



Virtual Constellations for Continuous Monitoring

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Earth Explorers

Multi dimensionality, multi-level nature of EO (satellites, HAPs, UAVs) presents connectivity, integration and interoperability challenges.

Credits: ESA



The RapidAI4EO Project

GOAL

- Establish the foundations for the next generation of rapid cadence land monitoring applications

STRATEGY

1. Creation of a spatio-temporal machine learning training dataset for land monitoring applications combining Sentinel-2 and Planet imagery at 500,000 patch locations in Europe
2. Development of a solution for higher frequency updates of the CORINE Land Cover inventory through detecting and classifying change from very high cadence observations via supervised and unsupervised DL classifiers

DURATION

- January 2021 – March 2023

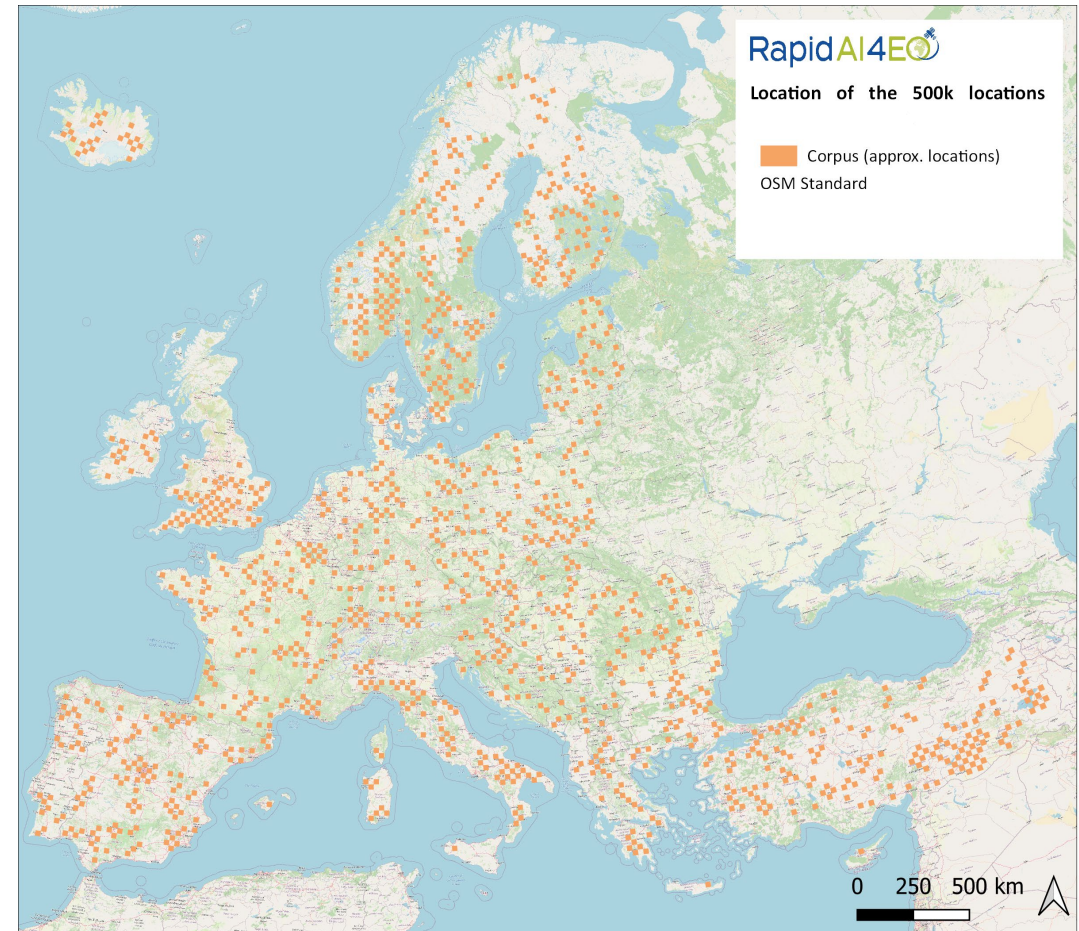
<https://rapidai4eo.eu/> <https://www.linkedin.com/company/rapidai4eo/>





