Fusion of Space and Ground Images for Crop Classification

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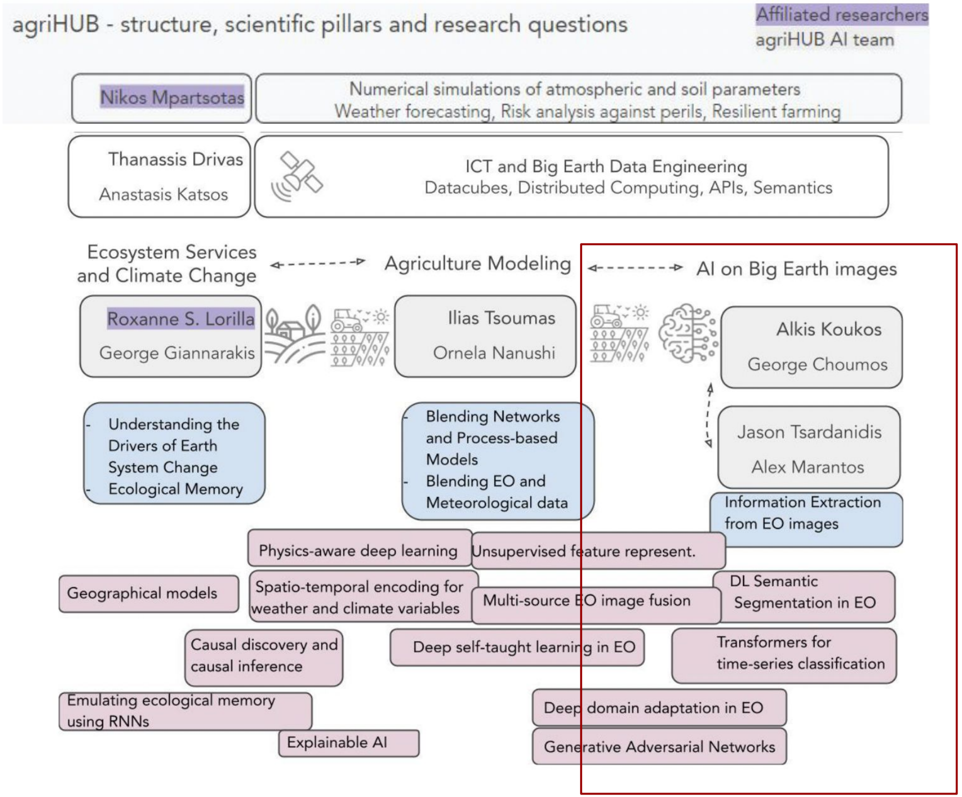


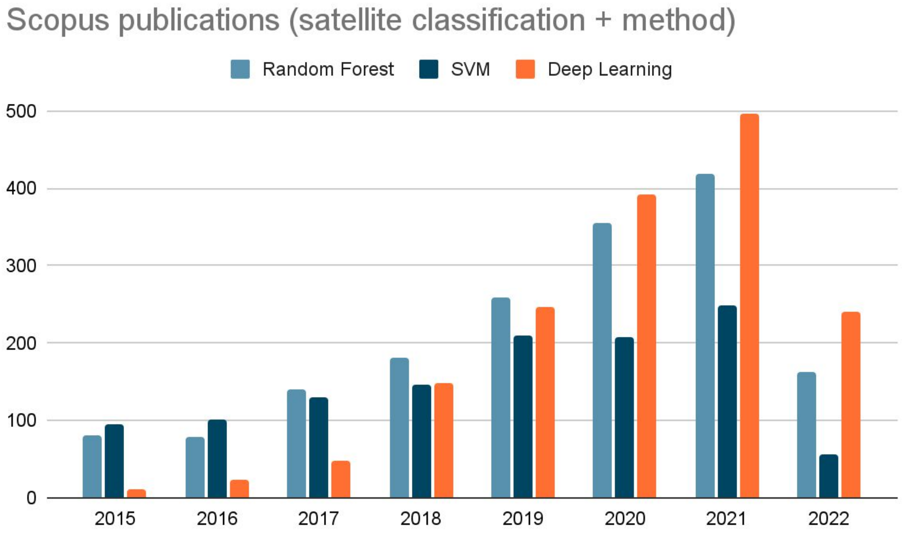
Domain of application is Agriculture

Emphasis in Computer Vision and Image Processing

Indicative tasks

- Image classification
- Semantic Segmentation
- Fill missing values in SITS
- etc.

Motivation — Deep Learning and Big EO data



Scopus publication with “dataset” in the title and “Sentinel” in the abstract

Year	Number
2017	8
2018	16
2019	29
2020	51
2021	56
2022	26

Motivation — AI as an enabler for CAP Monitoring

CAP Monitoring — Agricultural Subsidy Allocations

Farmers declare cropping practices to the Agricultural Paying Agencies

- ➔ Land Parcel Identification Systems data (LPIS)
- ➔ Containing parcel geometries
- ➔ Crop type declaration for each parcel
- ➔ 5% of declarations selected randomly for On The Spot Checks (OTSC)

Check for compliance - Random Sampling		
Declarations Pool	**Declaration vs OTSC**	**Action**
95%	*Irrelevant*	No inspection – Pay subsidies
5%	Agreement	Pay subsidies
	Disagreement	No subsidy / Penalty

Motivation — AI as an enabler for CAP Monitoring

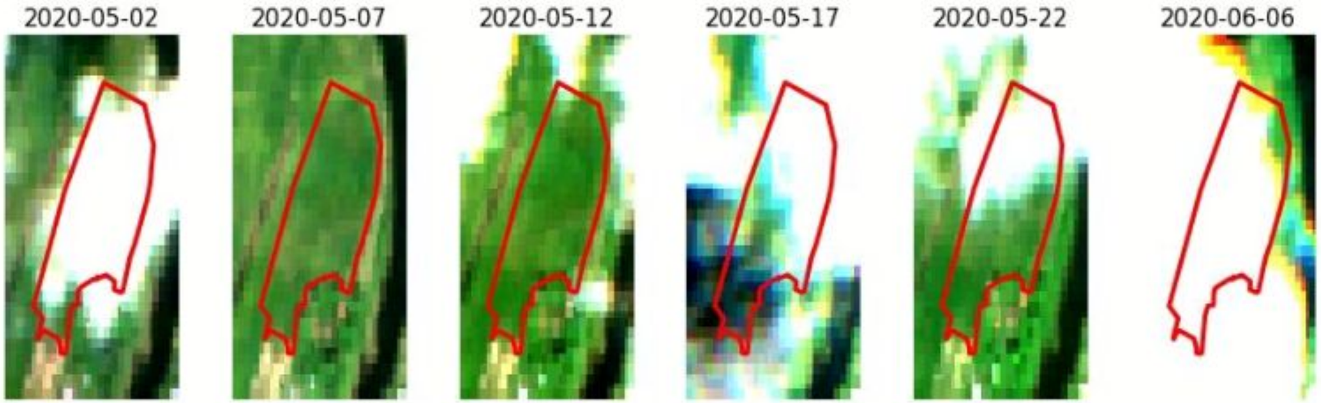
Current status —*Smart Sampling* — Crop Classification

- **Exploitation of Big satellite data (Sentinel-1 and Sentinel-2)**
- LPIS for annotations - Matching with satellite data using
  - parcel geometries and
  - crop type labels (declarations)
- AI models for crop classification trained on these data
- Sample field inspections on parcels appearing as non-compliant (classification vs declaration)

Smart Sampling	
Classification vs Declaration	Action
Strong Agreement	No further action required – Pay subsidies
Weak (Dis)agreement	Sample for field inspections
Strong Disagreement	No subsidy / Penalty / Field inspections

Limitations of Satellite Data - Towards Exhaustive Monitoring

- Satellite data can only get us this far
  - Spatial resolution (10m-60m)
  - Inappropriate for photo-interpretation
  - Temporal frequency limitations (cloud impact, 5-day revisit)



Towards Exhaustive Monitoring

- Exhaustive Monitoring → More data sources from Space to Ground / More data modalities
  - **Very High Resolution (VHR) satellite imagery**
  - **Unmanned Aerial Vehicles (UAV)**
  - **Street-level Images**

