living planet symposium | BONN 23–27 May 2022

TAKING THE PULSE OF OUR PLANET FROM SPACE

SELF-SUPERVISED LAND COVER MAPS USING TIME SERIES OF PLANET FUSION AND SENTINEL-1

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24/05/2022

Introduction

Planet creating an open 500,000-patch dataset of Planet Fusion under H2020 project RapidAI4EO (full release July 2022):

- 600 x 600 m patches with Corine Landcover Labels[1]
- Full timeseries for 2018, 2019 at 5-day cadence

Φ-lab complementing this dataset with Sentinel-1 timeseries:

- 6-day revisit using best choice Ascending relative orbit
- Testing on two subsamples – 3500 single class patches, 3500 multi-class patches

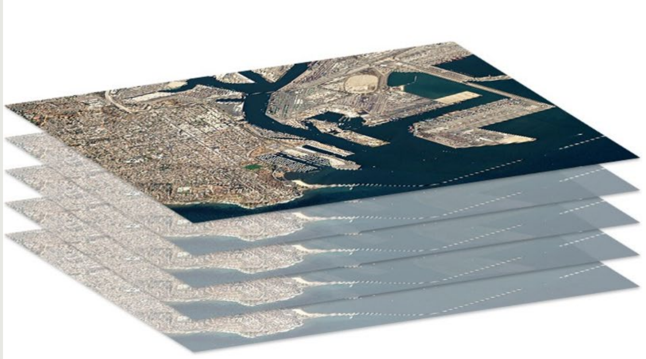
Objectives:

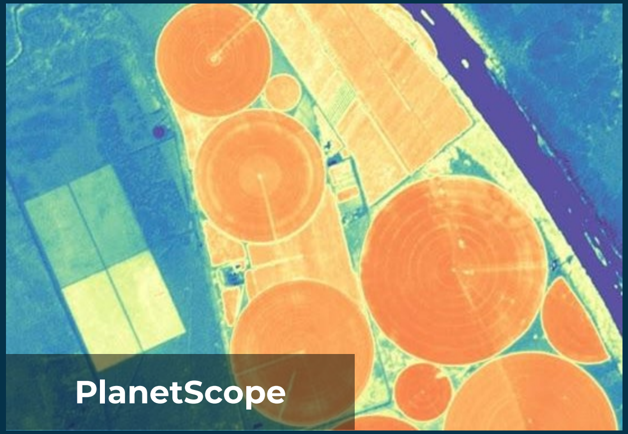
- Separate and fused dataset experiment
- Develop proof of concept for fused time series analysis using self-supervised learning

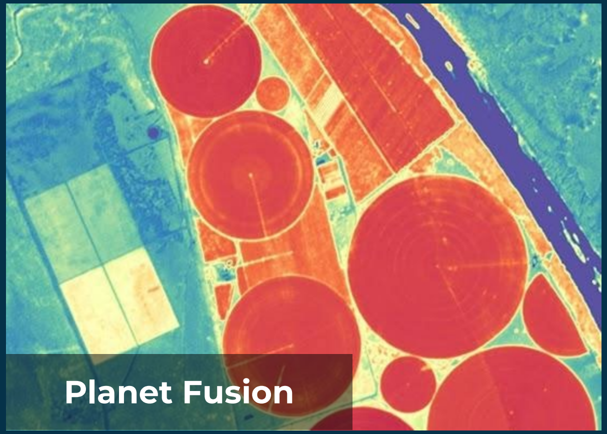
Dataset – Planet Fusion

- Harmonised output from many sensors
- Cloud masking & gap filling
- High resolution multispectral imagery with unprecedented cadence and completeness

