National-level crop field delineation in Mozambique using 1.5 m resolution SPOT data and transfer learning with pseudo-labels

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EO-based field delineation

Field-level analytics

- productivity indicators
- land management
- resource use

Quantifying field size

- land use intensity
- biodiversity
- policy

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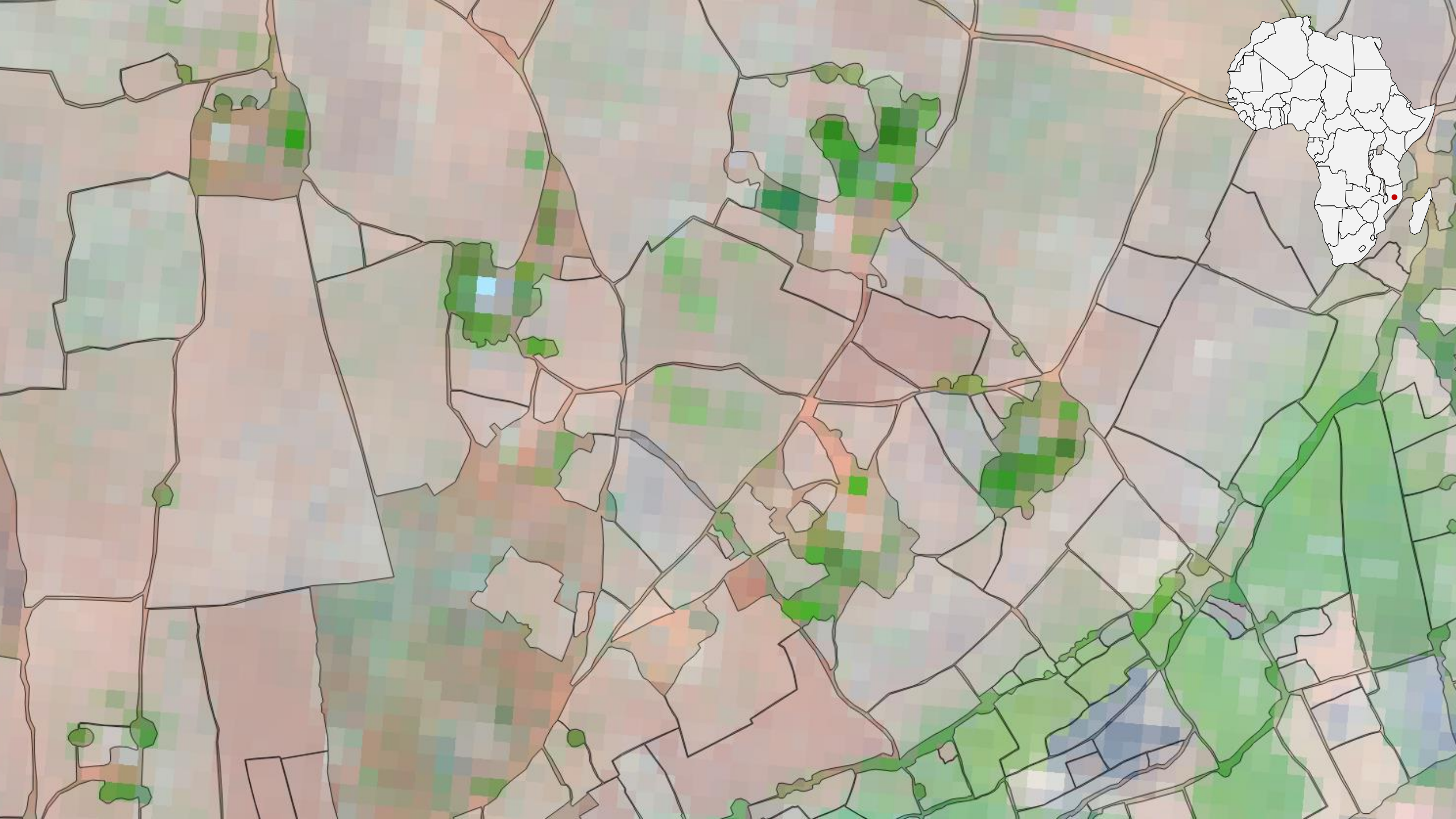
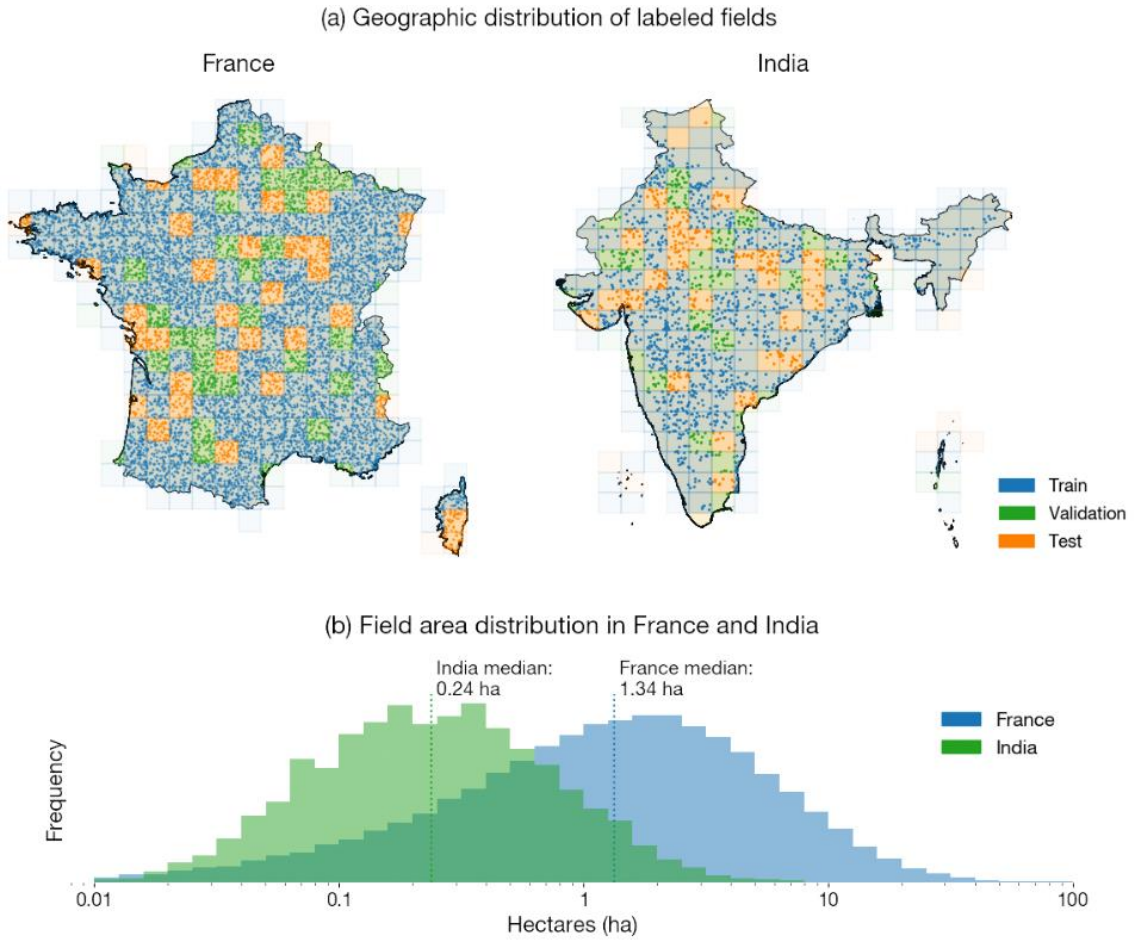
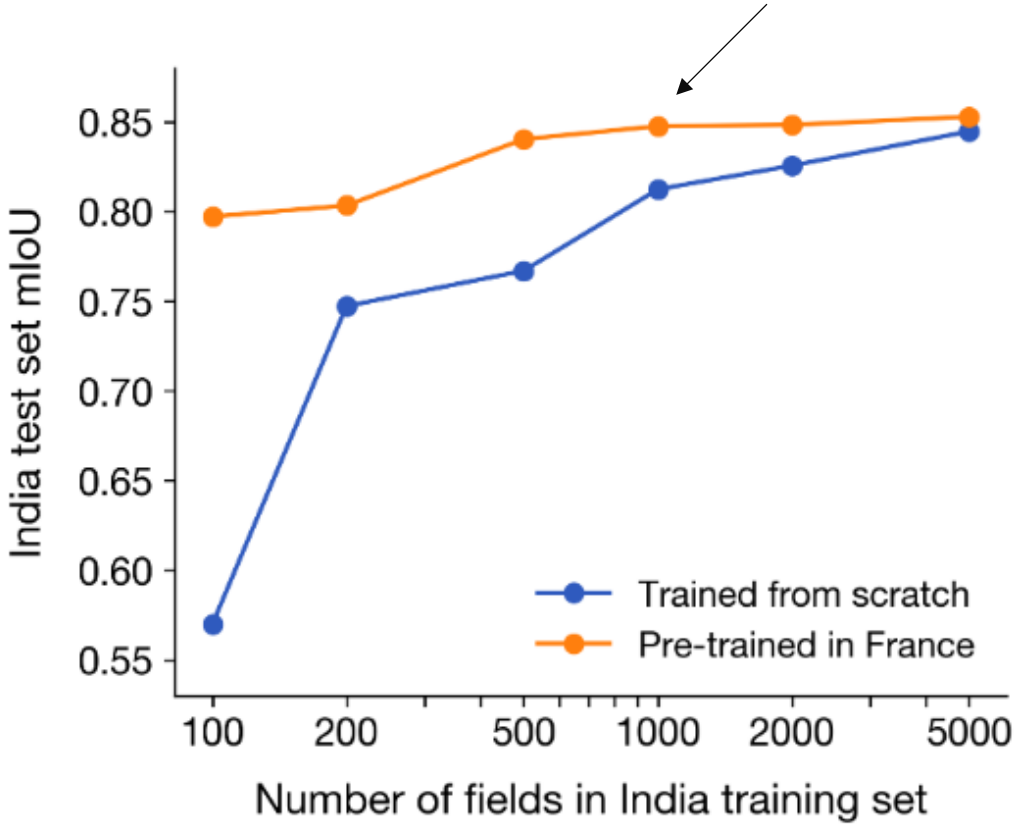
Stakeholders