Towards Exhaustive Monitoring	
Classification vs Declaration	Action
Strong Agreement	No further action required – Pay subsidies
Weak (Dis)agreement	Check street-level images
	If not enough – Fly UAVs
	If not enough - Field inspections
Strong Disagreement	No subsidy / Penalty / Field inspections

Data going from Space → to Ground

Images on the Street-Level

Challenges

Data going from Space → to Ground

Images on the Street-Level

Challenges

- Research focused on other domains (e.g., self-driving cars, traffic sign detection, etc.)
- Datasets mainly from urban areas
- Volume of data required to cover single satellite acquisition
- Attaching agricultural annotations to street-level images

Data going from Space → to Ground

Images on the Street-Level

Challenges → Needs/Requirements

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Data going from Space → to Ground

Images on the Street-Level

Challenges	Needs/Requirements
• Research focused on other domains (e.g., self-driving cars, traffic sign detection, person identification, etc.) • Datasets mainly from urban areas • Volume of data required to cover single satellite acquisition • Attaching agricultural annotations to street-level images	• Decentralization of data collection effort • Enhance focus on agricultural areas • Robust annotation framework for ground/street-level imagery

Data going from Space → to Ground

Images on the Street-Level

Challenges → Needs/Requirements → Solutions

Challenges

- Research focused on other domains (e.g., self-driving cars, traffic sign detection, person identification, etc.)
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Needs/Requirements

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Solutions

- Decentralization through Crowdsourcing

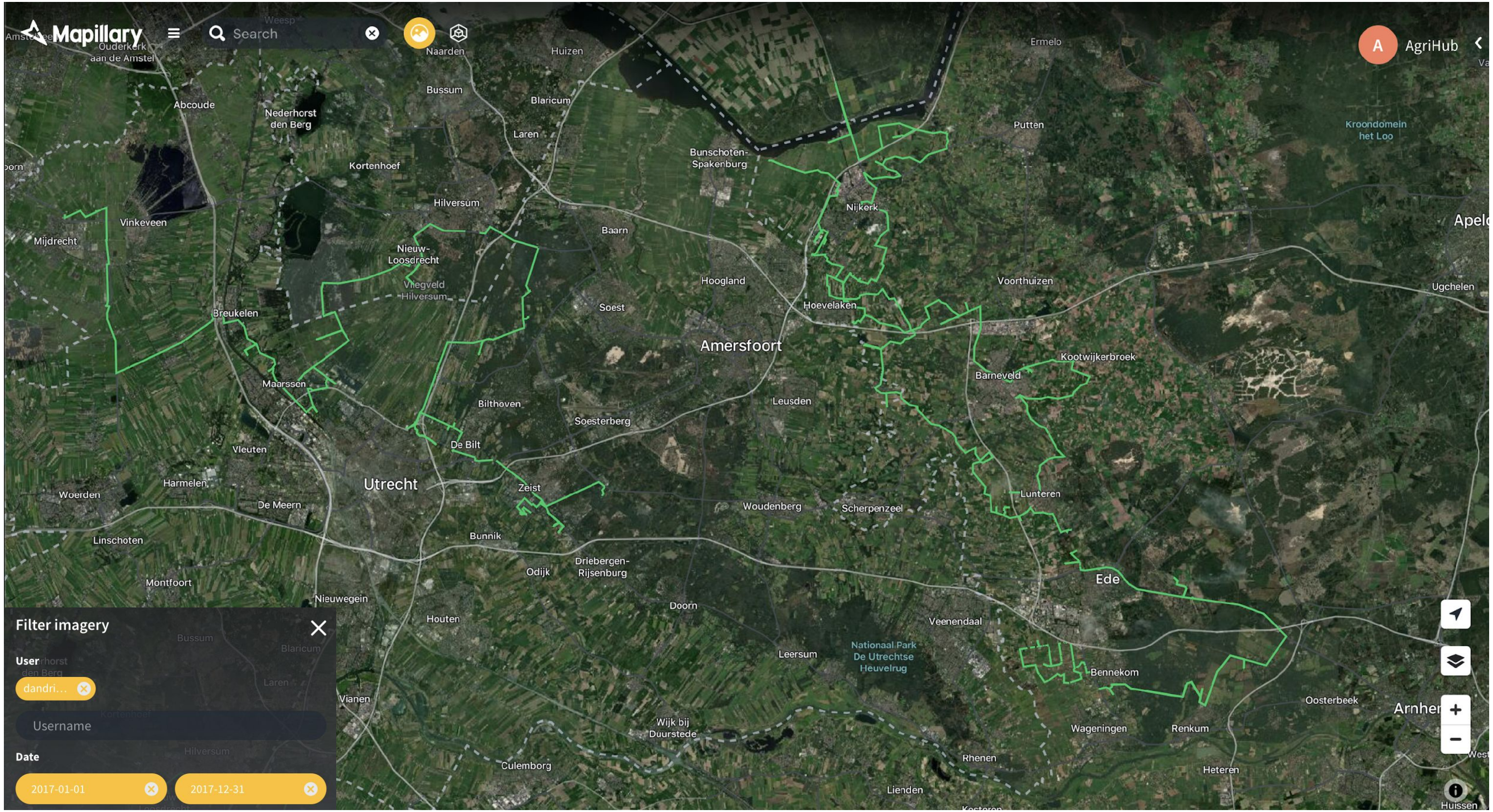
Mapillary

- Annotation through LPIS and coordinate transformations

DataCAP

- ***Space2Ground*** dataset availability

Mapillary Crowdsourcing Platform



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d'Andrimont, R., Lemoine, G. and Van der Velde, M., 2018. Targeted grassland monitoring at parcel level using sentinels, street-level images and field observations. Remote Sensing, 10(8), p.1300.

