

Global forest typology at 10-meter resolution for forest and land-use monitoring

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Distinguishing forest types—primary, naturally regenerating, planted, and plantation forests—from agricultural tree crops and other land uses is essential for carbon accounting, biodiversity assessment, conservation planning, and supply-chain regulation. However, no existing global dataset resolves this typology at high spatial resolution. We present the Forest Typology (ForTy) v1 dataset, a global 10-meter resolution map for 2020 that classifies all land into six categories aligned with FAO and EU Deforestation Regulation (EUDR) definitions: Primary Forest, Naturally Regenerating Forest, Planted Forest, Plantation Forest, Tree Crops and Agroforestry, and Other Land. A cascaded deep learning pipeline, trained on 1.7 million globally distributed samples, generates per-class probability maps from geospatial satellite embeddings by combining weakly supervised learning with active learning. Independent validation against 8,190 stratified random sites, each labeled by two experts, yields an overall accuracy of 90.2% for the six-class scheme, 94.8% for natural forest classification, and 95.5% for forest/non-forest classification.

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1. Background & Summary

Forests cover approximately 31% of the world’s land area, store roughly 662 gigatonnes (Gt) of carbon [1], and harbor the majority of terrestrial biodiversity [2]. Yet the ecological and economic value of a forest stand depends on its type and management history [3]: for example, primary forests differ from planted and plantation forests and agricultural tree crops by orders of magnitude in carbon density, species richness, and importance to indigenous peoples and local communities, as well as in legal status. Carbon accounting [4], biodiversity assessment, REDD+ verification, and land-use monitoring all require classification that goes beyond biophysical tree cover presence to distinguish natural forests from planted forests, plantation forests, and agricultural tree crops. Such typological detail is also critical for assessing progress toward the Kunming-Montreal Global Biodiversity Framework’s “30×30” target, which aims to protect 30% of the Earth’s land area by 2030 [5, 6]. Since primary and naturally regenerating forests harbor the highest biodiversity value, identifying their extent and spatial distribution at the national level is a prerequisite for prioritizing protection of remaining natural forests. In the absence of a globally consistent, high-resolution forest typology, forest monitoring efforts must fall back on binary tree cover as a proxy [7]—unable to report what forest or tree cover types are being lost or gained.

This gap carries growing policy consequences. The European Union’s Regulation on Deforestation-free Products (EUDR) mandates that commodities entering the EU market are both deforestation-free

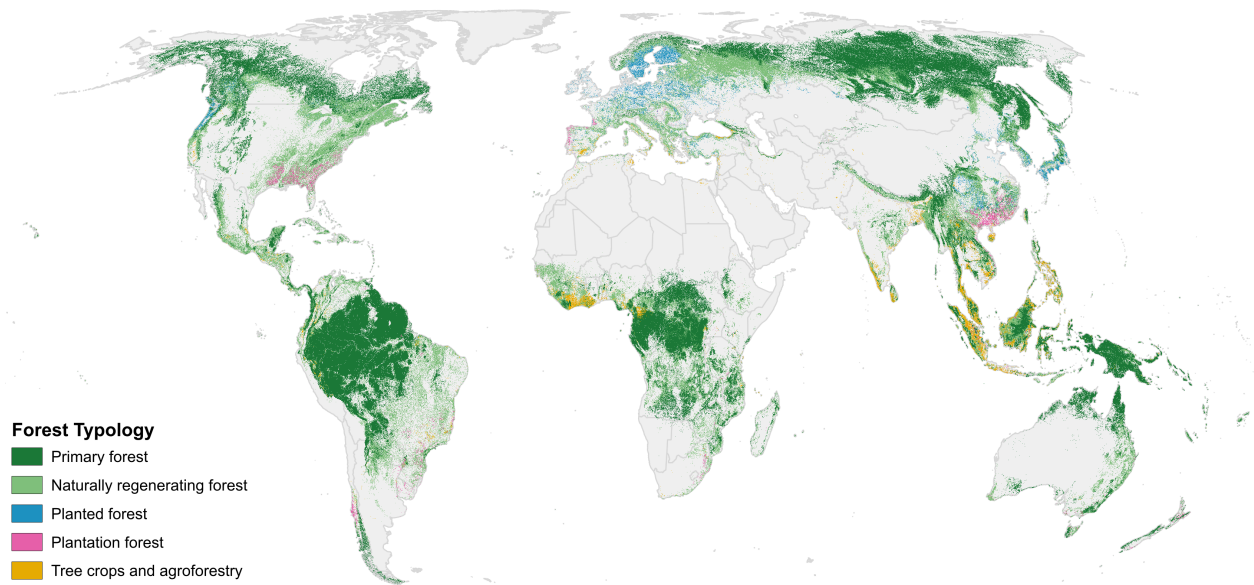


Figure 1 | Forest Typology 2020 (v1) in Equal Earth projection showing the majority class within each 1 km² cell.

32 and forest degradation-free, using December 31, 2020 as the baseline [8]. The EUDR distinguishes
 33 “deforestation” (conversion of forest to agricultural use) from “forest degradation” (structural changes
 34 within the forest land use, e.g., conversion of primary forests to plantations). Monitoring degradation
 35 and deforestation under this definition requires knowing the *baseline forest type* at each location, not
 36 merely whether trees are present [9, 8]. The EUDR further distinguishes forest from agricultural land
 37 use, explicitly excluding tree crop plantations and agroforestry systems from its definition of forest
 38 [10]. Compliance thus requires a mapping system that can both classify forests by type and reliably
 39 separate tree crops from timber plantations—a distinction often invisible in common high-resolution
 40 satellite imagery (compare for example Figure 5) and tree cover maps. Beyond the EUDR, the Tropical
 41 Forest Forever Facility (TFFF), which offers payments per hectare of standing tropical forest, will
 42 similarly need to exclude plantations and tree crops from eligible forest area to avoid crediting
 43 agricultural tree cover [11]; moreover, a forest typology that separates primary from secondary forest
 44 could support more comprehensive degradation monitoring beyond fire-based proxies in future TFFF
 45 methodology iterations. Recent analyses have highlighted that existing geospatial datasets fall short
 46 of the thematic detail required for these applications [12].

47 Several global and regional datasets have characterized parts of this typological spectrum, but none
 48 resolve the full multi-class typology at scale. Primary forest extent can only be approximated from
 49 tropical-only or coarse-resolution products [13, 14]. The Spatial Database of Planted Trees (SDPT)
 50 [15, 16] compiles known plantation boundaries from government, industry, and NGO sources, but its
 51 coverage remains geographically incomplete and temporally inconsistent. No global map separates
 52 agricultural tree cover (e.g., oil palm, rubber, cocoa) from forest. Lesiv et al. published the Global
 53 Forest Management map for 2015 at 100 m resolution [17], classifying forests into intact, managed
 54 (with or without logging), and planted categories. More recently, the Joint Research Centre (JRC)
 55 of the European Commission produced the Global Forest Cover (GFC2020) map [18, 19] and an
 56 associated Global Forest Types 2020 (GFT2020) product [20] to directly support the EUDR. The
 57 GFC2020 map provides a forest/non-forest binary at 10 m resolution, while the GFT2020 distinguishes
 58 primary, naturally regenerating, and planted forests [21]. The Natural Forests of the World (NFW)
 59 2020 dataset [22] is a global 10 m map distinguishing natural forest from all other land cover. At

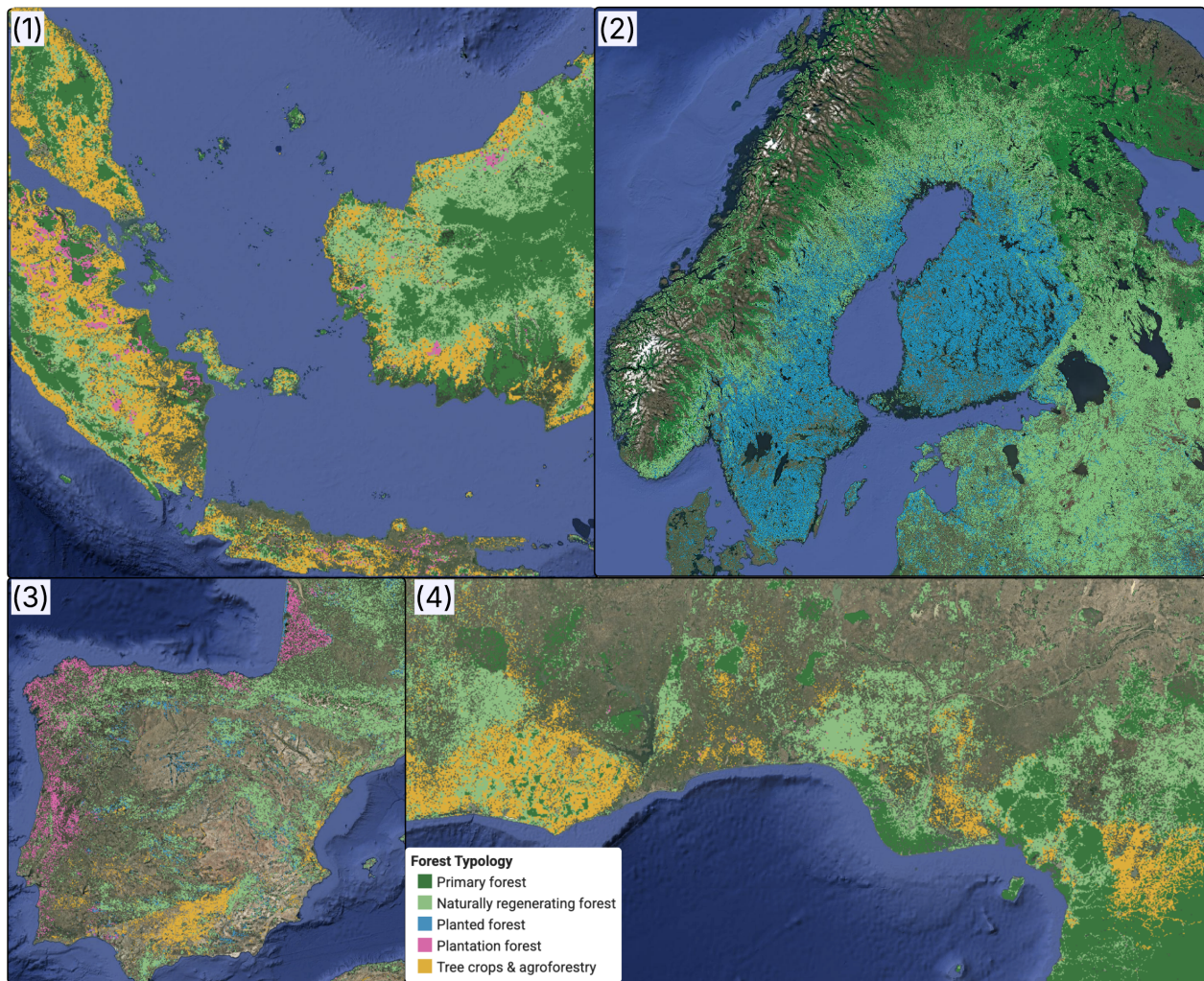


Figure 2 | Regional hotspot examples: (1) extent of tree crops, plantations, and remaining natural forests in South-East Asia, (2) planted forests in Scandinavia, (3) plantation and planted forests and tree crops on the Iberian Peninsula and in southern France, (4) agroforestry systems in West Africa.

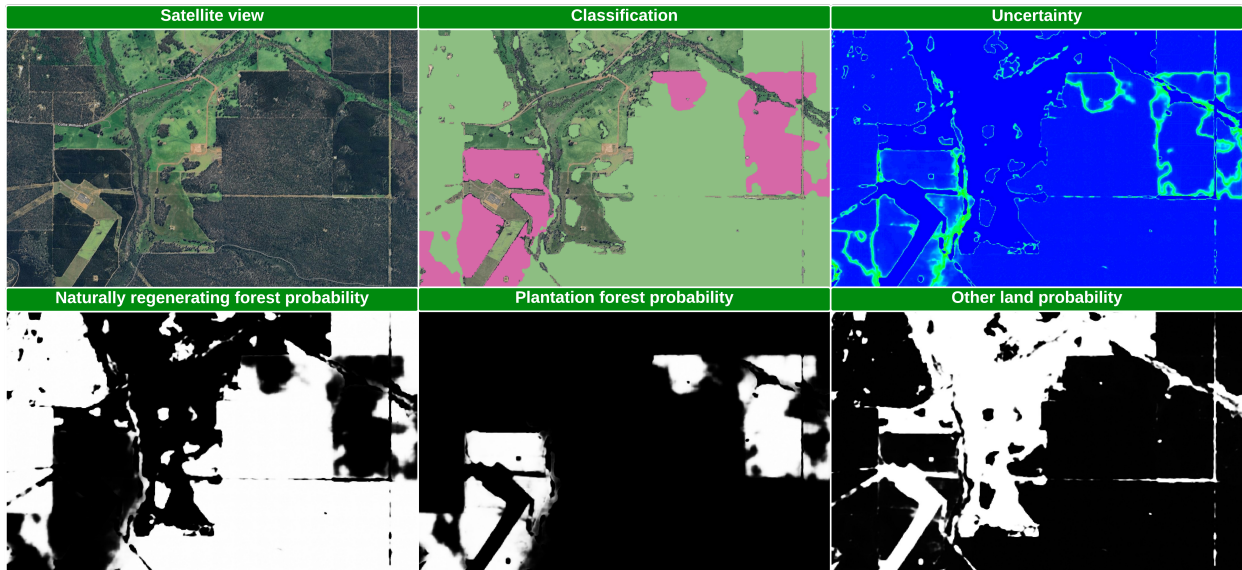


Figure 3 | Zoomed-in example over natural and plantation forests in South-East Australia (extent per panel: 5km x 3.5km). From top left to bottom right: satellite imagery (© Google Earth, Maxar Technologies, Airbus); Forest Typology predictions; estimation uncertainty; probability score of Naturally Regenerating Forest; probability score of Plantation Forest; probability score of Other Land use. Areas near field boundaries exhibit higher estimation uncertainty, and the probabilities deviate further from 0 and 1.