PlanetScope
LANDSAT-8
Sentinel-2
MODIS







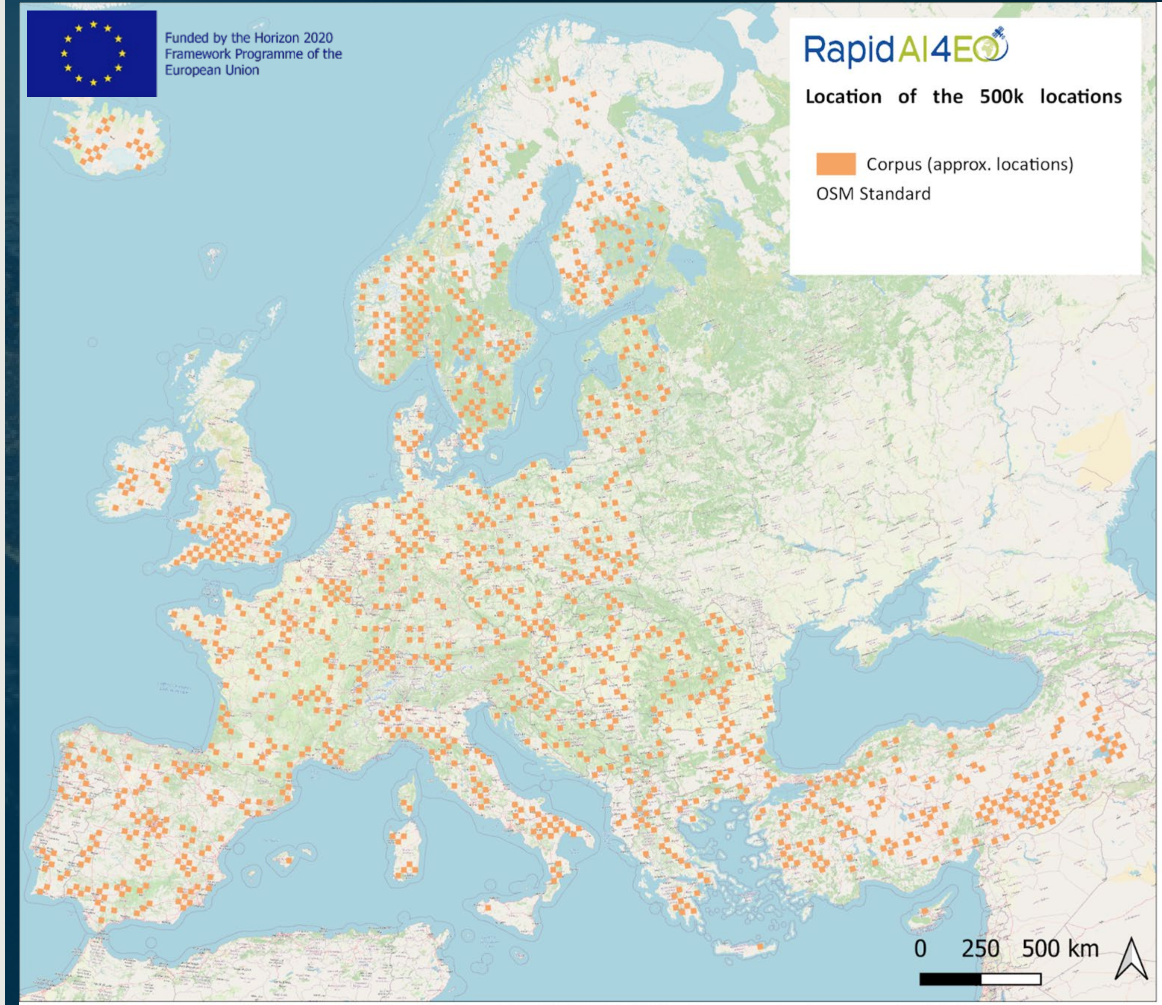
Open Dataset

Source: H2020 project RapidAI4EO 1/2021-3/2023

https://rapidai4eo.eu/

- Inspired by the BigEarthNet & Eurosat datasets
- Designed for LULC change detection use case, but generalisable to other problems
- 600m x 600m patches at 500,000 locations
- Sentinel-2 and Planet Fusion yearly time series
- Accounting for
  - CLC class distribution
  - Spatial distribution
  - Country representation
- Open sourcing in July 2022

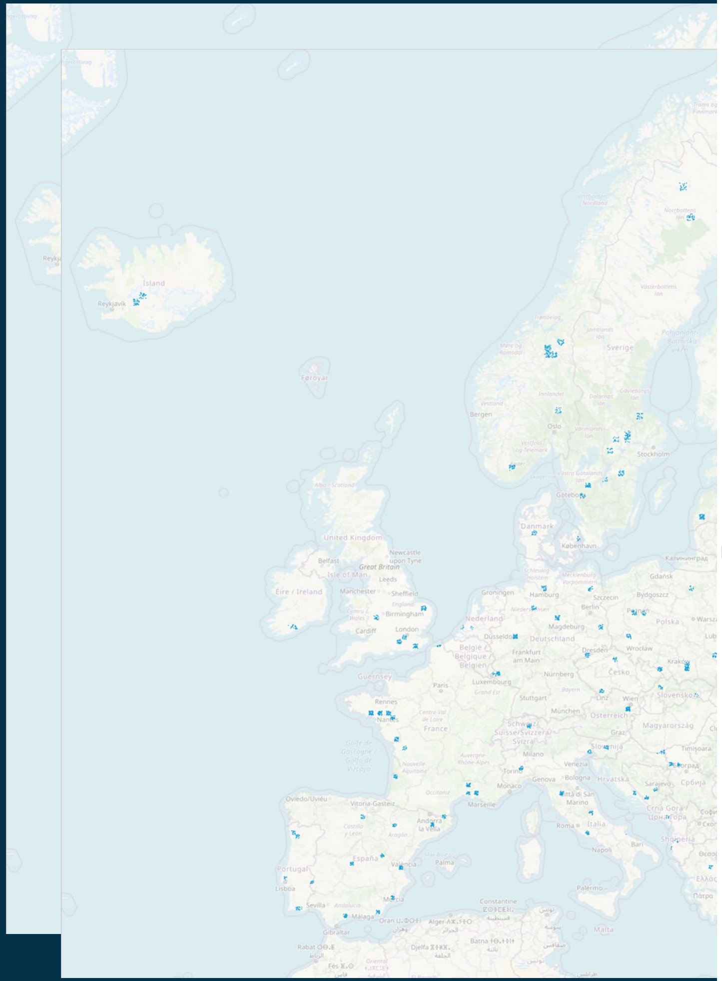
*** More info Wednesday 25/5 9.30 Session A3.07.1 *Land Cover - Methods and Algorithms, Science, Applications and Policy - 1*



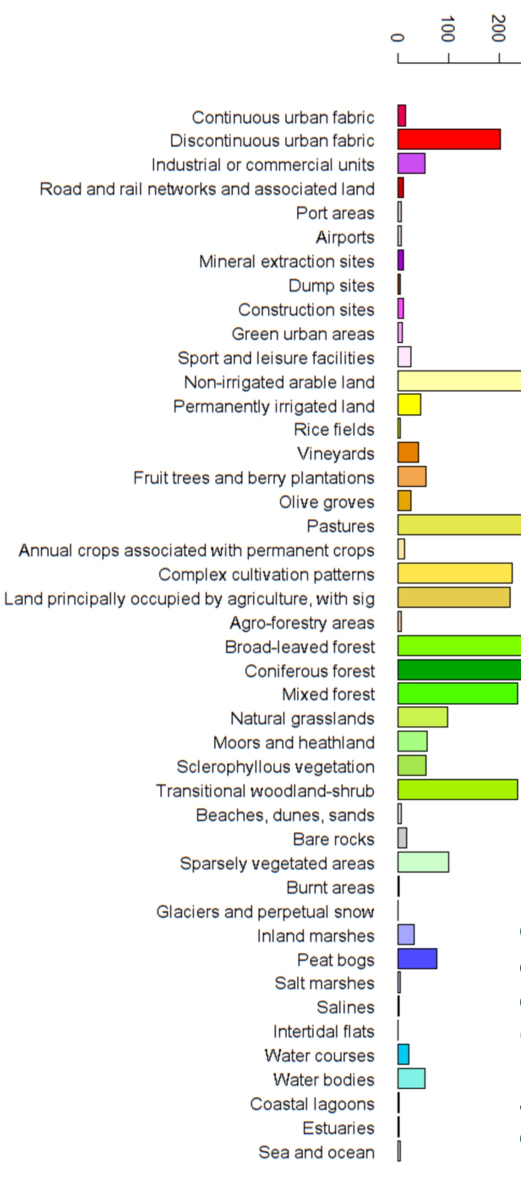
Base map and data from OpenStreetMap and OpenStreetMap Foundation (CC-BY-SA). © https//www.openstreetmap.org and contributors.

