Deep Learning for fusion of Sentinel-1 and Sentinel-2 data and grassland mowing detection

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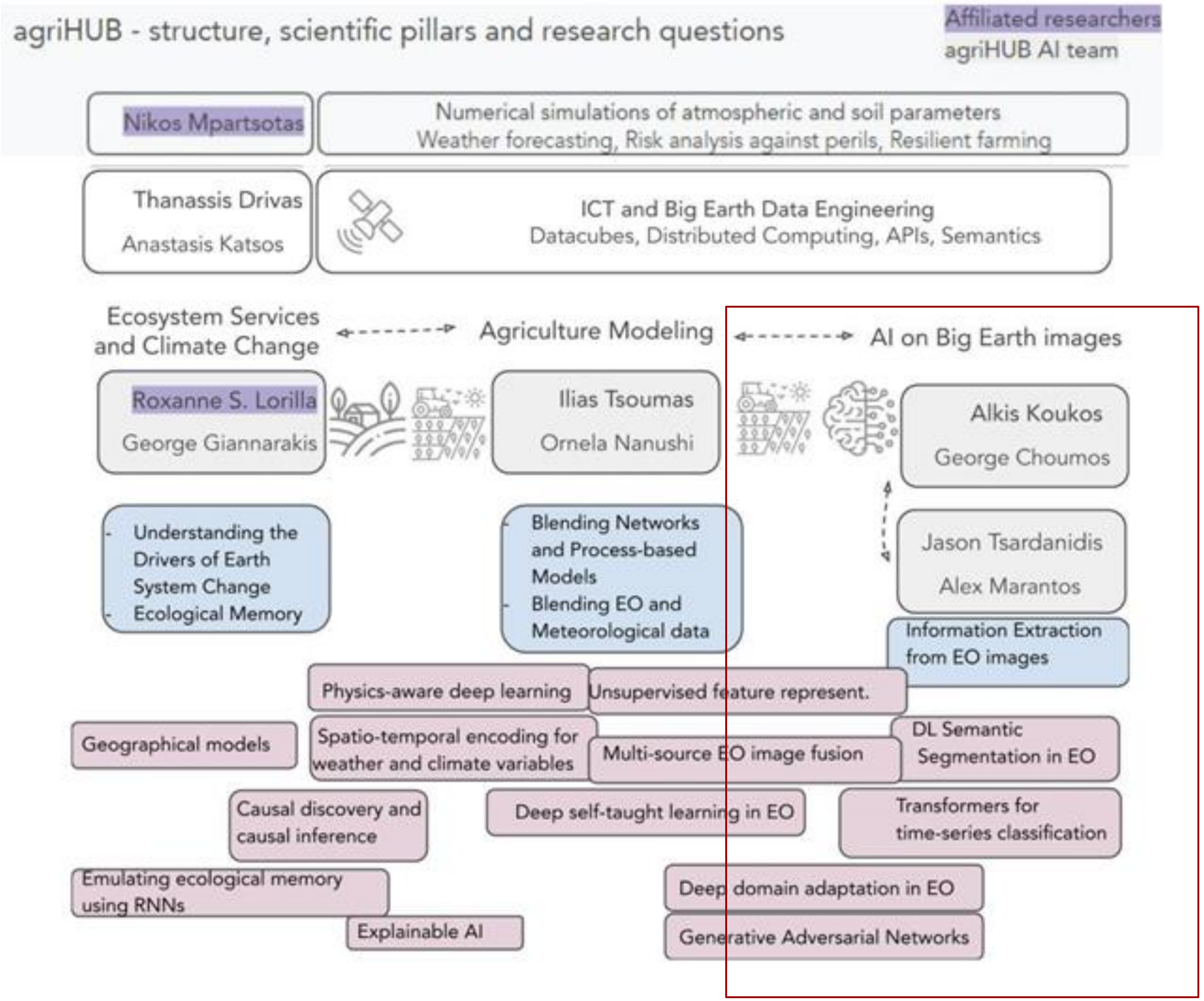


Domain of application is Agriculture

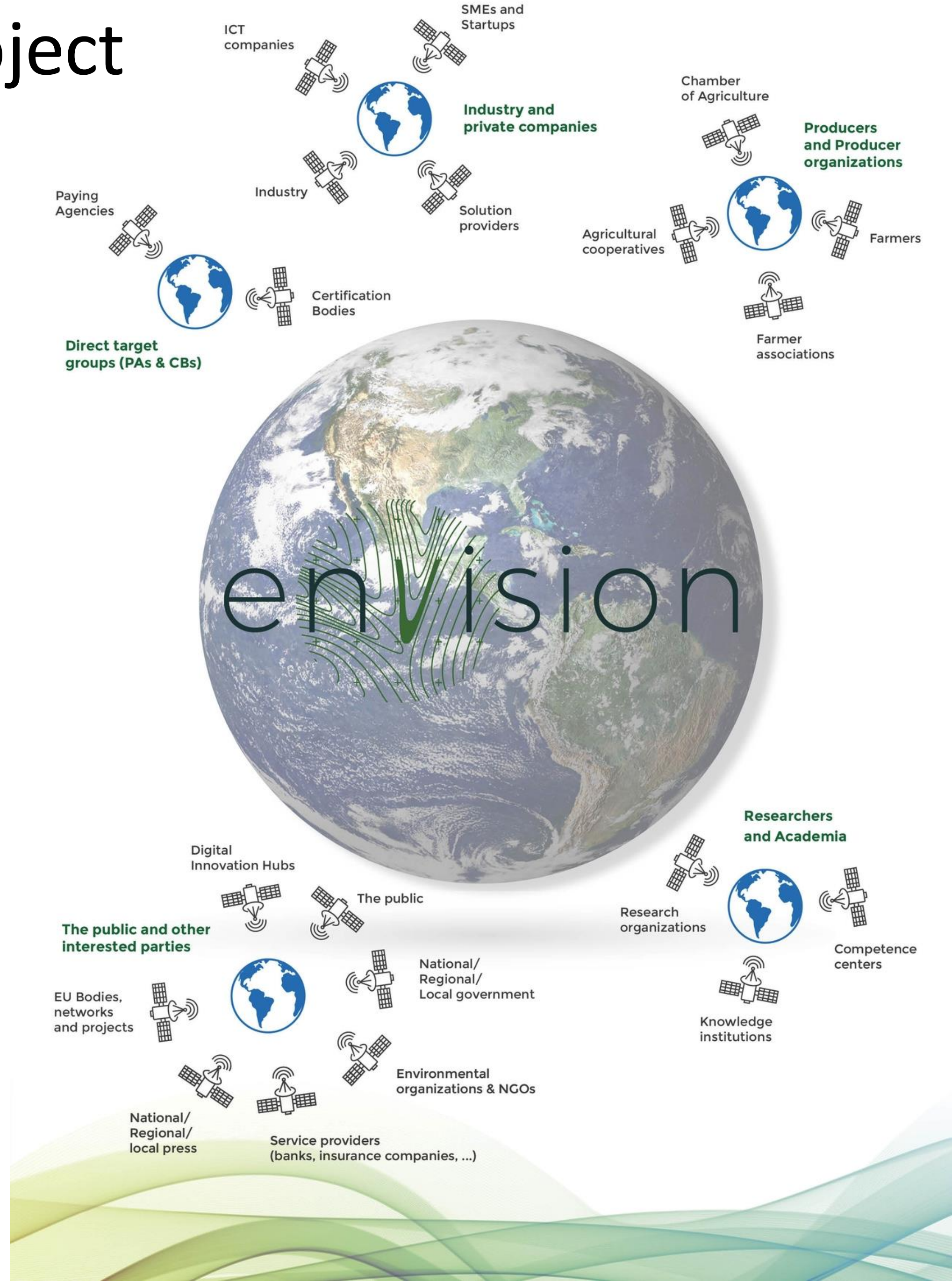
Emphasis in Computer Vision and Image Processing

Indicative tasks

- Image Classification
- Events Detection
- Fill missing values in SITS
- etc.

The ENVISION project

- CAP's environmental objectives contribution
- Tools for the continuous, large scale and uninterrupted monitoring of farm management activities with regards to sustainability.
- These tools reinforce the monitoring of environmental- and climate-friendly agricultural practices stemming from EU policy
- Towards CAP post-2020 and regional agricultural activities that do not severely impact the climate and nature.



ENVISION benefits

Farmer

- **Personalised** guidance
- **Boost the performance** of the cultivation
- Reduction of **administrative** burdens
- More **transparent** execution controls
- Avoid **penalties/ non-conformances**

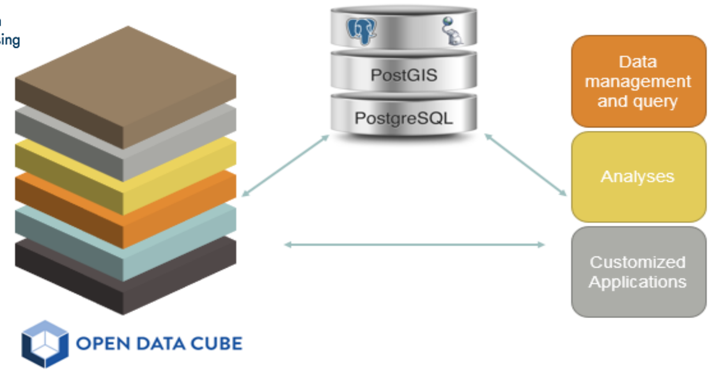
PAs and CBs

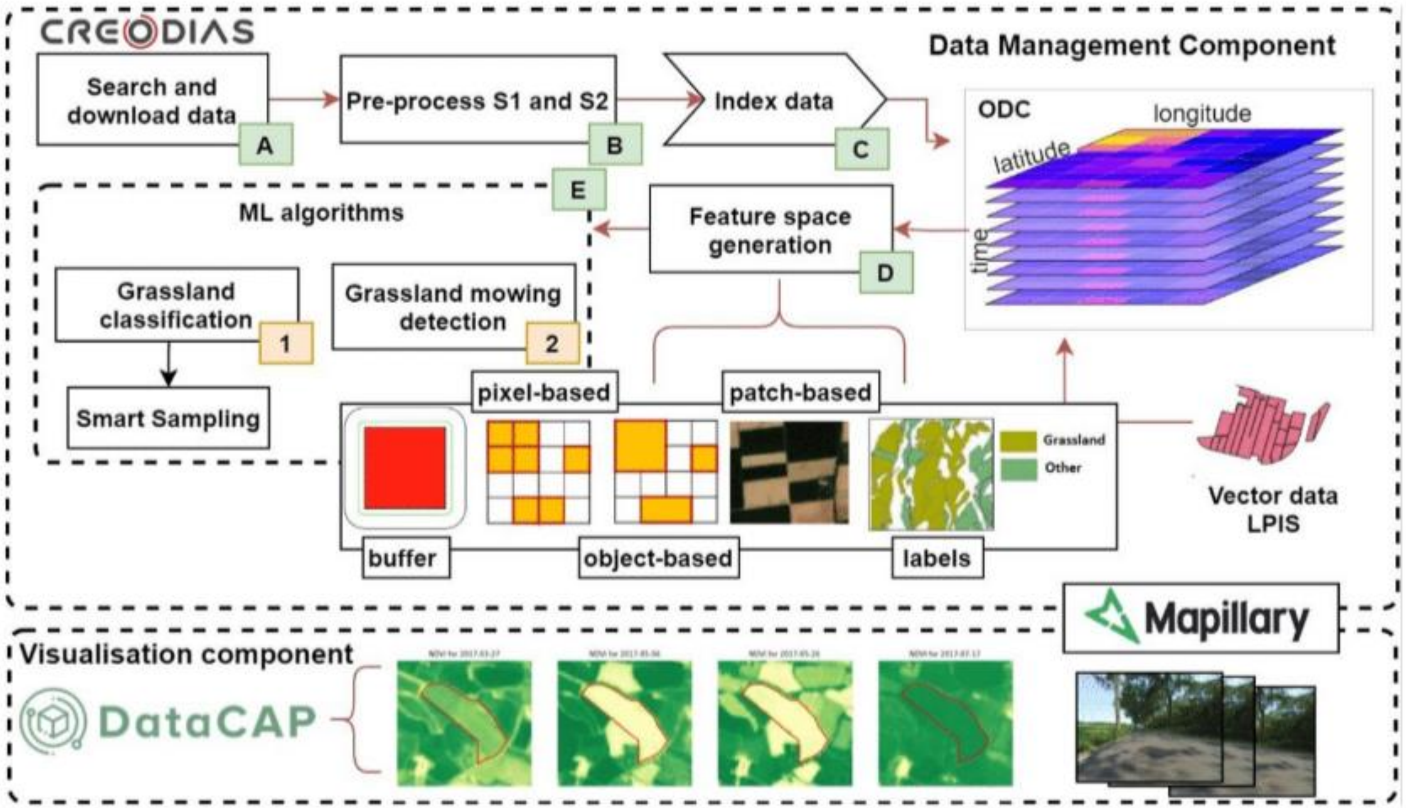
- More **targeted** on- field inspections
- Reduction of **costly & time-consuming** procedures
- Reduction of **operational and administrative** costs
- **Continuous monitoring** of farmland
- **Automated checks** based on EO data

Stakeholders

- **Better control system** based on satellite images
- Data **availability**, **accessibility** & **re-use**
- Design **more accurate** certifications
- **Modernise** the monitoring approach

Datacube in practice

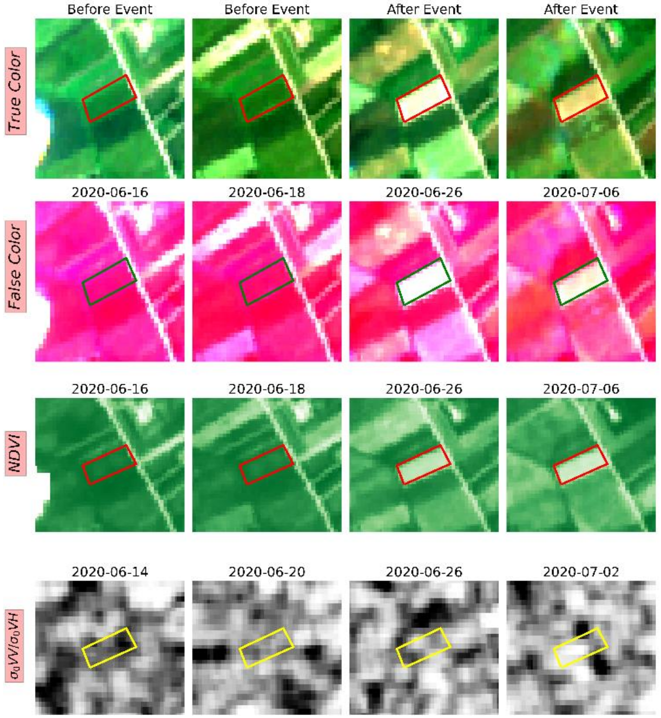


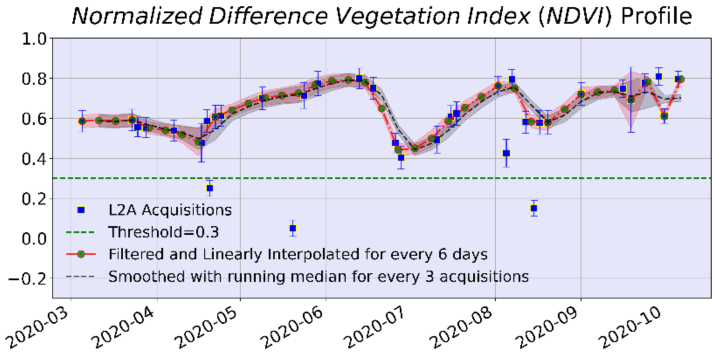


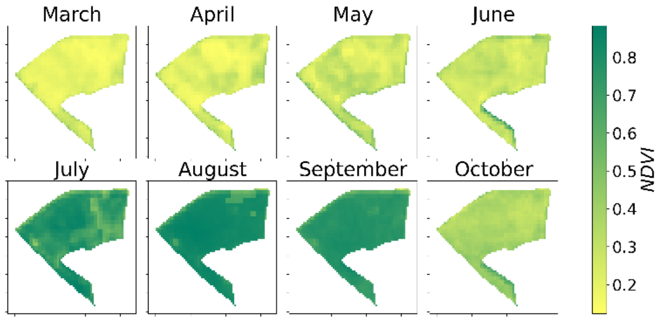
- Storage of various dataset, from Sentinel missions to LPIS
- Allow scalable continent scale processing of the stored data
- Creation of various feature spaces from the same data; Pixel-based, object-based, path-based

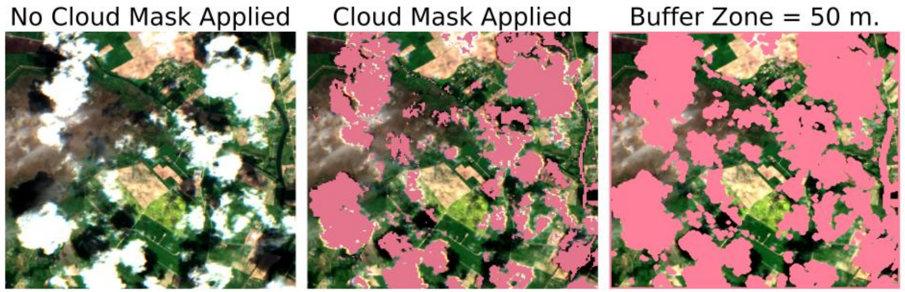
2 Full-Year Datacube datasets of Sentinel-1 and Sentinel-2 images for both Cyprus and Lithuania

Datacube on practice

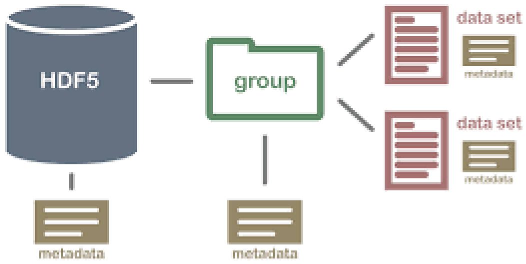






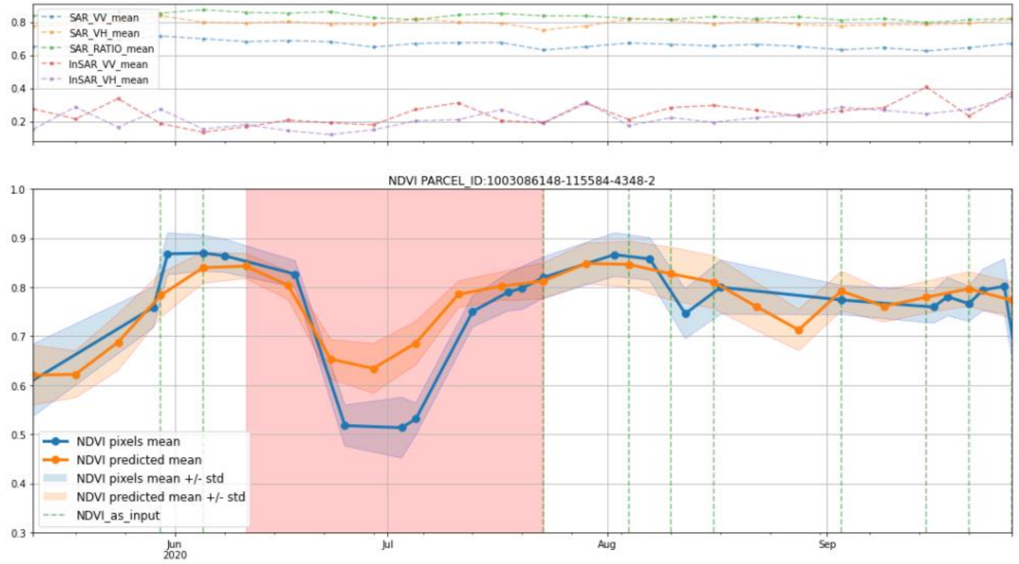


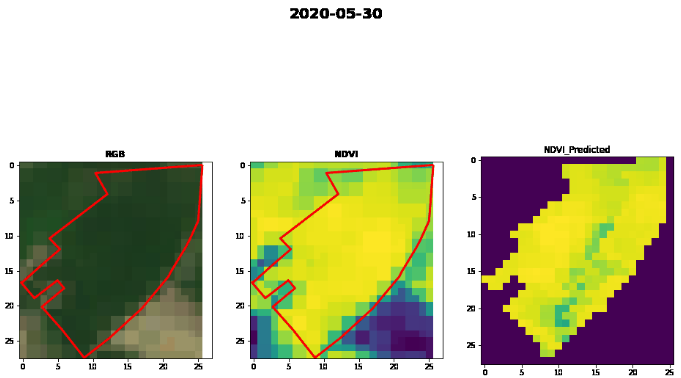
- Cloud Masking and Indices calculation
- Parcels Indexing and Rasterization
- Buffering
- Photo-interpretation
- Analytics and Summary Aggregated Statistics
- Fast and Easy subset extraction
- Pixel-wise Time-series preprocessing
- Etc.



Clouds and Small parcels

The ever present problems





Damn it's cloudy

- Employ validated fusion algorithms on Sentinel-1 and Sentinel-2 data to overcome cloud coverage

Damn that parcel is small

- Pixel-based classification and advanced AI algorithms can partly solve the problem
- Improved smart sampling to decide on the risk of false declaration even if the classification accuracy is suboptimal

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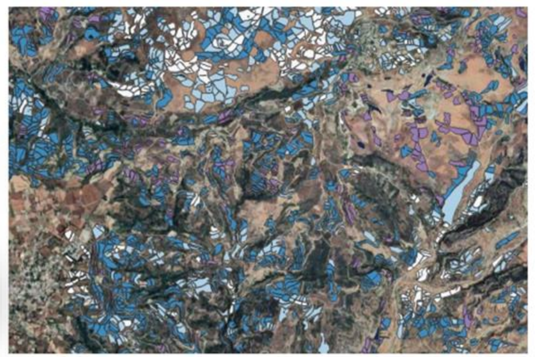
Analytics on Vegetation and Soil Index Time-series

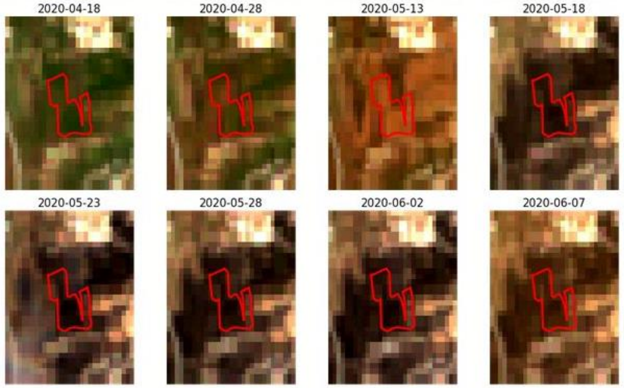
RUSLE estimation for Runoff Risk Assessment



EO Products provided

- **GAECs** and **SMRs** requirements – Incompliance Maps
  - Proximity to water-ways / Runoff Risk assessment for NVAs water pollution (**GAEC1/SMR1**)
  - Minimum soil cover for Soil Erosion (**GAEC 4**)
  - Stubble Burning Identification and Burnt Scar Mapping (**GAEC 6**)
- **Harvest Event Detection** and Detection of illegal activity on **Natura2000** regions
- Other GIS and **Analytics functionalities**:
  - Temporal/Zonal Statistics
  - Animations of temporal evolution of an area
  - Smart Multi-faceted Geospatial Queries
  - Index Anomalies
  - Trends detection

Stubble Burning Identification



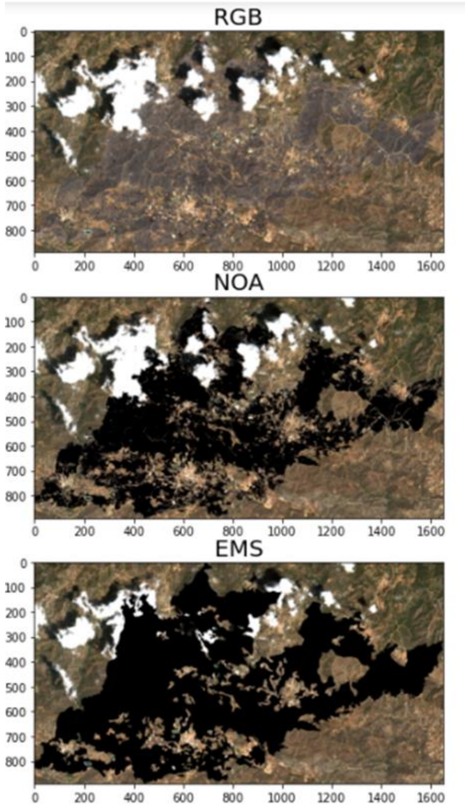
Harvest events detection (Lithuania)

