avery, R., Caylor, K., Eastman, J.R., Fishgold, L., Friedl, M.A., Jain, M., Kohli, D., Bayas, J.C.L., Lunga, D., McCarty, J.L., Pontius Jr., R.G., Reinmann, A.B., Rogan, J., Song, L., Stoynova, H., Ye, S., Yi, Z.-F., Estes, L., 2020. Accounting for training data error in machine learning applied to earth observations. Remote Sens. 12, 1034 doi:C0.3390/rs12061034.

ESRI (2023). Sentinel-2 10-meter land use/land cover. ESRI Living Atlas. ⟨https://livingatlas.arcgis.com/landcover/⟩.

European Commission. (2022). Green Deal: EU agrees law to fight global deforestation and forest degradation driven by EU production and consumption. ⟨https://ec.europa.eu/commission/presscorner/detail/en/IP_22_7444⟩.

FAO (2021). Crop land - pre-processed data points, part 3 (Uganda - 10m). Rome: Food and Agriculture Organization of the United Nations. ⟨https://storage.googleapis.com/fao-maps-catalog-data/projects/EOSTAT/Uganda/02_Crops_QC_SamplePoints.zip⟩.

E.U. Forest Observatory. (2023a). Global forest monitoring. Brussels: European Union. ⟨https://forest-observatory.ec.europa.eu/forest⟩.

E.U. Forest Observatory. (2023b). Global map of forest cover change. Brussels: European Union. ⟨https://forest-observatory.ec.europa.eu/forest/ghm⟩.

Gallemore, C., Delabre, I., Jespersen, K., Liu, T., 2022. To see and be seen: Technological change and power in deforestation driving global value chains. Glob. Netw. 22 (4), 615–630.

Gardner, T.A., Benzie, M., Börner, J., Dawkins, E., Fick, S., Garrett, R., Godar, J., Grimard, A., Lake, S., Larsen, R.K., Mardas, N., McDermott, C.L., Meyfroidt, P., Osbeck, M., Persson, M., Sembres, T., Suavet, C., Strasbourg, B., Trevisan, A., West, C., Wolvekamp, P., 2019. Transparency and sustainability in global commodity supply chains. World Dev. 121, 163–177.

Garrett, R.D., Levy, S., Carlson, K.M., Gardner, T.A., Godar, J., Clapp, J., Dauvergne, P., Heilmayr, R., de Polain de Waroux, Y., Ayre, B., Barr, R., Døvre, B., Gibbs, H.K., Hall, S., Lake, S., Milder, J.C., Rausch, L.L., Rivero, R., Rueda, X., Sarsfield, R., Soares-Filho, B., Villoria, N., 2019. Criteria for effective zero-deforestation commitments. Glob. Environ. Change 54, 135–147.

Grabs, J., Cammelli, F., Levy, S.A., Garrett, R.D., 2021. Designing effective and equitable zero-deforestation supply chain policies. Glob. Environ. Change 70, 102357.

Gustafsson, M.-T., Schilling-Vacaflor, A., & Lenschow, A. (2023). The politics of supply chain regulations: Towards foreign corporate accountability in the area of human rights and the environment? Regulation and Governance, early view. https://doi.org/10.1111/rego.12526.

Hoang, N.T., Taherzadeh, O., Ohashi, H., Yonekura, Y., Nishijima, S., Yamabe, M., Matsui, T., Matsuda, H., Moran, D., Kanemoto, K., 2023. Mapping potential conflicts between global agriculture and terrestrial conservation. Proc. Natl. Acad. Sci. 120 (23). https://doi.org/10.1073/pnas.2208376120.

Hord, R.M., Brooner, W., 1976. Land-use map accuracy criteria. Photogramm. Eng. Remote Sens. 42 (5), 617–677.

Hunt, D.A., Tabor, K., Hewson, J.H., Wood, M.A., Reymondin, L., Koenig, K., Schmitt-Harsh, M., Follett, F., 2020b. Review of remote sensing methods to map coffee production systems. Remote Sens. 12 (12), 2041. https://doi.org/10.3390/rs12122041.

Hunt, D.A., Tabor, K., Hewson, J.H., Wood, M.A., Reymondin, L., Koenig, K., Schmitt-Harsh, M., Follett, F., 2020a. Review of remote sensing methods to map coffee production systems. Remote Sens. 12 (12), 2041.

Hutchinson, C.F., 1982. Techniques for combining Landsat and ancillary data for digital classification improvement. Photogramm. Eng. Remote Sens. 48 (1), 123–130.

Jespersen, K., Grabs, J., Gallemore, C., 2024. Ratcheting up private standards by exploiting coopetition: The curious case of RSPO's adoption of zero-deforestation criteria. Ecol. Econ. 223, 108229.

Jha, S., Bacon, C.M., Philpott, S.M., Méndez, V.E., Läderach, P., Rice, R.A., 2014. Shade coffee: Update on a disappearing refuge for biodiversity. BioScience 64 (5), 416–428.

