



# SimCLR-S2

Self-supervised contrastive learning for irrigation detection  
in satellite imagery

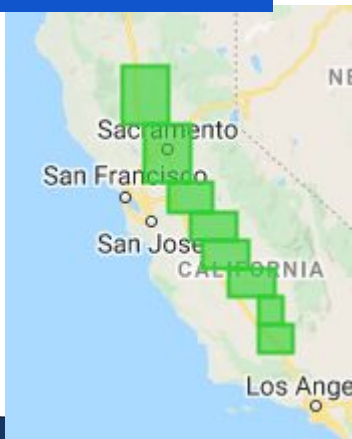
**Detect presence of irrigation in uncurated and  
unlabelled data**

Chitra Agastya, Ian Anderson, Sirak Ghebremusse

# Sources

## Sentinel-2 Images

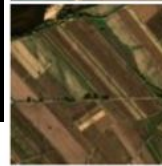
Central Valley, CA  
downloaded from Google Earth  
Engine



BigEarthNet-S2  
(BEN)



permanently irrigated land,  
sclerophyllous vegetation,  
beaches, dunes, sands,  
estuaries, sea and ocean

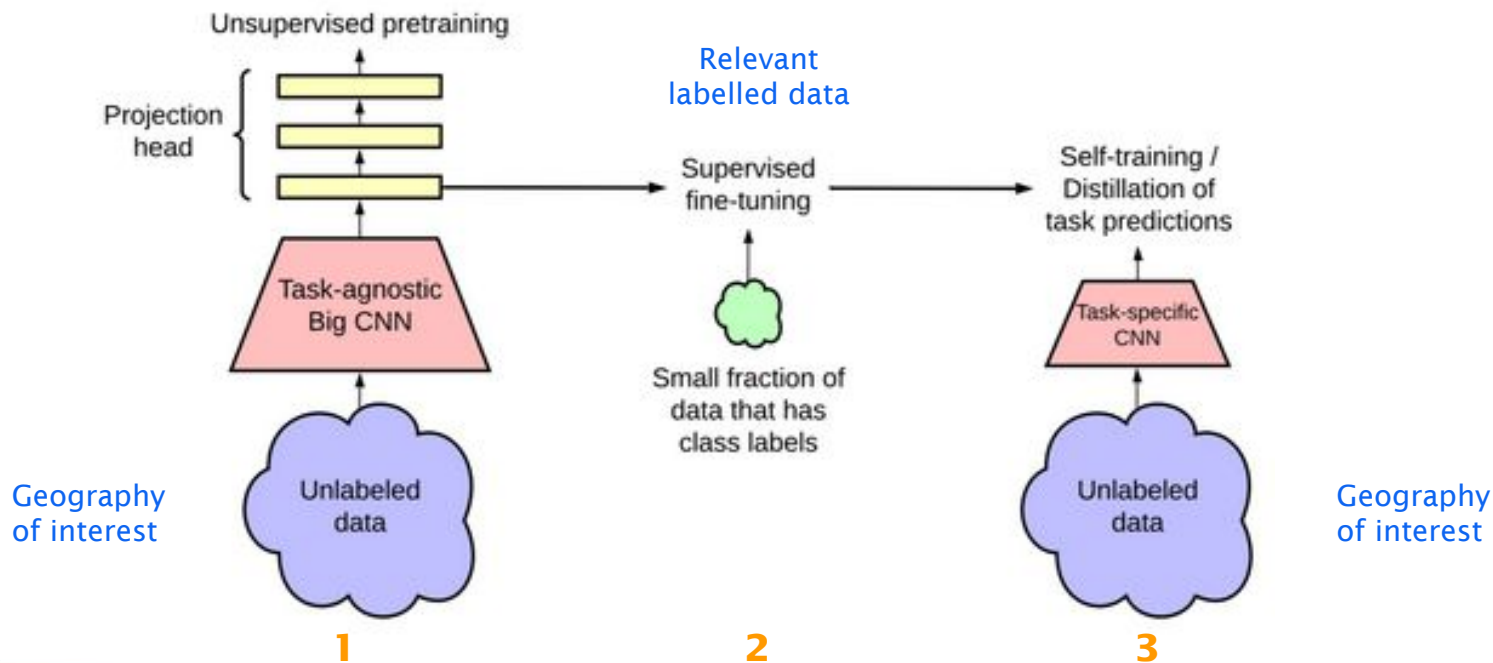


permanently irrigated land,  
vineyards, beaches, dunes,  
sands, water courses

- 590326 non overlapping images from 10 European countries
- Multi spectral images with 12 bands (i.e band 10 has been removed)
- Labelled images with multiple land cover classes, [permanently irrigated land](#) being one of them

