NDVI estimation based on Sentinel-1 SAR backscatter and a global Deep Learning model

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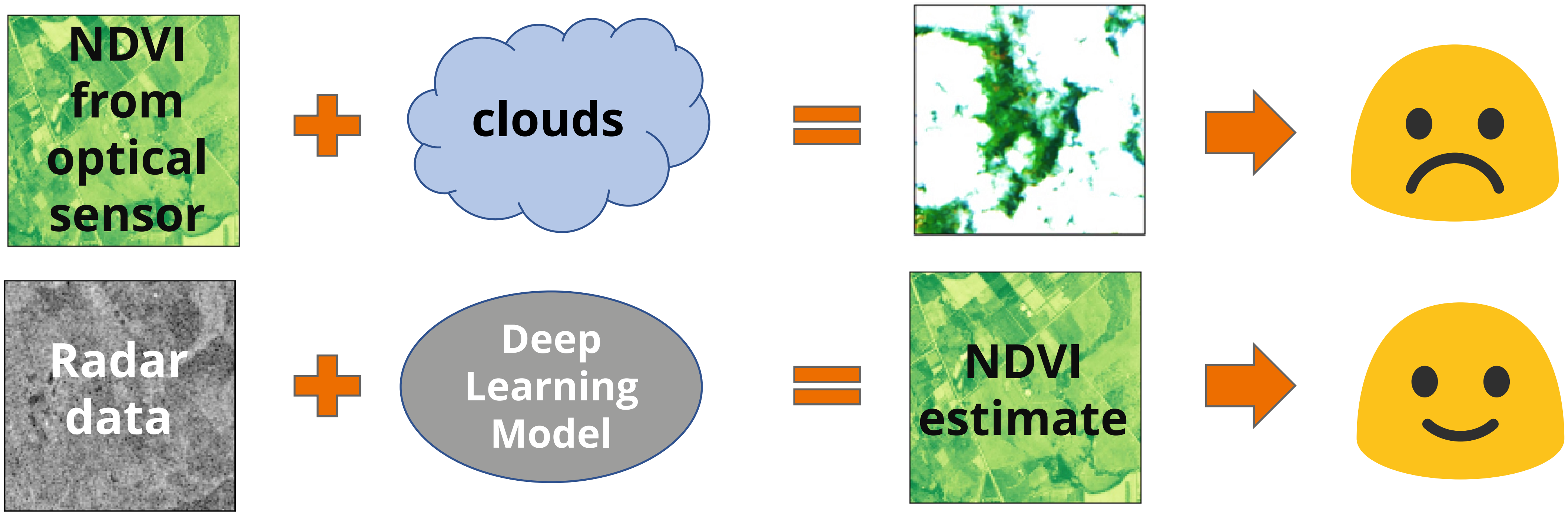
TL;DR



Can the NDVI be estimated globally with radar data and deep learning when it is cloudy and optical sensors don’t work?

What is the NDVI?

Normalized **D**ifference **V**egetation **I**ndex

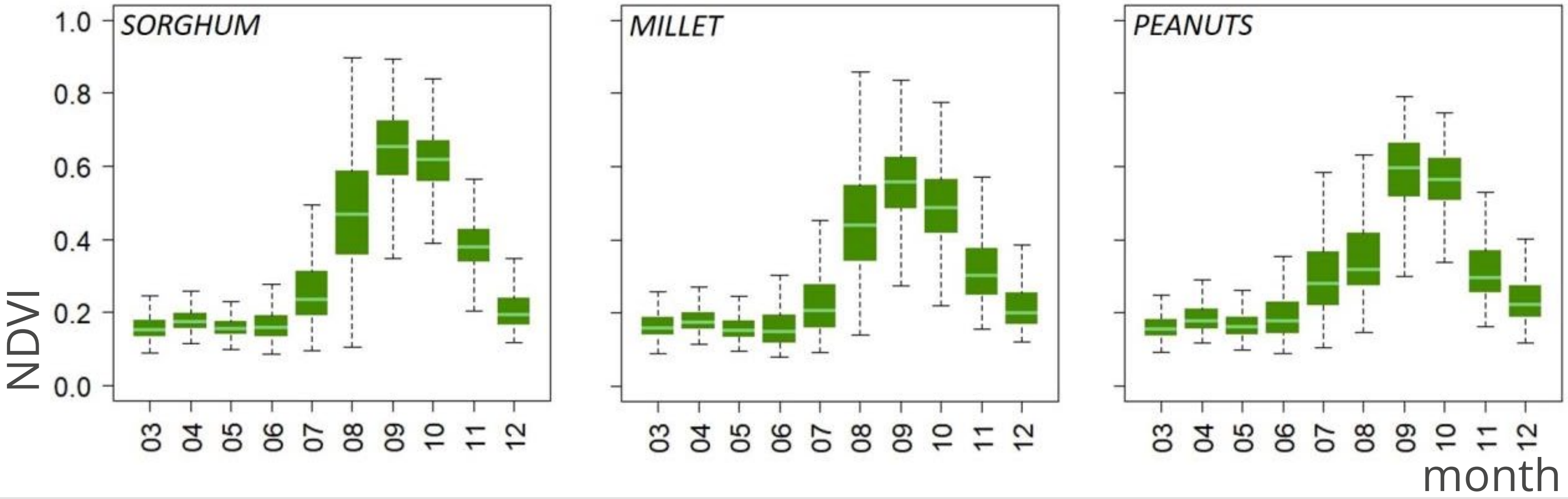
Information about living green vegetation