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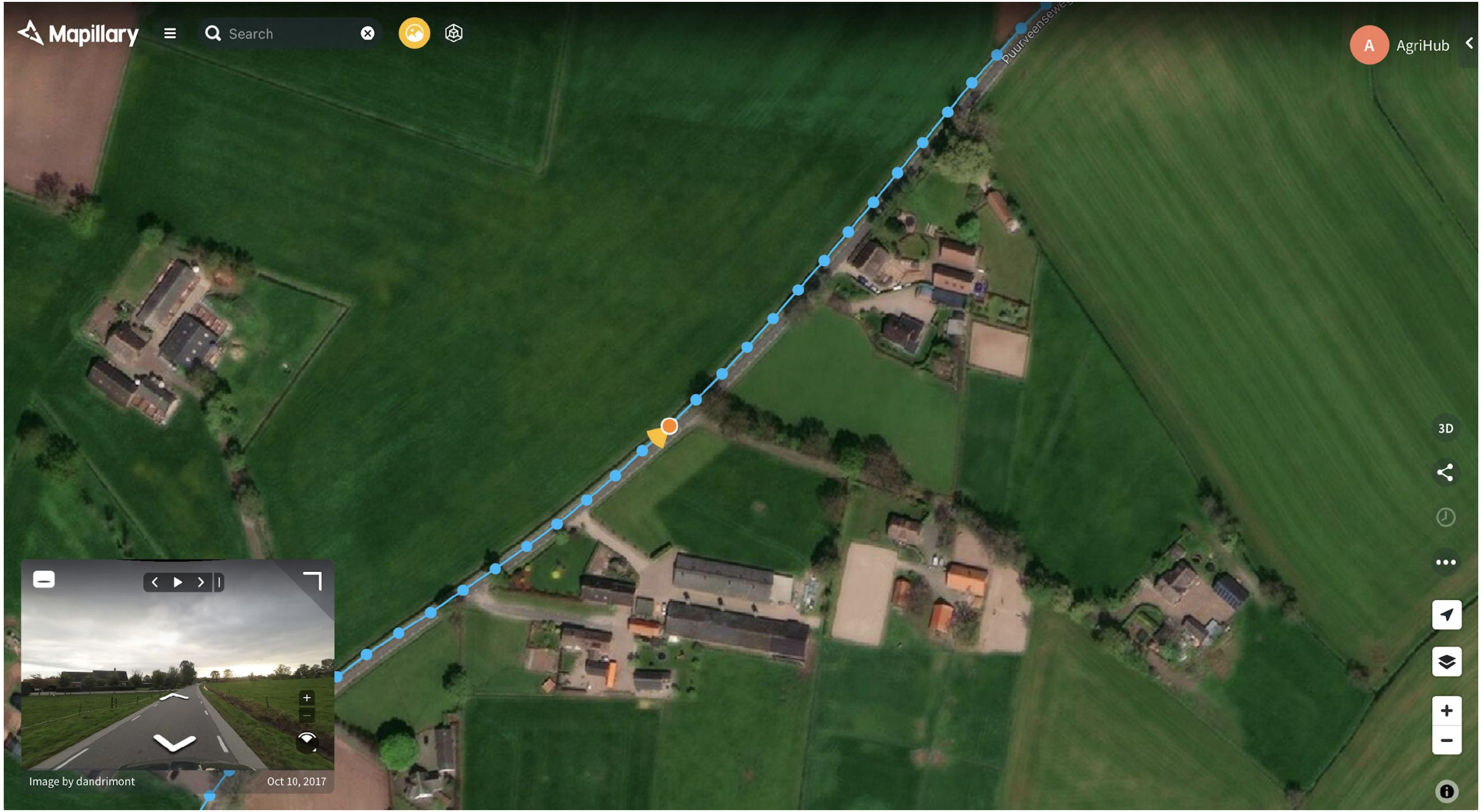
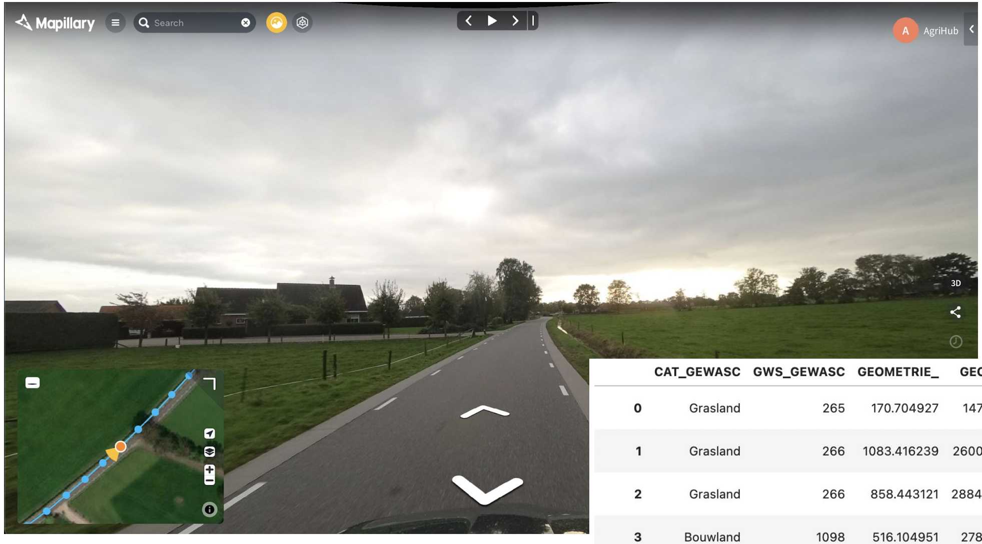
Mapillary Crowdsourcing Platform



Mapillary Crowdsourcing Platform

Annotating SLIs - DataCAP approach



Mapillary

Combining Street-level images in the Netherlands with Dutch LPIS labels openly available.

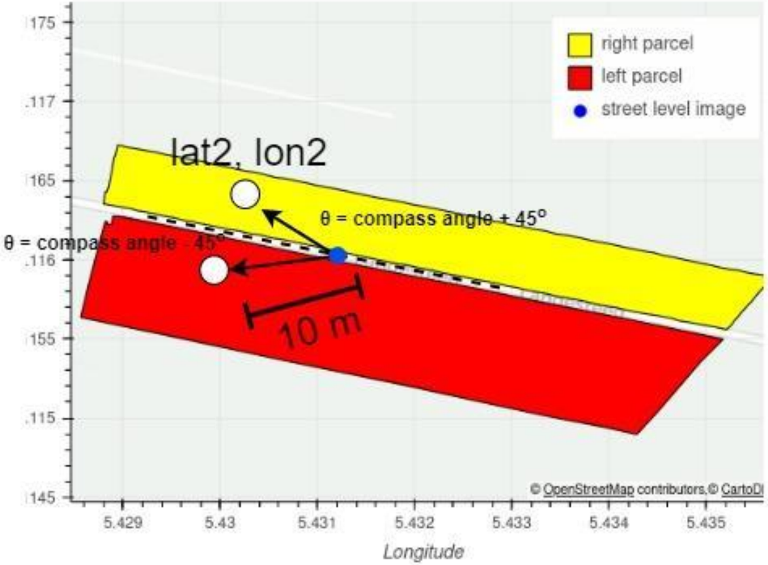
LPIS

	CAT_GEWASC	GWS_GEWASC	GEOMETRIE_	GEOMETRI_1	GWS_GEWAS	id	geometry
0	Grasland	265	170.704927	1472.436561	Grasland, blijvend	1	POLYGON ((607260.186 6850944.822, 607260.491 6...
1	Grasland	266	1083.416239	26008.169650	Grasland, tijdelijk	2	POLYGON ((607589.261 6849674.646, 607588.788 6...
2	Grasland	266	858.443121	28843.493760	Grasland, tijdelijk	3	POLYGON ((607937.264 6851070.654, 607394.081 6...
3	Bouwland	1098	516.104951	2783.437687	Peren. Aangeplant voorafgaande aan lopende sei...	4	POLYGON ((551847.903 6809201.124, 551847.749 6...
4	Grasland	265	911.993567	20414.915207	Grasland, blijvend	5	POLYGON ((551371.731 6827869.920, 551370.198 6...
...	...	...	...	...	...	...	...
55034	Grasland	265	100.022431	504.525746	Grasland, blijvend	55035	POLYGON ((589995.209 6841226.222, 590003.944 6...
55035	Grasland	265	400.141629	3930.653695	Grasland, blijvend	55036	POLYGON ((548720.576 6843754.469, 548700.911 6...
55036	Grasland	265	558.913736	11432.118162	Grasland, blijvend	55037	POLYGON ((620079.799 6847006.063, 620093.376 6...
55037	Grasland	265	168.449401	1558.859561	Grasland, blijvend	55038	POLYGON ((618496.803 6847468.779, 618466.965 6...
55038	Grasland	265	574.773859	9801.745443	Grasland, blijvend	55039	POLYGON ((545679.407 6822762.192, 545573.445 6...

DataCAP annotation approach

$$lat_2 = \arcsin\left(\sin lat_1 \cdot \cos \frac{d}{R}\right) + \cos lat_1 \cdot \sin \frac{d}{R} \cdot \cos \theta)$$

$$lon_2 = lon_1 + \arctan\left(\sin\theta \cdot \sin \frac{d}{R} \cdot \cos lat_1, \cos \frac{R}{d} - \sin lat_1 \cdot \sin lat_2\right)$$



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DataCAP

Demonstration

SLI-part

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Extending SLI coverage for Agriculture Purposes

- Field inspectors of agricultural PAs cover large distances while visiting parcels
- Take advantage of this fact to boost agricultural coverage of SLIs
- Minimize overhead by using current operational framework

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↓

- We could mount a camera on field inspector vehicles
- Automate capture per time and/or distance

