Synergizing Street-Level Data with Satellite Imagery in Agriculture

Iason Tsardanidis

Beyond Centre of EO Research & Satellite Remote Sensing
National Observatory of Athens

Content

<u>10:00 - 10:45 Introduction to Street-Level Data in Agriculture :</u>

- Mapillary platform and overview of street-level data in agriculture
- Importance of satellite imagery integration for comprehensive insights (Space2ground dataset)

<u>10:45-11:00 Short break</u>

<u>11:00 - 11:45 Practical Techniques for Data Processing and Annotation Strategies:</u>

- Advanced annotation techniques employing acquisition coordinate transformations using LPIS/GSAA
- Strategies to enhance the quality and relevance of street-level imagery (images filtering/clustering)
- Methods for integrating street-level data with satellite imagery for enhanced insights
- Brief overview of deep learning potentials and their application in agricultural data analysis

<u>11:45-12:00: Short break</u>

<u>12:00-13:30: Hand-on session (Lab):</u>

- Hands-on session using Mapillary for data processing and retrieval
- Synergistic exploitation of Satellite Image Times Series (SITS) with street level images
- Guided exercise focusing on crop identification utilizing street level images through deep learning architectures

<u>13:30-14:15: Lunch break</u>

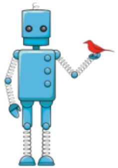
<u>14:15-15:00 Q&A and Wrap-Up</u>

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Citizen science & Distributed Systems

Citizen Science: active or passive engagement in scientific research or data collection efforts, to gather valuable information about the environment, wildlife, or other phenomena.

- High demand for environmental and meaningful scientific data
- Originated in the 19th century with projects like birdwatching (Charles Darwin - Origin of Species 1859)
- Often guided by professional scientists
- Multiple domains (EO, meteorology, astronomy, ecology, etc.,)
- Citizen science competitions, databases and projects: Zooniverse, Scistarter, eBird (birdwatching), and iNaturalist (biodiversity monitoring).
- It’s necessary to identify criteria for high data quality



scistarter
People-powered science.

ZOONIVERSE

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Crowdsourcing

amazon
mechanical turk

OpenStreetMap
The Free Wiki World Map

GEO-Wiki

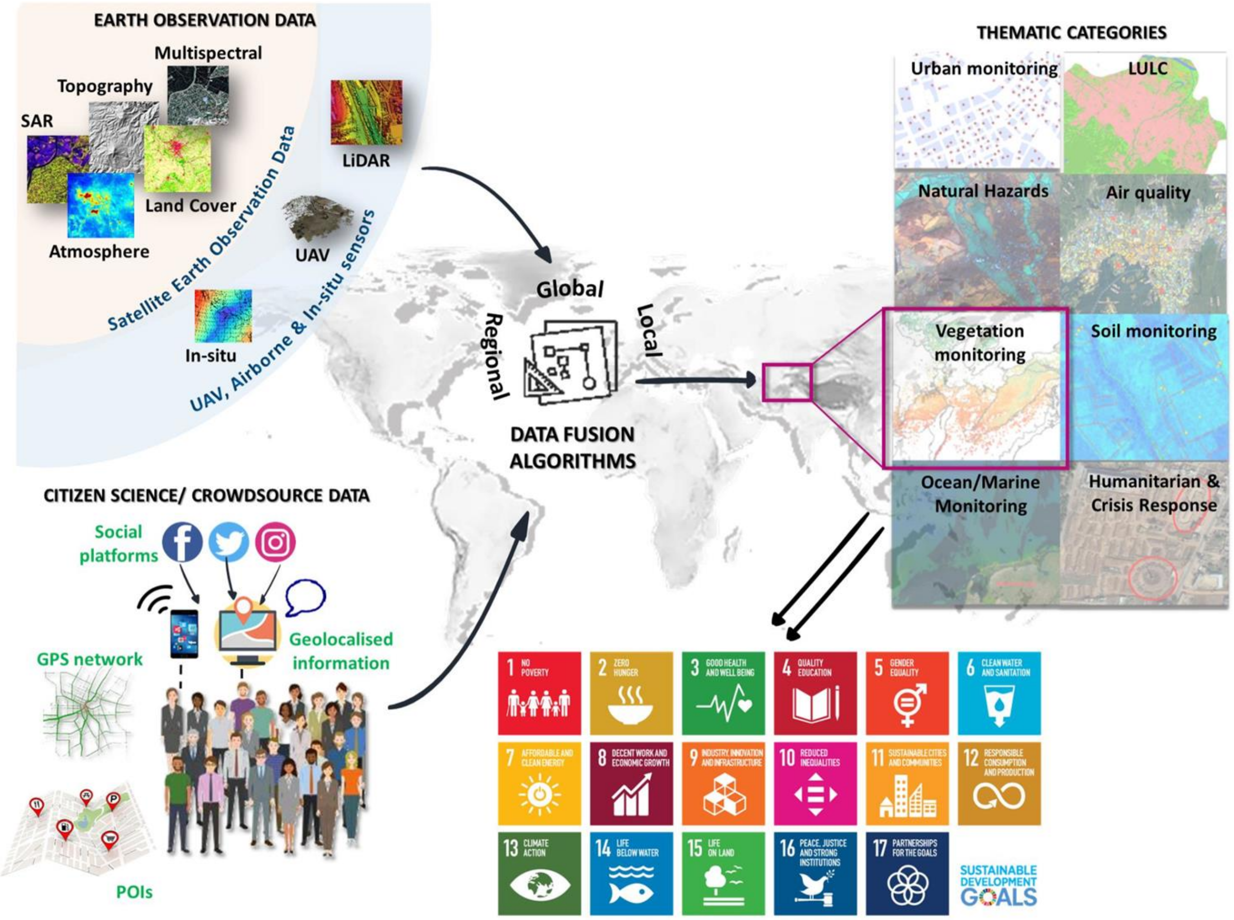
Mapillary

"Crowdsourcing involves obtaining work, information, or opinions from a large group of people who submit their data via the Internet, social media, and smartphone apps"

- Social media/networking services: Including commercial platforms, developed for sharing social information content (text, sound, image, and video).
- Photograph sharing services: Web services, sharing geotagged photos.
- Sensors: Low-cost sensors, such as magnetometers, accelerometers, etc.
- Smartphones: Mobile crowd-sensing devices including their functionalities of GPS, or geotagged photos, etc.
- Developed Platforms: Open access crowdsourcing platforms or marketplaces, such as Geo-Wiki, Open Street Map, Mapillary, MTurk, etc.
- Others: Mobile Apps, Gamification

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Need of Data Fusion in Earth Observation

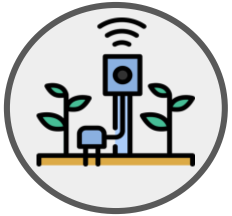


Karagiannopoulou, A. et al.
Data Fusion in Earth Observation and the Role of Citizen as a Sensor: A Scoping Review of Applications, Methods and Future Trends. Remote Sens. 2022, 14, 1263.
https://doi.org/10.3390/rs14051263

BEYOND
Centre of EO Research
and Satellite Remote Sensing

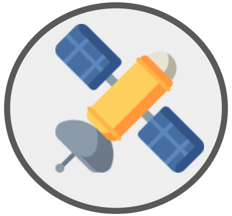
Monitoring of Agriculture Today

UAV



Sensors

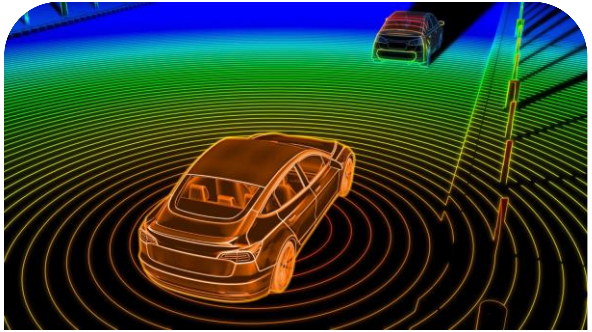
Field Inspectors

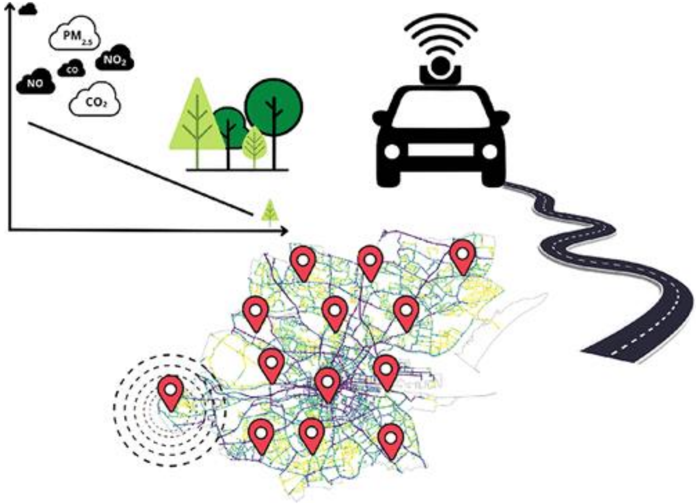


Satellite Imagery

Street-Level???

