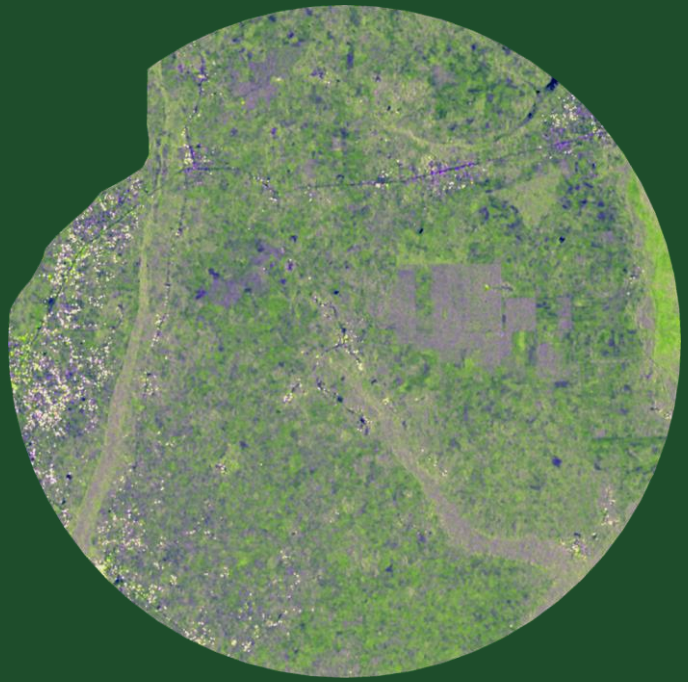
FEIC 2026 · ST6 GEOMATICS · PAPER CMT-31

Sentinel-1 SAR-Based Land Cover Classification and Object Detection for Agricultural Monitoring in Ita-Egbe, Nigeria

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Sentinel-1 γ^0 composite, dry season 2018/19

Faculty of Engineering International Conference (FEIC 2026) · 18–20 November 2026 · Akoka, Lagos

Presentation outline

1. Background and objectives
2. Study area and Sentinel-1 data
3. Methodology
4. Classification results
5. Object detection results
6. Implications and conclusions

Why radar for agricultural monitoring in Ogun State

Optical data gaps

Cloud is most frequent in the early and mid growing season, exactly when crop monitoring matters (Whitcraft et al., 2015).

Sentinel-1 C-band SAR

Active radar images through cloud, day and night; free 10 m VV + VH data on a regular revisit (Torres et al., 2012).

Smallholder mosaic

Ita-Egbe combines cassava, maize and vegetable plots, oil palm, settlements and narrow river channels.

Research question: how well can Sentinel-1 alone classify and detect land-cover types relevant to agriculture in Ita-Egbe and which machine-learning formulation suits SAR?

Aim and objectives

Aim: to evaluate Sentinel-1 SAR for land-cover classification and object detection in support of agricultural monitoring in Ita-Egbe.

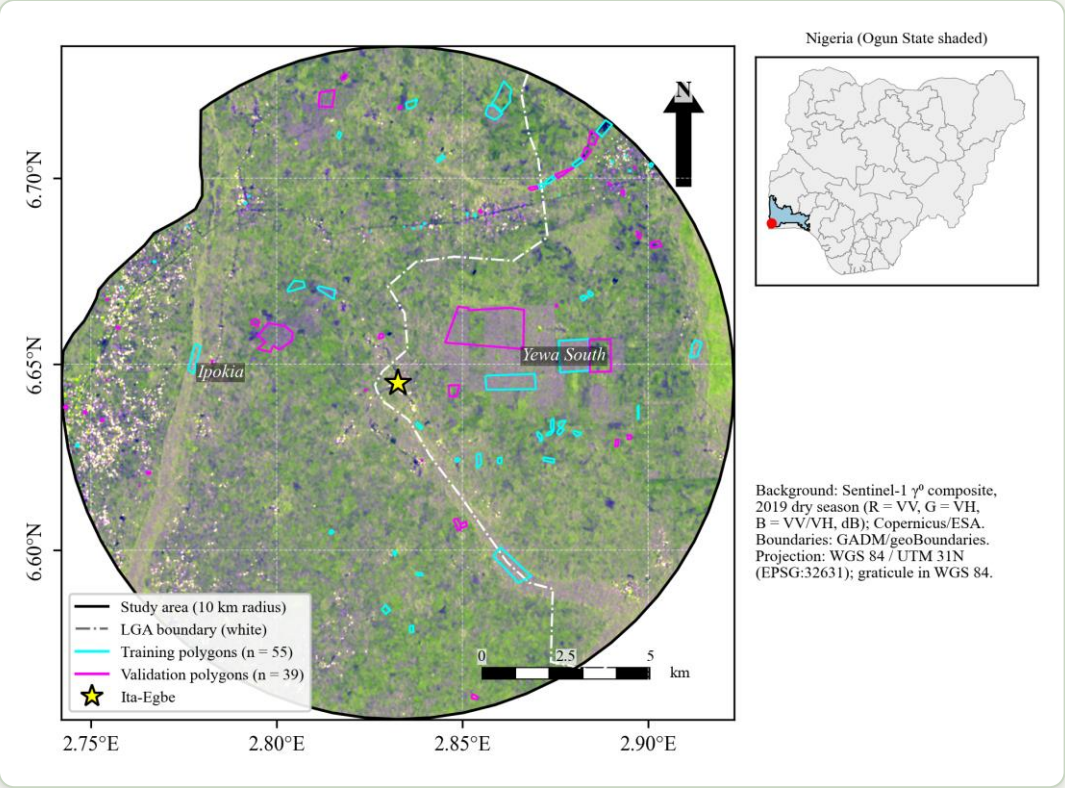
i Produce dry- and wet-season Sentinel-1 composites with a standard SNAP workflow