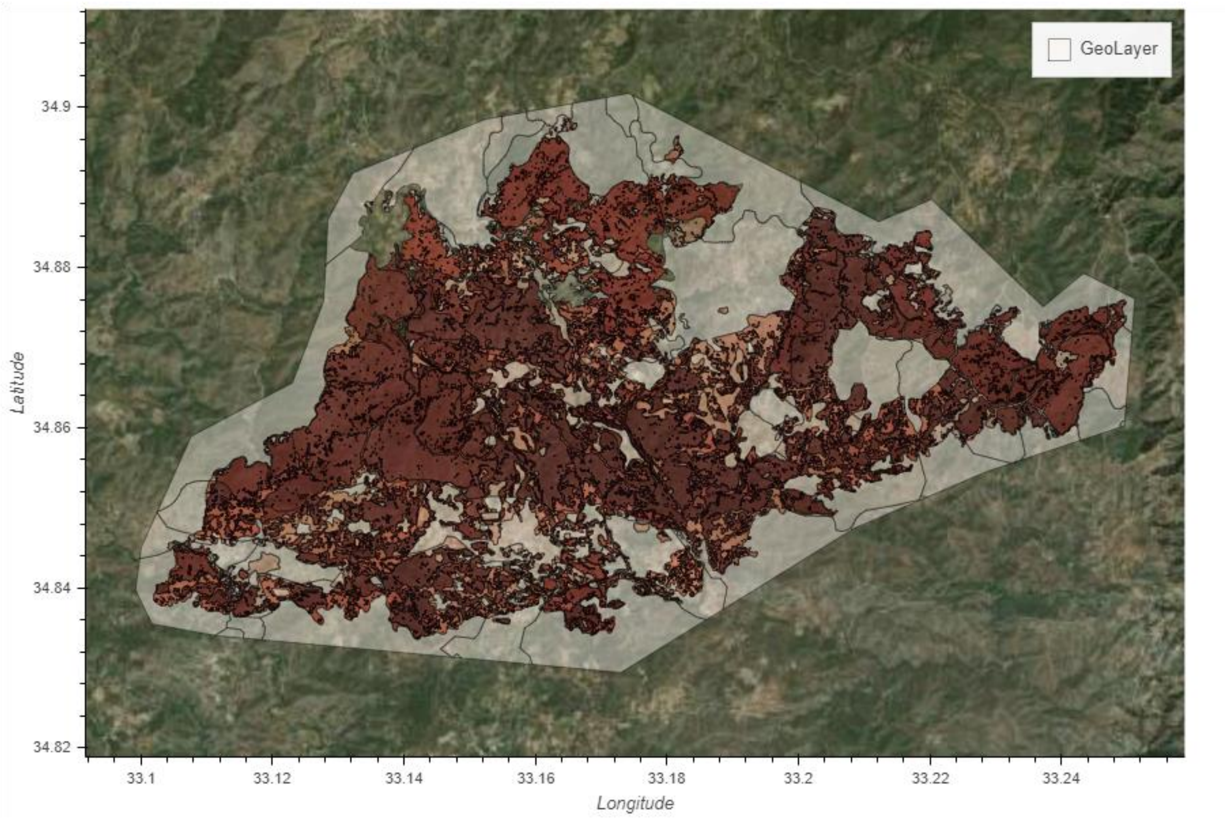
Illegal Activity detection on Natura2000 regions (Cyprus)

before after

Stubble Burning Identification and Burnt Scar Mapping

ALGORITHM CRASH TEST: Devastating Cyprus Forest Fire in July 2021



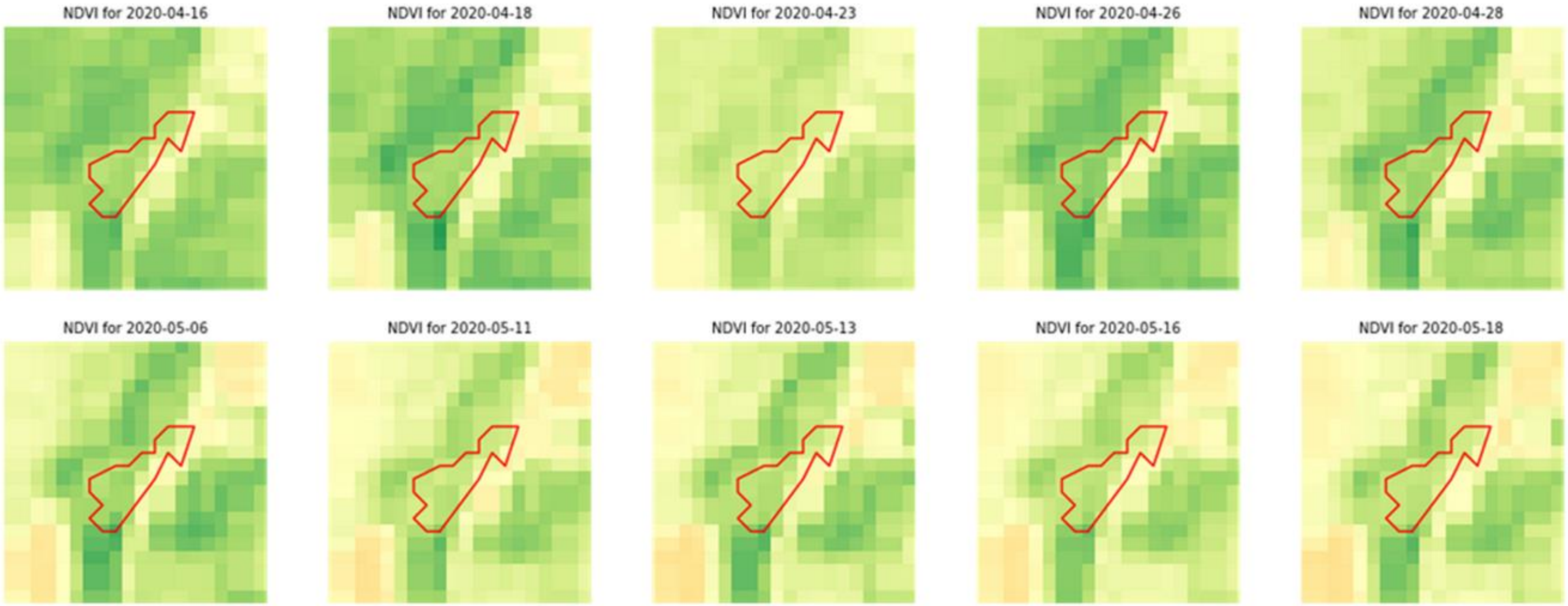


- Results Exported into parcel level in order to assist CAPO personnel on damage evaluation.

ENVISION Data Cube GeoTiffs ftp service

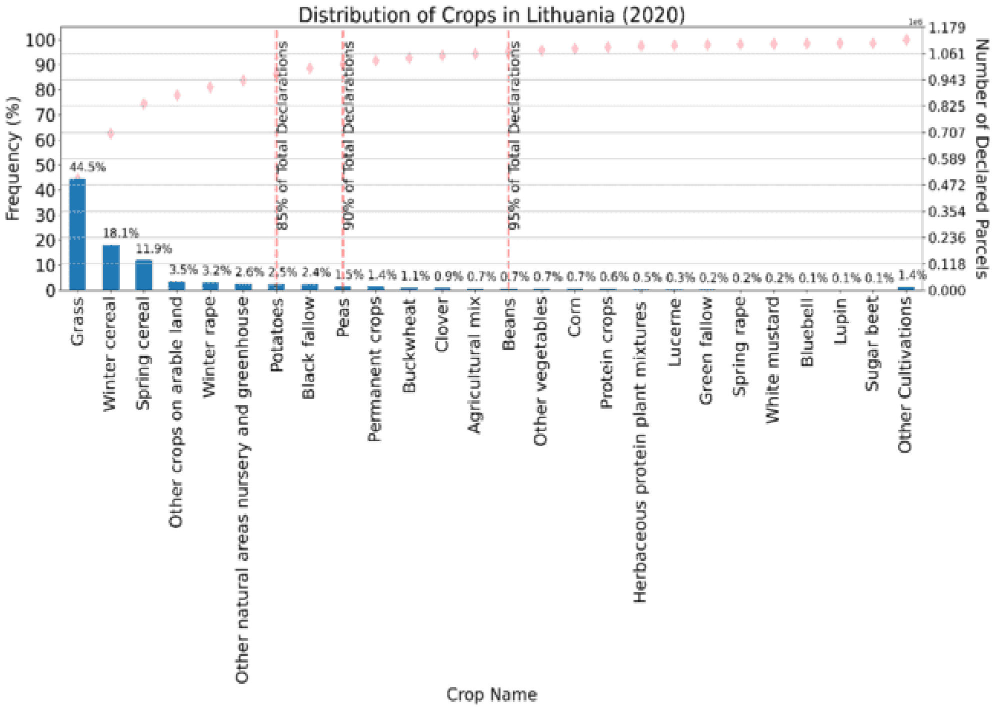
http://185.178.86.82/api/parcels/{id}/{starting_date}/{ending_date}/{band/index}

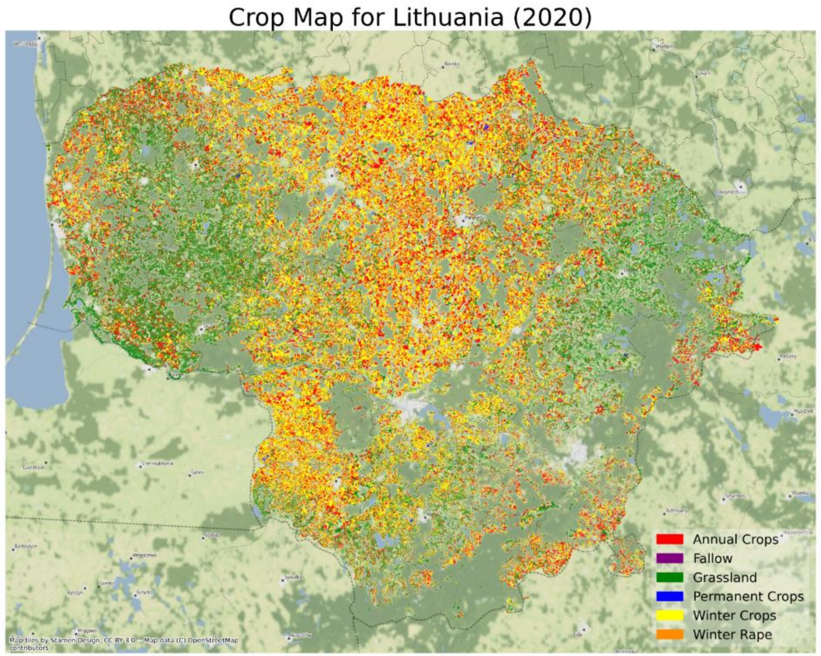
e.g. http://185.178.86.82/api/parcels/24/2021-11-01/2022-06-01/ndvi

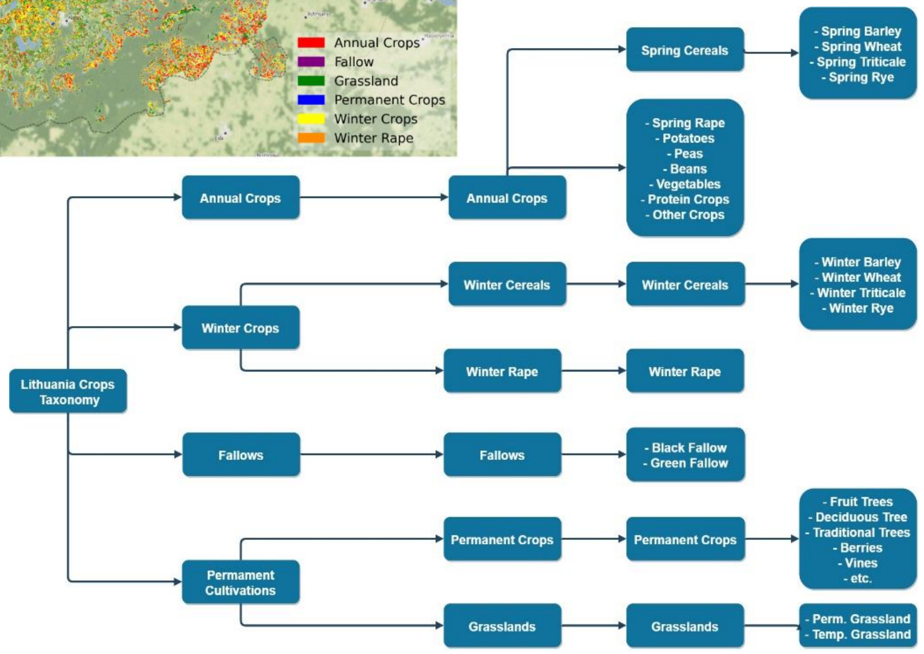


Cultivated crop type maps - Lithuania

Crops Distribution - Lithuania

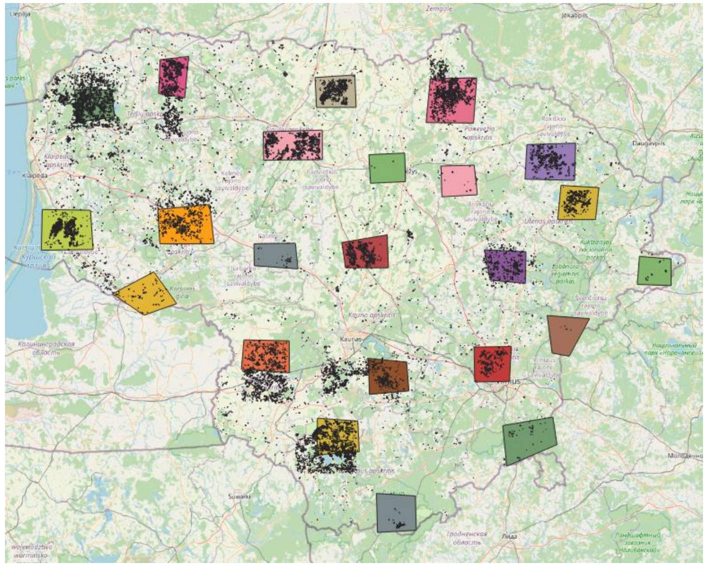


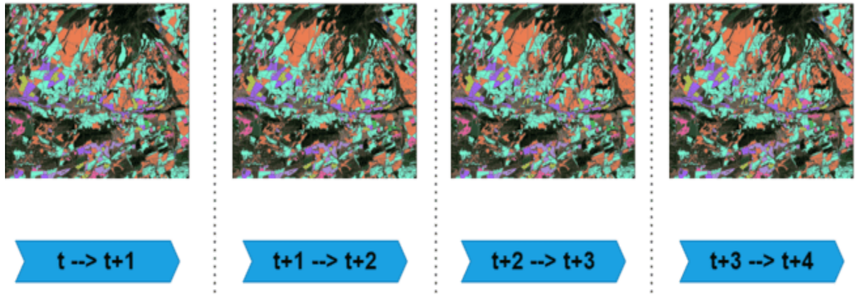




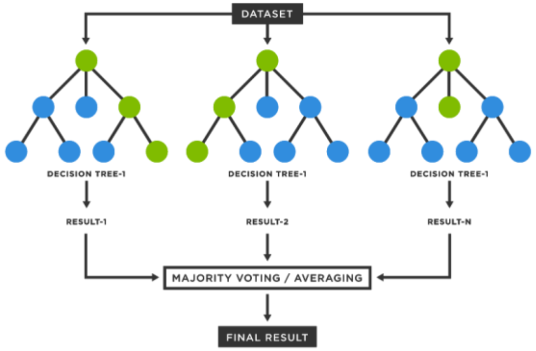
Cultivated crop type maps - Lithuania

Dynamic Crop Type Mapping





Random Forest



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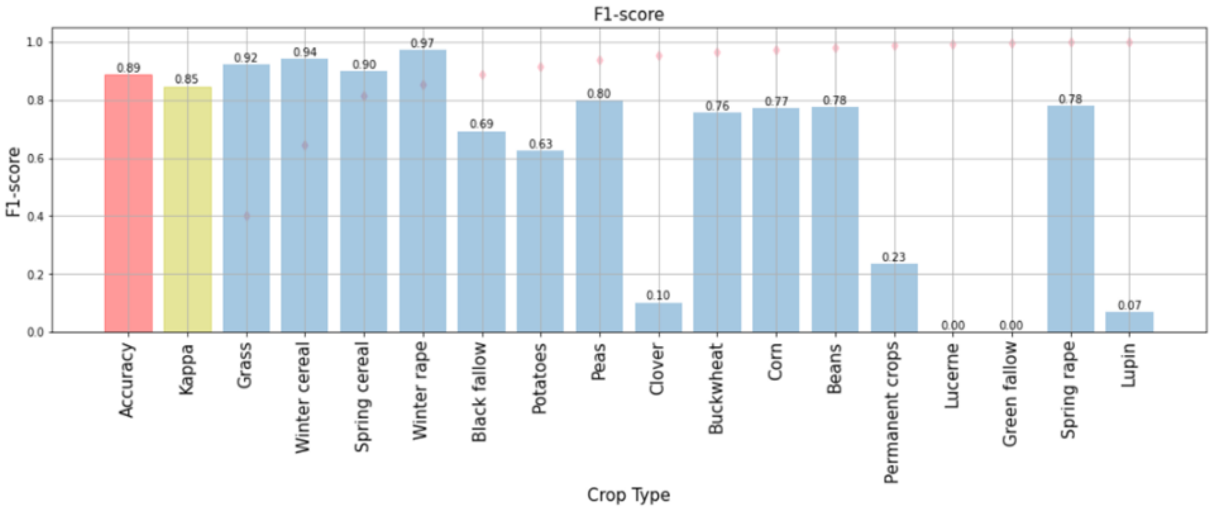
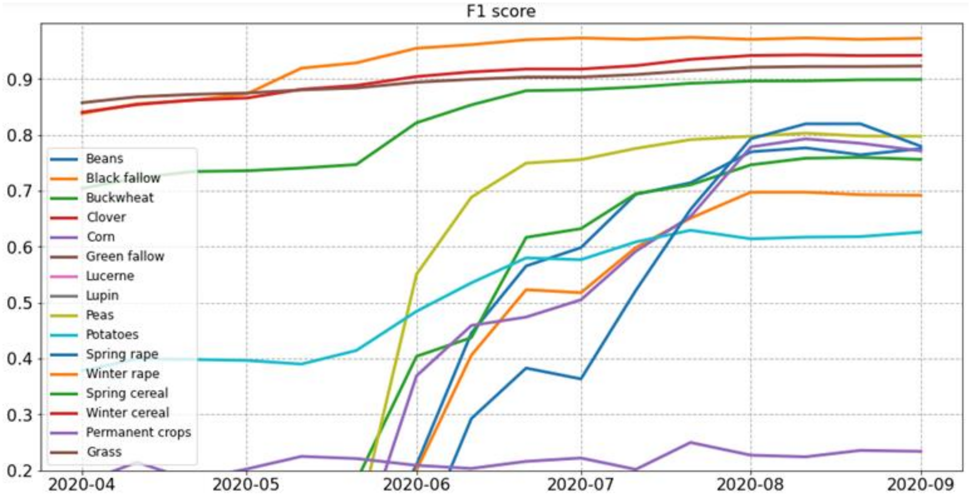
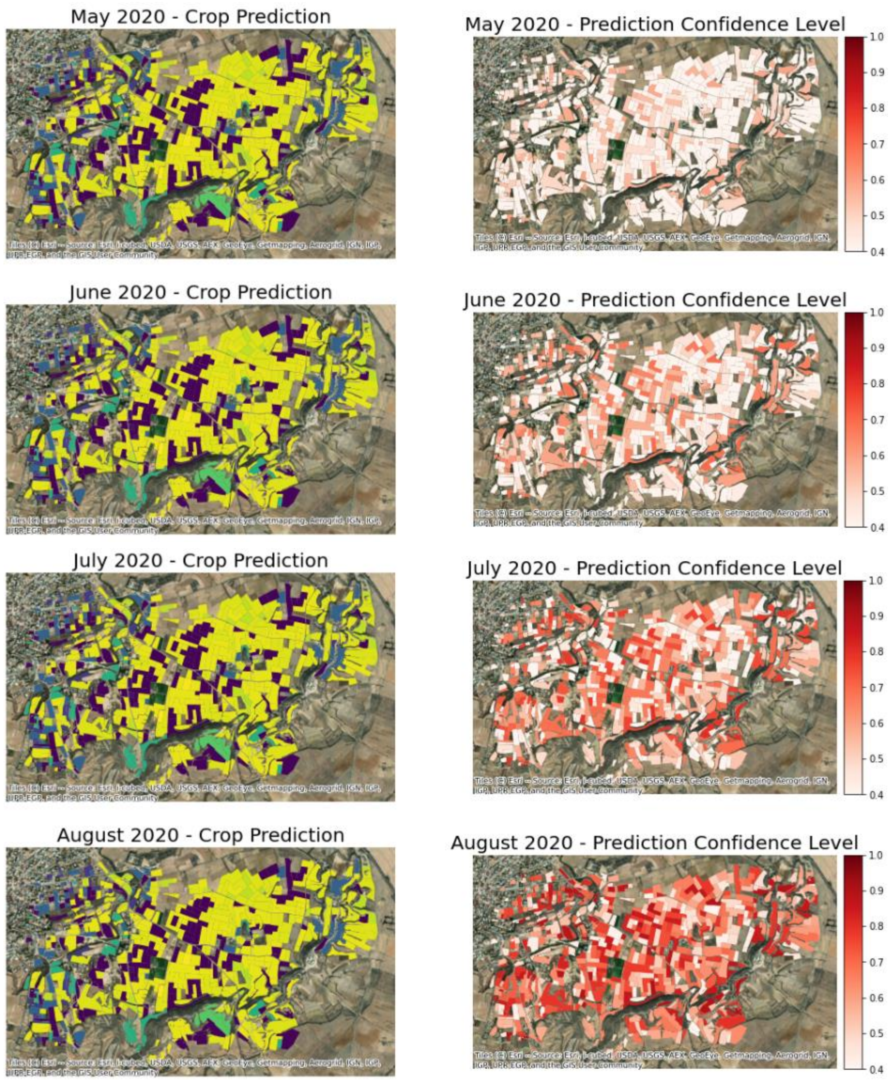
Cultivated crop type maps - Lithuania

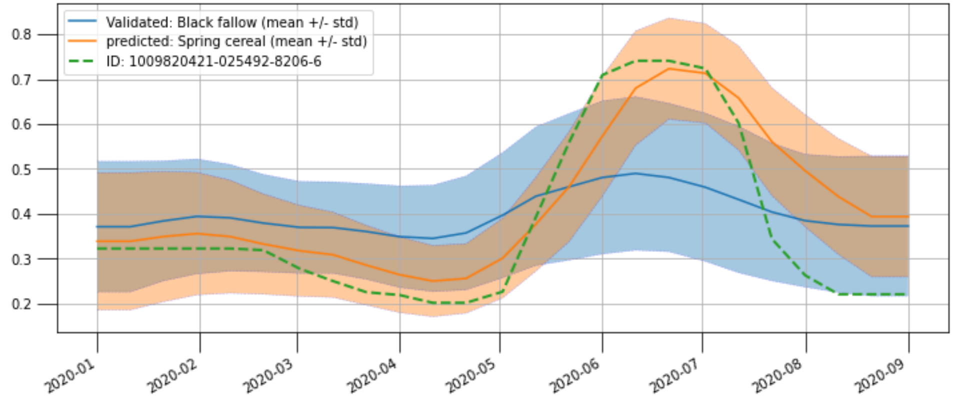




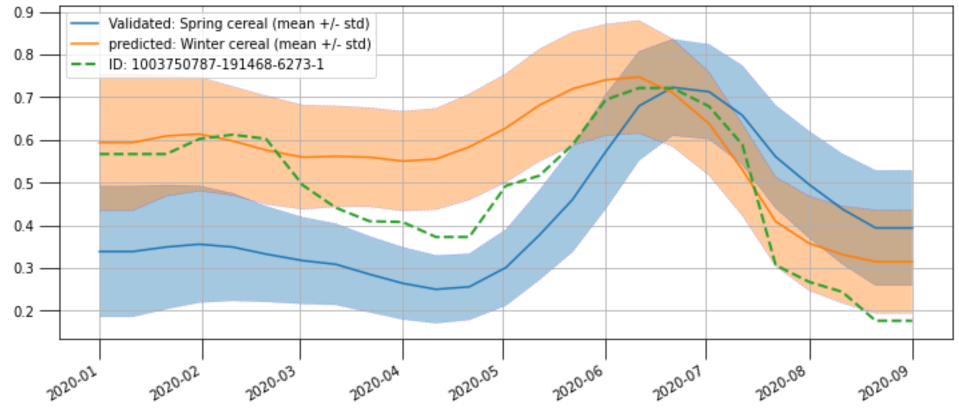


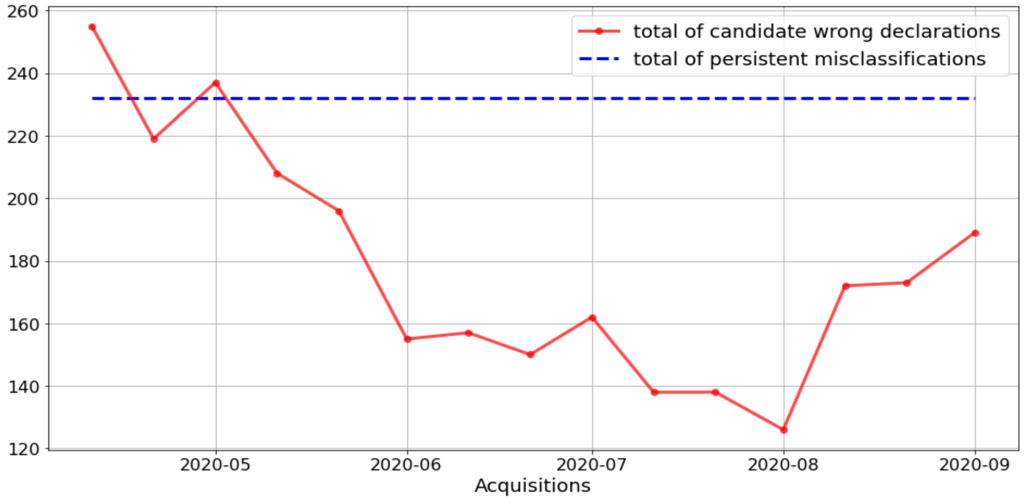
Cultivated crop type maps - Lithuania

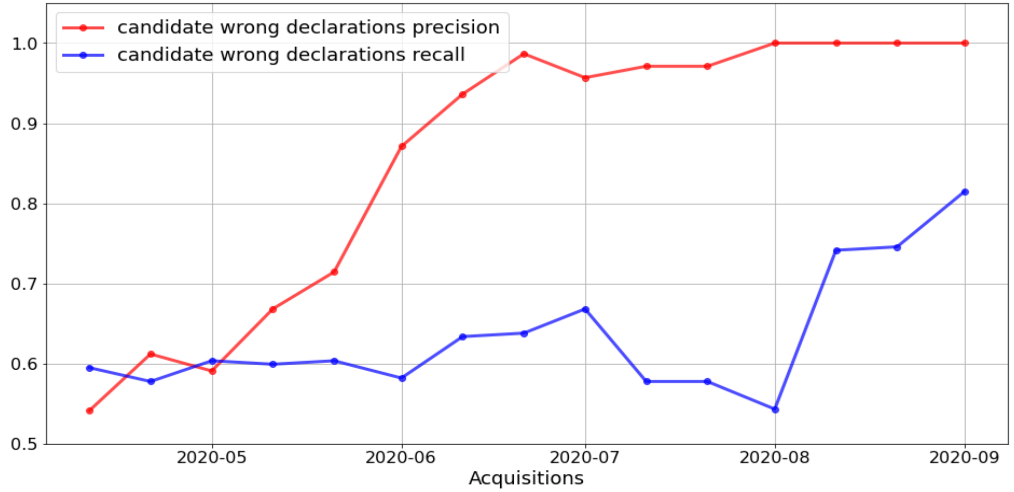
Example 1. NDVI of a case predicted as Spring Cereal and the label given is Black Fallow