Types of Street Level Data





- Imagery: Street-level imagery includes photographs, 360° street-view images or videos captured at ground level, providing visual representations of streets, buildings, landscapes, health and wellbeing, pollution etc.,

- Sensor Data: Data collected from sensors mounted on vehicles or street infrastructure, such as LiDAR data for measuring distances and elevations, or air quality sensors for monitoring environmental conditions.

- Other: GPS, Infra data, etc.,

- They provide **low-cost, rapid, high-resolution, and wide-scale** data capture, allowing for data-driven analysis → Reduce (or eliminate) site visits

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Street Level Data in Agriculture

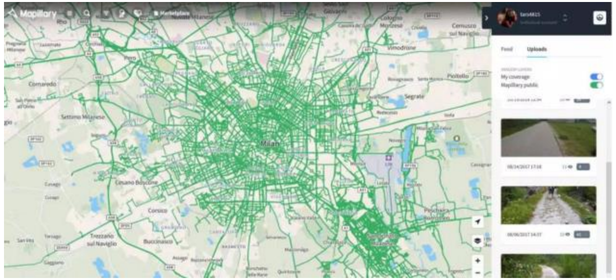
- Crop Identification
- Crop monitoring for health and growth assessment
- Mapping of farmland boundaries and field layouts
- Support for precision agriculture practices
- Identification and management of weeds and pests
- Estimation of crop yields
- Valuable data for agricultural research and development
- Decision support - Disputes Arrangement

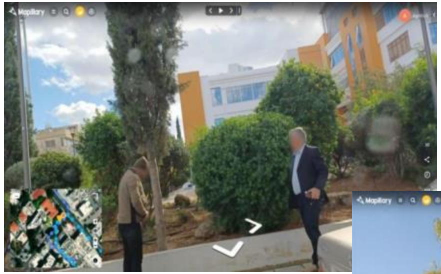
BEYOND
Centre of EO Research and Satellite Remote Sensing

Street Level Data - Mapillary Platform

Mapillary

- Cost-efficient – Easy to setup
- Open data with no restrictive licensing
- Crowdsourcing platform – Giving back to the community
- Customizable APIs for developers
- Detailed geospatial information
- Global coverage
- Segmentation of imagery - categorization of elements (e.g., roads, signs, and landmarks)
- Obfuscation / blurring of human faces and car plates





BEYOND
Centre of EO Research
and Satellite Remote Sensing

Street Level Data - Mapillary Platform

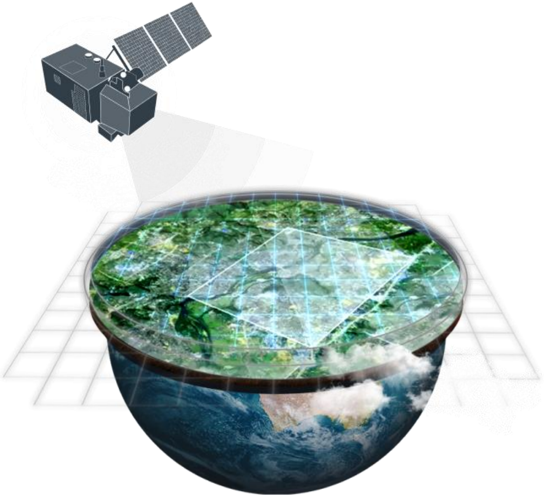
BEYOND
Centre of EO Research
and Satellite Remote Sensing

Street Level Data - Any Limitations? → Noisy Data

- **Temporal Limitations:** Data becomes outdated over time, hindering temporal analyses.
- **Dependence on Source:** Reliability varies based on the tool or source, requiring noise/duplicates filtering.
- **Depth and Distance Limitations:** Limited usefulness for depth and distance analyses.
- **Limited Coverage:** Scalability issues due to incomplete coverage.
- **Quality Variability:** Inconsistent quality across datasets.
- **Data Bias:** Subject to bias, leading to overrepresentation of certain areas or populations.
- **Integration Complexity:** Challenges arise from differing data formats.
- **Privacy Concerns:** Risks of capturing sensitive or private information.

BEYOND
Centre of EO Research
and Satellite Remote Sensing

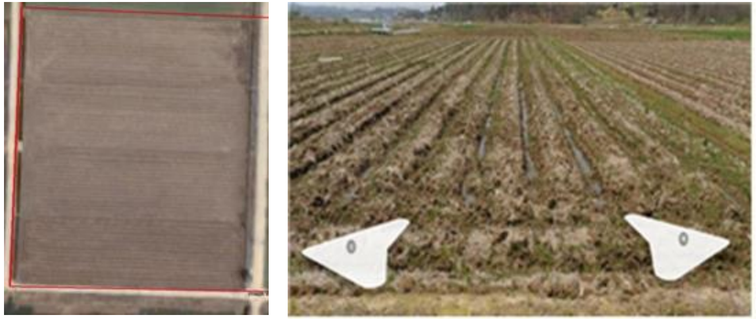
Toward an Integrated Earth-Observation Monitoring System



- Improved accuracy
- Cost-Effectiveness
- Enhanced spatial resolution
- Weather-related issues
- Integration of local community knowledge and adaptability
- Decision support / Validation

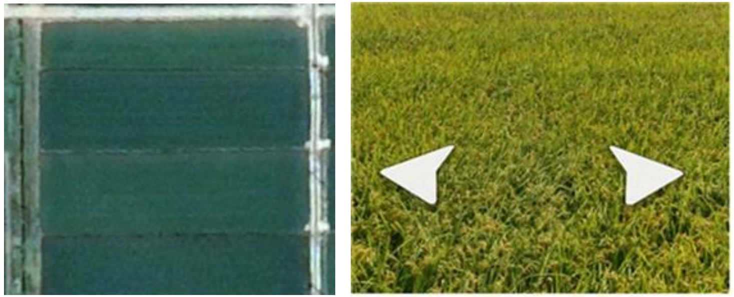
BEYOND
Centre of EO Research
and Satellite Remote Sensing

Integrated Earth-Observation Monitoring System and Agriculture



After harvesting and before sowing of rice (November to April): straightly rough pattern with dark brown color

After sowing and planting of other cropland (May to June): straight pattern with mixed blue and brown color

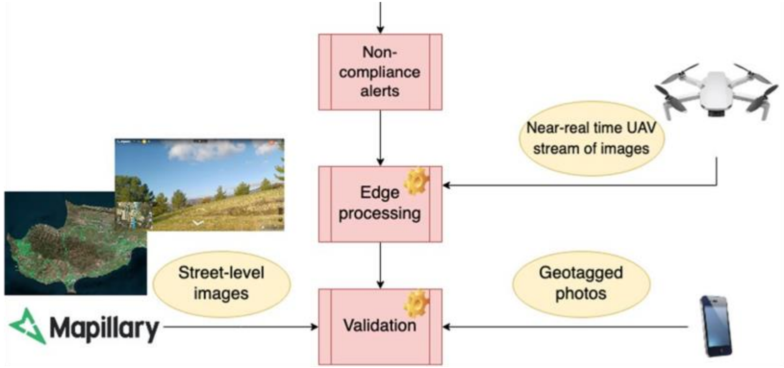


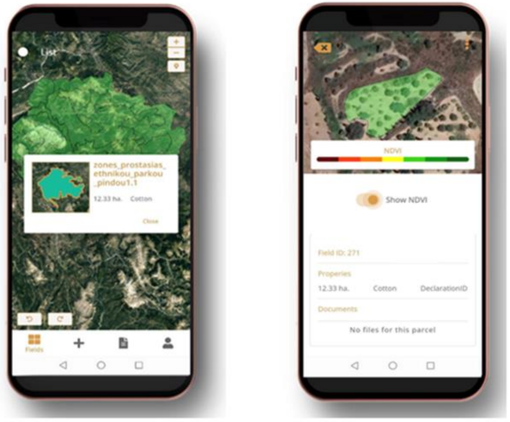
Growing rice (June to October): grainy surface with light green color

Growing crop (June to November): straight pattern with green color

Case of Cyprus - EO FOR CAP MONITORING

- EO-based tools for the continuous, large scale and uninterrupted monitoring of farm management activities.
- Deep Learning modules
- Combination of UAV and Street-Level images

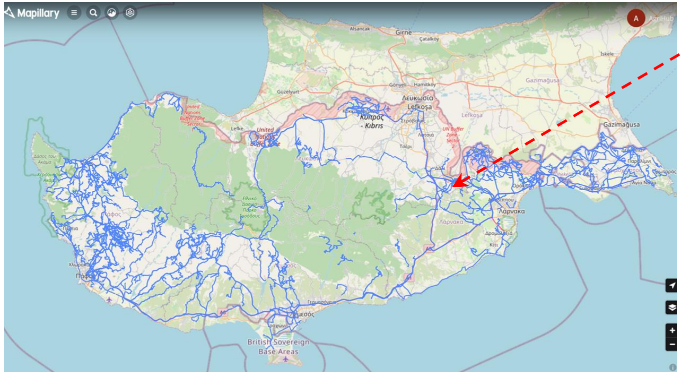




BEYOND
Centre of EO Research and Satellite Remote Sensing

Callisto Project - Street Level Data

Mapillary



- Proof of concept → Agriculture
- Methodology for annotation of street-level images with agricultural labels (LPIS)
- Callisto-generated labelled dataset → Mapillary annotated
- Callisto field campaigns with millions of street level images in Cyprus for several years (only one field inspector → high potentials)
- Joint publication with ENVISION project (MMM) → **DataCAP (http://62.217.82.91/)**

Scan Me

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Callisto Project - DataCAP Platform

Search for parcel id..

