# Transfer learning for smallholder field delineation in Sub-Saharan Africa

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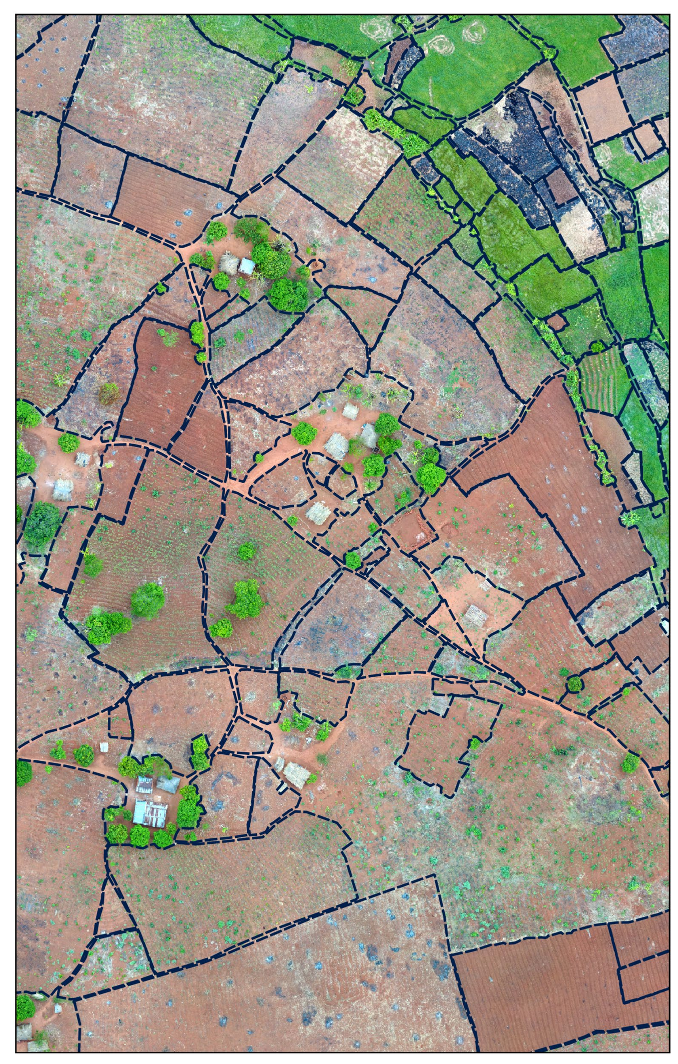
## SCOPE

### Problem statement

- Field delineations are Essential Agricultural Variables in light of SDGs [1]
- Deep learning for computer vision boosted state-of-the-art performance [2]
- Reference data constraints are a key challenge in smallholder contexts [3]
- Pre-trained models generalize across geographies when fine-tuned with region-specific data [4]
- Pseudo-labels [5] are a promising avenue to reduce reference data requirements



*UAV orthomosaic with manually delineated field boundaries in Northern Mozambique.*

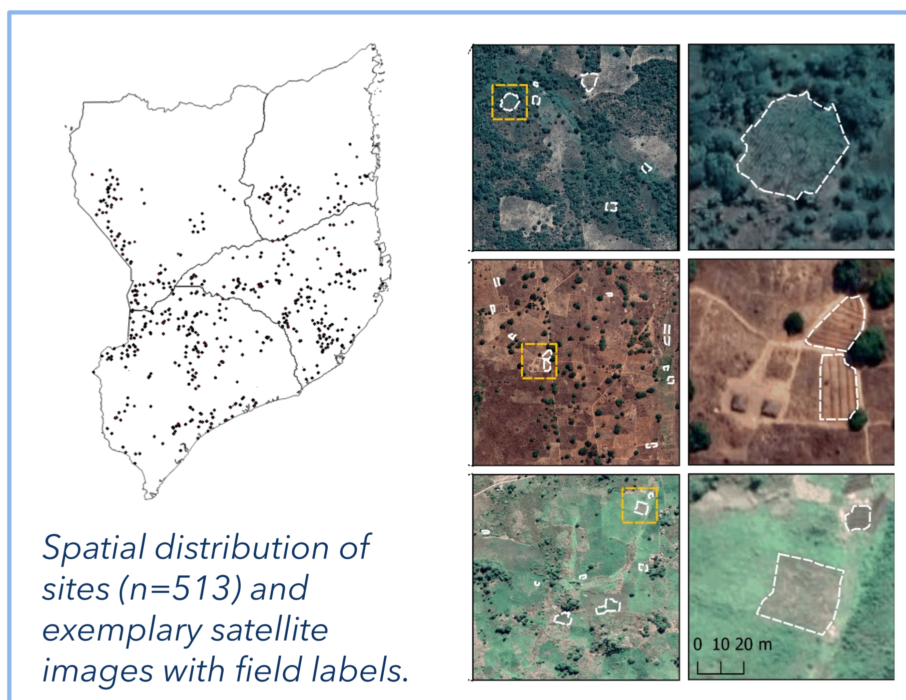
### Leveraging pseudo-labels for field delineation in data-scarce settings

