A3.10.1 Novel in-situ collection for agricultural and forest structure applications

DataCAP: Sentinel datacubes, crowdsourced street-level images and annotated benchmark datasets for the monitoring of the CAP

Wed, 25 May, 2022

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New CAP – Steering towards exhaustive monitoring

Checks for cultivated crop types and compliance with CAP guidelines Random Sampling → Smart Sampling^[1]

- •Al models trained with satellite data (Sentinels)
- Crop Classification outcomes compared with LPIS
- On-The-Spot-Checks (OTSCs) out of the disagreement pool
- Scalability: X Regularity: X



Smart Sampling						
Classification vs Declaration	Action					
Agreement	No further action required – Pay subsidies					
Disagreement	Sample from this pool for OTSCs					

[1] Rousi, Maria and Sitokonstantinou, Vasileios et al. "Semantically enriched crop type classification and Linked Earth Observation Data to support the Common Agricultural Policy monitoring." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 14 (2020): 529-552.





New CAP – Steering towards exhaustive monitoring

Smart Sampling → Wall-to-wall Monitoring (Exhaustive monitoring)

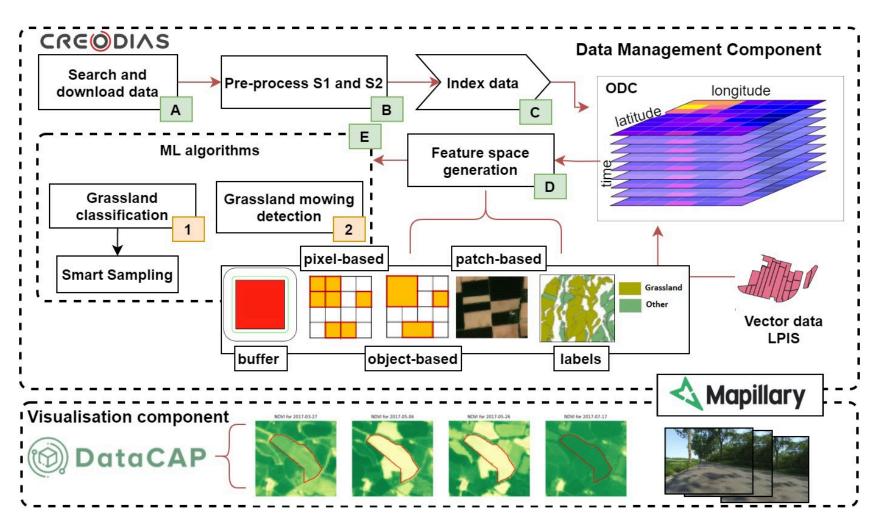
- •Post-2020 CAP
- Incorporation of heterogeneous data sources for Space-to-Ground coverage
 - Very High-Resolution satellite data
 - Unmanned Aerial Vehicles
 - > Street-level and in-field geo-tagged photos

Towards Exhaustive Monitoring						
Classification vs Declaration	Action					
Strong Agreement	No further action required – Pay subsidies					
Weak (Dis)agreement	Check street-level images					
Weak (Dis)agreement	If not enough – Fly UAVs					
Weak (Di)sagreement	If not enough - OTSCs					
Strong Disagreement	Correct declaration					