Example 2. NDVI of a case predicted as Winter Cereal and the label given is Spring Cereal



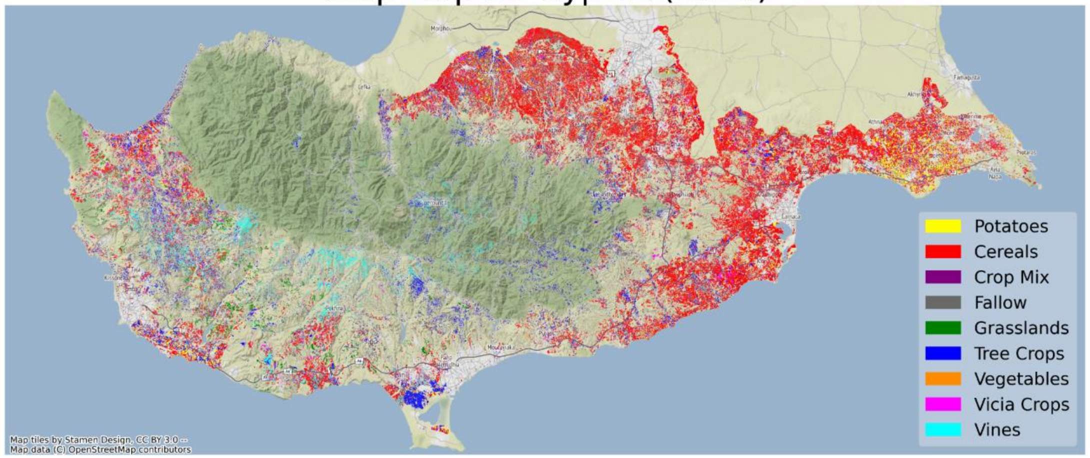


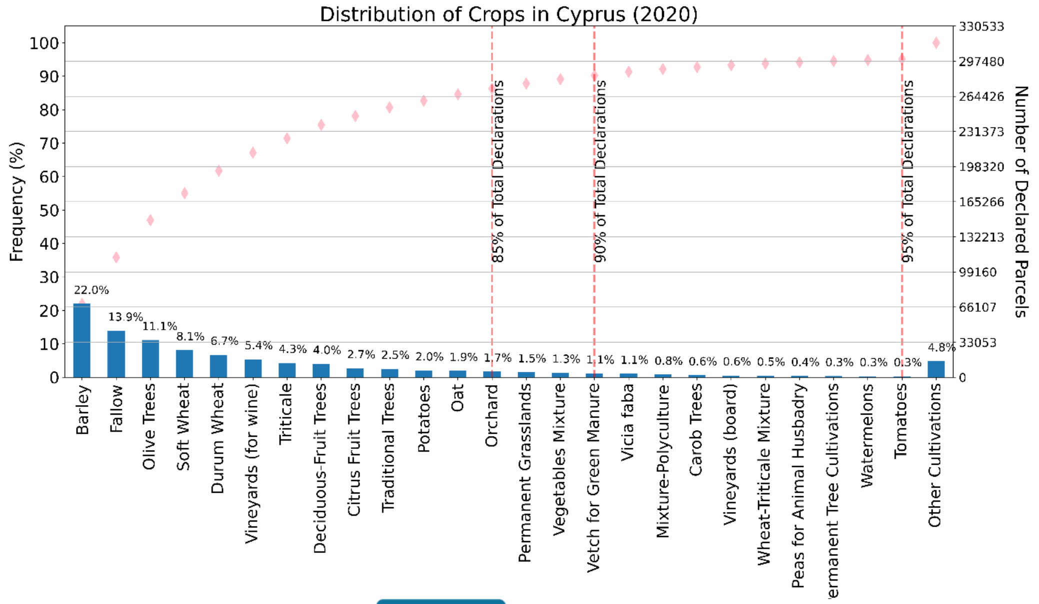


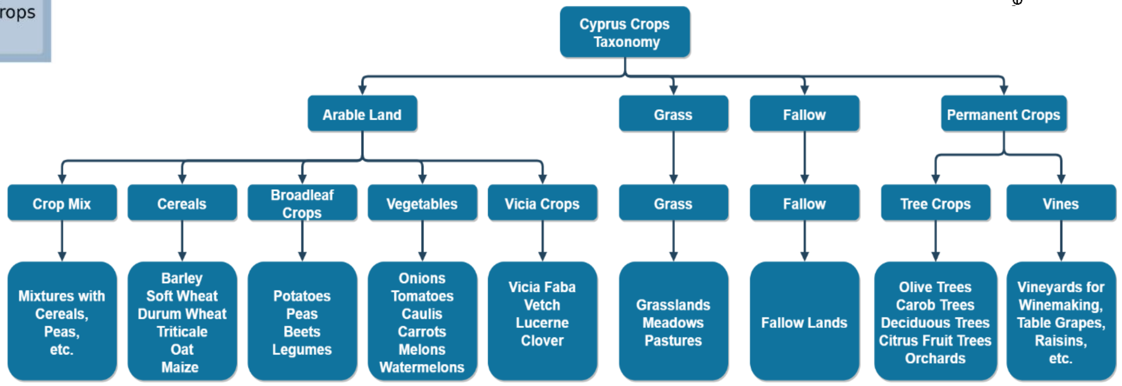
Cultivated crop type maps - Cyprus

Crops Distribution - Cyprus

Crop Map for Cyprus (2020)







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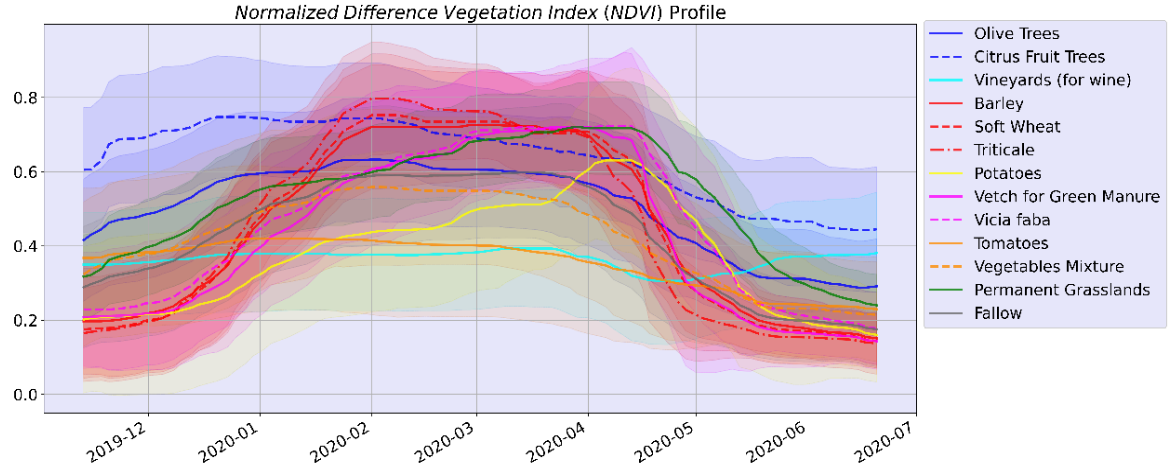
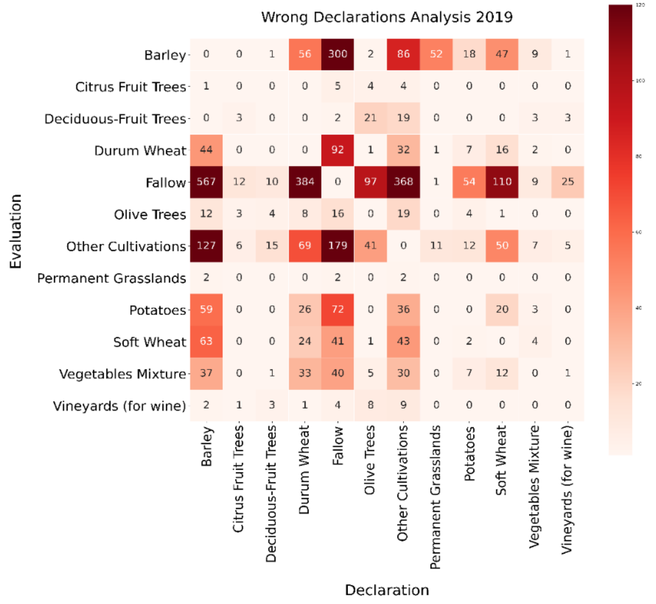
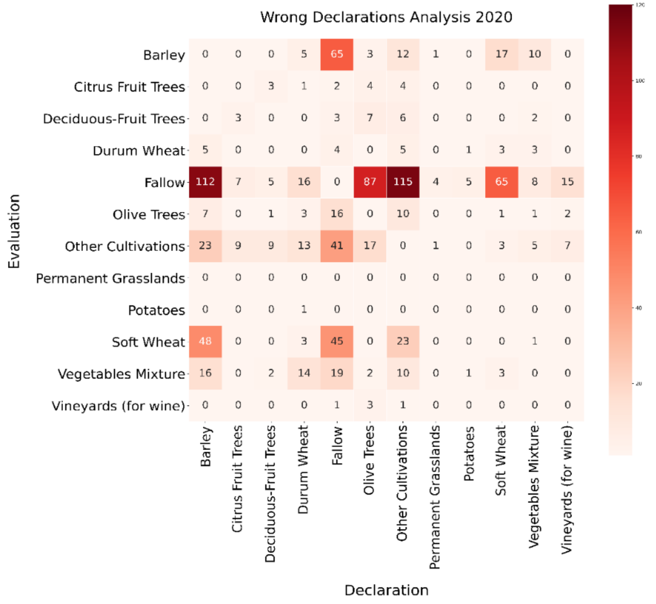
Cultivated crop type maps - Cyprus

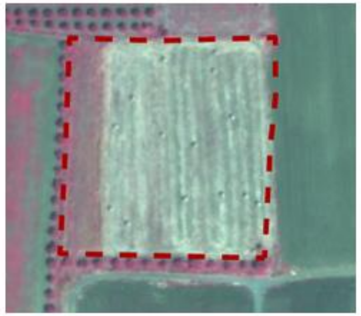
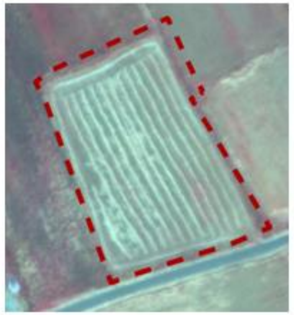




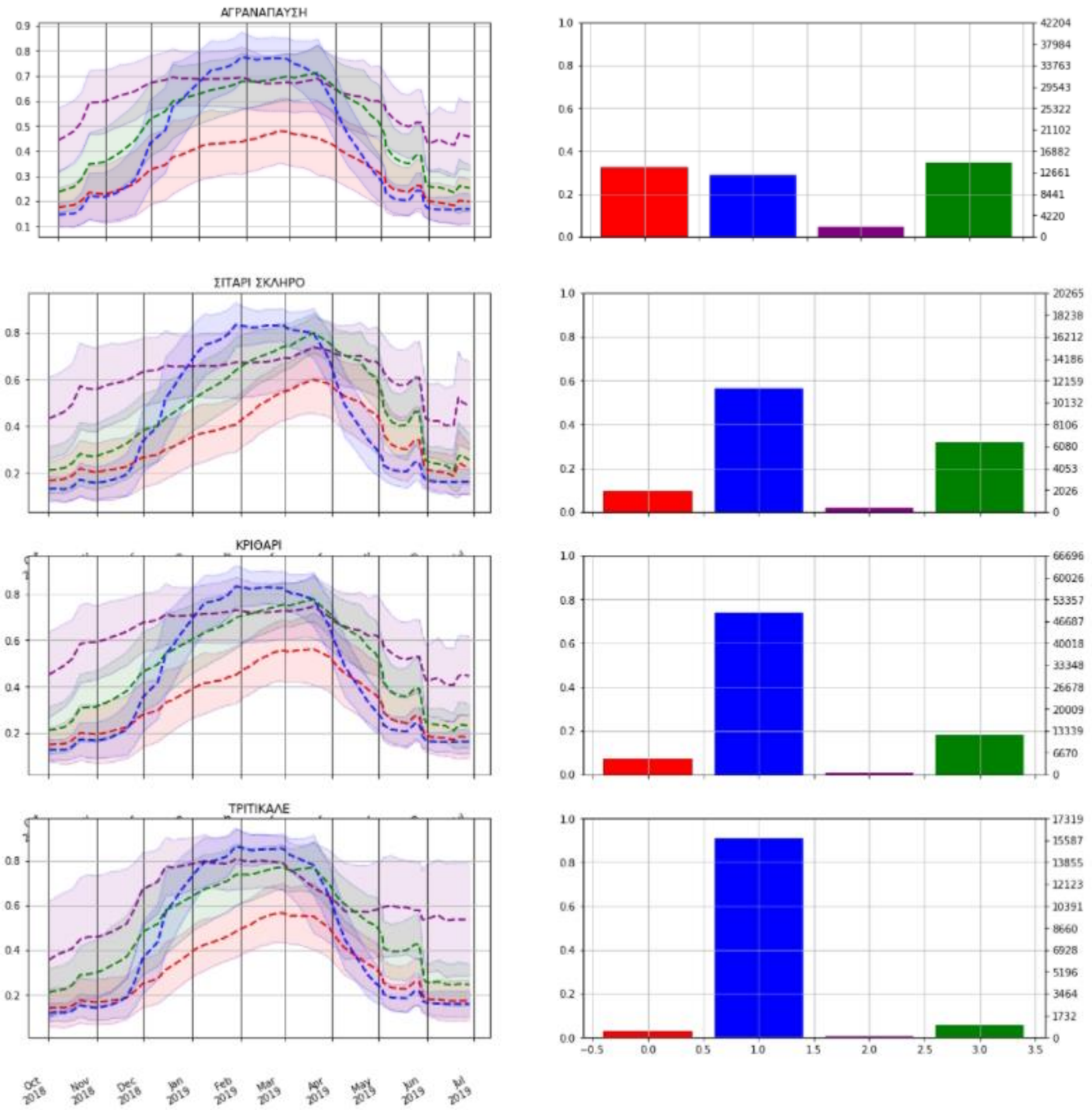


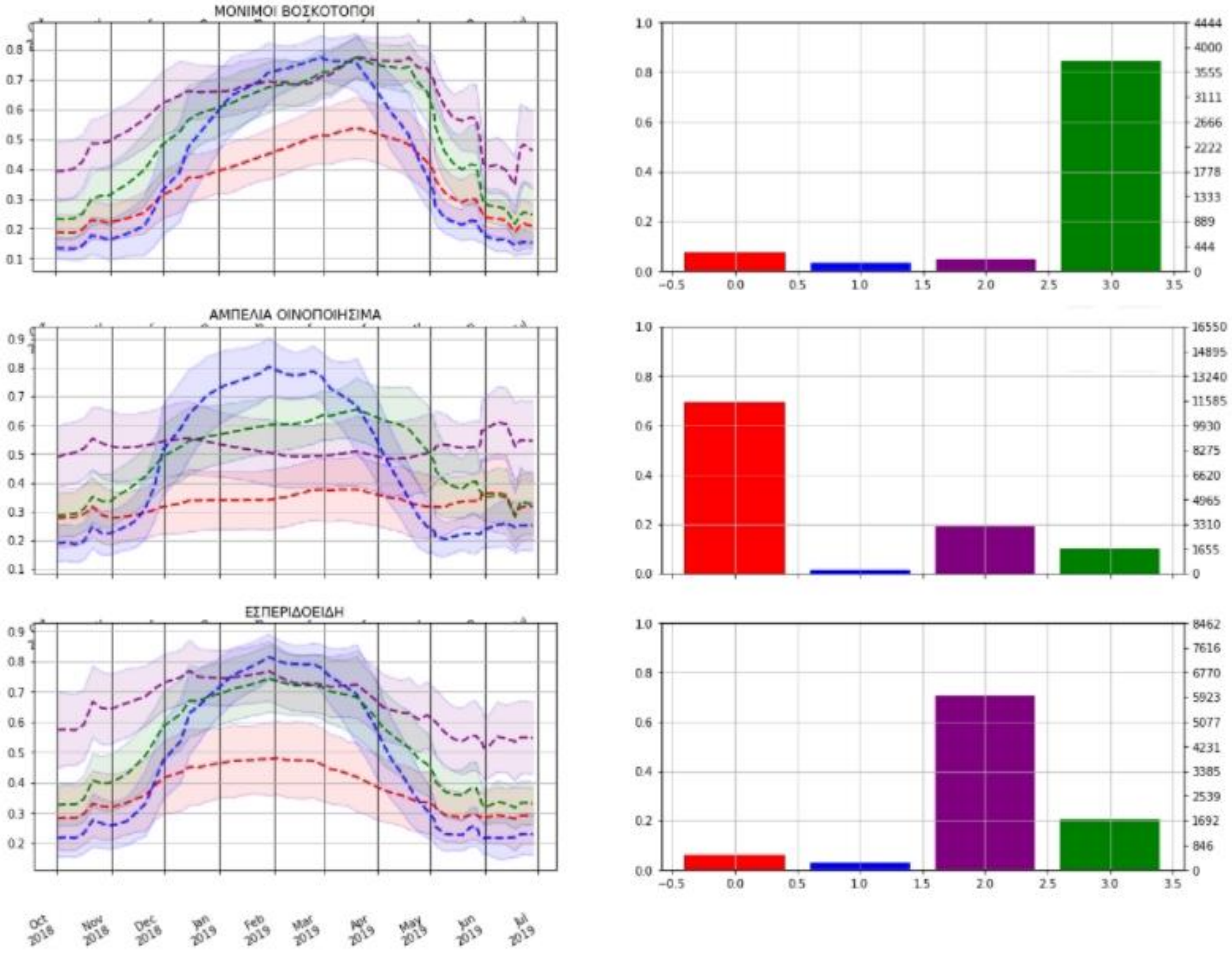
Fallow Land Case



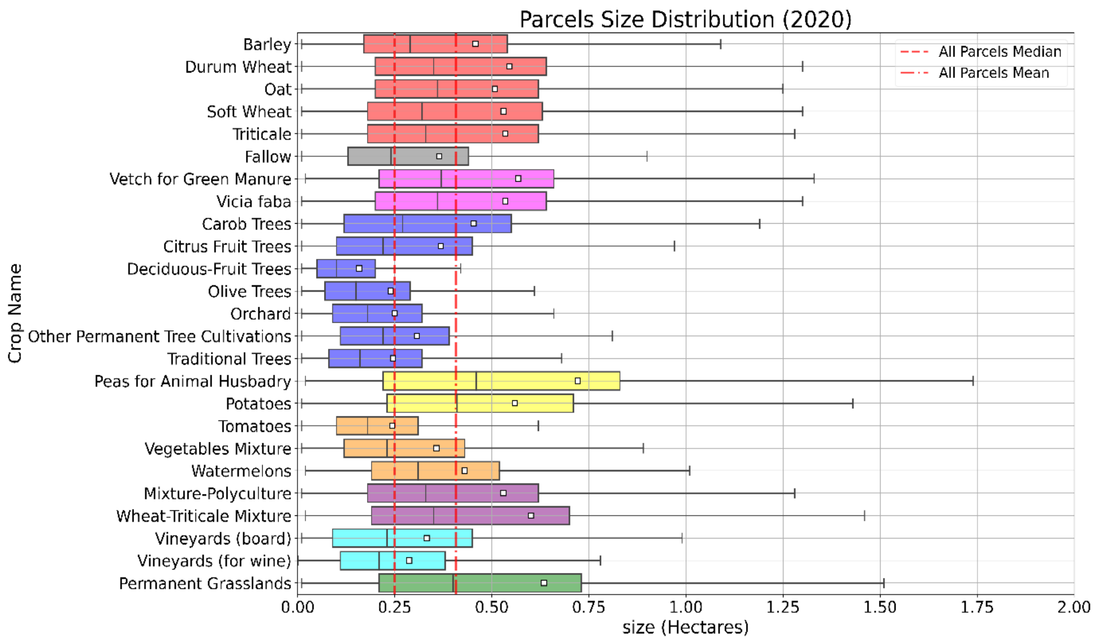
Cultivated crop type maps - Cyprus

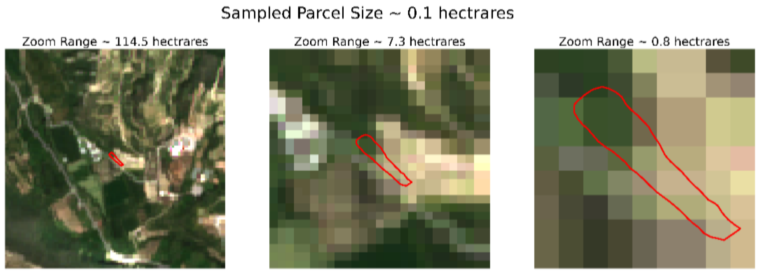




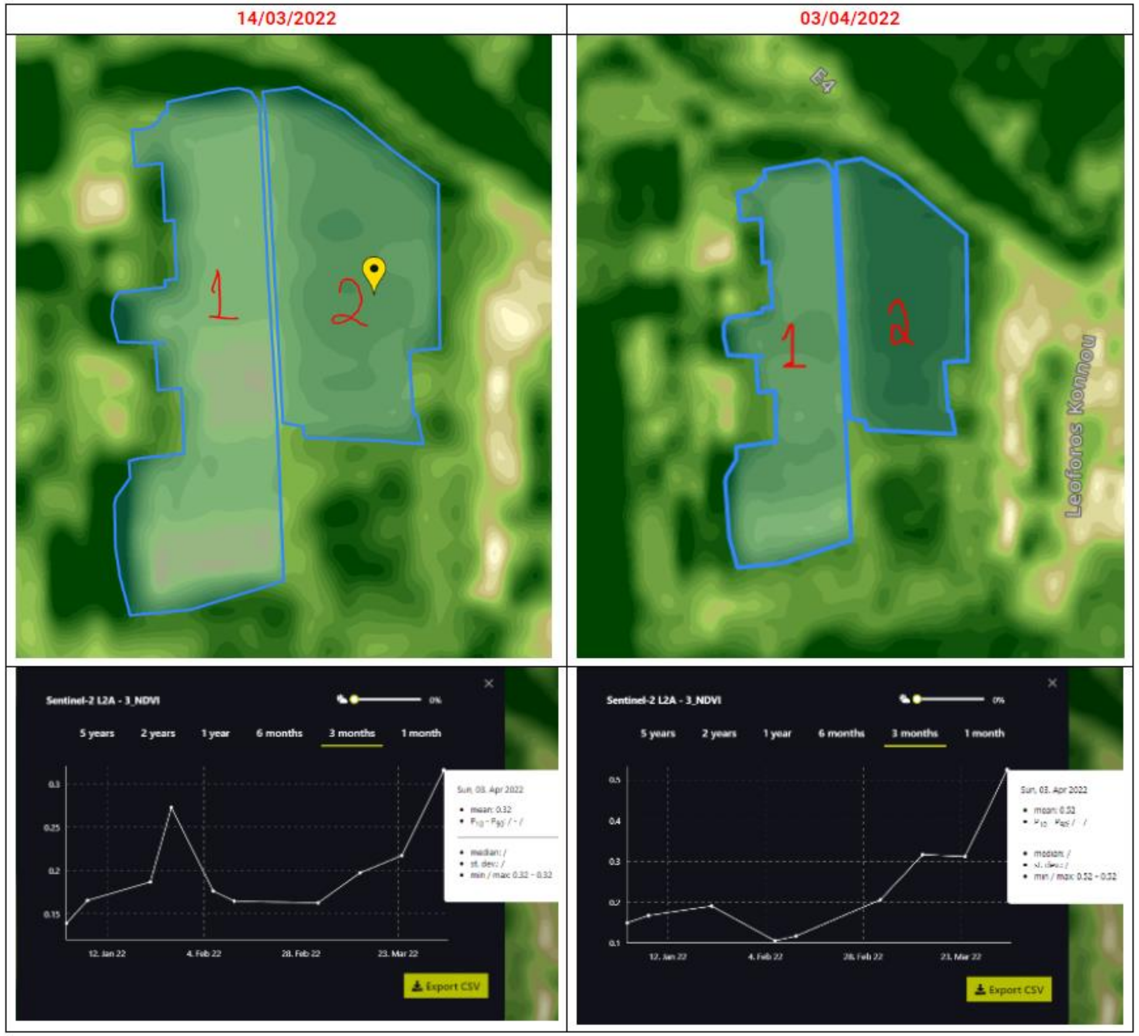
Cultivated crop type maps - Cyprus

Small Parcels Issue





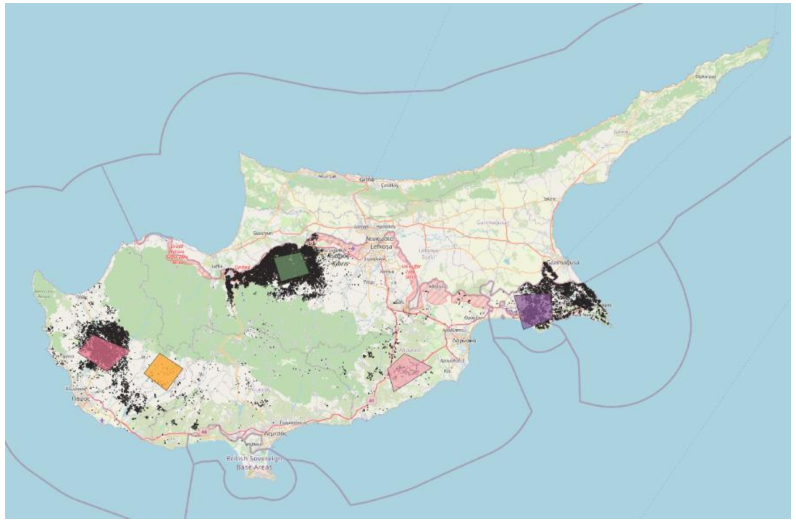
Cultivated crop type maps - Cyprus

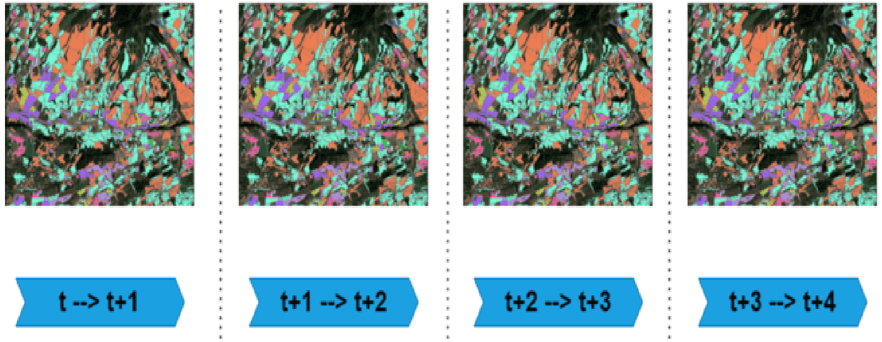


Greenhouses (Temporal vs Permanent)

