Semantic Segmentation for Land Use/Land Cover

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Introduction

Accurate **land use/cover (LULC)** data has several important applications, including environmental monitoring, urban planning, and population estimation.

We sought to develop a **high-accuracy**, **globally scalable**, and **fast inference** land use segmentation model.

Data

Imagery: ESA Sentinel-2 (25 diverse cities, 2 scenes each)

Labels: ESA WorldCover V200 (11 classes)

Validation: Hand-labelling (2 scenes)

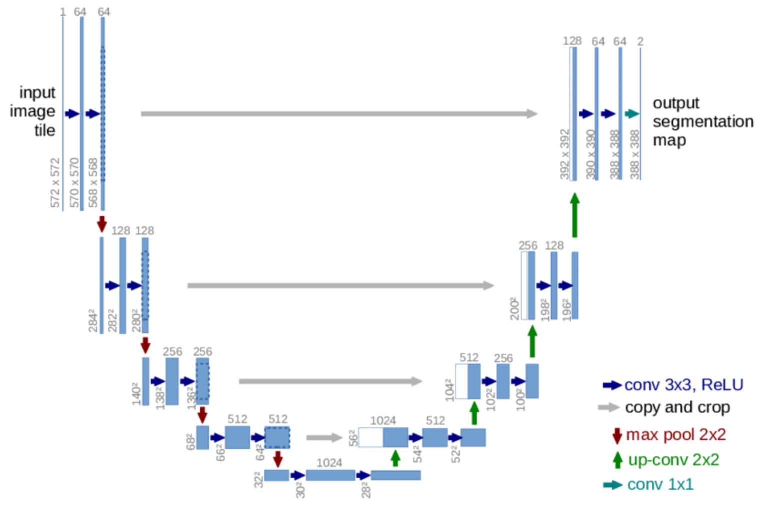
Methods

Semantic segmentation is a **computer vision task** that assigns class labels to every pixel of an image, enabling accurate and granular classification.

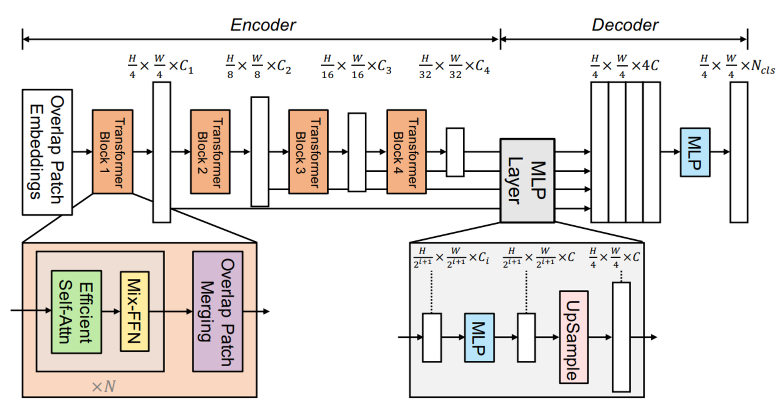
We trained and tested the following deep learning models:

- **U-Net**: Accepted baseline, **CNN** architecture [1]
- **SegFormer**: Efficient **transformer**-based architecture [2]
- **Prithvi EO2**: State-of-the-art **foundation model** [3]

U-Net Architecture [1]



SegFormer Architecture [2]