ii Classify five land-cover classes with Random Forest and validate against independent reference points

iii Train and test a YOLOv8s detector on SAR tiles and compare it with a pixel-level baseline

iv Assess what the results mean for operational agricultural monitoring

Study area: Ita-Egbe, Ogun State, Nigeria



Location

10 km buffer around Ita-Egbe (6.645°N, 2.833°E)

Extent

304.7 km², clipped to Ogun State; 6.555–6.736°N, 2.742–2.923°E

Boundary note

0.55 km from the Ipokia–Yewa South LGA line; datasets disagree, so a buffer is used

Land use

Cassava, maize and vegetables; oil palm plantations; rural settlements; river channels

Sentinel-1 data: ten scenes, one viewing geometry

10
GRDH IW scenes

VV + VH
dual polarisation

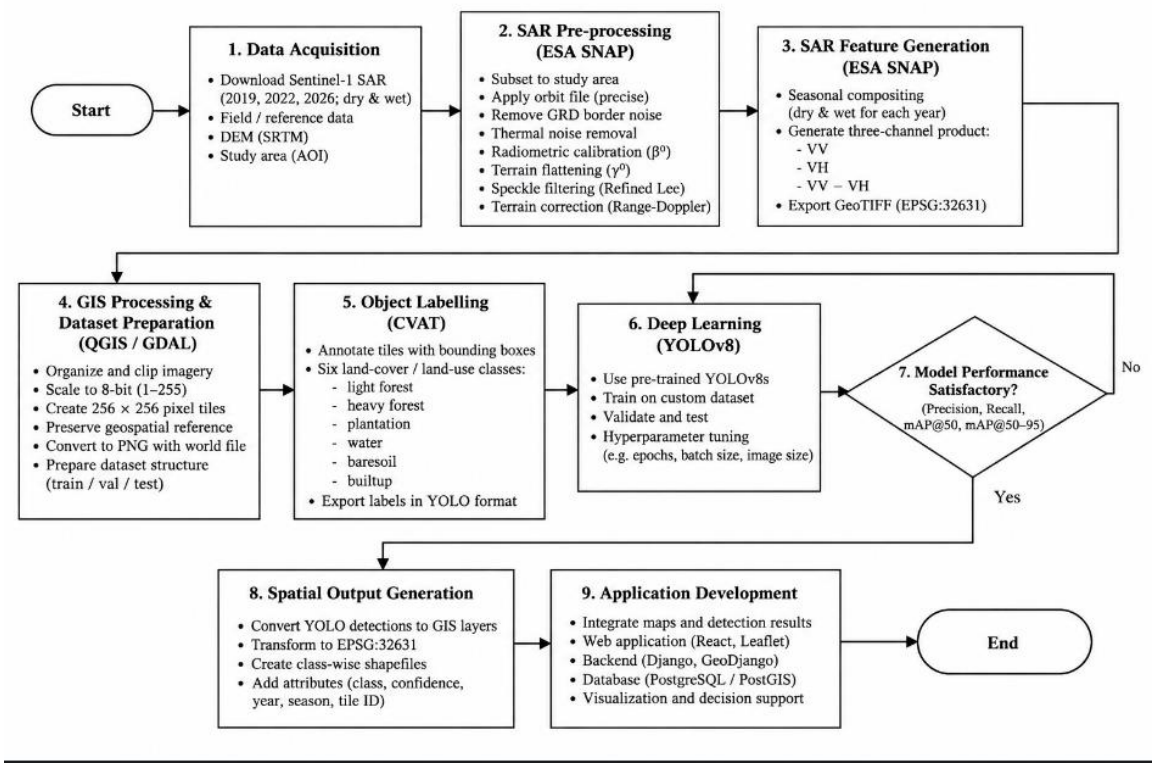
Orbit 1
ascending, ~18:01 UTC

10 m
terrain-corrected pixels

Season	Acquisition dates (UTC)	Sensor
Dry 2018/19	01 Nov · 25 Nov · 19 Dec 2018 · 12 Jan · 05 Feb 2019	Sentinel-1A
Wet 2019	05 Jun · 29 Jun · 23 Jul · 16 Aug · 28 Aug 2019	Sentinel-1A

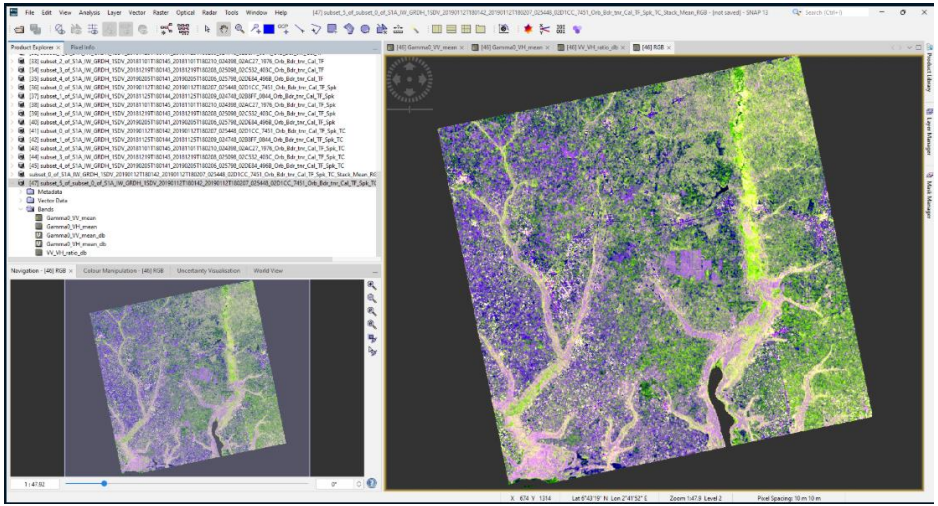
All scenes share relative orbit 1 (ascending), so incidence geometry is identical across dates. Data: Copernicus Sentinel-1 (ESA), obtained from the ASF DAAC; also distributed via the Copernicus Data Space Ecosystem.

