Estimating GHG emissions from land-use change in Cameroon using Collect Earth Online

Documenting Cameroon's national CEO workflow: from sample-based interpretation and analyst calibration ("mapathons") to IPCC-aligned land-use change and GHG reporting

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SINREX SUSTAINABLE SOLUTIONS

Wilpa CAPACITY DEVELOPMENT

MINISTERE DE L'ENVIRONNEMENT, DE LA PROTECTION DE LA NATURE ET DU DEVELOPPEMENT DURABLE
MINISTRY OF ENVIRONMENT, PROTECTION OF NATURE AND SUSTAINABLE DEVELOPMENT

ONACC
OBSERVATOIRE NATIONAL SUR LES CHANGEMENTS CLIMATIQUES
NATIONAL OBSERVATORY ON CLIMATE CHANGE

SIG Spatial Informatics Group

CfRN

1–Context & Objectives

- Cameroon’s forests cover ~66% of the national territory (~31 Mha)
- Central to:
  - climate regulation, biodiversity, livelihoods
  - national commitments to climate, biodiversity, and land restoration under the Rio Conventions

Challenge

Producing consistent, transparent, and reproducible estimates of:

- Land-use change
- Deforestation and degradation
- AFOLU greenhouse gas emissions

1–Context & Objectives

- Document and formalize Cameroon's national CEO-based land-use monitoring workflow used to generate IPCC-aligned land-use change and GHG estimates (2000–2023, FREL 2026)

- Describe the methodological framework supporting its implementation, including sampling design, interpretation protocols, decision rules, QA/QC procedures, and mapathon-based training.

- Highlight recommendations & lessons learned for institutionalization, capacity development, reproducible land-use monitoring to improve REDD+, FRELs, and national GHG reporting.

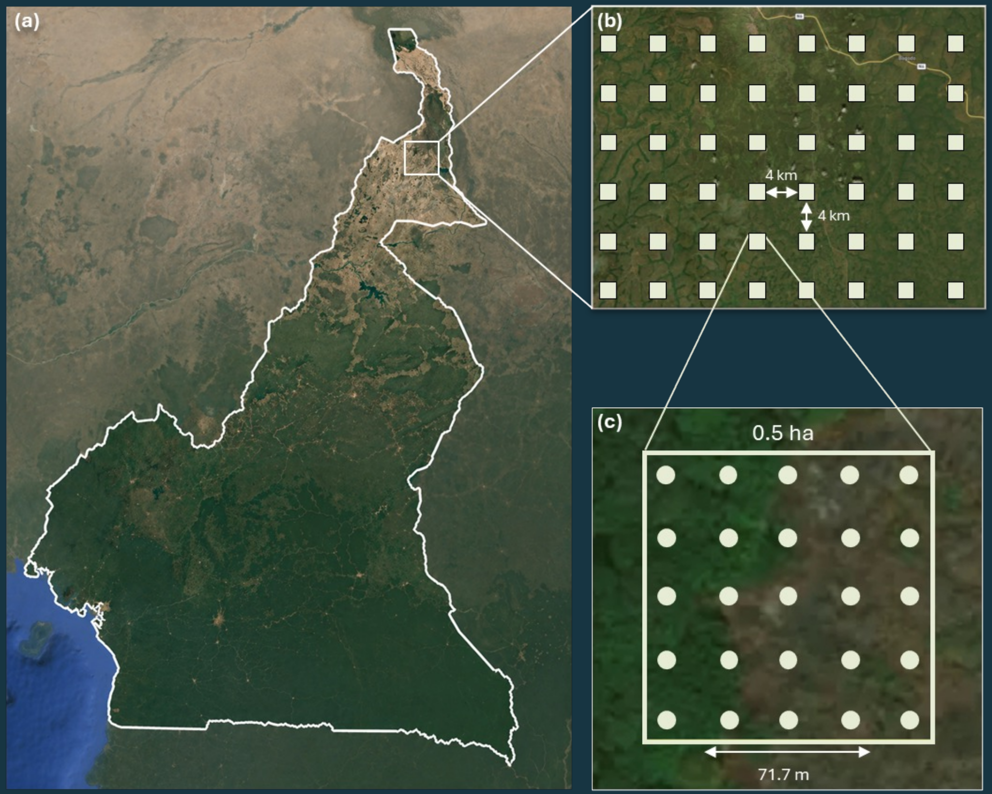
2–Sampling Design

National Sample Framework:

- Systematic 4 × 4 km grid
- 29,409 sample plots of 0,5 ha
- Annual interpretation from 2000–2023

Each plot divided into:

- 25 interpretation points
- 200 m^2 per point



Key considerations:

- The 4 × 4 km systematic grid provides robust national coverage and statistical precision but is less efficient for rare or high-impact classes/transitions. Large sample sizes (>29,000) may also propagate shared interpretation bias at scale

- As a first national assessment, the systematic grid provides a strong and transparent baseline that can progressively evolve toward a stratified, spatially balanced sampling design, with targeted sampling for rare land-use classes, high-impact transitions, and areas of known uncertainty

3–Activity Dataset & Land Classification System

Multi-sensor observations and supporting datasets enhanced the detection of forest extent, deforestation, degradation, burned areas, and subtle land-cover changes through time under cloud cover

Optical imagery

- Landsat 7
- Landsat 8
- Sentinel-2
- Planet

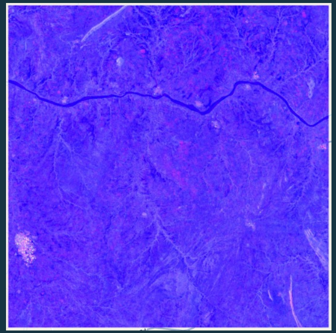
Radar imagery

- Sentinel-1

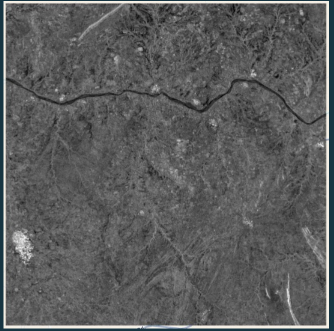
Supporting datasets

- NDVI NDFI Aqua
- MODIS fire products
- Historical imagery Google Earth Pro

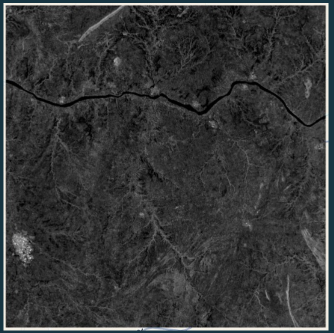
Landsat8_True Col.



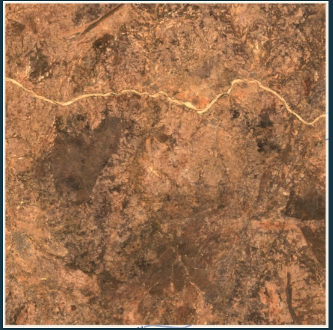
Sentinel1_RGB



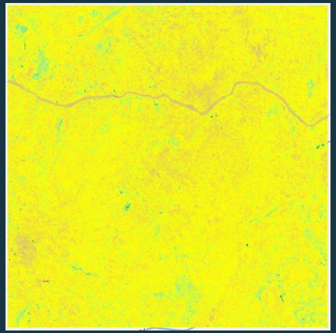
Sentinel1_VV-Pol.



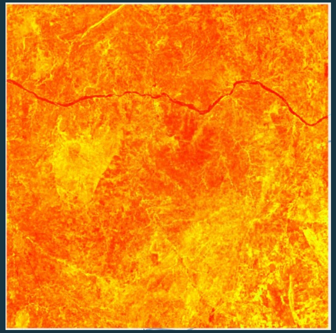
Sentinel1_VH-Pol.



Sentinel2_True Col.