Search

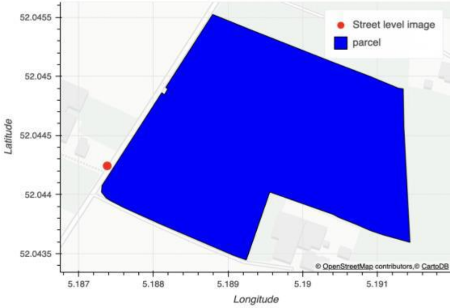
Maximum Decision Confidence: 100 %

Show Alerts Only | Show Street Level Images Only

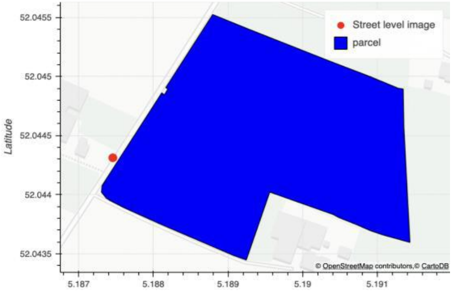
Parcel ID	Decision Confidence(%)	Declared Crop Type	Predicted Crop Type	Alert	Action	Street Level
53379	95.7	Grassland	Grassland	No	Verify	Show
45331	97.5	Grassland	Grassland	No	Verify	Show
25319	97.3	Grassland	Grassland	No	Verify	Show
6909	97.5	Grassland	Grassland	No	Verify	Show
16053	99.1	Grassland	Grassland	No	Verify	Show

Declared Crop Type: **Grassland** and Predicted Crop Type: **Grassland** Back

Sept. 24, 2017
(Parcel On The
left)



May 7, 2017
(Parcel On The
left)



BEYOND
Centre of EO Research
and Satellite Remote Sensing

Callisto Project - UAV

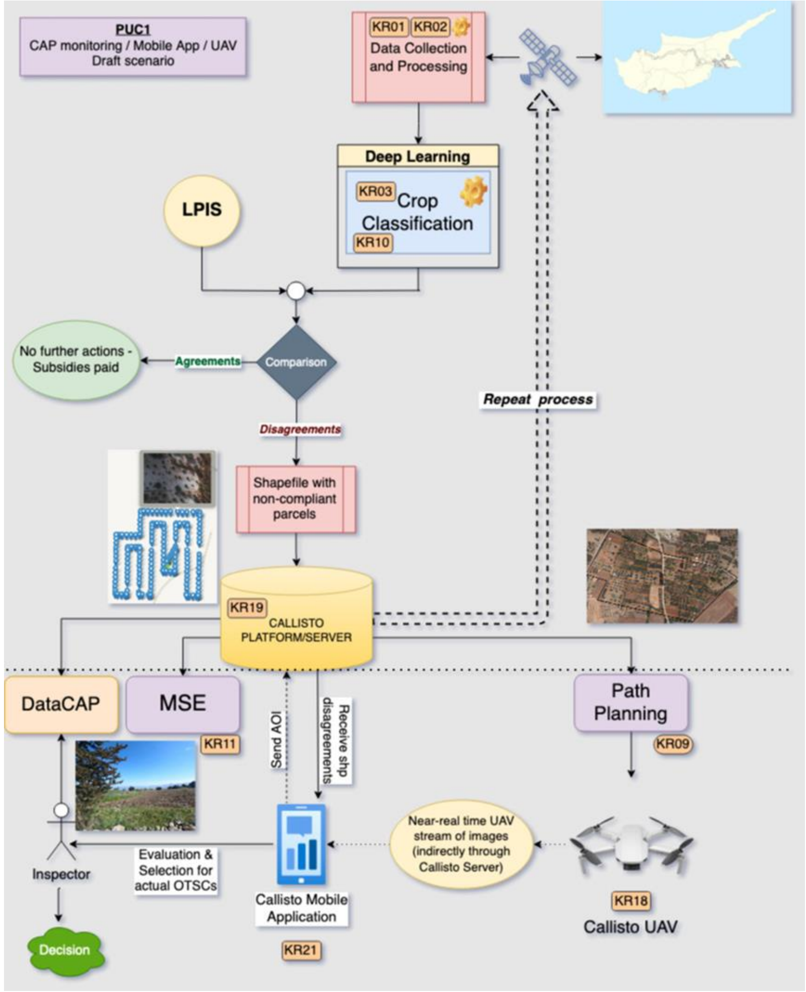
- Alert-driven UAV path planner
- Coverage Path Planning - Swipe and cover the whole parcel/area of interest
- Fast Inspection

flight video (edited by the field inspector)
https://www.dropbox.com/s/gueq8pw2cvguq7p/VID_20221007_152419.mp4?dl=0

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Callisto Project

- User Story Walkthrough



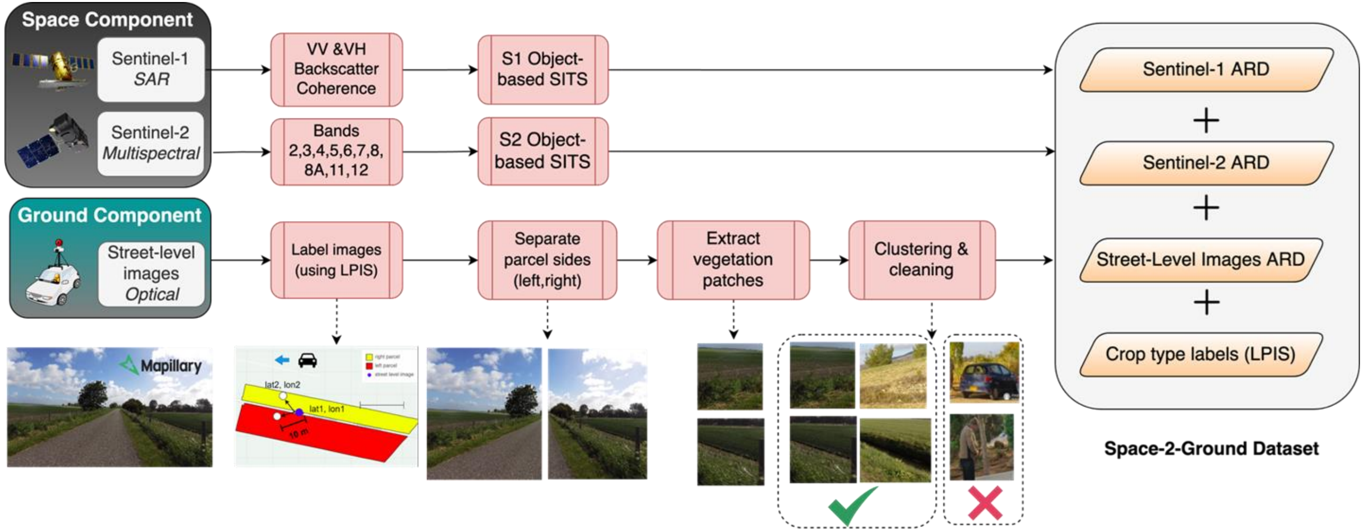
Callisto Project

https://www.youtube.com/watch?v=UOMi_LEmLyI

Space2ground Dataset

Datasets utilized in

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

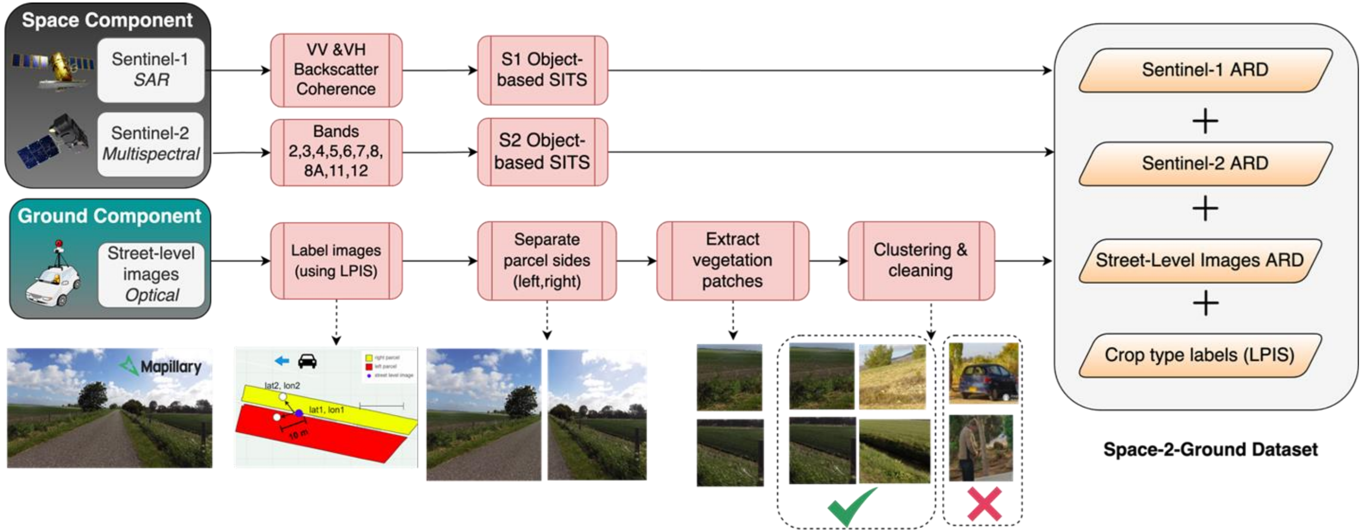


[1] G. Choumos, A. Koukos, V. Sitokonstantinou and C. Kontoes, «Towards Space-to-Ground Data Availability for Agriculture Monitoring,» 2022 IEEE 14th Image, Video, and Multidimensional Signal Processing Workshop (IVMSP), Nafplio, Greece, 2022, pp. 1-5, doi: 10.1109/IVMSP54334.2022.9816335.