Methodological framework



SAR pre-processing in ESA SNAP 13

Apply orbit file → Border & thermal noise removal → Calibration to β^0 → Terrain flattening (Cop-DEM 30 m) → Lee Sigma 7×7 → Terrain correction 10 m → Seasonal mean → dB



Terrain-flattened backscatter

$$\gamma^0_T = \beta^0 \cdot A_\beta / A_\gamma$$

A_β: reference area (beta); A_γ: area normal to the look direction, from the DEM (Small, 2011)

- Five scenes averaged per season in linear power, then dB
- Bands: VV, VH and R = VV − VH (dB)
- Lee Sigma 7×7, σ = 0.9 (Lee et al., 2009)

Classification design and reference data

Class	Definition	Train polygons	Validation points
Bare soil	Exposed or recently tilled land	7	60
Built-up	Settlements, roofs, paved areas	20	150
Farmland	Annual crops: cassava, maize, vegetables	13	90
Plantation	Perennial tree crops, mainly oil palm	11	50
Water	River channels and fringing wet vegetation	4	40

Random Forest

SNAP, 100 trees, 5,000 samples, one model per season

Dual-season model

6 features (VV, VH, R × 2 seasons), 300 trees, balanced weights

Independent validation

390 points in 39 polygons, never overlapping training (median 903 m apart)