Calculated using red and infrared spectral bands

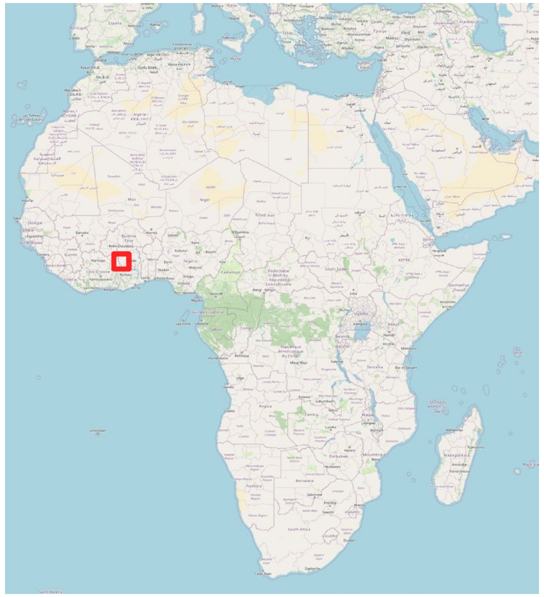
$$\mathrm{NDVI} = \frac{\mathrm{IR} - \mathrm{RED}}{\mathrm{RED} + \mathrm{IR}}$$

Application example:

- NDVI time series of plants shows phenology → allows yield predictions (Karst et al. 2020)



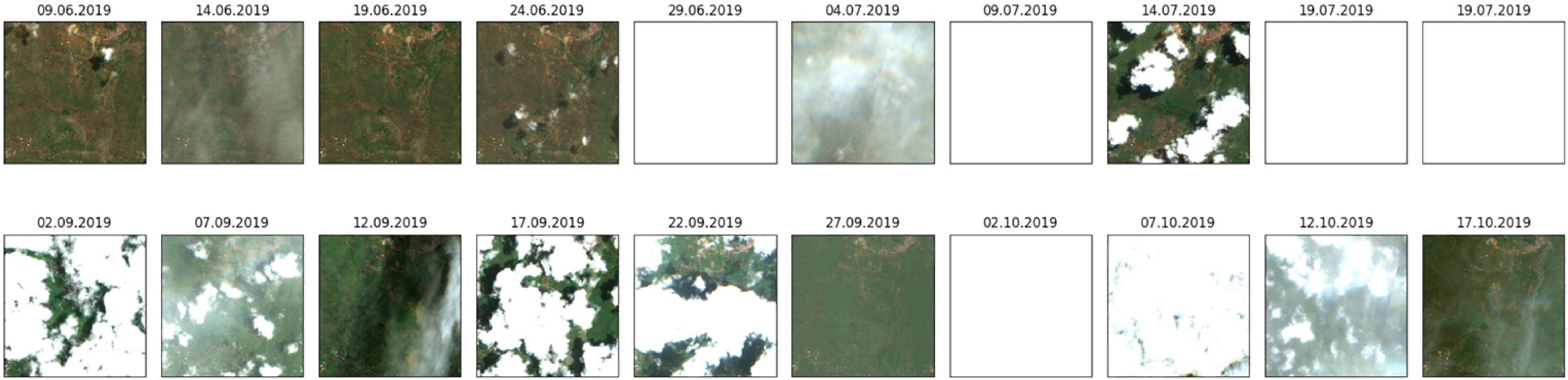
Problem: Clouds hinder optical sensors



Frequent cloud coverage especially in tropical and subtropical regions

Example: Subtropics, Burkina Faso

- Only cloudy images in rainy = growing season



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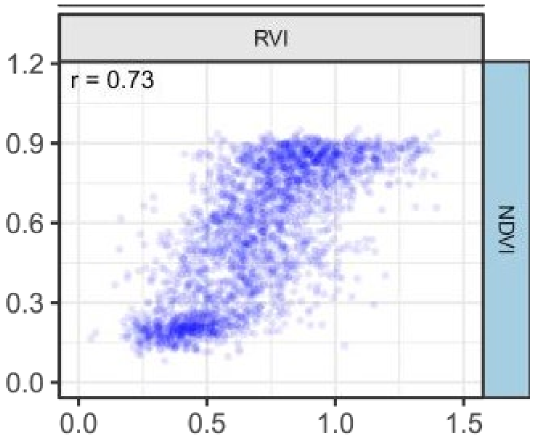
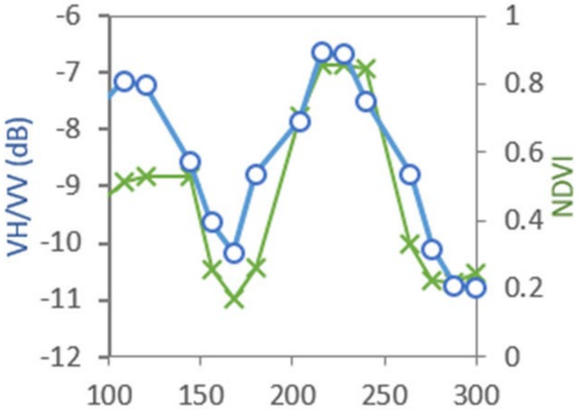
Related Research