- Governments
- Private sector
- Farmers
- NGOs



Transfer learning



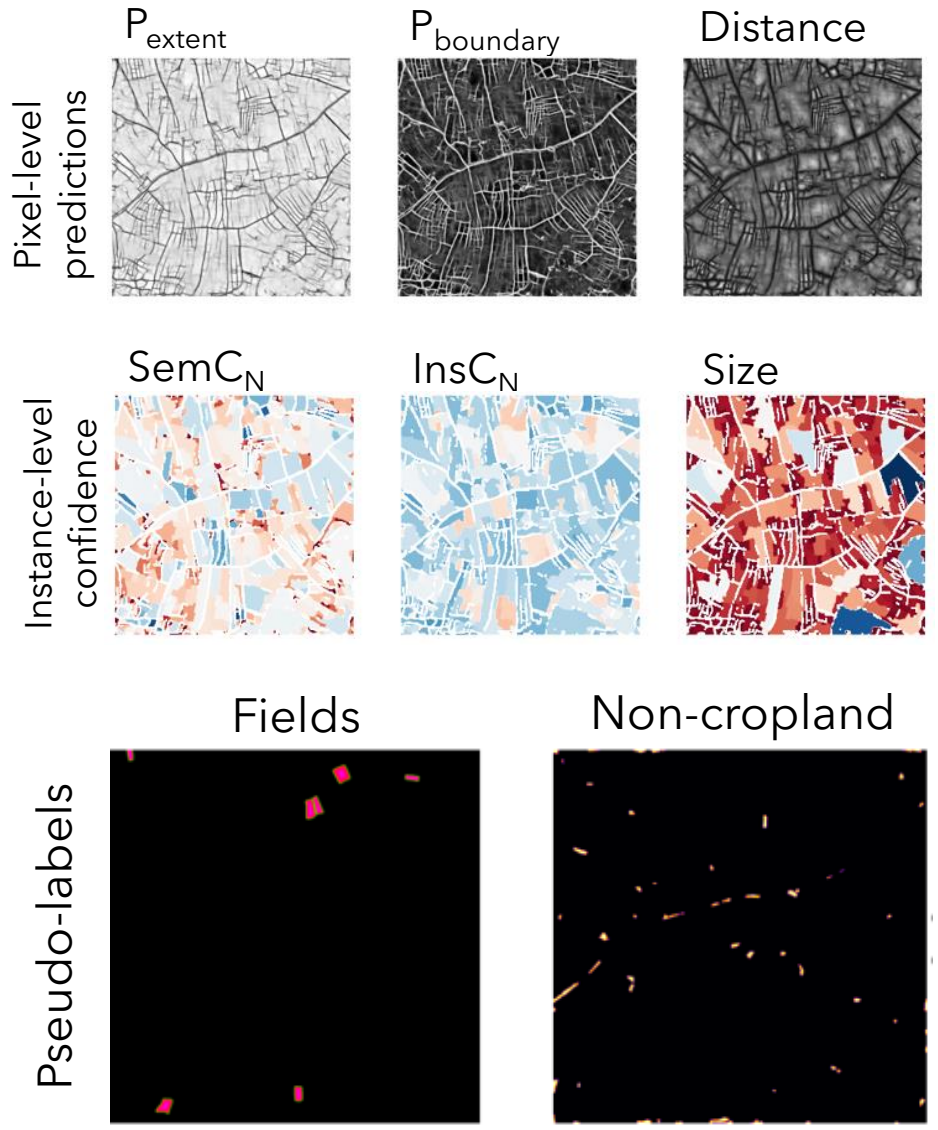


Wang, S., Waldner, F., & Lobell, D. B. (2022). Unlocking Large-Scale Crop Field Delineation in Smallholder Farming Systems with Transfer Learning and Weak Supervision. *Remote Sensing*, *14*(22), 5738. https://doi.org/10.3390/rs14225738

Pseudo-labels

- Rationale: Confident predictions in unlabeled data can serve as training data to transfer across domains

- Geographic domain adaptation for field delineation (Rufin et al. 2024)
  - Transfer from India to Mozambique
  - Adaptively selected pseudo-labels approach performance gains of human data
  - Pseudo-labels can be generated at scale