The RapidAI4EO project receives funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101004356.

Sentinel-1 / Planet Fusion Experiment sample



Distribution of Samples across Europe (subsample of final d

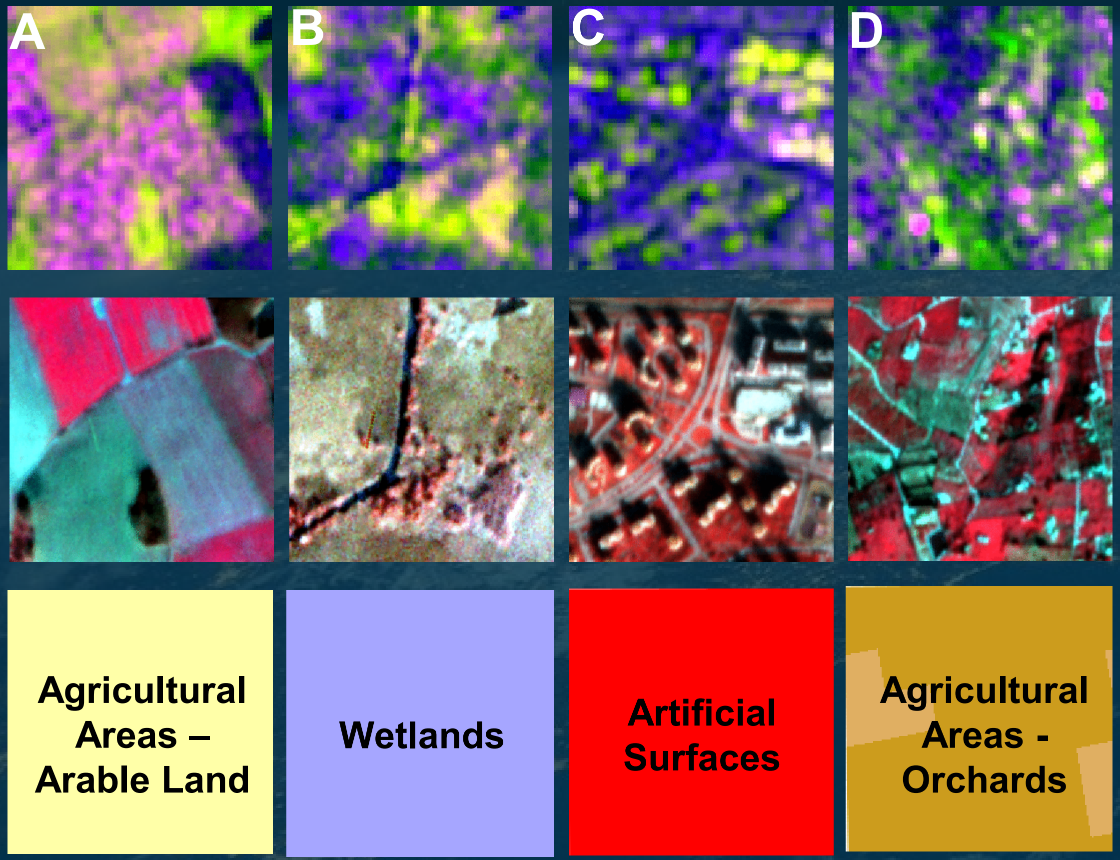


Corine Landcover class patch distribution (Mixed classes – representative of actual distribution)

Φ-lab complementing this dataset with Sentinel-1 timeseries:

- 6-day revisit using best choice Ascending relative orbit
- Testing on two subsamples – 3500 single class patches, 3500 multi-class patches
- Not all classes fully represented in single class patches, but level 1 classes relatively balanced
- Class Distribution of CORINE reflected in mixed class sample

Example of Sentinel-1, Planet Fusion, and CLC



Selection of fixed relative orbit for Sentinel 1 Ground Range Detected

Radiometric correction using Copernicus DEM; 2-month temporal filter

10 m pixel spacing (at Sentinel-1 limit)

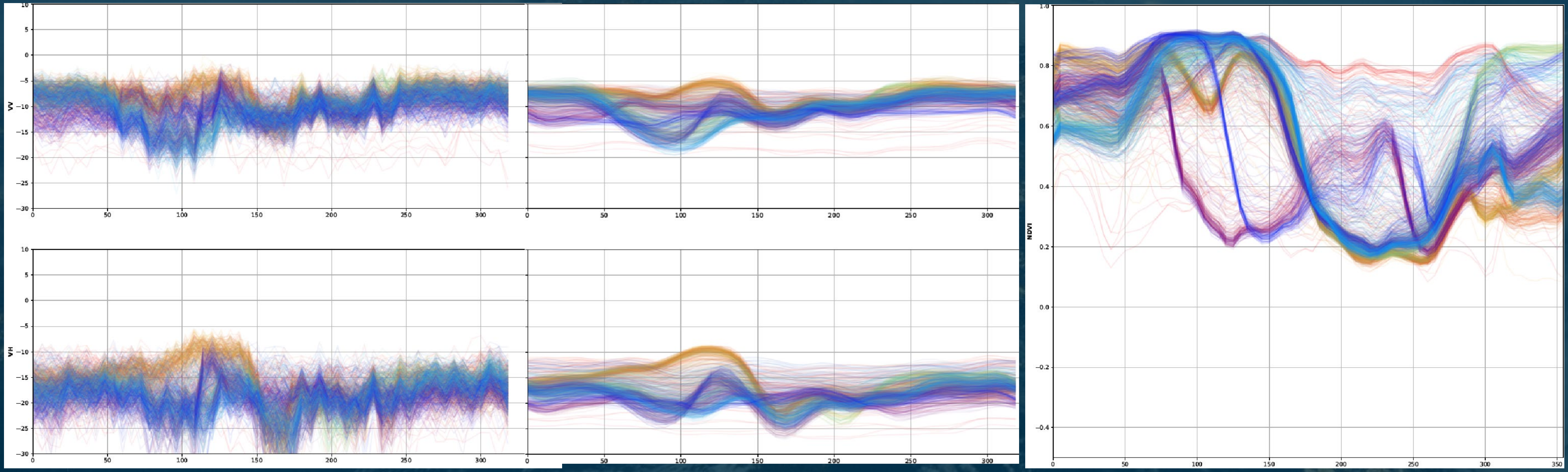
Processing and export from Google Earth Engine[1]

One year time series example: top row S1 RGB composite (VV,VH,VV-VH); middle row Planet false colour composite (NIR, R, G); bottom row Corine Land Cover 2018.