60 regional scale, the Tropical Moist Forest (TMF) dataset [23] provides long-term monitoring (1990–
 61 2025) of tropical forest disturbance and degradation at 30 m resolution, distinguishing intact from
 62 degraded and deforested areas. Jiang et al. [24] produced the first 10 meter resolution tree crop
 63 map for the South American continent. However, none of these products resolve the full multi-class
 64 typology—including primary and secondary forest sub-types, planted versus plantation forest, and
 65 tree crops—at global scale.

66 The challenge is three-fold. First, forest typology is fundamentally a *land use* classification, yet
 67 satellite remote sensing observes *land cover*. FAO definitions of forest types (primary, naturally
 68 regenerating, planted, plantation) are based on management history and intent rather than single-
 69 year observable biophysical properties [25]. A mature planted forest of native species may be
 70 spectrally indistinguishable from a naturally regenerated stand of the same age and composition;
 71 conversely, a forest that has burned (or an unstocked timber plantation after harvest) remains forest
 72 by definition, yet appears as bare ground and tree cover loss in satellite-derived change maps. Second,
 73 planted forests, plantation forests, and tree crops can share similar spectral and structural signatures,
 74 particularly in tropical regions where canopy closure is rapid [26]. Third, the expression of each class
 75 varies widely across biomes and management traditions, demanding exhaustive and geographically
 76 diverse training data to capture this variability in a single globally consistent model.

77 This paper introduces the Forest Typology (ForTy) v1 dataset, a global 10 m resolution map for
 78 the year 2020, classifying all land into six categories aligned with FAO forest definitions, which are
 79 referenced by the EUDR and other forest accounting frameworks: (1) Primary forest, (2) Naturally
 80 Regenerating forest, (3) Planted forest, (4) Plantation forest, (5) Tree crops and Agroforestry, and
 81 (6) Other land. Rather than hard categorical labels, the dataset distributes per-class probabilities,
 82 enabling users to adapt the classification to regional contexts and application-specific precision–recall
 83 trade-offs [22]. We describe the methodology, training data, and validation of a scalable deep learning

84 pipeline that estimates forest type from Earth observation data. The resulting global map is shown in
85 [Figure 1](#), with regional-scale examples in [Figure 2](#) and detailed zoom-ins in [Figure 3](#).

86 The following factors proved useful for training a single, globally consistent model to estimate forest
87 type at any location on Earth:

- 88 1. **Three-stage cascaded training** at different label granularities, temporal extents, and dataset
89 sizes, enabling the use of heterogeneous reference data sources;
- 90 2. **Geospatial satellite embeddings**, which encode multi-source, multi-temporal satellite observa-
91 tions into compact per-pixel representations;
- 92 3. **Label harmonization**, combining diverse regional and global reference datasets into a globally
93 consistent training corpus with hierarchical label structures;
- 94 4. **Weakly supervised learning with partial labels**, allowing the model to learn from samples
95 labeled at different levels of the class hierarchy; and
- 96 5. **Active learning**, iteratively refining training data in under-represented geographies and chal-
97 lenging biomes.

98 We validated the map against an independent, globally stratified random sample of 9,100 sites, of
99 which 8,190 were fully resolved¹ through expert consensus and used for accuracy estimation. Two
100 trained experts independently evaluated each site at 10 m resolution. The stratified overall accuracy
101 across all six classes reaches 90.2% (SE = 0.3%). For the binary natural forest versus non-natural
102 classification, overall accuracy reaches 94.8% (SE = 0.3%).

103 All map data and training code are publicly available to support regulatory compliance, conservation
104 planning, and forest monitoring research.

105 2. Methods

106 [Figure 4](#) provides an overview of the study design, from training data curation through three-stage
107 model training to global map generation and validation.

108 A key challenge is that the available high-quality reference data for forest types is limited, geographi-
109 cally uneven, and predominantly consists of point annotations denoting the majority class within a
110 $\sim 100\text{m} \times 100\text{m}$ area—not dense segmentation masks at 10 m resolution. Moreover, the diversity of
111 forest and tree crop land uses across the world’s biomes means that obtaining accurate training labels
112 in every region is essential, yet practically infeasible at scale. To address these data constraints, we
113 develop a cascaded three-stage design: the first stage trains on the available curated high-quality ref-
114 erence data—predominantly point-level annotations—to learn globally representative class patterns;
115 the second stage uses these initial predictions as pseudo-labels, refined by ancillary high-resolution
116 datasets, to scale training to over one million densely labeled patches at 10 m resolution across all land
117 regions; and the third stage leverages multi-year temporal context to improve temporal consistency
118 and reduce noise.

119 Each stage trains a model (Model-1, Model-2, Model-3) to perform dense semantic segmentation on
120 128×128 pixels at 10 m resolution ($1,280 \times 1,280$ meter patches), classifying each pixel into one of
121 six classes. Once trained, a model is applied for global inference, which can also cover years different
122 from the training year, based on the input data years. Each successive stage beyond the first derives
123 its training labels from the previous stage’s per-class probability maps, used as pseudo-labels and
124 refined with ancillary data.

¹At the time of writing this manuscript.

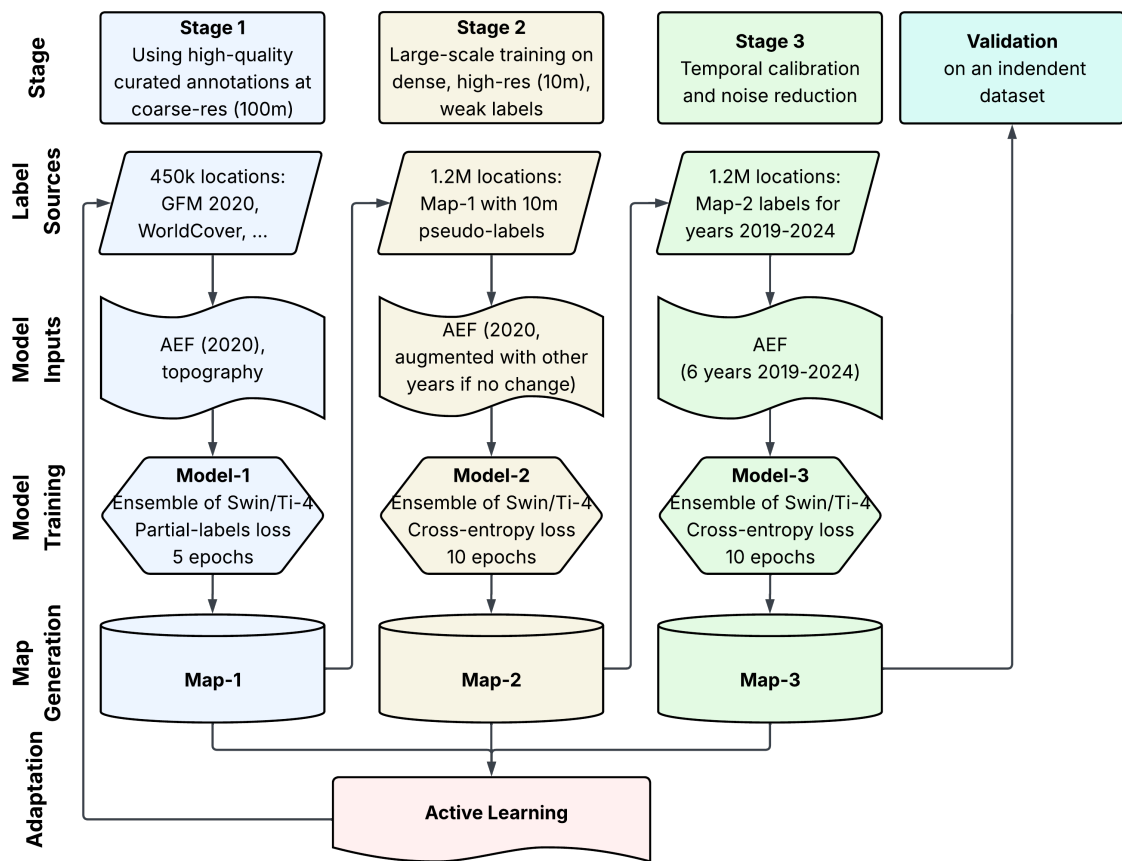


Figure 4 | Overall study design diagram for the multi-stage data flow, model training, and map generation.

2.1. Definitions

We adopt a six-class forest typology that maps to EUDR regulatory requirements. Following the FAO Global Forest Resources Assessment [3], the EUDR defines *forest* as land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10%, excluding land that is predominantly under agricultural or urban land use [8]. Within this forest definition, the six classes are distinguished by land use, management intensity, and rotation period as observed for the target year 2020.

- **Class 1: Primary Forest** (*Primary*). Natural forest of native species with no visible indications of human-caused disturbance.
- **Class 2: Naturally Regenerating Forest** (*NatReg*). Forests predominantly established through natural regeneration, including secondary forests recovering from disturbance and mixed forests where natural regeneration dominates.
- **Class 3: Planted Forest** (*Planted*). Forests established predominantly through planting or seeding. We introduce an operational 40-year rotation period threshold to distinguish the planted forest class from the more intensively managed plantation forest class defined below.
- **Class 4: Plantation Forest** (*Plantation*). Intensively managed forests characterized by one or two species, even age, regular spacing, and with a rotation period of ≤ 40 years.
- **Class 5: Tree Crops and Agroforestry** (*TreeCrop*). Agricultural plantations producing commodities other than wood (e.g., oil palm, rubber, fruit orchards), including agroforestry systems. Classified as agricultural land use under EUDR.
- **Class 6: Other Land** (*Other*). All non-tree land uses, sparse woody vegetation (canopy cover $< 10\%$), other wooded land, trees in urban environments, and small tree patches that do not meet forest thresholds.

Figure 5 shows examples of how the five forest and tree cover classes appear in high-resolution satellite imagery. Detailed definitions appear in Appendix A. Common tree species of planted/plantation forests and agricultural crops can be found in Supplementary Table 13 and Table 14.

2.2. Input data

The primary input to all model stages consists of AlphaEarth Foundations (AEF) embeddings [27]. AEF compresses multi-source, multi-temporal satellite observations (Sentinel-1, Sentinel-2, Landsat, ALOS PALSAR-2, and others) into annual per-pixel embedding vectors at 10 m resolution. Each embedding encodes spectral, temporal, and contextual information for a given pixel-year. For Stage 1 (Model-1), we supplement the AEF embeddings with topographic features derived from the Copernicus DEM at 30 m, upsampled to 10 m [28]. These features comprise elevation above sea level, slope, and slope aspect. Stages 2 and 3 use AEF embeddings as the sole input modality, covering 2019–2021 and 2019–2024, respectively.

2.3. Training data

We construct training data for the three model stages from a combination of curated reference datasets, external regional datasets, active learning campaigns, and pseudo-label generation from preceding stages. Table 1 summarizes all training data sources.

2.3.1. Model-1 label construction

The preprocessing pipeline constructs Model-1 labels by combining and filtering three source categories:

- **GFM reference data** [17]: At the core, we rely on expert labels from the original Global Forest Management (GFM) dataset that are mapped to the six-class Forest Typology scheme for the year 2020, as described below.

Table 1 | Training label data sources (Model-1: 450,275 samples; Model-2 uses the 1.2M pseudo-labeled patches and a subset of Model-1 sources; Model-3 uses only the 1.2M patch locations).