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Objectives

1) Compile a transferable workflow for smallholder field delineation

2) Produce national-level datasets of individual fields

3) Capture patterns and dynamics of cropland distribution and field size

4) Link field size dynamics to structural transformation of agriculture

Inputs

Very-high resolution satellite images

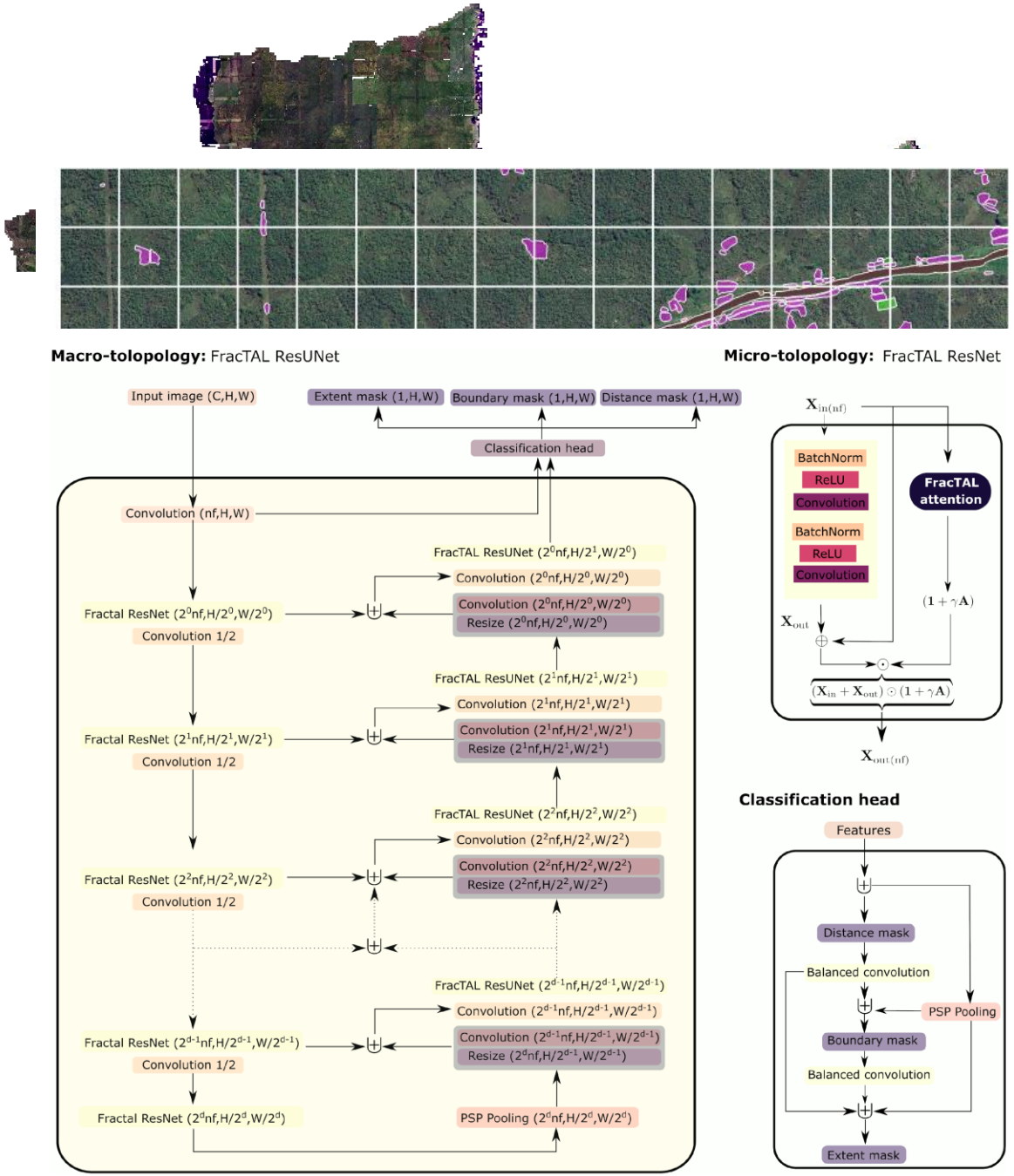
- SPOT 6/7 data (1.5 m)
- Wall-to-wall mosaics for 2017 (± 2 yrs) and 2023 (- 2 yrs)

Reference data

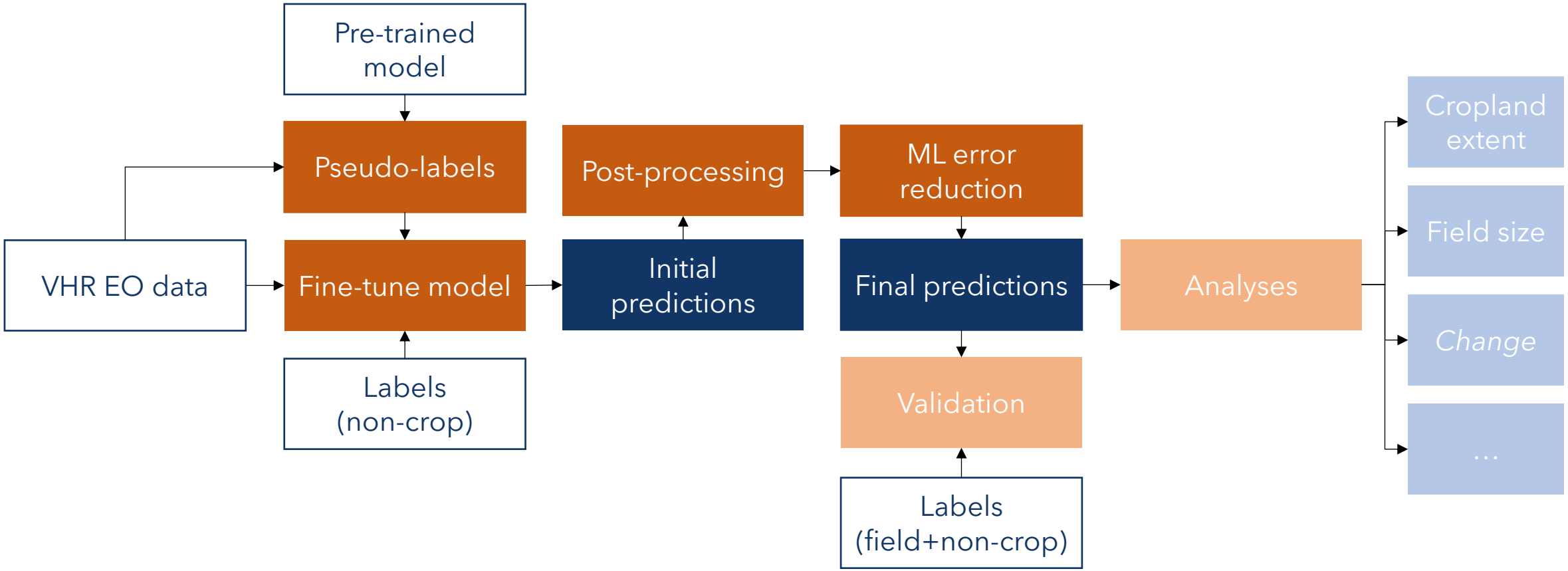
- Sparse labels for fields (n = 813)
- Sparse labels for non-cropland (n=342)
- Pseudo-labels for fields (n = 4,127)

