Leveraging satellite embeddings and national expert annotations for country-level forest land use mapping

Timothée Stassin[1*], Diego Marcos[2], Adolfo Kindgard[3], René Colditz[4], Anssi Pekkarinen[3], and Martin Herold[1]

[1]GFZ Helmholtz Centre for Geosciences, Potsdam, Germany.
[2]Inria, Montpellier, France.
[3]Food and Agriculture Organization of the United Nations, Rome, Italy.
[4]European Commission Joint Research Centre, Ispra, Italy.
[*]Corresponding author. E-mail: timothee.stassin@gfz.de

Abstract

Spatially explicit information on forest as a land use can support climate change mitigation and biodiversity conservation actions, as well as supply-chain regulations, but many countries lack recent forest maps consistent with international definitions. Here, we assess a simple and accessible workflow for country-level Forest/Non-Forest mapping using expert reference labels from the FAO Forest Resources Assessment Remote Sensing Survey (FRA RSS), AlphaEarth Foundations satellite embeddings, and Random Forest classifiers. At global scale, Random Forest models trained on satellite embeddings and expert labels achieved state-of-the-art performance for broad Forest/Non-Forest classification (overall accuracy of 91.3 ± 0.4%), when compared to a benchmark of human experts, a deep learning model, and a reference global map (GFC 2020). Performance remained high for coarse land use classification (4 classes) but was lower for finer-grained classification (16 classes). Country-level models trained and evaluated with national subsets of the reference data produced plausible 10 m forest base maps showing broad agreement with GFC 2020 and similar forest areas as reported to FRA 2025. However, country-level accuracy estimates were often affected by limited validation sample sizes and wide confidence intervals. These results suggest that lightweight models using satellite embeddings can provide a practical starting point for country-led uncertainty-aware forest land use mapping in accessible (cloud-)computing environments. Their operational use, however, depends on sufficient high-quality national reference data, expert review, and independent and statistically-robust validation.

1 Introduction

Reliable spatial information on forest as a land use is essential for climate change mitigation[1], biodiversity conservation[2, 3], and supply-chain regulation[4]. Yet mapping forest land use remains challenging because the Forest definition used in several international processes combines *land cover* criteria, such as tree height, canopy cover, and minimum area, with *land use* criteria, namely excluding "land that is predominantly under agricultural or urban land use"[5]. Tree cover alone is therefore insufficient to identify Forest: croplands and settlements with trees are Non-Forest, while temporarily unstocked areas remain Forest. These distinctions require contextual information and expert knowledge that are difficult to derive consistently from satellite imagery alone[6].

At the same time, rapid advances in Earth observation (EO) data availability, cloud computing, and artificial intelligence (AI) have greatly expanded the technical possibilities for high-resolution land monitoring[7]. However, these developments have not been matched equally by the capacity of mandated national institutions to adapt, validate, and integrate them into operational forest monitoring and reporting systems[8–10]. Recent global Forest products for 2020, including GFC 2020[11], Natural Forests of the World 2020[12], and Forest Typology 2020[13], provide valuable and globally consistent information at 10 m resolution. Nevertheless, their use at country level still requires careful assessment[14]. This gap is particularly evident where recent national Forest information is limited: for FRA 2025, 42 countries were unable to compile and submit national Forest data, and FAO relied on desk studies instead[15]. Bridging this implementation gap therefore requires accessible workflows that allow countries to combine recent EO and AI developments with their own expert knowledge and reference data, alongside externally produced global maps.

Countries and regional experts already play a central role in forest land use monitoring through the FRA[16]. The participatory FRA 2020 Remote Sensing Survey (FRA 2020 RSS) produced the largest forest land use reference dataset to date, with approximately 400,000 plots interpreted according to a 16-class land use legend by trained experts from 126 countries and territories using a common methodology[17, 18]. These labels provide an opportunity to explore whether country-owned or country-relevant expert data originally compiled for sample-based reporting can also be used for training classification models and evaluating forest land use mapping workflows[6]. This is particularly relevant if such workflows can be implemented sustainably with modest technical resources and without specialized deep learning infrastructure.

Satellite embeddings offer a practical way to simplify such workflows. Instead of requiring users to preprocess and combine multiple satellite image composites and ancillary datasets, embeddings provide compact per-pixel representations derived from large-scale EO data[19, 20]. Combined with lightweight models such as Random Forest classifiers[21], they may allow countries to reuse and pool existing reference data, reduce preprocessing requirements, and train models in accessible (cloud-)computing environments[22, 23]. Such an approach would not replace expert interpretation, statistically robust validation, and sample-based area estimates, but could provide a practical starting point for country-led map production[24]. The trained models and derived maps could also support more efficient use of available samples by identifying areas of disagreement or uncertainty and prioritizing where additional interpretation or sampling is most needed[6].

Here, we assess a simple Random Forest (RF) workflow using AlphaEarth Foundations (aef) satellite embeddings and FRA 2020 RSS expert labels for broad Forest/Non-Forest and finer land use mapping (Fig. 1). The objective is not to introduce a new global Forest product or a new modelling architecture, but to evaluate the potential and limitations of an accessible, country-oriented workflow. Specifically, we: (1) benchmark Random Forest models trained on satellite embeddings against conventional satellite imagery inputs, human experts, a deep learning model (FLUC-16)[6], and GFC 2020 v2[11]; (2) assess how performance varies with the number of training samples and how country-level validation is constrained by reference data availability; and (3) demonstrate uncertainty-aware country-level Forest/Non-Forest map production in Google Earth Engine for selected countries, comparing resulting spatial patterns and Forest areas with GFC 2020 v2 and FRA 2025 reported areas.

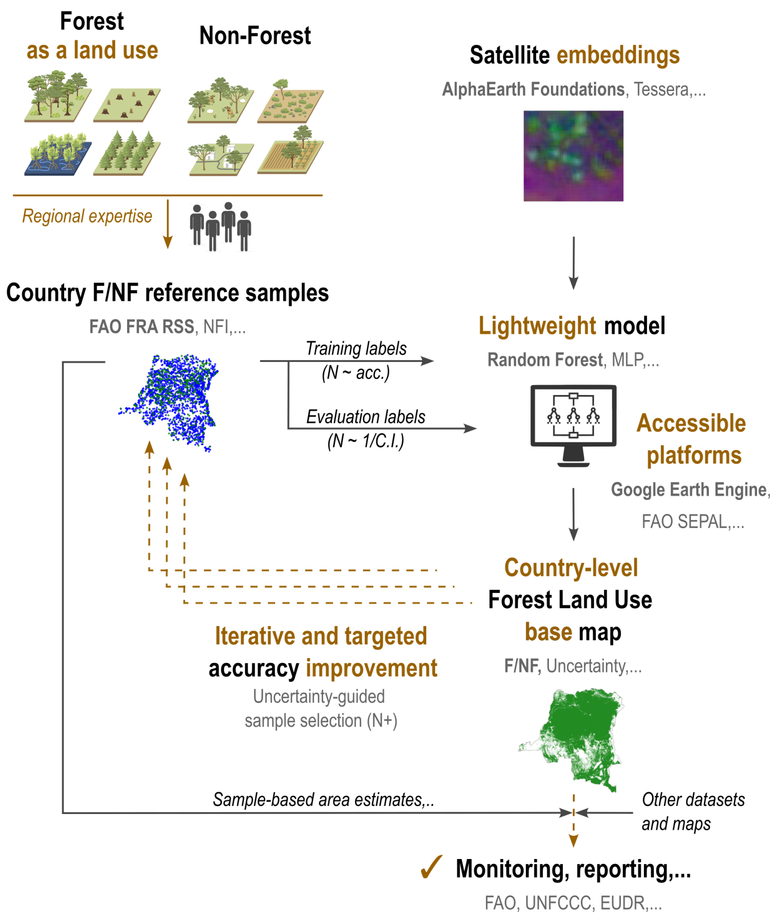

Figure 1: **Workflow for country-level forest land use mapping with lightweight models trained on satellite embeddings and expert reference data.** Expert reference data are combined with pre-computed Earth observation foundation model embeddings to train lightweight classifiers that can be deployed on accessible computing platforms, thereby enabling efficient country-level forest land use mapping. Independent training and evaluation reference samples are used for model development and accuracy assessment, respectively. Iteratively improvements can be achieved with additional reference data, for example with samples from areas of higher uncertainty. The resulting country-level forest land use base maps can contribute to Forest monitoring and reporting applications. Although this study focuses on the FAO FRA definition of forest as a land use[18], the framework is equally applicable to alternative forest definitions, provided that corresponding reference data are available.