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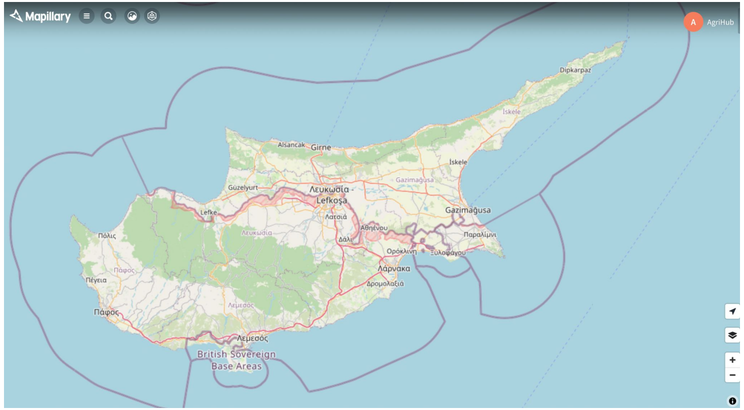
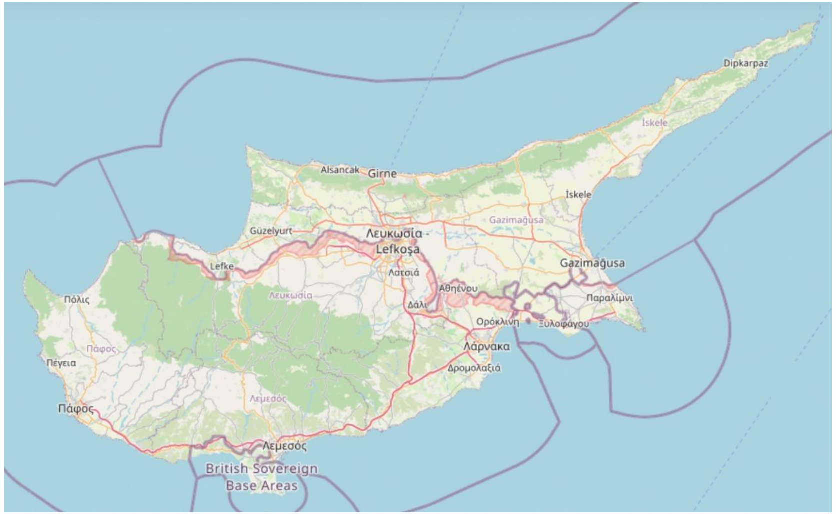
Let’s see the Cyprus / CAPO example:



H2020 CALLISTO - Field Campaigns

- NOA / CAPO collaboration on street-level image capture
- 2 Field Inspectors involved
  - 1 with regular acquisitions
  - 1 with occasional acquisitions
- Almost 1 year of acquisitions:



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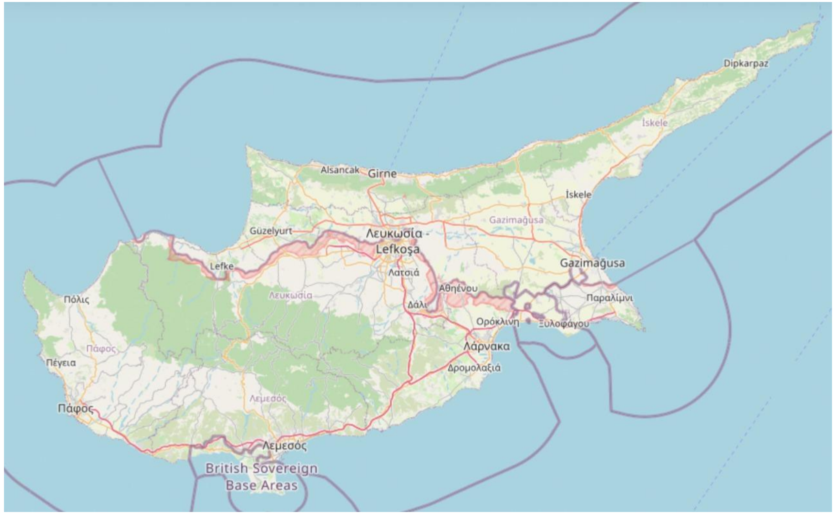

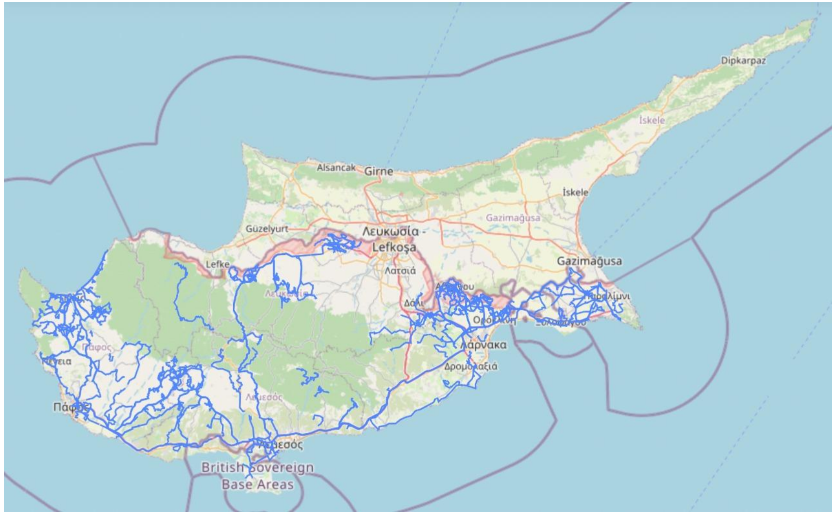

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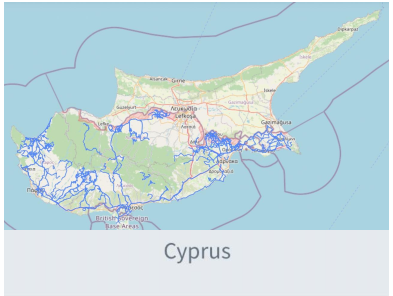
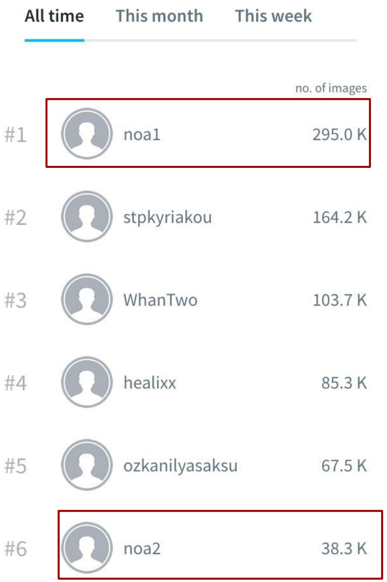
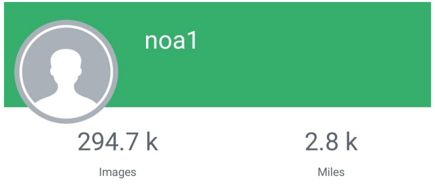
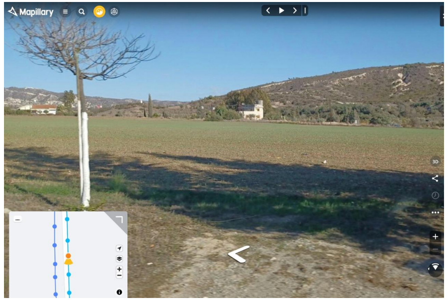


Achievements of field campaigns

- **~ 340k images** acquired up to now
- More than 5000 km distance covered!
- Top contributors in Cyprus for Mapillary
- Largely focused on Agricultural Areas
- Dispute resolutions - Potential for AI applications







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Field Campaigns — Acquisition Examples

Camera mounted on the front / windshield:
link to front-mounted camera sequence

Camera mounted on the side window:
link to side-mounted camera sequence

Action-camera sequence example:
link to action camera sequence

Exploiting agricultural SLI volume and DataCAP framework

- Street-level images are not only photo-interpretation material
- Volume available + DataCAP annotation framework
  - Potential for DL on SLIs
  - Potential of fusing Space & Ground components to a single dataset
- Common labels (LPIS) for Space (Sentinel-1/2) and Ground (SLI) components

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"Towards Space-to-Ground Data Availability for Agriculture Monitoring"

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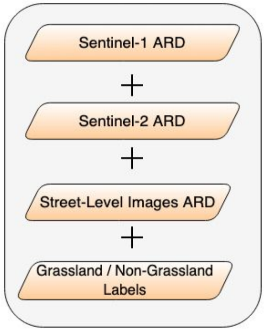
"Towards Space-to-Ground Data Availability for Agriculture Monitoring"

IVMSP Image Video And Multidimensional Signal Processing IEEE IEEE Signal Processing Society

Space2Ground Dataset

Space2Ground is a multi-level, multi-sensor, multi-modal dataset, annotated with grassland/non-grassland labels for agriculture monitoring. We combine Sentinel-1 SAR data, Sentinel-2 multispectral data and street-level images for the purpose of grassland detection.