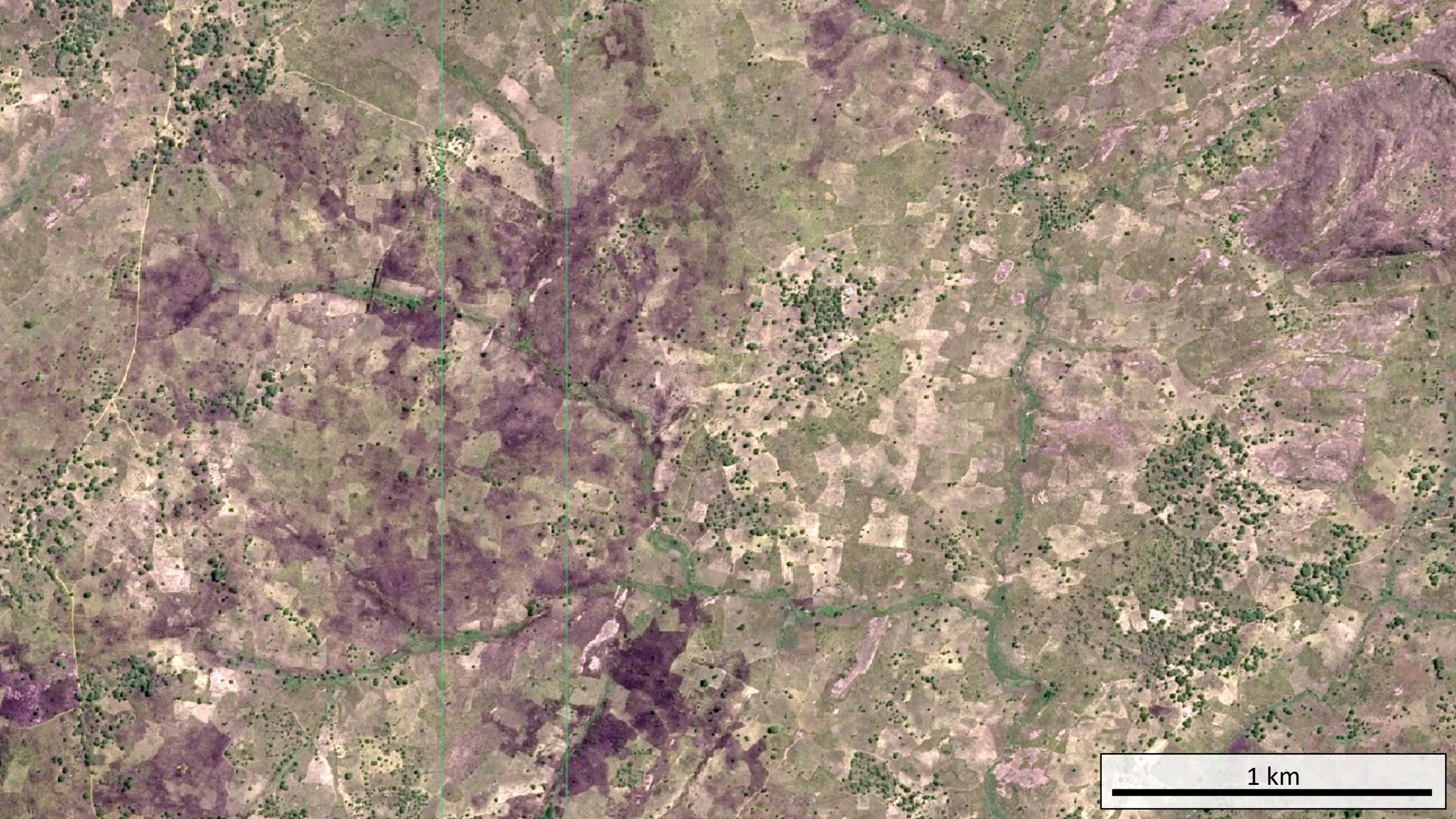
Framework

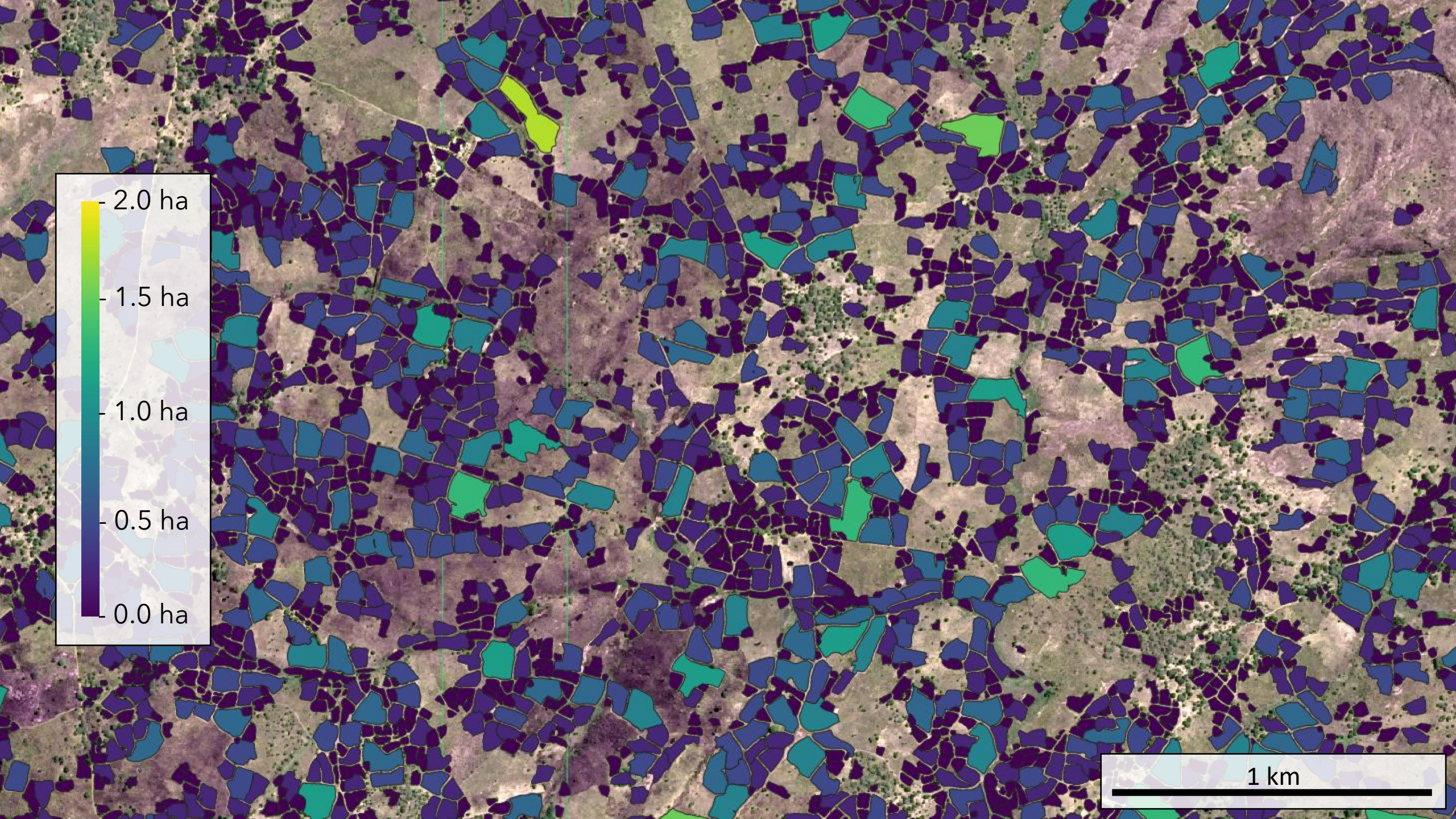
- DECODE (Waldner et al. 2021)
- FracTAL ResUNet w/ pre-trained model weights (Wang et al. 2022)