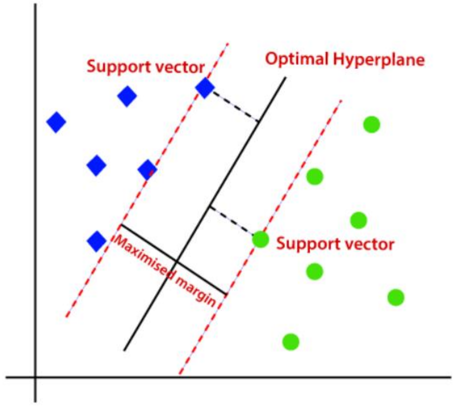
Cultivated crop type maps - Cyprus

Dynamic Crop Type Mapping

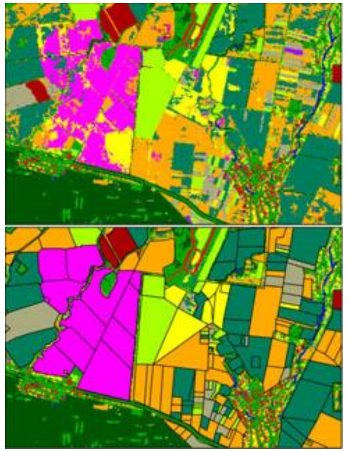




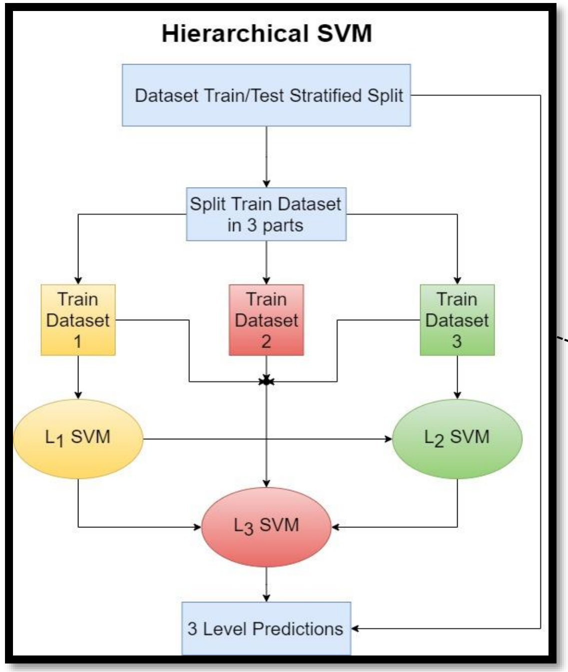
Support Vector Machine

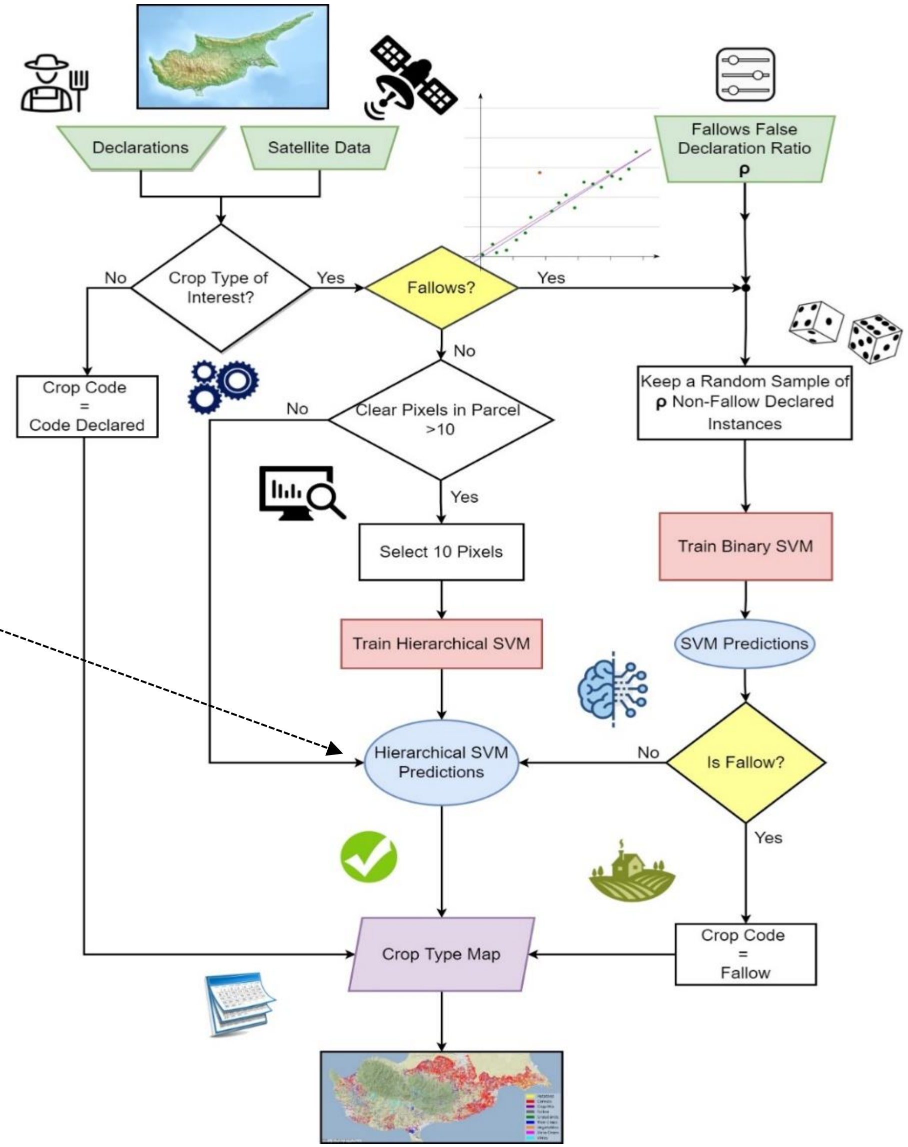


From Pixel to Parcel



Cultivated crop type maps - Cyprus





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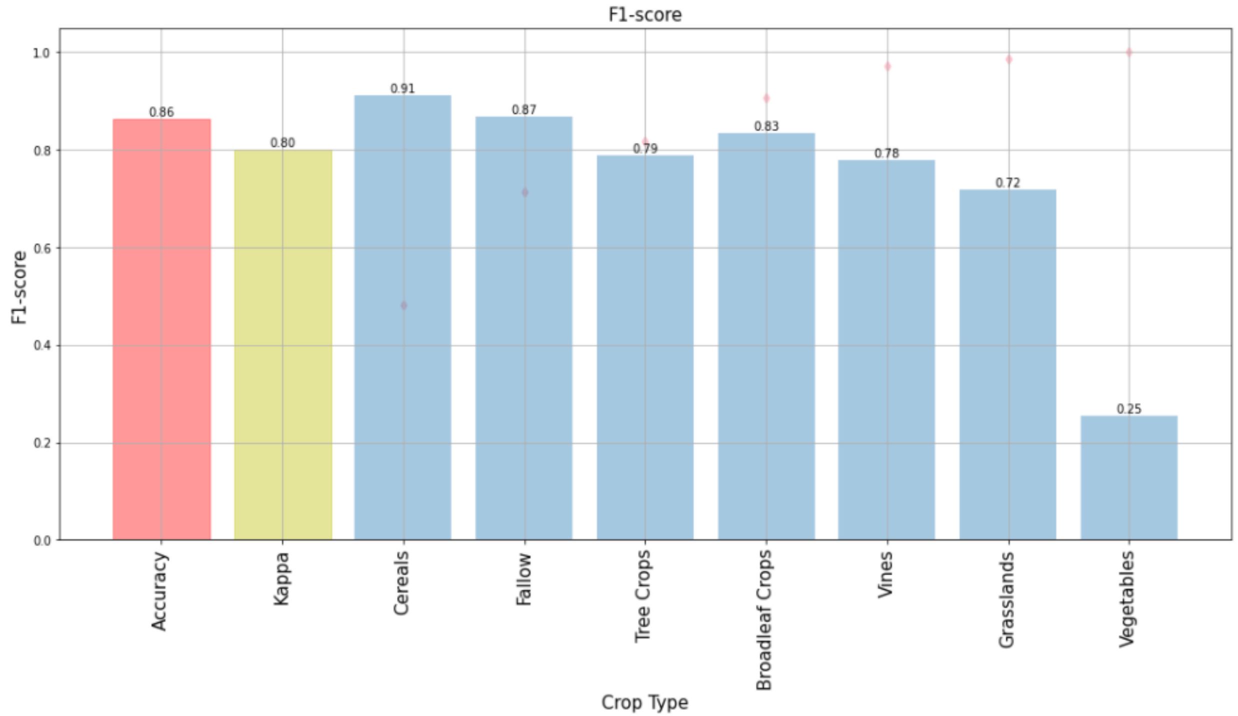
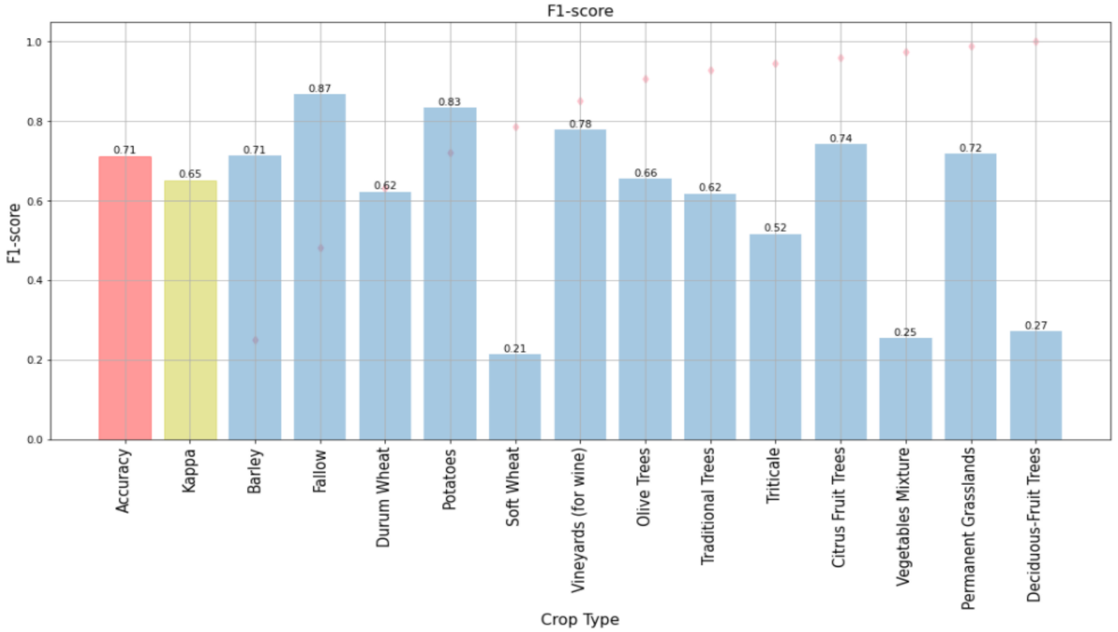
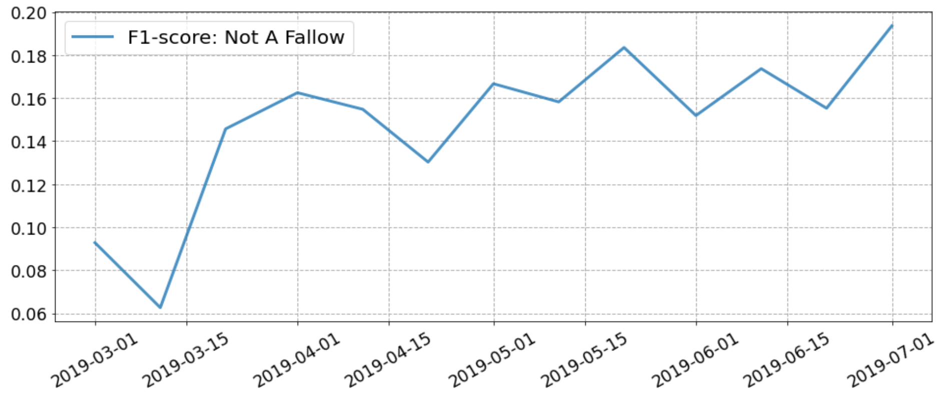






Cultivated crop type maps

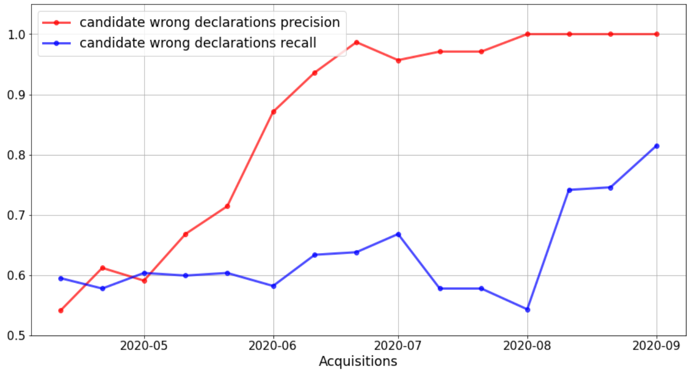
EO services

- **Smart Sampling for OTSC** (traffic light system): sophisticated algorithm evolving dynamically throughout the cultivation period by exploiting the current and the previously generated Crop Type Maps, to identify the most confident misclassifications and potentially false declarations.

  M. Rousi et al., "Semantically Enriched Crop Type Classification and Linked Earth Observation Data to Support the Common Agricultural Policy Monitoring," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 529-552, 2021, doi: 10.1109/JSTARS.2020.3038152

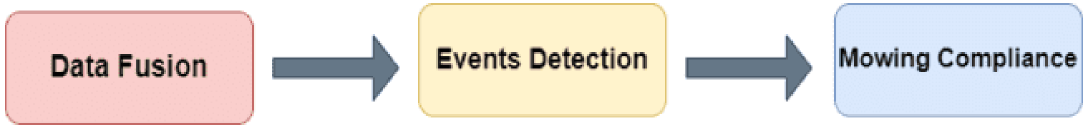
- **Crops Diversification Compliancy Maps (Greening I):** a compilation of if-conditions according to the Greening 1 set of rules which examines the hypothetical impacts between an actual truth and crop label mapped. Exploits LPIS and the declarations of the farmers.

Precision and Recall of smart sampling algorithm over cultivation period

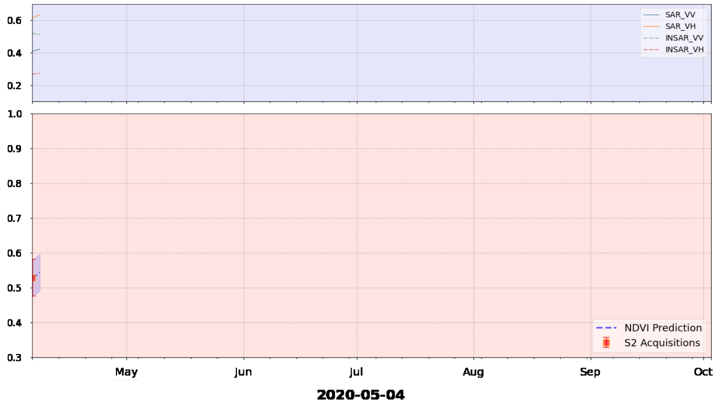


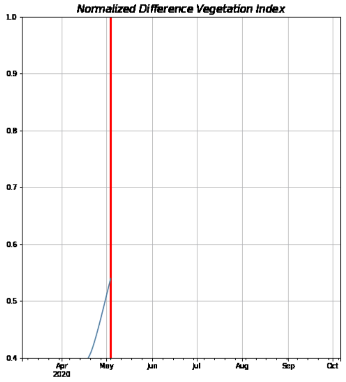
Greening I Compliance Map

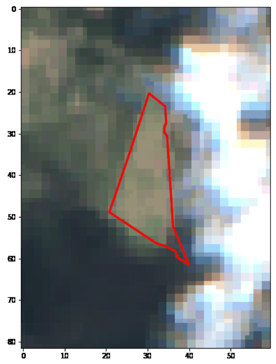
Grasslands Mowing Events Detection



- Reconstruction of NDVI based on S1 data (Cloud Coverage)
- Mowing events identification based on the new artificially created NDVI
- Mowing compliance results according national regulations





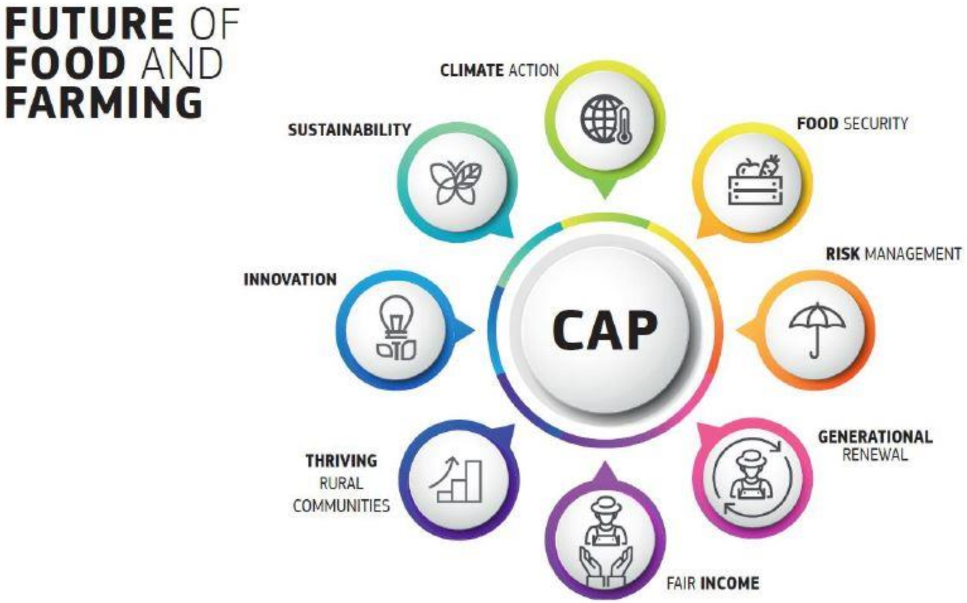


Deep Learning for fusion of Sentinel-1 and Sentinel-2 data and grassland mowing detection

Overview

- Grassland Monitoring for the Common Agricultural Policy (CAP)
- Extensive Cloud Coverage and S1-S2 Fusion
- Deep Learning for Event Detection
- Quantification of the Grassland Use Intensity and CAP monitoring
- Remarks & Future work

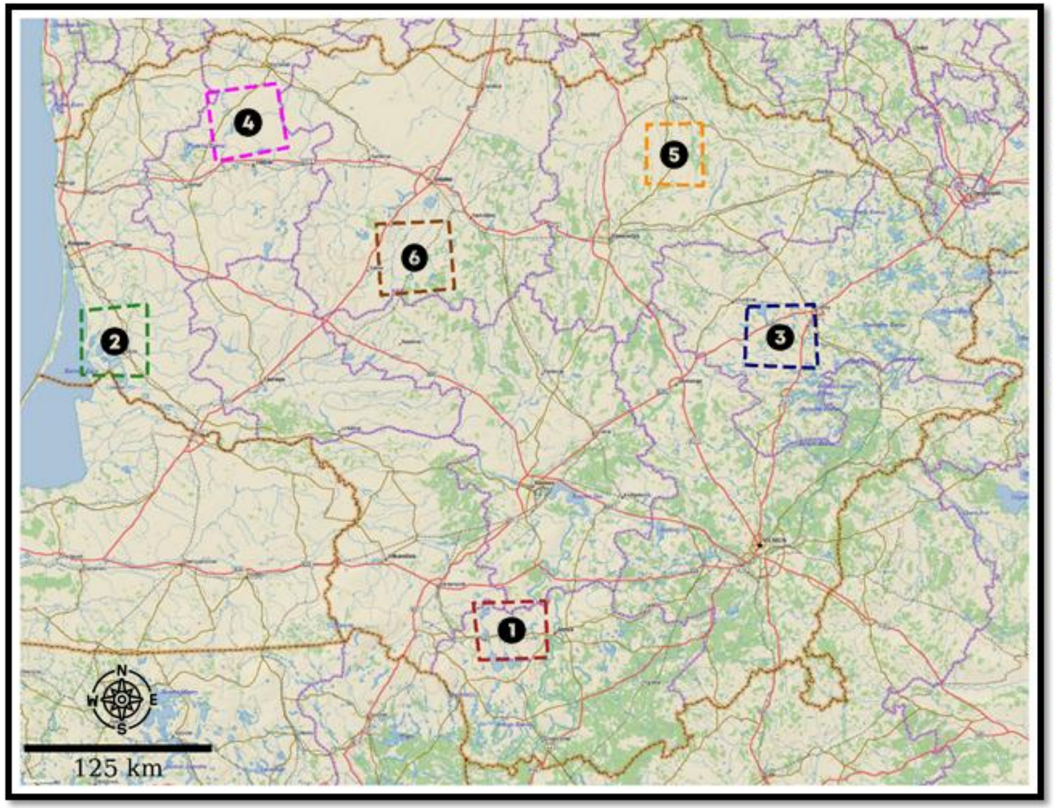
Grassland Monitoring for the Common Agriculture Policy (CAP)

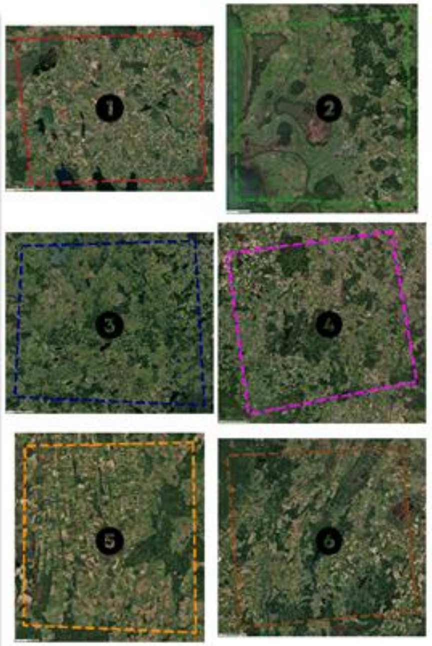


- Grasslands provide a wide range of ecosystem services (e.g. fodder for live stocking animals, wildlife habitats, carbon storage, soil erosion protection etc.)
- The Common Agricultural Policy (CAP) requires the systematic and timely remote monitoring of Agricultural Lands and Grasslands
- *Pillar I of CAP* - The detection of grassland mowing events at the parcel-level has been identified as a key data product to assess the compliance with respect several CAP measures, including the crop diversification and permanent grassland areas maintenance
- Most countries also define national regulations such as a reference date or period for the mowing of permanent grasslands, as well as grazing events, boundaries elements, mowing date or mowing within an agronomic year (e.g. Spain, Italy)
- *Pillar II of CAP* - Conceptual Design of targeted agro-ecological and climate-focused measures (CAP post-2020)

