Plume Segmentation from MethaneSAT with Cross-Sensor Transfer Learning and Physics-Informed Postprocessing

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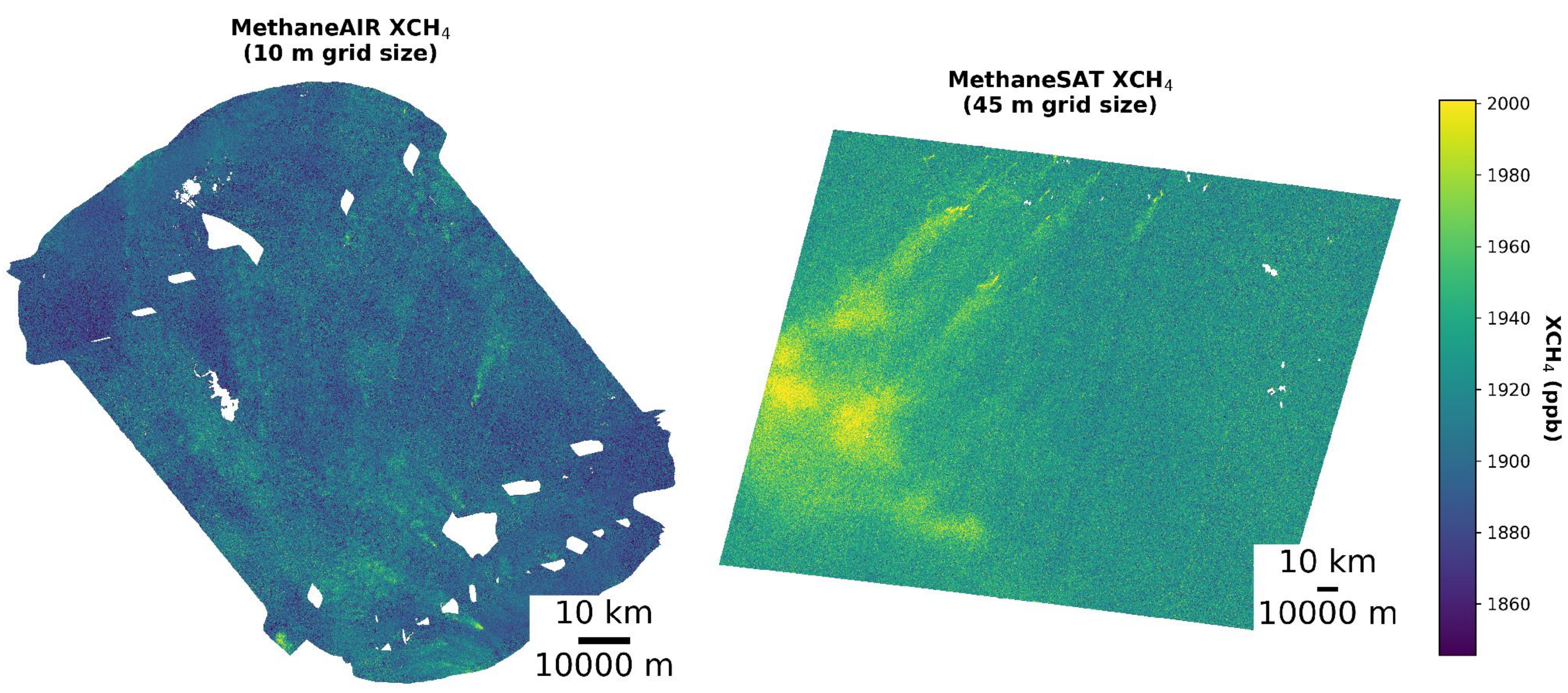
MOTIVATION

- MethaneSAT observes oil & gas basins revealing CH_4 plumes across 220×220 km areas. Along with its precursor MethaneAIR, use the same method to retrieve dry air mole fractions of methane **XCH4** [1]
- Automated detection is essential for global emission monitoring.