BEYOND
Centre of EO Research
and Satellite Remote Sensing

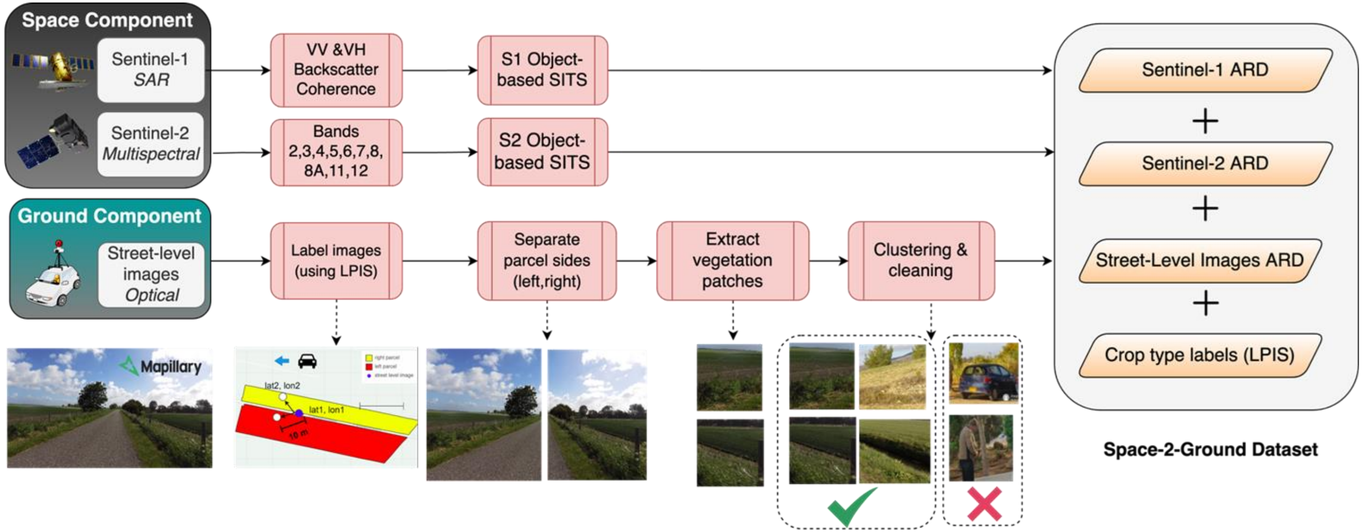
Space2ground Dataset (space component)

- 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)



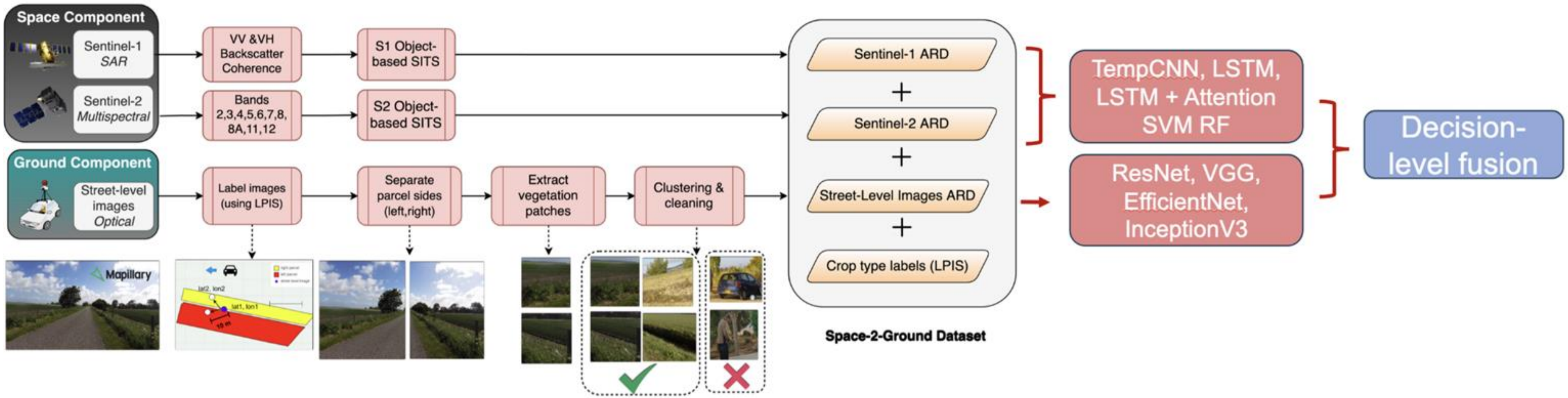
Space2ground Dataset (ground component)

- 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



Space2ground Dataset

- Decision level fusion → **Weighted Average** of all decisions

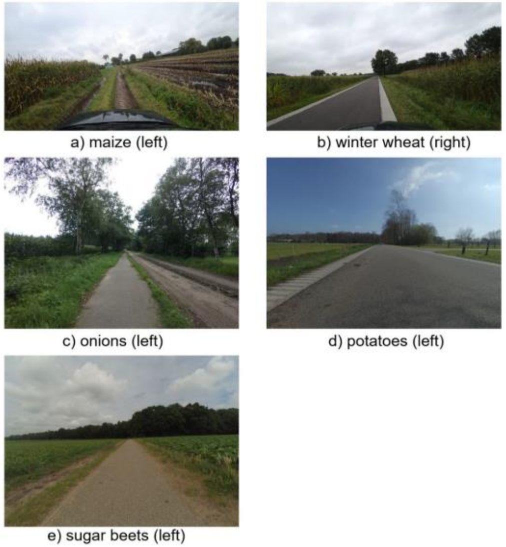


BEYOND
Centre of EO Research
and Satellite Remote Sensing

Space2ground Dataset

- **Space2Ground** – A dataset coming from areas of interest in the **Netherlands**, with a fusion of space (Sentinel-1/2) and ground (street-level) components for agriculture monitoring.

- **Space2Ground 2.0** – Improvements in the methodologies for data collection, cleaning, and fusion led to the generation of a new, improved dataset covering a significant part of **Cyprus**.