Sentinel2_NDVI



Landsat8_NDFI

Aqua MODIS

3–Activity Dataset & Land Classification System

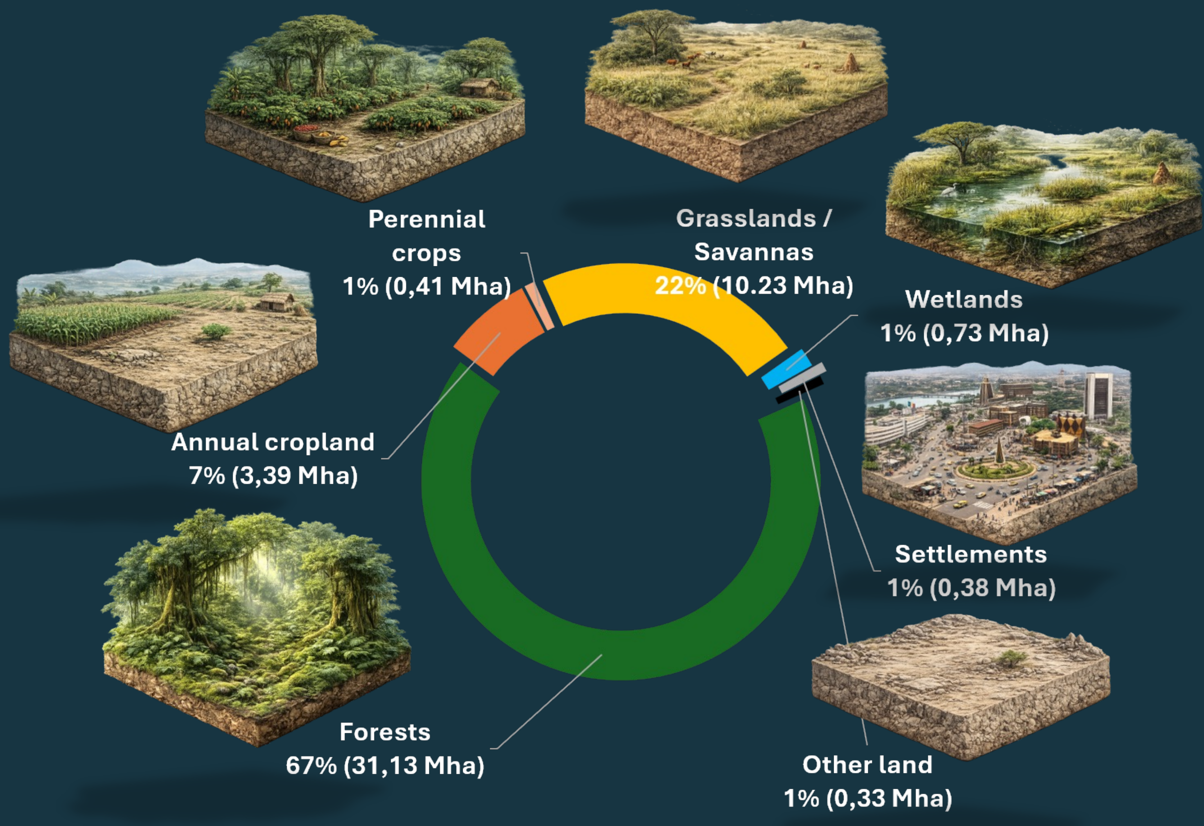
- **IPCC-aligned framework**
- **13 Subcategories adapted to national context**

National Forest Definition:

- ≥10% continuous canopy cover (→ REDD+ definition)
- ≠ Forest Code definition ≥30% continuous canopy cover

IPCC Category	National Subcategories
Forest	Dense humid forest
	Flooded and floodable forest
	Dry forest
	Planted forest
	Mangrove
Cropland	Annual crops
	Perennial crops
Grassland/Savanna	Grassland
	Herbaceous savanna
	Shrubby savanna
Wetlands	Wetlands
Settlements	Settlements
Other land	Other land

