



# Towards Frequent Update of Land Cover Maps

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UNIVERSITY OF ICELAND

### **EuroCC NCC Iceland – Simulation & Data Lab Remote Sensing**





Icelandic HPC Community Web page

- Simulation & Data Lab Communities ullet
  - Experts w.r.t. HPC in domain-specific topics ٠
  - Co-organizing the HDCRS Summer school 29<sup>th</sup> May - 2<sup>nd</sup> June, 2022 [https://www.hdcrs.com/summer-schools/2022-iceland/home



Simulation and Data Lab Remote Sensing



#### General information

The Simulation and Data Lab Remote Sensing (SimDataLab RS) leads to increase the visibility on interdisciplinary research between remote sensing and advanced computing technologies and parallel programming. This includes high-performance and distributed computing, quantum computing and specialized hardware computing. The SimDataLab RS is based at the University of Iceland and works together with the High-performance and Disruptive Computing in Remote Sensing (HDCRS) working group of the Geoscience and Remote Sensing Society (GRSS), Together with HDCRS, the SimDataLab RS disseminates information and knowledge through educational events, special sessions and tutorials at conferences and publication activities.

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Members



### Sentinel-2 Multispectral Images



> Twin polar-orbiting satellites with temporal resolution of 5 days









#### Data are free



### Processing Workflow for Updating Land Cover Maps





## Processing Workflow for Updating Land Cover Maps



### Fully automated framework

Can extract large number of labelled samples from open thematic products



C. Paris, L. Bruzzone, D. Fernández-Prieto, "A Novel Approach to the Unsupervised Update of Land-Cover Maps by Classification of Time Series of Multispectral Images," IEEE Transactions on Geoscience and Remote Sensing, Vol. 57, No. 7, pp. 4259-4277, 2019,

Rocco Sedona, Claudia Paris, Liang Tian, Morris Riedel, Gabriele Cavallaro, "An automatic approach for the production of a time series of consistent land-cover maps based on long-short term memory", IEEE International Geoscience and Remote Sensing Symposium (IGARSS) 2022 (accepted)



### **Initial Results**

Processing workflow ported to the DEEP-EST prototype system Classification map produced over a single Sentinel-2 tile

Urban Grass Not irrigated crops Annual crops Mineral Rocks Sand Broadleaves Conifers Shrub Lake Sentinel-2 image Old classification map New Classification map Snow (CORINE 2018) (SVM)







### **Initial Results**



LSTM using the 12 bands of pixels extracted from Sentinel-2 as features, sequences of 10/20 acquisitions (images) per year



Sentinel-2 image (2018)



LSTM Classification map (2018)







#### RH0

## **Initial Results**

RASE

DEEP-EST

Problem: real change or noise?





#### Sentinel-2 image (2019)



'AN AUTOMATIC APPROACH FOR THE PRODUCTION OF A TIME SERIES OF CONSISTENT LAND-COVER MAPS BASED ON LONG-SHORT TERM MEMORY',

R. Sedona, C. Paris, L. Tian, M. Riedel, G. Cavallaro, IGARSS2022 (accepted)

RH0 mention LUCAS Rocco Sedona - HI; 2022-02-23T18:08:32.585



## Current Work: Data Retrieval



Retrieval of Sentinel-2 time series for the Netherlands and related CORINE thematic maps



tile	num 2018	size 2018 [GB]	num 2019	size 2019 [GB]	num 2020	size 2020 [GB]
31UFT	17	16.16	14	15.33	19	20.91
31UGS	19	21.17	15	16.56	21	23.4
32ULC	20	22.08	18	19.55	20	21.16
31UGU	19	19.97	20	20.38	20	20.92
31UGV	20	18.68	17	15.5	27	21.7
31UFV	19	16.59	17	14.83	22	18.8
31UFU	18	16.65	15	15.24	21	21.31
31UFS	21	23.66	15	16.63	23	25.5
31UES	12	13.56	16	16.82	19	21.11
31UET	16	13.42	14	13.17	20	18.43
total	181	181.94	161	164.01	212	213.24



RH0 add total years Rocco Sedona - HI; 2022-02-23T18:08:08.632

## **Current Work: Data Pre-processing**



Aim: speed-up pre-processing and training set extraction (clustering) Ideas:

- Download acquisitions and corresponding land cover maps
- Create composites and harmonize data
- Process multiple tiles in parallel



## Next Steps: DL Model



Aim: Exploit time series with long sequences of data acquired over multiple years

Models: Recurrent models or transformers

Ideas:

- Keep into consideration the dynamics of the outputs, as we want to get an output year by year
- > Make prediction more robust and less noisy (retain cell state at prediction?)
- > Use convolution to exploit spatial correlation? Ex. ConvLSTM
- > Add regularization term to penalize change of label?
- Continual learning? Avoid catastrophic forgetting



## RASE

## LSTM

## Exploit temporal dynamics of the signal

- Recurrency
- > ability to remove or add information to the cell state
- Gates are a way to optionally let information through



https://www.researchgate.net/publication/329362532 Designin g neural network based decoders for surface codes



### Transformer





https://www.exxactcorp.com/blog/Deep-Learning/whatcan-you-do-with-the-openai-gpt-3-language-model

Vaswani, et al., 2017



## RASE

### ConvLSTM

### Temporal and spatial correlation

The ConvLSTM determines the future state of a certain cell in the grid by the inputs and past states of its local neighbors



Shi et al. in <u>Convolutional LSTM Network: A Machine Learning Approach for</u> <u>Precipitation Nowcasting</u>



## **Contrastive Learning**



### **Exploit unlabeled data**

- Train model to maximize agreement between different views of the same image
- What about RS data?



https://www.mdpi.com/2227-7080/9/1/2/htm



### **Continual Learning**



### New data is continuously acquired by Sentinel-2

- > How to incorporate information while avoiding catastrophic forgetting?
- Loss with decreasing weight for older samples?
- Fine tuning of the previous model?





## Distributed Deep Learning: What is it?



Problem: large models and dataset -> Solution: scale-up!

Data Parallelism



http://www.idris.fr/eng/ia/apprentissage-distribue-eng.html

### **Model Parallelism**



https://pytorch.org/docs/stable/pipeline.html



### **Distributed Deep Learning: Frameworks**







## Hyperparameter Tuning

- Many hyperparameters, such as learning rate, scheduler optimizer, etc.
- Large global batch size require extensive tuning
- Automatic Hyperparameter Tuning
- 'ACCELERATING HYPERPARAMETER TUNING OF A DEEP LEARNING MODEL FOR REMOTE SENSING IMAGE CLASSIFICATION', M. Aach, R. Sedona, A. Lintermann, G. Cavallaro, H. Neukirchen, M. Riedel, IGARSS2022 (accepted)





## RASE

### **Recap & Conclusion**

Still setting up the framework:

> Use composites?

Once data pre-processing is stable:

- Experiment with more DL models (exploit also spatial dimension)
- > Transition towards a feeding of the data as it becomes available
- > Virtual constellations? NASA Harmonized Landsat Sentinel

Big questions:

How to validate at large scale?



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