Used data from [croplands.org](#)  
for generalization testing

# SimCLR-S2



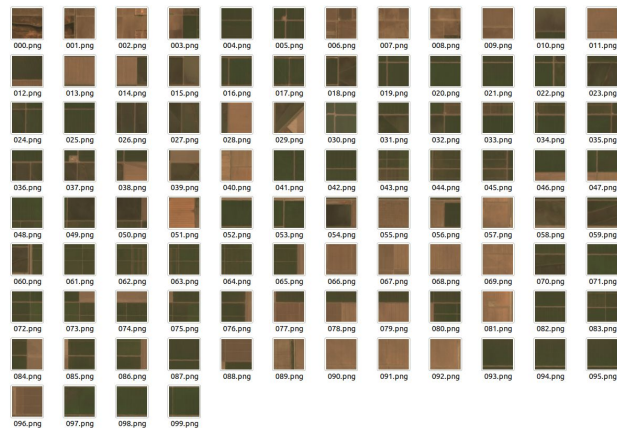
# Case Study 1

Evaluate precision on geography of interest

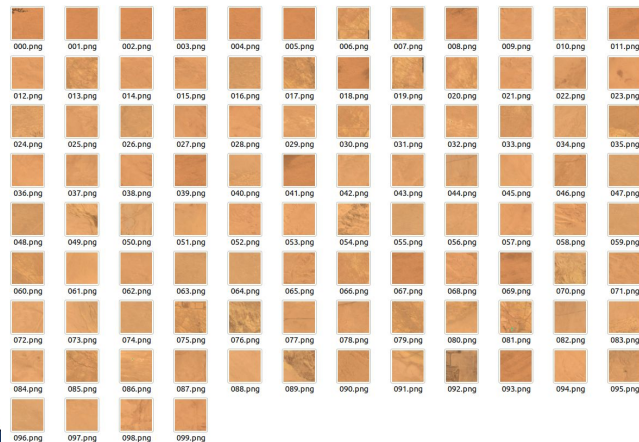
- Top 100 predictions of irrigated land with at least 99% confidence
- Supervised model's prediction confidence was far lower than that of SimCLR-S2 model
- Scoring done using Amazon Mturk and verified by visual inspection

*Table 1. A comparison of precision scores from SimCLR-S2 and supervised baseline on unseen data from different geography.*

Training data size (num records)	Precision (SimCLR-S2)	Precision (su- pervised)
190	<b>0.99</b>	0.11
570	<b>1.00</b>	0.2
1902	<b>0.99</b>	0.36
4756	<b>0.98</b>	0.95
9515	<b>1.00</b>	0.78
19024	<b>1.00</b>	0.47



SimCLR-S2: Top 100 predictions for irrigated land



Supervised: Top 100 predictions for irrigated land



# Case Study 2

Evaluate recall on an unrelated geography

- Ground truth sourced from croplands.org for 6 different countries: Brazil, India, Indonesia, Myanmar, Tunisia and Vietnam
- Download 0.5km x 0.5km land for ground truth coordinates from croplands.org
- SimCLR-S2 generalized better than supervised baseline models

*Table 2. A comparison of recall scores on SimCLR-S2 and supervised baseline for irrigated cropland from diverse geographies*

Country	Training data (num records)	Recall (SimCLR-S2)	Recall (supervised)
Brazil	190	<b>0.75</b>	0.5
India	190	<b>0.9</b>	0.67
Indonesia	570	<b>0.76</b>	0.07
Tunisia	570	0.78	<b>0.91</b>
Vietnam, Myanmar	190	<b>0.9</b>	0.00

# Questions?

# References

- G. Sumbul, M. Charfuelan, B. Demir, V. Markl, "[BigEarthNet: A Large-Scale Benchmark Archive for Remote Sensing Image Understanding](#)", *IEEE International Geoscience and Remote Sensing Symposium*, pp. 5901-5904, Yokohama, Japan, 2019.
- Chen et al., [A Simple Framework for Contrastive Learning for Visual Representations](#), ICML, 2020
- Chen et al., [Big Self-Supervised Models are Strong Semi-Supervised Learners](#), NeurIPS, 2020