Source	Samples	Description
<i>Core reference datasets:</i>		
GFM 2020	262,837	Crowd-sourced global forest management labels [17] mapped to six-class Forest Typology scheme. The annotations were first updated for 2020 by IIASA, and subsequently refined by Google through distributed human review, AI-assisted label processing, and rule-based heuristics.
ESA WorldCover v3	96,000	Augments GFM 2020 data with negative non-tree land cover classes (grassland, built-up, bare, ice, water, wetland, cropland) that provide “other” labels. Pixels with canopy height ≥ 1 m are masked to <i>unknown</i> [29].
<i>External tree crop and plantation datasets:</i>		
CIAT Vietnam	12,056	Tree crop labels from CIAT/CGIAR in Vietnam [30].
Wang et al. rubber	3,887	Rubber plantation training samples across Southeast Asia and Africa [31].
CIAT Ghana	3,443	Tree crop labels from CIAT/CGIAR in Ghana [30].
LACUNA tree crops	2,732	Tree crop labels for Ghana from the CERSGIS/Lacuna Fund [32].
SERVIR Mekong	2,228	Rubber and other plantation labels across the Mekong region [33].
Descals oil palm	972	Oil palm planting year labels [34].
Fricker Ucayali palm	933	Oil palm polygons in Ucayali, Peru [35].
Sheil et al. correction	481	Rubber deforestation correction labels [36].
Descals coconut	327	Closed-canopy coconut palm map [37].
Becerra cacao Peru	213	Cacao plantation polygons in Amazonia Peruana [38].
Jin cashew Benin	212	Smallholder cashew plantations in Benin [39].
<i>Internal annotations:</i>		
Internal annotations	19,911	Google-internal annotation campaigns: point and polygon annotations for tree crops, forests, and other land uses.
<i>Active learning (AL) (3 rounds, subsection 2.4):</i>		
AL Round 1: IFL-based	11,842	Primary/NatReg confusion correction using Intact Forest Landscape boundaries [14, 40].
AL Round 1: CORINE-based	1,505	Tree crop precision/recall corrections using CORINE Land Cover 2018 [41].
AL Round 1: model-based	8,784	Tree crop corrections from model disagreement, map inspection, and precision loss analysis.
AL Round 2: SDPT-based	1,016	Planted/plantation corrections in China, USA, Japan, Chile, S. Korea using SDPT [16].
AL Round 3: expert review	19,880	Expert-verified corrections: vineyard/banana overclassification, Miskito pine, missing plantations, primary forest overestimation [40].
<i>Stage 2 pseudo-labels (Model-2 and Model-3 only):</i>		
1.2M global patches	1,200,000	Globally distributed random locations. Labels from Model-1 pseudo-labels refined by ancillary datasets (Table 2).

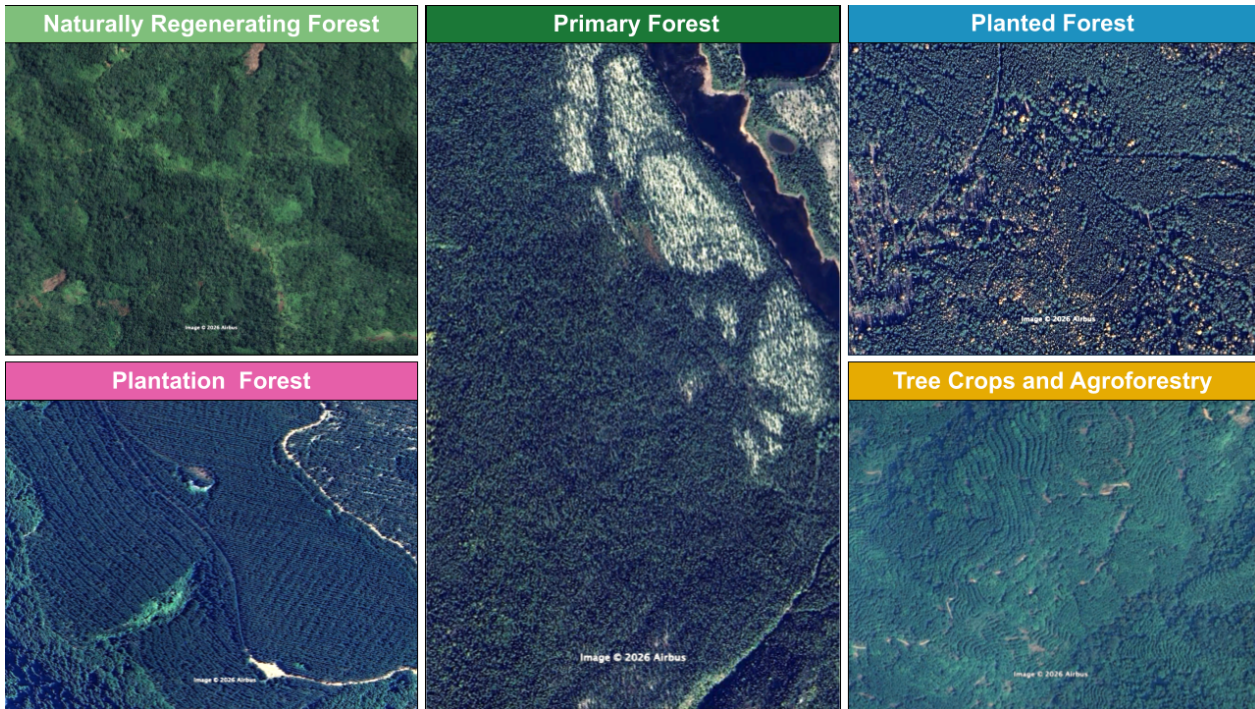


Figure 5 | Examples of high-resolution satellite imagery for the five forest and tree cover classes. Imagery © Google Earth, Maxar Technologies, Airbus.

- 170 • **WorldCover** [29]: Non-tree land cover classes (built-up, bare, water, ice, grassland, wetland,
- 171 moss/lichen, cropland) are assigned to “Other” (class 6). Tree cover, cropland, and mangrove
- 172 classes are masked to *unknown* to preserve label ambiguity if not already annotated via GFM.
- 173 • **Supporting and active-learning datasets**: Multiple regional and global reference sources
- 174 (Table 1) are mapped into the six-class label space. Some sources provide partial labels—multiple
- 175 annotations representing the set of possible classes. Unlabeled pixels are set to *unknown* and
- 176 excluded from the loss.

177 **GFM 2020 training data adaptation.** IIASA labeling team initially updated training labels in
 178 GFM 2015 to 2020. We additionally adjust these labels toward EUDR class definitions using a
 179 combination of automated reclassification and human review. We use non-expert annotators and
 180 Gemini-assisted high-resolution imagery analysis to identify and resolve inconsistencies between
 181 original source labels and EUDR definitions for planted and plantation samples. GFM class 53
 182 (agroforestry and other ambiguous tree cover) is resolved using a heuristic that considers canopy
 183 height [42], building proximity [43], WorldCover [29] tree coverage, and country of origin. A canopy
 184 height filter reclassifies forest pixels (classes 1–4) to “other” when the canopy height model reports
 185 height below 1 m.

186 2.3.2. Model-2 label construction

187 Training labels for the 1.2M global random patches fuse the Model-1 per-class probability map with
 188 ancillary geospatial datasets (Table 2) through a hierarchical assignment procedure:

- 189 1. **Natural forest identification.** The Natural Forests of the World (NFW) 2020 map [22] pro-
 190 vides an independent naturalness estimate. This layer is cross-referenced with Model-1 forest
 191 probabilities: pixels with NFW scores ≥ 0.5 are classified as primary or naturally regenerating
 192 forest based on the dominant Model-1 class.

- 193 2. **Managed forest and tree crop assignment.** For pixels classified as tree cover by WorldCover
 194 [29], the dominant Model-1 class (planted, plantation, or tree crops) is assigned when its
 195 probability exceeds 0.5.
- 196 3. **Non-forest assignment.** WorldCover non-tree classes are assigned to “other.” High-resolution
 197 building and road data [43, 44] override forest classifications. Pixels with Model-1 “other”
 198 probability ≥ 0.94 are classified as “other.”
- 199 4. **Regional external data corrections.** SDPT v3 [16] data from Canada is used for additional
 200 planted forest annotations in Canada. MapBiomass deforestation data [45] is used in Brazil to
 201 reclassify primary forest to naturally regenerating forest where anthropic use was detected in
 202 the past, and planted/plantation forest and tree crops to naturally regenerating forest where
 203 MapBiomass reports primary vegetation. USDA cropland data [46] is used over the United States
 204 to override planted/plantation classifications in favor of tree crops for known agricultural tree
 205 crops.
- 206 5. **GFC temporal adjustment.** Global Forest Change (GFC) [7] tree cover loss year is used to
 207 reclassify pixels with recent tree cover loss to the “other” land use class. The model may
 208 still predict a forest or tree crop class where strong signs of regrowth or planting are present.
 209 Wildfires are excluded from this reclassification using forest loss driver data [47].

Table 2 | Ancillary datasets used for Model-2 pseudo-label refinement.

Ancillary Source	Role in Model-2 Label Construction
ESA WorldCover 2020 [29]	Land cover class filtering for forest vs. non-forest assignment.
Natural Forests of the World 2020 [22]	Independent naturalness estimate for <i>Primary/NatReg</i> distinction.
Meta Canopy Height [42]	Height-based label filtering (forest classes require ≥ 1 m).
Google Buildings & Roads [43, 44]	Built area detection overrides forest to <i>Other</i> class.
Hansen GFC 2025 [7]	Year-specific deforestation detection.
MapBiomass [45]	<i>Primary</i> \rightarrow <i>NatReg</i> ; and <i>Planted</i> \rightarrow <i>NatReg</i> (Brazil).
USDA Cropland Data Layer [46]	<i>TreeCrop</i> identification in the United States.
SDPT v3 [16]	Selected planted forest detections.
Wildfire driver data [47]	Wildfire exclusion from Hansen loss reclassification.

210 2.3.3. Model-3 label construction

211 Multi-temporal training labels for Model-3 are generated using a heuristic based on the predictions of
 212 six inference maps from Model-2 (Stage 2), one per year from 2019 to 2024. For each pixel:

- 213 • If no tree cover loss was detected according to GFC 2025 data [7] and the estimated probability
 214 of the *Other* class changes by less than 0.7 across years (absolute difference between per-year
 215 probabilities), the class with the highest *mean probability* is used—providing noise reduction
 216 through averaging (note that there might still be change, within the *Other* or *TreeCrop* classes,
 217 but it does not affect our taxonomy).
- 218 • Otherwise—if tree cover loss was detected, or if the absolute change in *Other* class probability
 219 across years exceeds 0.7—*individual per-year predictions* are preserved, allowing the model to
 220 learn genuine land-cover transitions.

221 Across all stages, refinements and corrections apply only to the training labels; no post-processing is
 222 applied to the model predictions when generating the final map.

223 2.4. Active learning

224 We employ an active learning workflow to improve classification quality in under-represented geogra-
 225 phies and for classes that are difficult to distinguish globally. The process follows a cyclical *model*
 226 *training* \rightarrow *inference* \rightarrow *map generation* \rightarrow *expert feedback* \rightarrow *location identification* \rightarrow *annotation* \rightarrow

227 *retraining* loop.

228 After each training iteration, we generate a global inference map, which domain experts inspect to
 229 identify systematic misclassifications. These inspections—triggered primarily by expert feedback
 230 and visual map assessment (including historical analysis)—reveal regions and land-use types with
 231 insufficient training data coverage. For each identified error pattern, we create a targeted annotation
 232 campaign: annotators visually interpret high-resolution imagery, consult reference products, and
 233 review time series data at flagged locations, assigning corrected labels following the six-class Forest
 234 Typology scheme.

235 We conducted three major rounds of active learning, contributing approximately 43,000 additional
 236 training samples in total. All active learning samples are merged with the original training data and
 237 treated identically during training.

- 238 1. **Round 1** (22,131 samples): The first campaign targeted three main error patterns identified
 239 through initial map inspection: (a) areas of confusion between naturally regenerating and
 240 primary forests, where expert-verified Intact Forest Landscape (IFL) labels [14, 40] resolved
 241 ambiguity (11,842 samples); (b) regions with significant precision or recall losses for tree crops,
 242 particularly in Southeast Asia, West Africa, and South America (7,254 samples); and (c) areas
 243 with potential under-prediction of planted and plantation forests in China (407 samples).
- 244 2. **Round 2** (1,016 samples): The second campaign focused on both precision- and recall-motivated
 245 corrections in regions with a large fraction of planted and plantation forests: China, northwestern
 246 and southeastern USA, Japan, Chile, and South Korea.
- 247 3. **Round 3** (19,880 samples): The third campaign addressed a broader set of systematic errors: (a)
 248 over-classification of tree crops, including vineyards in Europe and banana plantations in West
 249 Bengal, India; (b) misclassification of natural pine forests as planted within the Miskito pine
 250 forests ecoregion in Central America; (c) primary forest overestimation in areas with noticeable
 251 human impact (Canada, Siberia, Turkey, USA); and (d) missing oil palm plantations in Africa
 252 and Indonesia and missing tropical plantations more broadly.

253 2.5. Model architecture and training stages

254 All three stages use the Swin Transformer v2 architecture [48], a common hierarchical vision trans-
 255 former that computes representations through shifted windows of self-attention [49]. We use the *Tiny*
 256 variant with patch size 4 (*SwinV2-Ti/4*) and a dense segmentation head. At each stage we train an
 257 ensemble of five independently initialized SwinV2-Ti/4 models, each producing separate predictions.
 258 During inference, predictions are averaged across ensemble members to improve model reliability.

259 All stages share the optimizer configuration listed in Table 3. Stage-specific parameters are noted in
 260 Table 4.

Table 3 | Shared training configuration across all stages.