2 Materials and methods

2.1 Reference data

We used reference labels from the FAO FRA 2020 Remote Sensing Survey (FRA 2020 RSS), which comprises approximately 400,000 globally distributed plot locations interpreted by trained local experts using satellite imagery for the reference year 2018[17]. Each sampling unit consists of a 40 ha hexagon for which experts estimated the proportions of *Forest*, *Other wooded land*, *Other land*, and *Water*. In addition, the main land use class was assigned for the 1 ha square plot located at the hexagon centroid, using a 16-class land use legend from the FRA 2020 RSS. In this study, labels were considered at three levels of thematic aggregation: 16 classes, 4 classes, and binary Forest/Non-Forest (Fig. S1).

For model training, pixel-level labels were derived by retaining homogeneous plots, defined as plots assigned to a single class based on the 40 ha class proportions, and assigning this class to the 10 m pixel located at the plot centre. This resulted in 214,807 training pixels. Country-level models were trained using the subset of training pixels intersecting the corresponding country boundaries from the FAO Global Administrative Unit Layers (GAUL)[25].

For the Google Earth Engine implementation, training labels were filtered to exclude plots affected by tree-cover disturbance between 2018 and 2020, based on the Hansen Global Forest Change product[26]. This filtering was applied to obtain country-level maps for the 2020 and allow comparison with the data reported to FRA and with the GFC 2020 v2 map[11].

Model evaluation used two independent reference datasets. First, we used the FRA 2020 RSS *accuracy assessment* dataset, comprising approximately 10,000 plots independently interpreted by three or four experts each. This dataset was used to evaluate model predictions pairwise against each human annotation at the 1 ha plot-centroid and 40 ha hexagon levels, thereby preserving the variability found in the pool of expert labels. Second, we used the CGLS-LC100 forest land use validation dataset (in short, CGLS), comprising 21,612 10 m pixel-level labels interpreted for Forest/Non-Forest classification for the reference year 2020 as part of the GFC 2020 v2 product validation[27, 28]. Country-level evaluation was performed on the subset of validation locations intersecting each corresponding FAO GAUL country boundary. Country-level models were only trained and evaluated for countries with more than 100 evaluation samples, including at least 20 samples labelled as Forest.

2.2 Satellite imagery and embeddings

Random Forest models based on AlphaEarth Foundations embeddings (RF-aef) used the 64 annual embedding bands as input features[19]. For global benchmarking, the RF-aef classifiers used the 2018 embeddings for training, corresponding to the FRA 2020 RSS reference year. For evaluation on the CGLS dataset, predictions were made using the 2020 embeddings.

To compare satellite embeddings with conventional remote sensing inputs, additional Random Forest models were trained using the same input modalities as FLUC-16 (78 features in total)[6]: Sentinel-2 annual composites for 2018 using RGB, NIR, SWIR1, and SWIR2 bands; ALOS-2

PALSAR-2 annual composites for 2017 using HH and HV polarizations[29]; and Landsat CCDC coefficients for 2018 for the thermal, RGB, NIR, SWIR1, and SWIR2 bands[30].

2.3 Random Forest model training

Random Forest pixel classifiers were trained using the `RandomForestClassifier` implementation from the `scikit-learn` Python library[31]. Default hyperparameters were used, except that the number of trees was set to 200. Three classifiers were trained at different thematic levels: RF-2 for the binary Forest/Non-Forest task, RF-4 for the four-class task, and RF-16 for the full 16-class land use task.

For country-level mapping in Google Earth Engine[22], RF-2-aef models were trained using `smileRandomForest`, also with the number of trees set to 200. This implementation was used to demonstrate a user-friendly, fully cloud-based workflow requiring no GPU resources.

2.4 Model evaluation

Model performance was evaluated at three levels. First, 1 ha plot-centroid predictions (i.e., majority label) were compared with the main land use labels from the FRA 2020 RSS *accuracy assessment* dataset. For this task, an averaged F1 score was computed by comparing model predictions with the label assigned by each independent expert, essentially following the FLUC-16 evaluation protocol described elsewhere[6].

Second, 40 ha hexagon-level class proportions were evaluated for the 4-class and Forest/Non-Forest tasks. For this evaluation, pixel-level predictions were aggregated to class proportions within each hexagon and compared with the class proportions estimated by each human expert. Performance was summarized using the annotator-averaged mean absolute error (MAE).

Third, binary Forest/Non-Forest predictions were evaluated at the 10 m pixel level using the independent CGLS validation dataset. Overall accuracy, producer's accuracy, and user's accuracy were computed with 95% confidence intervals[32]. For country-level evaluation, the same metrics were computed for countries meeting the minimum validation sample-size criteria described above.

Predictions from the RF-16 model were further aggregated to the 4-class and Forest/Non-Forest levels. Predictions from the RF-4 model were further aggregated to Forest/Non-Forest. This allowed direct comparison across classifiers trained at different thematic granularities.

2.5 Country-level inference and map comparison

Country-level Forest/Non-Forest maps were produced in Google Earth Engine using country-specific RF-2-aef classifiers trained in Google Earth Engine from the subset of FRA 2020 RSS training samples intersecting each FAO GAUL country boundaries. RF-2-aef models inference, wall-to-wall within the corresponding country boundaries, and using the 2020 AlphaEarth Foundations embeddings, yielded 10 m Forest/Non-Forest country-level maps. Prediction uncertainty was quantified by computing the Shannon entropy of the model output class probabilities[33].

The resulting country-level maps were evaluated in two complementary ways. First, Forest area was estimated by pixel counting and compared with the Forest area reported by countries to FRA 2025 for the year 2020. Second, the RF-aef maps were compared spatially with the GFC 2020 v2 map. Agreement with GFC 2020 v2 was summarized using the adjusted contingency parameter, and by comparing Forest area within 100 km $\times$ 100 km grid cells using ordinary least squares regression.

3 Results

3.1 Global benchmarking of RF-aef models

At global scale, Random Forest classifiers trained on AlphaEarth Foundations embeddings achieved performance comparable to both human experts and the FLUC-16 Vision Transformer (ViT) for the coarser land use tasks (Table 1). For the binary Forest/Non-Forest task, RF-aef models reached an annotator-averaged F1 score of 0.86, matching the inter-expert benchmark and the FLUC-16 model. Similar results were obtained for the 4-class task, where the RF-16-aef model reached an F1 score of 0.74, close to the inter-expert score of 0.75 and the FLUC-16 score of 0.74.

Performance decreased for the full 16-class task. The RF-16-aef model reached an F1 score of 0.45, below the inter-expert benchmark of 0.51 and the FLUC-16 score of 0.52. This suggests that the simpler RF-aef approach is competitive for Forest/Non-Forest and 4-class mapping, but remains less suitable for resolving the full 16-class thematic detail of the FRA 2020 RSS.