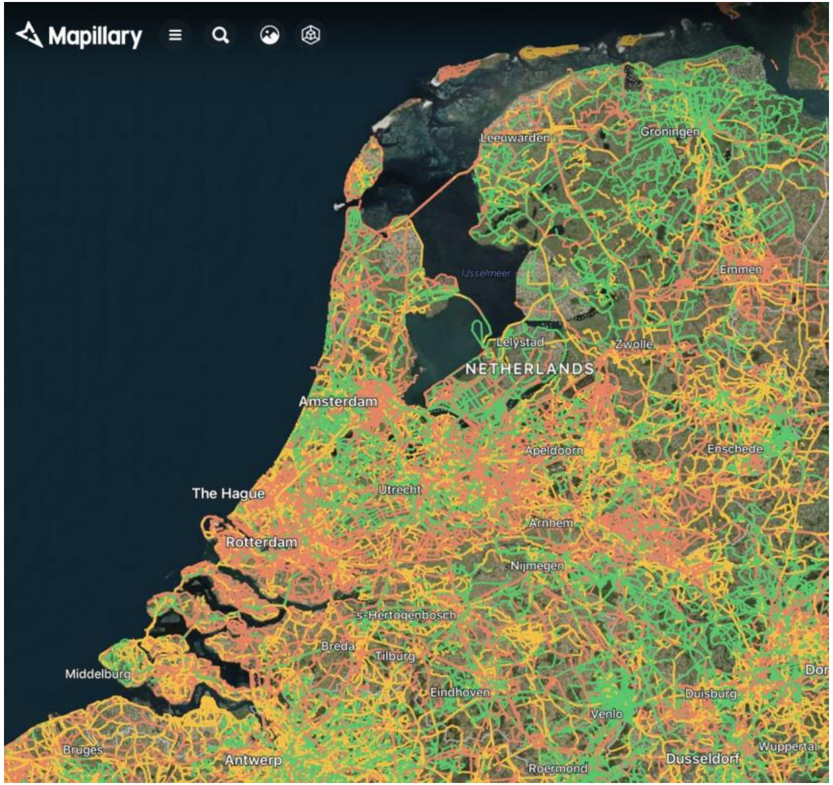
Sample of images in the Space2Ground

Sample of images in the Space2Ground 2.0

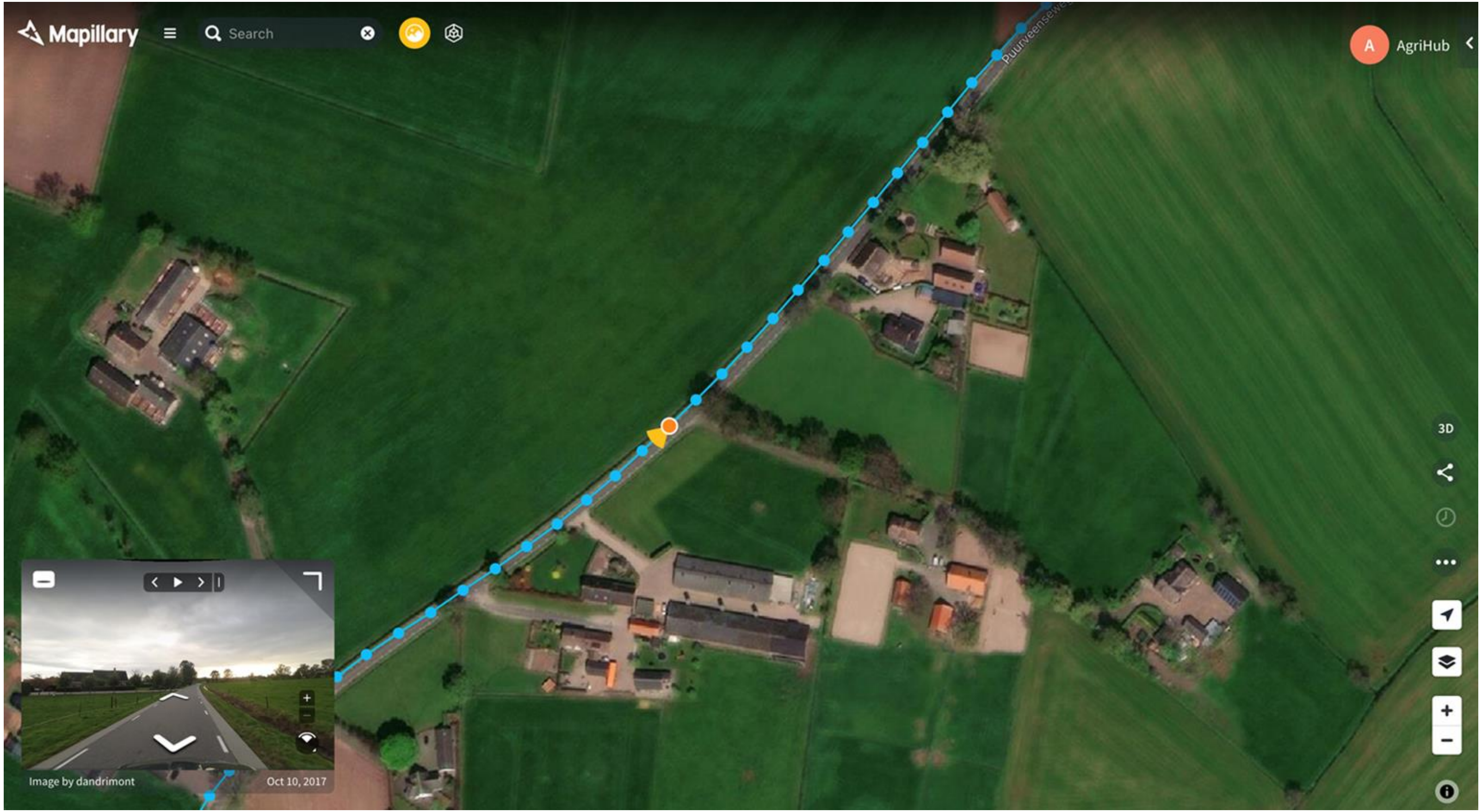
BEYOND Centre of EO Research and Satellite Remote Sensing

Data Availability for AI models

https://www.mapillary.com/



Data Availability for AI models

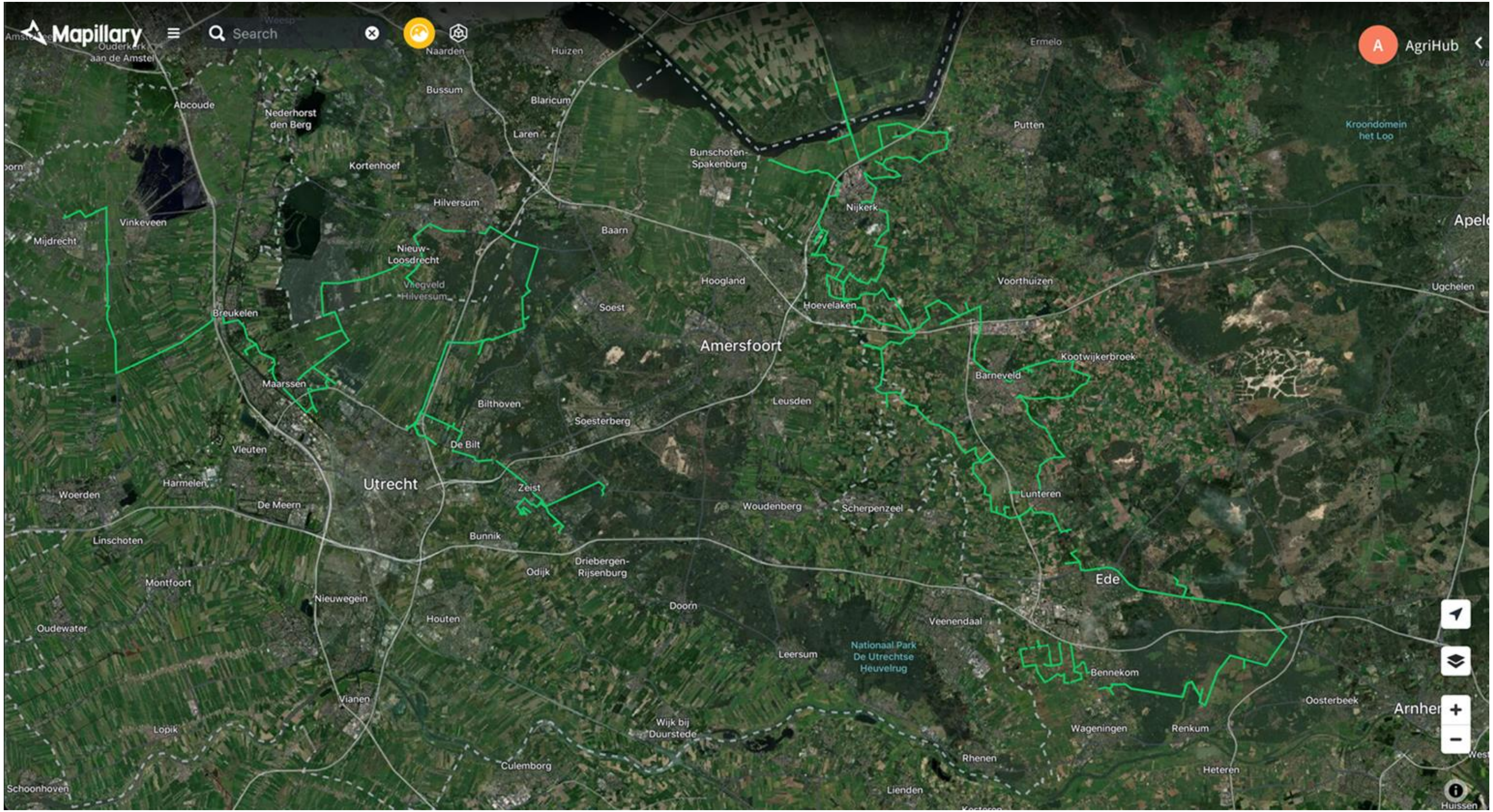


BEYOND
Centre of EO Research
and Satellite Remote Sensing

Data Availability for AI models

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Data Availability for AI models (Space2Ground 1.0)



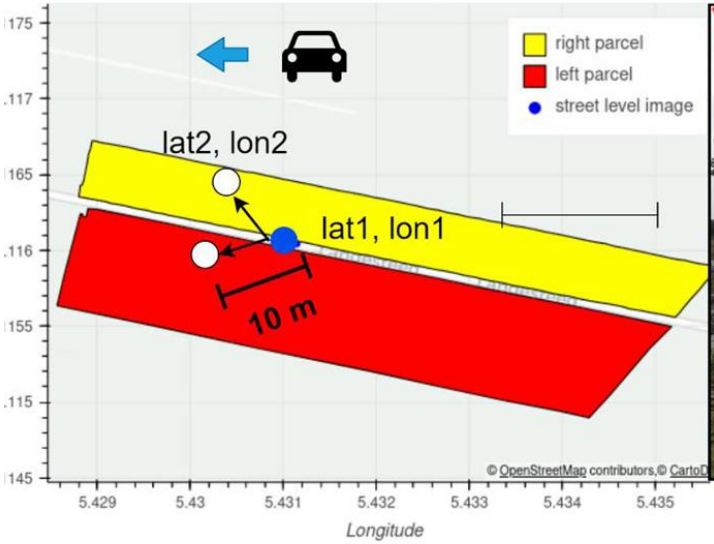
BEYOND
Centre of EO Research
and Satellite Remote Sensing

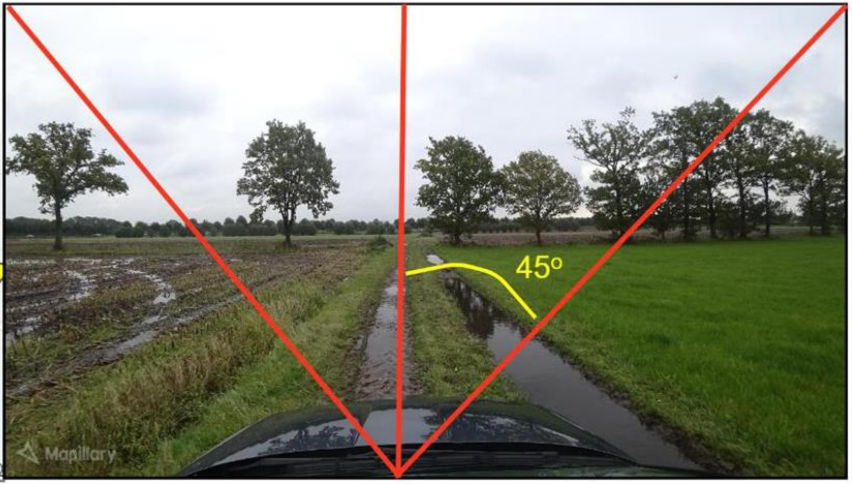
Data Fusion and Annotation Mapillary LPIS

	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...