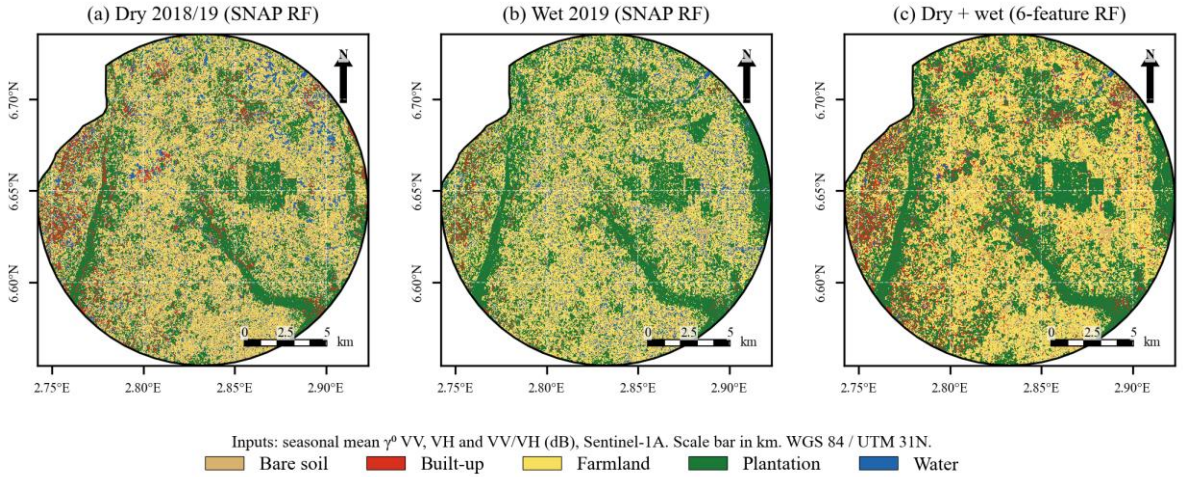
Reference polygons were interpreted from the SAR composites with OpenStreetMap support; no field survey was available.

Classification accuracy against independent points

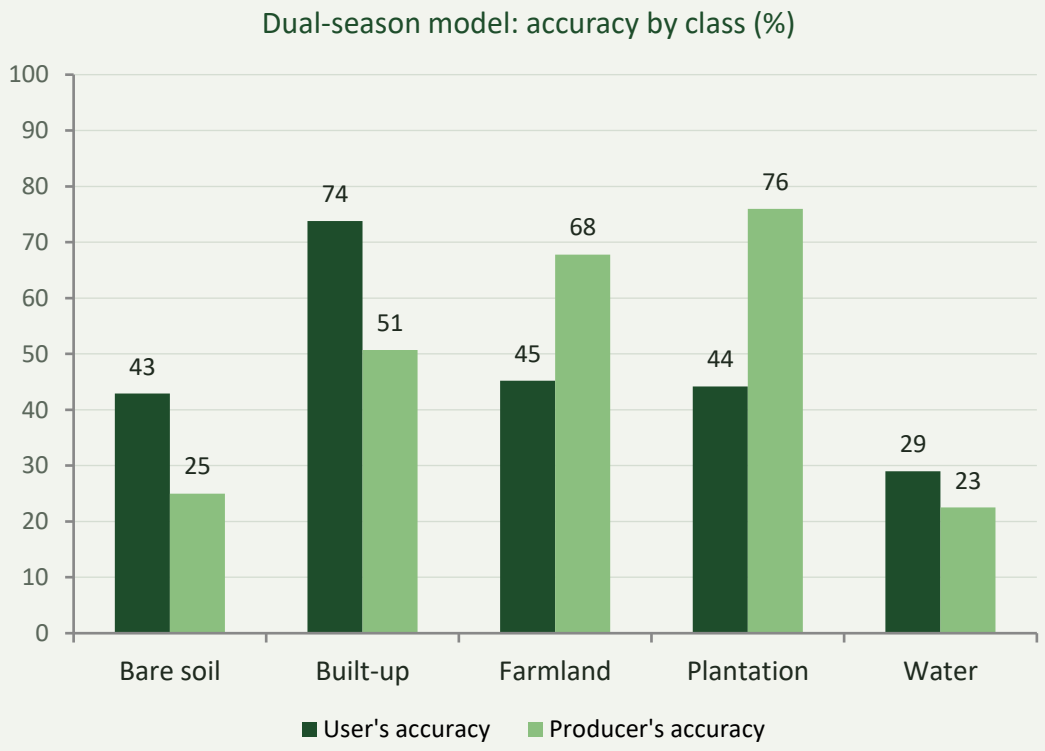
36.4%
Dry season 2018/19
κ = 0.21

33.6%
Wet season 2019
κ = 0.18

51.0%
Dry + wet combined
κ = 0.36



Which classes can radar map?



