

## Advancing Precision Agriculture with Few-Shot Learning: A Mixture-of-Experts Approach for Cereal Mapping

Amir Moncef Tighlit <sup>1</sup>, Meziane Iftene <sup>2</sup>, Mohammed El Amin Larabi <sup>2</sup>,

<sup>1</sup> Higher School of Computer Science (ESI-SBA), 22000 Sidi Bel Abbès, Algeria

<sup>2</sup> Department of Scientific and Technological Watch, Algerian Space Agency, 16000 Algiers, Algeria

### INTRODUCTION & AIM

Accurate crop maps are crucial for targeted agricultural management and effective decision support; however, generating these maps typically requires extensive, costly labeled training data, highlighting the need for methods that produce high-quality maps from small labeled datasets. To address this, our aim is to develop a data-efficient semantic segmentation pipeline specifically for cereal mapping by fine-tuning state-of-the-art vision foundation models and combining their individual strengths through a Mixture-of-Experts ensemble.

### METHOD

Sentinel-2 L2A imagery (vegetation-sensitive bands) was paired with field-collected polygons quality-controlled via NDVI time series, and after QC and sampling across growth stages we produced 124 image–mask pairs for training and validation; all patches were resized to 256x256, normalized per channel, and filtered to remove inconsistent or noisy samples identified during NDVI QC to keep the pipeline fast and robust for small datasets. We fine-tuned two complementary vision foundation models; Prithvi-EO (temporal/phenology cues) and Satlas (strong spatial priors), then froze the best expert weights to create a Mixture-of-Experts in which a small gating CNN learns image-dependent fusion, balancing representational power with data efficiency. Models were trained with AdamW using cross-entropy loss, and we ran careful augmentation experiments (RandAugment plus radiometric and geometric variants), since augmentation choices materially affected performance on the small dataset.