BEYOND
Centre of EO Research and Satellite Remote Sensing

Data Fusion and Annotation Mapillary LPIS



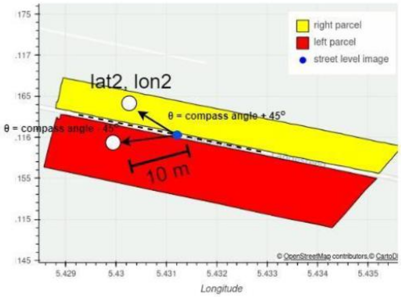


$$lat_2 = \arcsin\left(\sin lat_1 \cdot \cos \frac{d}{R}\right) + \cos lat_1 \cdot \sin \frac{d}{R} \cdot \cos\theta)$$

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

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Data Fusion and Annotation Mapillary LPIS



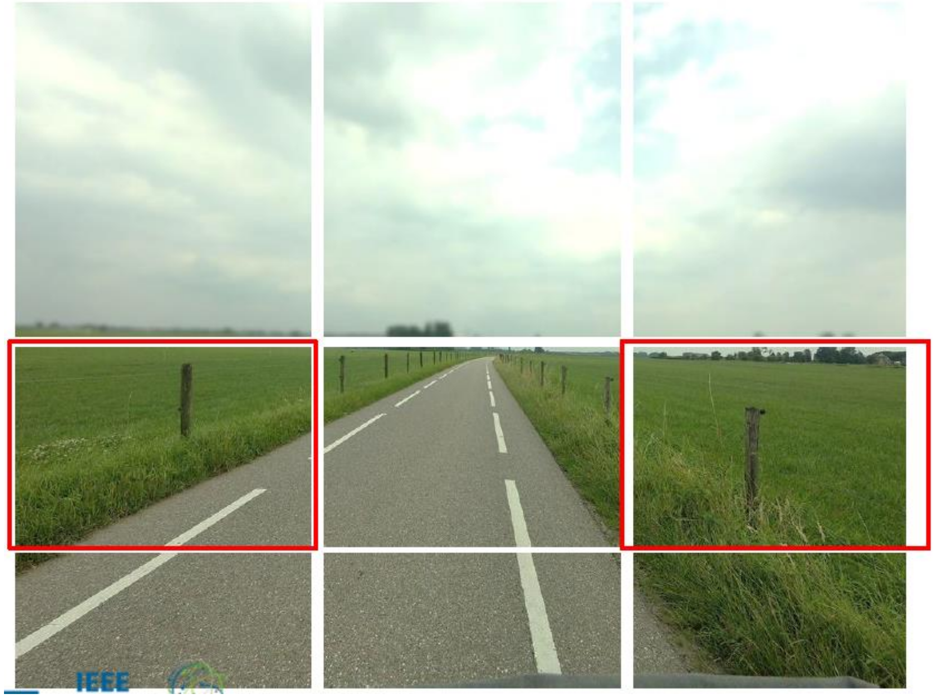
Split Image in half

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Data Fusion and Annotation Mapillary LPIS

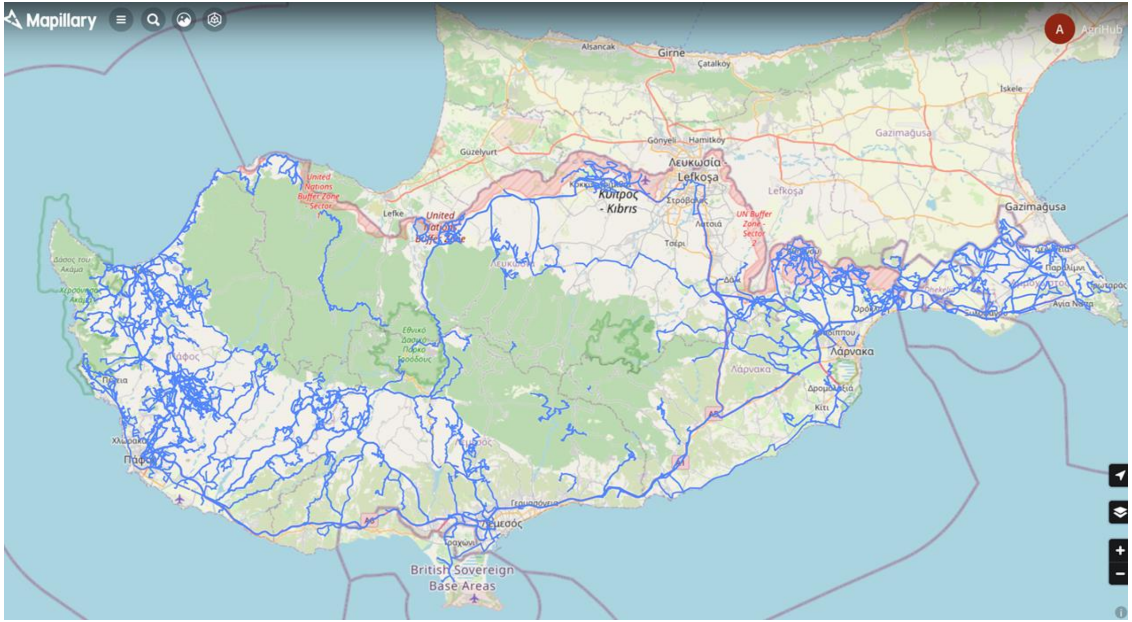
20%-50% of height
0%-30%
70%-100%
of width

Grassland vegetation patches
resized to (260,260) px



BEYOND
Centre of EO Research
and Satellite Remote Sensing

Data Availability for AI models (Space2Ground 2.0)



Cyprus

This week	This month	All time

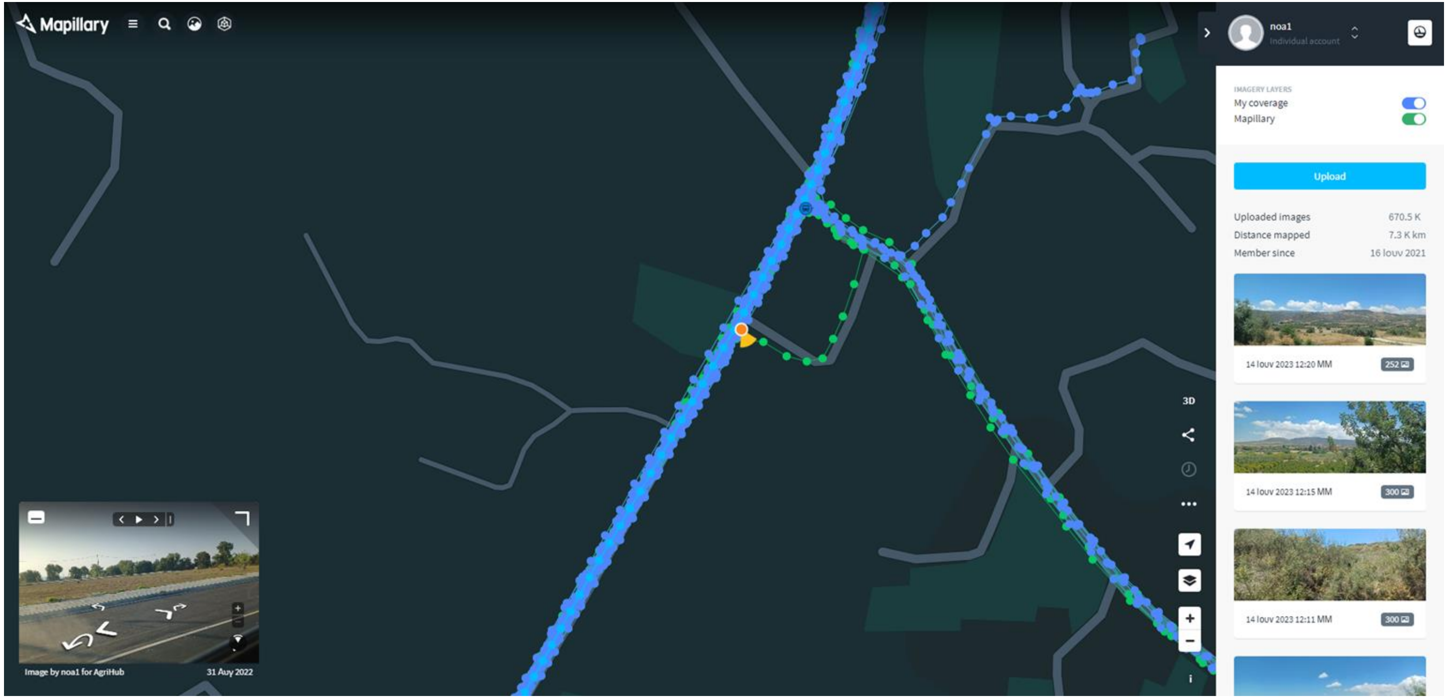
		no. of images
#1	noa1	634.9 K
#2	stpkyriakou	164.2 K
#3	WhanTwo	107.6 K
#4	healixx	85.3 K
#5	ozkanilyasaksu	67.5 K
#6	mapfool	43.5 K
#7	noa2	38.3 K