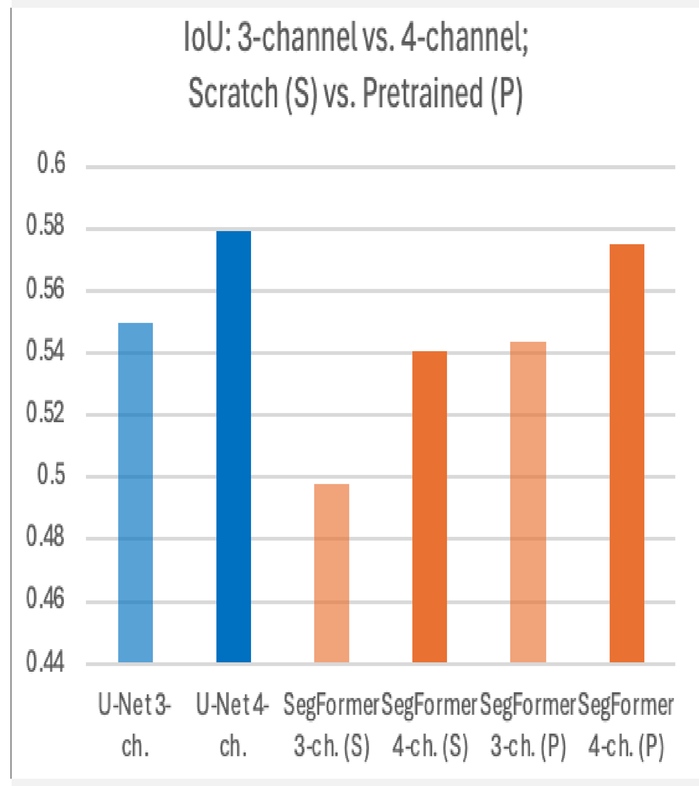


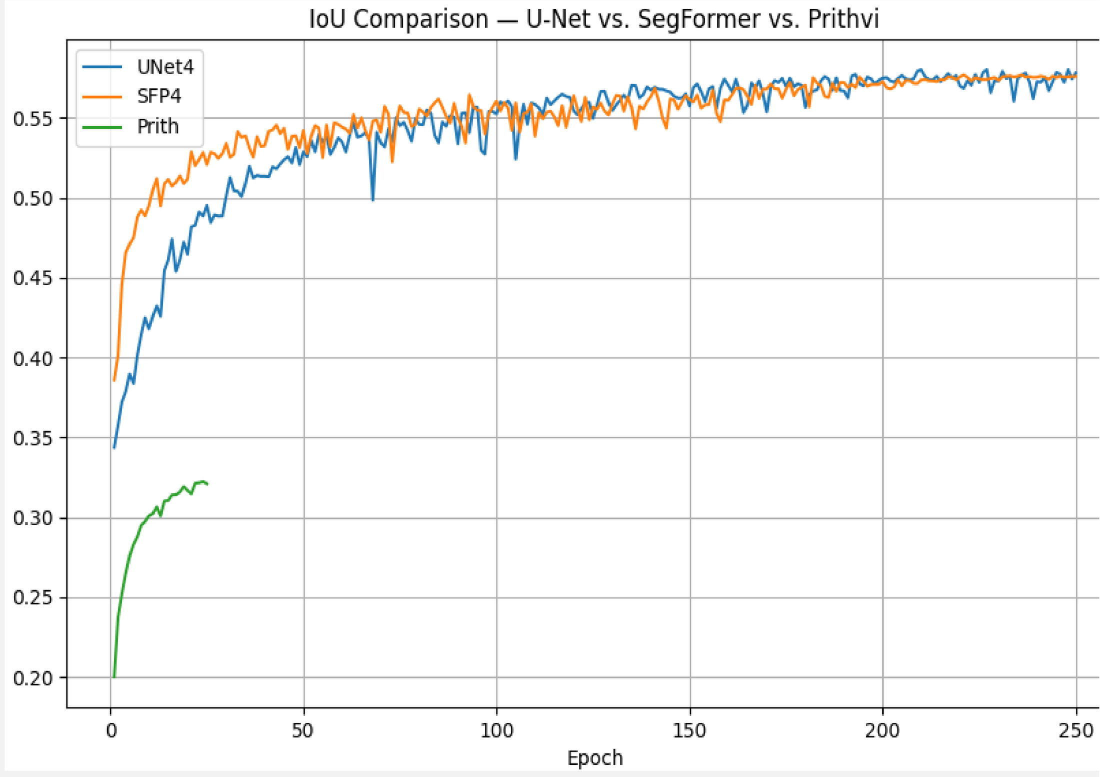
Experiments.

- *Input Data:* 3-channel (RGB imagery) vs. 4-channel (RGB + Near-Infrared).
- *Initialization & Training:* Training from scratch vs. finetuning from pretrained weights.
- *Model Size:* For pretrained models, testing small (3.7M params) vs. large (82M params) models.