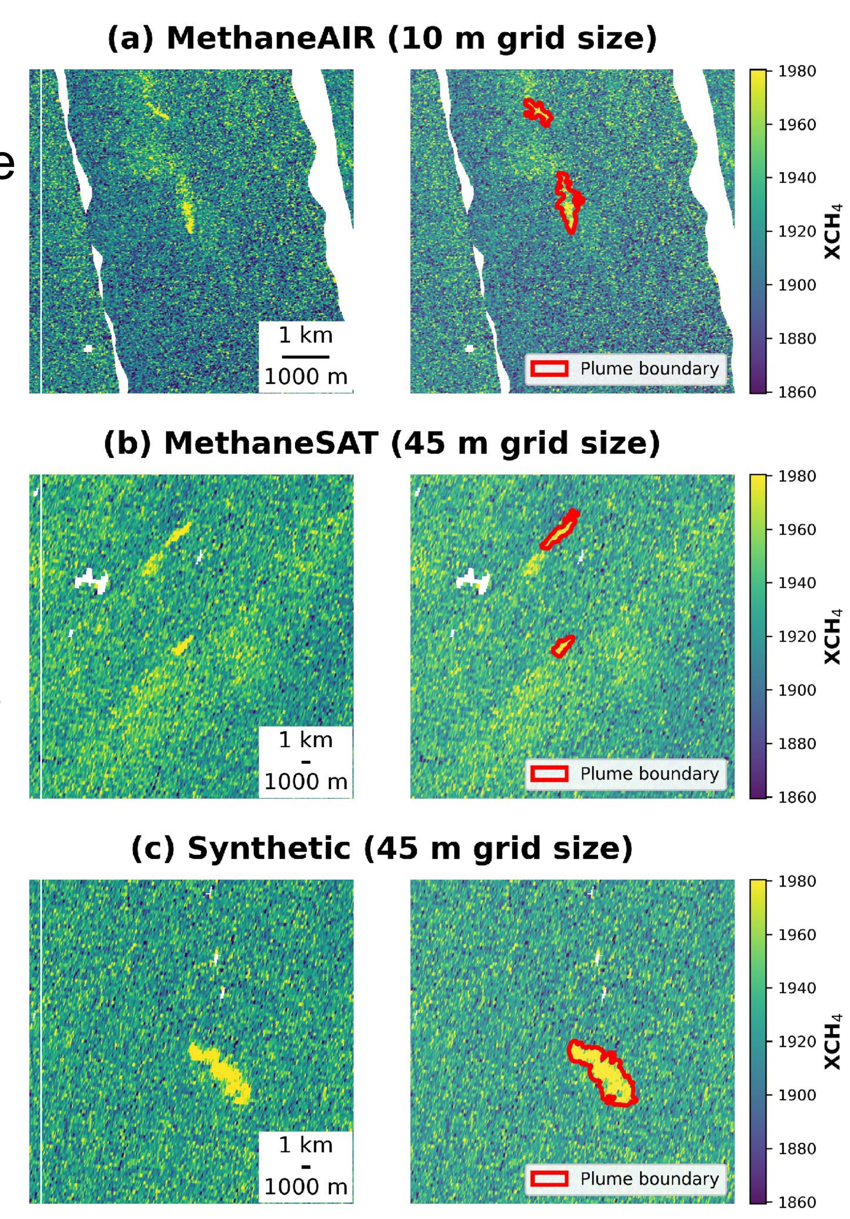
DATA

We generated labels using the wavelet method [2].