The RapidAI4EO Corpus

- The inspiration for the RapidAI4EO corpus comes from the BigEarthNet and Eurosat datasets
- 600m x 600m patches with Sentinel-2 (1 year) and Planet Fusion (2 years)
- Sampled at 500,000 locations, accounting for
 - CLC class distribution
 - Spatial distribution
 - Country representation
- Multi-class annotations based on CLC 2018
- Designed for LULC change detection use case, but generalisable to other problems
- **Open sourcing in July 2022**

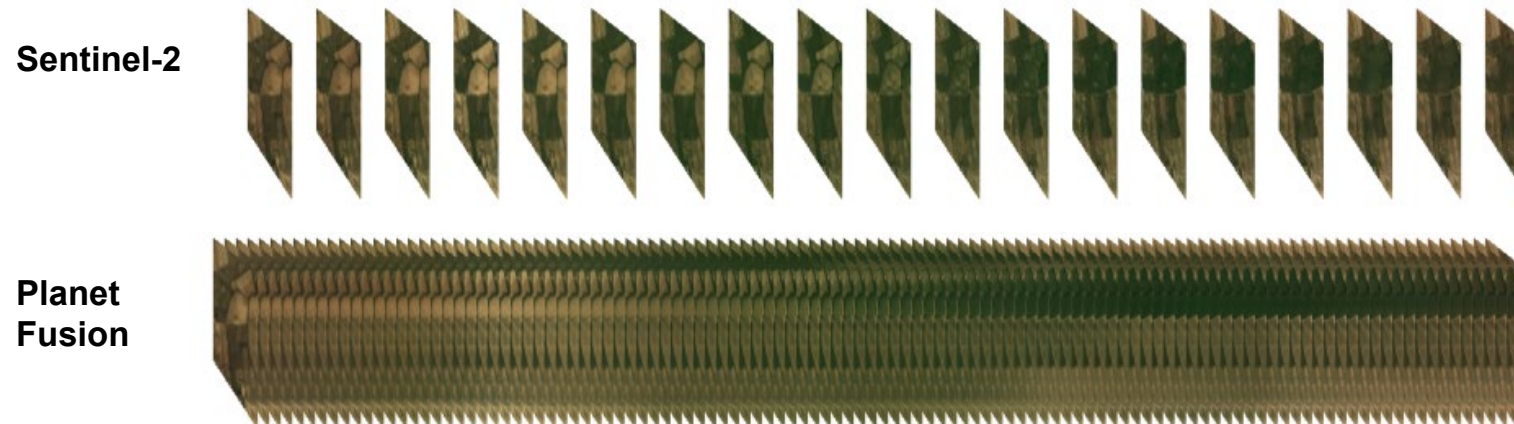
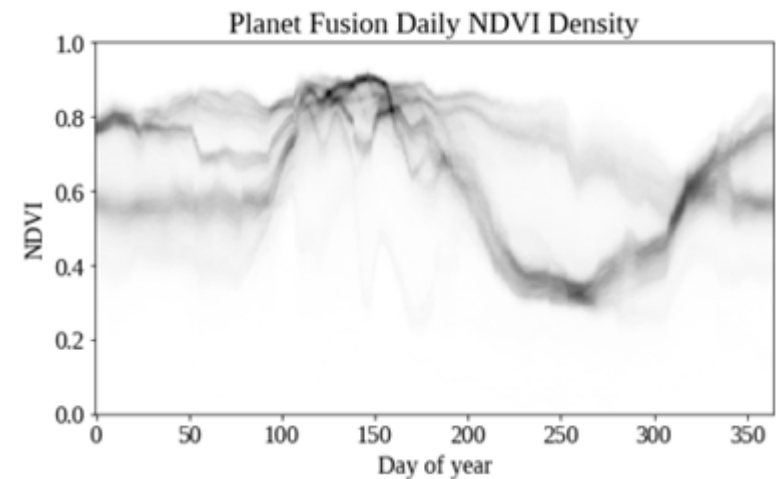
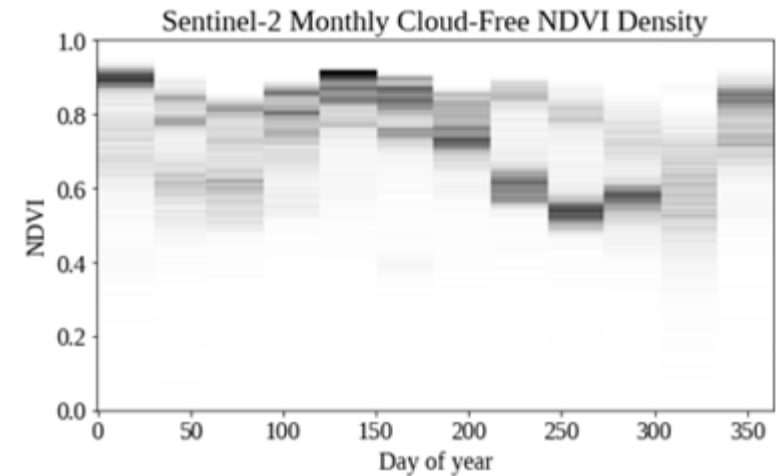