Subcategories effectively reported:



4–Integrated Framework for Activity Data, Emission Factors, QA/QC, & Capacity Building

Activity Data – A) A structured "mapathons" approach pre-production combined iterative capacity building with governance and bias tracking by bi-weekly reviews with ONACC and MINEPDED, with continuous updates to a bias registry & methodological guide:

1. **Training & Alignment (Plots 1–150)** →
2. **Paired calibration (Plots 151–300)** →
3. **Independent Analysis (Plots 301–600)** →
4. **Operational Production (Plots 601+)**

B) Production phase with QA/QC implementation for consistency between interpreters:

1. Blind Double Interpretation (Plots 1–600) Independent analysis by two experts, consensus if divergence.

2. Control Re-sampling ~30% of samples redistributed to verify cross-interpreter consistency.

3. Automated Validation System-level blocking of 'non-plausible transitions' (e.g., mangrove → dry forest).

4. External Validation Cross-referencing with national cartography and Global Forest Watch.

5–Emission Factor Data

Hierarchical EF approach:

- Tier 2 national data prioritized whenever robust Cameroon-specific estimates were available.
- Regional tropical studies used to fill gaps for comparable ecosystems.
- IPCC Tier 1 defaults applied where national or regional data were unavailable.

Main data sources:

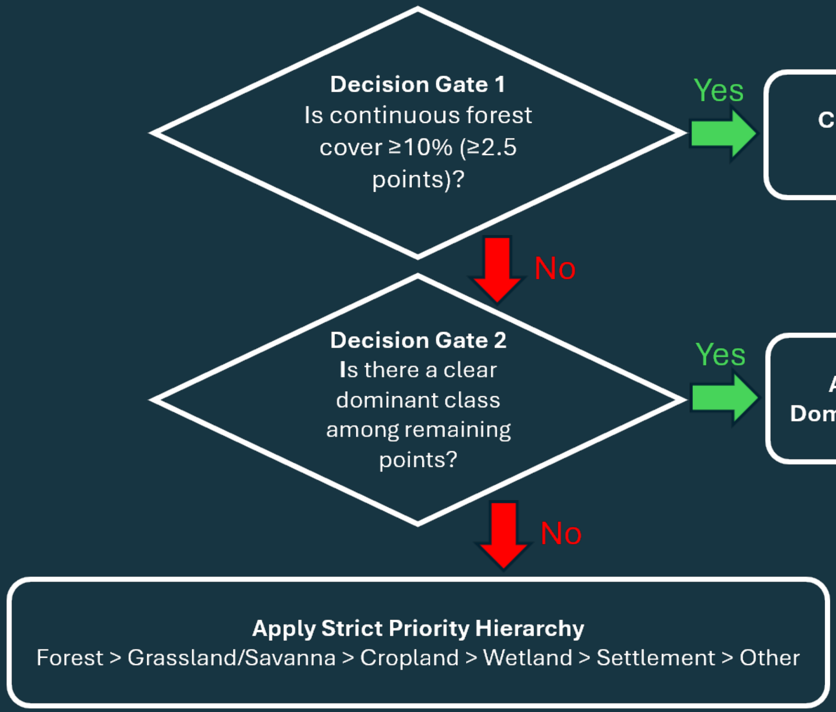
- National data (Tier 2): biomass, deadwood, SOC, fire dynamics, wood extraction (Dees et al., ONACC, Gueguim et al., FAOSTAT).
- Regional studies (FREL Gabon): mangroves, planted forests, biomass growth, deadwood.
- IPCC (Tier 1): biomass growth, litter, SOC, fire parameters, non-CO_2 emissions.