Correlation between SAR and NDVI shown for C-Band radar

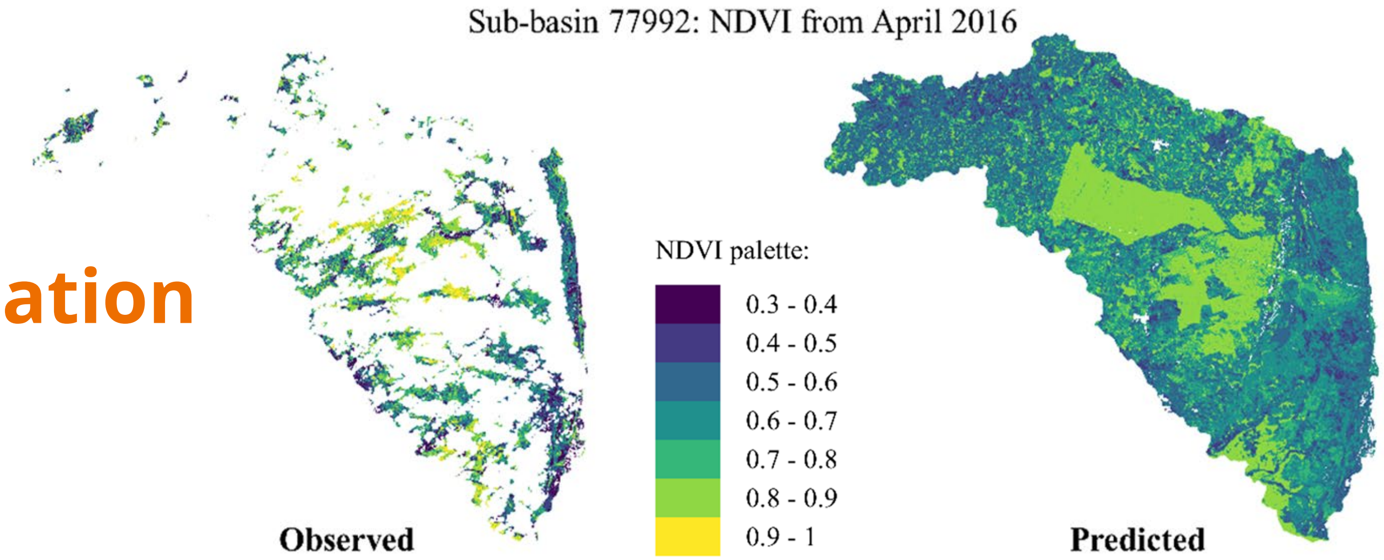




(Moran et al. 2012; Holtgrave et al. 2020; Alvarez-Mozos et al. 2021; Jiao et al. 2021)

Pixel-wise regression viable (Scarpa et al. 2018; Filgueiras et al. 2019; Santos et al. 2022)

- Only local studies with small areas
- Not tested on global scale



Research Gap: Global application possible?

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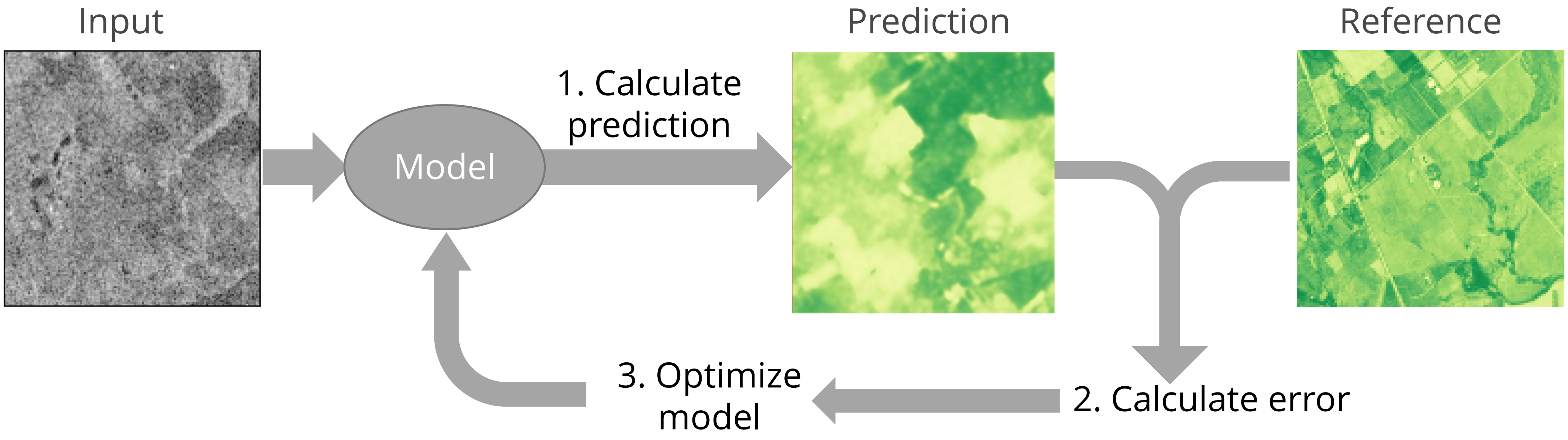
Deep Learning