With great help from

ΚΥΠΡΙΑΚΟΣ ΟΡΓΑΝΙΣΜΟΣ ΑΓΡΟΤΙΚΩΝ ΠΛΗΡΩΜΩΝ • CYPRUS AGRICULTURAL PAYMENTS ORGANISATION •

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Data Availability for AI models (Space2Ground 2.0)

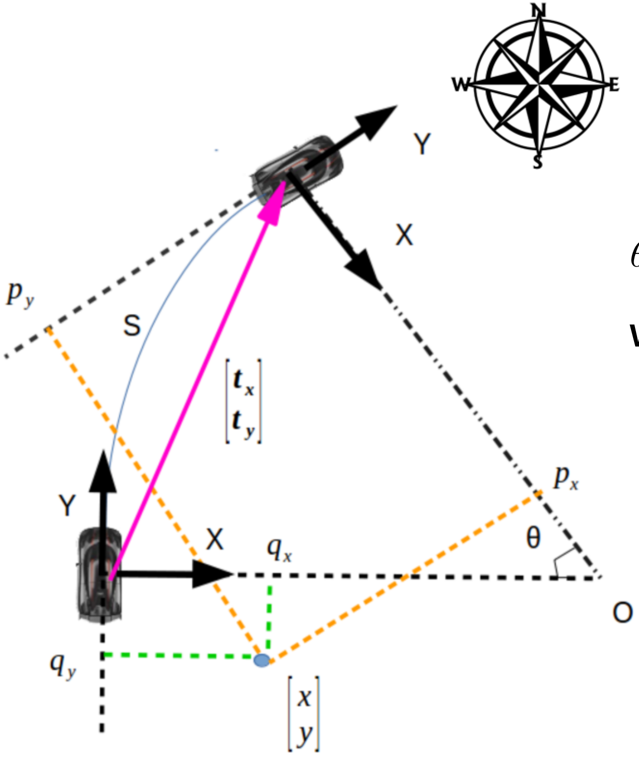


HERO9 Black

SM-A326B

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Compass Angle Assessment



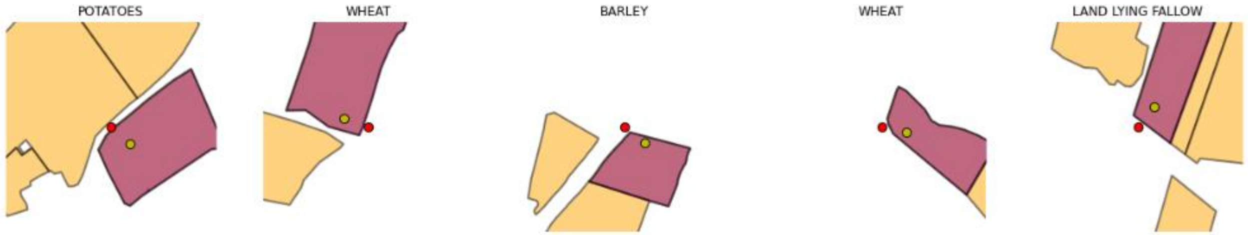
$$\theta = \arctan(\sin(\Delta lon)\cdot\cos(lat2)/(\cos(lat1)\cdot\sin(lat2)-\sin(lat1)\cdot\cos(lat2)\cdot\cos(\Delta lon)))$$

Where:

- θ is the angle between the two points in degrees
- Δlon is the difference in longitude between the points
- *lat1* is the latitude of the first point
- *lat2* is the latitude of the second point