Space-2-Ground Dataset



GitHub

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Achieving Exhaustive Monitoring - Data Availability

- Data sources from Space and Ground
  - Plethora of available data sources / datasets
  - Connection between Space and Ground components?

Space-2-Groud Data Availability	
Component	**Source / Dataset examples**
Space	BigEarthNet, DENETHOR, ZueriCrop, Sen4AgriNet, CropHarvest
Ground	iCrop, CropDeep, CWFID
Space & Ground	**?**

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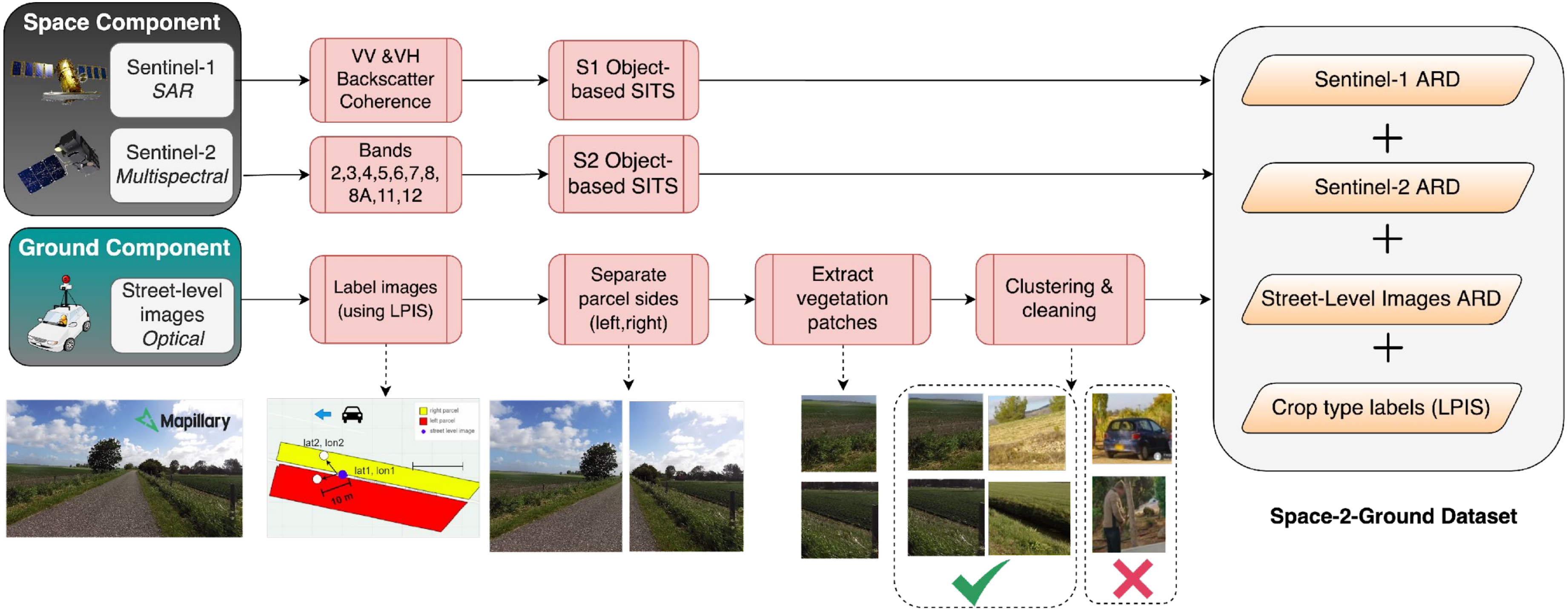
Space & Ground	✖

No datasets combining Space and Ground components exist!

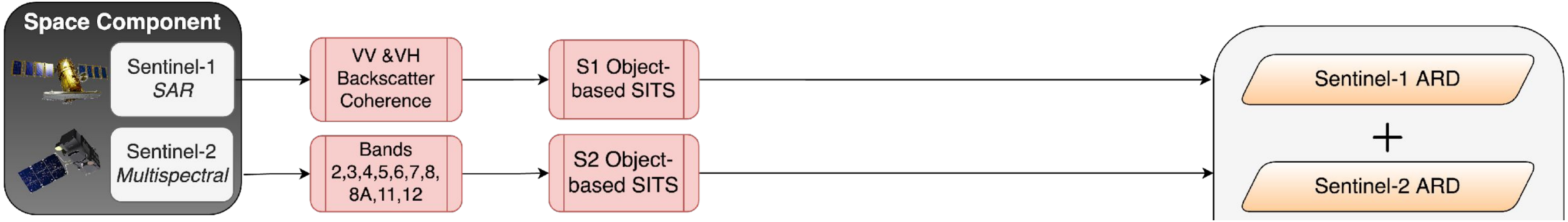
Space-2-Ground Dataset



Space-2-Ground Dataset - Components

Space Component

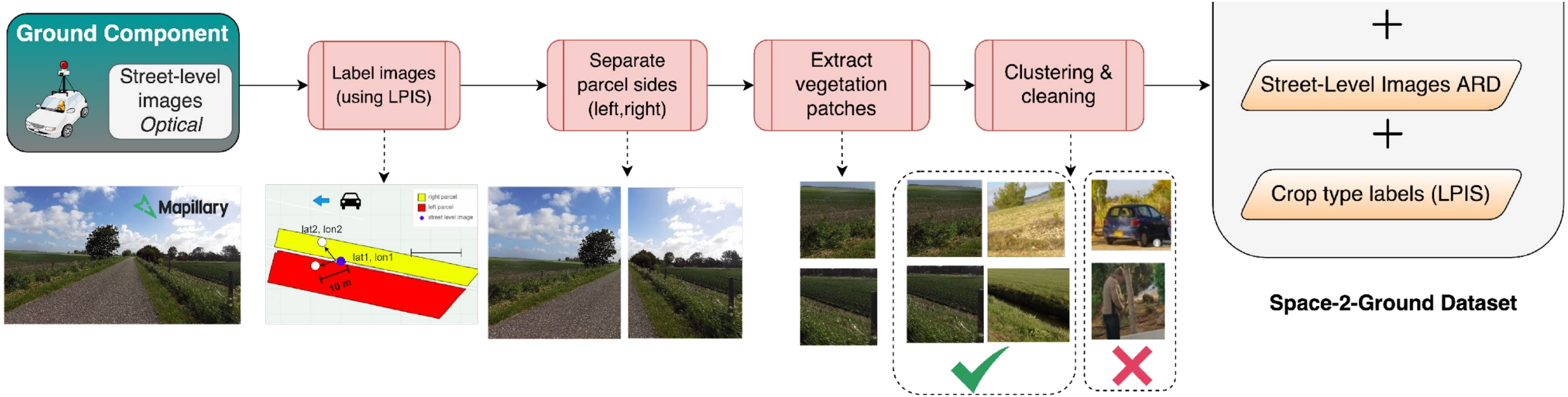
- Sentinel-1 Synthetic Aperture Radar data
  - VV & VH Backscatter & Coherence
  - S1 time-series data on the object-level (ie. parcel level)
- Sentinel-2 Multispectral data
  - Bands: B02, B03, B04, B05, B06, B07, B08, B8A, B11, B12
  - S2 time-series data on the object-level (i.e., parcel level)
- Parcel geometries used in order to aggregate on the object level (Land-Parcel Identification Systems data - LPIS)



Space-2-Ground Dataset - Components

Ground Component

- Street-level Images
  - Crowdsourced, openly-accessible data → Mapillary platform
  - Annotation using acquisition coordinate transformations and LPIS parcel geometries (based on DataCAP methodology)
  - Further preprocessing steps (both procedural and Machine Learning) to clean-up and isolate vegetation patches of each image side