# Appendix

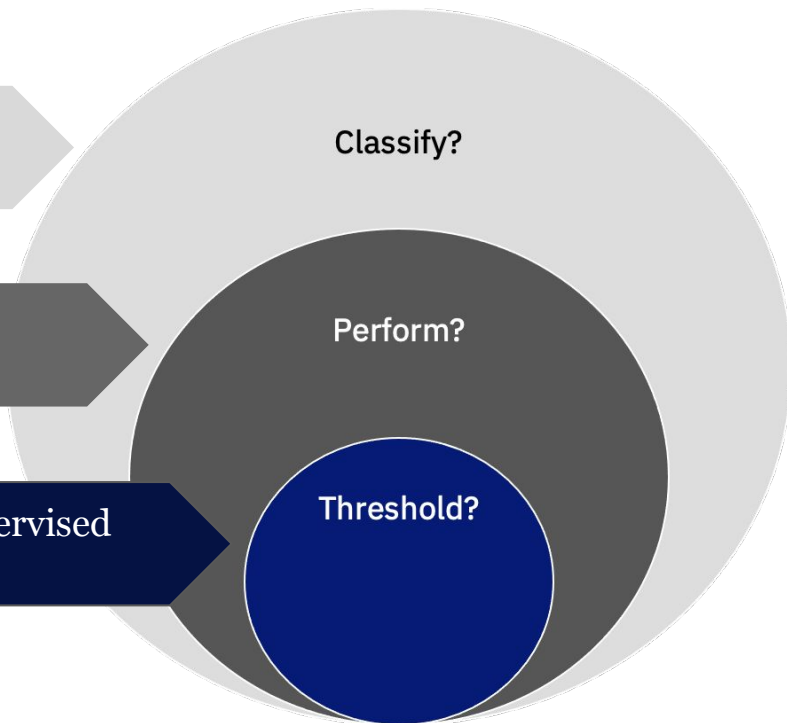


# Research Questions

Can we detect irrigation from satellite imagery with self-supervised contrastive learning?

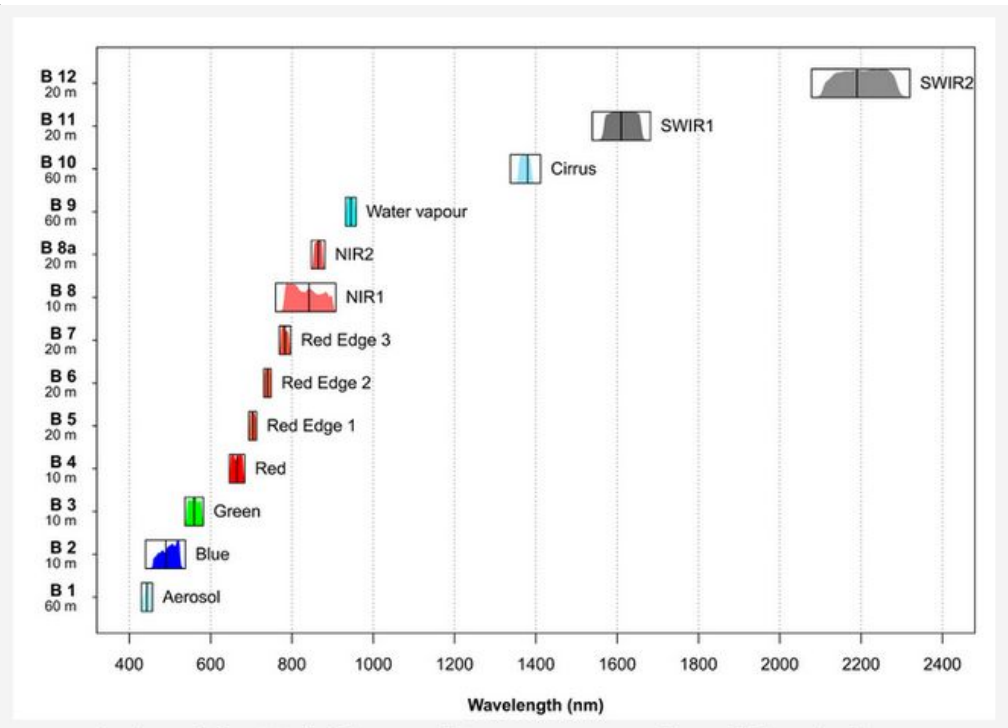
Can we achieve performance on par with supervised learning with a fraction of the dataset labelled?