AlphaEarth Foundations embeddings consistently improved Random Forest performance compared with conventional (i.e., "raw") satellite imagery inputs. This improvement was most visible for the 16-class task, where RF-aef reached an F1 score of 0.45 compared with 0.35 for the imagery-based RF model. For 40 ha class-proportion estimation, RF-aef models also achieved mean absolute errors close to the inter-expert benchmark.

3.2 Training sample size and country-level validation constraints

The global RF-2-aef model showed a rapid increase in performance with the number of training samples, followed by a plateau once a few thousand samples were used (Fig. 2 upper left). In contrast, and as expected, reducing the number of validation samples results in a higher uncertainty of the accuracy estimates, with 95% confidence interval widths increasing rapidly below a few thousand samples (Fig. 1 upper right). Global RF-2-aef eventually reached accuracies comparable to those of GFC 2020 v2, with overall accuracies of 91.3 $\pm$ 0.4% and 91.5 $\pm$ 0.4%, producer's accuracies of 86.6 $\pm$ 1.0% and 91.8 $\pm$ 0.8%, and user's accuracies of 84.8 $\pm$ 1.0% and 82.0 $\pm$ 1.0%, respectively. This indicates that, at global scale, the AlphaEarth Foundations embeddings provide informative features for Forest/Non-Forest classification even when the Random Forest classifier is trained with a limited number of reference labels.

At country level, model performance was first evaluated directly at independent validation sample locations, without producing wall-to-wall maps. The number of available training and evaluation samples varied strongly among countries (Fig. 2 and S2). Many country-level subsets contained only a few hundred training samples, and the number of independent evaluation samples was often

Table 1: **Global benchmarking of RF models for plot-level forest land use prediction.** RF models using AlphaEarth Foundations embeddings as input were compared with RF models using conventional satellite imagery inputs, human experts, and a Vision Transformer (ViT) deep learning model (FLUC-16) on the FRA 2020 RSS *accuracy assessment* dataset. Performance is reported as annotator-averaged F1 score for the 1 ha plot-centroid main land use task and annotator-averaged mean absolute error (MAE) for the 40 ha class-proportion task. (N) denotes the number of output classes used for model training; predictions from models trained with a larger number of classes were subsequently aggregated to broader classification levels.

Model	**N**	**Input**	**Main land use** (1 ha plot centroid) annotator-averaged F1 score (std)			**Class proportions** (40 ha plot) annotator-averaged MAE (std)	
			F/NF	**4-classes**	**16-classes**	**F/NF**	**4-classes**
Experts	16	VHR	0.86 (0.01)	0.75 (0.02)	0.51 (0.03)	13.17 (1.11)	10.94 (0.63)
RF	2	aef	0.86 (0.00)	–	–	12.68 (0.48)	–
RF	4	–	0.86 (0.01)	0.72 (0.02)	–	13.56 (0.78)	10.17 (1.19)
RF	16	–	0.85 (0.01)	0.74 (0.01)	0.45 (0.03)	15.03 (1.10)	10.49 (1.05)
RF	2	imag.	0.86 (0.00)	–	–	13.59 (0.42)	–
RF	4	–	0.85 (0.01)	0.69 (0.02)	–	14.58 (0.68)	11.18 (1.34)
RF	16	–	0.83 (0.01)	0.71 (0.02)	0.35 (0.01)	16.89 (1.32)	11.66 (1.26)
ViT*	16	imag.	0.86 (0.02)	0.74 (0.03)	0.52 (0.05)	–	–

*FLUC-16

substantially smaller. As a result, country-level accuracy estimates were associated with wide 95% confidence intervals, particularly where the number of Forest validation samples was limited (Table S2, Fig. S3 and S4). These results indicate that the main practical constraint for country-level uptake is more the availability of sufficient, high-quality, and representative reference data for both training and validation, than model implementation, which can be achieved with a simple Random Forest classifier.

3.3 Country-level forest mapping

In a second step, demonstration 10 m Forest/Non-Forest maps were produced in Google Earth Engine for three countries in three different regions (Fig. 3). Corresponding predictive uncertainty maps are provided in the Supplementary Information (Fig. S6). Pixel-counted Forest areas were broadly comparable to FRA 2025 reported areas, although this descriptive comparison does not account for classification error and should not be interpreted as validation of map-based area estimates. Further, the maps showed broad spatial agreement with GFC 2020 v2 (adjusted contingency parameter in the range 0.83-0.93), and a strong correlation between the Forest areas in the cells of a 100 km × 100 km grid (R^2 in the range 0.90-0.99). These results indicate that the two maps capture similar large-scale Forest distribution patterns. However, GFC 2020 v2 generally maps larger Forest areas than RF-2-aef (Fig. S5), and local discrepancies likely remain, especially in heterogeneous landscapes and areas where the distinction between forest land use and other tree-covered land uses is more ambiguous.

4 Discussion

This study demonstrates the potential of a simple, country-oriented workflow combining expert reference labels, satellite embeddings, and Random Forest classifiers for forest land use mapping. The objective was not to introduce a new classification algorithm or another global forest product, but to assess whether recent advances in EO representation can be connected to existing national expertise and reference data, such as those collected through the FRA RSS process, through a lightweight and accessible modeling workflow.

Random Forest classifiers are already widely used for land monitoring applications[34, 35]. The main contribution here is therefore not the classifier itself, but the use of satellite embeddings to simplify its implementation, in particular for the challenging monitoring of forest land use. RF models trained on AlphaEarth Foundations embeddings performed comparably to human experts, FLUC-16, and GFC 2020 v2 for distinguishing Forest from Non-Forest and for four broad land