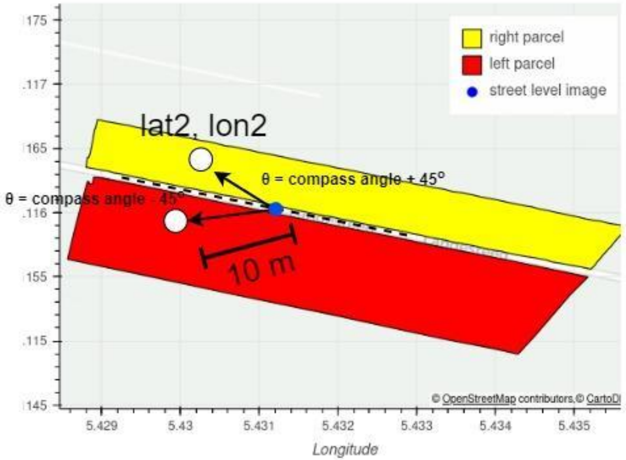
Initial Ground/Street-level Image

<u>Image Labels</u>

parcel id: 1, crop: Grassland

parcel id: 2, crop: Grassland

Split image in half - Separate labels

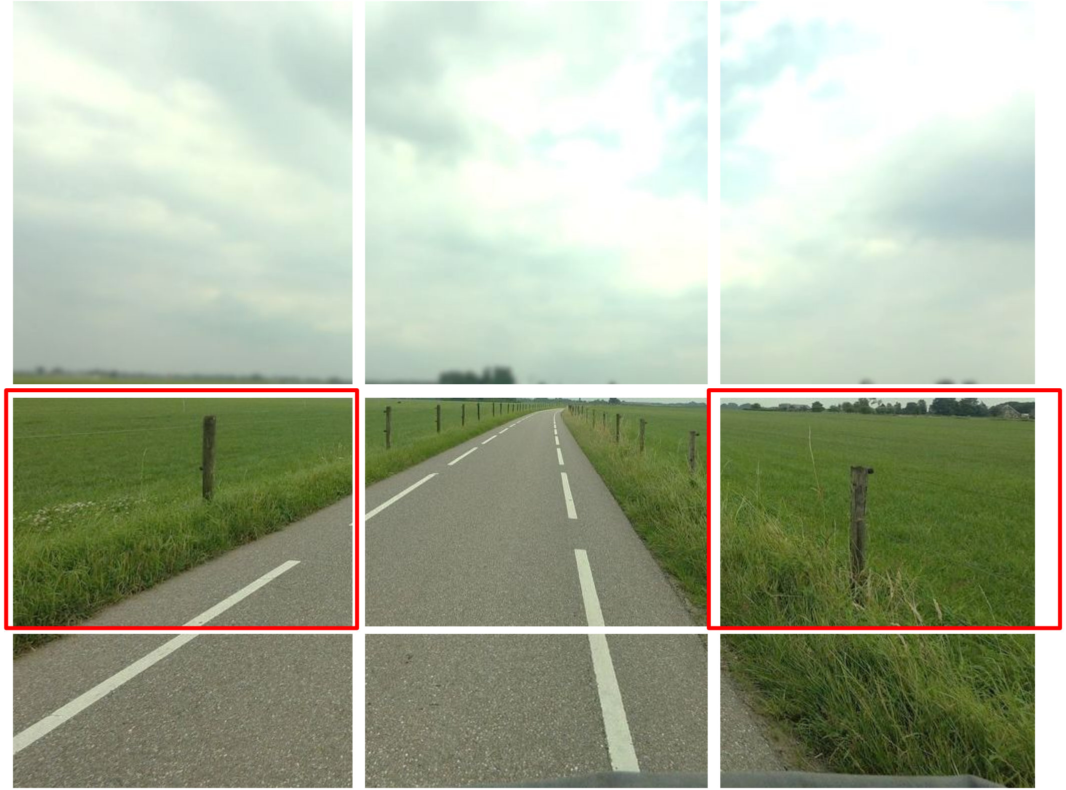


Extract vegetation patches

0%-30%
70%-100%
of width

20%-50% of height

Vegetation patches
resized to (260,260) px



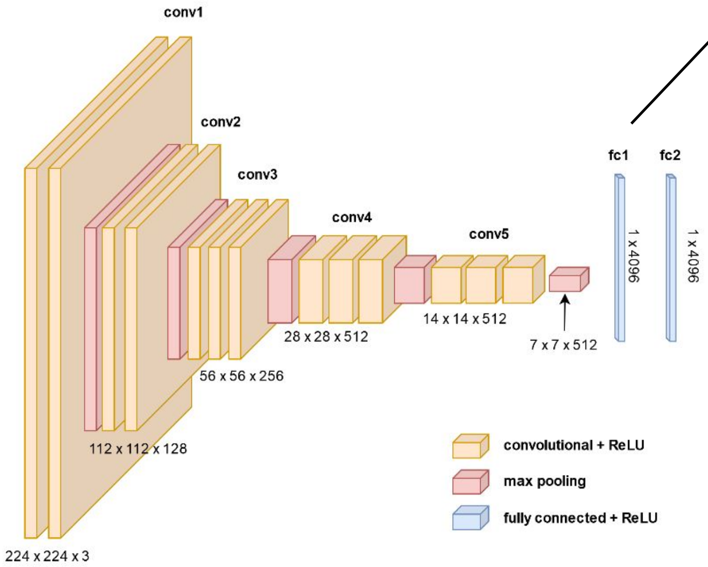
Grassland

Grassland

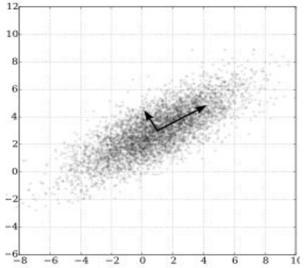
Clustering and Cleaning

vegetation patch

VGG16 representation



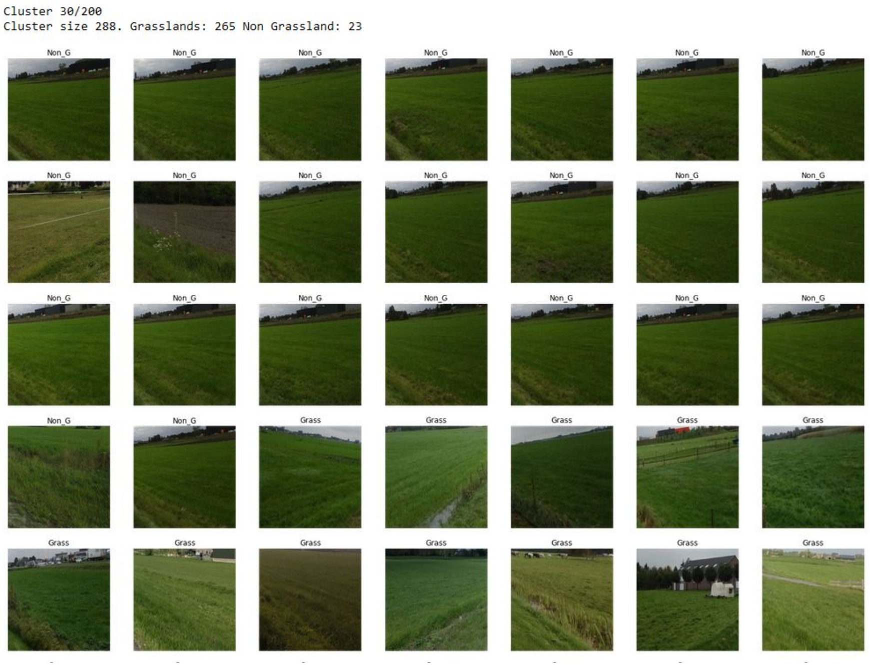
PCA



top 100 components

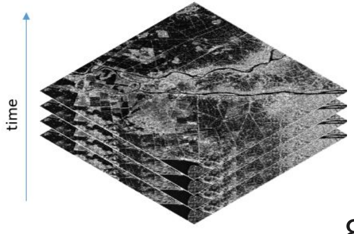
K-means

Clustering and Cleaning



sentinel-2

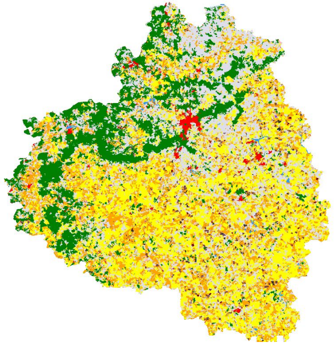
Benchmarking - Model fusion



8,875 Grasslands
1,227 Non Grasslands

Street-level images

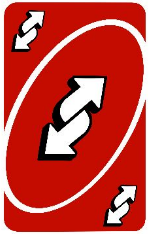
Crop classification
RF, SVM, TempCNN, LSTM,
LSTM + Attention