At what thresholds of labelled data is the self-supervised technique still effective?



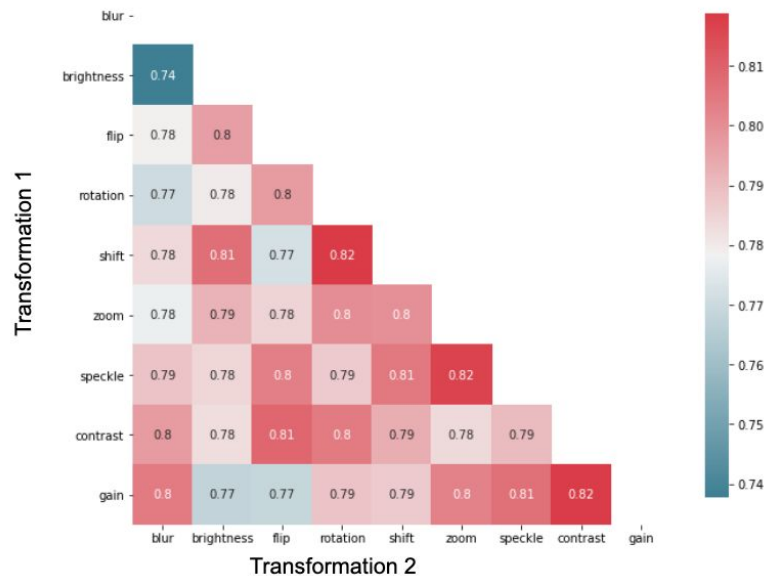
# Spectral Bands - Spatial and Pixel Resolution

Band	Description	BEN Pixel Resolution
B12	SWIR 2	60x60
B11	SWIR 1	60x60
B09	Water Vapor	20x20
B8A	Vegetation red edge 4	60x60
B08	NIR	120x120
B07	Vegetation red edge 3	60x60
B06	Vegetation red edge 2	60x60
B05	Vegetation red edge 1	60x60
B04	Red	120x120
B03	Green	120x120
B02	Blue	120x120
B01	Coastal aerosol	20x20