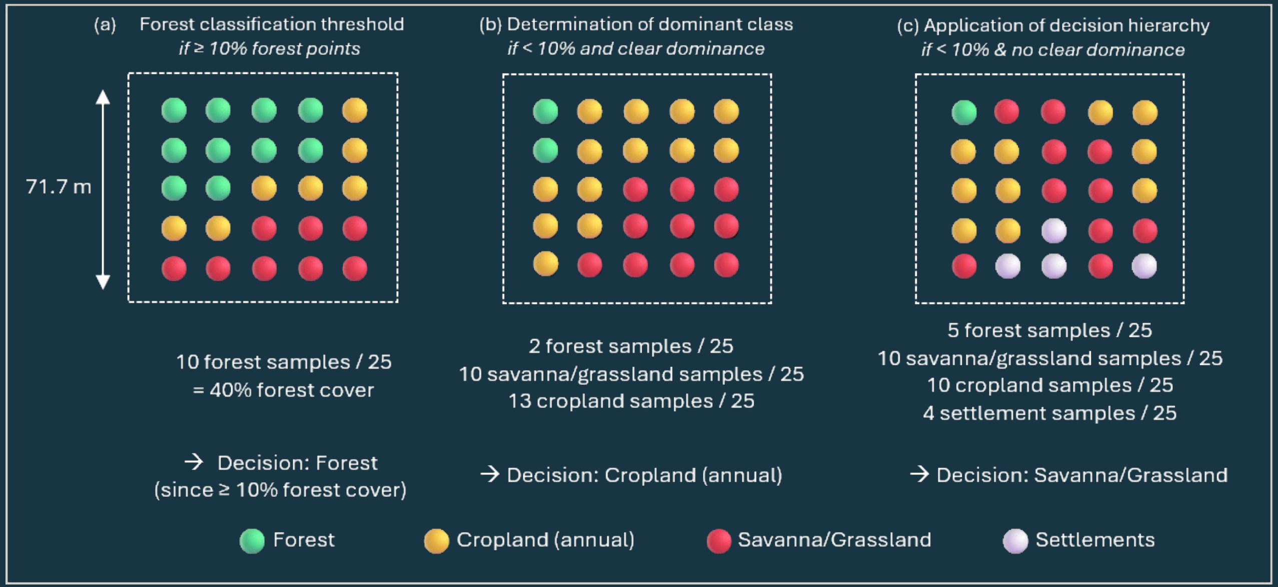
Harmonization:

- Carbon stocks harmonized across diverse data sources to ensure consistency.
- A consistent SOC reference value was adopted using national estimates validated against global datasets.
- All EF data integrated into a structured carbon-stock matrix supporting national GHG calculations.

Key considerations:
Uncertainty remains high due to limited national data (notably for biomass, soil carbon, degradation, and wood extraction); moving beyond Tier 1 through stronger inventories and data is key to reach Tier 2/3 and better reflect Cameroon’s variability

6–Decision Rules and Interpretation Protocol





Filter Checkpoint: Plausibility Matrix
Excludes biophysically unlikely transitions,
e.g. Mangrove → Dry Forest in one years

Key considerations:
class boundaries—especially degradation, savanna–forest mosaics, agroforestry, smallholder agriculture—can be interpretation-sensitive

7–Uncertainty Analysis

Approach:
IPCC Approach 2 with Monte Carlo simulations run in Argo
→ 10,000 iterations; fixed seed for reproducibility

Error categorization:
- Random: sampling variability (e.g., forest = 0.8%)
- Systematic: interpretation bias compared with global & national maps (94.41% concordance; deforestation bias = 1.26%)