MethaneAIR:
- 80+ annotated airborne scenes at 10 m grid size
- **1050 annotated plumes**

MethaneSAT:
- 27 annotated satellite scenes at 45 m grid size
- **110 annotated plumes**

Synthetic:
- WRF-LES/HRRR plumes [3] injected into MethaneSAT
- **185 annotated plumes**



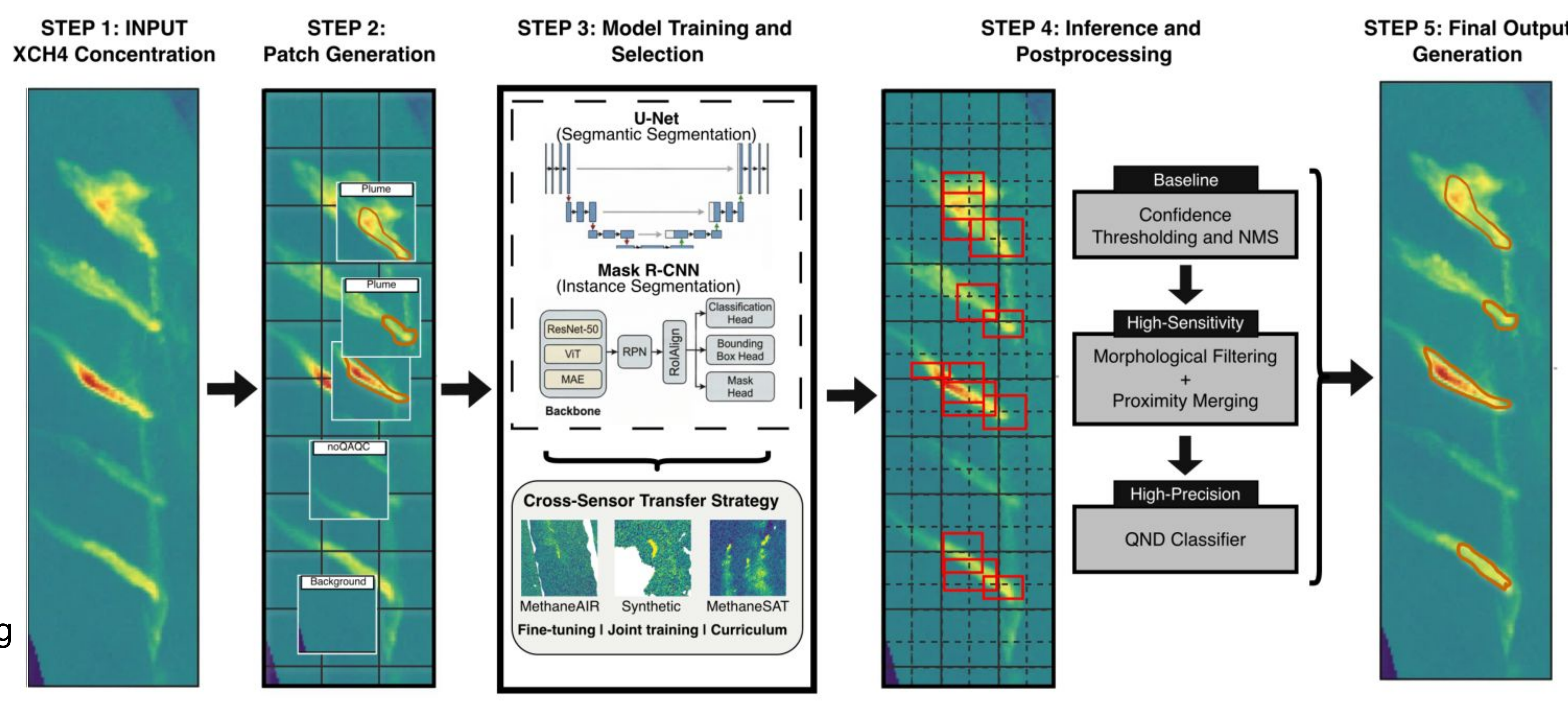
METHODS

Patch extraction
Plumes + False plumes + Background

Model Selection
Semantic vs Instance Segmentation

Cross-sensor transfer strategies:
- **Fine-tuning**: pre-train on MethaneAIR, fine-tune on MethaneSAT
- **Joint training:** mixed-batch training across domains
- **Curriculum**: progressive shift from synthetic to real scenes