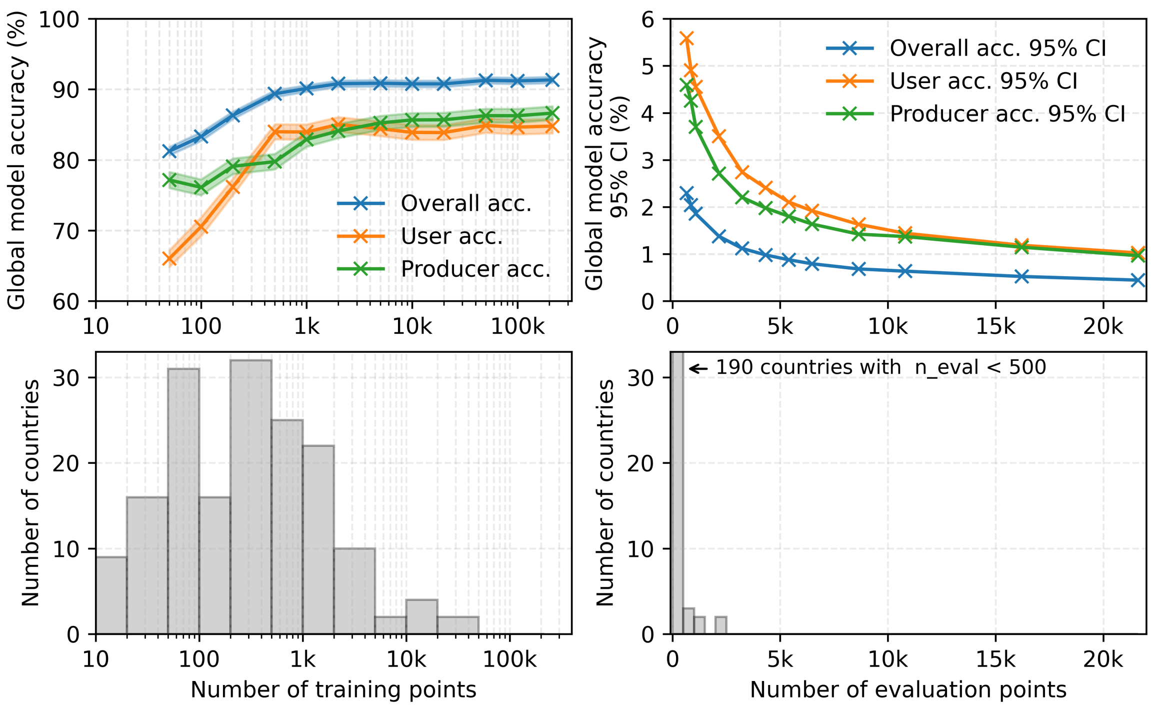

Figure 2: **Effect of training and evaluation sample size on global Forest/Non-Forest model performance.** The left panels show overall, user's, and producer's accuracies of the global RF-2-aef model on the independent CGLS pixel-level validation dataset as a function of training sample size. Models were trained using randomly selected subsets of the FRA 2020 RSS reference data and evaluated on the full validation dataset. The right panels show the 95% confidence interval widths as a function of validation sample size, for a global model trained on the full training dataset and evaluated on subsets of the validation data obtained by randomly sampling the specified fraction within each stratum. Histograms indicate the distribution of training and validation samples across countries, illustrating the variability in country-level data availability for model training and evaluation.

use categories (Table 1 and Fig. 2), while avoiding the preprocessing of multiple satellite and ancillary datasets. However, performance remained lower for more detailed land use classification (16 categories), confirming that simple pixel-level classifiers are less suitable for fine-grained land use mapping, which depends strongly on context, expert knowledge, and sometimes information not directly observable in single-year 10 m resolution satellite imagery or embeddings.

The country-level experiments highlight both the accessibility of the workflow and its dependence on suitable reference data (Fig. S2 and Fig. 3). The workflow can be implemented with limited technical resources and without the GPU-based training and inference of current state-of-the-art deep learning models[13], making it attractive for national institutions and end users. However, the number of available training and independent validation samples varied substantially among countries, and confidence intervals were often wide. Practical use of the workflow depends less on model complexity than on the availability of sufficient, high-quality, and representative reference data for both model training and independent validation. By remaining within the FRA RSS methodology, for which national experts have already been trained, the approach also allows labels to be pooled across neighboring countries sharing similar land use systems, thereby increasing the number and diversity of training samples where national datasets alone are limited. It could likewise be adapted to other reference years and class definitions where corresponding satellite embeddings and labels are available.

Country-level RF-aef Forest maps produced here as proof of concept for the Democratic Republic of the Congo, Germany, and Colombia, illustrate error patterns not captured by overall accuracy or mapped area alone. Germany showed comparatively high accuracy and balanced forest omission and commission errors. In Colombia, higher commission error indicates a tendency to overmap Forest, whereas in the Democratic Republic of the Congo, higher omission error indicates a tendency to miss Forest. These differences reinforce that the outputs should be treated as base maps for expert review, targeted sampling, and iterative improvement rather than as direct sources of Forest area estimates. The fact that GFC 2020 v2 mapped even more Forest in Colombia further shows that agreement between maps does not imply unbiased area estimates.

These findings reinforce the central role of regional experts in forest land use mapping. Regional experts possess the local ecological and land use knowledge needed to interpret complex cases, especially where Forest must be distinguished from croplands with trees (e.g., agroforestry systems) and settlements with trees, and Non-Forest from temporarily unstocked forests. Rather than replacing expert interpretation, lightweight modeling workflows such as RF-aef could support country-led mapping by providing preliminary maps, identifying areas of higher prediction uncertainty or disagreement with existing products, and helping prioritize additional validation or expert review. This is particularly relevant for countries lacking recent spatially explicit Forest information, or where global products alone may not fully reflect national definitions, land use practices, or local landscape complexity.

Several limitations should nonetheless be considered. First, RF-aef pixel classifiers were trained using labels derived from homogeneous FRA RSS plots and assigned to plot-centre pixels. This excluded heterogeneous plots, representing approximately 45% of the FRA 2020 RSS dataset. The limitation is therefore not only a reduction in training-sample quantity, but also a loss of potentially highly informative samples: heterogeneous plots are often more difficult for experts to interpret (Fig. S7) and may correspond to areas closer to class decision boundaries in the model feature space[6]. Second, temporal alignment between FRA RSS labels, CGLS validation data, GFC 2020 v2, and FRA 2025 reported Forest areas is imperfect, although disturbance filtering was applied where relevant. Third, country-level models were evaluated in this study only where a minimum number of validation samples was available. Confidence intervals remained large for several countries, indicating that more extensive validation datasets are typically required. Finally, comparisons with GFC 2020 v2 and reported FRA Forest areas provide useful consistency checks, but do not replace statistically robust country-level map validation.

Future developments should focus on strengthening the link between expert data collection, model training, and map validation. Collecting spatially explicit segmentation masks, rather than only plot-level class proportions, would enable the training of models that directly use spatial context. Such models could include lightweight neural networks suitable for training and inference in accessible computing environments, including platforms such as FAO SEPAL[23]. In parallel, collecting explicit information on label uncertainty would allow the use of training frameworks that account for ambiguous or uncertain labels, instead of treating all annotations as equally certain[36]. Integrating data collection and modeling more closely would also enable active-learning workflows, in which preliminary model outputs help identify uncertain areas for additional expert review[37].

5 Conclusion

Overall, the results support RF-aef as a practical proof-of-concept workflow for country-level forest land use mapping. Its main value lies in its simplicity, accessibility, and compatibility with expert reference data collected through existing international processes. Future work should prioritize higher-quality and more representative country-level training and validation datasets, integrated national expert review, and user-friendly tools that allow countries to iteratively refine models, assess uncertainty, and document map quality before operational use.