Parameter	Value
Optimizer	Adam
Learning rate	0.001
Weight decay	0.00003
LR schedule	Cosine decay with 10% warmup
Gradient clipping	Max norm 1.0
Batch size	512
Train data augmentation	Random spatial roll, flip, and rotation

2.5.1. Stage 1: Training on curated reference data

Model-1 trains a base classifier on 450,275 expert-labeled and curated reference samples (Table 1). The input consists of AEF embeddings for the year 2020 and elevation features. Training labels are constructed as described in section 2.3.1.

Model-1 uses a *partial label loss* with an entropy regularization weight of 0.1 [50, 51]. Fully labeled examples contribute standard cross-entropy loss. Partially labeled examples enable the model to learn from heterogeneous annotation granularity by allowing ambiguous, but limited, outputs.

2.5.2. Stage 2: Large-scale training

Model-2 scales training to over 1.2 million globally distributed, densely annotated samples at 10 m resolution (1,280m × 1,280m patches). The input consists of AEF embeddings. Training labels are constructed as described in section 2.3.2.

Additionally, Model-2 applies temporal augmentation by randomly selecting one of three input years (2019, 2020, or 2021) per training example when there is no change between years according to Global Forest Change (GFC) [7]. This increases the effective training set diversity by exposing the model to inter-annual variability in vegetation phenology and satellite acquisition conditions.

Model-2 uses the standard softmax cross-entropy loss (not partial labels) and trains for 10 epochs. The trained Model-2 ensemble is then applied independently to each year from 2019 to 2024, producing per-class probability maps that serve as input to Stage 3.

Table 4 | Stage-specific training parameters.

Parameter	Model-1	Model-2	Model-3
Epochs	5	10	10
Input modalities	AEF + elevation	AEF	AEF
Input years	2020	2020 (2019, 2021)	2019–2024
Temporal sampling	2020	2020 (or random year if no change)	All 6 jointly
Loss function	Partial label	Softmax CE	Softmax CE
Output classes	6	6	6 for each year

2.5.3. Stage 3: Temporal calibration

The third stage performs temporal calibration by jointly training on 1,200,000 samples across six years (2019–2024). This stage improves temporal consistency of the 2020 prediction by leveraging context from neighboring years while preserving land cover changes. For this, the model sees inputs for all 6 years at the same time, and has to make predictions for each year. Training labels are constructed as described in section 2.3.3.

All six years (2019–2024) of AEF composites are concatenated along the temporal axis, producing a six-frame input tensor per training example. The temporal patch size for the transformer inputs is set to 6, encoding the full six-year sequence at each spatial location within a single patch token. Cross-year information flow occurs through the spatial encoder and decoder.

Similarly to Model-2, Model-3 uses softmax cross-entropy loss and trains for 10 epochs. For the final 2020 map, the year-2020 slice of the ensemble output is extracted.

2.6. Map construction

We create an inference dataset covering all land areas at each stage using the same procedure. The final model (or ensemble of models) estimates class probabilities for each inference sample. To

294 reduce tiling artifacts, we perform inference with overlapping samples: adjacent sample centers are
 295 spaced 210 m apart, while each sample spans 1,280m × 1,280m. Estimates for overlapping pixels are
 296 weight-averaged using the inverse Euclidean distance from each pixel to its respective sample center.
 297 This overlapping inference strategy produces a seamless final map.

298 2.7. Class probabilities and uncertainty

299 The per-class probabilities are computed as the arithmetic mean of softmax outputs from five inde-
 300 pendently initialized models, a standard ensemble strategy that reduces epistemic uncertainty and
 301 improves calibration [52, 53]. The overlapping inference strategy (Section 2.6) provides additional
 302 smoothing. Aleatoric uncertainty—intrinsic ambiguity from overlap between forest types—is not
 303 explicitly modeled but is partially captured by the probability distribution itself: pixels near class
 304 boundaries naturally receive less confident predictions. The probabilities have not been post-hoc
 305 calibrated, so they should be interpreted as relative probability scores rather than calibrated posterior
 306 probabilities [54, 22].

307 3. Data Records

308 The Forest Typology 2020 v1 dataset consists of a global per-class probability map at 10 m resolution
 309 covering all land areas between 65°S and 84°N latitude. The map uses the Universal Transverse
 310 Mercator (UTM) coordinate system, has a spatial resolution of 10 m per pixel, and contains 8-bit
 311 unsigned integer (*uint8*) values (0–250) representing quantized probability scores.

312 The primary data record is a five-band raster:

Band	Band name	Type	Min	Max
1	PrimaryForest	<i>uint8</i>	0	250
2	NaturallyRegeneratingForest	<i>uint8</i>	0	250
3	PlantedForest	<i>uint8</i>	0	250
4	PlantationForest	<i>uint8</i>	0	250
5	TreeCropsAndAgroforestry	<i>uint8</i>	0	250

313
 314 The probability for the sixth class (*Other*) is obtained as the complement: $p_{\text{other}} = 250 - \sum_{i=1}^5 p_i$. A
 315 categorical map is derived by assigning each pixel to the class with the highest probability (*argmax*).
 316 Pixels where *Other* land holds the highest probability are assigned class value 6. The probability
 317 representation enables users to apply custom thresholds, assess estimation uncertainty, and compute
 318 uncertainty estimates for downstream applications.

319 4. Technical Validation

320 4.1. Global validation of forest types dataset

321 We conducted a global validation campaign using IIASA’s Geo-Wiki platform [55] for 9,100 sample
 322 sites (1,300 per stratum). Of these, 8,190 sites were fully resolved through expert consensus and
 323 constitute the Global Validation of Forest Types (GVFT) dataset used for all accuracy reporting. Of the
 324 remaining sites, 172 (1.9%) were labeled “not sure” by at least one expert due to insufficient satellite
 325 imagery or inherent land-use complexity; the remainder had not yet been fully resolved in consensus
 326 meetings at the time of analysis.

327 The validation uses a global stratified random sampling approach. We stratified sampling across seven
 328 preliminary map-based categories to ensure coverage of rare classes: the six Forest Typology classes
 329 plus an additional Potential Forest stratum, which captures areas mapped as tree cover in external
 330 layers such as Hansen/GLAD [7] and ESA WorldCover [29] but absent from the first five forest and
 331 tree cover strata.

332 We randomly distributed 1,300 sample sites per stratum. [Table 5](#) summarizes the stratum areas
 333 (in million hectares (Mha)) and sample counts. This sample size supports accuracy estimation at
 334 continental and regional levels. [Figure 6](#) visualizes the spatial distribution of the samples and their
 335 strata.

Table 5 | Validation strata: map-based area, total sample count, and breakdown of excluded samples. Unresolved sites had not yet completed expert consensus; “not sure” sites were labeled as uncertain by at least one expert.

Stratum	Area (Mha)	Samples	Unresolved	Not sure
1. Primary Forest	2,123.7	1,300	126	9
2. Naturally Regenerating Forest	1,797.9	1,300	133	18
3. Planted Forest	204.7	1,300	146	38
4. Plantation Forest	118.0	1,300	163	40
5. Tree Crops and Agroforestry	145.8	1,300	83	44
6. Other Land	7,644.6	1,300	12	1
7. Potential Forest	1,339.2	1,300	75	22
Total	13,374	9,100	738	172

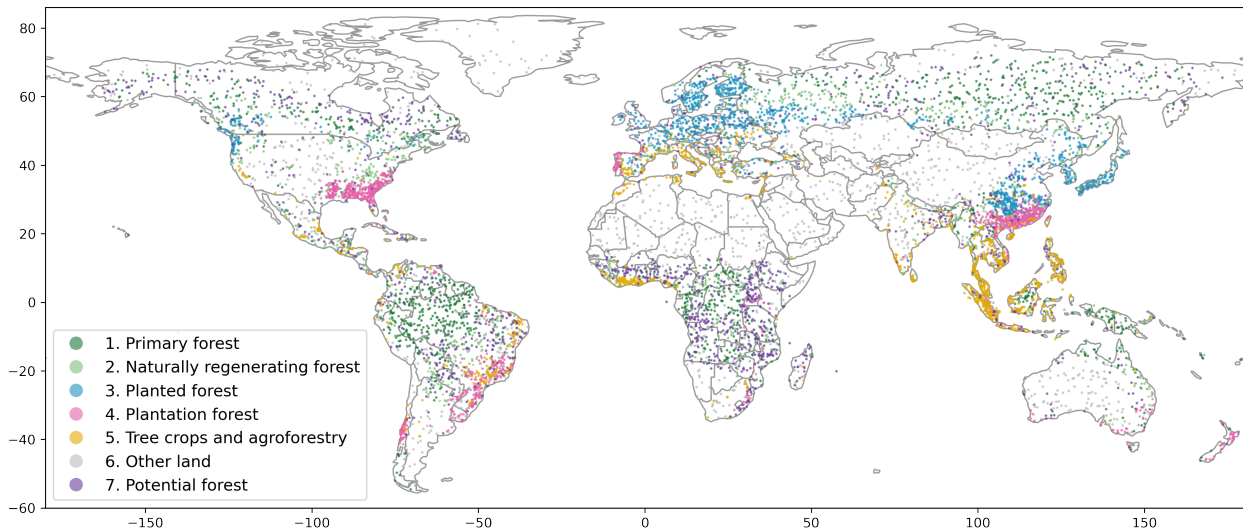


Figure 6 | Sample locations and strata of the GVFT dataset.

336 Two trained experts independently evaluated each sample site at two spatial scales: a 30m × 30m
 337 context window (3×3 grid of 10 m pixels) and the central 10m×10m pixel. For simplicity, all accuracy
 338 results reported in this paper are based on the central 10×10 m pixel. Experts based their assessments
 339 on the visual analysis of very high resolution imagery, contextual geospatial layers, long-term Landsat,
 340 Sentinel-2, and Sentinel-1 time series, and their regional expertise. For challenging cases, experts
 341 additionally consulted ground-truth information and area specialists. Disagreements were resolved
 342 through consensus meetings.

343 4.2. Accuracy assessment

344 We evaluate the Forest Typology v1 map against the GVFT dataset using the central 10 m pixel of each
 345 sample site for the 2020 annotations. We report stratified Overall Accuracy (OA), User’s Accuracy
 346 (UA; precision), Producer’s Accuracy (PA; recall), and their respective standard errors (SE), following
 347 established best practices for accuracy assessment of land cover products [56, 57]. We also report the
 348 F1-score, which is the harmonic mean of UA and PA: $F1 = \frac{2 \cdot UA \cdot PA}{UA + PA}$.

349 Because the Forest Typology map is distributed as a probability raster, users can derive categorical
 350 maps at application-specific operating points by varying the class assignment threshold. The accuracy
 351 metrics reported below correspond to the default argmax rule (each pixel is assigned to the class
 352 with the highest probability score). Users who require higher certainty may raise the probability
 353 threshold for a target class, trading Producer’s Accuracy for User’s Accuracy. Figure 7 illustrates this
 354 trade-off by plotting UA and PA as a function of the probability threshold for binary merged *natural*
 355 forest (primary + naturally regenerating), *all forests* (primary + naturally regenerating + planted +
 356 plantation), and *all planted forest* (planted + plantation) classes. The plots show 95% confidence
 357 intervals as $1.96 \times SE$. We discuss threshold selection further in the Usage Notes (section 5).

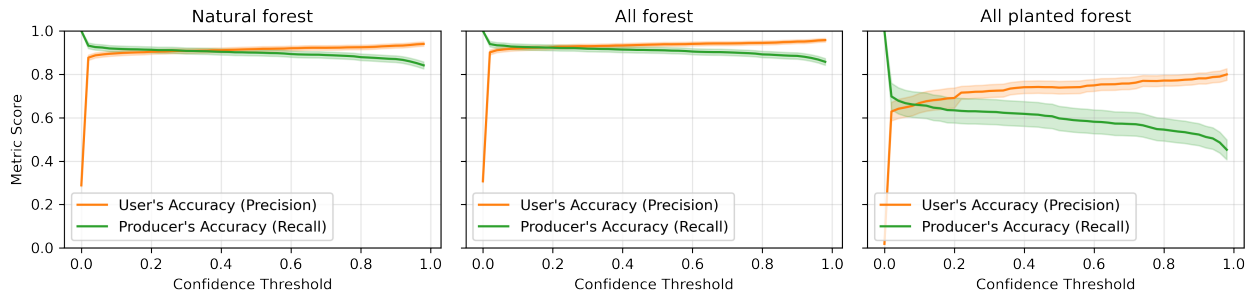


Figure 7 | User’s accuracy and producer’s accuracy as a function of probability threshold for the binary aggregations: (a) natural forest, (b) forest, and (c) planted forest. The shaded areas indicate 95% confidence intervals ($\pm 1.96 \times SE$).

358 Per-stratum sample count confusion matrices, broken down by the seven sampling strata, are provided
 359 in Table 16–Table 22 in the Appendix.

360 We present accuracy at multiple levels of class aggregation to characterize the map’s performance
 361 across use cases of varying thematic granularity.

362 Table 6 reports per-class accuracy for the full forest typology six-class scheme. The map achieves
 363 an overall accuracy of 90.2% ($SE = 0.3\%$). Primary forest reaches the highest forest-class F1-score
 364 (82.9%), followed by naturally regenerating forest (72.6%) and plantation forest (66.7%). The
 365 planted forest class shows the lowest F1-score (58.2%), reflecting the difficulty of distinguishing
 366 planted forests from both naturally regenerating forests and plantations based on satellite observations
 367 alone. The “other” class achieves the highest overall performance ($F1 = 96.4\%$).