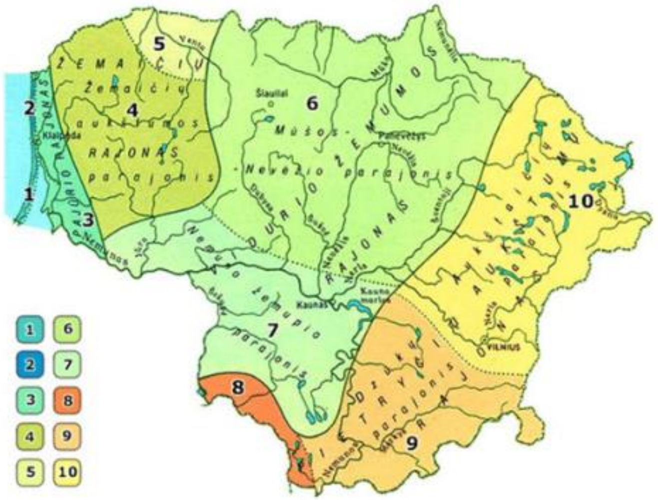
Study Area

The study was conducted in the country of **Lithuania (April-October 2020)**





1. Alytus
2. Klaipėda
3. Utena
4. Telšiai
5. Panevėžys
6. Šiauliai

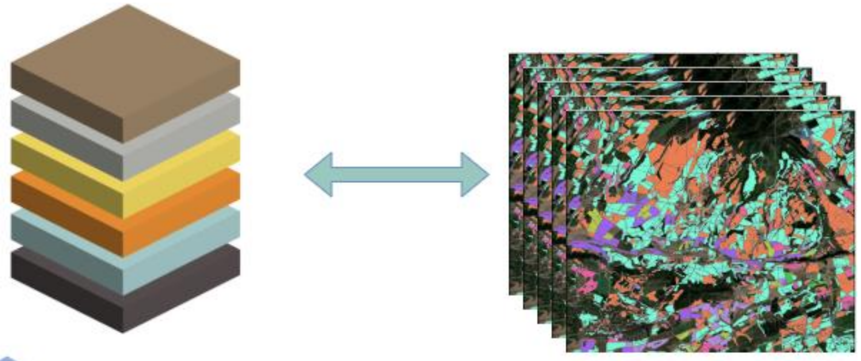


1. Curonian Spit
2. Seashore
3. Coastal Lowlands
4. Samogitian Highlands
5. Venta Midstream Lowlands
6. Mūša – Nevėžis
7. The Lower Reaches of Nemunas
8. Sudovia
9. Dzūkija
10. Higher Lithuania

** Based on Climatic Regionin of Lithuania 2013 (Lithuanian Hydrometeorological Service under the Ministry of Environment of Lithuania)*

Sentinel-2 Data

The study was conducted in the country of **Lithuania (April-October 2020)**

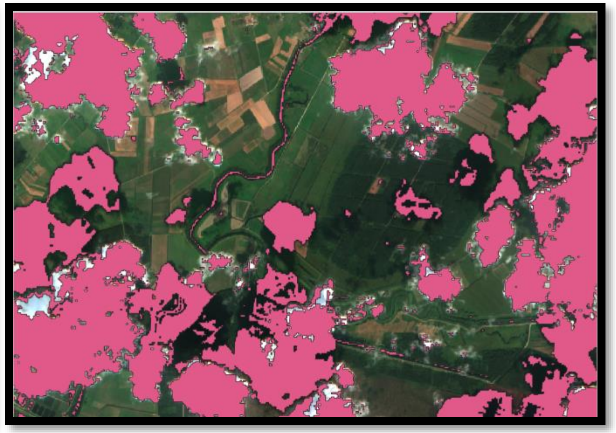


OPEN DATA CUBE

Sample parcels (area > 0.5 hectares) are taken from 6 different regions of Lithuania

Spatial Resolution: 10m x 10m

Sentinel-2 L2A
- **Normalized Difference Vegetation Index (NDVI)**
- **Scene Classification (SCL) based on sen2cor L2A processor**

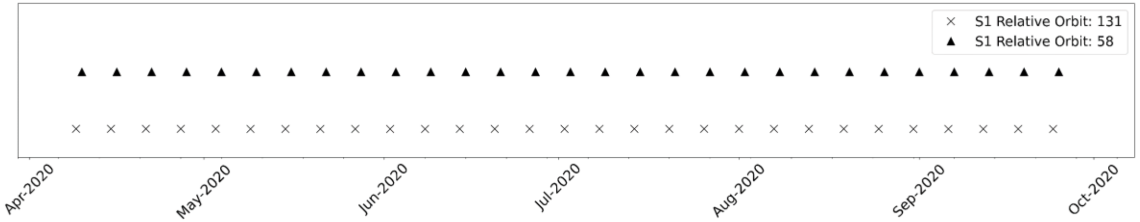


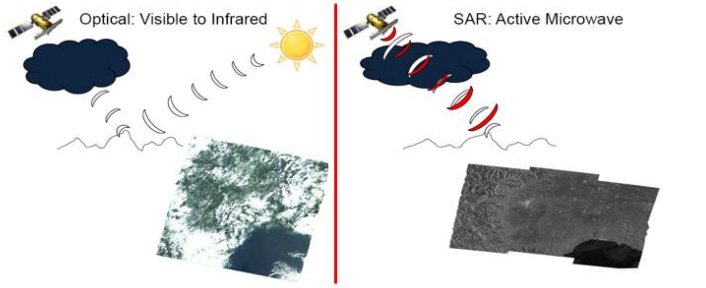
	T34UEG	T34UFG	T34UFF	T34VEH	T35ULA	T35ULB	T35UMB	T35VLC
Region 1			X		X			
Region 2	X							
Region 3						X	X	
Region 4				X				
Region 5						X		X
Region 6		X						

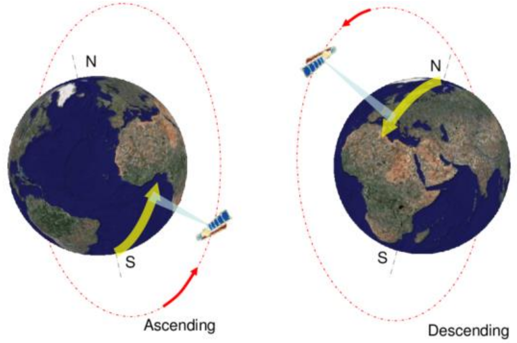
Sentinel-1 Data

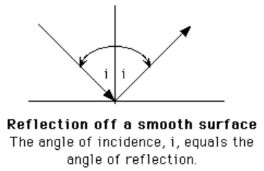
- Sentinel-1 GRD (rel. orbits: 58, 131) → Backscattering coefficients (VV-VH)
- Sentinel-1 Coherence (rel. orbits: 58, 131) →Coherence coefficients (VV-VH)

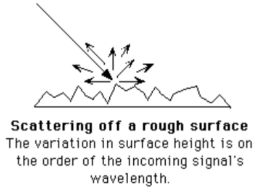
Spatial Resolution: 20m x 20m

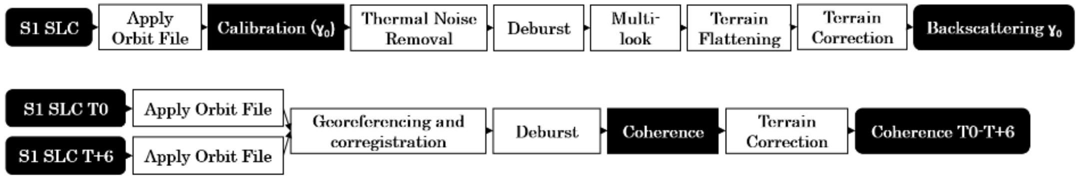












Rel.orbit 131

Rel.orbit 58

$$Mixed_{coherence} = \sqrt{coherence_{VV} \cdot coherence_{VH}}$$

$$Cross - Ratio_{\sigma_0} = \sigma_0 VH - \sigma_0 VV$$

$$Ratio_{\sigma_0} = \frac{\sigma_0 VV}{\sigma_0 VH}$$

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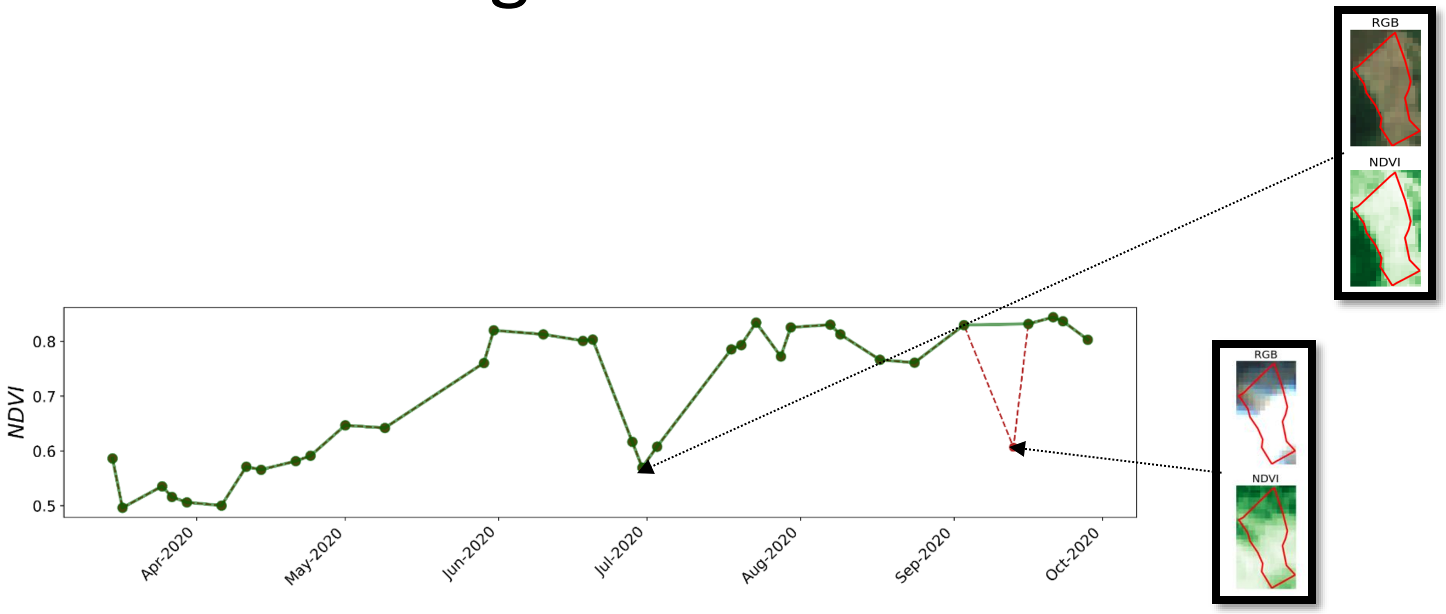
Cloud Masking

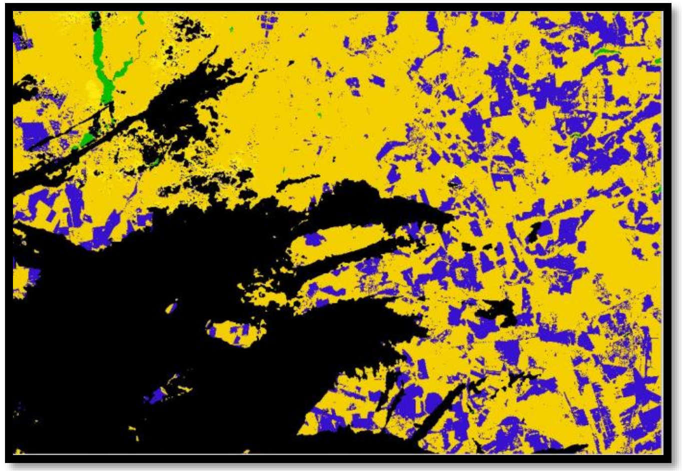
Algorithm 1 Identification of outlier cases and removal

procedure OUTLIERS DETECTION(α, β, γ)
    Read Series of size T: $S_T(t)$
    for $t \in T$ **do**
        $C_\alpha \rightarrow S_T(t) - S_T(t-1)$
        $C_\beta \rightarrow S_T(t+1) - S_T(t)$
        $C_\gamma \rightarrow C_\alpha - C_\beta$
        if ($C_\alpha \leq \alpha$ **and** $C_\beta \leq \beta$ **and** $C_\gamma \leq \gamma$) **then**
            $S_t \rightarrow$ **NaN**
        end if
    end for
end procedure

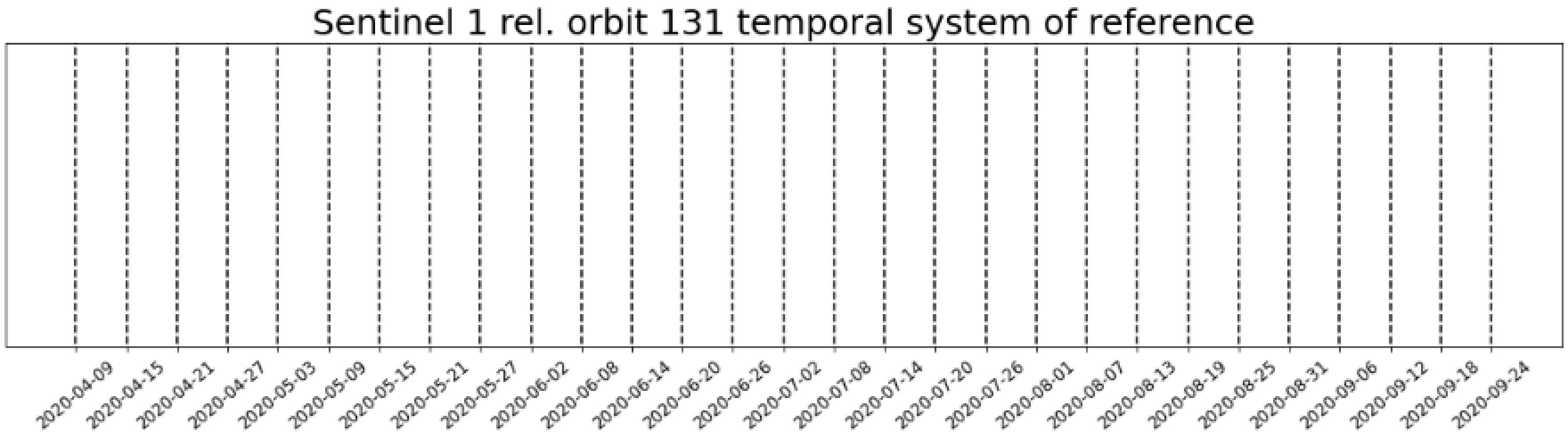


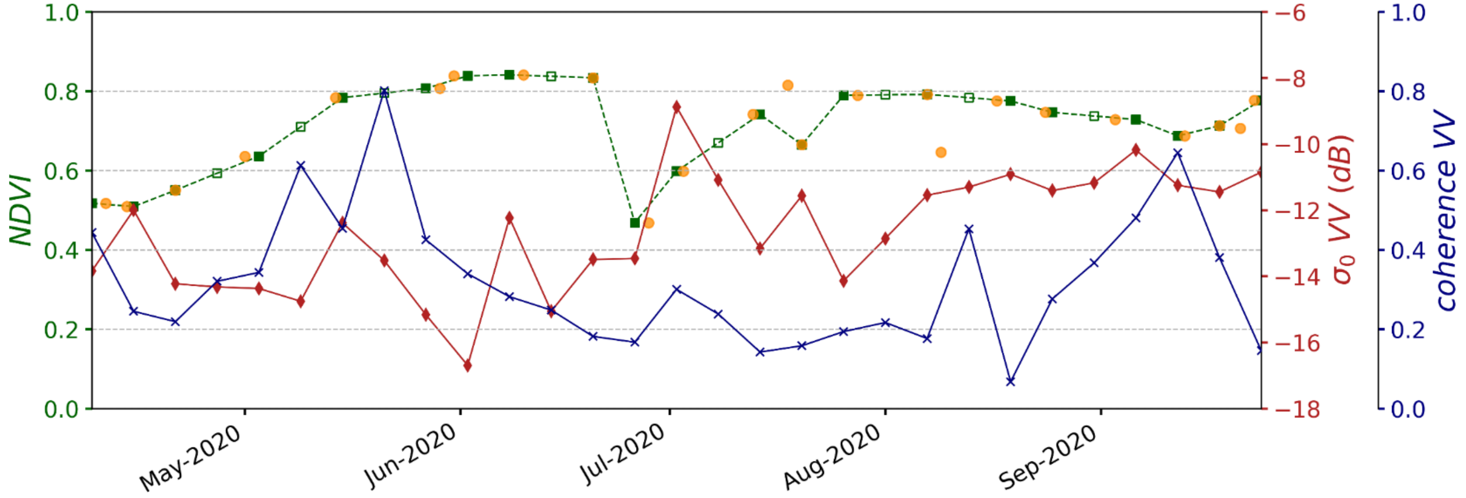
Other Masks:

- MAJA
- Fmask
- s2cloudless

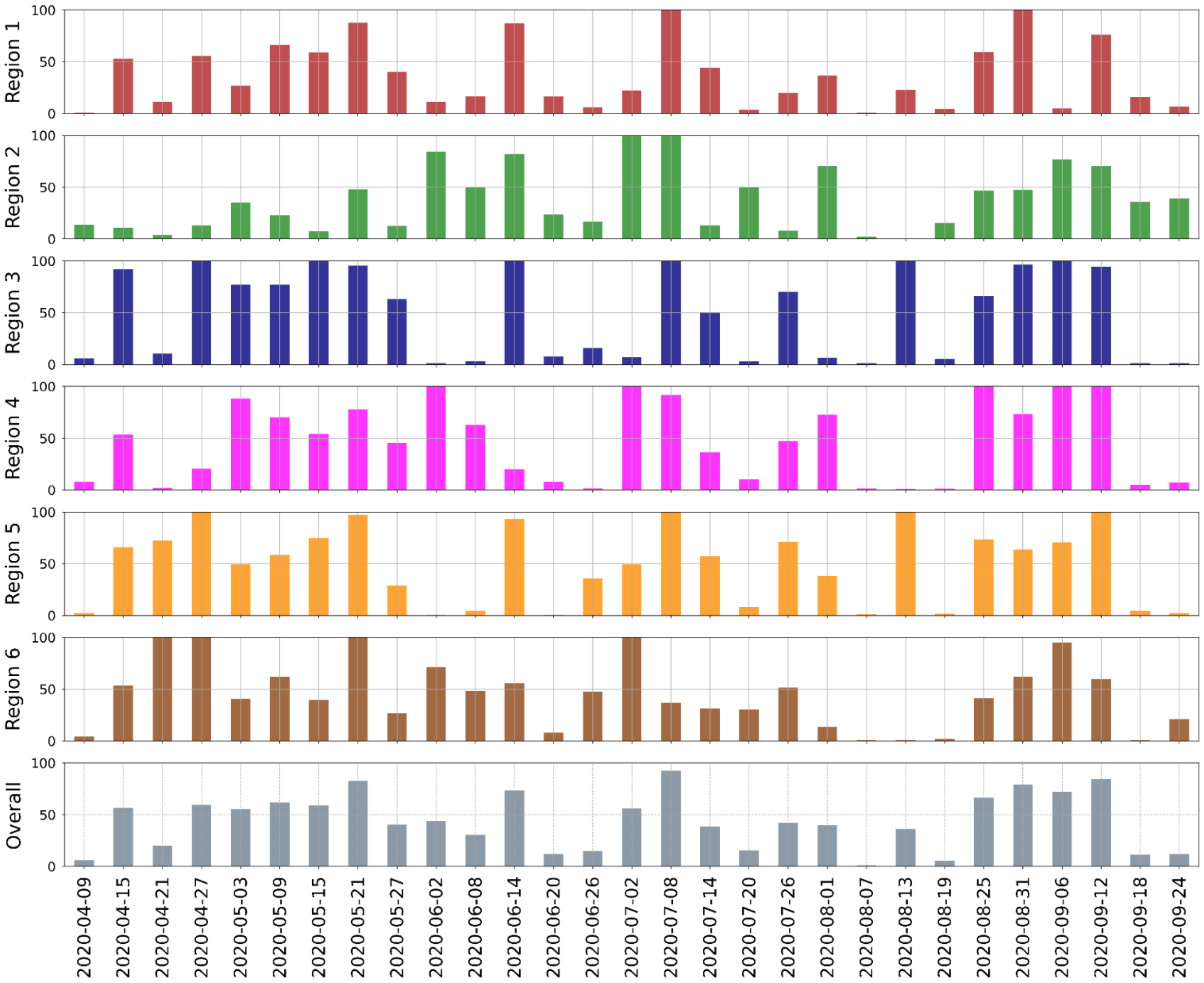


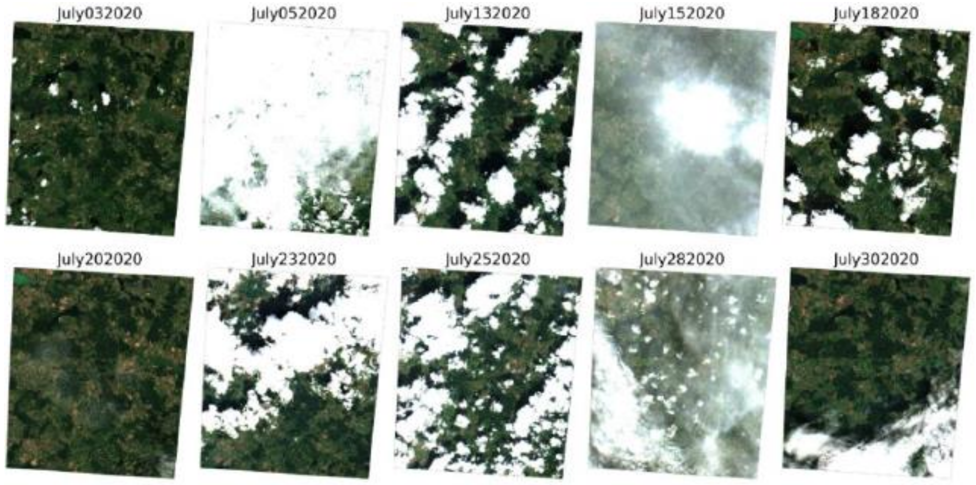
Common Temporal System of Reference

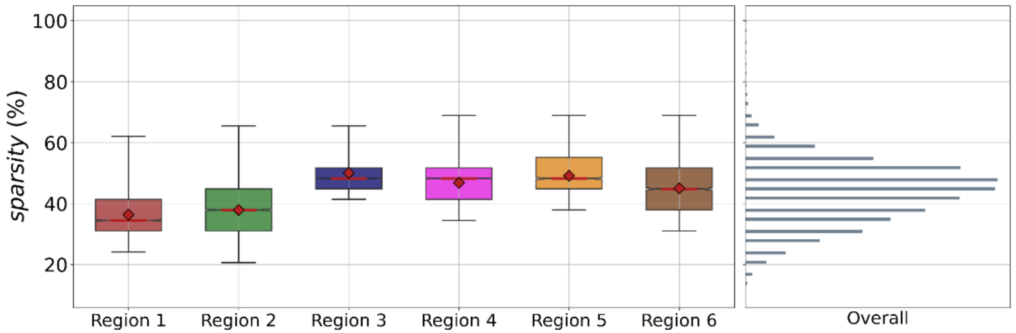




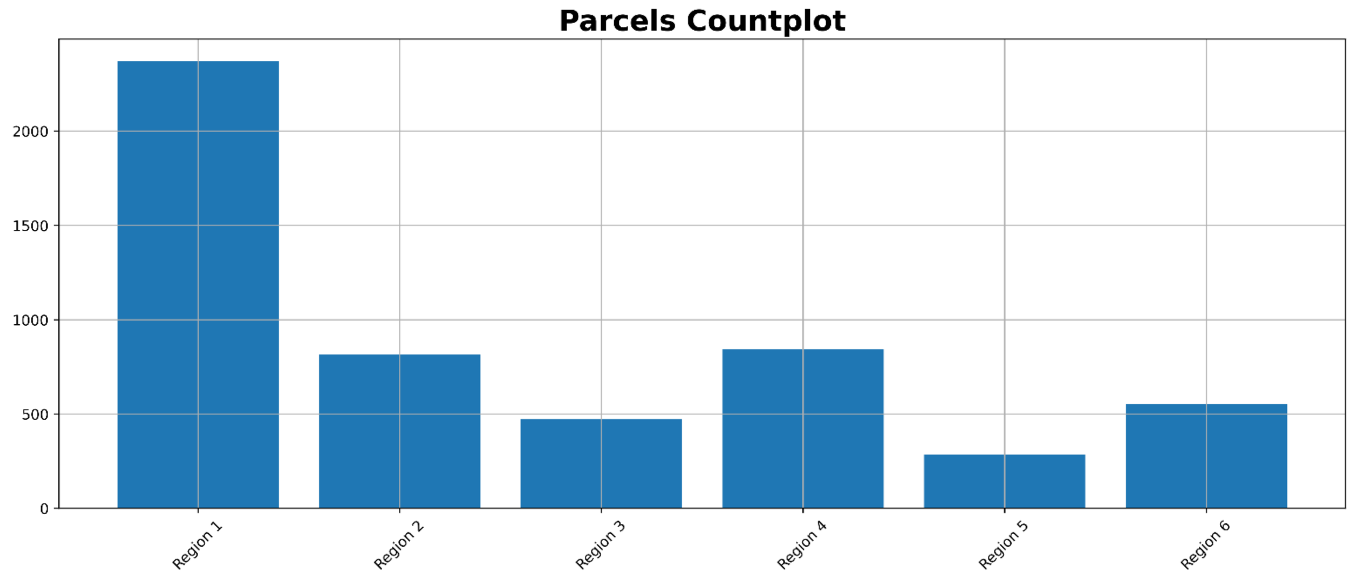
Sparsity due to Cloud Coverage and Artificial Masking