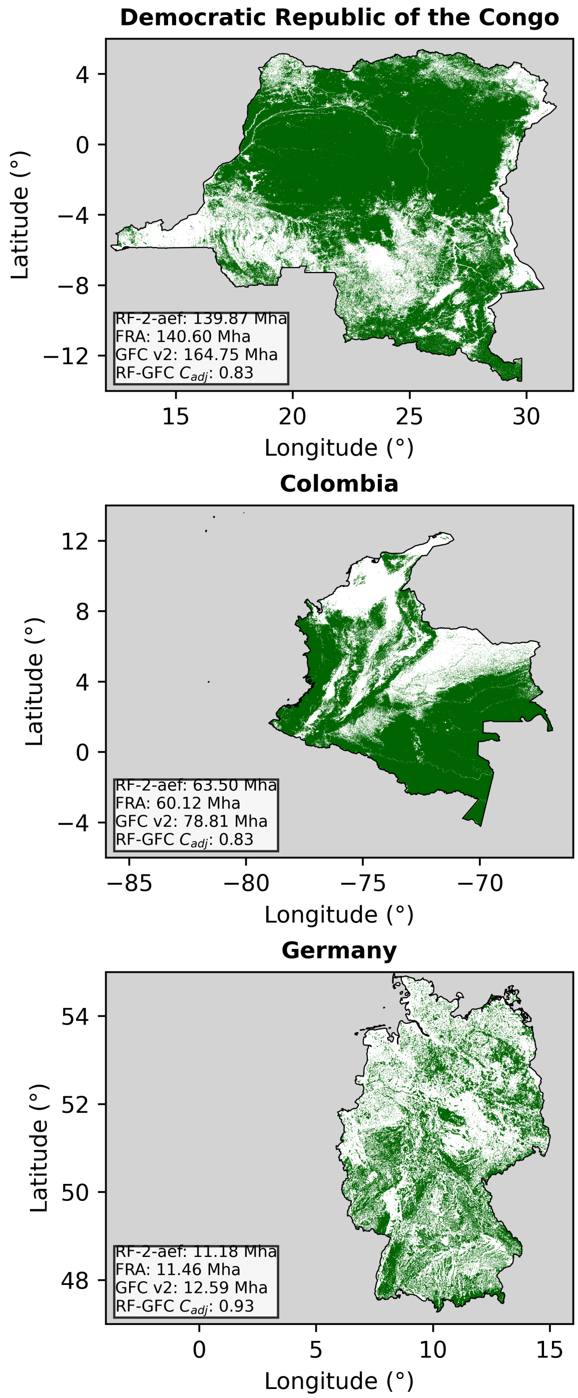

Figure 3: **Country-level RF-2-aef Forest/Non-Forest maps for selected countries.** Example 10 m Forest maps produced with country-specific RF-2-aef models trained in Google Earth Engine using national subsets of FRA 2020 RSS reference labels and AlphaEarth Foundations embeddings. Green pixels indicate areas classified as Forest. Insets report Forest area from RF-2-aef pixel counting, Forest area reported to FRA 2025 for the year 2020, Forest area from GFC 2020 v2 pixel counting, and the adjusted contingency coefficient (C_{adj}) between RF-2-aef and GFC 2020 v2.

Additional information

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Author Contributions

CRediT: Timothée Stassin: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; Diego Marcos: Conceptualization, Methodology, Resources, Supervision, Writing – review & editing; Adolfo Kindgard: Data curation, Resources, Writing – review & editing; René Colditz: Data curation, Resources, Validation, Writing – review & editing; Anssi Pekkarinen: Data curation, Funding acquisition, Resources, Writing – review & editing; Martin Herold: Funding acquisition, Resources, Supervision, Writing – review & editing

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Conflicts of Interest

The authors declare no competing interests.

Code Availability

Code is available (Python) on the GitHub repository [https://github.com/TmtStss/rfluc-aef], and (Google Earth Engine) on the Code Editor repository [users/tstassin/rfluc-aef].

Data Availability

FRA 2020 RSS data was accessed through the AI4FLUM project, further requests should be addressed to fra@fao.org. The evaluation dataset of pixel-level land use labels (Forest/Non-Forest) colocated with CGLS-LC100 is available from JRC[27]. The demonstration Forest maps are available as Google Earth Engine assets (Germany: projects/frarssmap/assets/rf-aef/v2/Germany, Colombia: projects/frarssmap/assets/rf-aef/v2/Colombia, Dem. Rep. Congo: projects/frarssmap/assets/rf-aef/v2/DRC).

Declaration of generative AI use

During the preparation of this work T.S. used ChatGPT by OpenAI to assist code writing for model training and evaluation, and to help structure the results. After using this tool, T.S. reviewed and edited the content as needed and takes full responsibility for the content of the published article.

Correspondence

Correspondence should be addressed to T.S.

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Supplementary Materials

FRA 2020 RSS land use legend

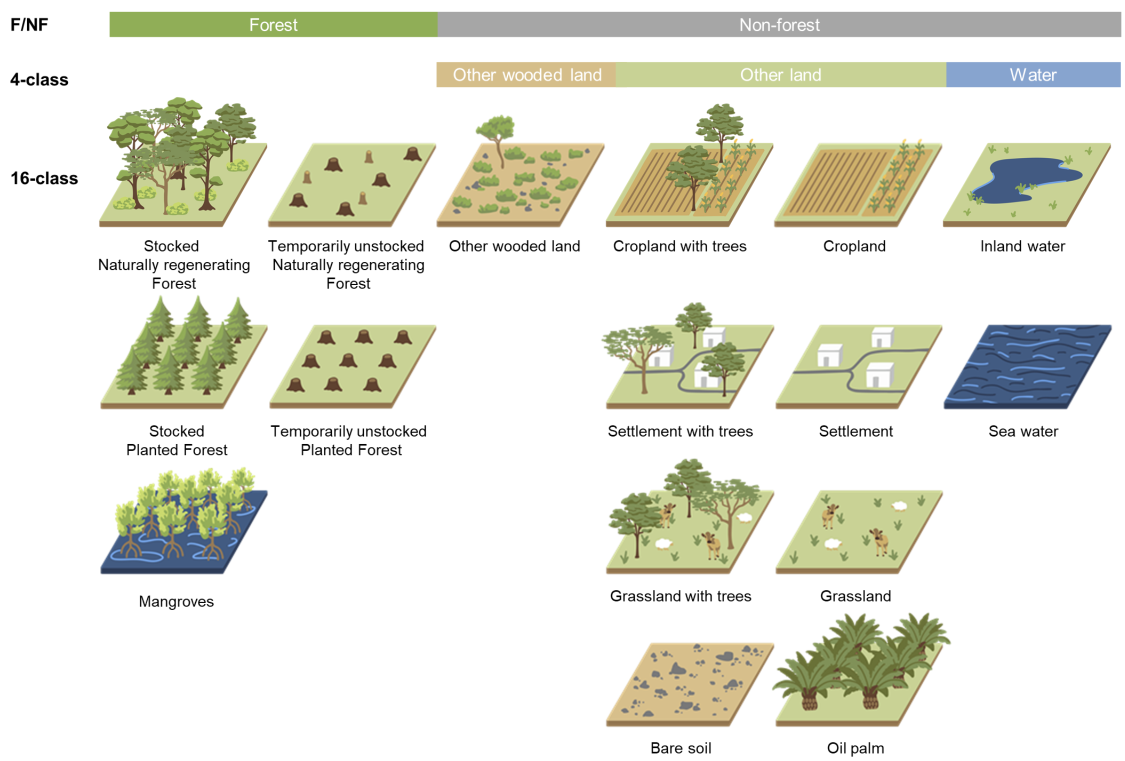

Figure S1: **Land use classification hierarchy adopted in this study based on the FAO FRA Remote Sensing Survey**. Classes are organized into three levels, progressing from a binary Forest/Non-forest classification to four broad land use classes and 16 detailed land use classes[17, 18]. Illustrative examples of the detailed classes are shown.

Global RF-aef and GFC 2020 v2 evaluation

Table S1: **Global RF-2-aef model performance evaluation at pixel-level**. Overall, producer's, and user's accuracy with 95% confidence intervals on the independent CGLS pixel-level validation dataset. Comparison with GFC 2020 v2.

	Accuracy (95% CI)			Dataset size	
	Overall	Producer	User	Training	Validation
RF-2-aef	91.3 (0.4)	86.6 (1.0)	84.8 (1.0)	214807	21612
GFC 2020 v2	91.5 (0.4)	91.8 (0.8)	82.0 (1.0)	-	21612

Country-level RF-aef evaluation

Table S2: **Country-level accuracies (overall, producer, and user) and 95% confidence intervals, with dataset sizes for training and validation**. Accuracy values are reported for the positive class and as percentages. Confidence intervals of 0 or undefined (NaN) indicate that the validation sample contained no commission or omission errors for that metric, reflecting the observed confusion matrix and the distribution of samples across strata.