Supervised Learning, many examples needed

Train model to learn relations inside the data

But: prediction only good for similar data distribution

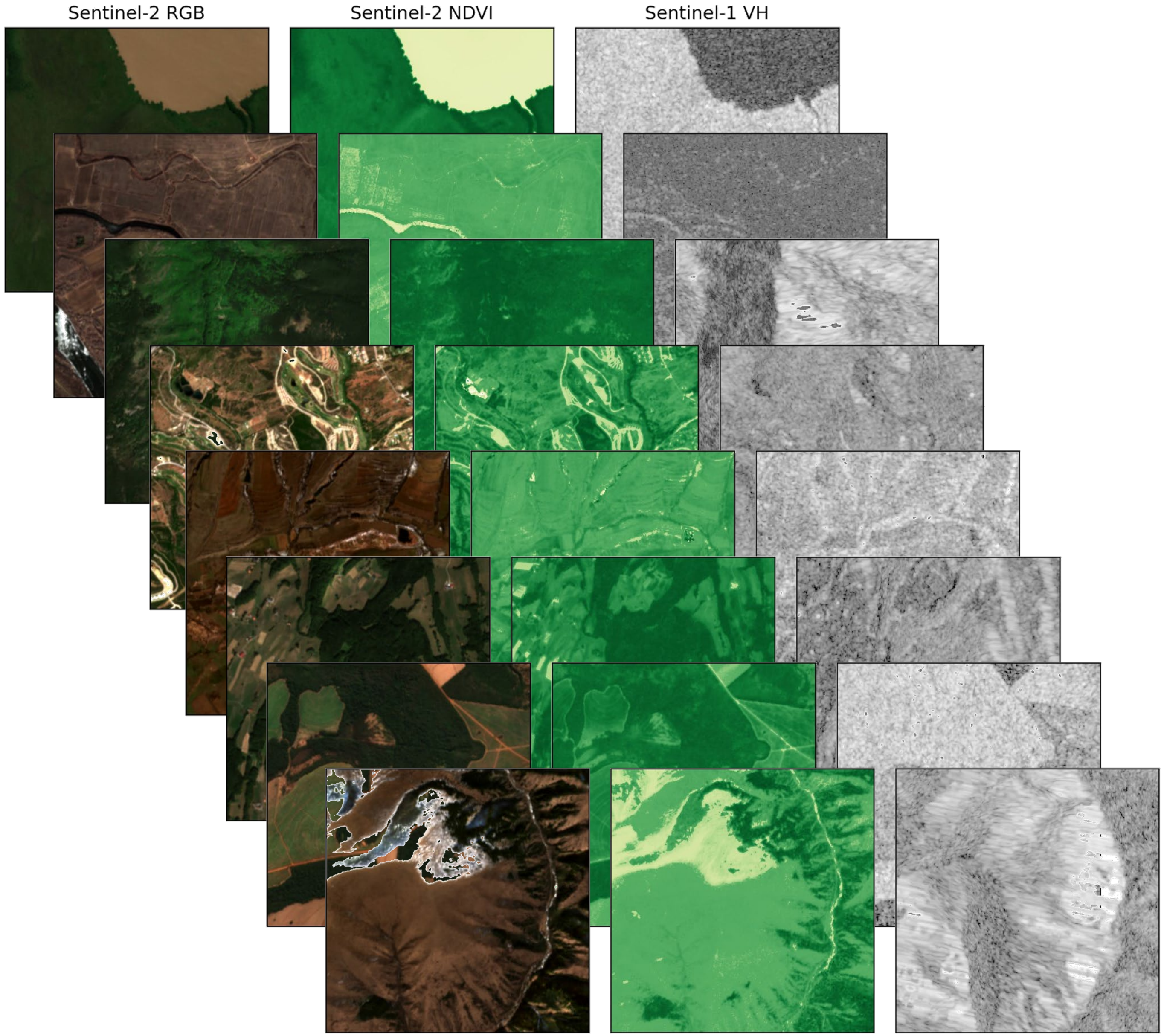


Dataset requirements

Timely paired radar and
cloud free optical data

Capture all vegetation conditions
→ Different land cover, climates, and seasons

Global application → Images from the whole world

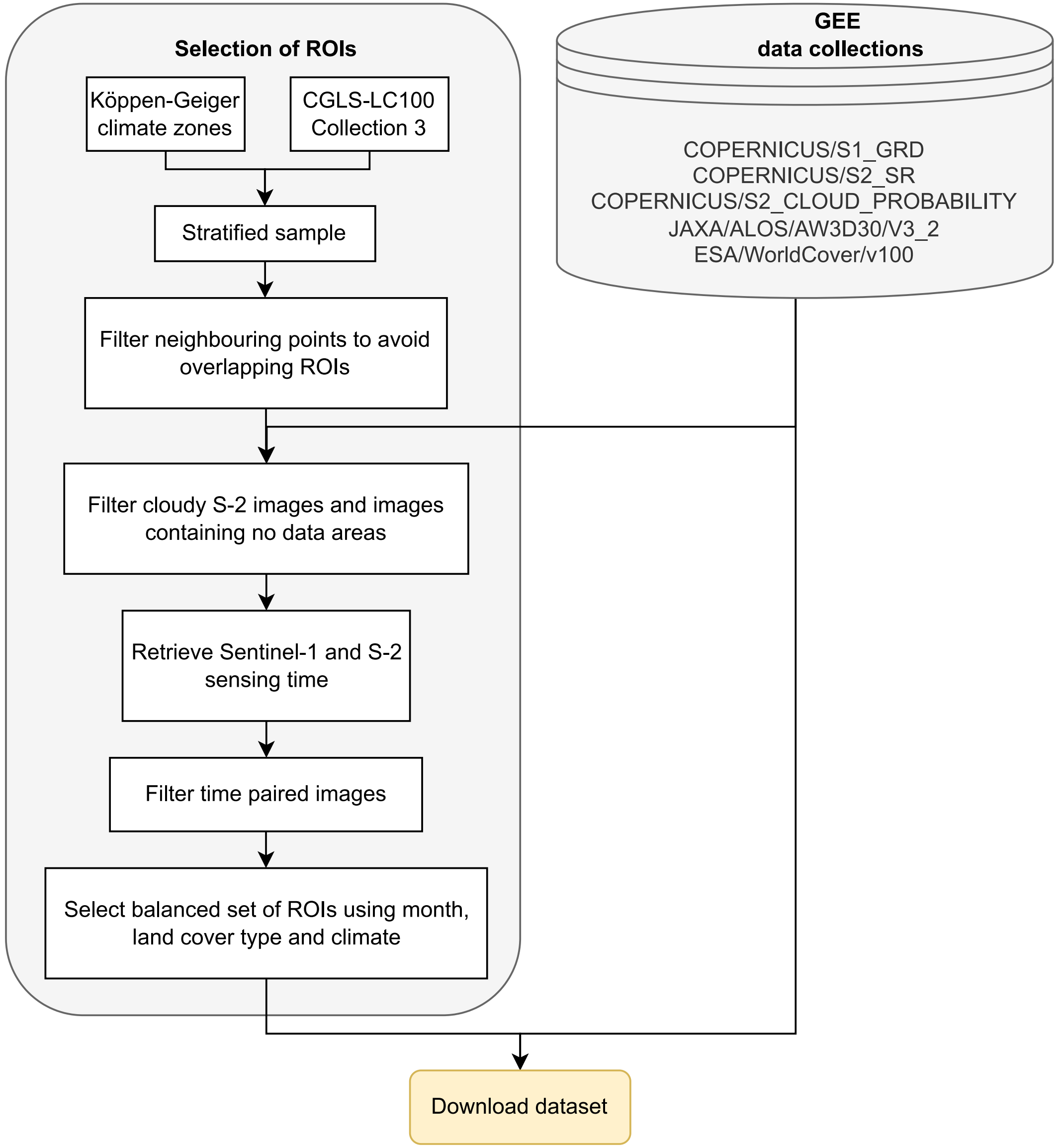


Dataset creation

Google Earth Engine used

Steps:

1. Select locations using climate and land cover
2. Filter cloudy Sentinel-2 images
3. Select temporal close Sentinel-1 and -2 images
4. Filter to have balanced seasonality, land cover, and climates
5. Download images



SEN12TP dataset

Sentinel-**1** and Sentinel-**2** data, **t**imely **p**aired

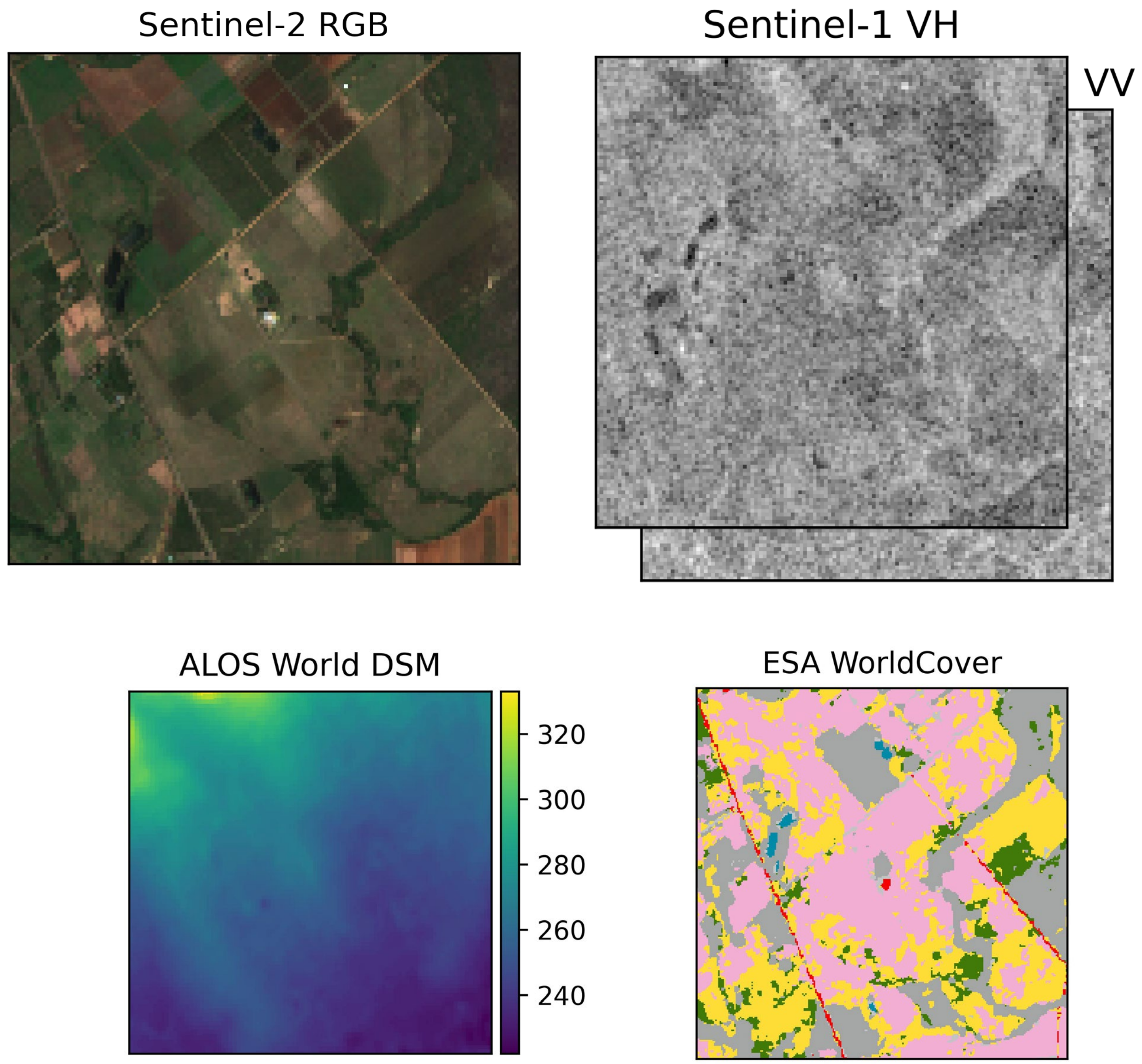
Included data:

- Sentinel-1: GRD, IW, VV and VH polarization
- Sentinel-2: Level-2A
- ALOS World 3D DSM
- ESA WorldCover v100, land cover type