Mapped best

Plantation (PA 76.0%) and farmland (PA 67.8%)

Missed often

Built-up: reliable when mapped (UA 73.8%) but under-detected

Weakest

Bare soil and water (PA ≤ 25.0%)

Check matters

SNAP's internal estimate (69–73%) used training-area pixels and overstated accuracy

Object detection experiment with YOLOv8s

Tiles

242 tiles of 256 × 256 px from six seasonal epochs (2019, 2022, 2026); fixed dB stretch

Labels

Bounding boxes for six classes: dense and sparse woody vegetation, plantation, water, bare soil, built-up

Training

COCO-pretrained YOLOv8s, 150 epochs, batch 16, image size 256

Subset	Locations	Tiles	Instances
Train	18	108	246
Validation	13	78	120
Test	10	56	99

Split by tile location, so no area appears in more than one subset, no spatial leakage. Only six water instances in the test set.

Detection results on the held-out test tiles

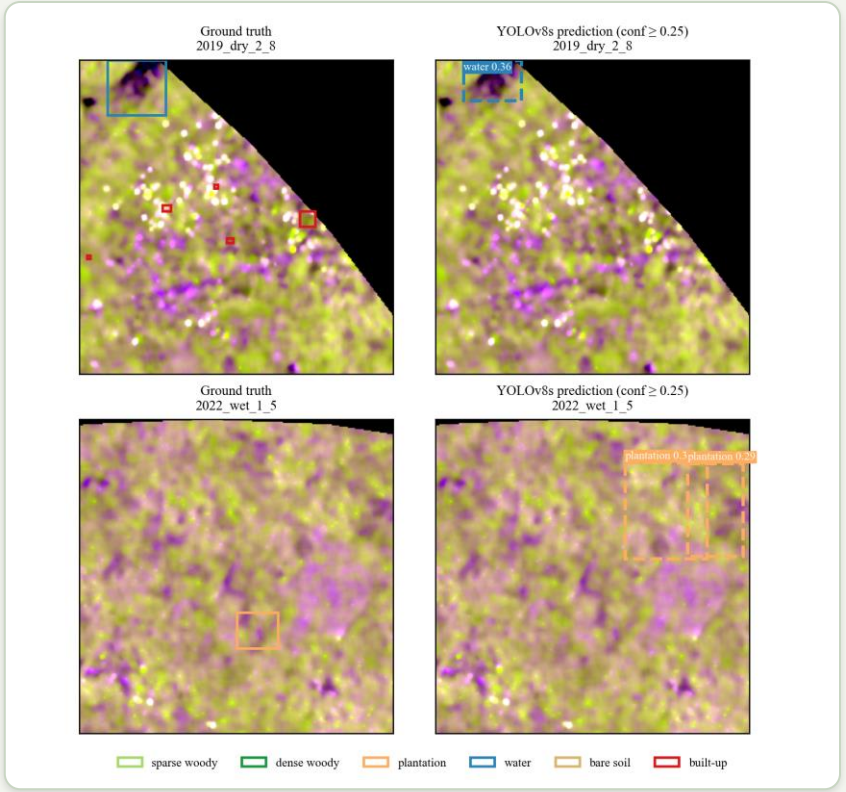
0.167
Precision

0.083
Recall

0.083
mAP50

0.055
mAP50-95

Only water was detected (mAP50 0.495; precision 1.0, recall 0.5), from just six test instances. The other five classes had no true positives.



Is the radar or the method to blame?