	Accuracy (95% CI)			Dataset size	
Country	Overall	Producer	User	Train	Val
Angola	91.2 (6.7)	77.7 (20.8)	89.1 (8.6)	2156	179
Argentina	96.5 (1.6)	81.1 (12.5)	74.2 (13.9)	4723	451
Australia	82.2 (1.8)	40.8 (3.9)	77.7 (5.7)	10770	2439
Bolivia	94.7 (4.1)	92.2 (6.7)	98.6 (2.0)	3326	133
Brazil	86.3 (2.5)	93.2 (2.0)	81.6 (3.5)	24472	1271
Canada	87.7 (2.2)	98.3 (2.0)	72.5 (4.5)	11928	993
Chile	90.5 (8.6)	70.0 (36.8)	65.3 (34.3)	2515	266
China	95.6 (1.6)	92.5 (4.9)	91.8 (2.9)	6723	990
Colombia	70.0 (3.3)	93.3 (7.4)	53.7 (5.3)	1669	185
Democratic Republic of the Congo	81.2 (6.1)	65.6 (10.0)	99.8 (0.2)	4462	430
Ethiopia	90.9 (4.9)	21.0 (20.2)	100.0 (nan)	1967	166
Finland	93.7 (2.9)	95.4 (5.9)	89.2 (7.8)	371	167
France	94.5 (4.1)	95.6 (6.3)	92.6 (7.1)	1178	257
Germany	96.7 (2.7)	95.1 (5.3)	95.9 (5.7)	541	139
India	95.0 (3.7)	93.8 (5.7)	73.7 (20.8)	5066	295
Indonesia	89.1 (10.0)	90.6 (6.3)	86.0 (19.0)	12520	284
Italy	98.8 (0.8)	99.4 (0.6)	98.7 (1.0)	792	169
Madagascar	90.6 (8.8)	62.5 (34.9)	81.0 (34.1)	1882	121
Mexico	86.4 (11.0)	47.9 (23.3)	92.0 (5.3)	3464	458
Mozambique	60.3 (7.6)	51.7 (9.4)	58.5 (15.5)	1370	106
Myanmar	76.3 (13.3)	59.9 (19.2)	99.9 (0.2)	1930	126
New Caledonia	82.8 (10.8)	94.3 (3.3)	80.9 (14.7)	30	107
New Zealand	93.7 (3.7)	96.3 (5.1)	85.7 (8.8)	680	187
Nigeria	92.9 (4.5)	83.3 (16.9)	76.0 (17.6)	1253	197
Norway	91.3 (10.8)	96.4 (2.2)	91.1 (14.5)	261	161
Peru	92.7 (6.5)	90.3 (10.0)	97.5 (4.3)	2060	188
Poland	85.5 (3.9)	88.4 (10.8)	65.1 (9.4)	396	129
Romania	94.3 (5.9)	94.7 (7.8)	85.9 (16.1)	332	104
Russian Federation	85.5 (6.3)	83.6 (11.8)	83.7 (2.4)	23426	2280
South Africa	94.4 (2.7)	83.6 (17.2)	42.8 (22.5)	3414	261
Spain	84.5 (5.9)	100.0 (0.0)	58.9 (14.1)	1332	414
Sweden	76.6 (7.8)	97.4 (2.5)	71.3 (10.0)	687	207
Ukraine	97.2 (2.0)	87.6 (10.4)	92.8 (7.8)	661	238
United Republic of Tanzania	74.1 (12.2)	56.5 (19.4)	81.6 (19.2)	4798	131
United States of America	89.1 (3.7)	79.3 (10.0)	80.3 (6.7)	18959	1262
Venezuela	86.4 (4.9)	73.6 (9.2)	99.9 (0.2)	1714	147
Zambia	86.6 (6.5)	100.0 (nan)	80.6 (8.6)	1360	129

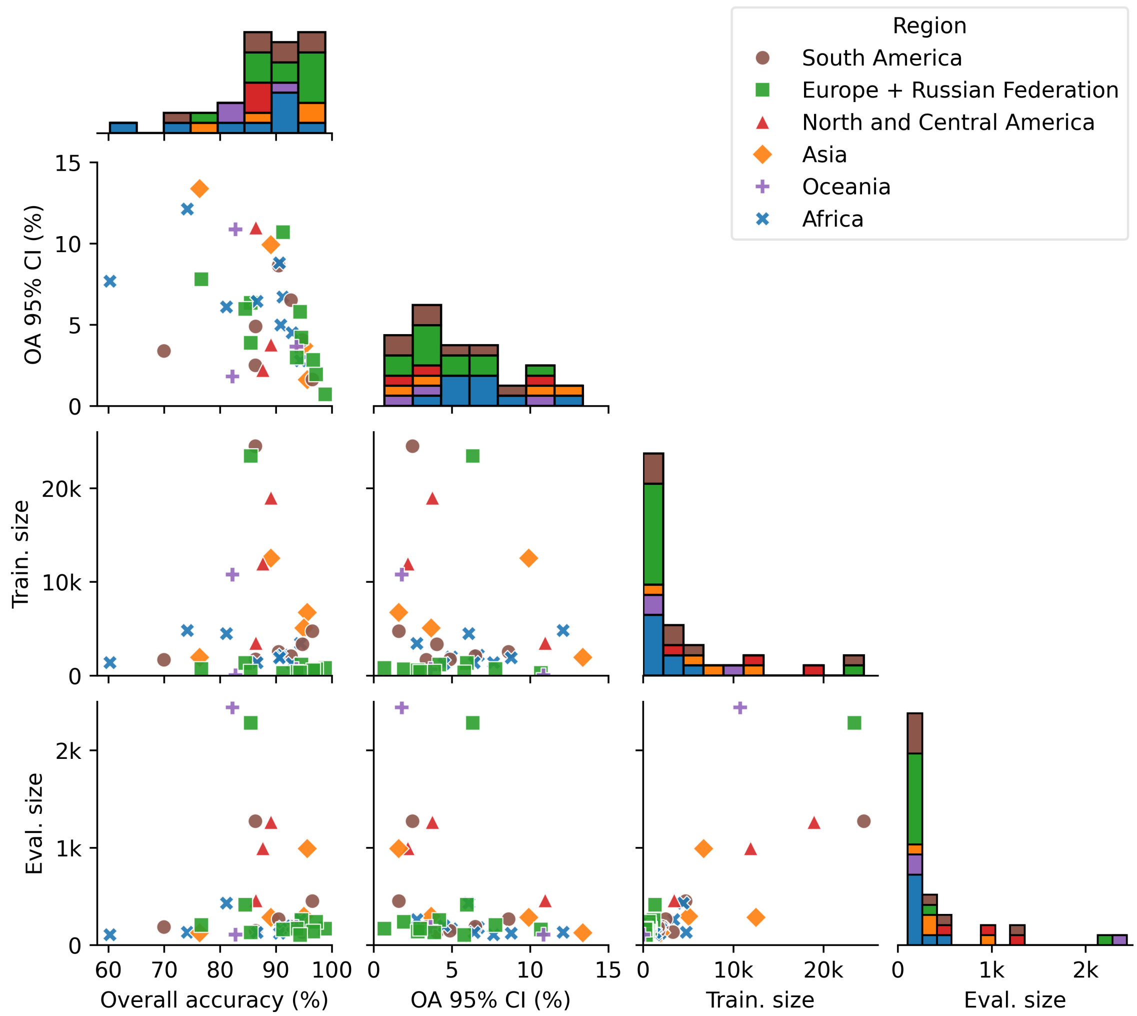

Figure S2: **Country-level RF-2-aef performance and reference-data availability.** Scatterplot matrix showing the relationship between country-level overall accuracy, the width of the 95% confidence interval on overall accuracy, the number of FRA 2020 RSS training samples, and the number of CGLS evaluation samples. Each point represents one country and colors indicate regions. Histograms on the diagonal show the distribution of each variable across countries.