Table 6 | Per-class accuracy for the full six-class scheme (consensus samples). $OA = 90.22\%$, $SE = 0.34\%$.

Class	F1	UA \pm SE	PA \pm SE
Primary	82.9%	77.9% \pm 1.1%	88.5% \pm 1.1%
NatReg	72.6%	81.1% \pm 1.2%	65.8% \pm 1.4%
Planted	58.2%	65.1% \pm 1.8%	52.6% \pm 3.7%
Plantation	66.7%	74.4% \pm 3.1%	60.4% \pm 3.2%
TreeCrop	62.1%	76.9% \pm 2.8%	52.1% \pm 4.2%
Other	96.4%	95.4% \pm 0.4%	97.3% \pm 0.2%

368 When primary and naturally regenerating forests are merged into a single *natural* forest class, and
 369 planted and plantation forests are merged into *all planted* forest (Table 7), overall accuracy increases
 370 to 93.9% ($SE = 0.3\%$). For the binary classification of *natural* forest versus all other land cover,

Table 7 | Per-class accuracy with merged *all natural* (classes 1 and 2), *all planted* (classes 3 and 4), and *all forest* classes (classes 1, 2, 3, and 4).

Class	F1	UA \pm SE	PA \pm SE
All Natural Forests	90.9%	91.6% \pm 0.5%	90.2% \pm 0.7%
All Planted Forests	66.1%	74.3% \pm 1.4%	59.5% \pm 2.8%
All Forests	92.6%	94.0% \pm 0.5%	91.2% \pm 0.7%

371 overall accuracy reaches 94.8% (SE = 0.3%). For the binary classification of *all forests* (classes 1–4)
 372 versus non-forest, overall accuracy reaches 95.5% (SE = 0.3%), with forest F1 = 92.6%.

373 When one merges *Planted* and *Plantation* forest classes, and the *TreeCrop* class into *Other* [20], the
 374 remaining four-class scheme (Primary, NatReg, Planted, and Other) achieves OA = 90.9% (SE =
 375 0.3%). Further detailed per-continent accuracy breakdowns are provided in Table 23 and Table 24 in
 376 the Supplementary.

377 4.3. Comparison to other forest maps

378 We evaluate the Forest Typology map against other publicly available global forest maps on the same
 379 GVFT validation dataset. For binary forest/non-forest classification (Table 8), Forest Typology yields
 380 the highest overall accuracy among the compared products: JRC GFC2020 [18], ESA WorldCover
 381 2020 [29], and ALOS PALSAR FNF4 [58]. For the four-class forest type scheme comparable to JRC
 382 GFT classes (Table 9), Forest Typology improves overall accuracy by 3.1 percentage points over JRC
 383 GFT2020, with consistent gains across all classes—most notably for primary forest (+6.0 pp F1) and
 384 planted forest (+8.6 pp F1).

Table 8 | Forest/non-forest classification accuracy of the Forest Typology map and other global forest maps evaluated on the GVFT dataset.

Map	OA	OA SE	Forest F1	Non-forest F1
JRC GFC2020 (v3)	93.6%	0.3%	89.7%	95.4%
JRC GFC2020 (v2)	92.5%	0.3%	88.5%	94.5%
JRC GFC2020 (v1)	91.8%	0.3%	87.3%	94.0%
ESA WorldCover 2020	91.6%	0.3%	86.8%	93.8%
ALOS PALSAR FNF4	86.9%	0.5%	80.9%	90.1%
ForTy 2020	95.5%	0.3%	92.6%	96.8%

Table 9 | Four-class forest type accuracy (JRC GFT scheme: primary, naturally regenerating, planted, other) evaluated on the GVFT dataset. F1-scores reported per class.

Map	OA	OA SE	Primary F1	NatReg F1	Planted F1	Other F1
JRC GFT2020 (v1)	87.8%	0.4%	76.9%	66.7%	57.2%	95.3%
ForTy 2020	90.9%	0.3%	82.9%	72.3%	65.8%	96.7%

385 4.4. Spatial agreement with independent datasets

386 We also compare the Forest Typology map spatially against three independent datasets that charac-
 387 terize well-defined subsets of the forest typological spectrum: Intact Forest Landscapes (IFL) 2020
 388 [14, 40], the Primary Humid Tropical Forests product [13], and the SBTN Natural Lands map [59].

389 For each comparison, we report the fraction of the external product’s area that falls within expected
 390 Forest Typology classes in [Table 10](#). These are consistency checks rather than accuracy assessments:
 391 disagreements may originate from either map.

392 **Intact Forest Landscapes (IFL).** IFL delineates contiguous blocks of primary forest and associated
 393 natural ecosystems larger than 500 km² with no signs of significant human activity [14]. Within
 394 the IFL 2020 extent, 99.998% of the area is classified by the Forest Typology map as either primary
 395 forest, naturally regenerating forest, or other land (non-forest portions of IFL such as water, rock, and
 396 ice). Only 0.002% of the IFL area falls within the planted, plantation, or tree crop classes, confirming
 397 strong spatial consistency between the two products for intact natural forest areas.

398 **Primary Humid Tropical Forests (PHTF).** The pan-tropical primary humid forests was mapped
 399 circa 2001 [13]. We exclude all tree cover loss from 2001 to 2020 [7] to approximate the 2020
 400 primary forest extent. Of this adjusted area, 90.4% is classified as primary forest by the Forest
 401 Typology map, and 99.1% as either primary or naturally regenerating forest. The remaining 0.9%
 402 largely corresponds to non-forest land cover.

403 The 9.6% of primary humid tropical forest area that the Forest Typology map classifies as naturally
 404 regenerating rather than primary can be attributed to various factors: (a) PHTF may include mature
 405 secondary forests that were not recognizable from the used Landsat imagery; (b) omissions in the tree
 406 cover loss data that was used to propagate the data from 2001 to 2020; and (c) a spatial buffering
 407 effect in the Forest Typology primary forest class, inherited from the training data. The global forest
 408 management (GFM) dataset [17], which provides the primary training labels for the primary versus
 409 naturally regenerating distinction, was collected through visual interpretation of high-resolution
 410 imagery. In this process, interpreters tended to classify mature forest stands in proximity to roads,
 411 settlements, or agricultural land as naturally regenerating rather than primary, even when the canopy
 412 appeared undisturbed. The Forest Typology model learned and generalized this spatial pattern from
 413 the training data, resulting in a conservative primary forest class that systematically excludes forest
 414 edges near human infrastructure. This is a property of the training data labeling convention rather
 415 than an explicit model design choice.

416 **SBTN Natural Lands.** The Science Based Targets Network (SBTN) Natural Lands map [59] identifies
 417 areas of natural land cover globally. Within the SBTN natural land extent, 98.9% is classified by
 418 the Forest Typology map as primary forest, naturally regenerating forest, or other land. The 1.1%
 419 classified as planted, plantation, or tree crop may reflect either Forest Typology commission errors in
 420 managed landscapes or areas where the SBTN product extends its natural land designation into land
 421 with some degree of management.

Table 10 | Spatial agreement between the Forest Typology map and three independent datasets. Each row reports the percentage of the external dataset’s area classified into expected Forest Typology classes.

External dataset	Expected Forest Typology classes	Agreement
IFL 2020	Primary OR NatReg OR Other	99.998%
Primary Humid Tropical [†]	Primary	90.4%
Primary Humid Tropical [†]	Primary OR NatReg	99.1%
SBTN Natural Lands	Primary OR NatReg OR Other	98.9%

[†]After excluding tree cover loss 2001–2020 [7].

4.5. Area estimates by forest type

We report area estimates using two complementary approaches: sample-based estimates derived from the stratified validation sample, following the methodology of [56, 57, 60], and map-based estimates obtained by pixel counting. Table 11 compares both approaches at the continental level for merged forest type classes. Detailed per-class breakdowns by continent are provided in Table 25 and Table 26 in the Appendix.

Globally, the sample-based estimate of total forest area (classes 1–4) is 4,142 Mha \pm 105 CI₉₅, compared to map-based estimate of 4,037 Mha (Table 11). Natural forest (primary + naturally regenerating) accounts for the vast majority at 3,890 Mha (sample-based) versus 3,838 Mha (map-based). Within this, primary forest contributes 2,038 Mha and naturally regenerating forest 1,852 Mha (see Table 25), together covering approximately 29% of the world’s land area. Differences between sample-based and map-based estimates reflect the known tendency of pixel counting to overestimate classes with high commission error and underestimate those with high omission error; sample-based estimates correct for this bias [56]. Planted forests (251 Mha sample-based, 199 Mha map-based) are comparatively small but regionally significant. Tree crops and agroforestry cover an estimated 196 Mha (sample-based), predominantly in Asia.

The continental distribution reveals distinct patterns (Table 11). Asia holds the largest natural forest area (1,238 Mha), followed by South America (865 Mha), Africa (692 Mha), and North America (680 Mha). Planted forests are concentrated in Europe (89 Mha) and Asia (84 Mha). Africa shows the largest discrepancy between sample-based and map-based forest estimates (695 vs. 601 Mha), suggesting substantial forest omission in the map. Standard errors are generally small relative to the area estimates, reflecting adequate sample sizes across most continent–class combinations, though some rare classes (e.g., planted forest in Africa and tree crops in Australia) have wide confidence intervals due to limited validation samples. Per-country area estimates for the countries with the largest forest areas are provided in Table 27 in the Appendix.

Table 11 | Sample- and map-based area estimates per continent (Mha, CI₉₅ = 1.96 × SE). *N* is the number of consensus validation samples.

Continent	<i>N</i>	Forest		Natural		Planted		TreeCrop	
		Sample \pm CI ₉₅	Map	Sample \pm CI ₉₅	Map	Sample \pm CI ₉₅	Map	Sample \pm CI ₉₅	Map
Africa	1,320	694.6 \pm 53.1	601.2	692.3 \pm 53.1	598.4	2.2 \pm 0.8	2.8	51.5 \pm 13.3	27.4
Asia	2,847	1321.5 \pm 59.0	1309.2	1237.5 \pm 56.7	1242.7	84.0 \pm 16.3	66.5	106.1 \pm 20.9	84.3
Aust. & Oc.	277	167.2 \pm 30.9	144.2	163.6 \pm 30.8	140.9	3.6 \pm 0.9	3.3	7.9 \pm 12.2	0.3
Europe	1,167	373.2 \pm 26.2	374.6	284.6 \pm 23.5	293.9	88.6 \pm 11.6	80.7	12.2 \pm 10.7	5.4
N. America	1,345	739.5 \pm 45.0	744.8	679.6 \pm 43.3	712.8	59.8 \pm 12.4	32.0	10.2 \pm 5.6	4.1
S. America	1,189	879.5 \pm 36.7	862.6	864.9 \pm 36.7	848.9	14.6 \pm 1.7	13.7	9.9 \pm 4.8	8.6
Global	8,190	4141.7 \pm 105.3	4036.7	3890.4 \pm 102.6	3837.6	251.3 \pm 23.9	199.0	195.9 \pm 31.0	130.2

4.6. Limitations

Classification boundaries. The FAO-based definitions underlying the Forest Typology classification rely on management intent and history, which are not directly observable from single-year satellite imagery. The model infers these categories from proxy indicators—spectral signatures, canopy structure, and spatial context—introducing irreducible uncertainty at class boundaries. This is most pronounced for the distinction between primary forest and naturally regenerating forest, where mature secondary forests can be spectrally and structurally indistinguishable from undisturbed primary forests. In addition, the primary forest class boundary is conservative near human infrastructure, a spatial buffering effect inherited from the labeling conventions of the GFM training data [17], as discussed in subsection 4.4. Planted forests exhibit the lowest classification accuracy among all forest classes,

457 as they overlap spectrally with naturally regenerating forests at one end and plantation forests at
458 the other. Mixed agroforestry systems—where tree crops such as cocoa or coffee grow beneath a
459 native canopy—remain among the most challenging classes; while this study represents a significant
460 advance, shaded agroforests can still be misclassified as natural forest in some regions.

461 **Definitional ambiguities.** The FAO forest definition includes land with trees “able to reach [the]
462 thresholds in situ” (>0.5 ha, >5 m height, >10% canopy cover), encompassing temporarily unstocked
463 areas such as recently harvested plantations awaiting replanting or forests in early post-disturbance
464 recovery. Because the map is derived from a single year of satellite observations, such areas may
465 appear as non-forest and be classified as Other Land, even though they remain forest under the
466 FAO definition by management intent. Similarly, the 40-year rotation threshold used to distinguish
467 planted forest from plantation forest (see [subsection A.2](#)) is an operational proxy; the FAO and EUDR
468 definitions rely on management intensity criteria that are not directly observable from imagery. The
469 Other Land class subsumes other wooded land (OWL), which is a distinct EUDR category; implications
470 for degradation monitoring are discussed in [subsection A.2](#).