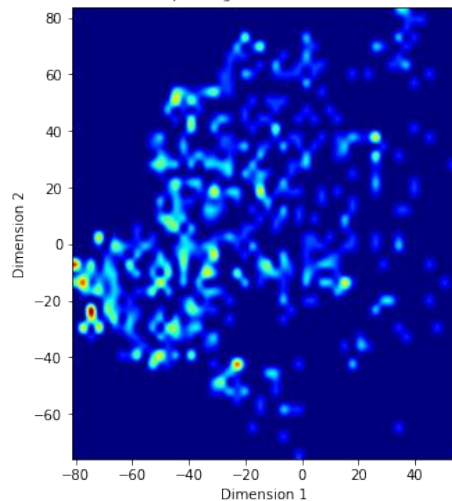


# Results: Stage 1 SimCLR-S2 Pre-training

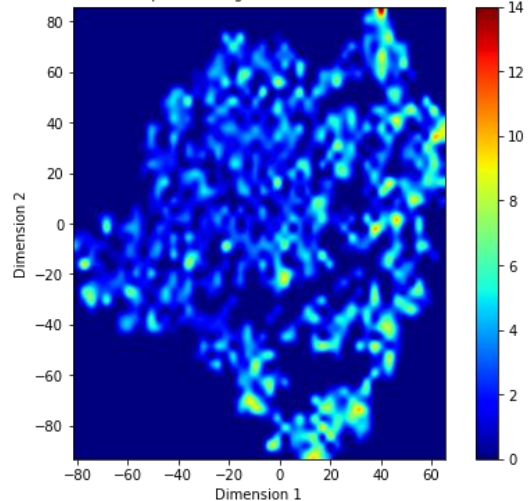
SimCLR-S2 Augmentation pairs



Heatmap of Irrigated t-SNE Latent Vectors



Heatmap of Non-Irrigated t-SNE Latent Vectors

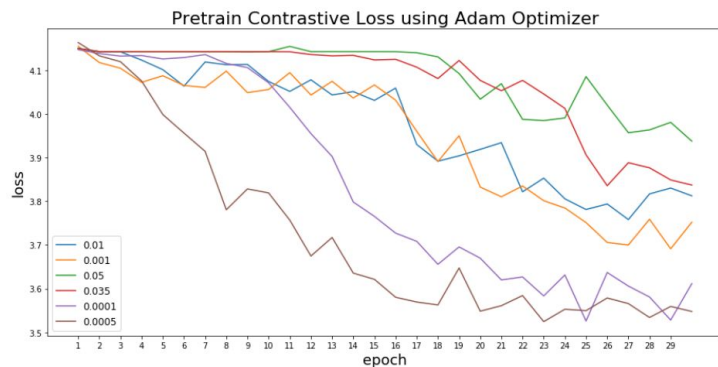


*We drop the bottom 25%*

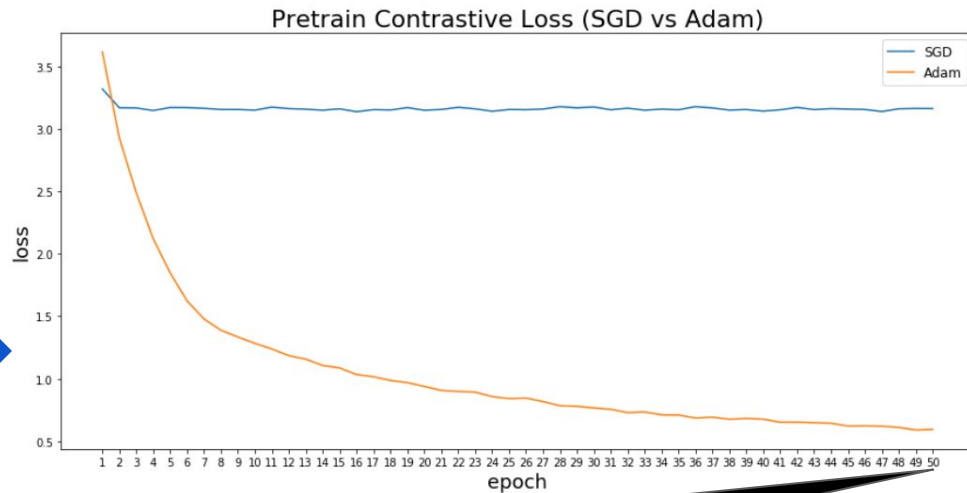
# Results

## Stage 1 SimCLR-S2: Pre-training Contrastive Loss

### Hyper parameter tuning



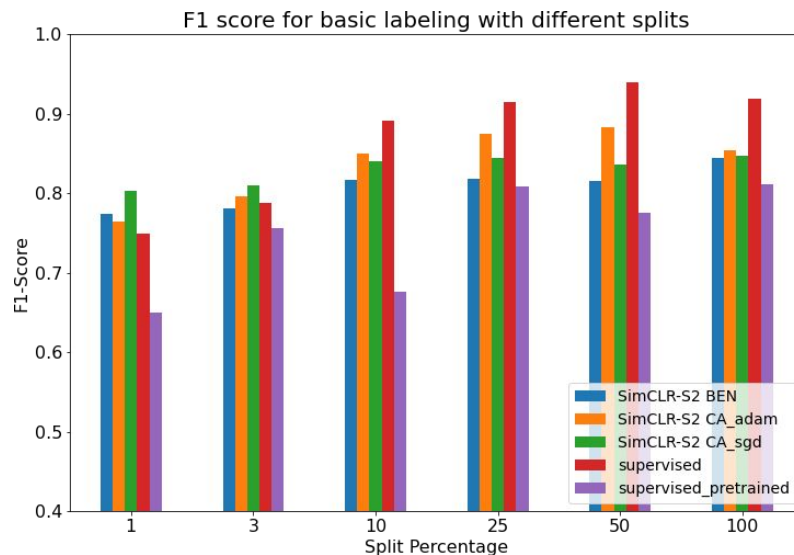
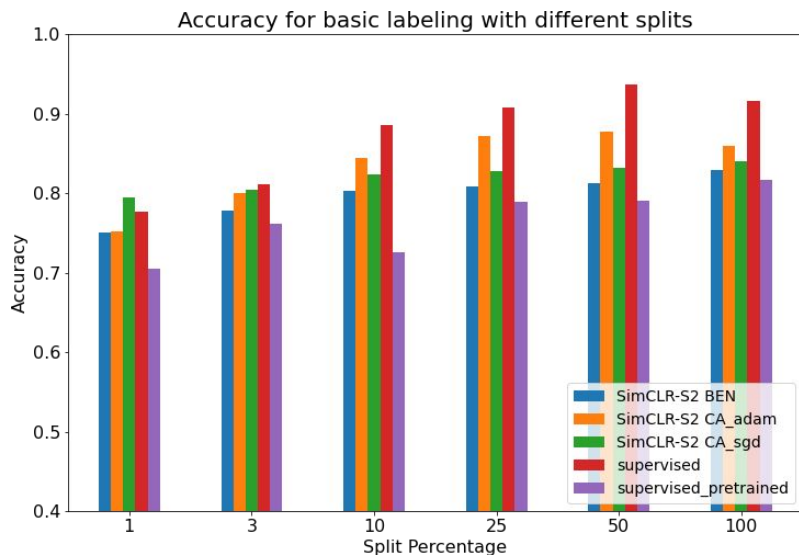
*Tuning done on smaller sample for 30 epochs*