[1]Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*.

Data Exploration – Timeseries Non-irrigated arable land

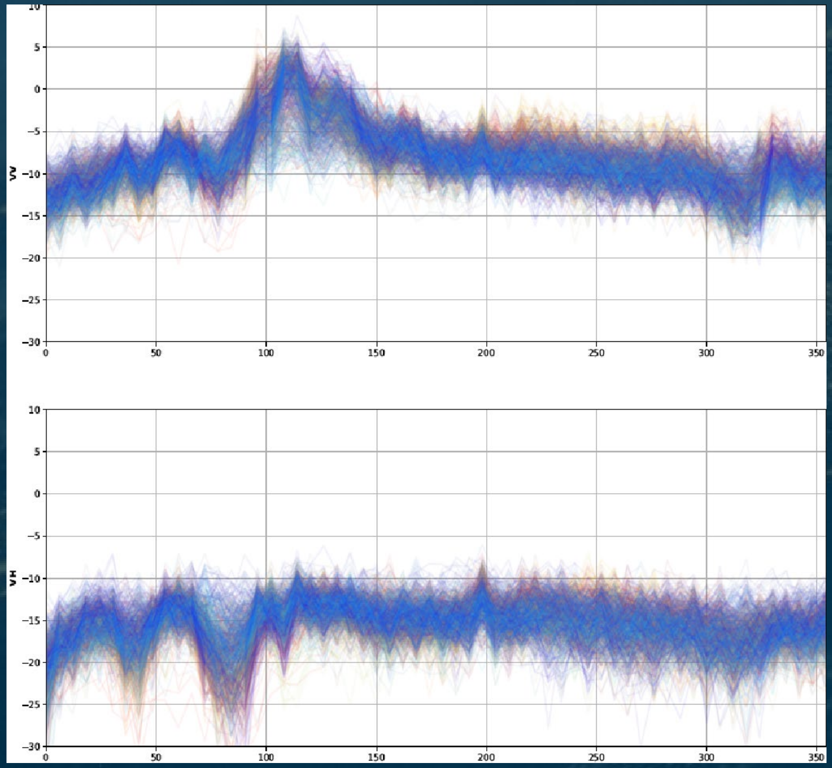
A: S1 Unfiltered S1 Spatiotemporal filter Planet NDVI

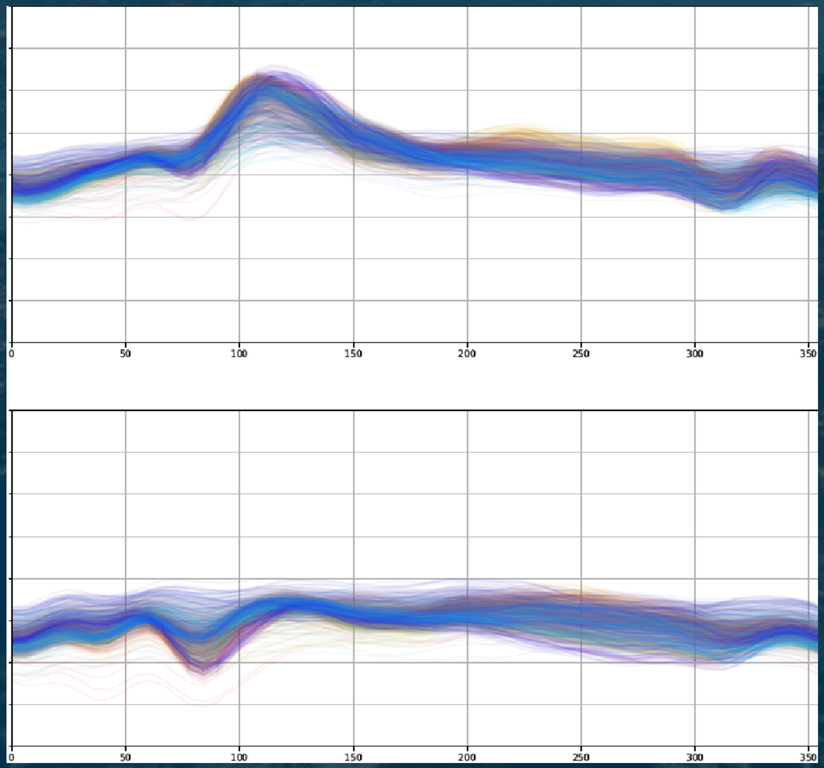


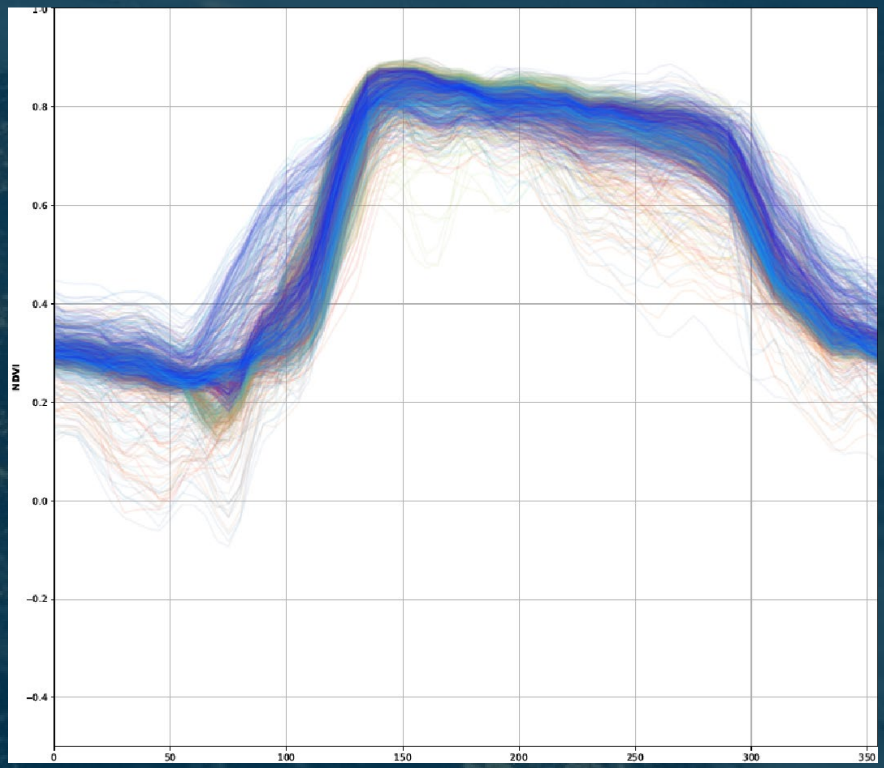
Individual Patch pixel plots: colours represent spatial proximity. CLC: Non-irrigated arable land