A comprehensive data solution for monitoring the CAP



in the office



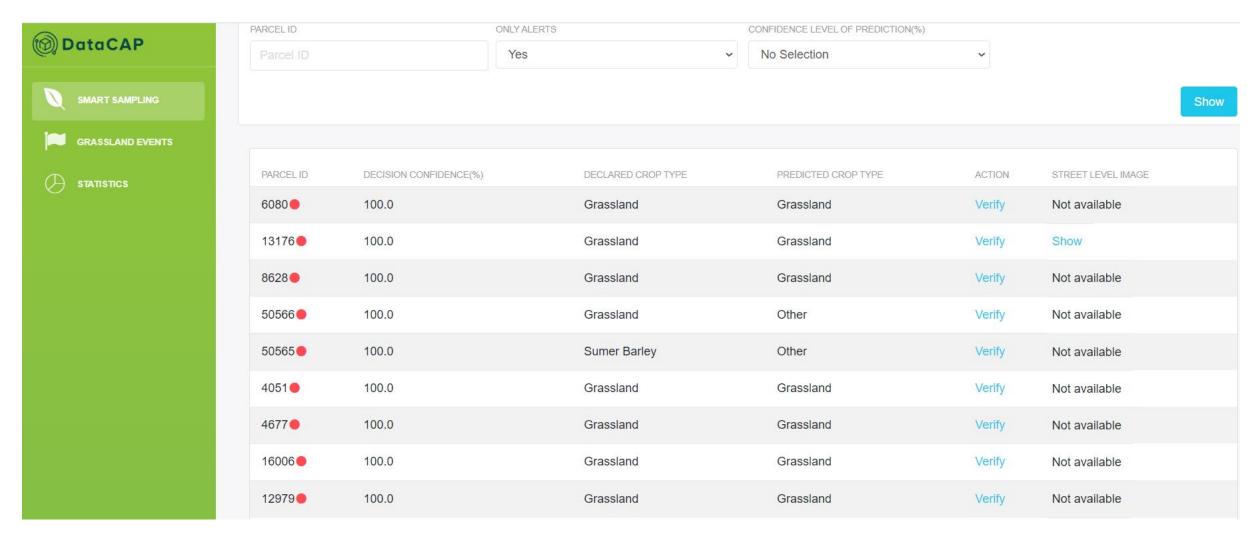








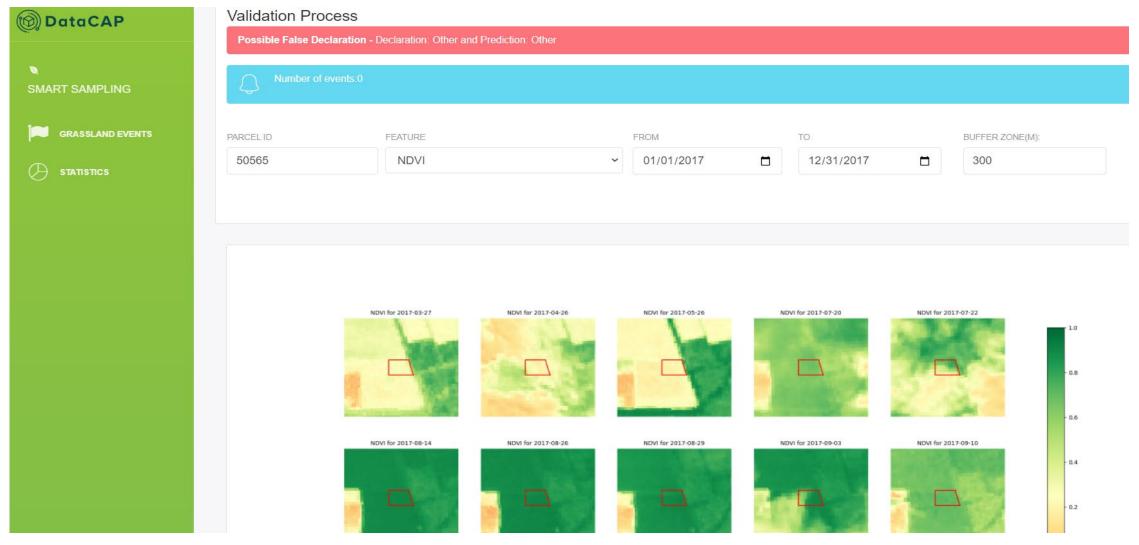
DataCAP GUI







DataCAP GUI

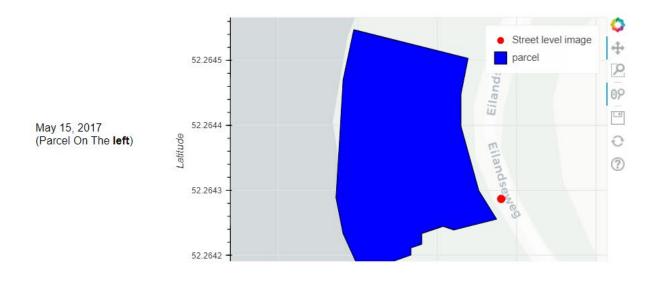






DataCAP GUI

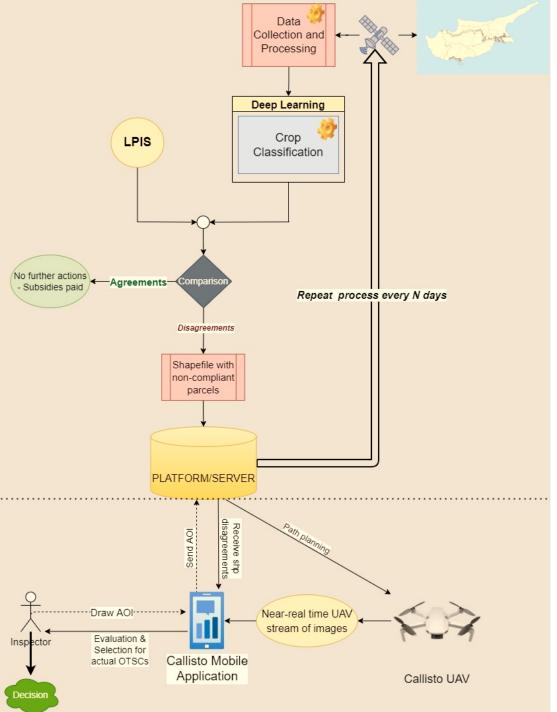








DataCAP



near the field









Collection of street-level images

Street-Level Images

- Campaigns
 - Acquisition methodology
 - Cost-efficient, easy to set up by inspectors & using existing operational framework
 - Mapillary platform analysis
 - Action cam (better results than smartphone)