Bounding-box detection

YOLOv8s, COCO-pretrained

0.083

test mAP50 (mAP50-95 = 0.055)

Only 4 boxes on 56 test tiles; only water matched

Pixel classification

Random Forest, same tiles and labels

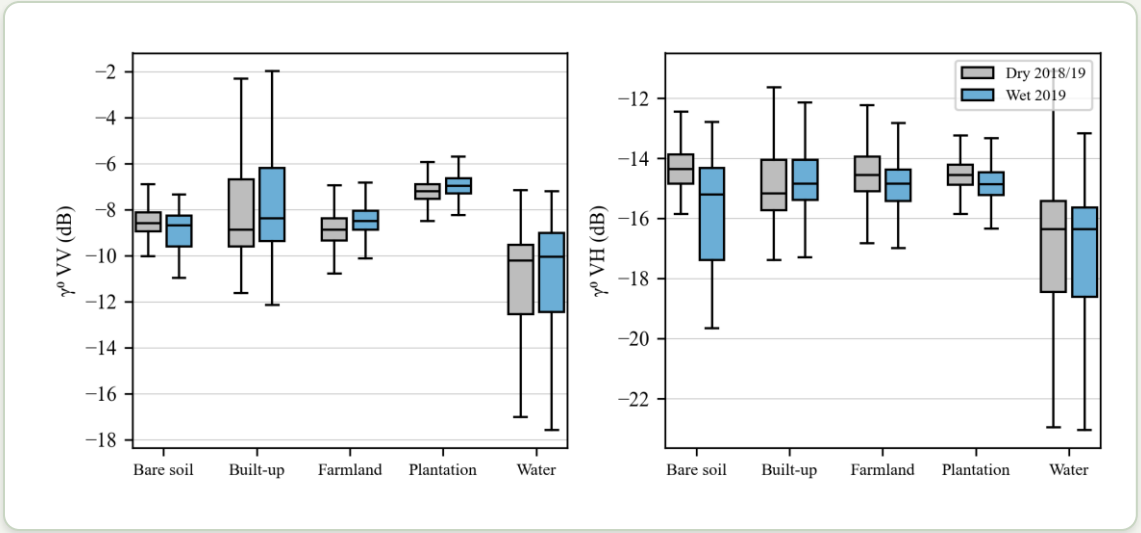
58.6%

overall accuracy (κ = 0.49, macro-F1 = 0.54)

Raw channels only: 47.7%; adding 7×7 texture helps

Same SAR data, very different outcome: the bottleneck is the task formulation. Land cover is area-type 'stuff' without object boundaries, segment it, do not box it.

Why the classes overlap in Sentinel-1 backscatter



Seasonal mean γ^0 of training-polygon pixels; grey = dry 2018/19, blue = wet 2019

- All classes sit within ~3 dB in VV and ~2 dB in VH: overlap, not algorithm choice, limits accuracy

0.92 / 1.00
mean JM, dry / wet

1.34
mean JM, both seasons

Jeffries–Matusita distance ranges 0–2; ≥ 1.9 indicates good separability.

- Bare soil vs farmland: JM = 0.08 (dry) - almost identical
- "Water" polygons: median VV ≈ -10.2 dB, not open water (−18 to −25 dB)
- Wet − dry change below 1.3 dB for every class

What this means for agricultural monitoring

Usable now

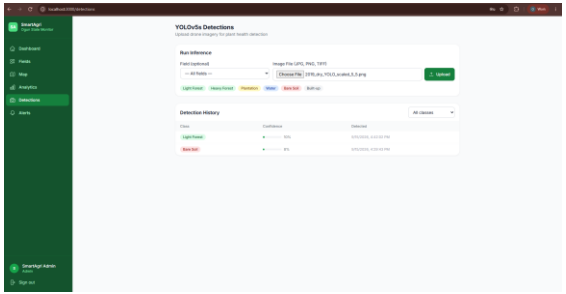
- Cloud-free seasonal observation of the area
- Farmland and plantation extent with both seasons (PA 67.8% / 76.0%)

Not yet reliable

- Bare soil, water and built-up areas
- Crop condition and phenology: seasonal change < 1.3 dB

Delivery

- Prototype web map shows layers and detections
- Outputs guide field visits; they do not replace them



The monitoring application prototype (React/Leaflet front end, FastAPI back end) displays the classified layers and detections on a web map for farmers and extension officers. Its user evaluation is planned work.

Conclusions and future work

Conclusions

- Single-season Sentinel-1 maps: 33.6–36.4% accuracy
- Combining dry and wet seasons: 51.0% (κ = 0.36)
- Classes overlap strongly in C-band backscatter
- Bounding-box detection is the wrong formulation for land cover

Future work

- Dense time series and interferometric coherence
- Field survey and very-high-resolution reference labels
- Stratified random validation for area estimates
- Semantic segmentation (U-Net) instead of boxes

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Thank you

Questions and discussion

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