Data Exploration – Timeseries Inland Marshes

B: S1 Unfiltered VV;VH | S1 Spatiotemporal filter | Planet NDVI



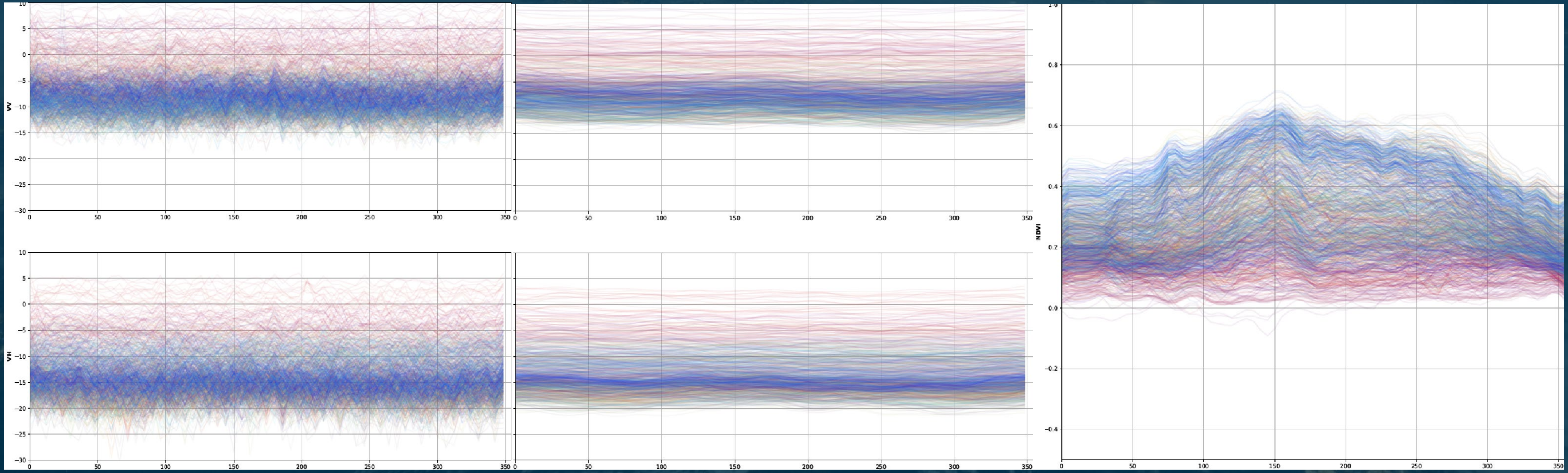




Individual Patch pixel plots: colours represent spatial proximity. CLC: Inland marshes