Physics-informed postprocessing
- **Baseline:** IoU suppression+Confidence
- **High sensitivity:** Morphology + Merging
- **High Precision:** QND classifier [4]



RESULTS

Patch-level

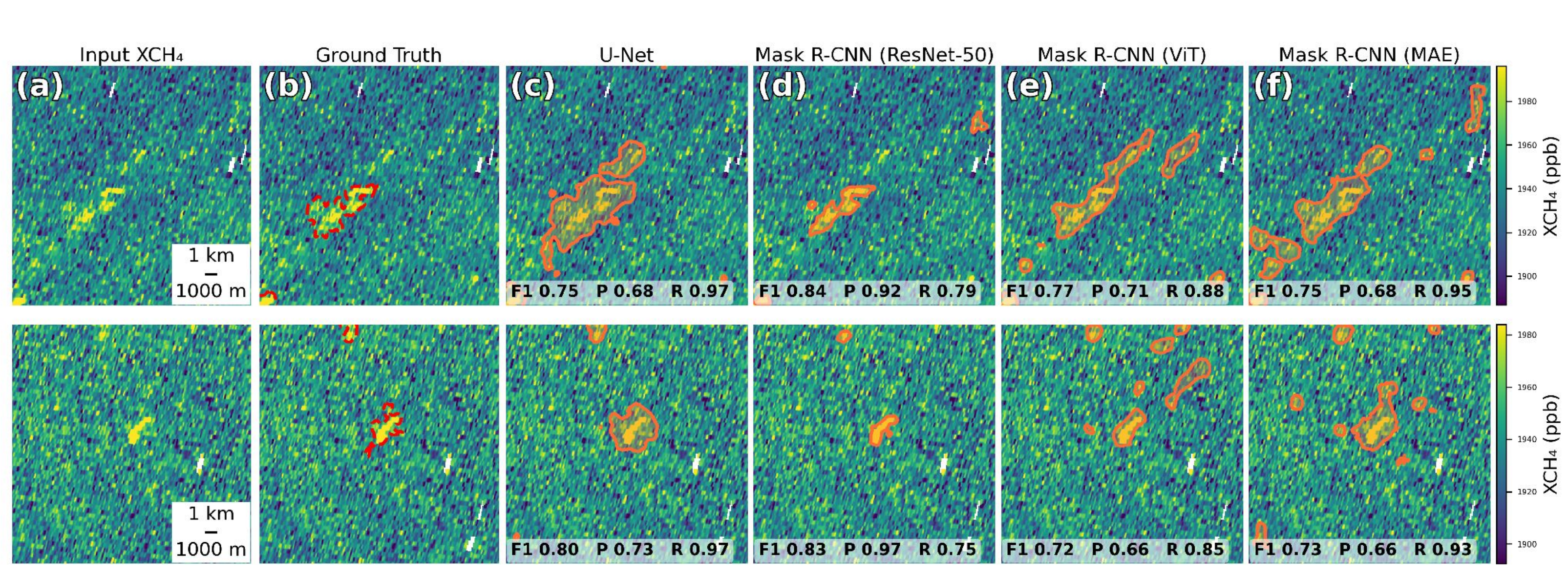
- Mask R-CNN with ResNet-50 architecture outperformed U-Nets and variants across MethaneAIR and MethaneSAT.

Model	F1
U-Net	64.41±1.09
Mask R-CNN (ResNet)	**74.90±1.57**
Mask R-CNN (ViT)	67.33±2.63
Mask R-CNN (MAE)	67.32±0.83

MethaneAIR

Model	F1
U-Net	65.03±6.43
Mask R-CNN (ResNet)	**70.51±5.50**
Mask R-CNN (ViT)	66.98±7.02
Mask R-CNN (MAE)	66.86±7.20