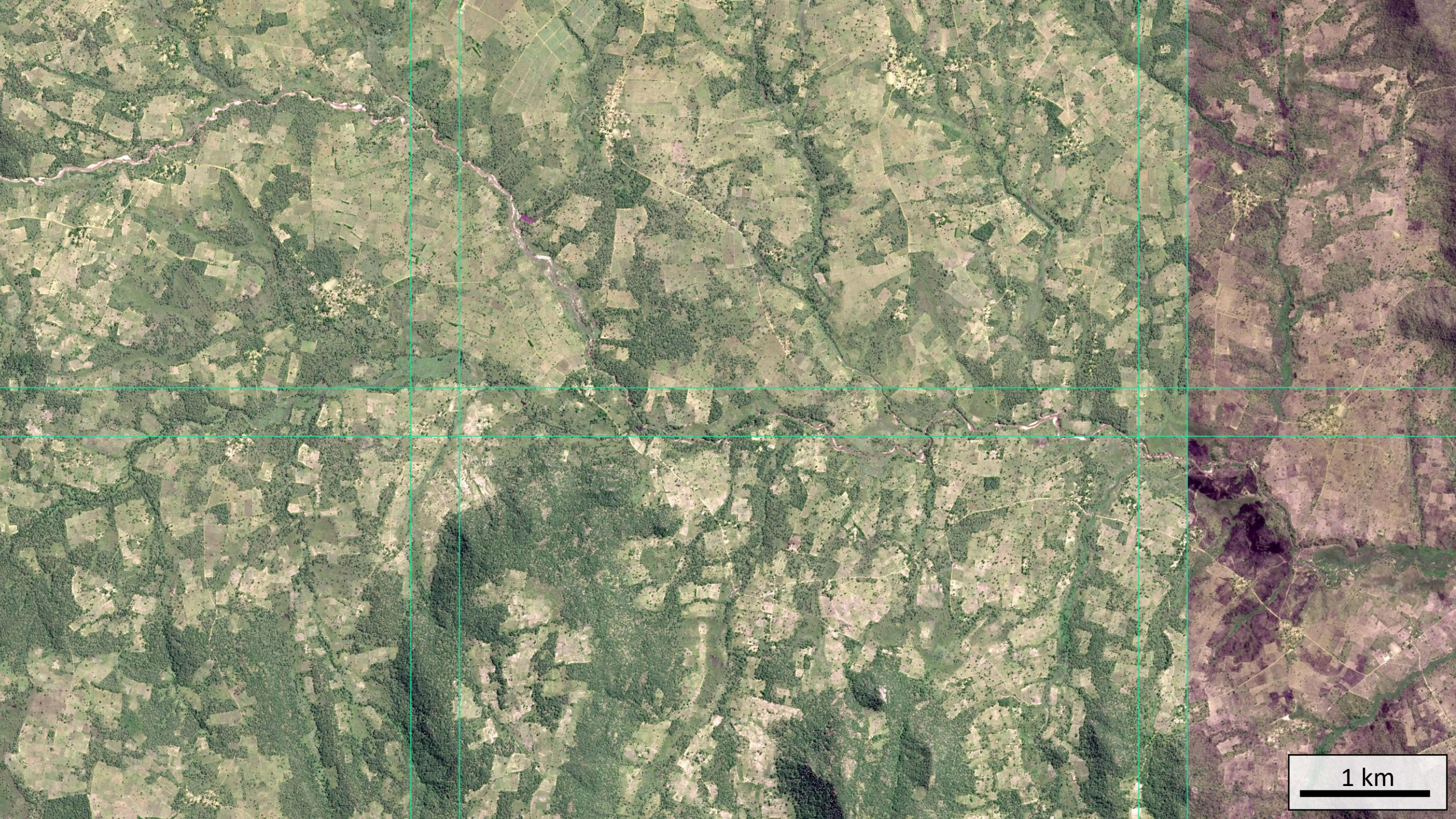


Workflow

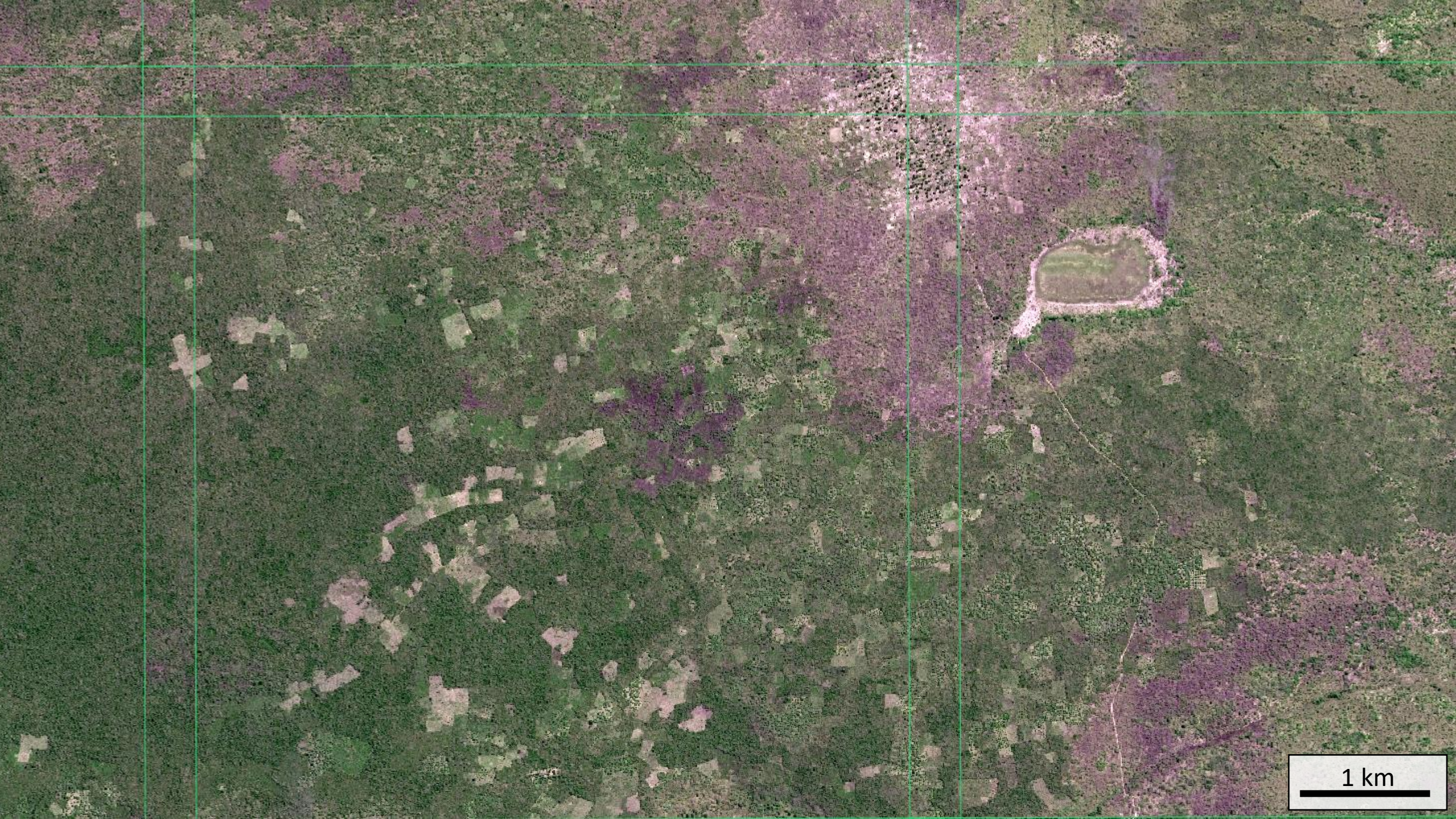

Pre-trained model
Pseudo-labels
VHR EO data
Fine-tune model
Labels (non-crop)
Post-processing
Initial predictions
ML error reduction
Final predictions
Validation
Labels (field+non-crop)
Analyses
Cropland extent
Field size
Change
…