Data Exploration – Timeseries Discontinuous Urban Fabric

C: S1 Unfiltered | S1 Spatiotemporal filter | Planet NDVI

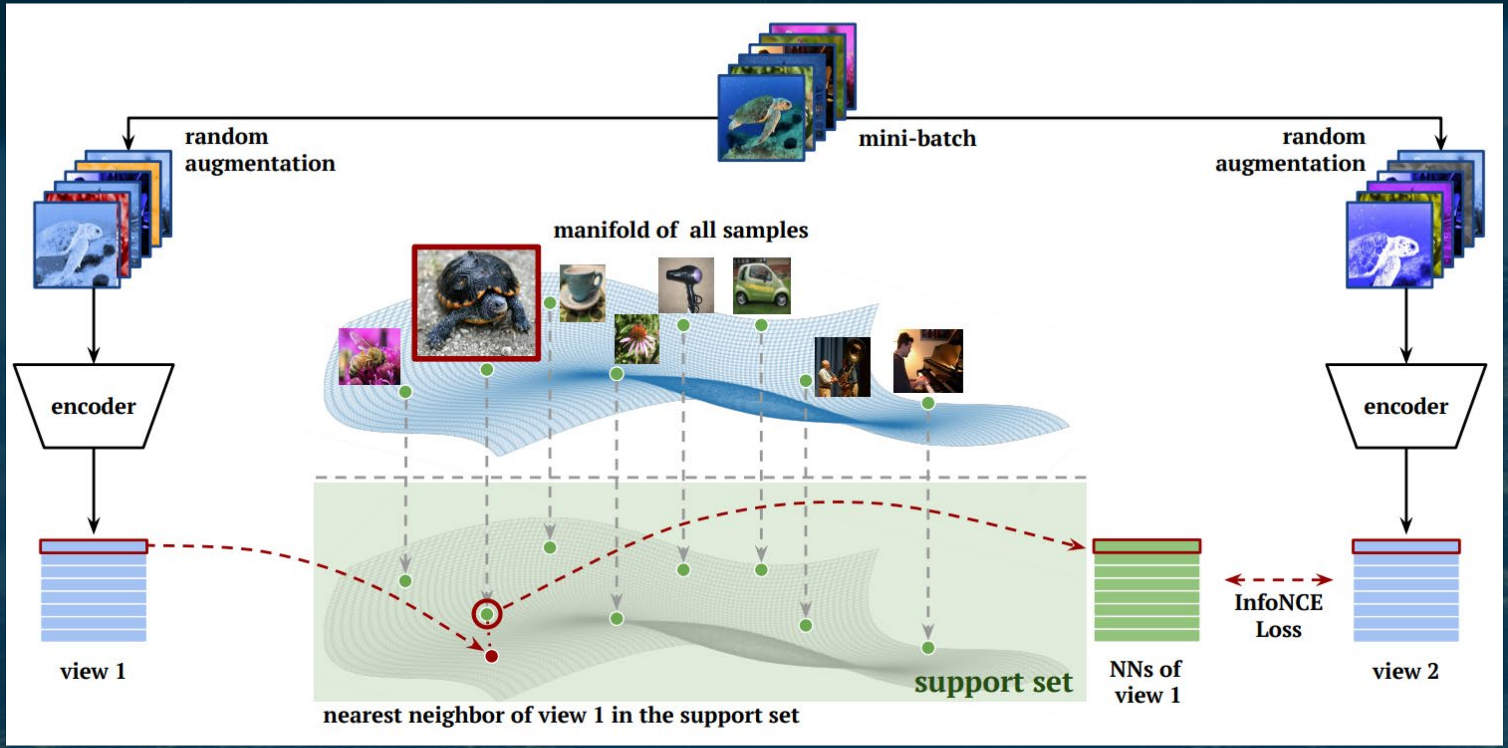


Individual Patch pixel plots: colours represent spatial proximity. CLC: Discontinuous Urban Fabric

Training and Experimental Setup

- Self-supervised learning with the 2018-2020 time series from 10,500 patches of mixed data
- 10-by-10 windows of Planet data (and 3-by-3 for Sentinel-1) are spatially averaged for each training sample, to reduce noise.
- 400 samples taken per patch, so >4 million training samples total

Method



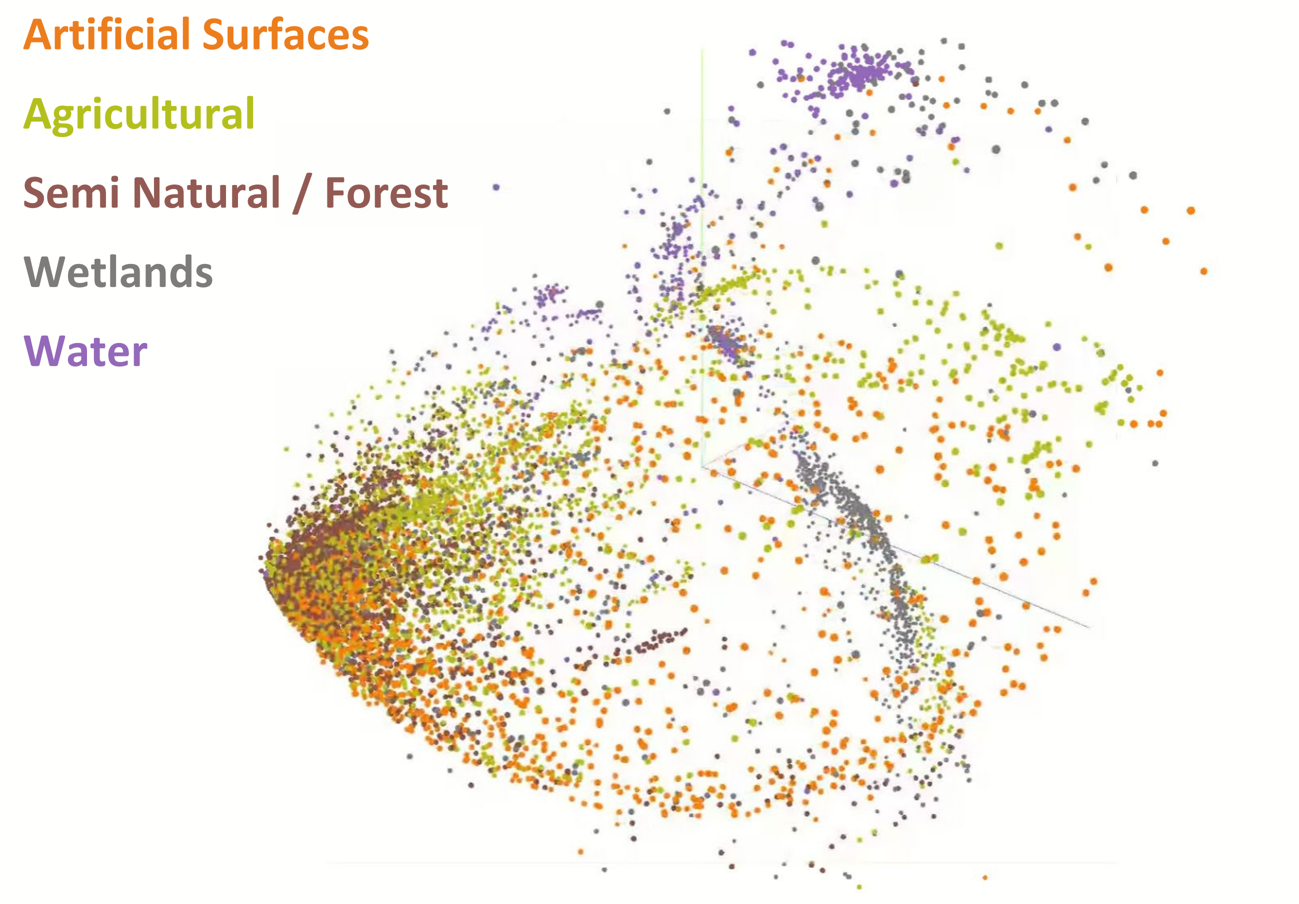
Method adapted and image from “With a Little Help from My Friends: Nearest-Neighbor Contrastive Learning of Visual Representations” by Dwibedi et al. 2021 https://doi.org/10.48550/arXiv.2104.14548

Augmentation

- Masking augmentation which removes sections of time series randomly.
- On average, three sections are removed from each time series (could be more or less, in Poisson distribution).
- Each masked section is between 3 and 15 time steps
- Data has an extra channel which indicates whether a timestep is masked, so that the masking value (zero) is not confused with data that actually has that value.