Study region: Northern Mozambique

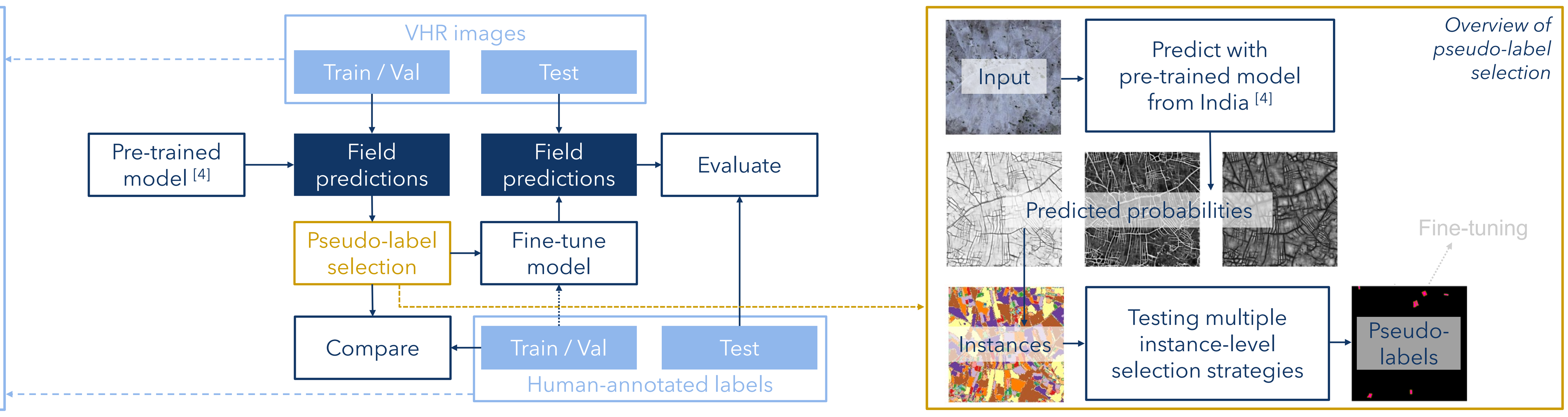
Main objectives:

1) Create field delineation pseudo-labels similar to human annotated labels.
2) Assess the performance of fine-tuning with pseudo-labels against human labels
3) Explore added value of complementing human and pseudo-labels

## WORKFLOW



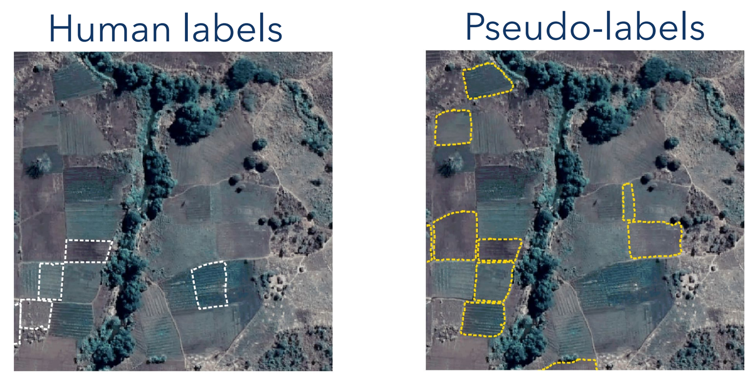
*Spatial distribution of sites (n=513) and exemplary satellite images with field labels.*




## RESULTS

### 1) Characteristics of pseudo-labels

- Selection strategy determines properties.
- Field size & seasonal distribution of pseudo-labels similar to human labels.