MethaneSAT

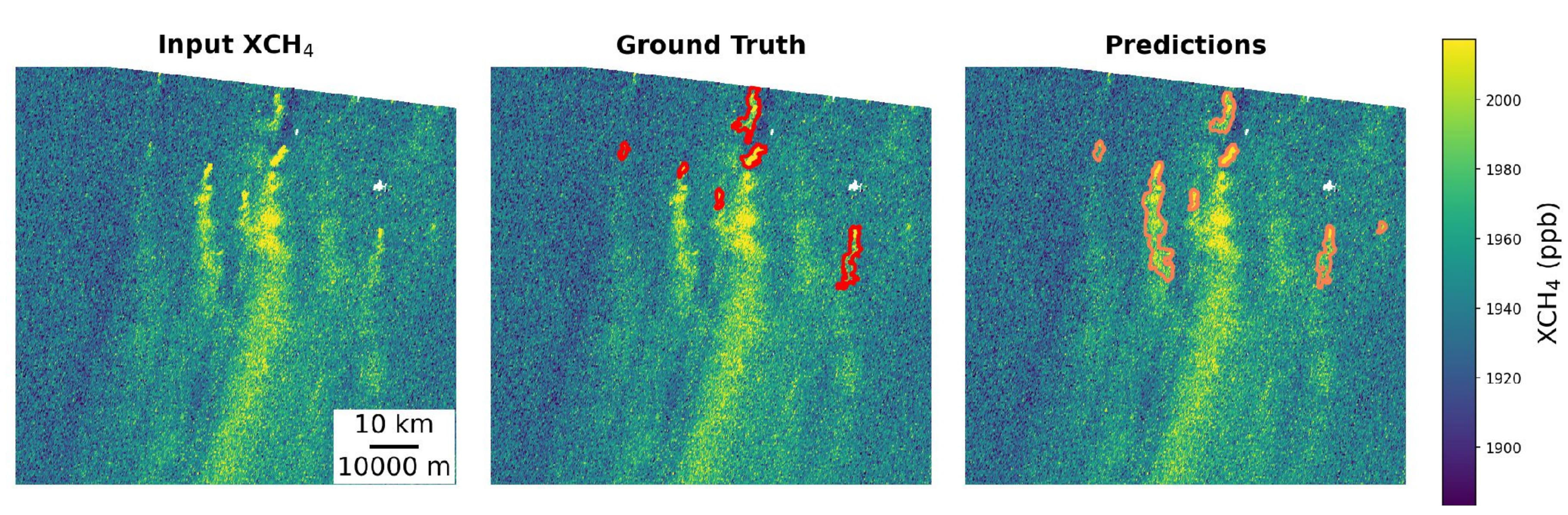


Scene-level

- Fine-tuning is the best cross-sensor strategy
- High-sensitivity archives the best overall F1-scores
- High-precision removes almost all FP.

Strategy	Mode	TP	FP	FN	F1
MethaneSAT-only	Baseline	18	63	4	0.35±0.03
	High Sensitivity	16	47	6	0.38±0.05
	High Precision (QND)	12	9	10	0.56±0.09
Fine-Tuning	Baseline	22	15	0	0.74±0.05
	High Sensitivity	21	8	1	**0.81±0.07**
	High Precision (QND)	15	1	7	0.79±0.05
Joint	Baseline	22	23	0	0.65±0.06
	High Sensitivity	21	15	1	0.72±0.03
	High Precision (QND)	16	5	6	0.76±0.03
Curriculum	Baseline	22	24	0	0.65±0.08
	High Sensitivity	21	13	1	0.74±0.10
	High Precision (QND)	16	4	6	0.76±0.09

MethaneSAT using ResNet-50 backbone



CONCLUSIONS

- Mask R-CNN outperforms U-Net.
- Fine-tuning from MethaneAIR is the most effective cross-sensor transfer strategy.
- Physics-informed postprocessing yields two operational modes: High-Sensitivity (P=0.71, R=0.94) and High-Precision (P=0.92, R=0.70)
- Framework demonstrated on full MethaneSAT operational archive

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