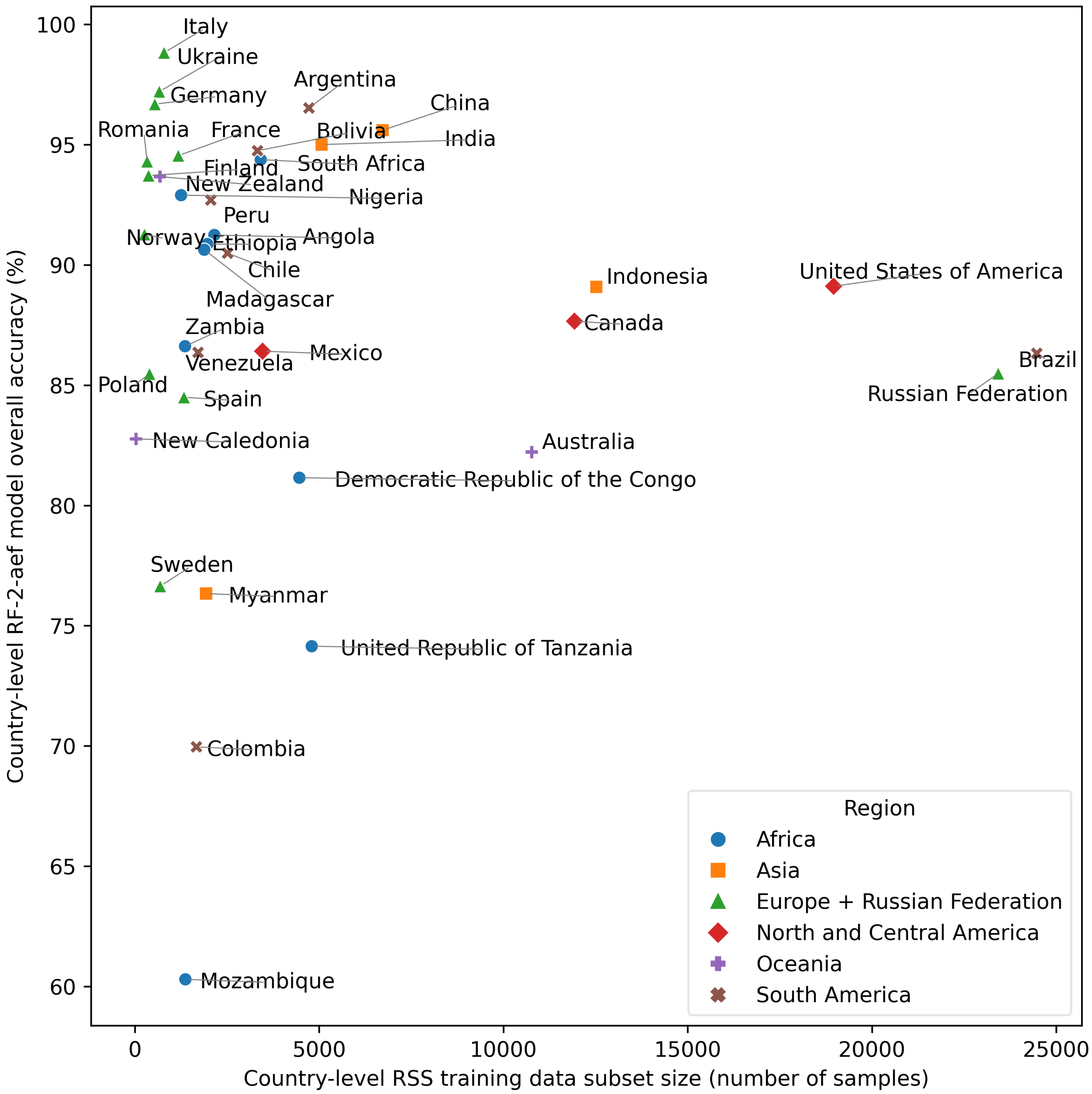

Figure S3: **Country-level RF-2 training and evaluation: overall accuracy vs training dataset size**. For each country, the overall accuracy on the pixel-level validation dataset samples is plotted against the number of training samples, with the countries colored by region. Only the points in the training and validation datasets within the country boundaries were retained.

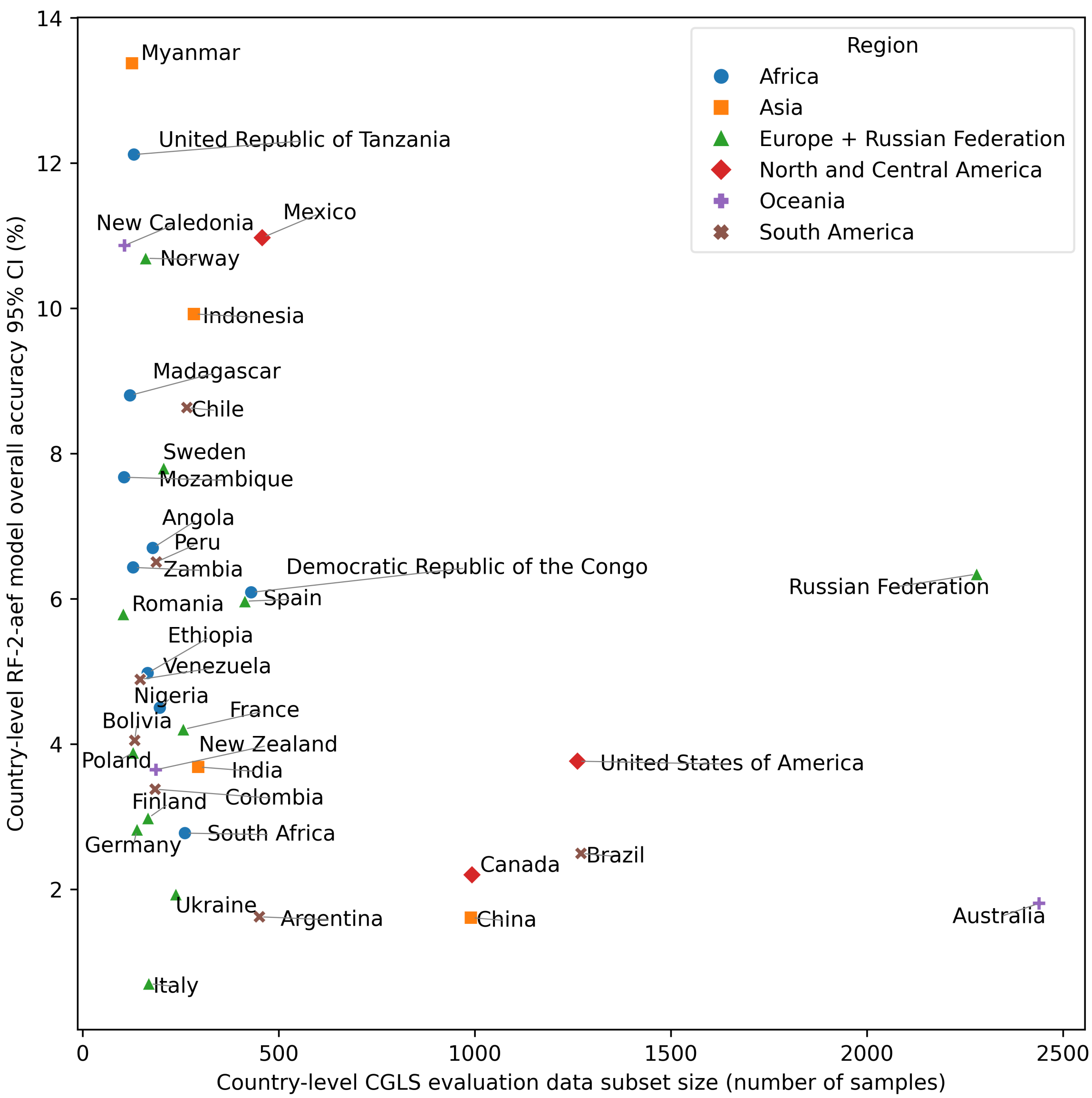

Figure S4: **Country-level RF-2 training and evaluation: overall accuracy 95% confidence interval vs evaluation dataset size**. For each country, the overall accuracy 95% confidence interval on the pixel-level validation dataset samples is plotted against the number of validation samples, with the countries colored by region. Only the points in the training and validation datasets within the country boundaries were retained.

