

ESA-ECMWF WORKSHOP 2021: Machine Learning for Earth System Observation and Prediction



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Journal reference

A. Montanaro, D. Valsesia, G. Fracastoro, E. Magli, "Self-supervised learning for joint SAR and multispectral land cover classification", arXiv preprint arXiv:2108.09075, 2021

The Problem: Weakly Supervised Learning in Remote Sensing Imagery

- End-to-end DL models not able to outperform standard ML methods
- Lack of large labeled datasets
- Difficulty to fuse multiple imaging modalities
- ▶ Some solutions:
- ► Transfer Learning from CV suffer from domain gaps
 - ▶ RGB vs Multichannel
 - ▷ Object-Centric vs Many Objects at different scale
 - Different Spatial Resolution among multisensor data
- Self-Supervised Learning is strictly related to CV:
 - Pretext Tasks involve geometric transformations
 - Contrastive Learning is not able to build HR feature maps
 - \triangleright CV \rightarrow Well separated clusters
 - ▶ RS → Overlapped clusters (metropolis and village)

Spatial-Spectral Context Learning

- Universal Framework for multichannel data
- Extracts Features able to capture material properties
- ▶ 2 Self-Supervised approaches trained sequentially

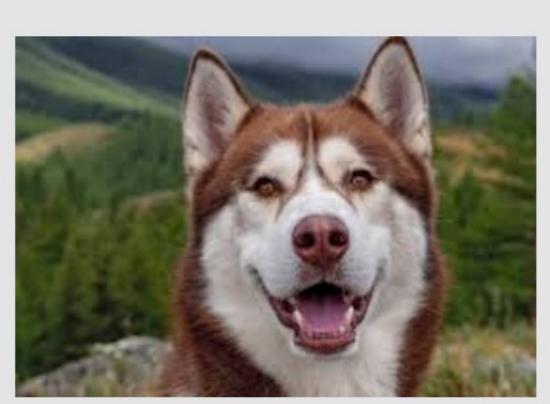
UniFeat

- ▶ Promoting pixel-wise similarity of low-level features between two different channels
- ▶ Single-Channel Feature Extractor and Projection head

▶ CoRe

- ▶ Reconstruct a degraded input to represent the spectrum highly informative for material properties
- Degradation Process (Channel Dropout, Cutout, Blur)





Data Fusion Contest 2020 (Track 2)

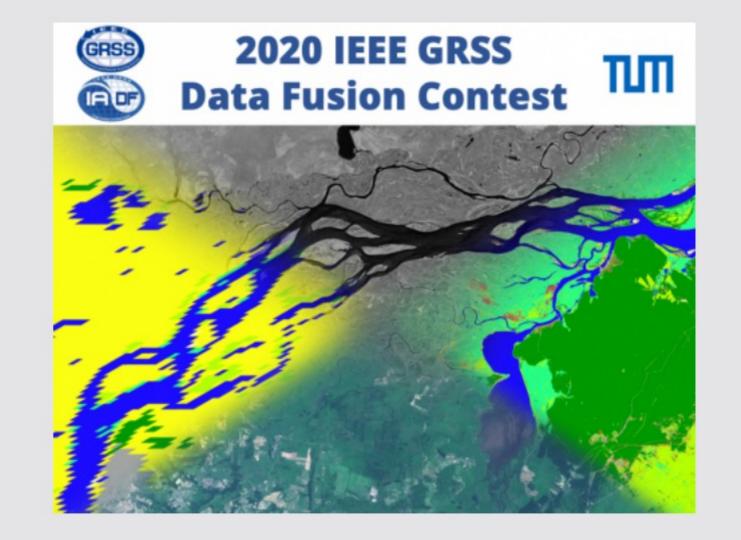
► High Resolution Land Cover Classification

Dataset:

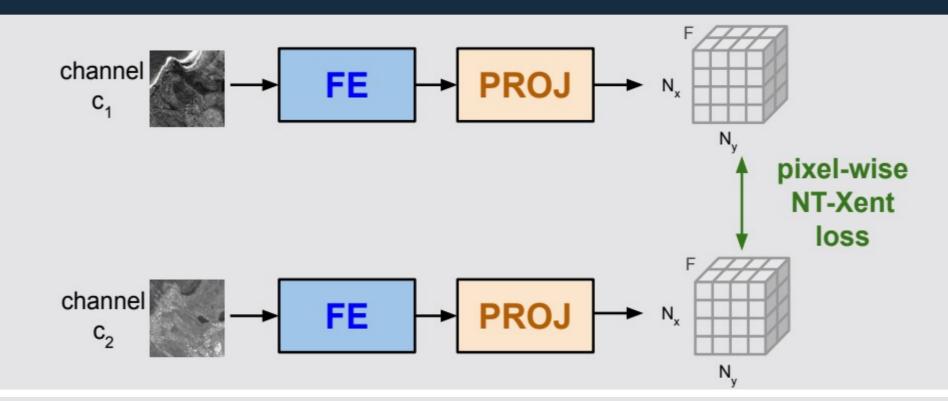
- ▶ Train: 986 images
 Test: 5128 images
- ▶ Annotated HR (10m) maps 10 classes
- S1 (2 polarization bands)S2 (13 multispectral bands)