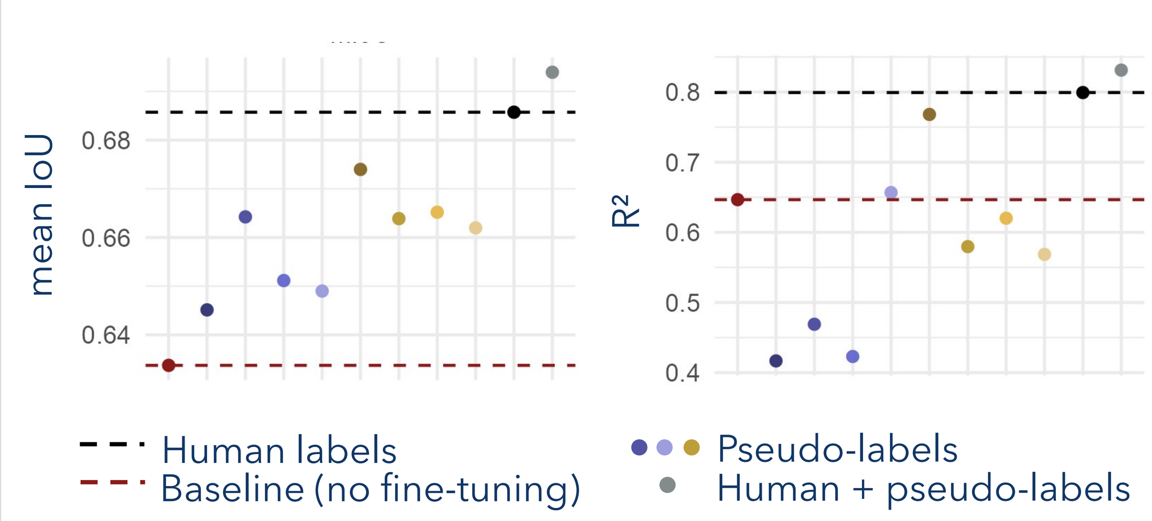



- Spatial agreement high, with mean intersection over union (mIoU*) of up to 0.8.

*IoU=

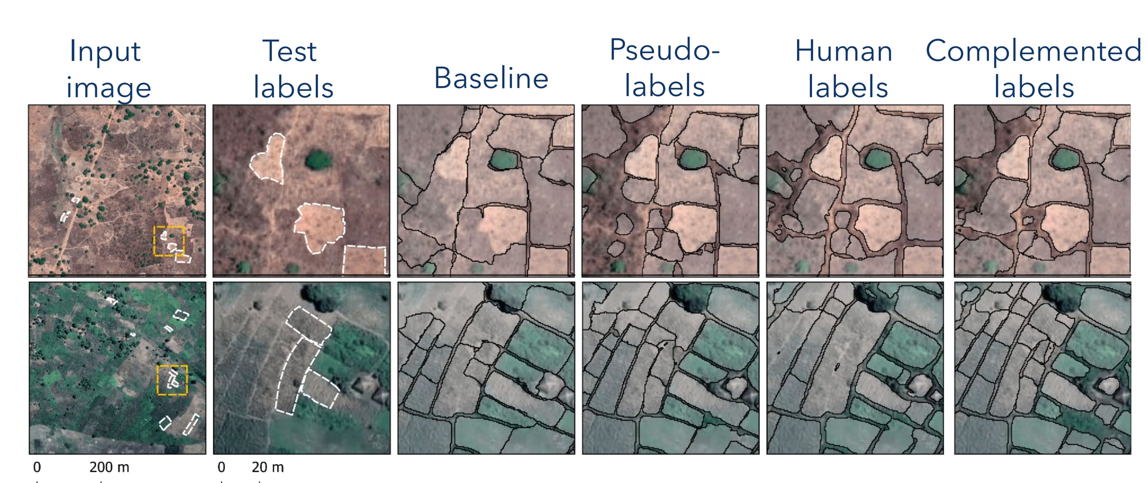
### 2) Fine-tuning with pseudo-labels

- Best set of pseudo-labels (●) achieved 77% of gain in mIoU (spatial agreement), 65% of decrease in RMSE, and 68% of gain in R² (field size estimation) obtained by human labels only.




### 3) Complementing human labels

- Complementing human and pseudo-labels (●) outperformed human labels across all metrics and use cases.
- Additional performance gains of 16% (mIoU), 8% (RMSE), and 21% (R²).




## TAKE-HOME MESSAGES

- Fine-tuning field delineation models for target geography improved performance throughout.
- Best set of pseudo-labels approached performance gains obtained from human labels.
- Complementing pseudo-labels with human labels outperformed using only human labels.
- Pseudo-labels can be generated at scale, supporting field delineation in data-scarce settings.

Interested? Reach out:
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[2] Waldner & Diakogiannis (2020): „Deep Learning on Edge: Extracting Field Boundaries from Satellite Images with a Convolutional Neural Network". Remote Sensing of Environment. https://doi.org/10.1016/j.rse.2020.111741.
[3] Nakalembe & Kerner (2023): Considerations for AI-EO for agriculture in Sub-Saharan Africa. Environmental Research Letters. https://doi.org/10.1088/1748-9326/acc476.
[4] Wang, Waldner, Lobell (2022): „Unlocking Large-Scale Crop Field Delineation in Smallholder Farming Systems with Transfer Learning and Weak Supervision". Remote Sensing. https://doi.org/10.3390/rs14225738.
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