 - Giving back to the community **Mapillary crowdsourcing platform**
 - √ 300 k street-level images already uploaded Top contributors in Cyprus
- •Annotation through LPIS matching "DataCAP" publication on MMM Callisto generated dataset

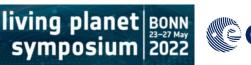




Sitokonstantinou, V., et al. (2022). DataCAP: A Satellite Datacube and

Policy. In International Conference on Multimedia

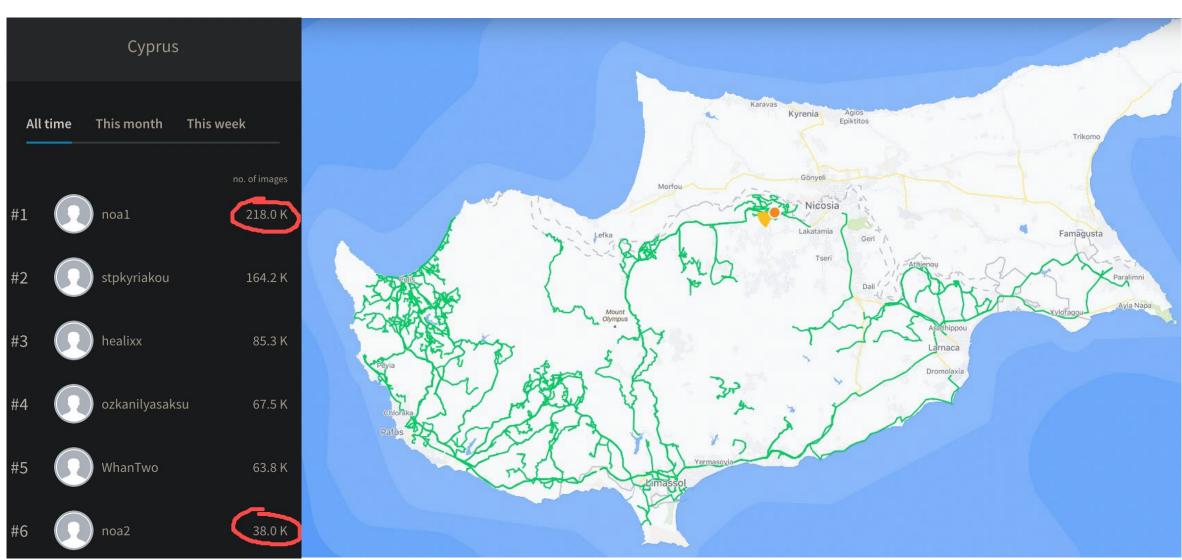
Crowdsourced Street-Level Images for the Monitoring of the Common Agricultural







Street-level image from Cyprus (Mapillary)