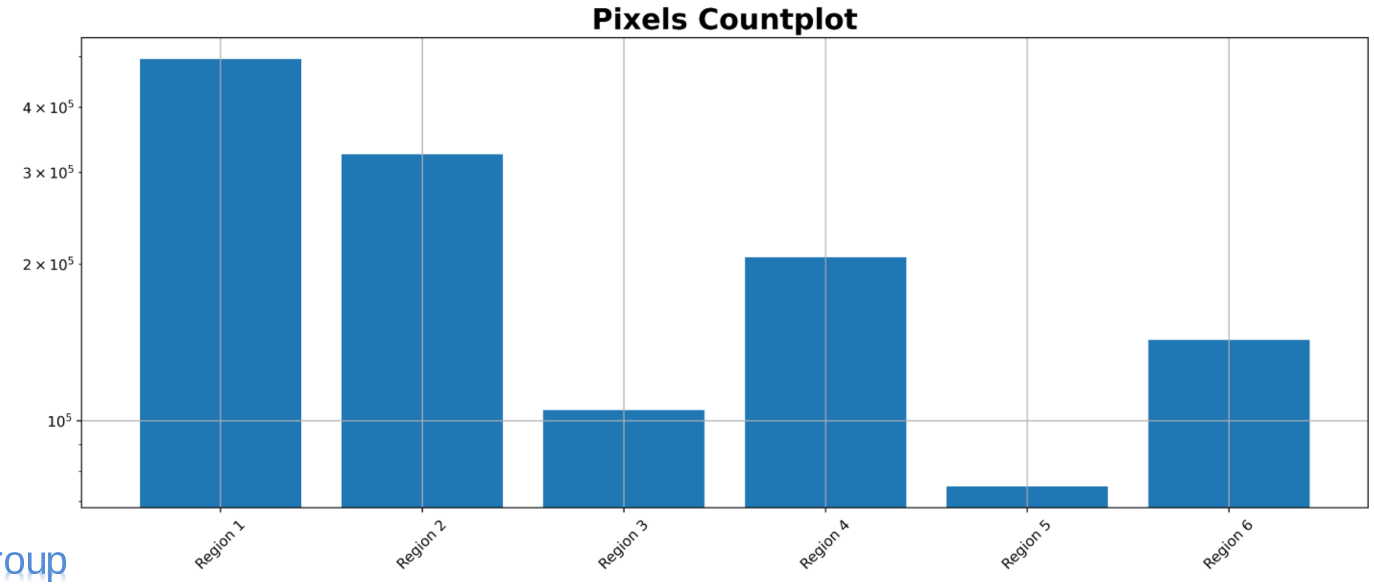




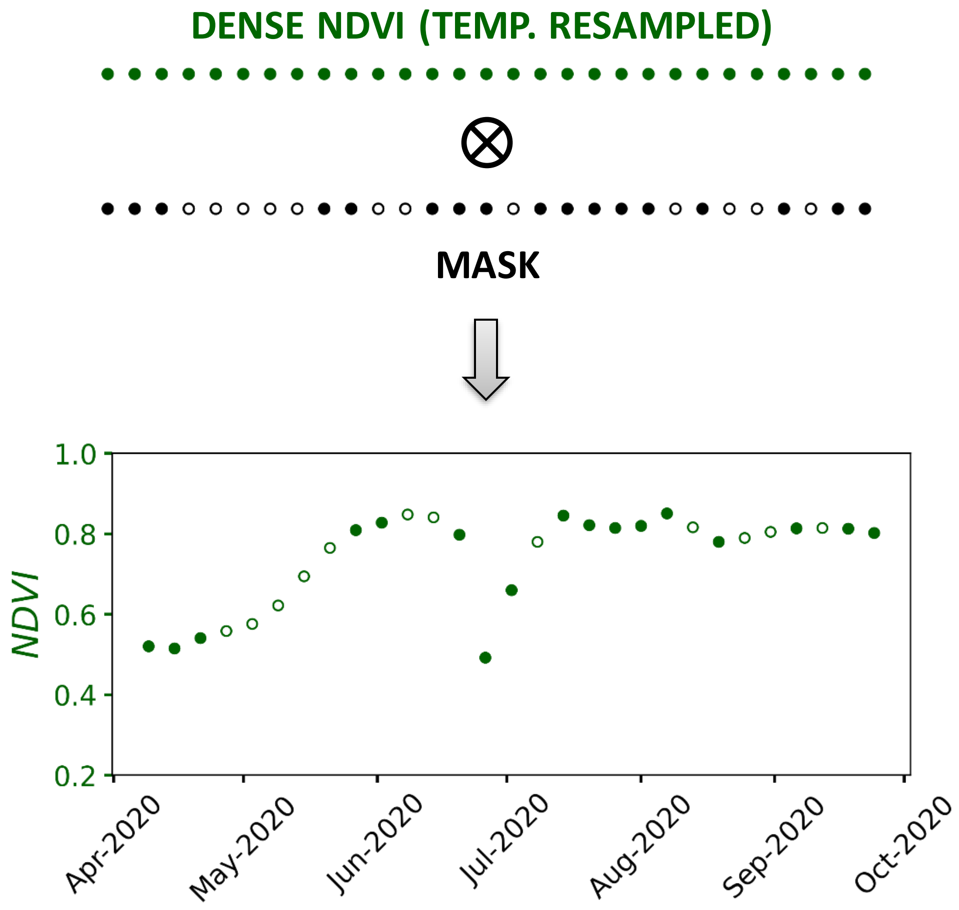


Dense Time-series



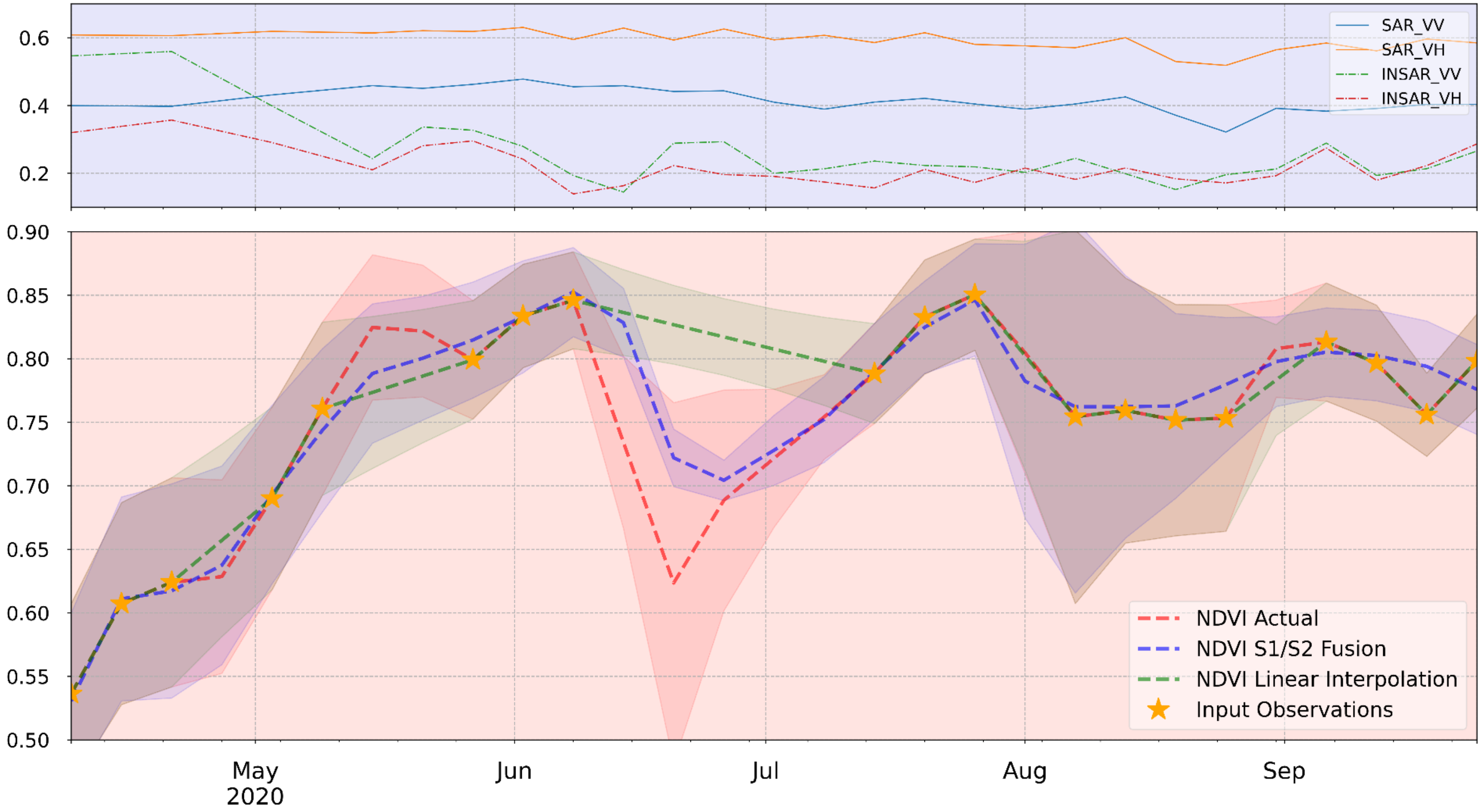


Artificial Masking on Dense Time-series



Why not Temporal Interpolation?

- What when we have large gaps ?
- What when we have steep drops ?



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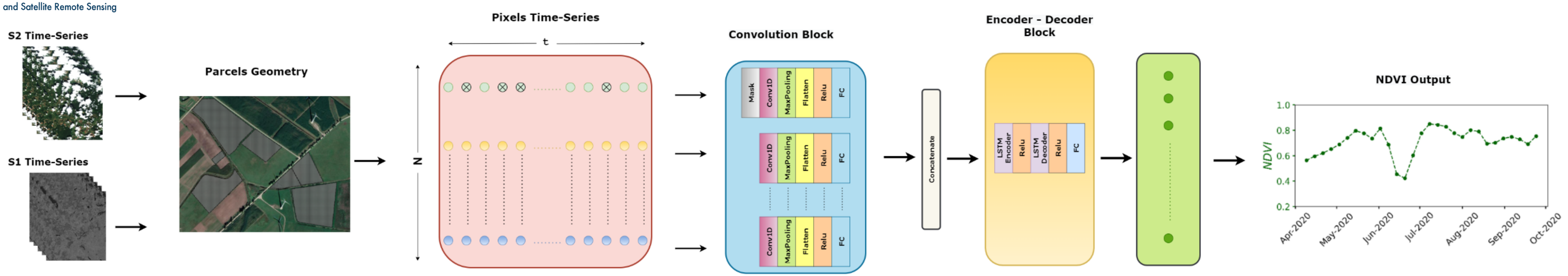
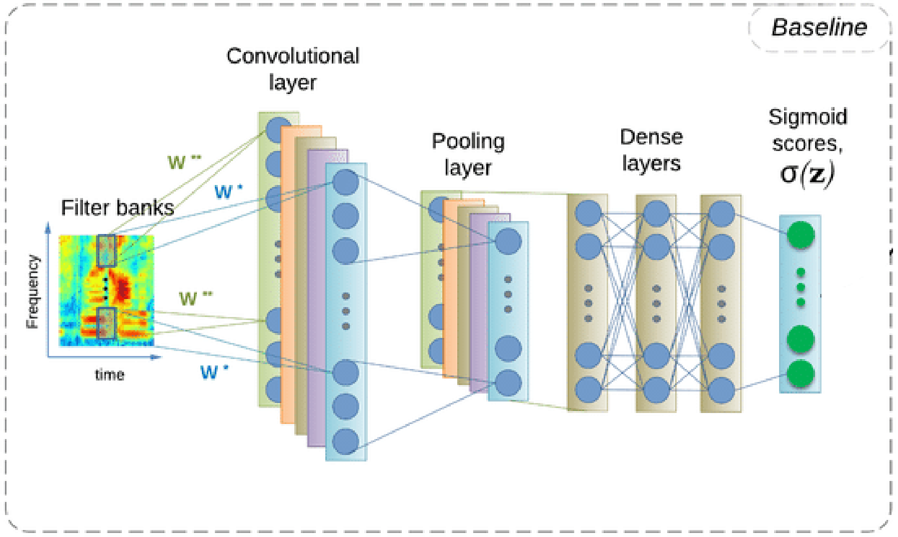
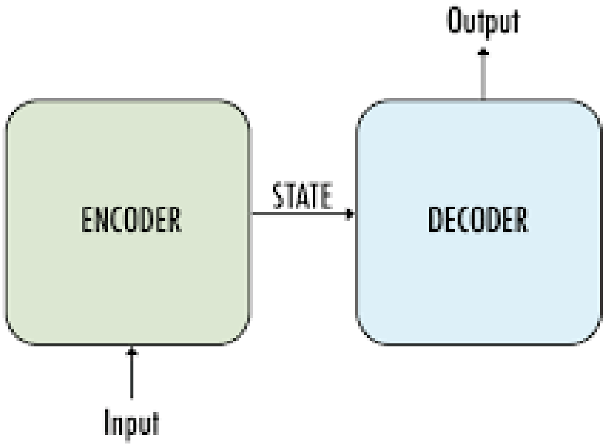
Sentinel-1/Sentinel-2 Fusion Model



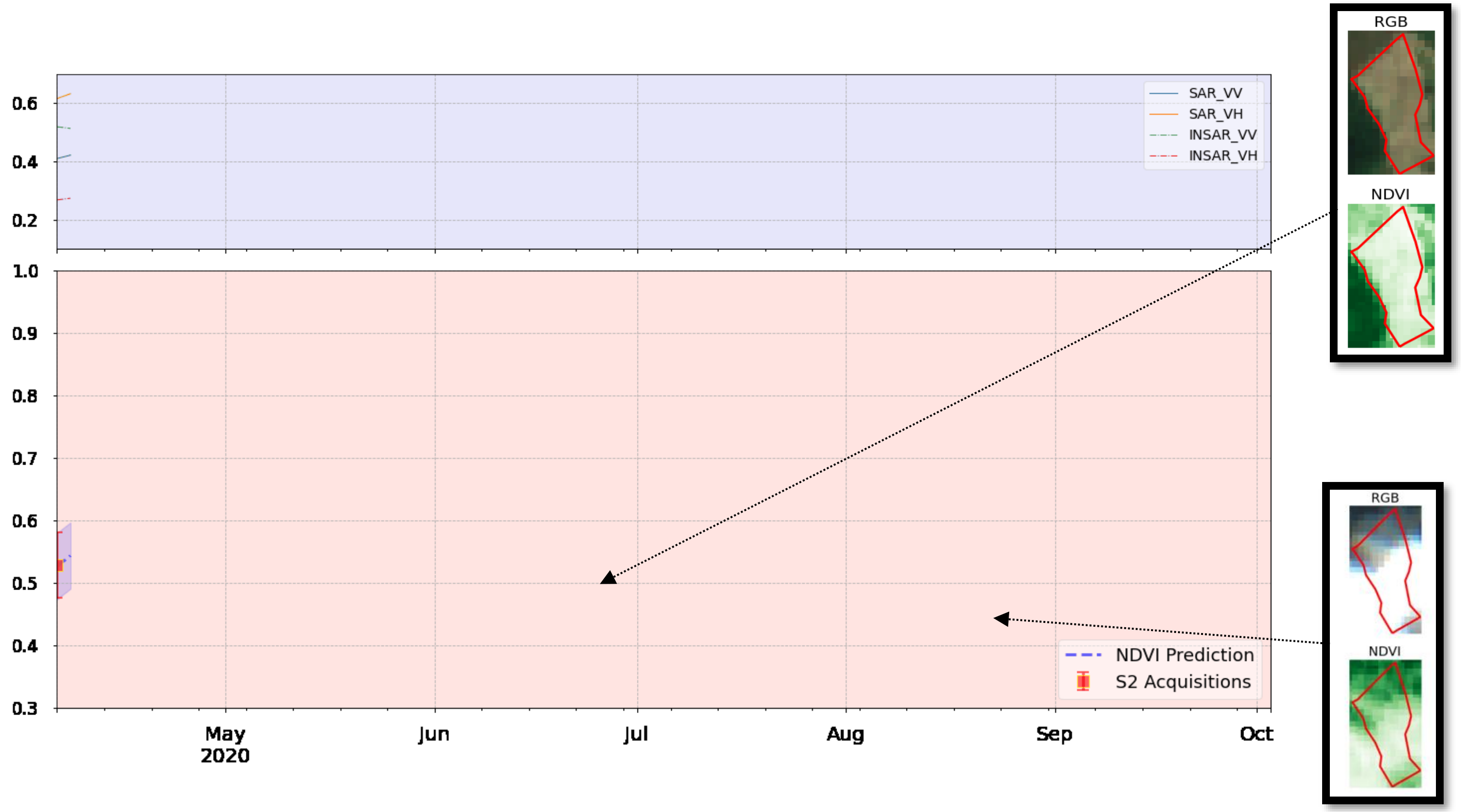




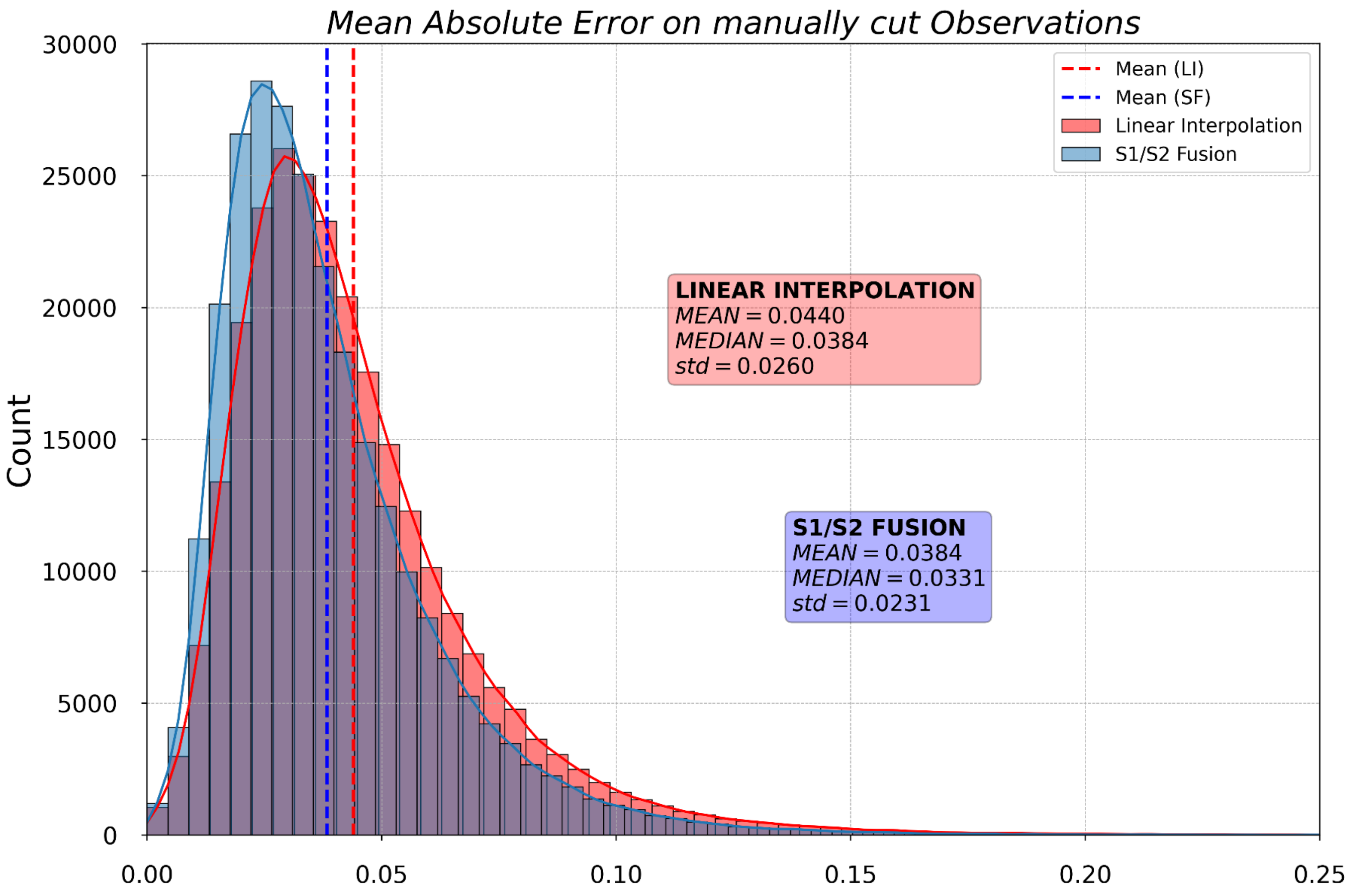
TensorFlow + Keras

```
Total params: 82,881
Trainable params: 82,881
Non-trainable params: 0
```