Contrastive loss between view 2 and nearest neighbours of view 1 from support set

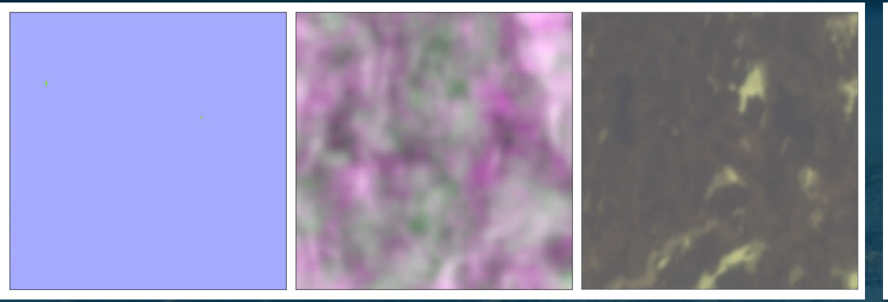
Method



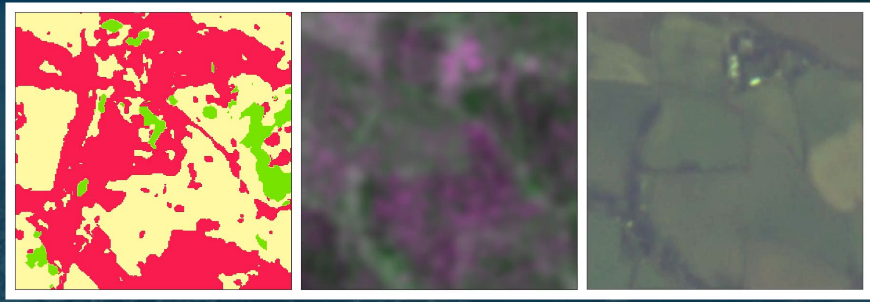
Five level 1 CLC Classes in the embedding space after 25 epochs

- Encoder is a simple 1D convolutional network (where the convolutions act along the time dimension). Reducing the input time series down to a single vector of 64 feature dimensions.
- When using both Planet and Sentinel-1, each is given a separate encoder, and the outputs are concatenated afterwards ("late fusion")
- 5 classes
- Models with Planet, Sentinel-1, and both are tested, with and without self-supervised encoders

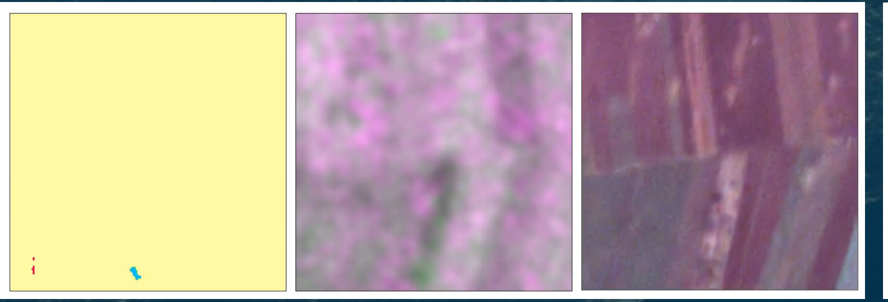
Results – Classification (level-1), Sentinel-1 and PF Timeseries