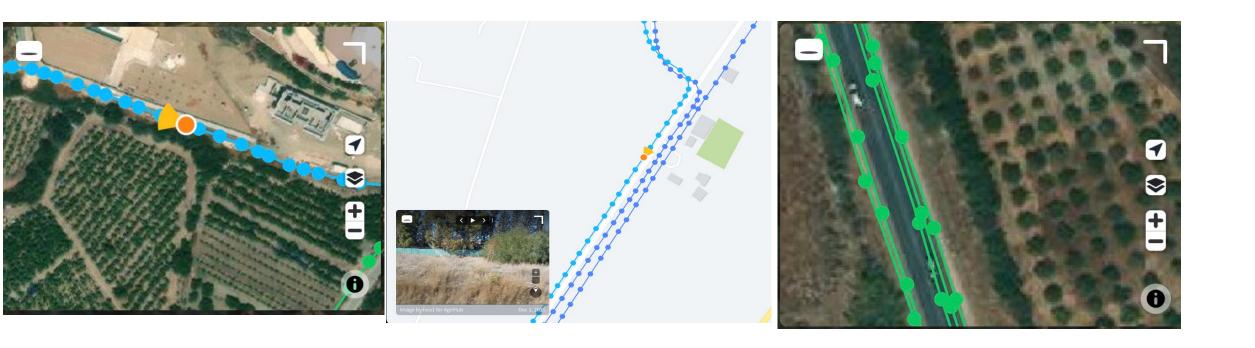






esa

Visiting multiple times within season

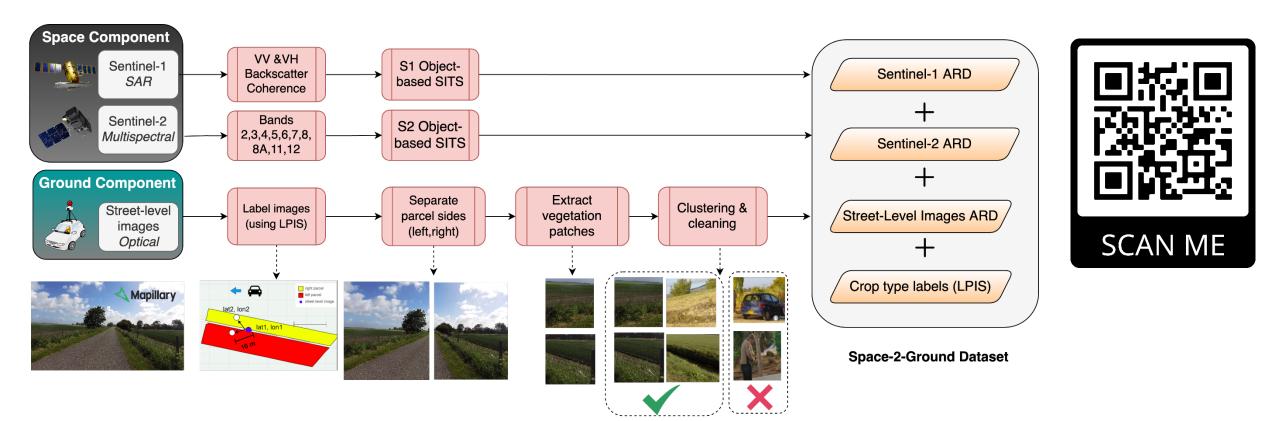






Space-to-ground data availability

Choumos, G.*, Koukos, A.*, Sitokonstantinou, V. and Kontoes, C. (2022). Towards space-to-ground data availability for agriculture monitoring. In 2022 IEEE 14th Image, Video, and Multidimensional Signal Processing Workshop, IVMSP.

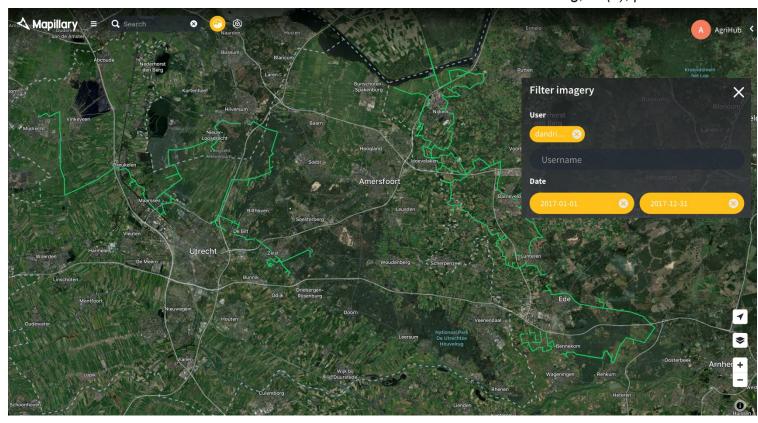






Campaign for collecting street-level images of grasslands in the Netherlands

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.