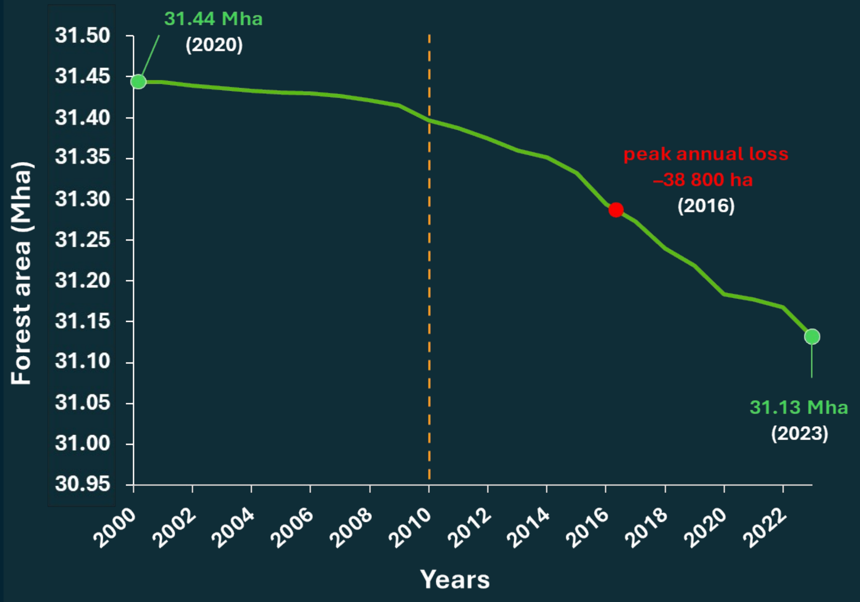
Monte Carlo Modeling

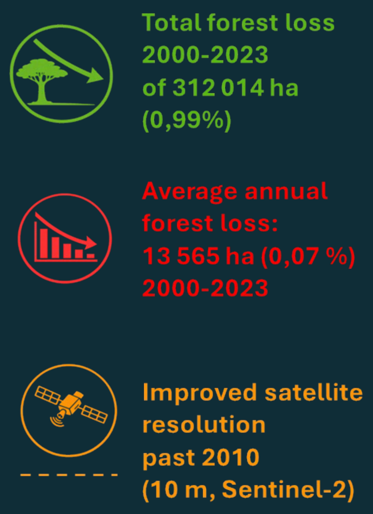
- Distributions: Inputs (activity data, emission factors, wood volumes) assigned triangular probability distributions (min., mode, max.)
- High uncertainty handling: Variables with >100% uncertainty used asymmetric distributions to avoid negative surface values
- Iterations: 10,000 runs per variable to ensure convergence to a stable distribution
- Reproducibility: Fixed random seed ensures external auditors can replicate results

Final Uncertainty Calculation
Uncertainty derived from simulation mean ± σ; 95% confidence interval (×1.96); example result: Net carbon absorption uncertainty (2020) = 32.1%.

8–Key Results: Land use Dynamics and Emissions Estimates (2000–2023)

Forests dominate the landscape (67%) but declined by 312 Kha (–0.99%)





•Observed trend: Forest cover ~67 % of national territory; average annual loss ~0.07 % – no significant acceleration over 23 years.

•Resolution effect (major bias): The shift to 10 m imagery (Sentinel-2, post-2010) mechanically increases detection of small disturbances. Pre- and post-2010 estimates are not directly comparable.

•Comparison with regional benchmarks:

- Our systematic 4×4 km grid is transparent and reproducible.
- However, Shapiro et al. (2026) use a spatially balanced stratified design – more efficient for detecting changes in rare classes (e.g., fragmented forests). Our grid likely underestimates losses in fragmented agricultural frontiers.

•Key takeaway: The trend (stability) is robust. The absolute area (312,014 ha) is not.