Development of Datasets

Multiformat Data

Source	Spatial resolution	Temporal resolution	Spectral resolution
Sentinel-2	10-60m	1 cloud-free image/month 2018	12 bands
Planet Fusion	3m	1 gap-filled image/every 5 days 2018-2019	4 bands



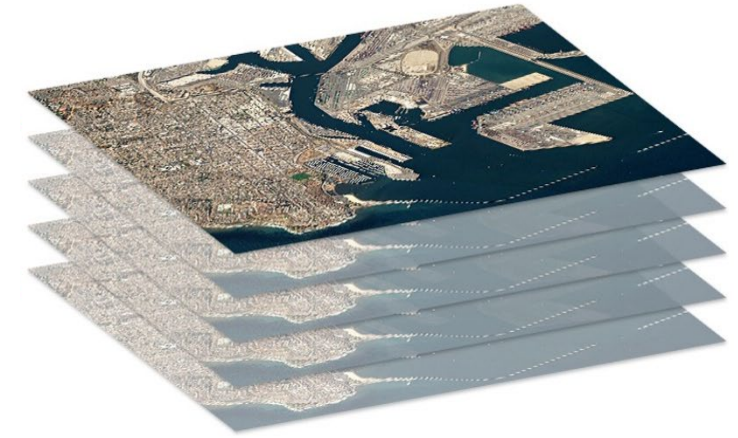


Development of Datasets

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



CubeSat-Enabled Spatio-Temporal Enhancement Method (CESTEM, Houborg and McCabe, 2018) <https://doi.org/10.1016/j.rse.2018.02.067>

INPUTS

PS - TOAR



HLS (L8 and S2)