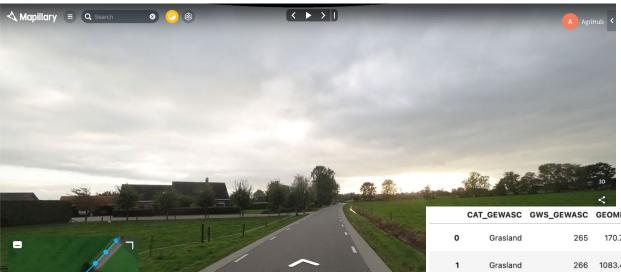












Combining Street-level images in the Netherlands with Dutch LPIS labels openly available.

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

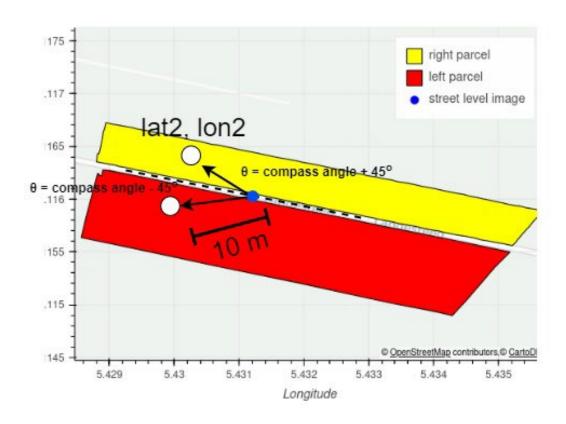






 $lat_2 = \arcsin\left(\sin lat_1 \cdot \cos \frac{d}{R}\right) + \cos lat_1 \cdot \sin \frac{d}{R} \cdot \cos \theta$