471 **Temporal constraints.** The map represents land cover as of the year 2020, derived from multi-
472 temporal satellite composites that aggregate observations across an entire calendar year. Changes
473 occurring late in the compositing period may not be fully captured, introducing a temporal lag of up
474 to several months. Following wildfire events, distinguishing the pre-fire forest type from subsequent
475 regeneration or land-use conversion is particularly challenging from a single-year observation window.
476 Consequently, recently burned forests may carry higher classification uncertainty, and burned areas
477 may be temporarily misclassified as “other land” or as a different forest type during the early stages
478 of recovery. In practice, forest areas affected by fire in 2020 should be interpreted with caution, as
479 their classification may not reflect the pre-disturbance forest type.

480 **Spatial resolution.** At 10 m resolution, mixed pixels at forest-type boundaries may not resolve
481 fine-scale transitions accurately. Sub-pixel heterogeneity, particularly in smallholder landscapes, can
482 reduce classification precision. Isolated tree patches near the FAO forest area threshold (0.5 ha)
483 and areas at the canopy cover boundary (10%) are inherently ambiguous and may be inconsistently
484 classified. Additionally, the model input data’s effective resolution might be worse than 10 m.

485 **Probability calibration.** The per-class probabilities represent ensemble-averaged softmax outputs
486 and have not been post-hoc calibrated. While ensemble averaging generally improves calibration
487 compared to single-model predictions, the probabilities may not precisely reflect true posterior class
488 membership [53]. Users requiring well-calibrated probabilities for quantitative risk assessment should
489 consider regional recalibration using independent reference data.

490 5. Usage Notes

491 The Forest Typology v1 map is distributed as a five-band probability raster (uint8, values 0–250)
492 covering the five forest and tree cover classes. The “other” class probability is computed as $250 - \sum_{i=1}^5 p_i$.
493 A categorical map is derived by taking the argmax across all six class probabilities. For binary
494 forest/non-forest masks, probabilities for classes 1–4 can be summed, versus the remainder. Similarly,
495 natural or managed forest distinction is obtained by summing classes 1–2 (natural) and 3–4 (managed),
496 respectively.

497 The probability representation supports custom thresholding for applications with different precision-
498 recall trade-offs:

- To prioritize user’s accuracy (minimizing commission errors, i.e., high confidence that mapped forests are truly of that type), select a higher probability threshold.
- To prioritize producer’s accuracy (minimizing omission errors, i.e., capturing most of the actual forest of a given type), select a lower threshold.
- To seek a balance, choose a threshold near the intersection of the UA and PA curves (see [Figure 7](#)), or where both accuracies are acceptably high for the application.

Even with multi-class probabilities, one can provide different weights per category probability, and thus adjust the final multi-class map.

We note that the distributed probabilities are *ensemble-averaged softmax outputs* and may not be perfectly calibrated as true posterior class probabilities. Users are encouraged to evaluate the probability distribution in their region of interest and, if necessary, apply domain-specific threshold selection using local validation data, as recommended in [22, 54].

6. Data Availability

6.1. Forest Typology dataset

The Forest Typology v1 map for 2020 at 10 m resolution is available at <https://figshare.com/s/397762230d67d091cf9b>, and on Google Earth Engine (GEE) under asset ID

`projects/nature-trace/assets/forest_typology/forest_typology_2020_v1_0_collection`

A GEE App to analyze the data is available at <https://nature-trace.projects.earthengine.app/view/forest-typology-2020>. The dataset is licensed under the Creative Commons Attribution 4.0 International License (CC-BY 4.0). We provide the dataset as Cloud Optimized GeoTIFFs (COGs). Record details are described in [section 3](#).

6.2. Classification layer dataset

For convenience, we release the extracted classification layer as a separate dataset. It is available for download at <https://figshare.com/s/441a563c296b0d20cc63>, and on Google Earth Engine under asset ID

`projects/nature-trace/assets/forest_typology/forest_typology_2020_v1_0_classification`

It is a single-band raster collection in COGs, with a spatial resolution of 10 m per pixel, with values between 1 and 6 for the six classes of Forest Typology. The dataset is licensed under the Creative Commons Attribution 4.0 International License (CC-BY 4.0).

6.3. Validation dataset

The Global Validation of Forest Types (GVFT) dataset contains the stratum, the consensus label, the geographic coordinates, and the Forest Typology class mapped to that location. It is subject to updates, as the validation campaign experts continue to resolve disagreeing and unsure samples. The validation dataset is provided as a comma-separated values (CSV) file, and will be made available upon publication. During the review process it can be inspected in Earth Engine at <https://nature-trace.projects.earthengine.app/view/forest-typology-2020-val>.

7. Code availability

We generated the training dataset and the final map using the *GeeFlow* library (<https://github.com/google-deepmind/geeflow>), which uses Google Earth Engine [61] as its computational backend. The code for model training, inference, and evaluation is available in the *JEO* code repository (<https://github.com/google-deepmind/jeo>).

540 8. Author Contributions

541 Conceptualization: AR, EG, MN, MS, PP, RS, SC; Methodology: AR, MN; Software: AR, LS, MC, MN,
542 MO, MR, RR, YJ; Validation: AR, ML, MN, MS, PP, RS; Formal analysis: AR, MN, PP; Investigation:
543 AR, LS, MC, MN, MO, MR, PP, RR, YJ; Resources: CS, DP, MN; Data Curation: AR, IG, ML, MN, MSh,
544 NC, PP, SF; Writing - Original Draft: MN; Writing - Review & Editing: AR, CS, DM, EG, ML, MN, MO,
545 MR, MS, PP, RS, SC, YJ; Visualization: MN, MO, RS; Supervision: MN; Project administration: CS, DP,
546 EG, MN.

547 9. Competing Interests

548 The authors declare no competing interests.

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565 [org/server/api/core/bitstreams/531a9e1b-596d-4b07-b9fd-3103fb4d0e72/](https://openknowledge.fao.org/server/api/core/bitstreams/531a9e1b-596d-4b07-b9fd-3103fb4d0e72/content)
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723 A. Supplementary Definitions

724 The forest typology is strictly aligned with the definitions set forth in Article 2 of the EU Deforestation
 725 Regulation (EUDR) 2023/1115. We adopt the FAO-based structural thresholds for forest definition
 726 (> 0.5 ha, > 5 m height, > 10% canopy cover) while maintaining a clear distinction between forest
 727 land and agricultural tree crops (e.g., oil palm, rubber), the latter being classified as agricultural land
 728 use under the regulation. This hierarchical alignment ensures that the Forest Typology v1 map can
 729 serve as a direct tool for verifying both deforestation (conversion of forest to agriculture) and forest
 730 degradation (conversion of primary forest to plantation forest, other wooded land (OWL) or planted
 731 forest, or the conversion of naturally regenerating forests to plantations or OWL).

732 A.1. EUDR definitions

733 The EU Deforestation Regulation (EUDR) 2023/1115 [8] adopts forest type definitions from the FAO
 734 Global Forest Resources Assessment [3]. The following definitions from Article 2 of the regulation
 735 govern the Forest Typology classification:

Forest Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10%, or trees able to reach those thresholds in situ. It does not include land that is predominantly under agricultural or urban land use.

Primary Forest Naturally regenerated forest of native tree species, where there are no clearly visible indications of human activities and the ecological processes are not significantly disturbed.

Naturally Regenerating Forest Forest predominantly composed of trees established through natural regeneration. This includes forests where it is impossible to distinguish between planted and naturally regenerated, and mixed forests where natural regeneration is expected to constitute the major part of the growing stock at maturity.

Planted Forest Forest predominantly composed of trees established through planting and/or deliberate seeding, provided that these are expected to constitute more than 50% of the growing stock at maturity.

Plantation Forest A sub-category of planted forest that is intensively managed and meets all the following criteria at planting and stand maturity: one or two species, even age class, and regular spacing.

Agricultural Use Use of land for the purpose of agriculture, including for agricultural plantations (e.g., fruit trees, oil palm, rubber). Note: These are explicitly excluded from the definition of “Forest” under EUDR.

736 A.2. Scope and operational choices

737 We made two design choices in the Forest Typology classification for operational efficiency and to
 738 align with regulatory definitions:

739 **Planted vs. plantation forest: the 40-year rotation proxy.** The FAO and EUDR definitions distin-
 740 guish planted forest from plantation forest by management intensity criteria—monoculture, even-age
 741 class, and regular spacing—rather than by a specific rotation period. Because management intensity
 742 is not directly observable from satellite imagery, we adopt an operational 40-year rotation period
 743 threshold as a potentially observable proxy in time series data: planted forests with rotation periods
 744 exceeding 40 years are classified as planted forest, while those with shorter rotations are classified
 745 as plantation forest. This threshold was chosen to separate fast-rotation industrial plantations (e.g.,

746 eucalyptus pulpwood, short-rotation acacia) from slower-rotation planted forests (e.g., mahogany,
747 long-rotation pine).

748 **Other wooded land (OWL).** The EUDR recognizes other wooded land—areas with 5–10% canopy
749 cover, or combined tree, shrub, and bush cover exceeding 10%—as a distinct category. Conversion of
750 primary forest to OWL constitutes forest degradation under the regulation. In the Forest Typology
751 map, OWL is subsumed into the *Other* class and is not resolved as a separate class. We might address
752 this in future work.

753 A.3. GVFT annotation labels

754 The Global Validation of Forest Types (GVFT) dataset uses 13 annotation labels. Expert annotators
755 select from these labels when interpreting each sample site.

Primary forest Naturally regenerated forest of native tree species with no clearly visible indications of human activities, and undisturbed ecological processes. Minimum area is > 0.5 ha.

Naturally regenerated forest Forest predominantly composed of native or introduced trees established through natural regeneration, including mixed stands where natural trees will dominate at maturity. Minimum area is > 0.5 ha.

Planted forest Forest predominantly established through planting or deliberate seeding (exceeding 50% of growing stock at maturity) with a rotation period exceeding 40 years. Minimum area is > 0.5 ha.

Plantation forest Intensively managed planted forest meeting criteria of one or two species, even age class, and regular spacing. Rotation period is a maximum of 40 years (commercial teak is automatically classified here). Minimum area is > 0.5 ha.

Primary burnt forest Primary forest that has been significantly damaged by fire, where all trees are dead but still standing.

756 Forest and Tree-Based Labels.

Tree crops Clearly visible large- or medium-scale plantations where the main commodities are tree crops (e.g., rubber, oil palm) or orchards (e.g., olive, fruit trees).

Agroforestry (mixed tree crops) Systems featuring cocoa, coffee, or shaded tree crops grown alongside other crops underneath (e.g., alley cropping, mixed tree crops, palms).

Agroforestry (nature-close) Systems where tree crops are mixed with native trees, shrubs, or woody plantations.

Silvopasture The practice of integrating trees, forage, and the grazing of domesticated animals in a mutually beneficial way.

757 Agricultural and Agroforestry Labels.

Other wooded land (Woodland) Land that is not technically a forest (canopy cover of 5% to

10%, or combined tree/shrub/bush cover > 10%) exceeding 0.5 ha. Currently falls outside the regulatory scope of the EUDR.

Other trees Isolated elements falling outside standard forest thresholds, such as single trees on agricultural fields, pastures, tree shelterbelts, trees in urban/built-up areas, or small parks < 0.5 ha.

Other land Areas containing no trees, but which can include shrubs.

Not sure Used when there are insufficient data or imagery to decide on the correct class.

758 **Other Labels.** The mapping of GVFT labels to Forest Typology classes is outlined in [Table 12](#).

Table 12 | Forest Typology Class Definitions and Aggregation Schema for Validation Labels.

Forest Typology Class	Operational Definition	Validation Labels (GVFT)
Class 1: Primary Forest	Naturally regenerated forest of native species with no clearly visible indications of human activity and undisturbed ecological processes. Area > 0.5 ha.	<ul style="list-style-type: none"> • Primary forest • Burnt primary forest
Class 2: Naturally Regenerated Forest	Forests predominantly established through natural regeneration. Includes secondary recovery, native/introduced mixed regeneration, or coppice. Width > 20 m if shelterbelt.	<ul style="list-style-type: none"> • Naturally regenerated forest
Class 3: Planted Forest	Forests predominantly established through planting or seeding where the rotation period > 40 years.	<ul style="list-style-type: none"> • Planted forest
Class 4: Plantation Forest	Intensively managed, even-aged monocultures with regular spacing. Rotation period ≤ 40 years. Planted Teak is always grouped here.	<ul style="list-style-type: none"> • Plantation forest
Class 5: Tree Crops and Agroforestry	Agricultural plantations producing commodities other than wood (e.g., rubber, oil palm, fruit orchards, shaded cocoa/coffee). Treated as agricultural land under EUDR.	<ul style="list-style-type: none"> • Tree crops • Agroforestry (mixed) • Agroforestry (nature-close)
Class 6: Other Land	Residual non-tree land uses, sparse woody vegetation (canopy cover < 10%), or elements falling outside FAO forest specifications.	<ul style="list-style-type: none"> • Other land • Other wooded land • Other trees • Woodland • Silvopasture

759 A.4. Planted forest and tree crop species types

760 The following tables are provided as a reference guide to illustrate the diversity of species within
 761 the planted forest and tree crop classes; no characteristics from these tables were used for model
 762 development or training. [Table 13](#) lists tree species common to planted and plantation forest. [Table 14](#)
 763 lists common agricultural tree crop species.