*loss seems to continue on a downward trend*

# Results

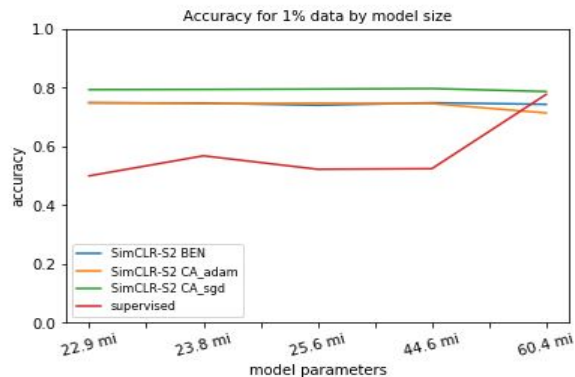
## *Stage 2 SimCLR-S2 results vs supervised baseline*



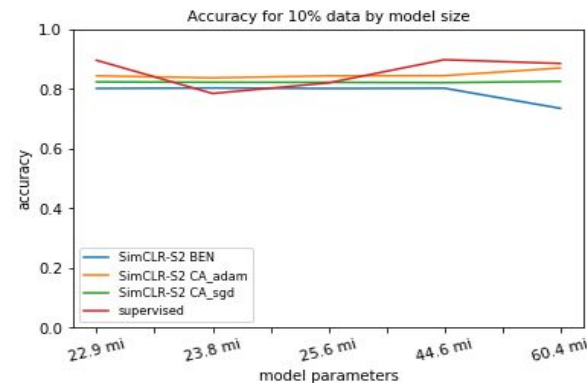
Performance of SimCLR-S2 fine-tuning results versus Supervised Baselines  
Architecture: ResNet152

# Results

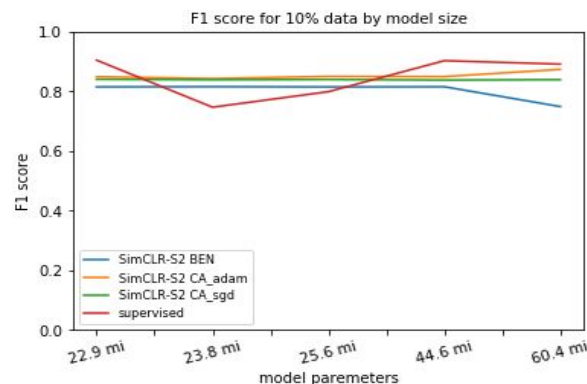
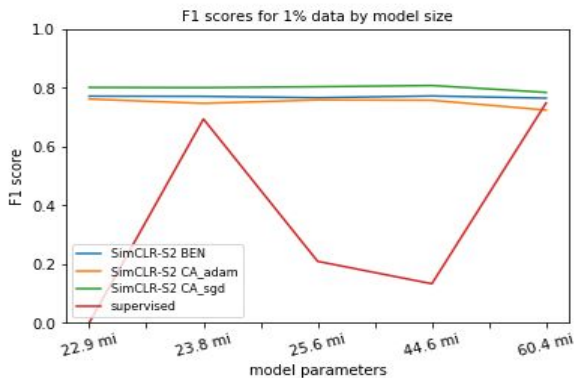
## Stage 3 SimCLR-S2 results vs supervised baseline