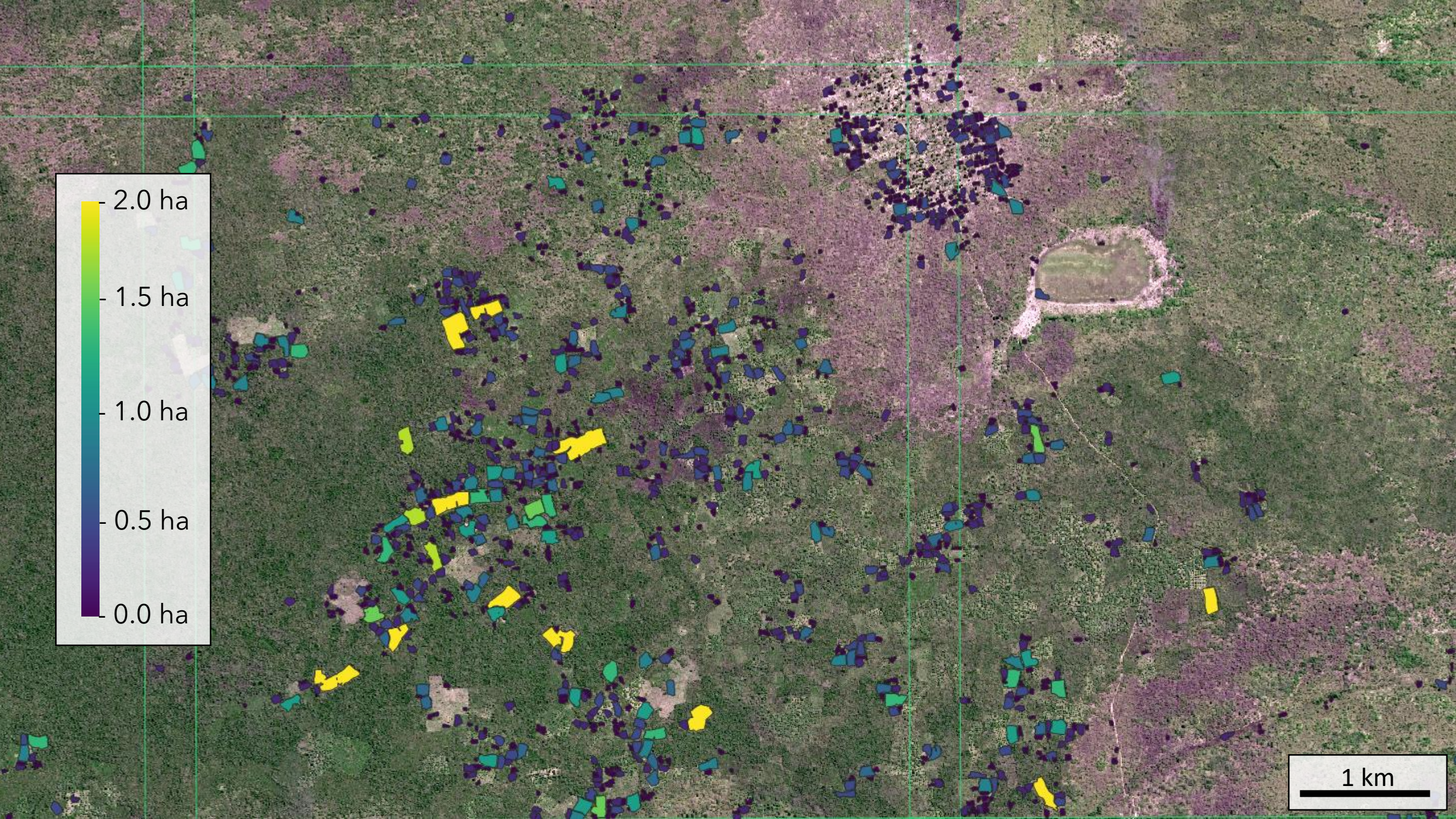

1 km


2.0 ha
1.5 ha
1.0 ha
0.5 ha
0.0 ha
1 km


1 km


2.0 ha
1.5 ha
1.0 ha
0.5 ha
0.0 ha
1 km


1 km


2.0 ha
1.5 ha
1.0 ha
0.5 ha
0.0 ha
1 km

Evaluation – Thematic Accuracy

Preliminary results

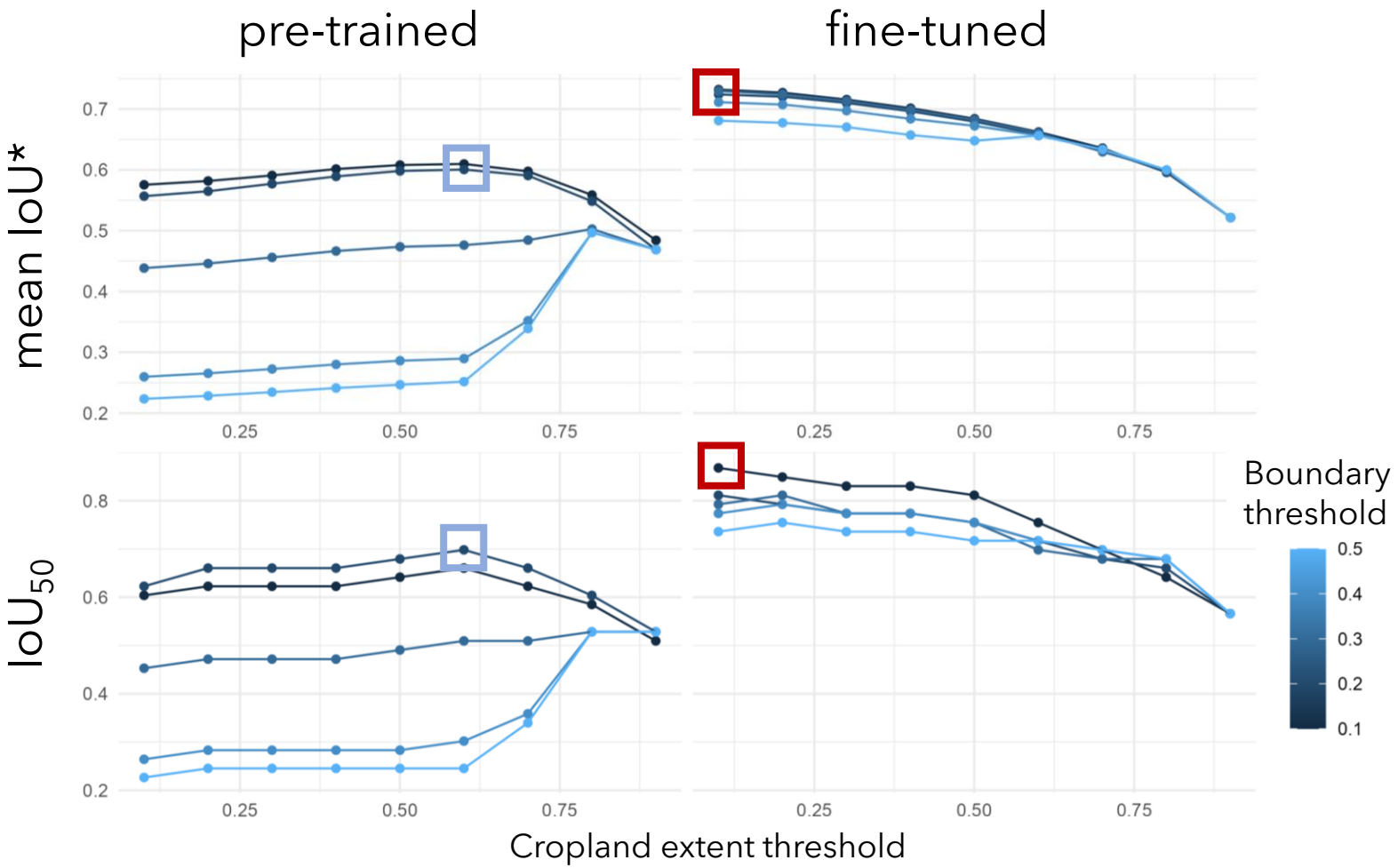
Multi-scale ML model to remove falsely detected fields