764 Notable exceptions include banana/plantain and vineyards, which may appear woody but are not

765 trees and therefore are excluded from the *Tree Crops and Agroforestry* class, unless they form part of
766 an agroforestry system.

Table 13 | Common tree species in planted and plantation forests (primary product and major regions only as a guide, not exhaustive).

Common Name	Scientific Name	Primary Product	Major Regions
Acacia	<i>Acacia mangium</i>	Pulp, Timber	SE Asia
Bamboo*	<i>Bambusoideae</i>	Culms, Shoots	E. Asia, SE Asia, SoAm, Africa
Chinese Fir	<i>Cunninghamia lanceolata</i>	Timber	E. Asia
Eucalyptus	<i>Eucalyptus</i> spp.	Pulp, Timber	SoAm, Aus, SE Asia, Africa
Gmelina	<i>Gmelina arborea</i>	Pulp, Timber	W. Africa, SE Asia
Loblolly Pine	<i>Pinus taeda</i>	Pulp, Timber	NoAm, SoAm
Mahogany	<i>Swietenia macrophylla</i>	Timber	CeAm, SoAm, SE Asia
Paulownia	<i>Paulownia</i> spp.	Timber	E. Asia, Europe, NoAm
Poplar	<i>Populus</i> spp.	Timber	E. Asia, Europe, NoAm
Radiata Pine	<i>Pinus radiata</i>	Pulp, Timber	Oceania, SoAm, S. Africa
Sitka Spruce	<i>Picea sitchensis</i>	Timber	Europe, NoAm
Teak	<i>Tectona grandis</i>	Timber	SE Asia, W. Africa, CeAm

*Biologically grass, but classified as Forest by FAO.

Table 14 | Common agricultural tree crop species (primary product and major regions only as a guide, not exhaustive).

Common Name	Scientific Name	Primary Product	Major Regions
Almond	<i>Prunus dulcis</i>	Nut	USA, Aus, Spain
Apple	<i>Malus domestica</i>	Fruit	China, Poland, USA, Chile
Avocado	<i>Persea americana</i>	Fruit	Mexico, Peru, Chile, USA
Cashew	<i>Anacardium occidentale</i>	Nut	W. Africa, India, Vietnam
Citrus / Orange	<i>Citrus</i> spp.	Fruit	Brazil, USA, China, Med.
Cocoa	<i>Theobroma cacao</i>	Bean	Ivory Coast, Ghana, Ecuador
Coconut	<i>Cocos nucifera</i>	Nut, Water	SE Asia, S. Asia, Pacific, Caribbean
Coffee	<i>Coffea</i> spp.	Bean	Brazil, Vietnam, Colombia
Date Palm	<i>Phoenix dactylifera</i>	Fruit	Middle East, N. Africa, USA
Macadamia	<i>Macadamia</i> spp.	Nut	Aus, S. Africa, USA
Mango	<i>Mangifera indica</i>	Fruit	India, Thailand, Mexico
Oil Palm	<i>Elaeis guineensis</i>	Oil	SE Asia, W. Africa, SoAm
Olive	<i>Olea europaea</i>	Oil, Fruit	Spain, Italy, Greece, Tunisia
Pistachio	<i>Pistacia vera</i>	Nut	Iran, Turkey, USA
Rubber	<i>Hevea brasiliensis</i>	Latex	Thailand, Indonesia, Vietnam

767 B. Strata Areas by Continent

Table 15 | Map-based stratum areas by continent (in Mha).

	Africa	Asia	Australia & Oc.	Europe	North America	South America
Primary forest	321.98	725.70	90.63	65.10	337.09	583.18
Naturally regenerating forest	330.83	513.52	58.93	216.48	386.11	292.07
Planted forest	0.22	83.59	0.01	103.12	17.73	0.00
Plantation forest	5.54	42.55	7.21	5.39	31.87	25.49
Tree crops and agroforestry	19.25	82.42	0.42	18.93	6.17	18.62
Other land	1842.11	2740.40	623.04	491.62	1377.39	670.04
Potential forest	491.48	282.84	42.05	83.04	241.22	198.59

768 C. Per-Strata Confusion Matrices

Table 16 | Stratum 1: Primary forest ($N = 1,165$). Rows: estimated class; columns: reference class. Bold values are correct classifications (diagonal).

	Primary	NatReg	Planted	Plantation	TreeCrop	Other	Total
Primary	918	125	0	0	0	45	1,088
NatReg	8	30	1	0	0	0	39
Planted	0	0	0	0	0	0	0
Plantation	0	0	0	0	0	0	0
TreeCrop	0	0	0	0	0	0	0
Other	16	3	0	0	0	19	38
Total	942	158	1	0	0	64	1,165

Table 17 | Stratum 2: Naturally regenerating forest ($N = 1,149$). Rows: estimated class; columns: reference class. Bold values are correct classifications (diagonal).

	Primary	NatReg	Planted	Plantation	TreeCrop	Other	Total
Primary	83	112	1	1	0	9	206
NatReg	37	702	27	6	15	63	850
Planted	0	0	2	0	0	0	2
Plantation	0	2	1	0	0	0	3
TreeCrop	0	2	0	0	5	1	8
Other	4	23	0	0	3	50	80
Total	124	841	31	7	23	123	1,149

Table 18 | Stratum 3: Planted forest ($N = 1,116$). Rows: estimated class; columns: reference class. Bold values are correct classifications (diagonal).

	Primary	NatReg	Planted	Plantation	TreeCrop	Other	Total
Primary	0	4	4	0	0	0	8
NatReg	1	185	73	13	0	22	294
Planted	2	171	441	36	2	25	677
Plantation	0	0	0	1	0	1	2
TreeCrop	0	1	0	0	1	0	2
Other	0	13	11	11	5	93	133
Total	3	374	529	61	8	141	1,116

Table 19 | Stratum 4: Plantation forest ($N = 1,097$). Rows: estimated class; columns: reference class. Bold values are correct classifications (diagonal).

	Primary	NatReg	Planted	Plantation	TreeCrop	Other	Total
Primary	0	2	0	2	0	0	4
NatReg	0	72	11	28	2	7	120
Planted	0	4	3	10	0	1	18
Plantation	0	80	17	511	7	27	642
TreeCrop	0	0	0	1	6	3	10
Other	0	19	2	63	8	211	303
Total	0	177	33	615	23	249	1,097

Table 20 | Stratum 5: Tree crops and Agroforestry ($N = 1,173$). Rows: estimated class; columns: reference class. Bold values are correct classifications (diagonal).

	Primary	NatReg	Planted	Plantation	TreeCrop	Other	Total
Primary	0	1	0	0	0	0	1
NatReg	0	29	1	2	6	5	43
Planted	0	3	1	0	0	0	4
Plantation	0	0	0	2	1	0	3
TreeCrop	0	29	1	4	666	92	792
Other	0	20	1	10	48	251	330
Total	0	82	4	18	721	348	1,173

Table 21 | Stratum 6: Other land use ($N = 1,287$). Rows: estimated class; columns: reference class. Bold values are correct classifications (diagonal).

	Primary	NatReg	Planted	Plantation	TreeCrop	Other	Total
Primary	0	0	0	0	0	0	0
NatReg	0	1	0	0	0	0	1
Planted	0	0	0	0	0	0	0
Plantation	0	0	0	0	0	0	0
TreeCrop	0	0	0	0	0	0	0
Other	10	8	1	0	4	1,263	1,286
Total	10	9	1	0	4	1,263	1,287

Table 22 | Stratum 7: Potential Forest ($N = 1,203$). Rows: estimated class; columns: reference class. Bold values are correct classifications (diagonal).

	Primary	NatReg	Planted	Plantation	TreeCrop	Other	Total
Primary	9	3	0	0	0	7	19
NatReg	0	18	0	0	1	9	28
Planted	0	0	0	0	0	0	0
Plantation	0	0	0	0	0	0	0
TreeCrop	0	1	0	0	10	8	19
Other	60	73	3	1	28	972	1,137
Total	69	95	3	1	39	996	1,203

769 D. Per-Continent Accuracy

770 This section provides detailed classification accuracy broken down by continent. [Table 23](#) summarizes
771 overall accuracy and per-class F1-scores, while [Table 24](#) reports the full user's accuracy, producer's
772 accuracy, and their standard errors for each class–continent combination, along with the number of
773 predicted and reference samples.

774 Overall accuracy is consistent across continents, ranging from 88.5% (Europe) to 90.7% (South
775 America). However, per-class performance varies substantially. Primary forest F1-scores are highest
776 in South America (92.6%), where large contiguous tropical forests are well-represented, and lowest
777 in Australia (65.8%), where the small validation sample ($N = 277$) limits statistical power. Naturally
778 regenerating forest achieves the most uniform performance across continents (62.5–79.5% F1).

779 Rare class–continent combinations should be interpreted with caution. For example, tree crops in
780 Australia ($N_{\text{ref}} = 5$), planted forest in Africa ($N_{\text{pred}} = 0$), and plantation forest in Europe ($N_{\text{ref}} = 32$)
781 yield unstable estimates with large standard errors.

Table 23 | Per-continent classification accuracy for the six-class Forest Typology scheme. N is the number of validation samples. OA = overall accuracy. All values in %.

	N	OA \pm SE	Primary F1	NatReg F1	Planted F1	Plantation F1	TreeCrop F1	Other F1
Asia	2,847	90.2 \pm 0.6	82.7	70.4	46.4	52.1	69.7	97.0
Africa	1,320	90.5 \pm 0.8	78.0	62.5	–	80.0	57.1	96.2
N. America	1,345	90.2 \pm 0.7	77.3	78.1	39.4	78.0	50.2	96.4
S. America	1,189	90.7 \pm 0.9	92.6	75.1	–	82.1	59.7	94.9
Europe	1,167	88.5 \pm 1.1	76.1	79.5	69.7	36.3	40.6	96.5
Austr. & Oc.	277	89.4 \pm 1.9	65.8	69.2	–	93.1	6.8	95.1
Global	8,190	90.2 \pm 0.3	82.9	72.6	58.2	66.7	62.1	96.4

Table 24 | Detailed per-continent and per-class accuracy for the six-class Forest Typology scheme. $N_{\text{pred}}/N_{\text{ref}}$: samples predicted as / referenced as each class. UA = user's accuracy, PA = producer's accuracy.

Continent	Class	N_{pred}	N_{ref}	UA \pm SE	PA \pm SE	F1
Africa	Primary	218	226	80.6 \pm 2.6	75.5 \pm 3.4	78.0
	NatReg	147	199	73.6 \pm 3.7	54.4 \pm 3.8	62.5
	Plantation	17	18	82.4 \pm 9.2	77.8 \pm 9.7	80.0
	TreeCrop	136	148	90.6 \pm 2.4	41.7 \pm 6.1	57.1
	Other	802	728	93.6 \pm 0.8	99.0 \pm 0.2	96.2
Asia	Primary	472	371	74.1 \pm 2.0	93.6 \pm 1.4	82.7
	NatReg	420	583	84.5 \pm 2.2	60.3 \pm 2.6	70.4
	Planted	224	135	43.9 \pm 3.3	49.2 \pm 9.2	46.4
	Plantation	236	287	62.7 \pm 6.4	44.5 \pm 4.4	52.1
	TreeCrop	547	526	75.2 \pm 3.7	64.9 \pm 6.2	69.7
	Other	948	945	96.7 \pm 0.6	97.2 \pm 0.3	97.0
Australia & Oceania	Primary	52	44	66.0 \pm 6.5	65.5 \pm 8.8	65.8
	NatReg	42	55	83.5 \pm 6.2	59.1 \pm 8.0	69.2
	Plantation	29	29	93.1 \pm 4.7	93.1 \pm 4.7	93.1
	TreeCrop	2	5	100.0 \pm 0.0	3.5 \pm 3.3	6.8
	Other	152	144	93.0 \pm 2.1	97.4 \pm 0.8	95.1
Europe	Primary	39	28	67.1 \pm 7.6	87.9 \pm 5.7	76.1
	NatReg	288	334	79.8 \pm 3.0	79.2 \pm 2.6	79.5
	Planted	418	371	74.1 \pm 2.2	65.8 \pm 4.4	69.7
	Plantation	24	32	48.5 \pm 10.1	29.0 \pm 7.2	36.3
	TreeCrop	48	47	62.8 \pm 6.9	30.0 \pm 13.9	40.6
	Other	350	355	96.3 \pm 1.0	96.7 \pm 0.7	96.5
North America	Primary	196	171	71.4 \pm 3.2	84.4 \pm 2.4	77.3
	NatReg	282	289	80.1 \pm 2.6	76.3 \pm 2.9	78.1
	Planted	53	91	84.9 \pm 4.9	25.6 \pm 4.7	39.4
	Plantation	212	198	82.5 \pm 2.6	73.9 \pm 7.6	78.0
	TreeCrop	37	44	94.6 \pm 3.7	34.1 \pm 9.9	50.2
	Other	565	552	96.5 \pm 0.6	96.3 \pm 0.6	96.4
South America	Primary	339	302	88.2 \pm 1.7	97.5 \pm 1.2	92.6
	NatReg	193	264	85.6 \pm 2.7	66.9 \pm 3.2	75.1
	Plantation	130	137	84.6 \pm 3.1	79.6 \pm 3.4	82.1
	TreeCrop	54	44	58.7 \pm 12.1	60.7 \pm 14.0	59.7
	Other	473	439	94.2 \pm 1.1	95.5 \pm 0.8	94.9
Global	Primary	1,326	1,148	77.9 \pm 1.1	88.5 \pm 1.1	82.9
	NatReg	1,375	1,736	81.1 \pm 1.2	65.8 \pm 1.4	72.6
	Planted	701	602	65.1 \pm 1.8	52.6 \pm 3.7	58.2
	Plantation	650	702	74.4 \pm 3.1	60.4 \pm 3.2	66.7
	TreeCrop	831	818	76.9 \pm 2.8	52.1 \pm 4.2	62.1
	Other	3,307	3,184	95.4 \pm 0.4	97.3 \pm 0.2	96.4

782 E. Supplementary Area Estimates

783 This section provides detailed area estimates by continent and country. [Table 25](#) reports sample-based
 784 area estimates per forest type class by continent, computed from stratified area proportions following
 785 [\[56\]](#). [Table 26](#) reports the corresponding map-based estimates obtained by pixel counting. [Table 27](#)
 786 reports sample-based and map-based area estimates for countries with at least 100 validation samples.
 787 The area estimates in [Table 27](#) are for the merged Forest (classes 1–4), Natural forest (classes 1–2),
 788 Planted forest (classes 3–4), and TreeCrop (class 5) classes.