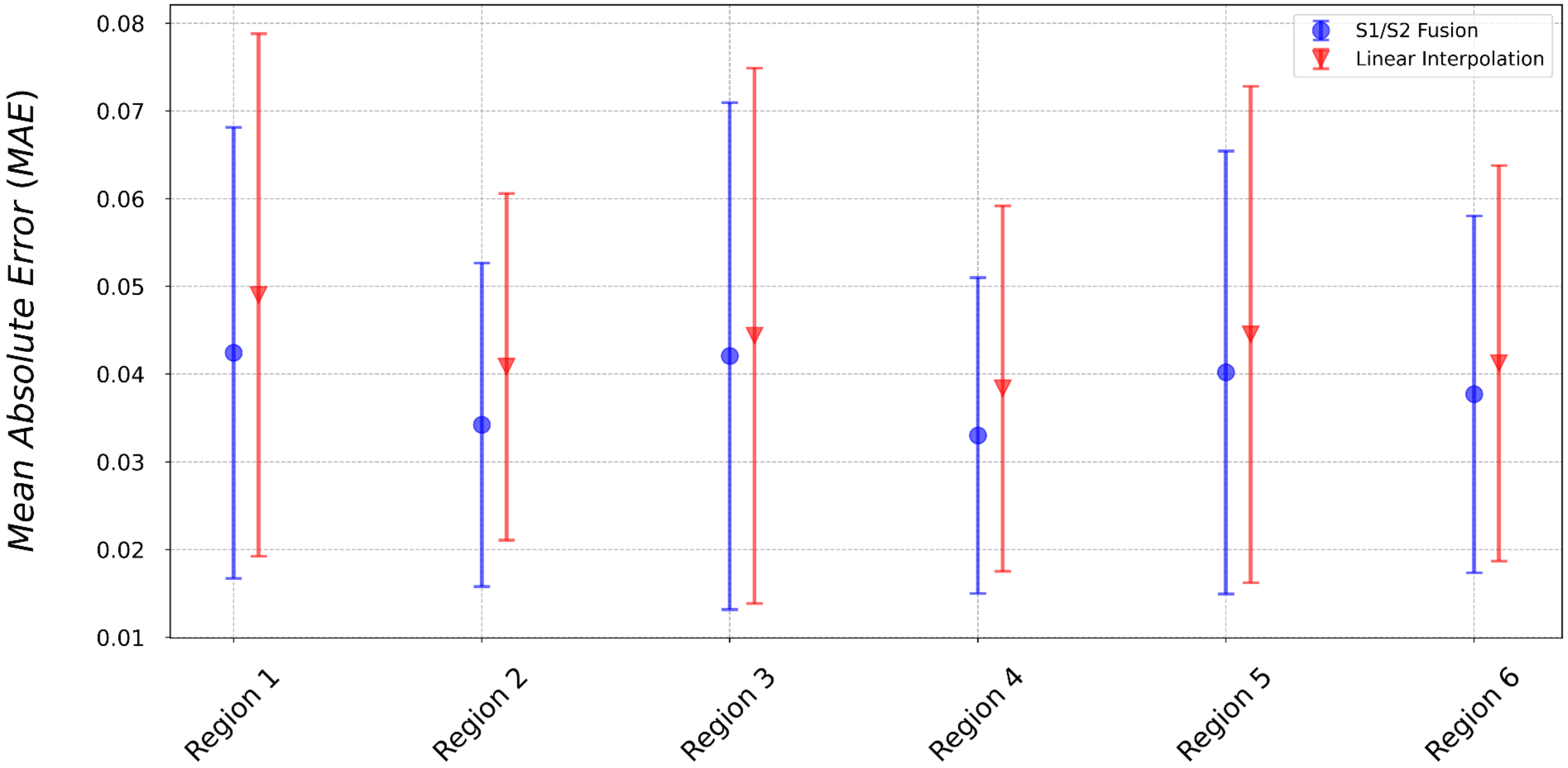
Sentinel-1/Sentinel-2 Fusion



Sentinel-1/Sentinel-2 Fusion Results



Sentinel-1/Sentinel-2 Fusion Results



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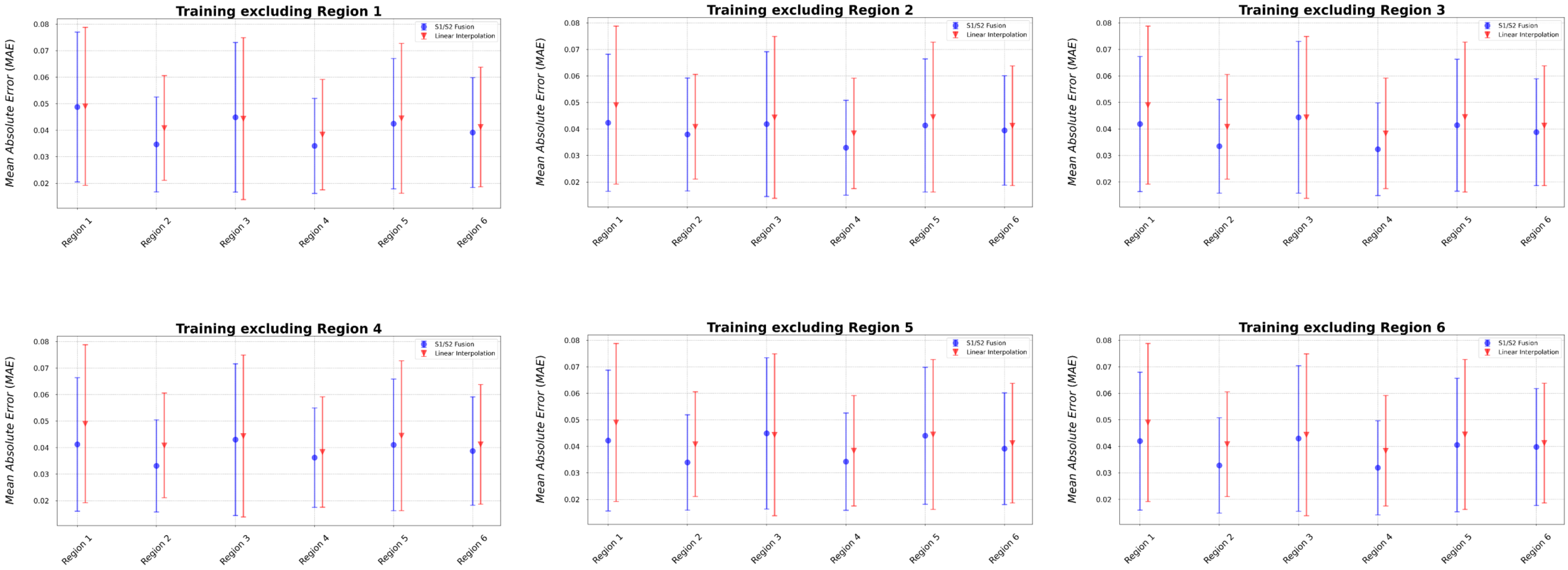
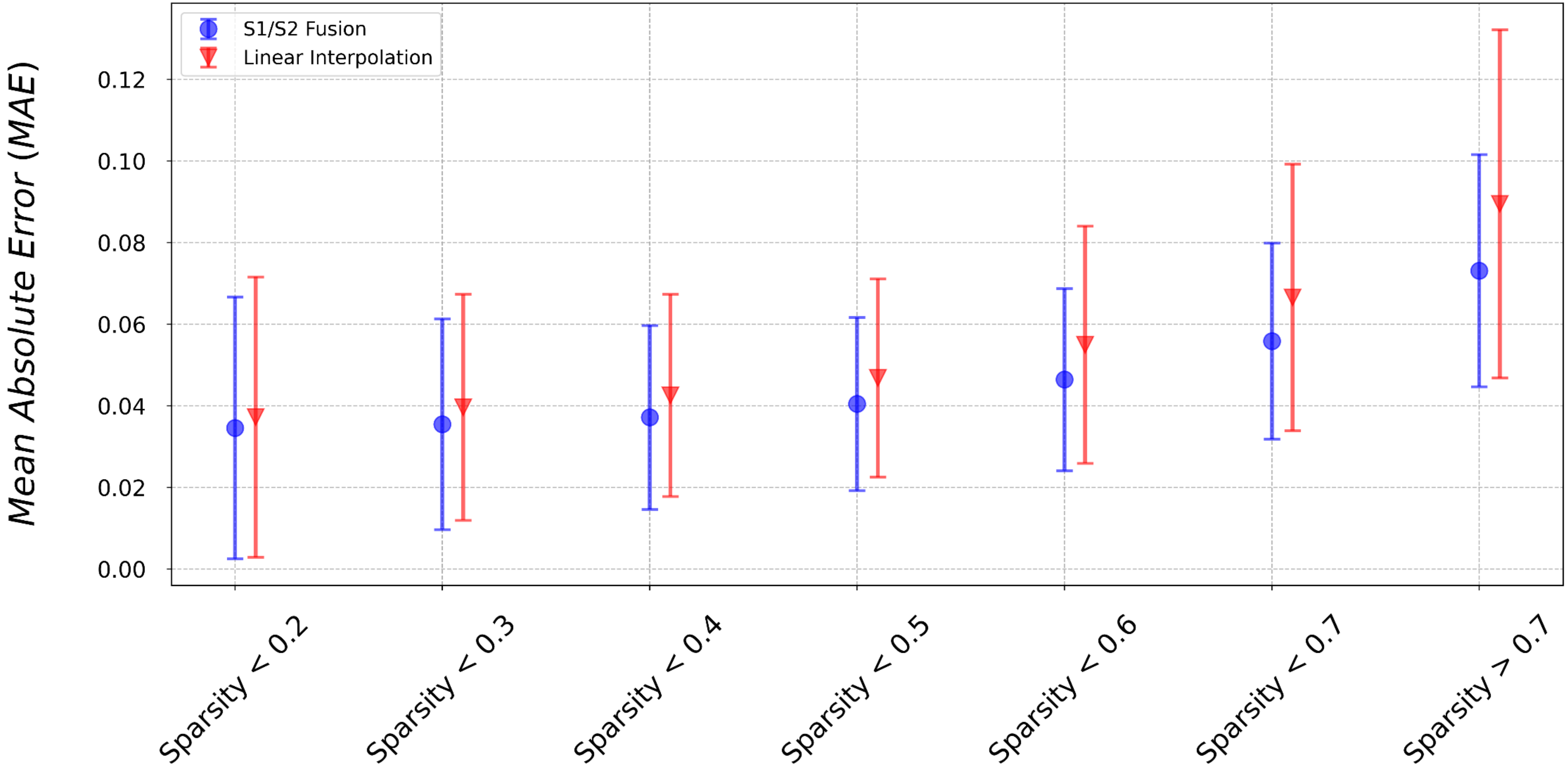
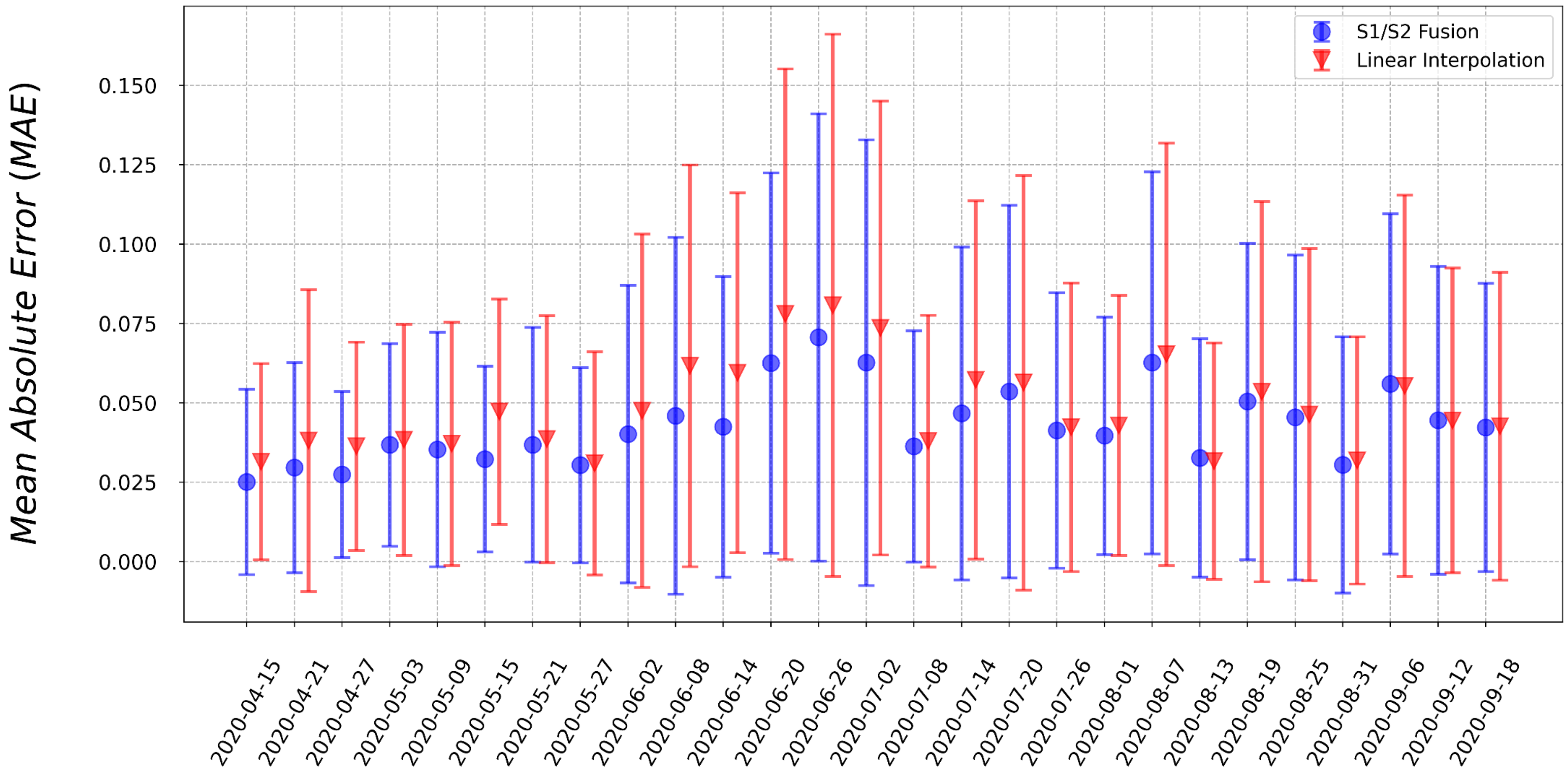
Sentinel-1/Sentinel-2 Fusion Results



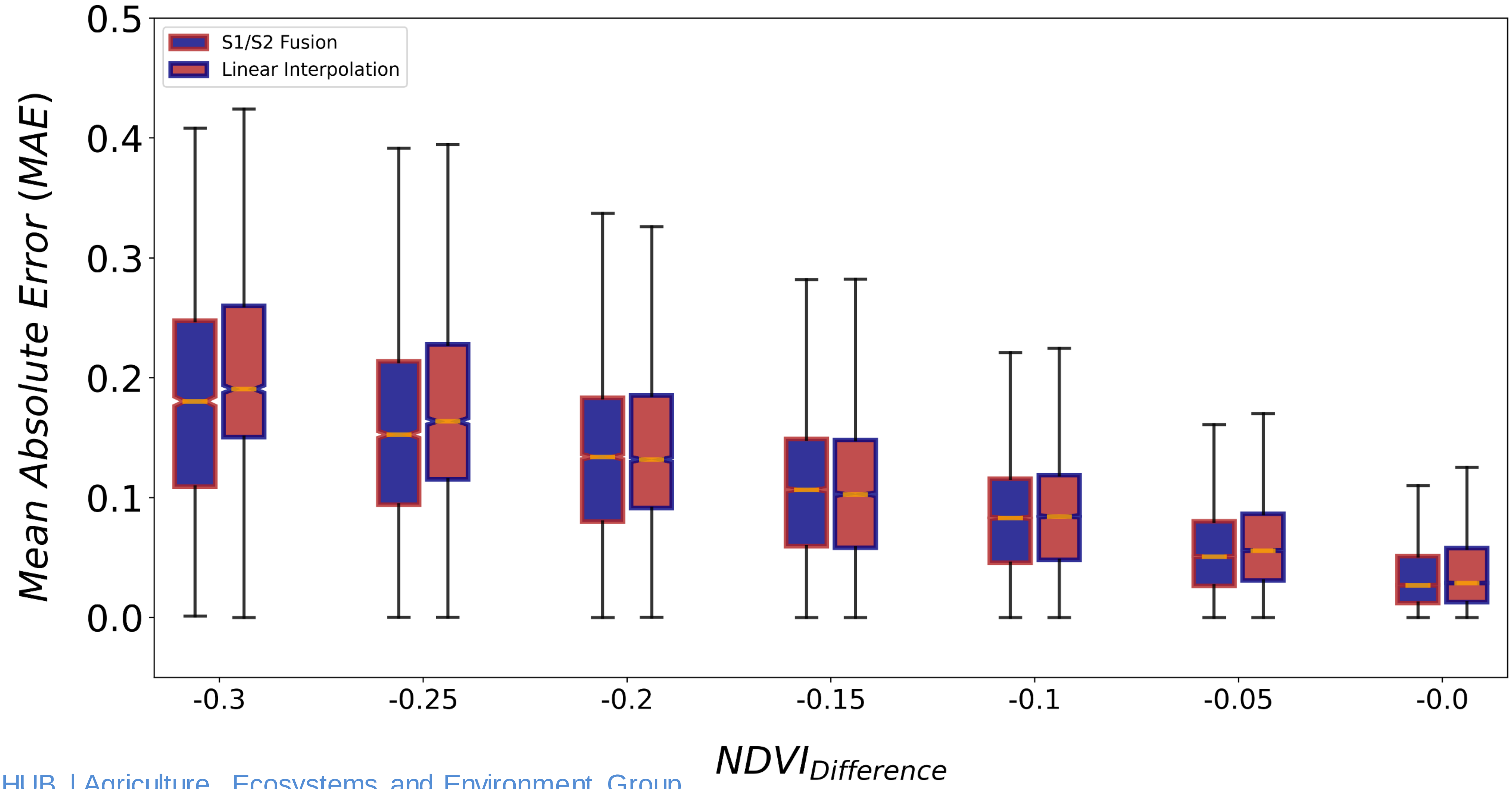
Sentinel-1/Sentinel-2 Fusion Results



Sentinel-1/Sentinel-2 Fusion Results



Sentinel-1/Sentinel-2 Fusion Results



Sentinel-1/Sentinel-2 Fusion Results

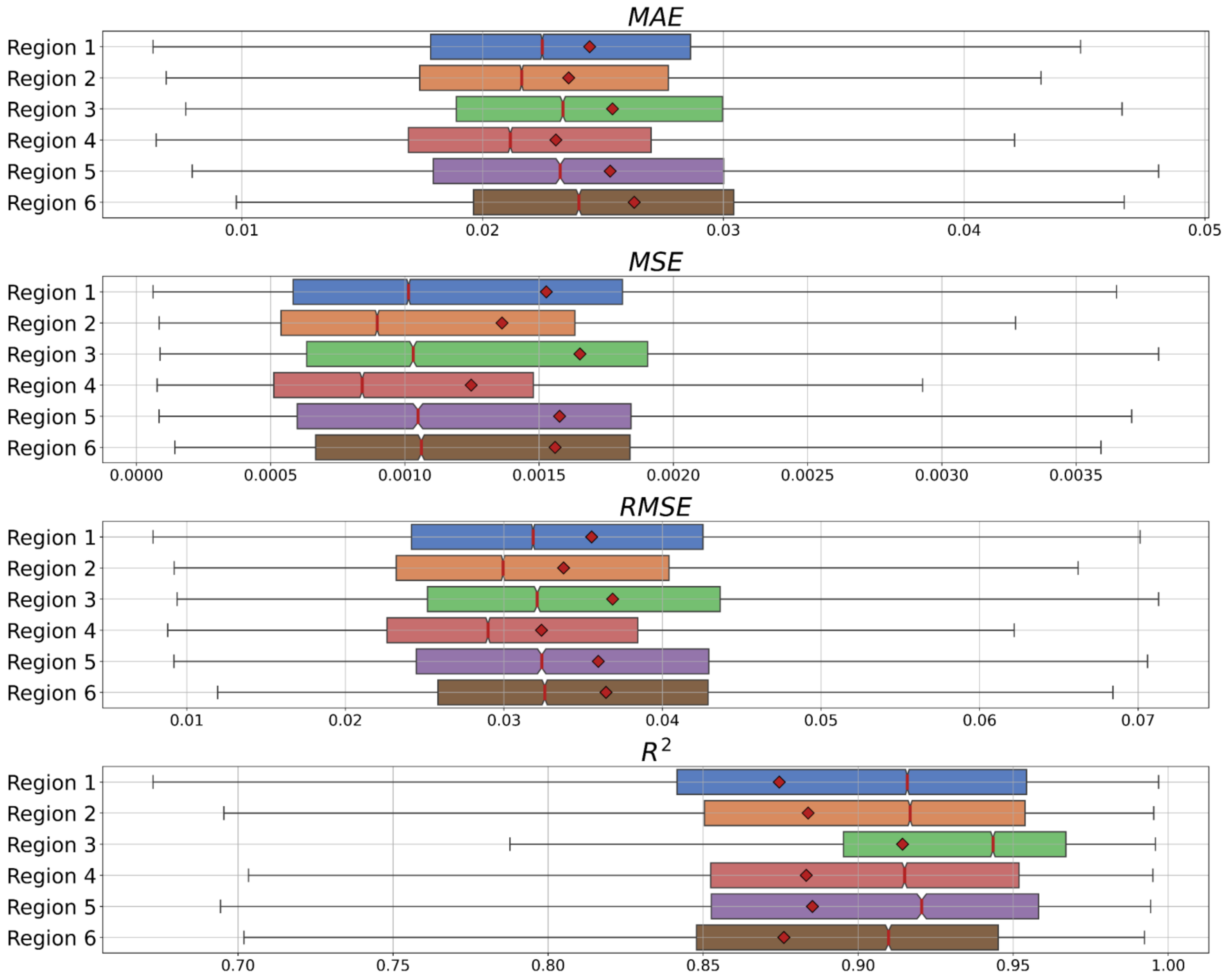
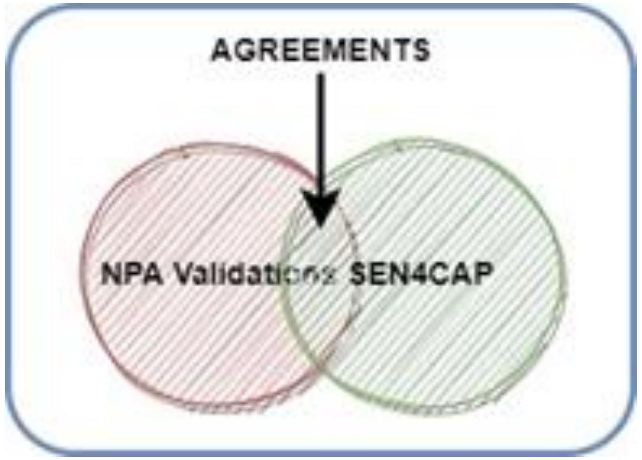
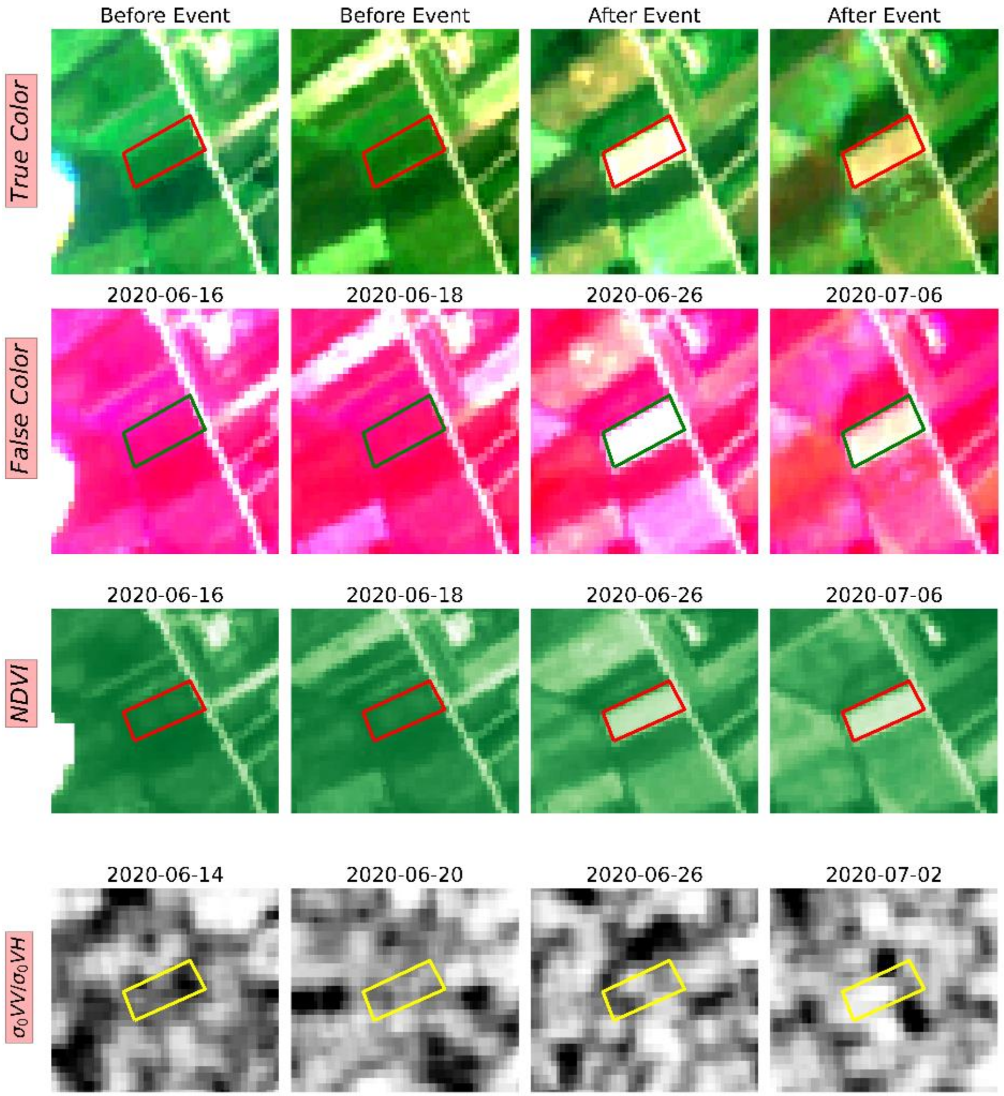
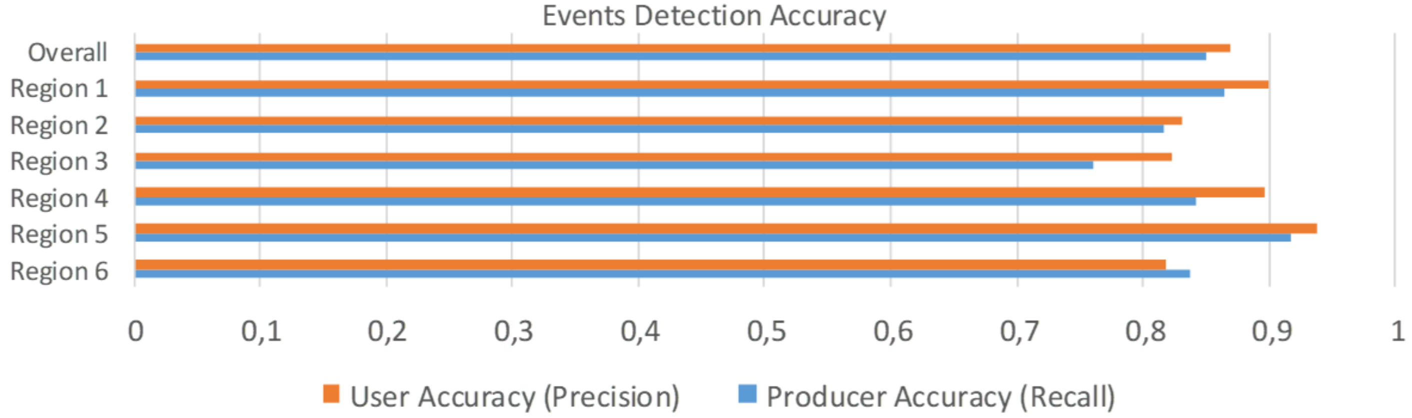