1% data split



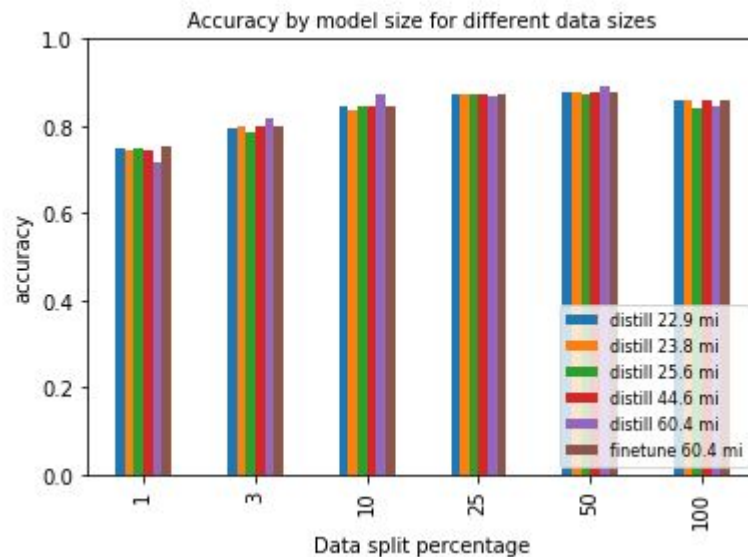
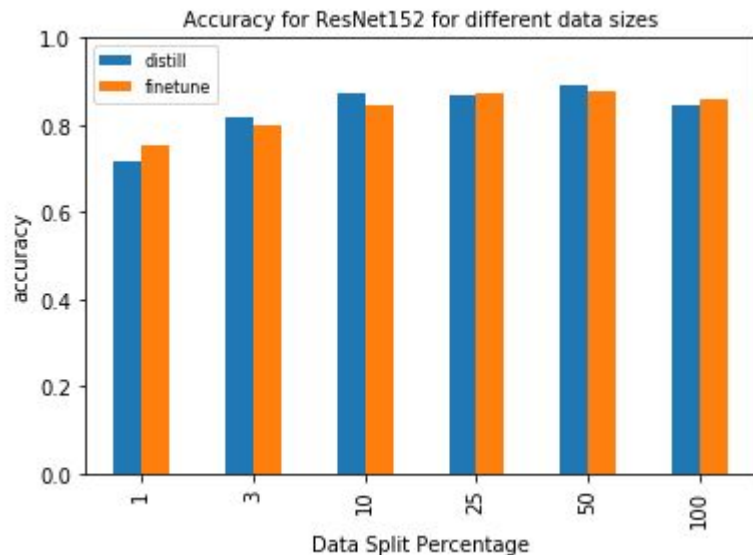
10% data split





# Results

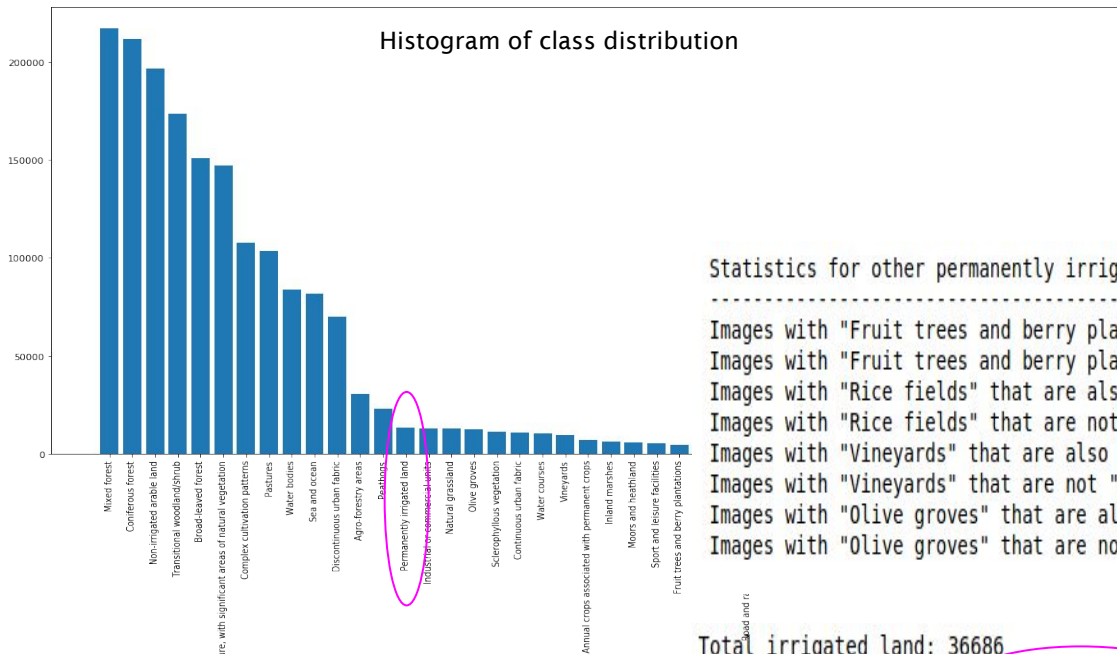
## *Stage 3 SimCLR-S2 : Distill vs Fine-tune*