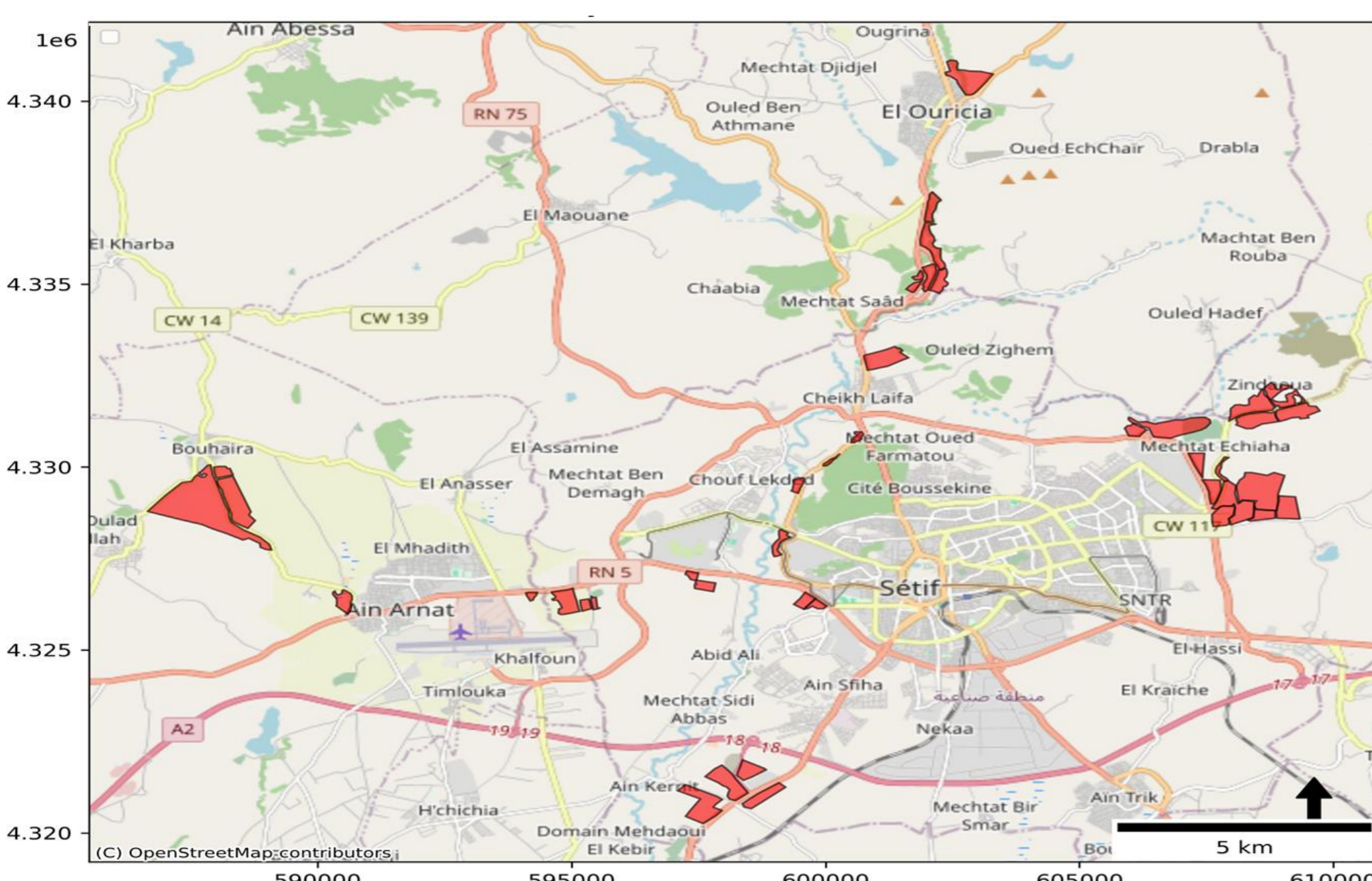


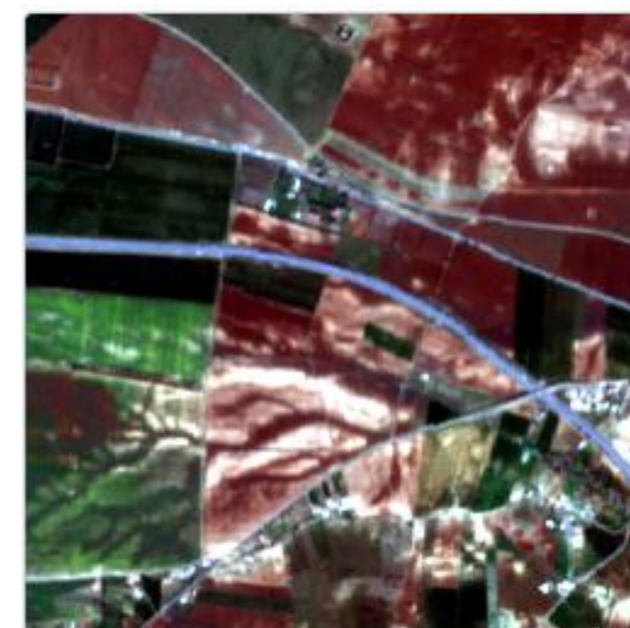
Figure 1: The primary study area in Setif, Algeria. The ground truth cereal parcel polygons collected for this research are highlighted in red.

### RESULTS & DISCUSSION

Prithvi was evaluated under four different configurations with data augmentation (baseline, geometric, radiometric, RandAugment). RandAugment achieved 81.42% Overall Accuracy. Satlas, specifically the Radiometric Augmentation model, performed significantly better, achieving 96.93% Overall Accuracy and 94.12% Cereal Class IoU, surpassing Prithvi. See Table 1 for details. These results highlight how large supervised pretraining supplies strong spatial priors, temporal cues enhance class separability, and adaptive gating combines both to reduce variance and produce more consistent crop maps.

Table 1: Comparative Performance: Champion Prithvi (RandAugment) vs. Champion Satlas (Radiometric Augmentation).

Metrics	Prithvi (RandAugment)	Satlas (Radiometric Aug.)
Overall Accuracy %	81.42	<b>96.93</b>
IoU (Overall/Macro) %	68.65	<b>94.04</b>
IoU (Cereal Class) %	68.17	<b>94.12</b>
Validation Loss	0.4146	<b>0.3427</b>



(a) Original (RGB Composite)



(b) Segmentation Overlay (Cereal in Red)

Figure 2: Qualitative segmentation result.

### CONCLUSION

Fine-tuning vision foundation models and combining them through a Mixture-of-Experts yields a compact, data-efficient pipeline capable of producing highly reliable cereal maps. This approach demonstrates how modern pre-trained models can be adapted to achieve strong performance even with limited annotated data, offering a practical path toward scalable applications in precision agriculture.

### FUTURE WORK / REFERENCES

Next steps are to evaluate cross-region transfer, extend to multi-crop mapping with longer time series, and add interpretability tools (gating attention / saliency) to increase operational trust and ease adoption.

1. S. Mohammadi, M. Belgiu, and A. Stein, "Few-shot learning for crop mapping from satellite image time series," *Remote Sensing* 16(6), 1026 (2024).
2. S. Lu, J. Guo, J. R. Zimmer-Dauphinee, et al., "Vision foundation models in remote sensing: A survey," *arXiv preprint arXiv:2408.03464v2* (2024)