OUTPUT

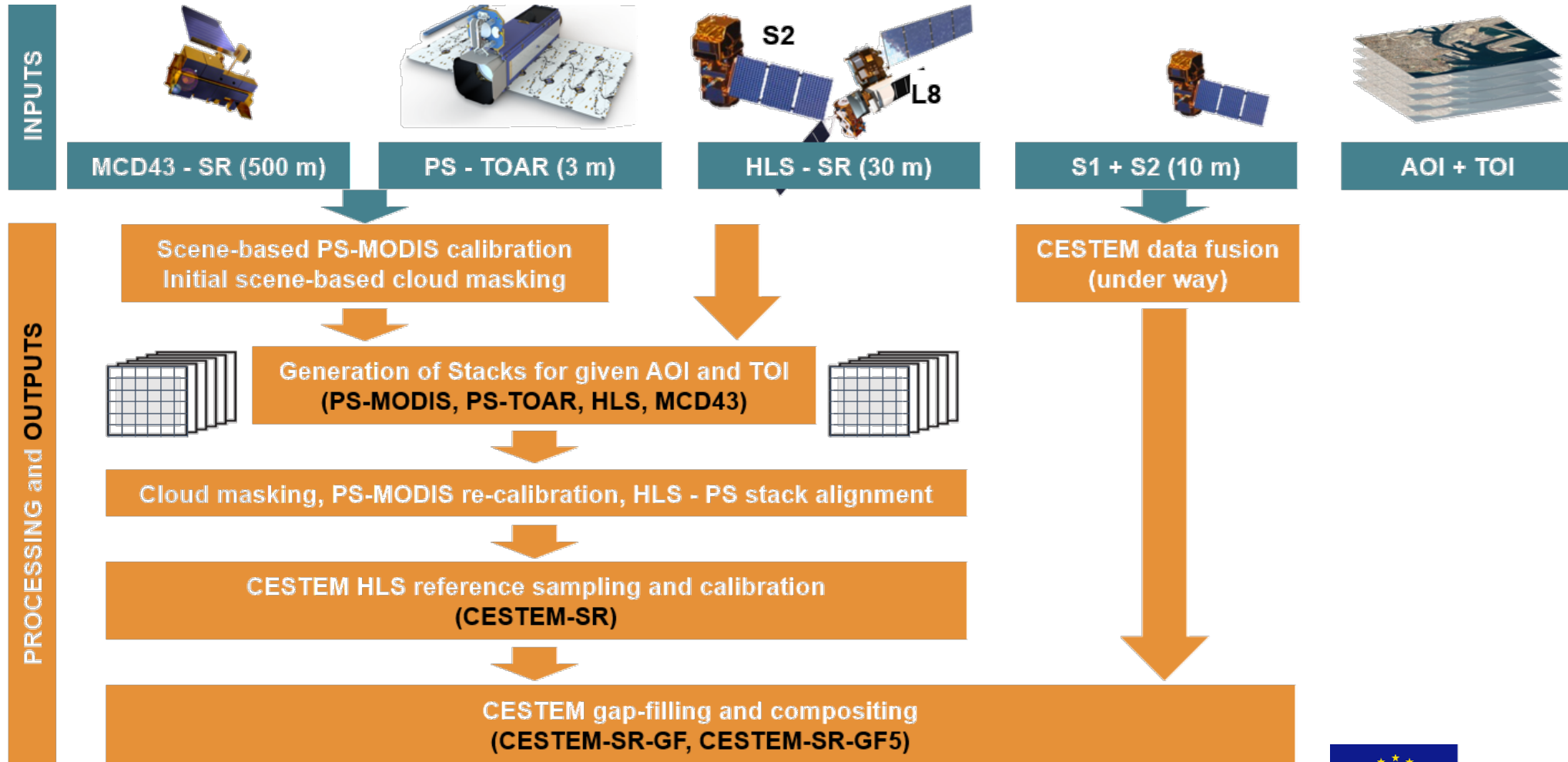
CESTEM - SR (gap-filled)



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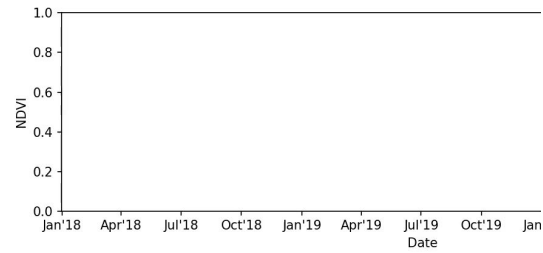


Next Generation Monitoring via Sensor Fusion

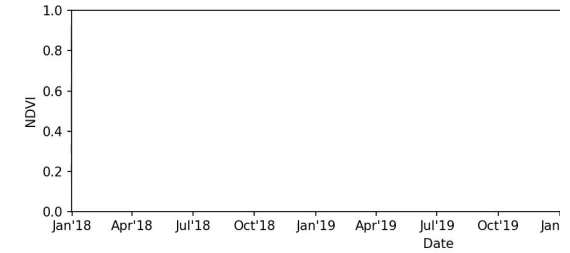




Examples of Stable Land Cover Behavior

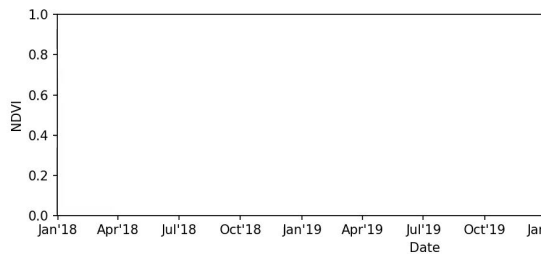
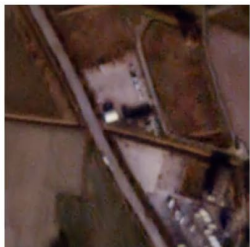