Results

- **4-channel** models outperformed 3-channel models.
- **Pretrained** models outperformed from-scratch models.
- **Larger weight** models outperformed smaller weight models.





Confusion Matrices:

U-Net (4-channel): 86.05% overall accuracy

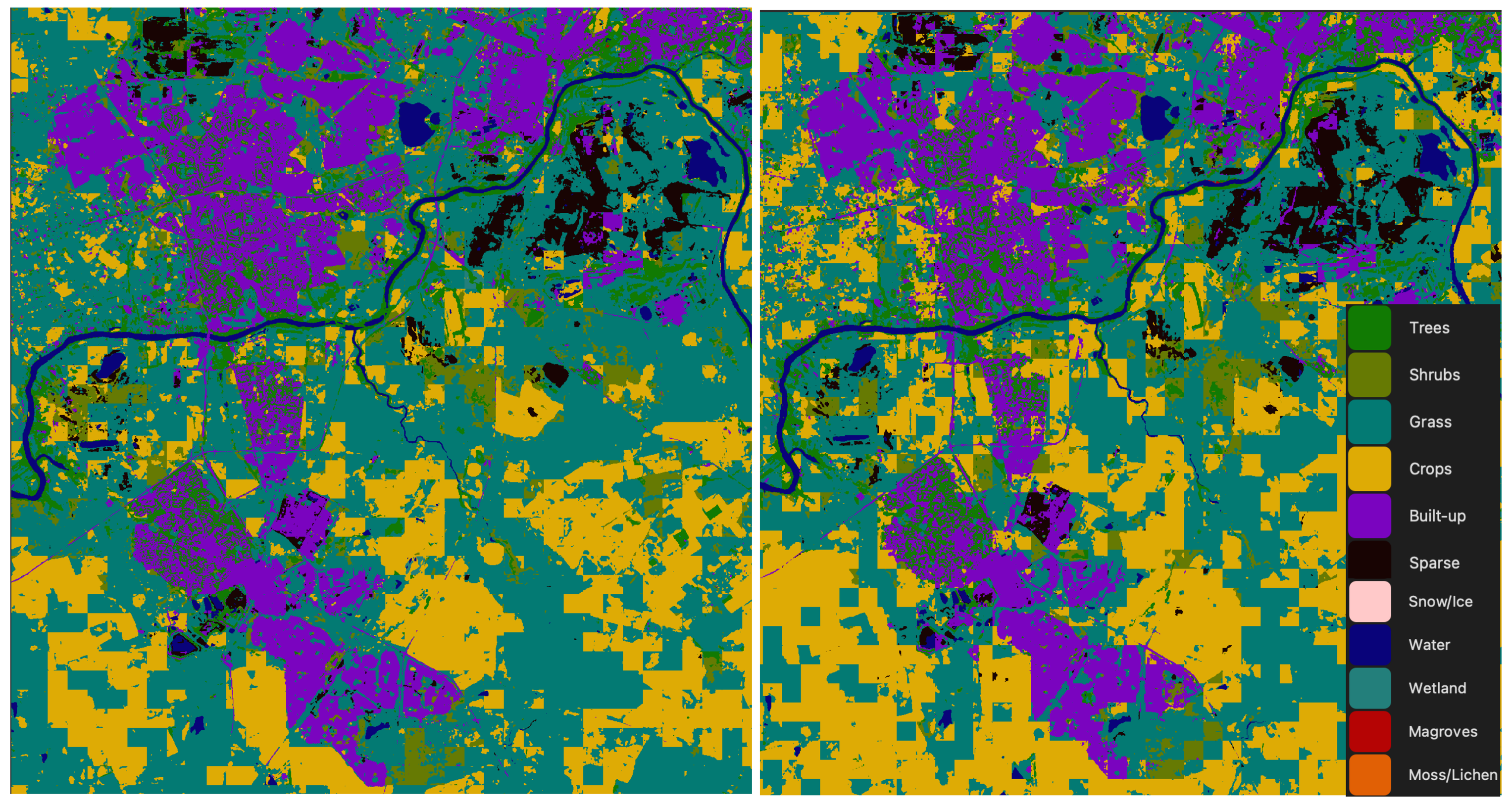
	Trees	Shrubs	Grass	Crops	Built-up	Bare	Water	Wetlands	Mangroves	Moss/Lichen
Trees	**91.66**	0.79	2.05	1.59	1.43	0.03	2.29	0.07	0.06	0.02
Shrubs	18.76	**70.63**	6.81	2.52	1.00	0.14	0.11	0.02	0.02	0.00
Grass	14.19	2.15	**73.80**	6.56	1.93	0.57	0.28	0.26	0.04	0.21
Crops	7.59	0.64	5.97	**84.10**	1.05	0.21	0.23	0.18	0.03	0.00
Built-up	7.14	0.39	2.24	2.08	**86.65**	1.27	0.18	0.00	0.04	0.00
Bare	2.45	0.16	5.60	1.59	6.31	**82.89**	0.84	0.01	0.02	0.15
Water	8.42	0.00	0.23	0.29	0.13	0.07	**90.54**	0.26	0.05	0.00
Wetlands	15.23	0.06	15.91	11.21	0.27	0.07	9.16	**47.34**	0.75	0.00
Mangroves	12.78	0.00	1.24	3.68	0.29	0.00	4.16	0.17	**77.69**	0.00
Moss/Lichen	11.56	0.00	45.12	0.18	0.09	0.15	0.55	0.25	0.01	**42.09**