Country-level F/NF maps evaluation

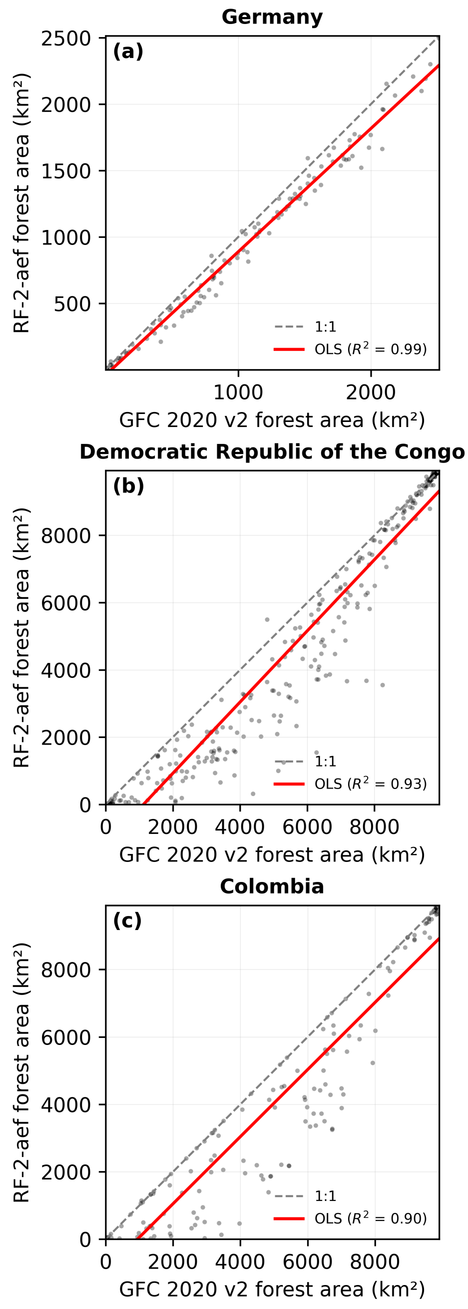

Figure S5: **Comparison of forest area estimates from RF-2-aef and GFC 2020 v2 across 100 km × 100 km grid cells in (a) Germany, (b) the Democratic Republic of the Congo, and (c) Colombia.** Each point corresponds to the Forest area within a single grid cell. The dashed gray line denotes the 1:1 relationship, while the red line represents the ordinary least squares (OLS) regression fit. High R^2 values indicate strong agreement in the spatial distribution of Forest area between the two datasets.

Country-level F/NF maps uncertainty

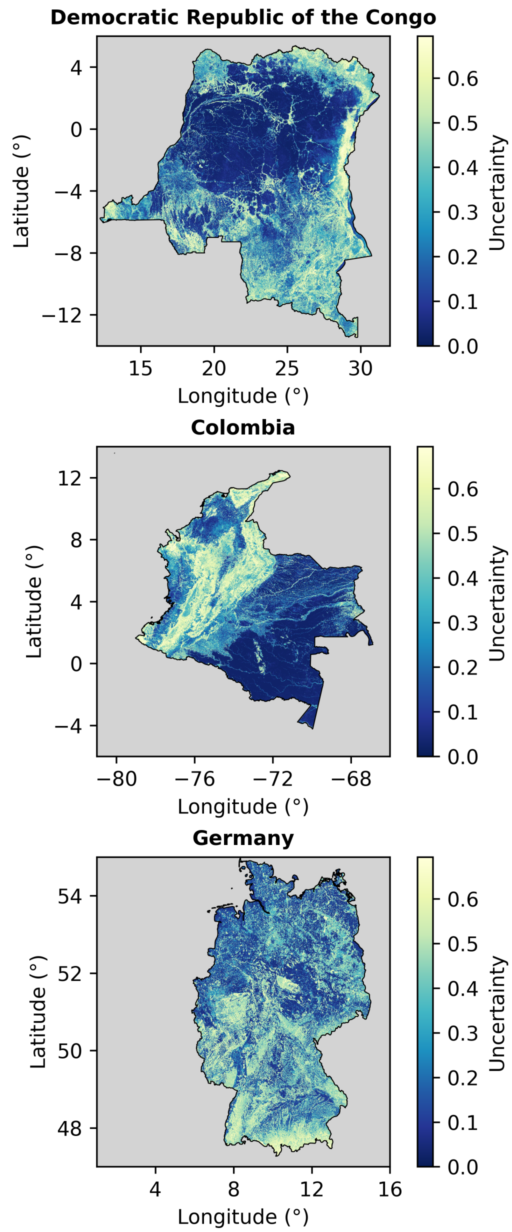

Figure S6: **Country-level RF-2-aef Forest/Non-Forest uncertainty maps for selected countries.** Predictive uncertainty associated with the country-specific RF-2-aef Forest/Non-Forest maps for the Democratic Republic of the Congo, Colombia, and Germany. Uncertainty is computed as the Shannon entropy of the predicted class probabilities. Higher values indicate higher uncertainty; for two output classes and natural logarithms, the maximum entropy is 0.693.

Inter-annotator agreement in the FRA 2020 RSS *accuracy assessment*

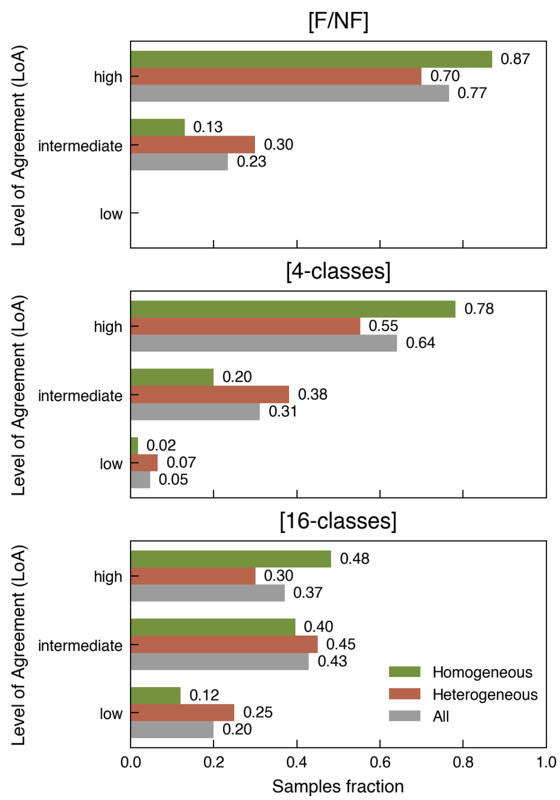

Figure S7: **Inter-annotator level of agreement in the FRA 2020 RSS *accuracy assessment* dataset for homogeneous and heterogeneous plots**. Proportion of samples with *high* (all annotators agree), *intermediate* (two distinct labels), or *low* (three or more distinct labels) levels of agreement for the binary Forest/Non-Forest (F/NF), 4-class, and 16-class classification of the plot 1-ha centroid main land use. Results are shown separately for homogeneous (single class in the 40-ha plot) and heterogeneous plots (multiple classes), and for all samples combined.