January 2018

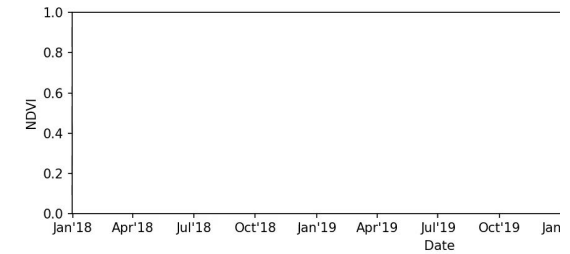


January 2018

Examples of Change



January 2018



January 2018

← 2 years →

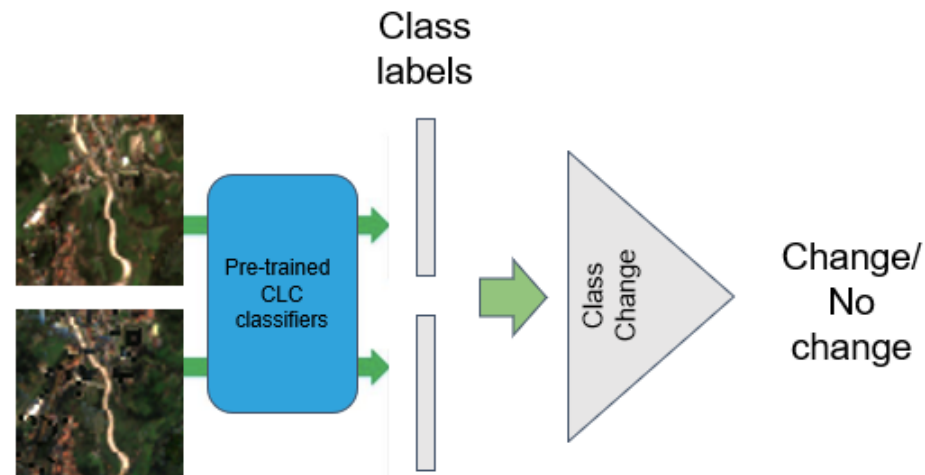
← 2 years →



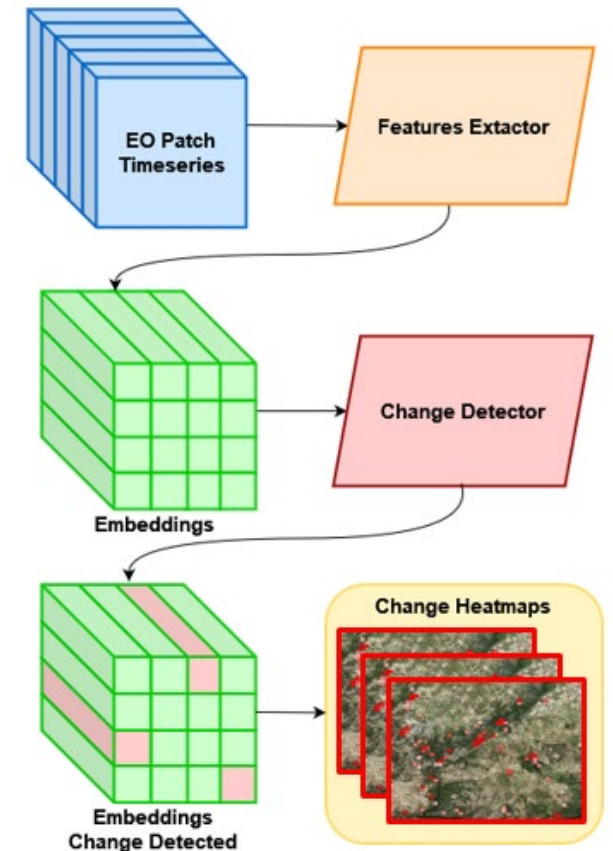
Change Detection Model Development

Deep Learning for detecting changes

- Supervised (CNN, LSTM, ConvLSTM) and unsupervised (auto-encoder, triplet-loss)
- Derive heat maps of change to prioritize areas for map updates