SegFormer (4-channel, pretrained): 85.84% overall accuracy

	Trees	Shrubs	Grass	Crops	Built-up	Bare	Water	Wetlands	Mangroves	Moss/Lichen
Trees	**90.36**	1.01	2.68	2.15	1.54	0.05	1.99	0.14	0.05	0.04
Shrubs	16.77	**71.07**	7.84	2.97	1.04	0.17	0.13	0.01	0.01	0.00
Grass	13.40	2.40	**73.02**	7.45	1.94	0.89	0.31	0.30	0.03	0.26
Crops	7.07	0.79	5.93	**84.46**	1.06	0.25	0.24	0.16	0.03	0.01
Built-up	7.23	0.50	2.81	2.54	**85.13**	1.49	0.25	0.01	0.05	0.00
Bare	2.33	0.17	4.73	1.55	5.42	**84.94**	0.71	0.02	0.01	0.12
Water	6.12	0.00	0.25	0.27	0.10	0.12	**92.88**	0.22	0.03	0.00
Wetlands	11.94	0.03	15.59	12.82	0.21	0.07	10.98	**47.71**	0.64	0.02
Mangroves	14.76	0.00	1.77	4.81	0.26	0.15	6.32	0.60	**71.33**	0.00
Moss/Lichen	8.84	0.00	42.90	0.22	0.05	0.67	0.57	0.45	0.00	**46.30**

Prithvi (4-channel, less epochs): 70.07% overall accuracy

Inference (U-Net vs. SegFormer)



Conclusions

- U-Net and SegFormer achieved very similar performance.
- When evaluated on **unseen** cities, performance **drops dramatically**, indicating need for a larger training base.
- Compared to our prior model, **granularity** is much higher, and **inference** is 1,000x faster.
- In the future, we plan to explore **few-shot** experiments to understand data efficiency and model adaptation to distinguishing residential vs. non-residential built-up land.

Citations

[1] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In *Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18* (pp. 234-241). Springer international publishing.

[2] Xie, E., Wang, W., Yu, Z., Anandkumar, A., Alvarez, J. M., & Luo, P. (2021). SegFormer: Simple and efficient design for semantic segmentation with transformers. *Advances in neural information processing systems*, *34*, 12077-12090.

[3] Szwarcman, D., Roy, S., Fraccaro, P., Gíslason, Þ. E., Blumenstiel, B., Ghosal, R., ... & Moreno, J. B. (2024). Prithvi-eo-2.0: A versatile multi-temporal foundation model for earth observation applications. *arXiv preprint arXiv:2412.02732*.

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