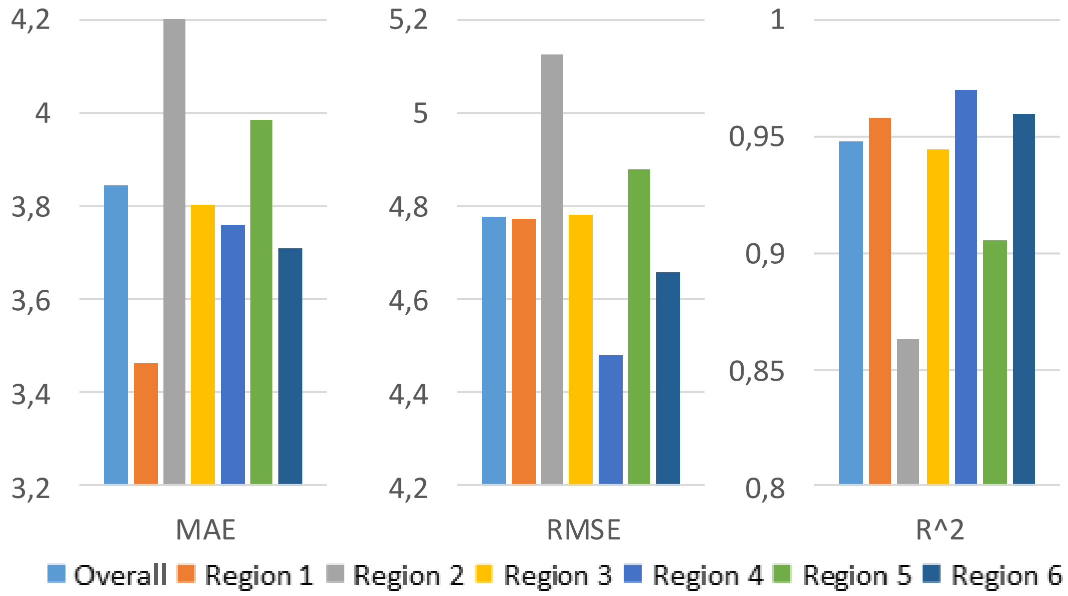
Photo-Interpretation Process for Validation Instances



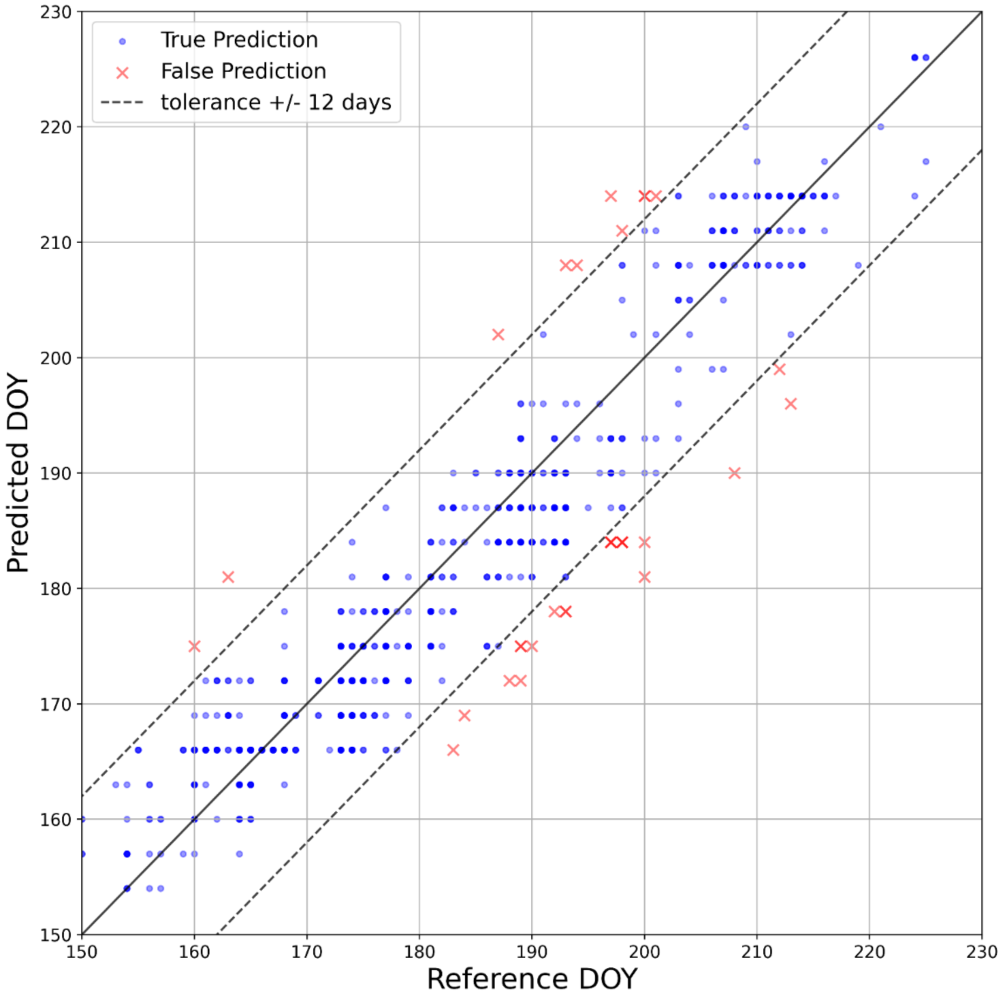


Deep Learning for Events Detection

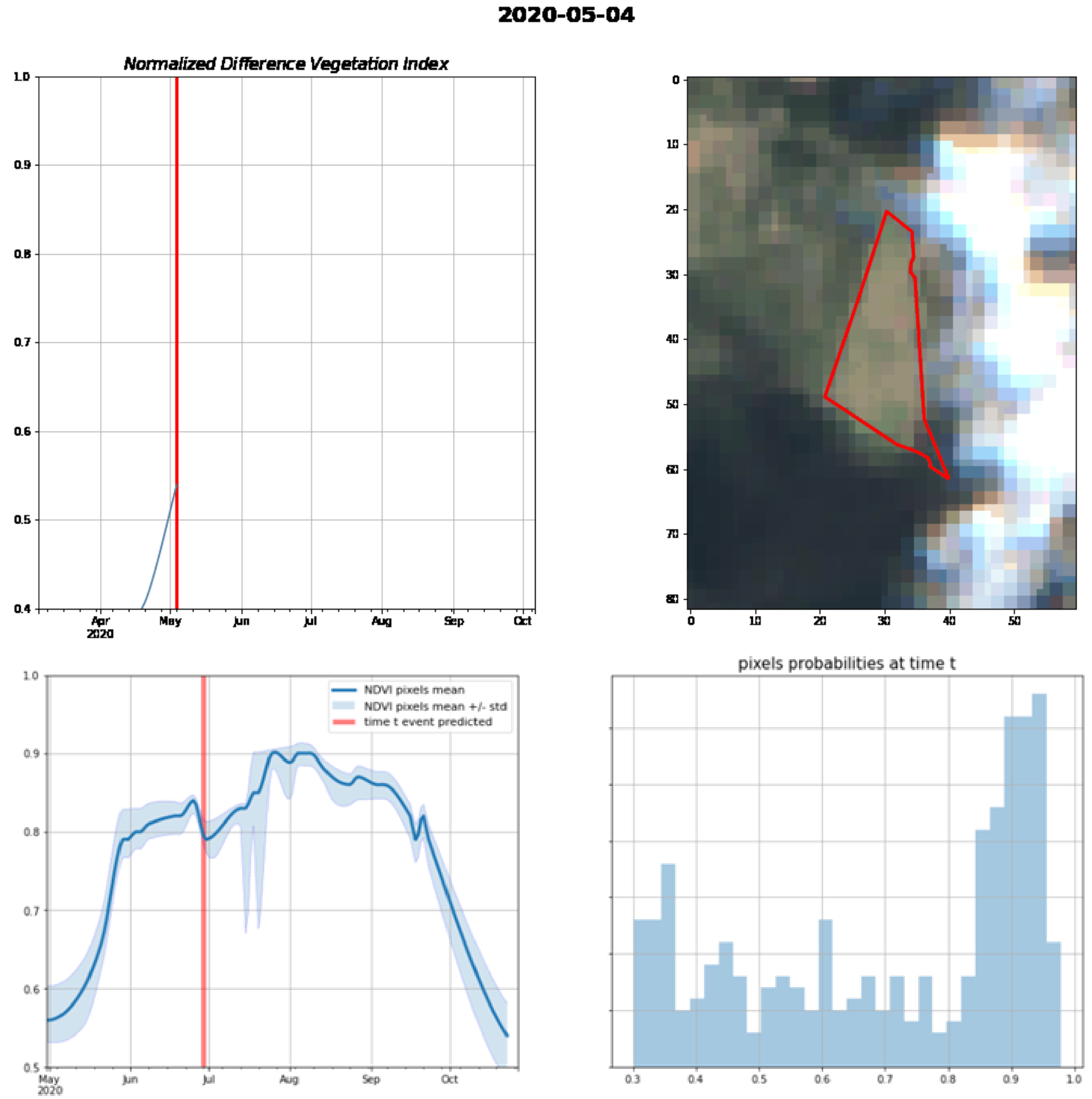


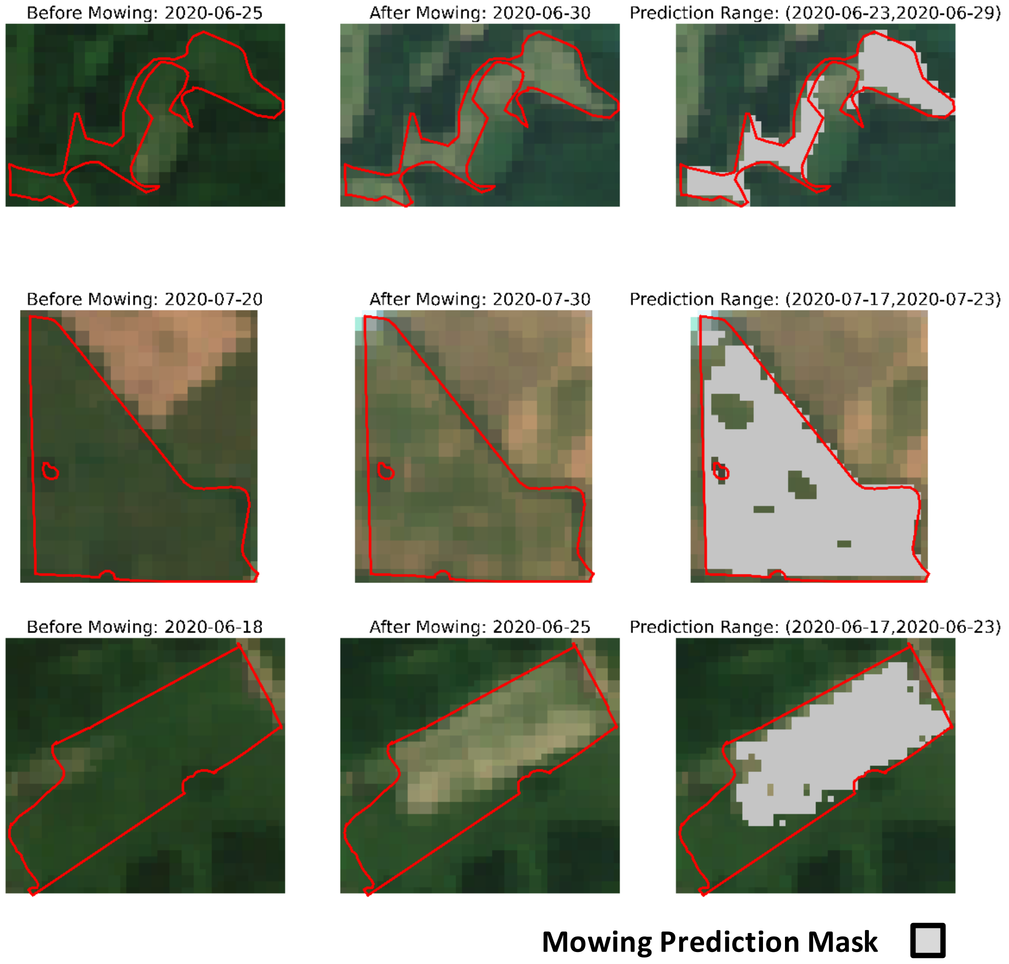


Reference day of the year (DOY) for the mowing events and the DOY predicted by the model

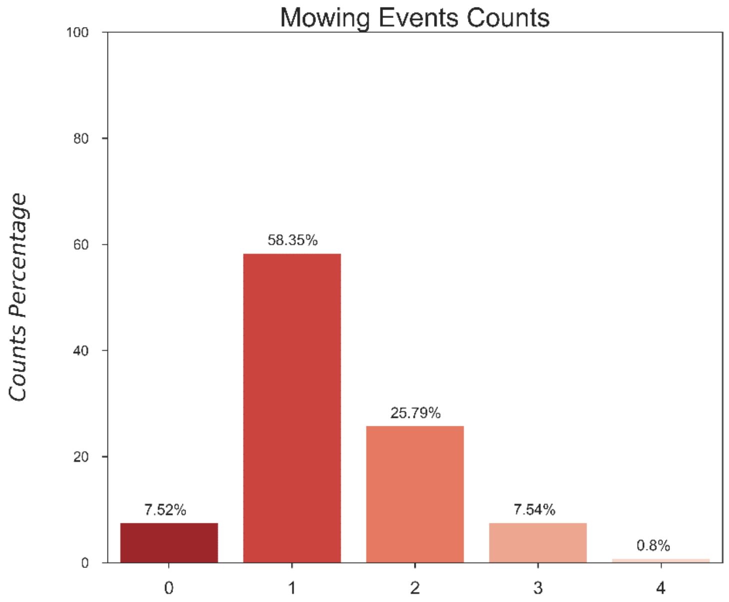


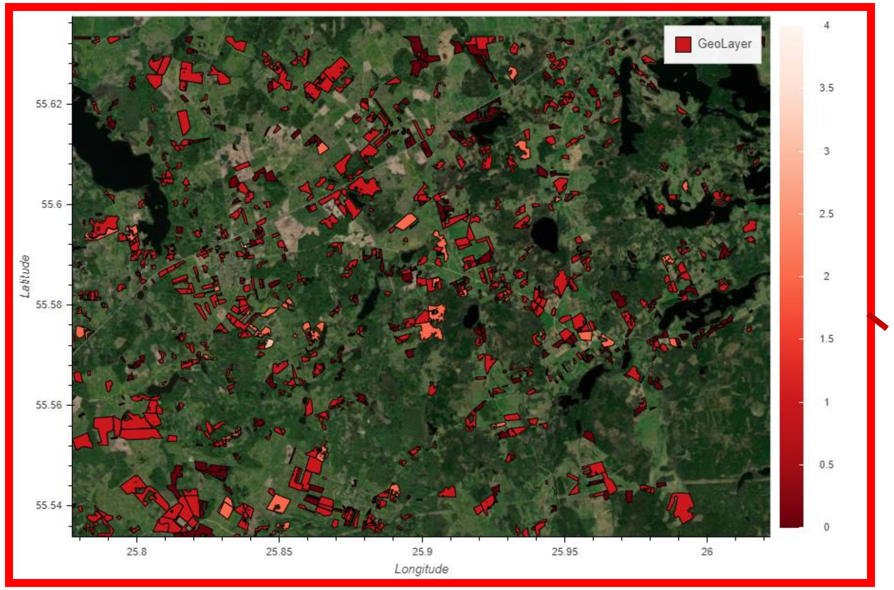
Deep Learning for Events Detection

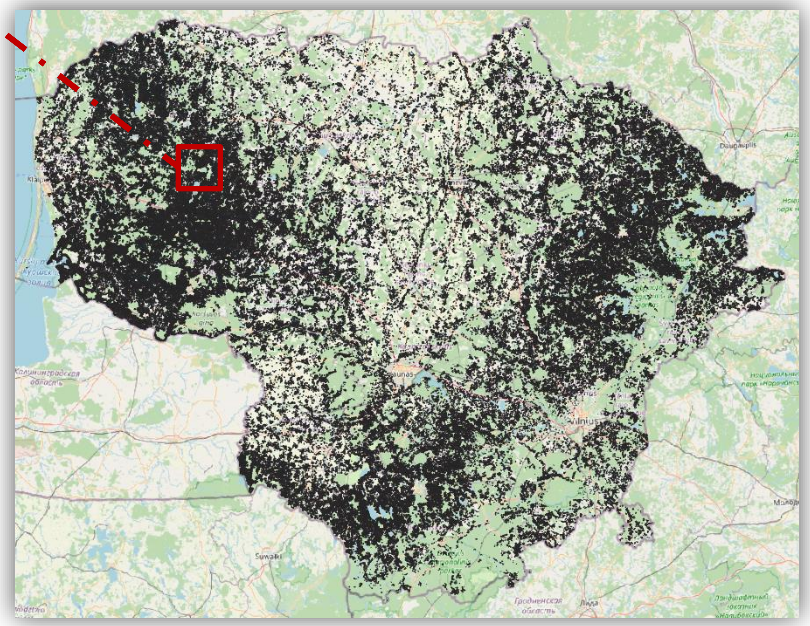




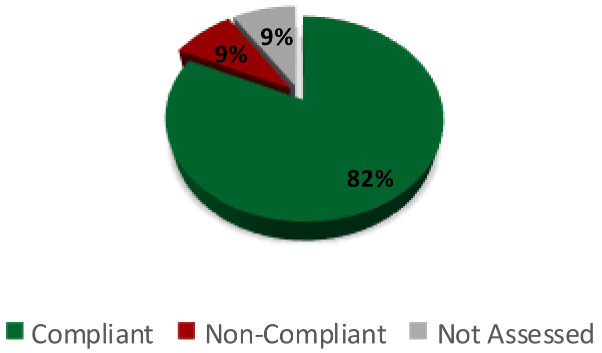
Towards exhaustive CAP monitoring & Quantification of Grassland Use Intensity





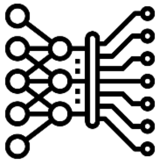


Compliance (at least one mowing event until 1st of August)



Remarks & Future work

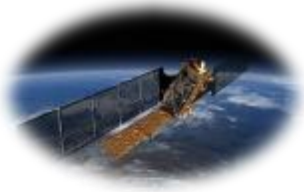
- A pixel-wise (DL) routine that can create dense NDVI time-series integrating both Synthetic Aperture Radar (Sentinel 1) and the available cloud free Sentinel 2 acquisitions
- An original Deep Learning Mowing Detection Algorithm based on Recurrent Neural Networks



- Meteorological and other ancillary metadata (e.g. topographic, DOY, LPIS subclass etc.) integration

- Evaluate more sophisticated architecture layers (e.g. self-attention)
- Analyze grasslands management activity of Lithuania and provide an eco-scheme knowledge

- Generalization of pipeline to a variety of similar event detection tasks on SITS (e.g. Stubble Burning Detection)
- Sentinel-1B anomaly that occurred on 23 December 2021 is still on-going



Synergies

NIVA – NEW IACS VISION IN ACTION
sen4cap – common agricultural policy
DIONE
EO4AGRI
MEF4CAP
e-shape
FIRE
VITIGEOSS

enVision

DataCAP
Cyprus Agricultural Payments Organisation

NMA – NACIONALINĖ MOKĖJIMO AGENTŪRA

CALLISTO

Eiffel – GEOSS APPLICATIONS FOR CLIMATE CHANGE

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Publications & Conferences

IVMSP 2022
26 - 29 JUNE 2022
Nafplio, Greece

Drivas, T., Sitokonstantinou, V., Tsardanidis, I., Koukos, A., Kontoes, C., & Karathanassi, V. (2022). A Data Cube of Big Satellite Image Time-Series for Agriculture Monitoring

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28th
2022

Sitokonstantinou, V., Koukos, A., Drivas, T., Kontoes, C. and Karathanassi, V., 2022. Datacap: A satellite datacube and crowdsourced street-level images for the monitoring of the common agricultural policy.

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living planet symposium
BONN 23-27 May 2022
TAKING THE PULSE OF OUR PLANET FROM SPACE

Tsardanidis, I., Sitokonstantinou, V., Koukos, A., Drivas, T. and Kontoes, C. 2022. Deep Learning Methods for Grassland Activity Monitoring.

Sitokonstantinou, V., Koukos, A., Choumos G., Kontoes, C. DataCAP: Sentinel datacubes, crowdsourced street-level images and annotated benchmark datasets for the monitoring of the CAP

AGU FALL MEETING
New Orleans, LA & Online Everywhere
13–17 December 2021

Tsardanidis, I., Sitokonstantinou, V., Koukos, A., Drivas T. and Kontoes, C., "Deep Learning for Event Detection on Grasslands", B42C-07 presented at 2021 AGU Fall Meeting, 13-17 Dec.

On-going Journal Publication

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IEEE GRSS
Geoscience and Remote Sensing Society

IEEE Transactions on Geoscience and Remote Sensing

8.125	0.04471	1.5	12.2
Impact Factor	Eigenfactor	Article Influence Score	CiteScore Powered by Scopus

Deep Learning for cloud gap filling on NDVI time-series

Iason Tsardanidis, Alkiviadis Koukos, Vasileios Sitokonstantinou, Thanassis Drivas and Charalampos Kontoes

***Abstract*—The demand of interrupted optical time series is essential for the detection of events on grasslands. Nevertheless, the continuity of the Sentinel-2 time-series is often hindered by intense cloud coverage, which is even more of an issue for northern European countries. A collaborative exploitation of both Sentinel-2 observations that are characterized as cloud free and the Sentinel-1 Synthetic Aperture (SAR) measurements which can be provided on a fixed time step can alleviate the current problem. Taking into consideration the ability of Deep Learning architectures to track temporal patterns and identify correlations between optical and SAR data, we propose a CNN-RNN based model that exports dense NDVI time-series of a static 6-day time resolution in order to detect events on grasslands. In this study, pixel-level data from 7 different areas of Lithuania extracted using an Analysis Ready Datacube (ARD) for the direct comparison of the most usual gap-filling methodologies and ours on a random selected time frames of variable sizes. Finally, it is demonstrated that our model is able to provide dense artificially created NDVI time-series that can be deployed on the context of a fully operational scenario and improve the accuracy of event identification task on grasslands, as well as to eliminate the abrupt changes and noise of NDVI time series due to cloudy observations that applied masks are frequently not able to filter out.**

***Index Terms*—S1-S2 Fusion, Satellite Image Time-series, Event Detection, Deep Learning.**

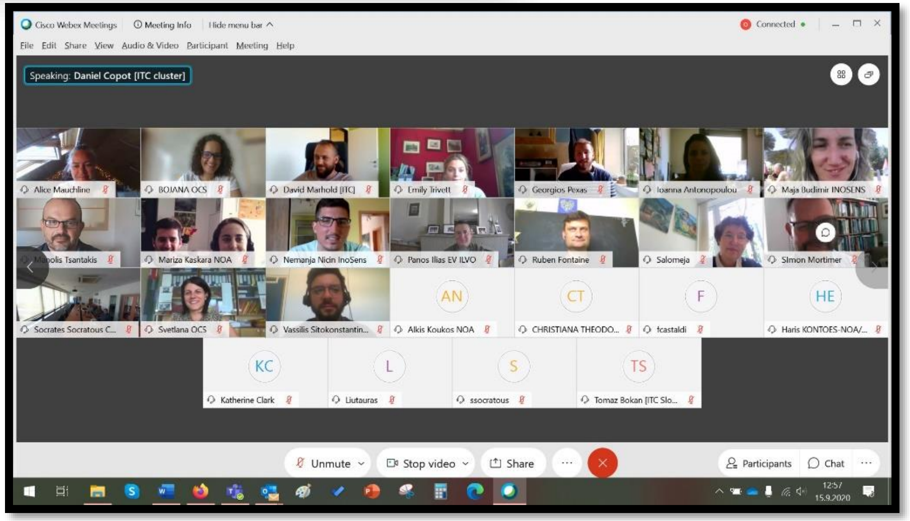
I. Introduction

THE ever-increasing availability of remote sensing data throughout the last decades, have direct impact on the development of agricultural land and practices monitoring . The maintenance of croplands is one of the basic pillars of the socio-economic human activity. The Sentinel constellations provide timely and accurately information of the high spatial and temporal resolution, with no charge, which paves the way to the enhancement of a plethora of applications related to crop management, food security, climate change and control range of ecosystem services, such as provision of fodder for live stocking animals, wildlife habitats, filtering or retention functions of waterways and greenhouse gas emissions, carbon storage, pest control, crop pollination and protection against soil erosion [10], [11]. Therefore, in order to ensure their high ecological value but also regulate their controlled development and shield their vulnerability, European Union introduced in 2003 the Common Agricultural Policy (CAP). This is a financial support system of subsidies directed to EU farmers in order to enhance agricultural productivity and quality in tandem with the maintenance of natural sources management of rural areas and the balanced territorial development. For this reason, following CAP's 2013 reformation, a detailed knowledge of the grassland use intensity and compliance monitoring of every applicant is necessary for the administration and control of requested support from the EU Member States' (MS) paying agencies (PA) and control bodies (CB) (1st pillar of the CAP, European Commission, 2013a) and the consolidation of agro-ecological measures for climate change (2nd pillar of the CAP, European Commission, 2013b) [12], [13].

In general, the vast majority of grasslands monitoring works related remote sensing are addressing issues regarding the discrimination of the different grassland categories (permanent, temporal, etc.) from other land-cover types. Only few of them are entirely focused on the assessment of grassland management intensity and detection of activity [13], and in most cases, under the solely exploitation of optical Earth Observation (EO) data (MODIS, RapidEye, Landsat-8, Sentinel-2)[2], [14], [15], [16], [17] or any combination of them (e.g. NASA Landsat-Sentinel Harmonized dataset)[13]. Several studies though, evaluate the mapping of the mowing or grazing frequency using statistical methods over multi-spectral time series on regional[16] or national scale[13], [11], [2].

Overleaf

ENVISION Team Meetings and Travels



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Thank you!

IMAGINATION
TAKES US
BEYOND
OUR LIMITS