Crop classification
Pre-trained on Imagenet -
ResNet, EfficientNet, VGG,
Inception v3

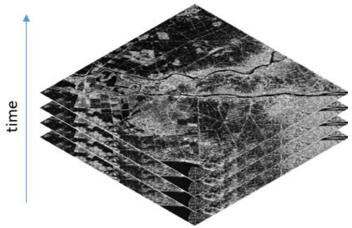
Low confidence decisions

Reverse decision



sentinel-2

Model fusion



Street-level images

Crop classification
RF, SVM, TempCNN, LSTM, LSTM + Attention

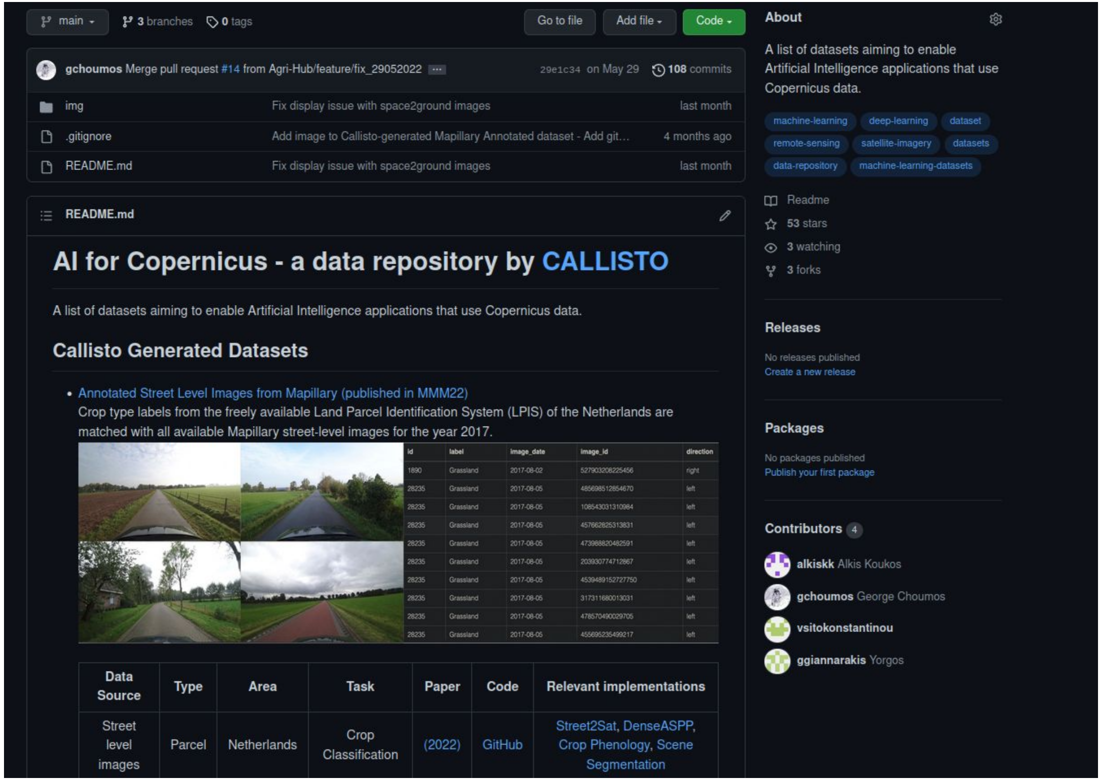
Method	SVM	RF	TempCNN	LSTM	LSTM+Attention
Accuracy	93.69%	94.68%	95.22%	95.14%	95.20%
F1 score	85.22%	88.08%	89.96%	89.85%	90.05%

Inception v3 = 85%

Low confidence decisions

CALLISTO Data Repository - AI4Copernicus

https://github.com/Agri-Hub/Callisto-Dataset-Collection/



Space-to-Ground v2 - Work in Progress

Improving the Ground-component

- Large percentage of street-level acquisitions are noisy and become difficult to use
- Vegetation extraction
    - Unlike satellite imagery, it is difficult to isolate parcels and extract vegetation parts of image
    - Images ignored because of which part vegetation appears in
    - Rule based approach can only get us that far

Can we improve our data? How?

Space-to-Ground v2 - Work in Progress

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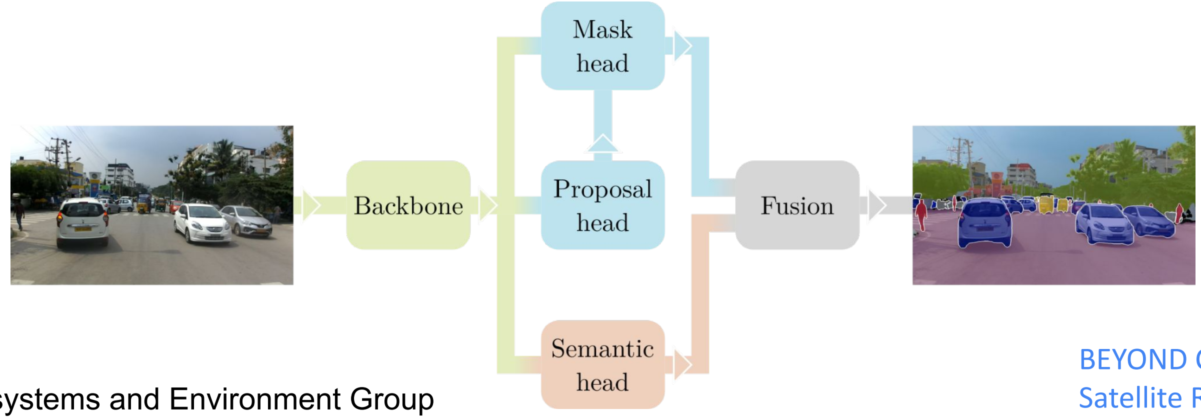
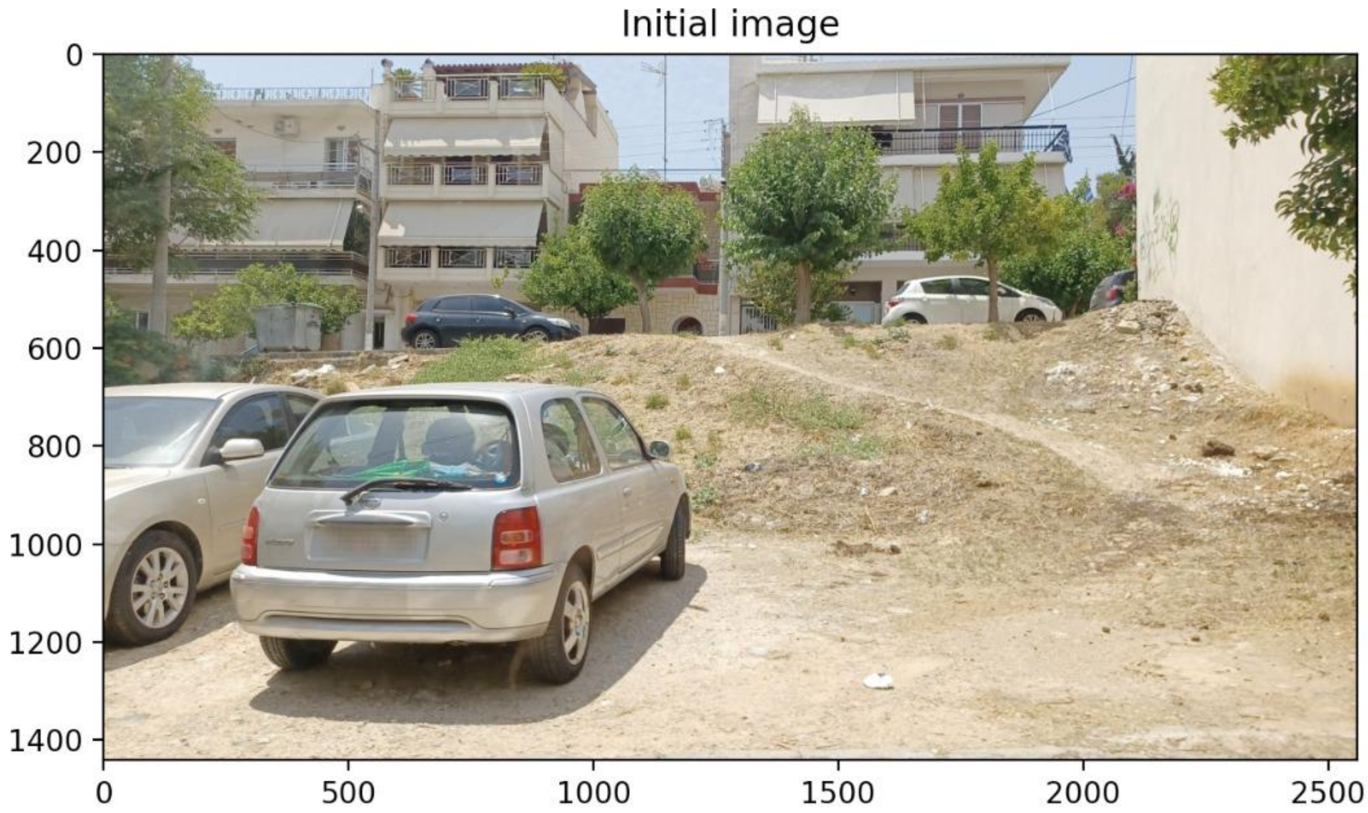
Semantic Segmentation