- Overall accuracy (field-level) 0.77
- Commission error reduced from 0.62– to 0.12
- Omission error raised to 0.10

		Label: Non-crop	Label: Crop
Prediction	Non-crop	0.517	**0.104**
	Crop	**0.124**	0.255

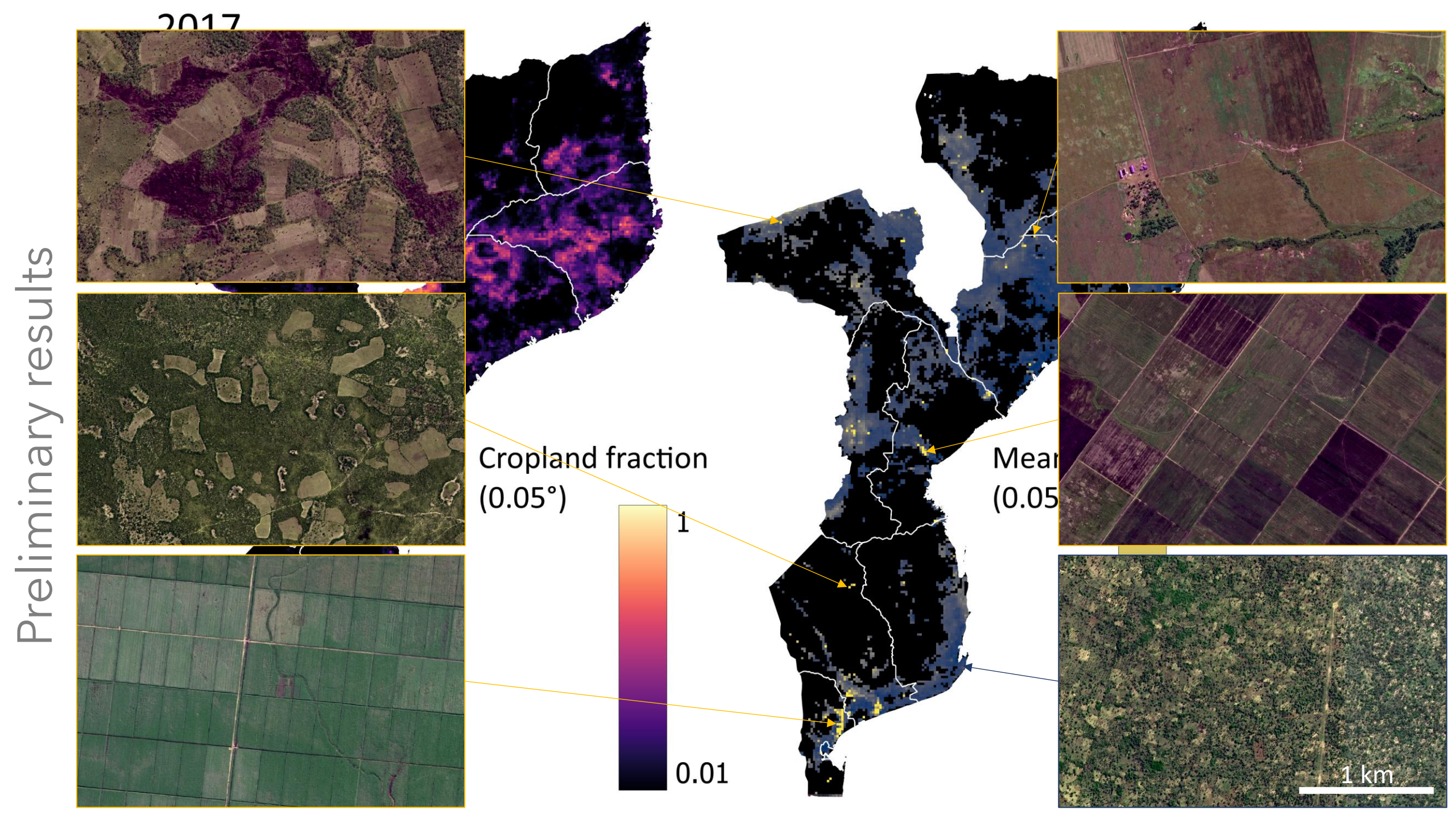
Evaluation – Spatial Agreement

Preliminary results



- Fine-tuning increased performance (~+0.15)
- Spatial agreement high
  - mIoU >0.70
  - IoU50 >0.85
- Suitability for field-level analytics to be confirmed

** Intersection over union*


2017
Preliminary results
Cropland fraction
(0.05°)
1
0.01
1 km

Thank you for your attention!

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Rufin, P., Wang, S., Lisboa, S. N., Hemmerling, J., Tulbure, M. G., & Meyfroidt, P. (2024). Taking it further: Leveraging pseudo-labels for field delineation across label-scarce smallholder regions. *International Journal of Applied Earth Observation and Geoinformation*, 134, 104149. https://doi.org/10.1016/j.jag.2024.104149

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Waldner, F., Diakogiannis, F. I., Batchelor, K., Ciccotosto-Camp, M., Cooper-Williams, E., Herrmann, C., Mata, G., & Toovey, A. (2021). Detect, Consolidate, Delineate: Scalable Mapping of Field Boundaries Using Satellite Images. Remote Sensing, 13(11), 2197. https://doi.org/10.3390/rs13112197