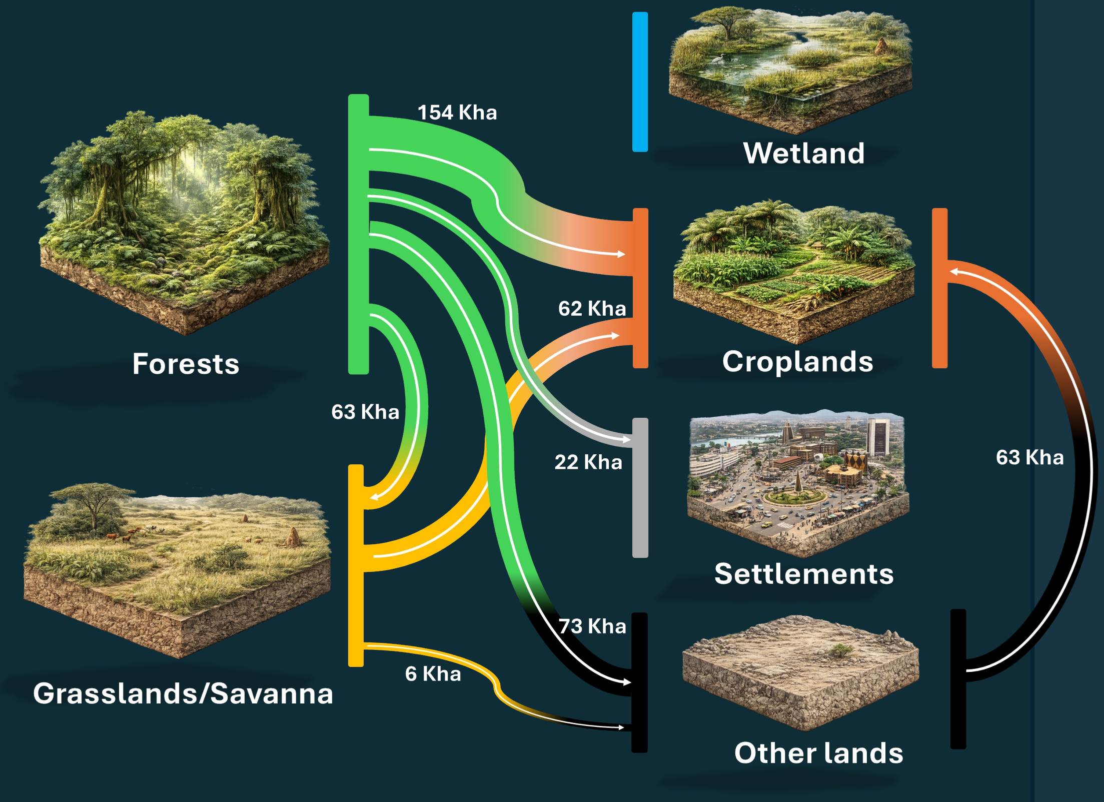
8–Key Results: Land use Dynamics and Emissions Estimates (2000–2023)

•**Dominant conversion:** Forest → croplands (~154,000 ha over 23 years).

•**Why this is a lower-bound estimate:**

- Small-scale agricultural clearings (< 0.5 ha) are **difficult to detect** within a 0.5-ha plot.
- Renaudineau et al. (2025) show that at 30 m resolution, land-cover products systematically **underestimate small-scale disturbances** compared to very-high-resolution imagery.
- Plausible bias: Actual conversion could be **significantly higher**, especially in fragmented agricultural zones.

•**Recommendation:** Complementary very-high-resolution sampling (e.g., Planet, SPOT) over a subset of plots would be needed to quantify this detection gap.



8–Key Results: Land use Dynamics and Emissions Estimates (2000–2023)

Driver	Key finding	Caveat
Agricultural expansion	Dominant driver (~154,000 ha) – confirms the *"rural complex"* concept of Shapiro et al. (2023)	Attribution relies on **visual interpretation** (subject to interpreter bias)
Fuelwood extraction	>10 M m^3/year (FAOSTAT) – a major degradation driver	FAOSTAT data are **national aggregates, not spatially explicit** – we don't know where or if it is sustainable
Timber harvesting	~3.4 – 5.4 M m^3/year	Shapiro et al. (2023) found that **artisanal logging is the only driver increasing over time** – our study cannot confirm this trend for Cameroon
Other (mining, flooding)	Localised impacts	Under-detected in optical imagery (especially mining)

8–Key Results: Land use Dynamics and Emissions Estimates (2000–2023)

•**Observed trend:** Net sink decreased from ~110,045 kt CO_2e (2020) to ~105,203 kt CO_2e (2023) – a **~4.4 % decline**.