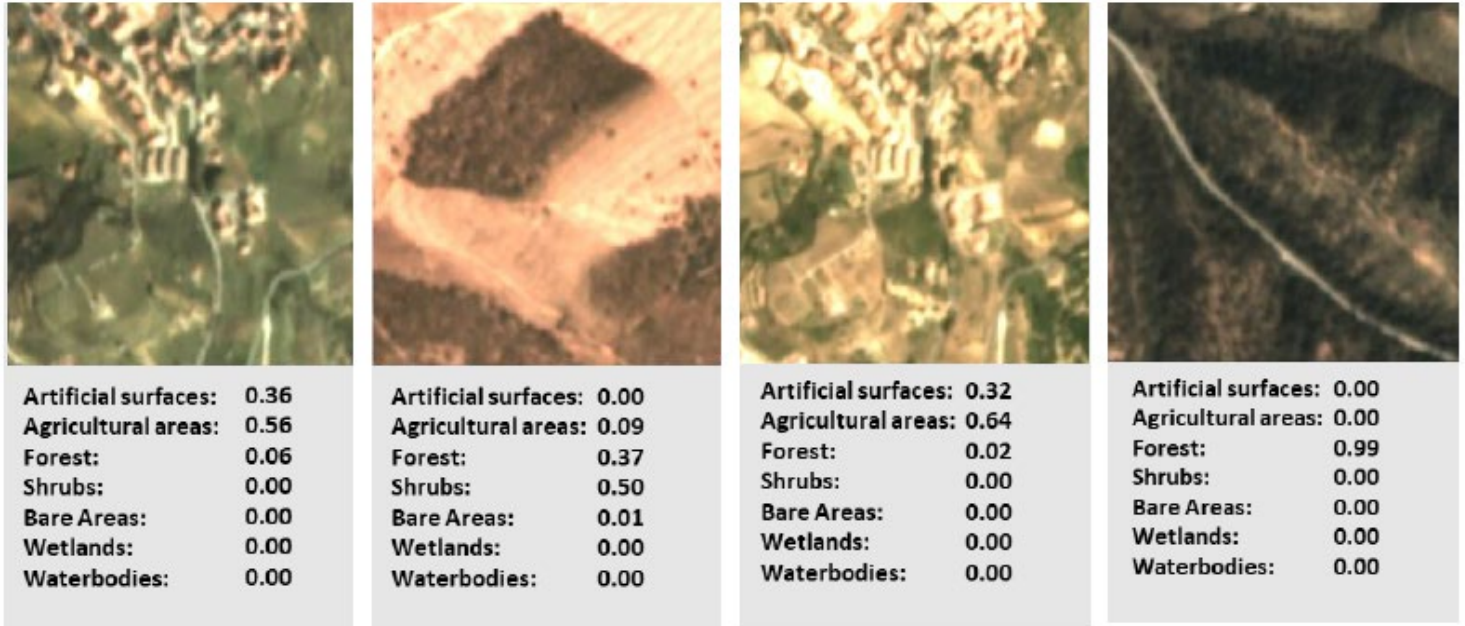
Change Detection approach with class labels



Unsupervised change detection workflow



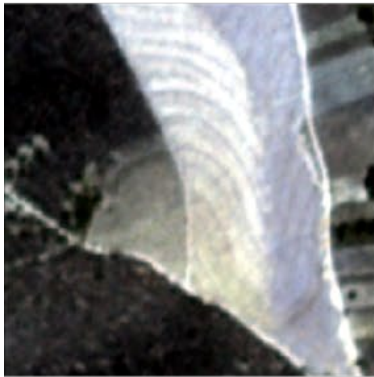
ML Models Learn to Recognize Land Cover Mixes





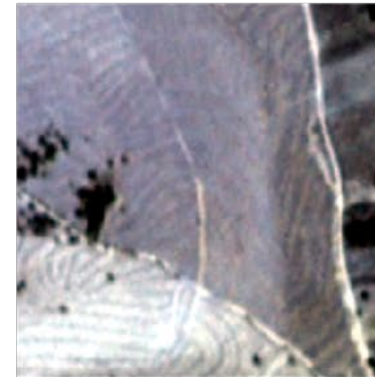
Convolutional Neural Network Activation Map