Jolivot, A., Lebourgeois, V., Leroux, L., Ameline, M., Andriamanga, V., Bellon, B., Castets, M., Crespin-Boucaud, A., Defourny, P., Diaz, S., Dieye, M., Dupuy, S., Ferraz, R., Gaetano, R., Gely, M., Jahel, C., Kabore, B., Lelong, C., Le Maire, G., Lo Seen, D., Muthoni, M., Ndao, B., Newby, T., Melo De Oliveira Santos, C.L., Rasoamalala, E., Simoes, M., Thiaw, I., Timmermans, A., Tran, A., Begue, A., 2021. Harmonized in situ JECAM datasets for agricultural land use mapping and monitoring in tropical countries. Earth Syst. Sci. Data 13 (12), 5951–5967.

Keane, J., Agrawal, P., Mendez-Parra, M., & Debowicz, D. (2024). *Avoiding a 'green squeeze': Supporting least developed countries navigate new greening trade measures*. London: Overseas Development Institute Working Papers. ⟨https://odi.org/en/publications/avoiding-a-green-squeeze-supporting-least-developed-countries-navigate-new-greening-trade-measures⟩.

Kelley, et al., 2018b. Using Google Earth Engine to map complex shade-grown coffee landscapes in northern Nicaragua. Remote Sens. 10, 952. https://doi.org/10.3390/rs10060952.

Kelley, L.C., Pitcher, L., Bacon, C., 2018a. Using Google Earth Engine to map complex shade-grown coffee landscapes in northern Nicaragua. Remote Sens. 10, 952. https://doi.org/10.3390/rs10060952.

Koenker, R., 2022. quantreg: Quantile Regression. R. Package Version 5, 88. ⟨https://CRAN.R-project.org/package=quantreg⟩.

Koenker, R., Hallock, K.F., 2001. Quantile regression. J. Econ. Perspect. 15 (4), 143–156.

Kumar, M. (2023). The EU's regulation on deforestation-free products and the role of Earth observation. *GeoAwesome*, 14 April. ⟨https://geoawesomeness.com/eo-hub/eu-regulation-on-deforestation-free-products-and-the-role-of-earth-observation/⟩.

Lambin, E.F., Furumo, P.R., 2023. Deforestation-free commodity supply chains: Myth or reality? Annu. Rev. Environ. Resour. ⟨https://www.annualreviews.org/doi/pdf/10.1146/annurev-environ-112321-121436⟩ 18 April.

Li, T.M., 2024. Securing oil palm smallholder livelihoods without more deforestation in Indonesia. Nat. Sustain. 7, 387–393.

Lugo-Pérez, J., Hajian-Forooshani, Z., Perfecto, I., Vandermeer, J., 2023. The importance of shade trees in promoting carbon storage in the coffee agroforest systems. Agric., Ecosyst. Environ. 355, 108594. https://doi.org/10.1016/j.agee.2023.108594.

Lyons-White, J., Pollard, E.H.B., Catalano, A.S., Knight, A.T., 2020. Rethinking zero deforestation beyond 2020 to more equitably and effectively conserve tropical forests. One Earth 3 (6), 714–726.

Maskell, G., Chemura, A., Nguyen, H., Gornott, C., Mondal, P., 2021. Integration of Sentinel optical and radar data for mapping smallholder coffee production systems in Vietnam. Remote Sens. Environ. 266, 112709. https://doi.org/10.1016/j.rse.2021.112709.

Morales-Barquero, L., Lyons, M.B., Phinn, S.R., Roelfsema, C.M., 2019. Trends in remote sensing accuracy assessment approaches in the context of natural resources. Remote Sens. 11, 2305. https://doi.org/10.3390/rs11192305.

Nelson, M.D., Garner, J.D., Tavernia, B.G., Stehman, S.V., Riemann, R.I., Lister, A.J., Perry, C.H., 2021. Assessing map accuracy from a suite of site-specific, non-site specific, and spatial distribution approaches. Remote Sens. Environ. 260, 112442. https://doi.org/10.1016/j.rse.2021.112442.

Oldoni, L.V., Sanches, I.D.'A., Picoli, C.A., Covre, R.M., Fronza, J.G., 2021. LEM+ dataset: For agricultural remote sensing applications. Data Brief. 33, 106553. https://doi.org/10.1016/j.dib.2020.106553.

Parra-Paitan, C., zu Ermgassen, E.K.H.J., Meyfroidt, P., Verberg, P.H., 2023. Large gaps in voluntary sustainability commitments covering the global cocoa trade. Glob. Environ. Change 81, 102696.

Pendrill, F., Gardner, T.A., Meyfroidt, P., Persson, U.M., Adams, J., Azevedo, T., Bastos Lima, M.G., Bauman, M., Curtis, P.G., De Sy, V., Garrett, R., Godar, J., Goldman, E. D., Hansen, M.C., Heilmayr, R., Herold, M., Kuemmerle, T., Lathuillière, M.J., Rieiro, V., Tyukavina, A., 2022. Disentangling the numbers behind agriculture-driven tropical deforestation. Science 377 (6611). https://doi.org/10.1126/science.abm9267.