2200 ROIs with 20km x 20km

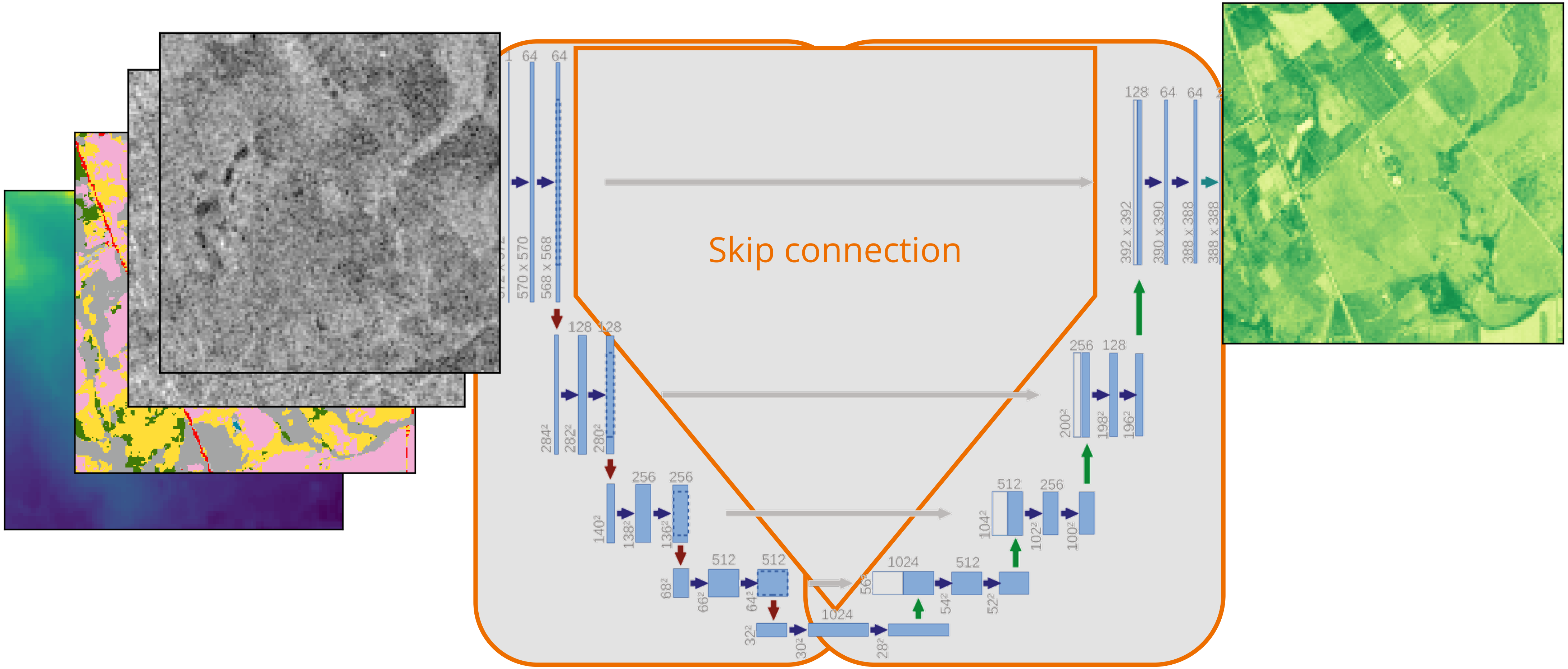
~240GB

Will be published soon



Deep neural network

Off-the-shelf architecture: U-Net (Ronneberger et al. 2015)

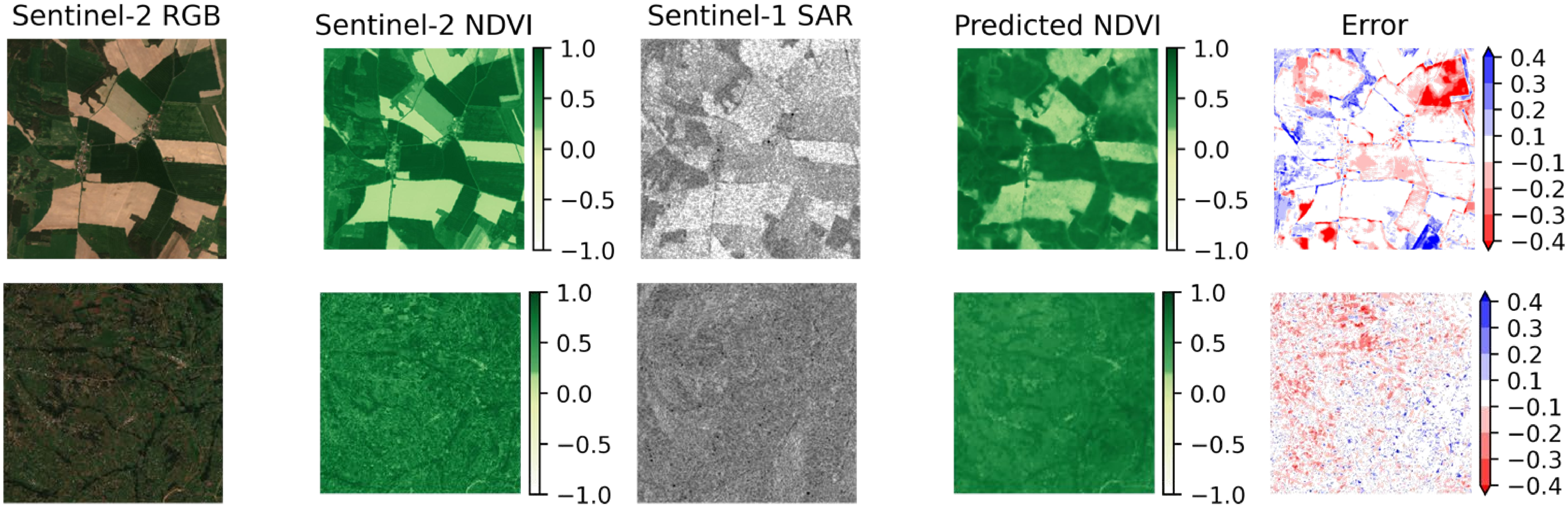


Results

How good are the model predictions?