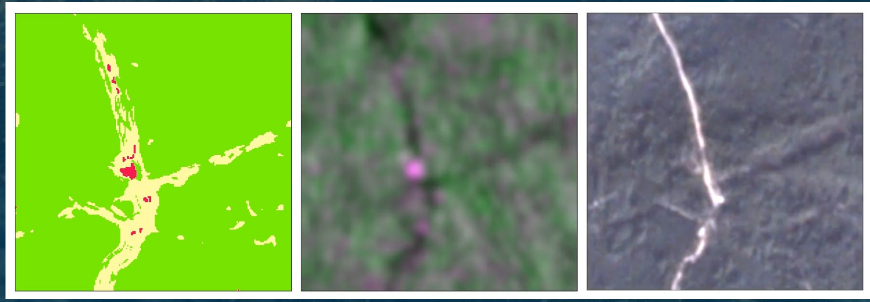
LABEL: WETLANDS



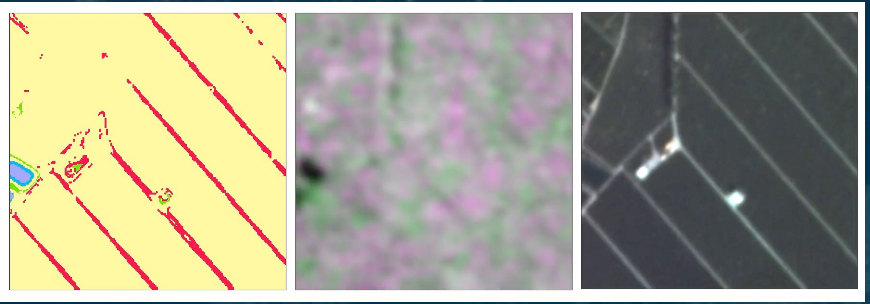
LABEL: AGRI



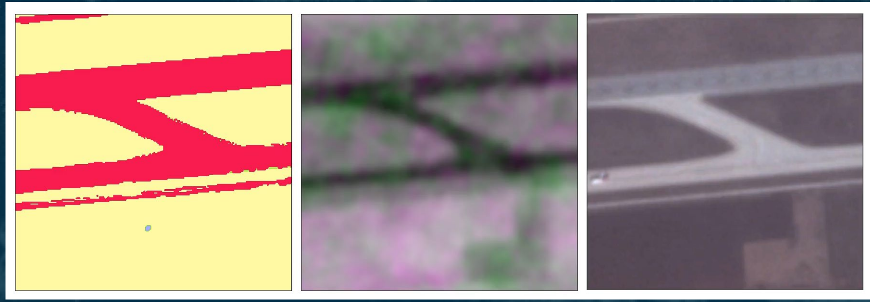
LABEL: AGRI



LABEL: SEMI NATURAL / FORESTS



LABEL: AGRI

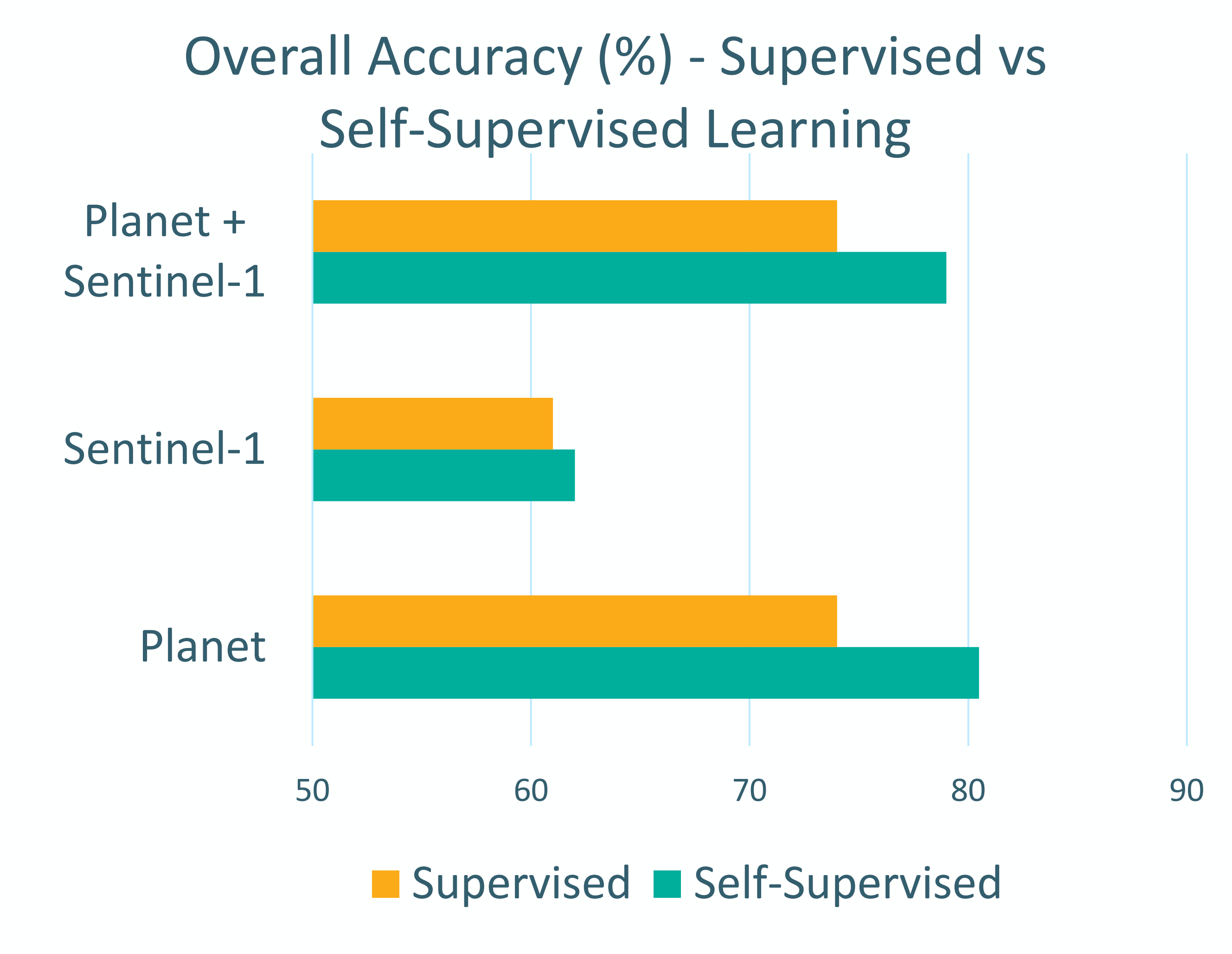


LABEL: AGRI

Results: Supervised vs Self-Supervised Learning

So far, we have tested supervised (full training dataset) against self-supervised (mixed samples dataset)

- Consistent improvement with self supervised method in all data combinations
- Accuracy for just Sentinel-1 quite low, and the addition to Planet data causes a decrease (particularly in self-supervised approach)



Results: Confusion Matrices, Precision, Recall, F1

esa

Self Supervised: Planet + S-1

Actual \ Predicted	Artificial Surfaces	Agri.	Semi Natural / Forest	Wetlands	Water
AS	0.86	0.08	0.03	0.01	0.01
Ag	0.15	0.78	0.06	0.01	0.01
SN/F	0.11	0.1	0.76	0.03	0.01
We	0.09	0.02	0.1	0.77	0.02
Wa	0.04	0.01	0.01	0.14	0.79

←Slightly Better Artificial Surfaces overall accuracy

Better total overall accuracy →

Some class confusion between Artificial ← Surfaces, Agricultural → and Semi Natural / Forest

Self Supervised: Planet

Actual \ Predicted	Artificial Surfaces	Agri.	Semi Natural / Forest	Wetlands	Water
AS	0.81	0.13	0.04	0.01	0.01
Ag	0.08	0.85	0.06	0.0	0.0
SN/F	0.08	0.09	0.78	0.03	0.01
We	0.1	0.02	0.1	0.75	0.02
Wa	0.05	0.02	0.02	0.12	0.79

	Planet and Sentinel-1				
	Artificial Surfaces	Agricultural	Semi Natural/Forest	Wetlands	Water
Precision	0.683	0.843	0.788	0.757	0.697
Recall	0.717	0.803	0.787	0.833	0.61
F1-Score	0.7	0.822	0.788	0.793	0.651

	Planet Only				
	Artificial Surfaces	Agricultural	Semi Natural/Forest	Wetlands	Water
Precision	0.712	0.821	0.796	0.805	0.704
Recall	0.669	0.832	0.825	0.789	0.686
F1-Score	0.69	0.827	0.81	0.797	0.695

Conclusions/Next steps

Self-supervision is vital for the training performance, and to avoid overfitting whilst allowing the encoder to learn a useful representation.

In this experiment Sentinel-1 didn't always add useful information during training. This could be because it just offered the model more information to overfit on, the patch size being better suited to Planet data resolution rather than the limit (or just below the limit) of Sentinel-1

Next Steps:

- Process additional data for supervised training, to avoid overfitting
- Experiment with different augmentations and encoder architectures (e.g. attention, LSTM)
- Explore interannual variation in 2019 dataset

Thanks for Listening!

Reminder: More info Wednesday 25/5 9.30 Session A3.07.1 *Land Cover - Methods and Algorithms, Science, Applications and Policy - 1*

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