TILE-ID: 29N-26E-183N/33_17



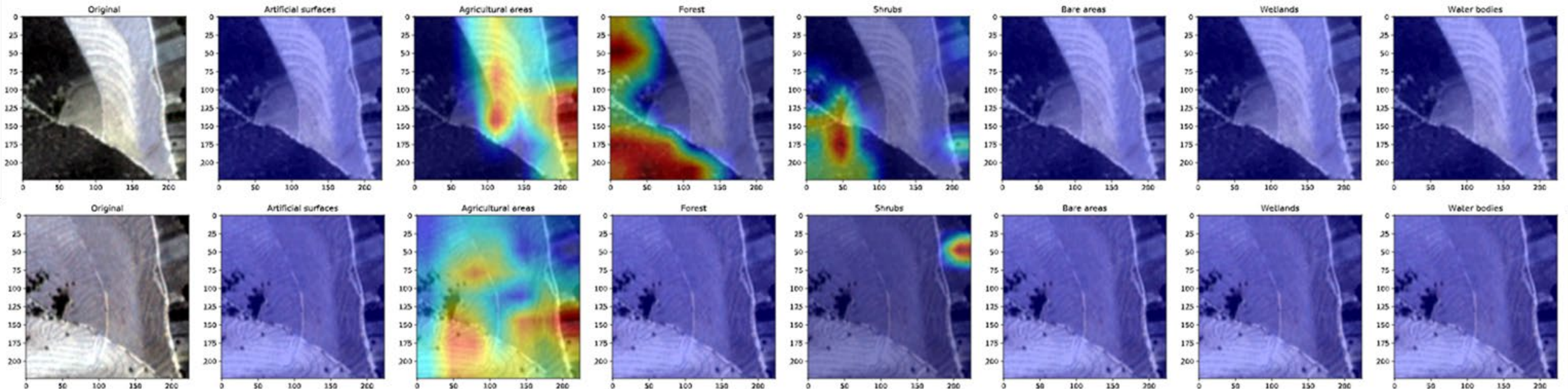
July, 2018

Artificial surfaces: 0.00
Agricultural areas: 0.45
Forest: 0.27
Shrubs: 0.25
Bare Areas: 0.00
Wetlands: 0.00
Waterbodies: 0.00



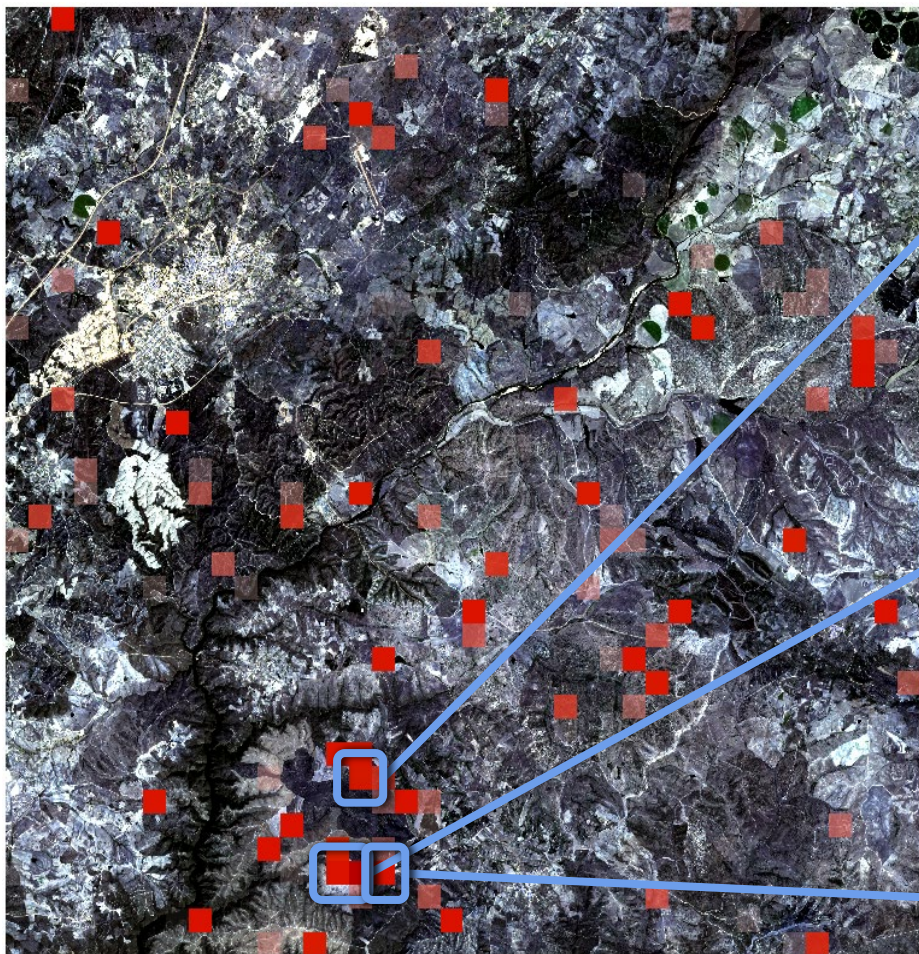
September, 2018

Artificial surfaces: 0.00
Agricultural areas: 0.97
Forest: 0.00
Shrubs: 0.01
Bare Areas: 0.00
Wetlands: 0.00
Waterbodies: 0.00