Distillation shows an improvement over finetune scores for many architectures and many data split percentages

# BigEarthNet EDA - True Class

Histogram of class distribution



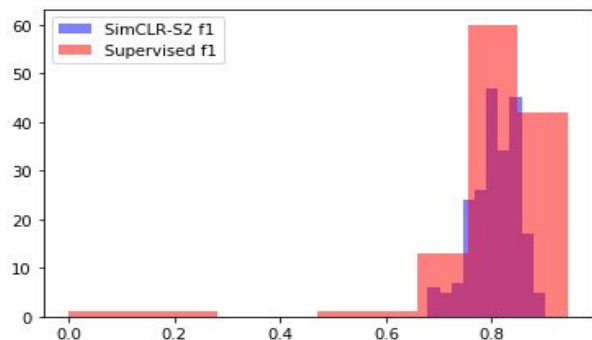
Statistics for other permanently irrigated cropland that are not included in "Permanently irrigated land"

Images with "Fruit trees and berry plantations" that are also "Permanently irrigated land": 445  
 Images with "Fruit trees and berry plantations" that are not "Permanently irrigated land": 4309  
 Images with "Rice fields" that are also "Permanently irrigated land": 1504  
 Images with "Rice fields" that are not "Permanently irrigated land": 2289  
 Images with "Vineyards" that are also "Permanently irrigated land": 1377  
 Images with "Vineyards" that are not "Permanently irrigated land": 8190  
 Images with "Olive groves" that are also "Permanently irrigated land": 2770  
 Images with "Olive groves" that are not "Permanently irrigated land": 9768

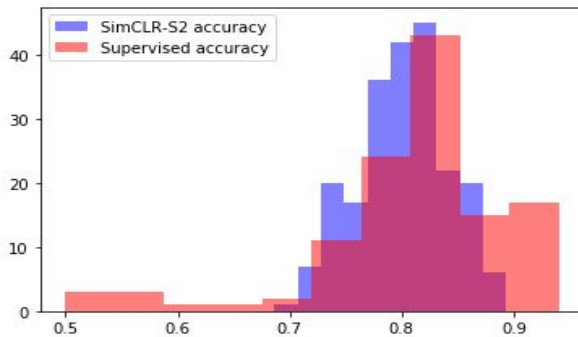
Total irrigated land: 36686

% Total irrigated land: 6.2145323092664055

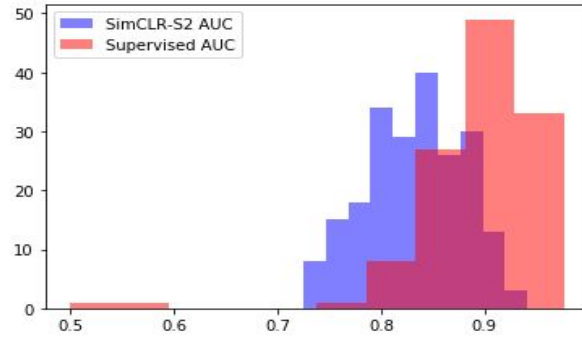
# SimCLR-S2 - Impact on performance



(a) F1 Score



(b) Accuracy



(c) AUC Score

SimCLR-S2 seems to be bringing the scores closer. So smaller datasets see a big improvement in performance.

# t-SNE Results of Pretrained BigEarthNet Latent Vectors