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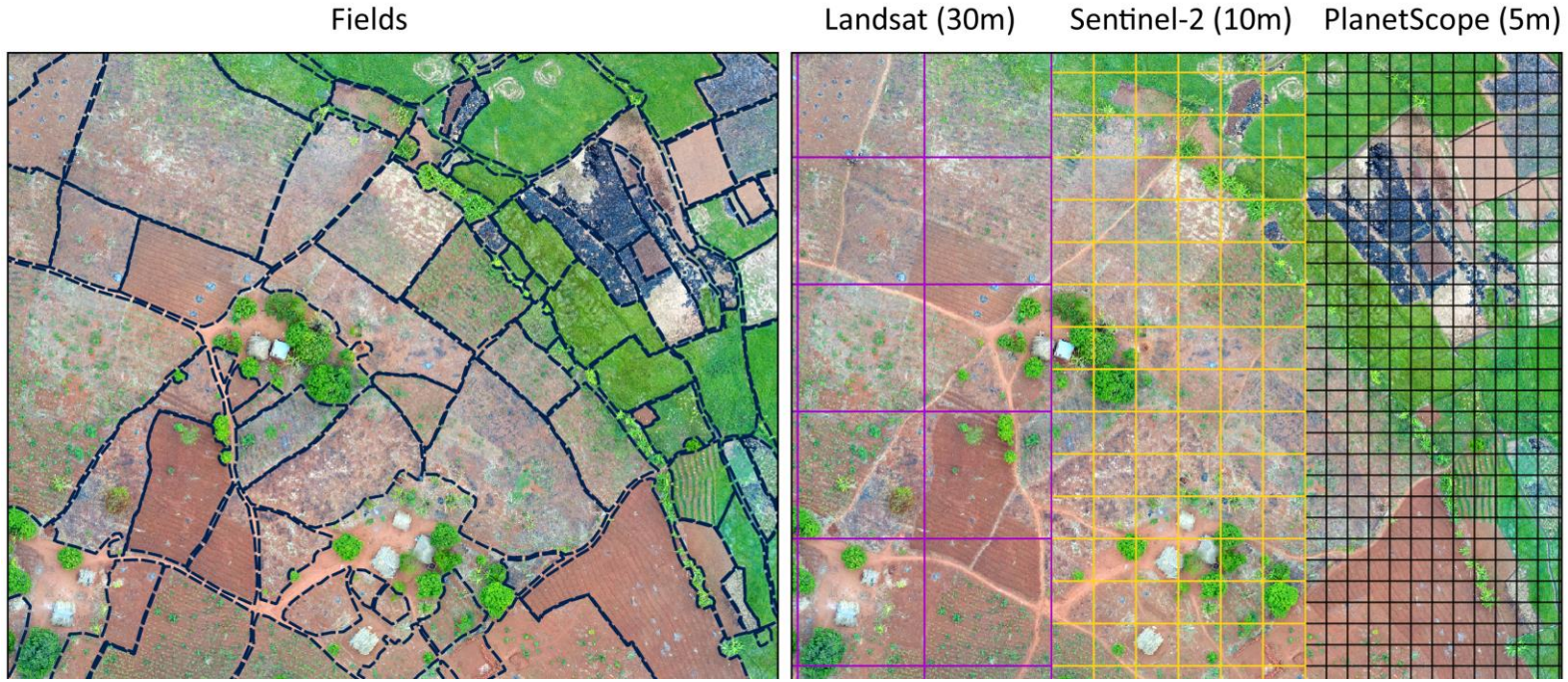
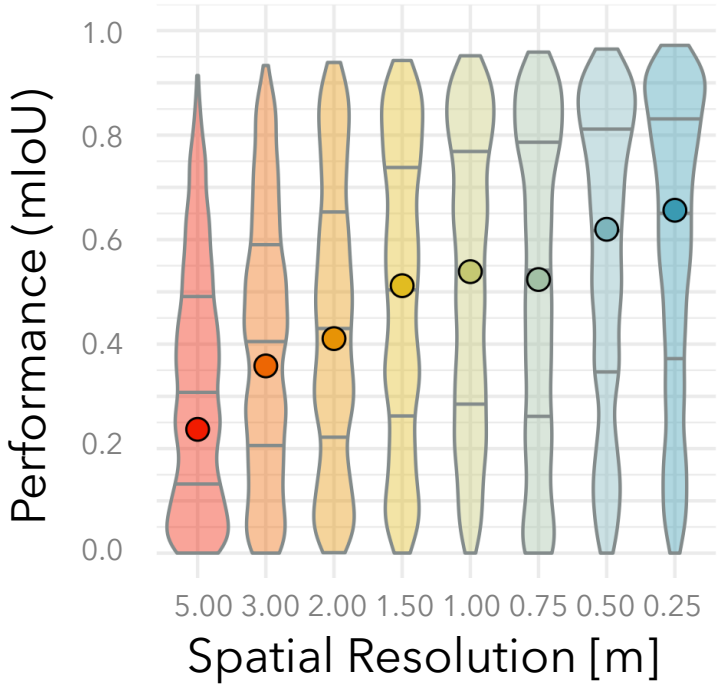
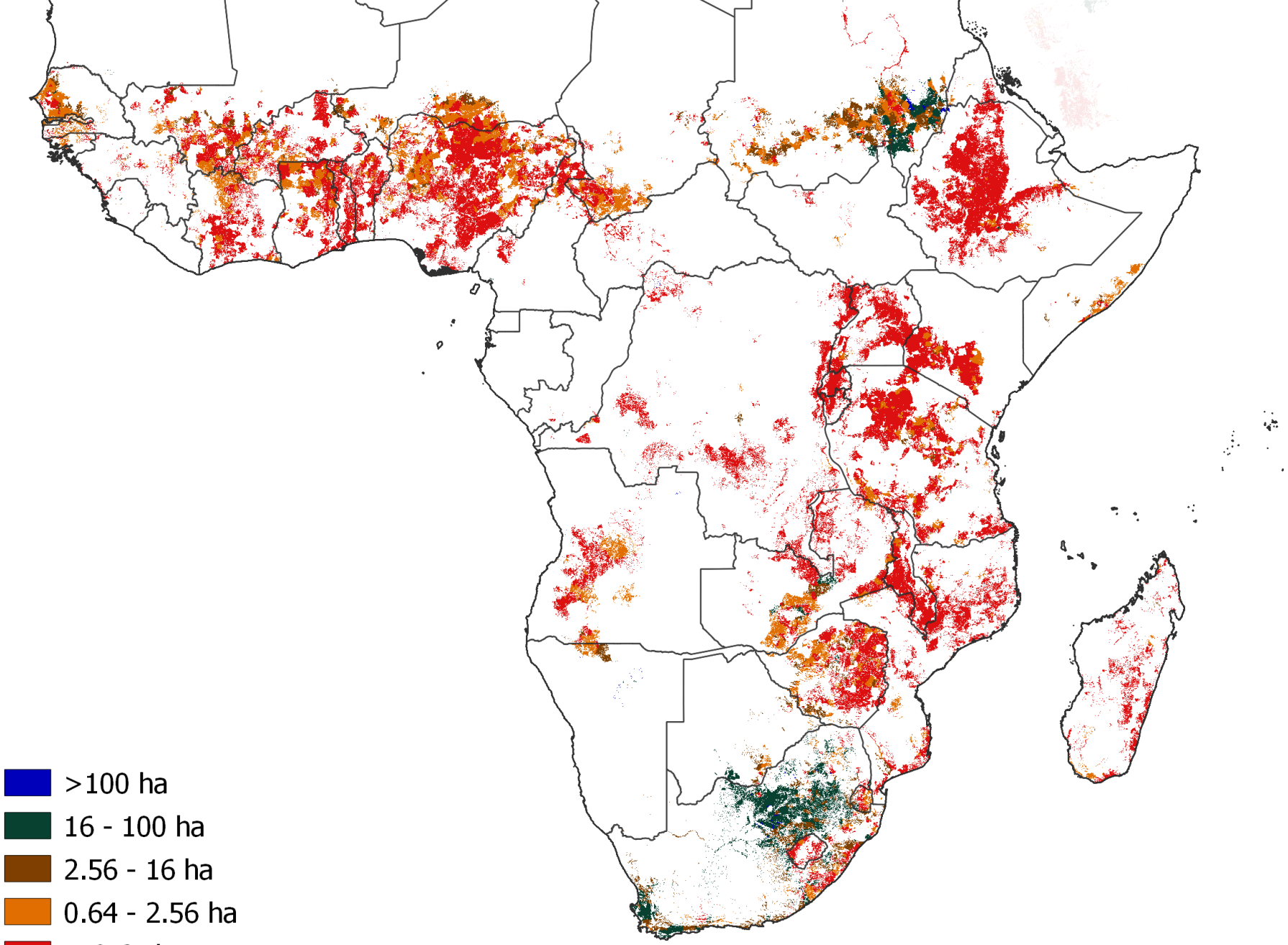




Our definition of „field“

“A unit of land designated for agricultural production, which can be delineated by its physical appearance through markers of land management or land tenure in a specific point in time.”



Lesiv et al. (2019). Estimating the global distribution of field size using crowdsourcing. *Global Change Biology*, *25*(1), 174–186. https://doi.org/10.1111/gcb.14492