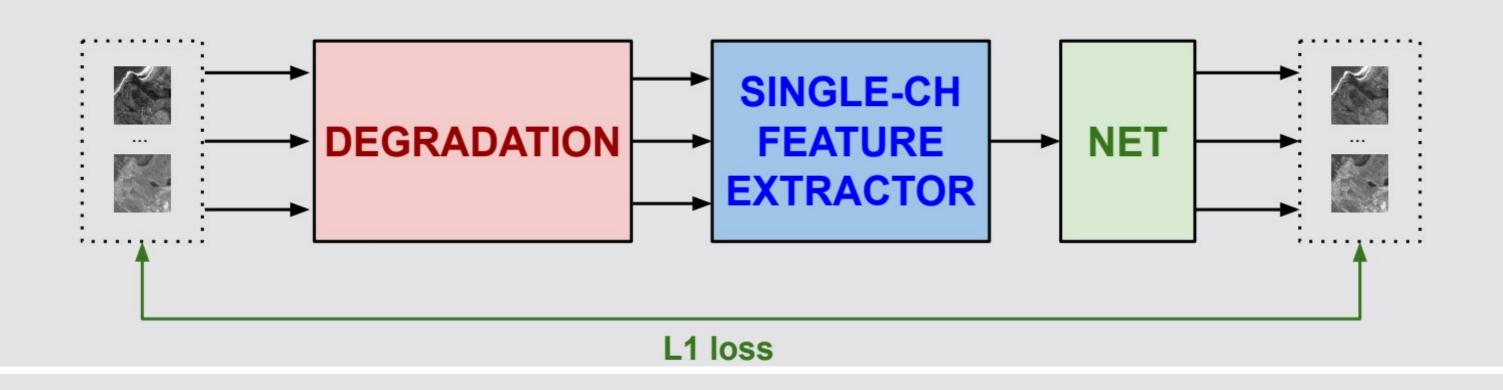
Experimental Setting

- Linear Protocol
- ▶ Fine-Tuning

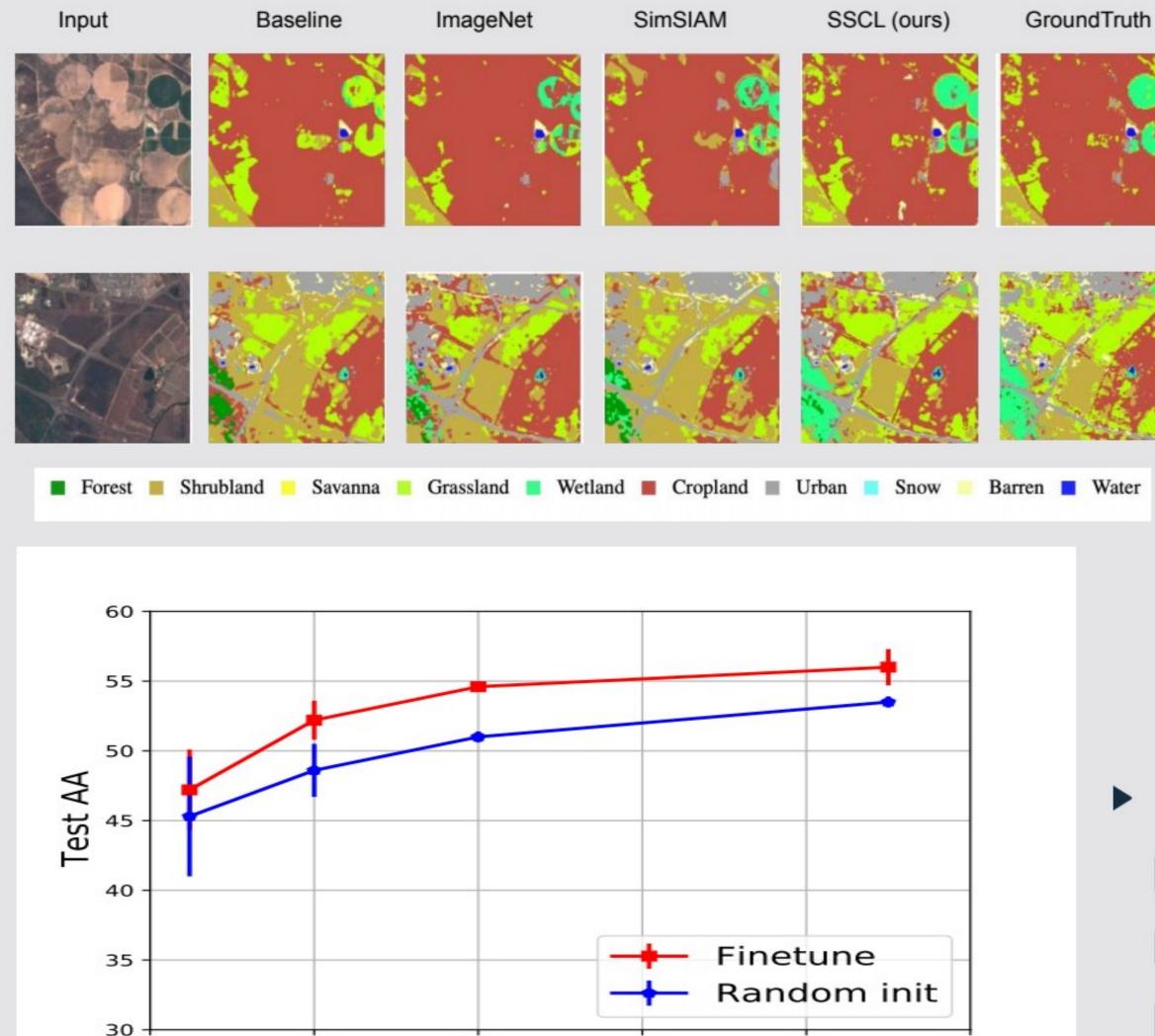


CNN Architecture





Results



No. samples

800

1000

	Baseline	ImageNet	SimSiam	SSCL
Forest	74.6 ± 5.7	77.7 ± 4.7	$\textbf{75.5} \pm \textbf{1.3}$	83.8 ± 1.7
Shrubland	56.3 ± 1.9	50.7 ± 7.0	$\textbf{46.4} \pm \textbf{7.1}$	60.1 ± 4.5
Grassland	33.3 ± 5.9	$\textbf{35.4} \pm \textbf{8.1}$	37.4 ± 4.2	39.5 ± 8.0
Wetlands	11.0 ± 2.1	9.3 ± 3.7	13.4 ± 3.6	12.1 ± 2.4
Croplands	32.1 ± 5.3	36.8 ± 5.4	28.1 ± 4.1	29.4 ± 1.1
Urban	79.6 ± 3.9	77.1 ± 3.5	79.8 ± 6.9	78.9 ± 4.1
Barren	40.9 ± 5.2	42.2 ± 6.7	43.4 ± 10.3	44.8 ± 5.3
Water	99.2 ± 0.2	99.3 ± 0.1	99.3 ± 0.1	99.3 ± 0.1
AA	53.4 ± 1.3	53.6 ± 0.9	52.9 ± 1.1	56.0 ± 1.1
OA	65.1 ± 1.9	66.4 ± 0.8	64.6 ± 1.3	67.8 ± 0.9

- Legend
 - ▶ Baseline: Standard train procedure with randomly initialized model
 - ▶ ImageNet: Train by using Transfer Learning from an architecture trained on ImageNet dataset.
- SimSiam: Train by finetuning the pretrained self-supervised model through SimSiam technique.
- SSCL: Train finetuning the proposed self-supervised model.

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