Evaluation on unseen test data

Model	**MAE** $\downarrow$	**Pearson** $\uparrow$	**SSIM** $\uparrow$
$\sigma^\circ_{\mathrm{VV}}$, $\sigma^\circ_{\mathrm{VH}}$, Worldcover, DSM	0.1119	0.8181	0.5935

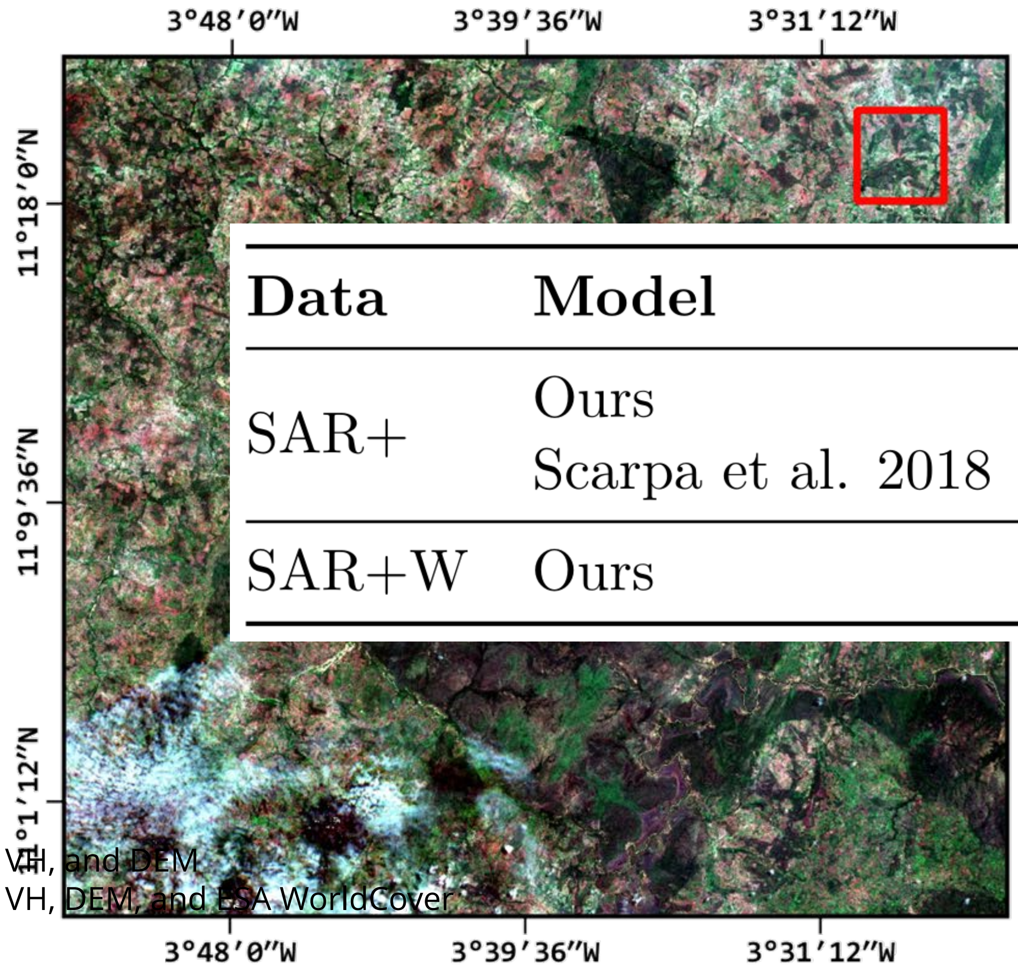


MAE Mean Absolute Error,
Pearson Pearson correlation index $\in [0, 1]$
SSIM Structural similarity index $\in [0, 1]$

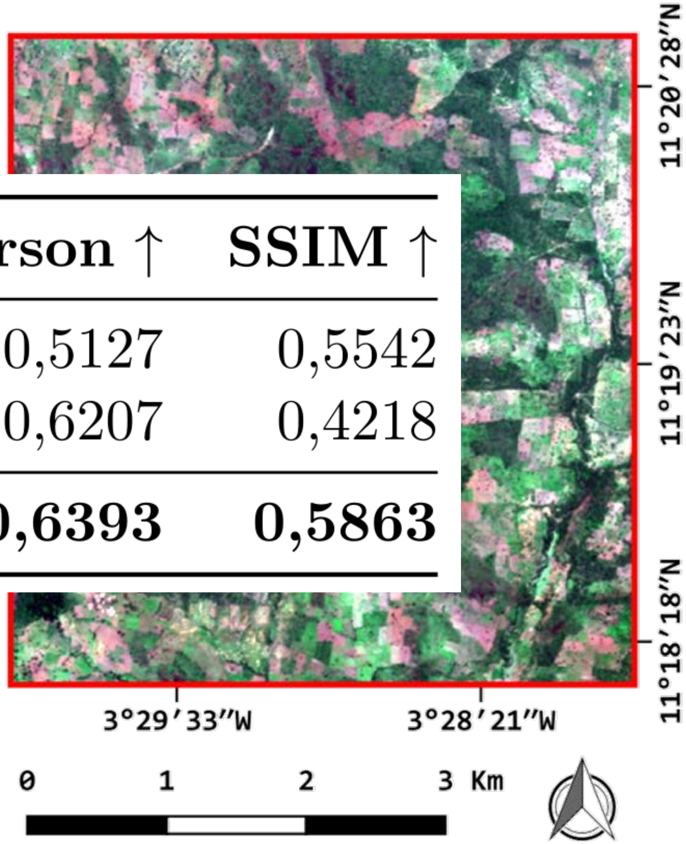
$\uparrow$ higher values are better
$\downarrow$ lower values are better

How does our method compare to other research?