- Isolate vegetation through semantic segmentation
- Greatly increase the amount of images utilized
- Potential for identification of more items of interest within each image (animals, buildings, etc.)



Space-to-Ground v2 - Semantic Segmentation



Space-to-Ground v2 - Semantic Segmentation

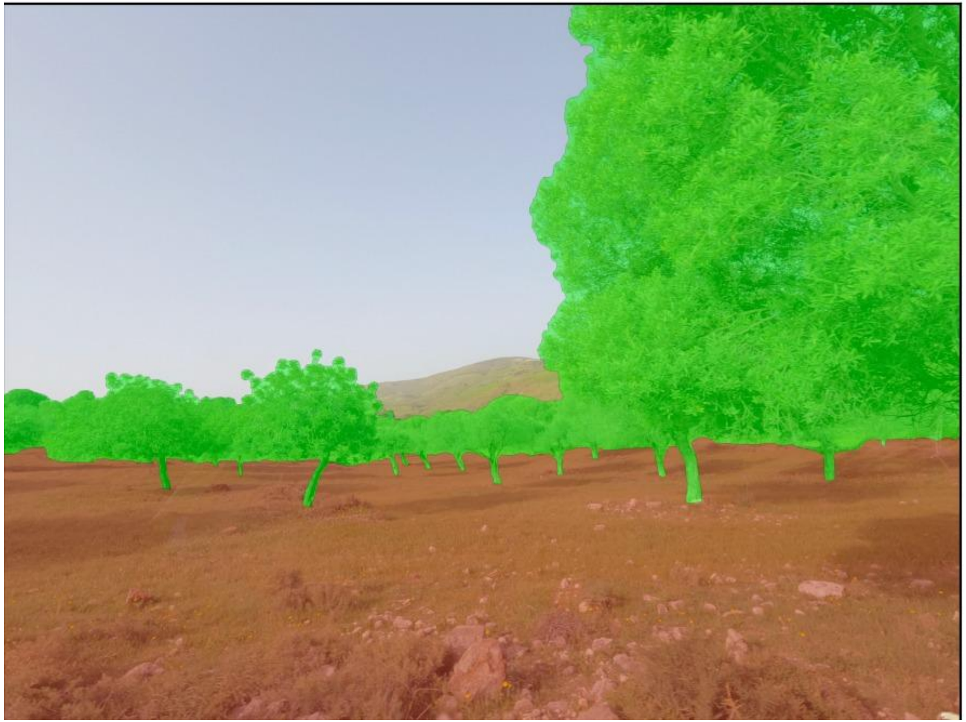
Initial image

Image detections

Space-to-Ground v2 - Semantic Segmentation

Initial image

Image detections



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Space-to-Ground v2 - Semantic Segmentation

Initial image

Image detections

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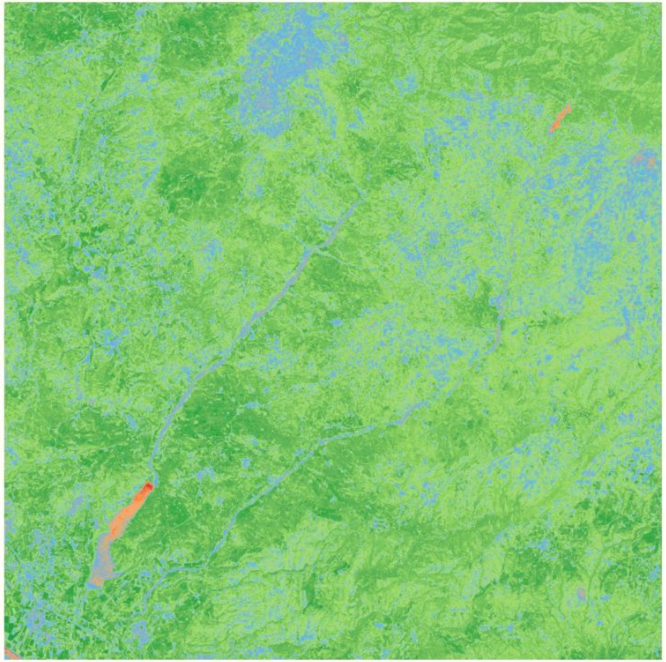
Alternative Data Sources

UAV images

Planetscope images



Publications

Choumos, G., Koukos, A., Sitokonstantinou, V. and Kontoes, C., 2022. Towards Space-to-Ground Data Availability for Agriculture Monitoring

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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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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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

Sitokonstantinou, V., Koukos, A., Drivas, T., Kontoes, C., Papoutsis, I. and Karathanassi, V., 2021. A Scalable Machine Learning Pipeline for Paddy Rice Classification Using Multi-Temporal Sentinel Data

Sitokonstantinou, V., Papoutsis, I., Kontoes, C., Lafarga Arnal, A., Armesto Andrés, A.P. and Garraza Zurbano, J.A., 2018. Scalable parcel-based crop identification scheme using Sentinel-2 data time-series for the monitoring of the common agricultural policy.

Rousi, M., Sitokonstantinou, V., Meditskos, G., Papoutsis, I., Gialampoukidis, I., Koukos, A., Karathanassi, V., Drivas, T., Vrochidis, S., Kontoes, C. and Kompatsiaris, I., 2020. Semantically enriched crop type classification and linked earth observation data to support the common agricultural policy monitoring

Remarks & Future work

- Enhance quality of the datasets:
  - Improve street level annotation methodology
  - Quality Assessment of street-level images (e.g. No Reference/ Reference IQA)
  - Identify the agriculture part of the image using Semantic Segmentation and apply on side captures
  - Augment semantic segmentation labels, by adding crop types instead of merely vegetation

- Create analysis ready benchmark dataset from our campaigns in Cyprus containing 100s of thousands of images & enhance street-level image based crop classification

- Explore DL models for early and late fusion of space and ground data
  - Lightweight DL models
  - SOTA DL architectures (Transformers, RNNs, etc)

Thank you