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







Initial Image







Split image in half



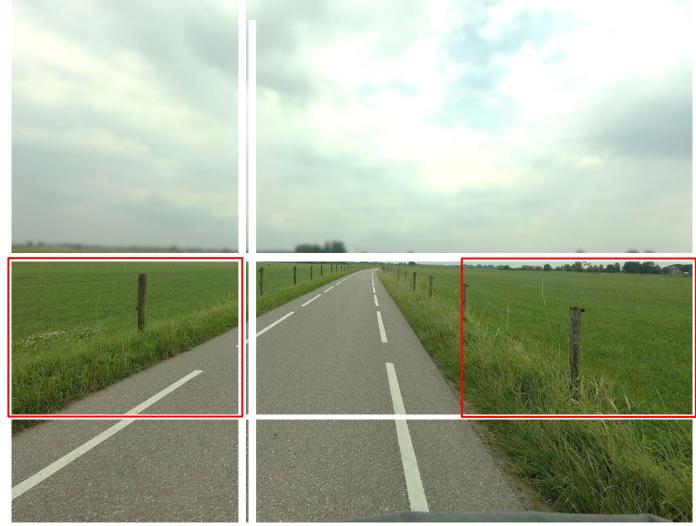




Vegetation patches

20%-50% of height

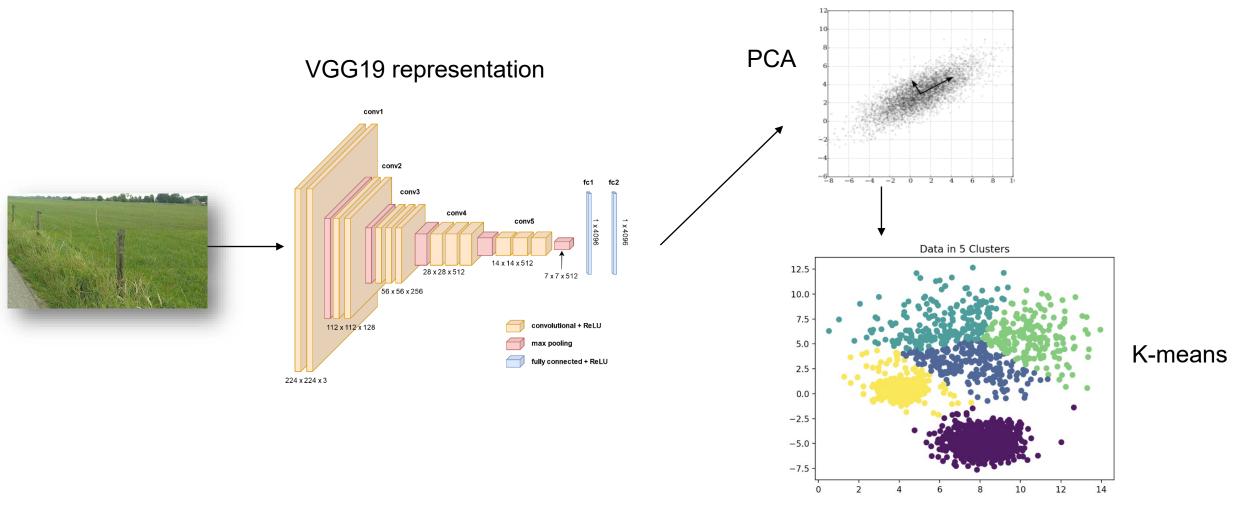
0%-30% 70%-100% of width







Clustering and Cleaning







Clustering and Cleaning

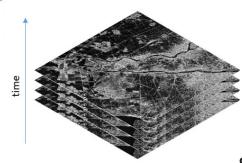






sentinel-2

Model fusion



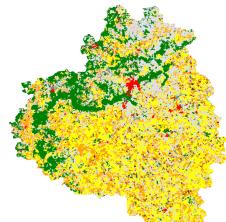
8,875 Grasslands

1,227 Non Grasslands





RF, SVM, TempCNN, LSTM, LSTM + Attention



Crop classification

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

Crop classification

Low confidence decisions



Reverse decision

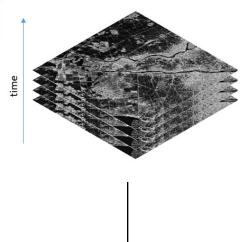












Crop classificationRF, SVM, TempCNN,
LSTM, LSTM + Attention

Model fusion

Street-level images



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









Space-to-ground dataset

Uses

Train, Validate and Test AI models Photo-interpretation Dispute resolution

Other tasks

Inference at the edge Domain adaptation Synthetic data generation

Fusion tasks

Measurement fusion Feature fusion Late fusion (decision fusion)

Downstream tasks

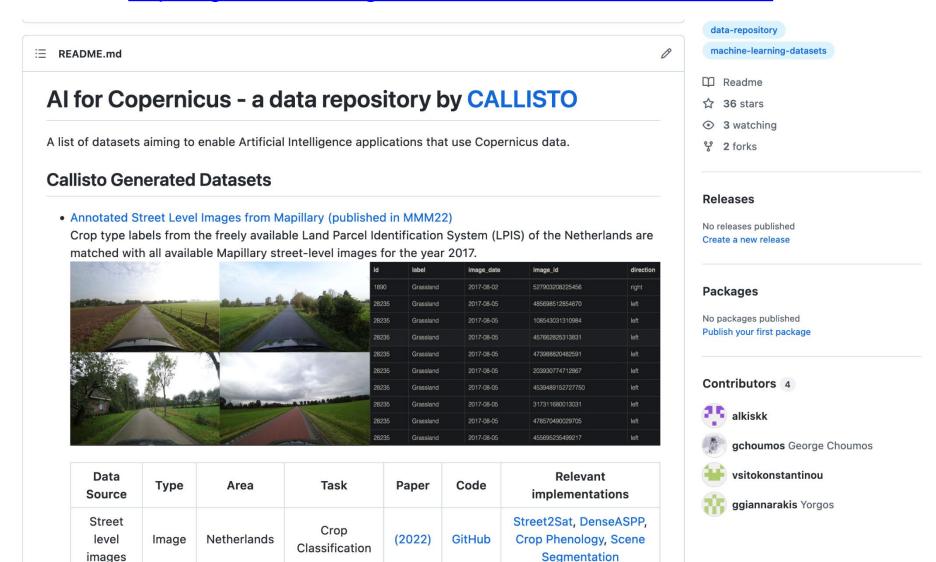
Crop classification
Phenology classification
Damage detection etc.





Al for EO data repository

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



Al for EO data repository

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

Thematic domains

Agriculture
Land change
Water quality
Air quality
Other

Types of datasets

EO with labels
EO without labels
In-situ and ground-level datasets
Geo-referenced labels

Information per entry

Available code
Available paper
Available model (git repo)
Other appropriate models (manual matching)
Other appropriate labels (manual matching)



Remarks & Future work

- Experiment with architectures for No Reference Image Quality Assessment of street-level images
- Identify the agriculture part of the image using Semantic Segmentation and apply on side captures
- Create analysis ready benchmark dataset from the campaigns in Cyprus containing 100s of thousands of images \rightarrow enhance street-level image based crop classification
- Explore DL models for early and late fusion of space and ground data







Thank you!

Smart sampling of OTSCs



DataCAP



Space-to-Ground dataset



Al for EO repo



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https:// callisto-h2020.eu/



https://envision-h2020.eu/