Compare with test set published in Scarpa et al. 2018



Data	Model	Pearson ↑	SSIM ↑
SAR+	Ours	0,5127	0,5542
	Scarpa et al. 2018	0,6207	0,4218
SAR+W	Ours	**0,6393**	**0,5863**

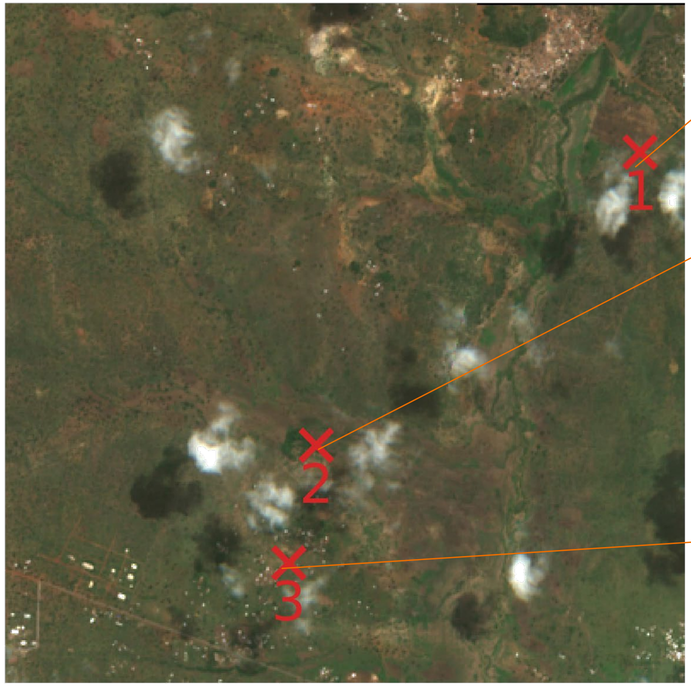


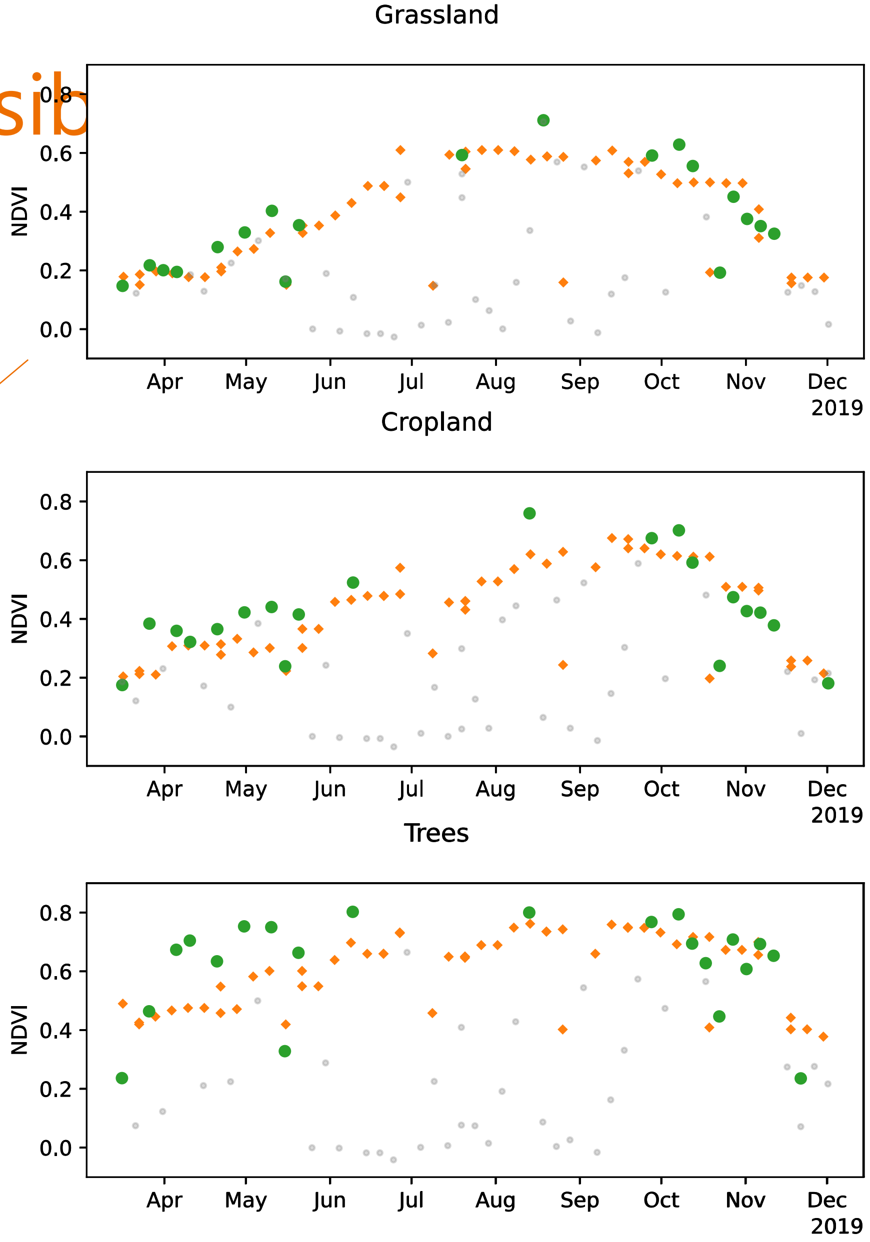
SAR+ VV, VH, and DEM
SAR+W VV, VH, DEM, and ESA WorldCover

G. **Scarpa**, M. Gargiulo, A. Mazza, R. Gaetano, "A CNN-based fusion method for feature extraction from Sentinel data", *Remote sensing*, 10.2, Art no. 236, **2018**.

Time series enhancement possib

Proof of concept to enhance optical NDVI time series with Sentinel-1 derived NDVI





Take away

Estimation of NDVI possible with C-Band SAR and deep learning

Global approach viable

Densification of NDVI time series seems promising

Thank you for the attention!

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