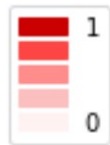
Detected Change (26E-183N)



Tile_id: 33_17

3rd Quarter, 2018

RapidAI4EO

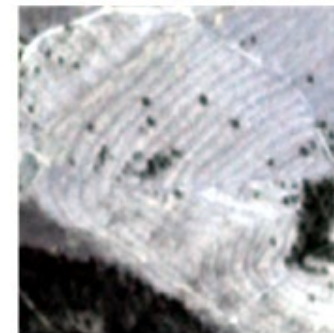


ESA Living PI



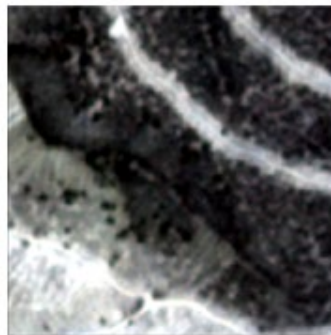
July, 2018

Artificial surfaces:	0.00
Agricultural areas:	0.02
Forest:	0.91
Shrubs:	0.05
Bare Areas:	0.00
Wetlands:	0.00
Waterbodies:	0.00



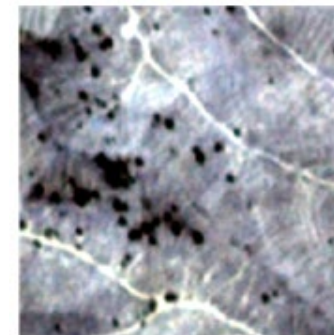
September, 2018

Artificial surfaces:	0.00
Agricultural areas:	0.74
Forest:	0.12
Shrubs:	0.11
Bare Areas:	0.00
Wetlands:	0.00
Waterbodies:	0.00



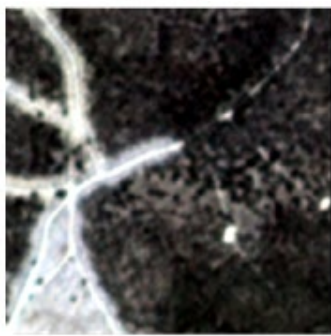
July, 2018

Artificial surfaces:	0.00
Agricultural areas:	0.15
Forest:	0.10
Shrubs:	0.72
Bare Areas:	0.01
Wetlands:	0.00
Waterbodies:	0.00



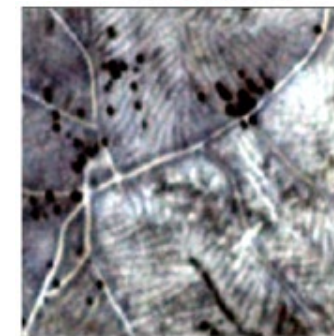
September, 2018

Artificial surfaces:	0.00
Agricultural areas:	0.97
Forest:	0.00
Shrubs:	0.01
Bare Areas:	0.00
Wetlands:	0.00
Waterbodies:	0.00



July, 2018

Artificial surfaces:	0.00
Agricultural areas:	0.02
Forest:	0.95
Shrubs:	0.01
Bare Areas:	0.00
Wetlands:	0.00
Waterbodies:	0.00



September, 2018

Artificial surfaces:	0.00
Agricultural areas:	0.99
Forest:	0.00
Shrubs:	0.00
Bare Areas:	0.00
Wetlands:	0.00
Waterbodies:	0.00



Key Takeaways

- The RapidAI4EO corpus is inspired by the BigEarthNet and EuroSat datasets. The main innovation is the addition of **high cadence time series** at all locations.
- High cadence time series improve our understanding of land use. They open the door to a new family of high fidelity ML models that can **disentangle phenology from structural change and learn the dynamism of land covers**.
- Results from the supervised ML models already show the advantage of including high cadence temporal information in change classification models.

Experiments with 15 classes (L2)

Method	Sensor	Months	F1-Score
ResNet-50	Sentinel-2*	All	74.24
ResNet-50	Planet Fusion**	All	77.30
LSTM	Planet Fusion**	All	80.10

* Monthly

** Daily



Thank you!

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