Pendrill, F., Persson, U.M., Godar, J., Kastner, T., Moran, D., Schmidt, S., Wood, R., 2019. Agricultural and forestry trade drives large share of tropical deforestation emissions. Glob. Environ. Change 56, 1–10.

Perroy, R., & Collier, E. (2021). *2020 update to the Hawai'i statewide agricultural land use baseline*. Honolulu, HI, US: Hawaii State Department of Agriculture. ⟨https://planning.hawaii.gov/gis/download-gis-data-expanded/⟩.

Pham, T.T., Nguyen, D.T., Dao, T.L.C., & Hoang, T.L. (2020). *Preparing Vietnam for new rules on international market: Zero deforestation production and business*. Working Paper 257. Bogor, Indonesia: Center for International Forestry Research. ⟨https://www.cifor.org/publications/pdf_files/WPapers/WP257Pham.pdf⟩.

Regulation (EU) 1115/2023. *Regulation (EU) 2023/1115 of the European Parliament and of the Council of 31 May 2023 on the making available on the Union market and the export from the Union of certain commodities and products associated with deforestation and forest degradation and repealing Regulation (EU) No 995/2010*. ⟨https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32023R1115⟩.

Rushton, D. (2019). Map of the month: Bringing smallholder coffee farmers out of poverty. *Carto*. 5 December. ⟨https://carto.com/blog/enveritas-coffee-poverty-visualization⟩.

Santiago, J. (2022). *Has the EU forgotten about smallholder coffee farmers?*. Coffee Intelligence. ⟨https://intelligence.coffee/2022/12/eu-green-deal-coffee-farmers/⟩.

Sun, H., Zhang, F., Raza, S.T., Zhu, Y., Ye, T., Rong, L., Chen, Z., 2023. Three decades of shade trees improve soil organic carbon pools but not methane uptake in coffee systems. J. Environ. Manag. 347, 119116. https://doi.org/10.1016/j.jenvman.2023.119166.

Tamga, D.K., Latifi, H., Ullmann, T., Baumhauer, R., Thiel, M., Bayala, J., 2023. Modelling the spatial distribution of the classification error of remote sensing data in cocoa agroforestry systems. Agrofor. Syst. 97, 109–119.

Torchiana, A.L., Rosenbaum, T., Scott, P.T., & Souza-Rodrigues, E. (2022). Improving estimates of transitions from satellite data: A hidden Markov model approach. Working Paper. ⟨http://www.ptscott.com/papers/hmm_error_correction.pdf⟩.

Treanor, N.B., & Saunders, J. (2021). *Tackling (illegal) deforestation in coffee supply chains: What impact can demand-side regulations have?* Washington, DC: Forest Trends. ⟨https://www.forest-trends.org/wp-content/uploads/2021/02/10-things-to-know-about-coffee-production.pdf⟩.

Tricco, A.C., Lillie, E., Zarin, W., O'Brien, K.K., Colquhoun, H., Levac, D., Moher, D., Peters, M.D.J., Horsley, T., Weeks, L., Hempel, S., Akl, E.A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M.G., Garritty, C., Lewin, S., Godfrey, C.M., Macdonald, M.T., Langlois, E.V., Soares-Weiser, K., Moriarty, J., Clifford, T., Tunçalp, Ö., Straus, S.E., 2018. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Ann. Intern. Med. 169 (7), 467–473.

Tsendbazar, N., Xu, P., Herold, M., Lesiv, M., & Duerauer, M. (2022). *WorldCover: Product validation report*. Paris: European Space Agency. Document WorldCover_PVR_v2.0. ⟨https://worldcover2021.esa.int/data/docs/WorldCover_PVR_V2.0.pdf⟩.

Verhaeghe, E., Ramcilovic-Suominen, S., 2024. Transformation or more of the same? The EU's deforestation-free products regulation through a radical transformation lens. Environ. Sci. Policy 158, 103807.

Weather, L., & Ellis, K. 2022. *Corporate implementation, impacts, and reporting on no-deforestation & "nature positive" post 2020*. Washington, DC: Forest Trends and Supply Change. ⟨https://www.forest-trends.org/publications/corporate-implementation-impacts-and-reporting/⟩.

Wickham, H., 2016. ggplot2: Elegant Graphics for Data Analysis. Springer, New York.

Wilke, C. (2023). *ggridges: Ridgeline Plots in 'ggplot2'*. R package version 0.5.5. ⟨https://wilkelab.org/ggridges/⟩.

Zhunusova, E., Ahimbisibwe, V., Sen, L.T.H., Sadeghi, A., Toledo-Aceves, T., Kabwe, G., Günter, 2022. Potential impacts of the proposed EU regulation on deforestation-free supply chains on smallholders, indigenous peoples, and local communities in producer countries outside the EU. For. Policy Econ. 143, 102817.