Table 25 | Sample-based area estimates per forest type class by continent (Mha \pm CI₉₅, CI₉₅ = 1.96 \times SE).
 N is the number of consensus validation samples.

	<i>N</i>	Primary	NatReg	Planted	Plantation	TreeCrop	Other
Africa	1,320	394.1 \pm 38.8	298.2 \pm 36.2	0.1 \pm 0.2	2.1 \pm 0.8	51.5 \pm 13.3	2244.2 \pm 43.1
Asia	2,847	661.1 \pm 38.1	576.4 \pm 42.0	38.4 \pm 14.0	45.5 \pm 8.5	106.1 \pm 20.9	3063.0 \pm 40.8
Austr. & Oc.	277	90.8 \pm 25.0	72.8 \pm 18.1	0.0 \pm 0.0	3.6 \pm 0.9	7.9 \pm 12.2	636.4 \pm 29.2
Europe	1,167	52.7 \pm 12.8	231.9 \pm 19.7	84.5 \pm 11.5	4.1 \pm 1.4	12.2 \pm 10.7	608.5 \pm 16.5
N. America	1,345	305.8 \pm 28.6	373.9 \pm 32.5	35.8 \pm 11.3	24.0 \pm 5.0	10.2 \pm 5.6	1677.3 \pm 27.7
S. America	1,189	550.4 \pm 23.6	314.5 \pm 28.1	0.3 \pm 0.3	14.3 \pm 1.6	9.9 \pm 4.8	880.9 \pm 25.3
Global	8,190	2038.4 \pm 70.7	1852.0 \pm 74.3	160.1 \pm 22.0	91.1 \pm 9.4	195.9 \pm 31.0	9146.3 \pm 77.0

Table 26 | Map-based forest area estimates per forest type class by continent (Mha).

	Primary	NatReg	Planted	Plantation	TreeCrop	Other
Africa	353	246	0	3	27	2362
Asia	859	383	40	26	84	3097
Austr. & Oc.	87	54	0	3	0	667
Europe	62	232	77	3	5	614
N. America	366	347	11	21	4	1678
S. America	604	245	0	14	9	899
Global	2330	1508	129	70	130	9317

789 Several continent-level discrepancies between sample-based and map-based area estimates reveal
 790 systematic patterns in the map’s classification behavior.

791 In Asia, the map assigns 859 Mha to primary forest, whereas the sample-based estimate is 661 Mha
 792 ([Table 25](#), [Table 26](#)). Conversely, naturally regenerating forest is underestimated by the map (383 Mha)
 793 relative to the sample-based estimate (576 Mha). The total natural forest area is similar under both
 794 approaches (map: 1,243 Mha; sample: 1,238 Mha), indicating that the discrepancy is largely a
 795 redistribution between primary and naturally regenerating forest rather than an overall forest area
 796 bias. This pattern is most pronounced in Russia ([Table 27](#)), where vast boreal forests are difficult
 797 to classify along the primary–naturally regenerating gradient from satellite imagery alone. The
 798 distinction between undisturbed primary boreal forest and forests with historical or low-intensity
 799 management is inherently ambiguous in these regions.

800 In North America, the sample-based planted forest estimate (60 Mha) is nearly double the map-based
 801 estimate (32 Mha), suggesting that the map misclassifies a substantial fraction of planted forests—
 802 likely as naturally regenerating forest—particularly in the southeastern United States, where pine
 803 plantations can be spectrally similar to regenerating natural stands at certain growth stages.

804 In Africa, the sample-based total forest estimate (695 Mha) exceeds the map-based estimate (601 Mha)
 805 by approximately 94 Mha, the largest absolute discrepancy among all continents. This gap likely
 806 reflects the omission of sparse woodland and savanna forests near the FAO canopy cover threshold

Table 27 | Sample- and map-based area estimates (Mha) with 95% Confidence Intervals ($1.96 \times SE$) for countries with largest forest areas.

Country	N	Forest		Natural		Planted		TreeCrop	
		Sample \pm CI ₉₅	Map	Sample \pm CI ₉₅	Map	Sample \pm CI ₉₅	Map	Sample \pm CI ₉₅	Map
Russia	911	858.1 \pm 25.4	853.6	839.3 \pm 26.5	841.1	18.1 \pm 7.2	12.5	0.2 \pm 0.3	0.1
Brazil	726	479.3 \pm 18.8	473.8	469.8 \pm 18.8	465.7	10.6 \pm 2.9	8.0	4.4 \pm 2.4	3.8
Canada	462	419.1 \pm 22.3	396.6	395.7 \pm 23.8	389.9	21.2 \pm 8.8	6.7	0.0 \pm 0.0	0.0
USA	687	294.0 \pm 14.6	315.1	250.7 \pm 16.3	282.5	41.4 \pm 8.7	32.6	1.3 \pm 0.5	1.3
China	816	202.9 \pm 14.3	193.6	142.9 \pm 9.7	151.5	61.0 \pm 15.0	42.2	22.6 \pm 18.0	5.3
DRC	166	161.9 \pm 5.6	157.7	161.9 \pm 5.6	157.7	0.0 \pm 0.0	0.1	4.6 \pm 4.5	0.8
Australia	233	158.6 \pm 27.2	132.7	156.8 \pm 27.3	130.9	1.7 \pm 0.7	1.8	6.4 \pm 12.2	0.2
Indonesia	345	125.1 \pm 4.8	123.4	122.7 \pm 4.8	120.9	2.3 \pm 0.6	2.5	29.2 \pm 4.8	29.3
Mexico	121	53.9 \pm 6.6	59.7	53.9 \pm 6.6	59.6	0.0 \pm 0.0	0.1	2.7 \pm 2.5	1.4
India	142	53.1 \pm 10.3	51.2	50.1 \pm 11.1	50.6	2.8 \pm 3.6	0.6	9.4 \pm 6.0	9.4
Sweden	107	26.0 \pm 3.2	25.6	9.3 \pm 3.6	12.1	16.3 \pm 4.2	13.5	0.0 \pm 0.0	0.0
Viet Nam	100	15.8 \pm 1.2	14.3	13.2 \pm 1.1	11.9	2.6 \pm 0.6	2.4	4.7 \pm 1.7	3.5

807 (10%), which are widespread across the Sahel, Miombo, and other dry woodland ecosystems.

808 In Australia and Oceania, the sample-based tree crop estimate (7.9 ± 12.2 Mha) has a 95% confidence
 809 interval wider than the point estimate itself, reflecting the very small number of tree crop validation
 810 samples in this region. The map-based estimate is 0.3 Mha. While the discrepancy is large in relative
 811 terms, both estimates are small in absolute terms, and the wide confidence interval indicates that the
 812 sample-based estimate is not statistically distinguishable from zero at conventional significance levels.

813 Per-country forest proportions and the 30×30 biodiversity target

814 [Figure 8](#) presents per-country forest composition as a proportion of total land area for countries
 815 with at least 100 validation samples. For each country, four horizontal bars are shown (from top to
 816 bottom): (1) *sample-based estimates*, derived from the stratified validation sample following [56],
 817 with 95% confidence intervals at each class boundary; (2) *map-based estimates*, obtained by pixel
 818 counting from the Forest Typology classification map; (3) *strata-based proportions*, reflecting the
 819 areas assigned to each stratum during the stratified sampling design, including a “potential forest”
 820 stratum that captures areas not classified as forest but considered likely to contain forest; and (4) a
 821 thin red bar indicating the *relative country land area*, normalized so that the largest country (Russia)
 822 reaches 100%, providing visual context for absolute scale.

823 These per-country proportions complement the absolute area estimates in [Table 27](#) by normalizing
 824 for country size, enabling direct comparison of forest composition across nations of vastly different
 825 extents. The 95% confidence intervals reflect the statistical uncertainty of the sample-based estimates;
 826 however, for countries with few validation samples, confidence intervals may be artificially narrow
 827 because the stratified estimator cannot capture classification variability from a small, homogeneous
 828 sample—estimates for such countries should be interpreted with particular caution. These estimates
 829 are based on the 8,190 currently resolved validation sites; resolution of the remaining samples may
 830 refine per-country results, particularly for under-sampled countries.

831 The Forest Typology dataset can provide a spatially explicit evidence base for identifying regions
 832 where remaining natural forests—alongside other natural ecosystems—warrant prioritized protection,
 833 contributing to area-based conservation targets such as the Kunming-Montreal 30×30 framework.

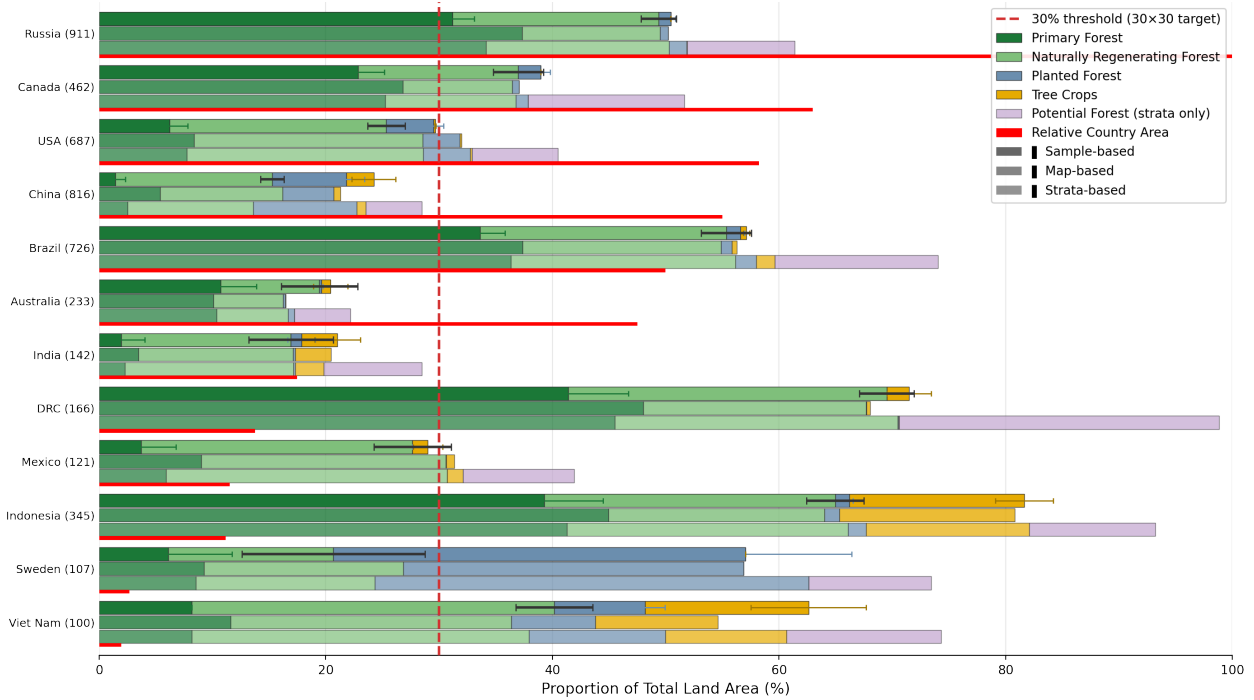


Figure 8 | Forest and tree cover by type as estimated proportions of total country land area for countries with at least 100 validation samples. The 4 bars per country show: (1) sample-based estimates with 95% confidence intervals at each class boundary, (2) map-based estimates, (3) strata proportions, (4) relative country land area. The dashed red line marks the 30% threshold of the 30x30 biodiversity target. Numbers in parentheses indicate the number of validation samples per country. The thick black error bar indicates CI₉₅ for all natural forests (primary and naturally regenerating).