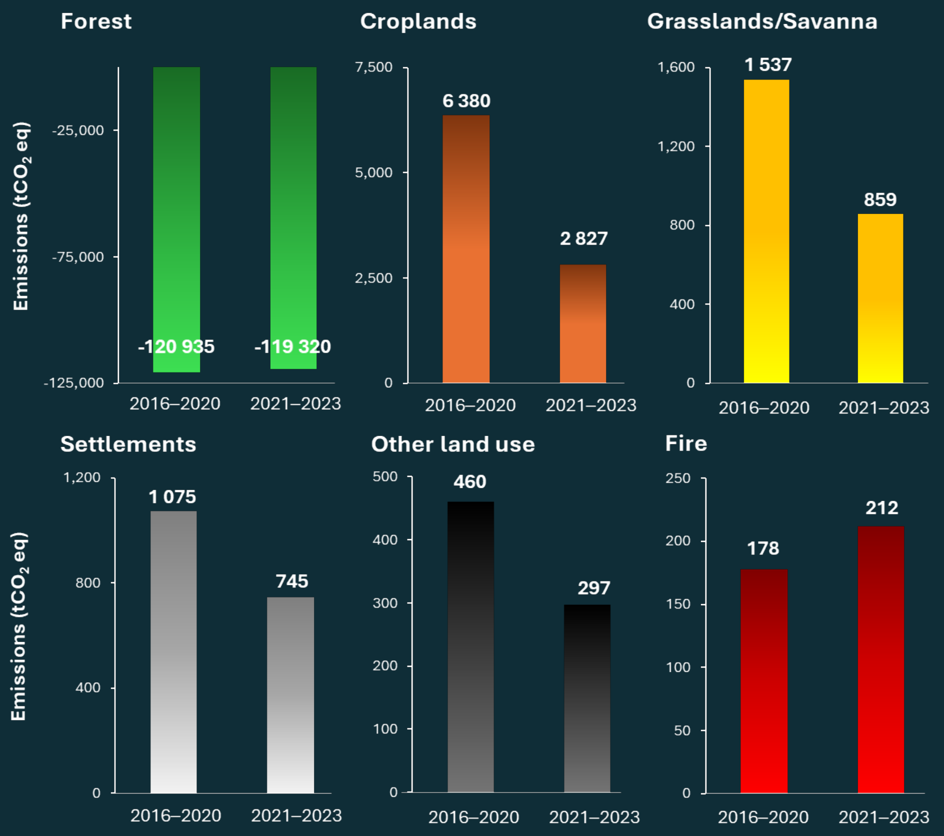
•**Statistical caution:**

- Overall uncertainty on emissions is **32.1 %** (Slide 10).
- A **4.4 % change is well within the margin of error** – we **cannot** confidently state that the sink is truly declining.

•**Additional uncertainty from map products:**

- Renaudineau et al. (2025) showed that forest area estimates can vary by **>250,000 km²** depending on the global land-cover product used.
- This variability alone could shift our emission totals by **> ±20 %**.

•**Main bottleneck:** Emission factors for soil organic carbon (SOC) are still largely based on IPCC **Tier 1** defaults. This is the **top priority** for improving accuracy.



9–Conclusion & Improvement Pathways

→ Strengths:

✓ National coverage
✓ Transparent methodology
✓ Strong QA/QC
✓ Capacity building through mapathons

→ Priority Improvements:

1. Institutionalization & sustainability: Embed the workflow within MINEPDED/ONACC through permanent teams, continuous training, updated protocols, and an improvement roadmap.
2. Classification sensitivity: Refine degradation, agroforestry, and savanna–forest mosaic definitions and introduce confidence scoring.
3. Sampling & interpretation bias: Transition toward stratified, spatially balanced sampling and stronger bias controls.
4. Temporal consistency: Prioritize Sentinel-era estimates and report confidence by period.
5. Emission factors: Expand Tier 2/3 datasets to reduce reliance on Tier 1 values.
6. Uncertainty reporting: Disaggregate uncertainty sources and target dominant contributors.


Q&A