BEYOND
Centre of EO Research
and Satellite Remote Sensing

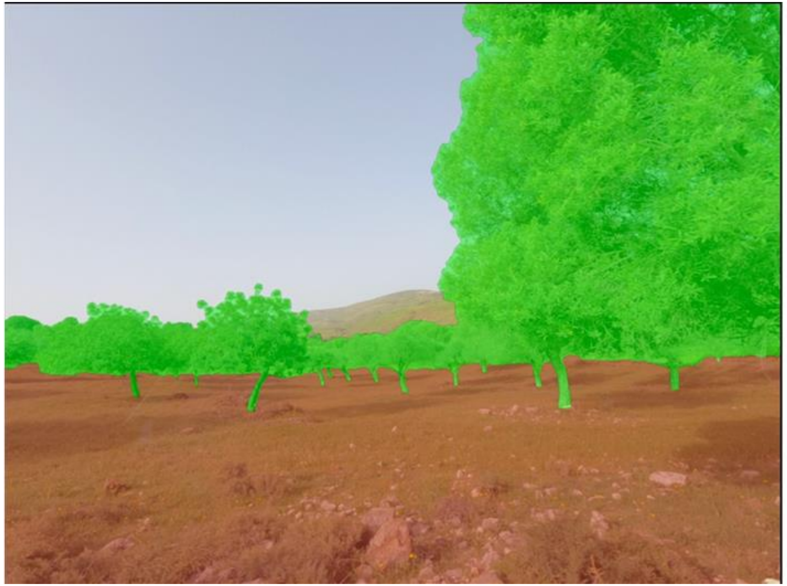
LPIS Annotation



BEYOND
Centre of EO Research
and Satellite Remote Sensing

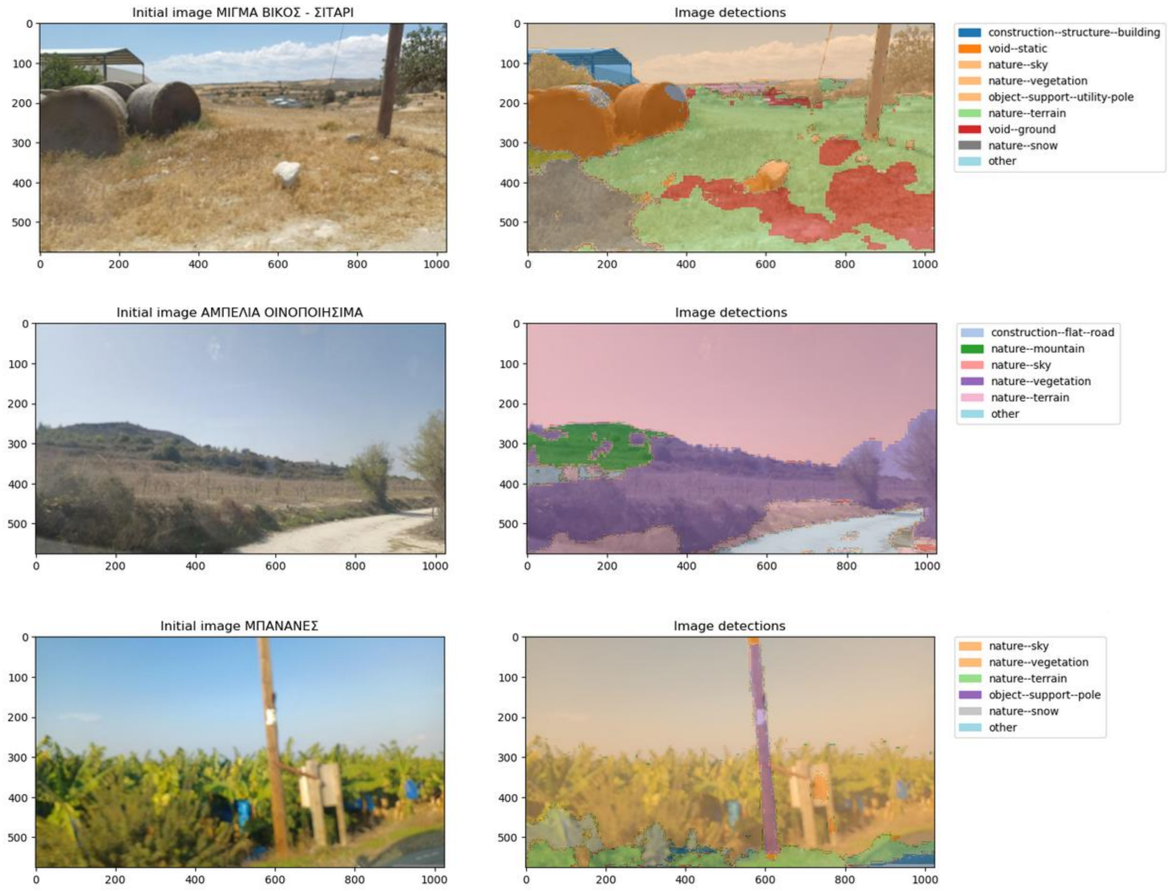
Semantic Segmentation

Vegetation extraction on Street-Level Images



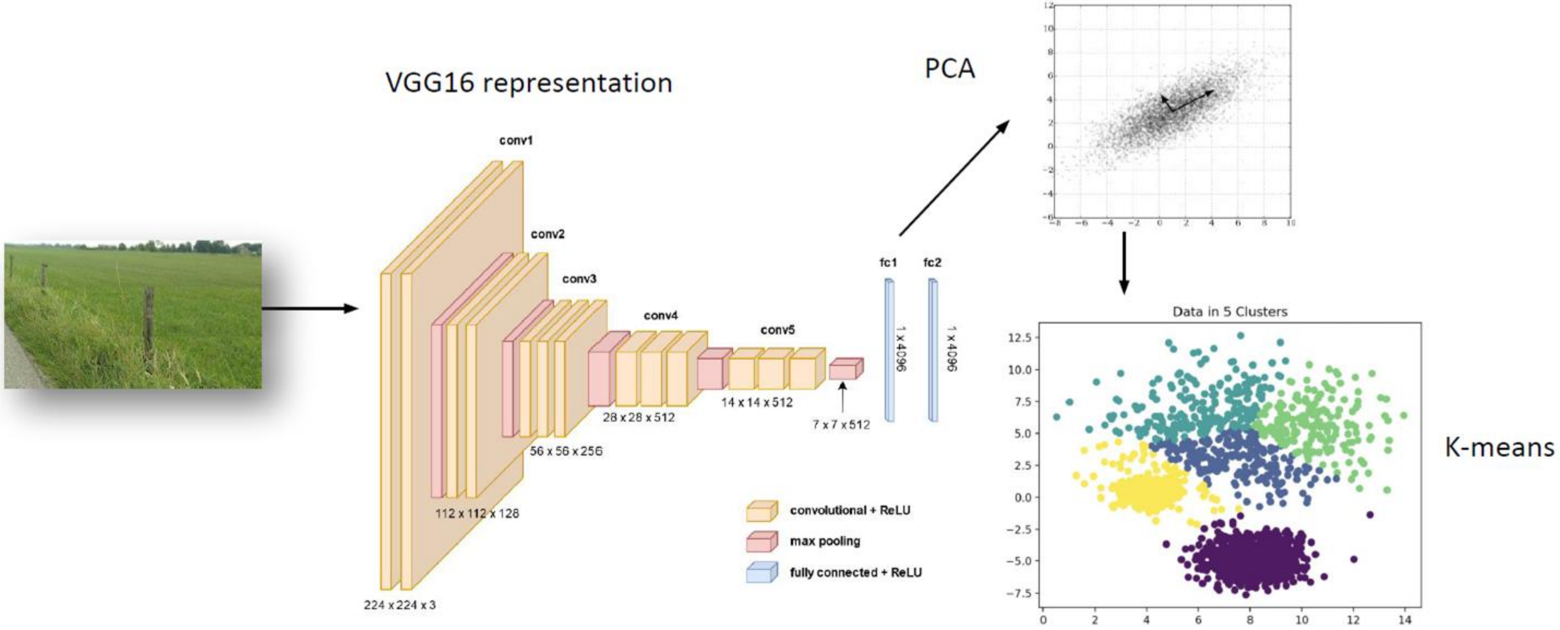
BEYOND
Centre of EO Research
and Satellite Remote Sensing

Semantic Segmentation



BEYOND Centre of EO Research and Satellite Remote Sensing

Clustering and Cleaning



BEYOND
Centre of EO Research
and Satellite Remote Sensing

Clustering and Cleaning

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Clustering and Cleaning

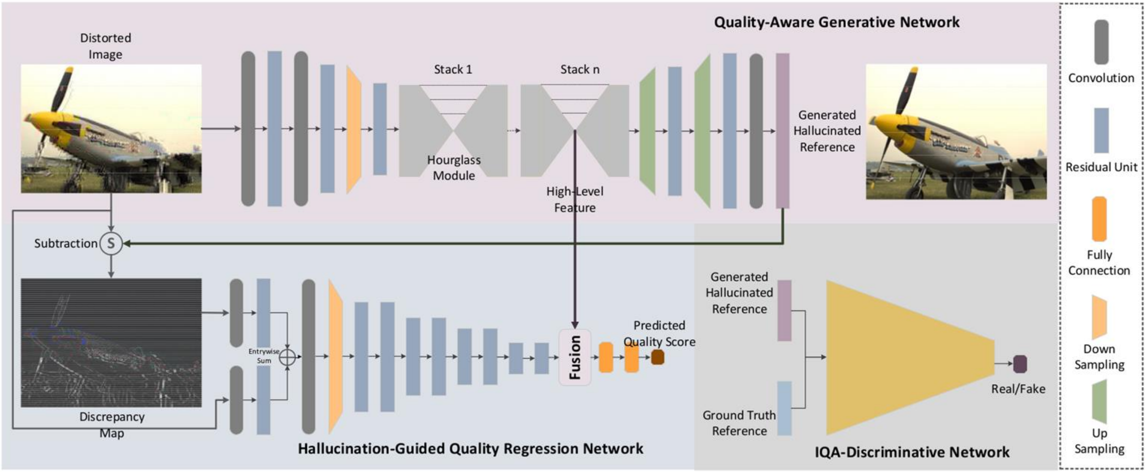
```
Cluster 1/120
Cluster size 661.
ΑΓΡΑΝΑΠΑΥΣΗ           111
ΕΛΙΕΣ                 110
ΔΕΝΤΡΑ ΠΑΡΑΔΟΣΙΑΚΑ     74
ΣΙΤΑΡΙ ΣΚΛΗΡΟ          70
ΚΡΙΘΑΡΙ                68
ΑΜΠΕΛΙΑ ΟΙΝΟΠΟΙΗΣΙΜΑ   66
```

BEYOND
Centre of EO Research
and Satellite Remote Sensing

No-Reference Image Quality Assessment (NR-IQA)

Automatically detecting and discarding images of bad quality

- Natural Scene Statistics methods
  - BRISQUE: Analyzes natural scene statistics.
  - PIQE: Measures local variations in pixel intensities.
  - NIQE: Uses natural image statistics and frequency domain information.
- DL methods (Hallucinated-IQA, MANIQA, hyperIQA, CLIP-IQA, TReS etc.)



Original Image	JPEG2K Compression	Heavy Compression	Gaussian Noise	Median Blur
26.8286	30.7417	33.0692	79.8751	72.7044

and Satellite Remote Sensing

No-Reference Image Quality Assessment (NR-IQA)

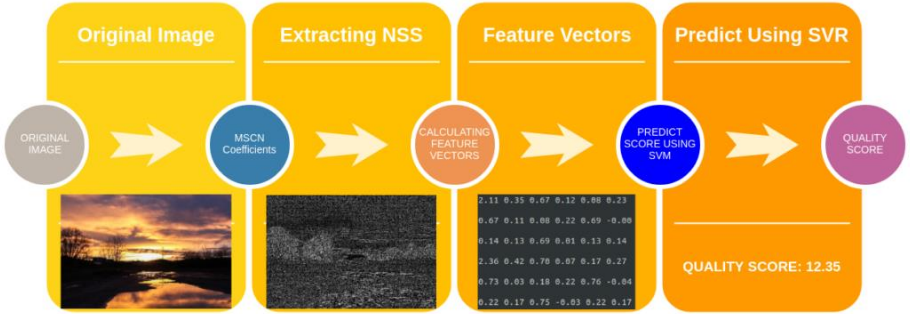
Blind/Referenceless Image Spatial QUality Evaluator (**BRISQUE**) model

It uses only the image pixels to calculate features without the need of any transformations

- Compute the locally normalized luminance (or mean subtracted contrast normalized (**MSCN**) coefficients) via local mean subtraction and divisive normalization

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C}, \qquad \boldsymbol{\mu} = \boldsymbol{W} * \boldsymbol{I}, \qquad \boldsymbol{\sigma} = \sqrt{\boldsymbol{W} * (\boldsymbol{I} - \boldsymbol{\mu})^2}$$

- Fit a Generalized Gaussian Distribution (GGD) to the MSCN coefficients (features 1-2)
- Calculate pairwise products of neighboring MSCN coefficients along four directions i) Horizontal H, ii) Vertical V, iii) Main-diagonal D1 and iv) Secondary-diagonal D2.
- Fit an Asymmetric Generalized Gaussian Distribution (AGGD) to the i) H pairwise ii) V pairwise products, iii) D1 pairwise products and iv) D2 pairwise products.
- Predict quality score using a pre-trained SVR model.



Feature Range	Feature Description	Procedure
1 - 2	Shape and Variance.	GGD fit to MSCN coefficients.
3 - 6	Shape, Mean, Left Variance, Right Variance	AGGD fit to Horizontal Pairwise Products
7 - 10	Shape, Mean, Left Variance, Right Variance	AGGD fit to Vertical Pairwise Products
11 - 14	Shape, Mean, Left Variance, Right Variance	AGGD fit to Diagonal (left) Pairwise Products
15 - 18	Shape, Mean, Left Variance, Right Variance	AGGD fit to Diagonal (Right) Pairwise Products

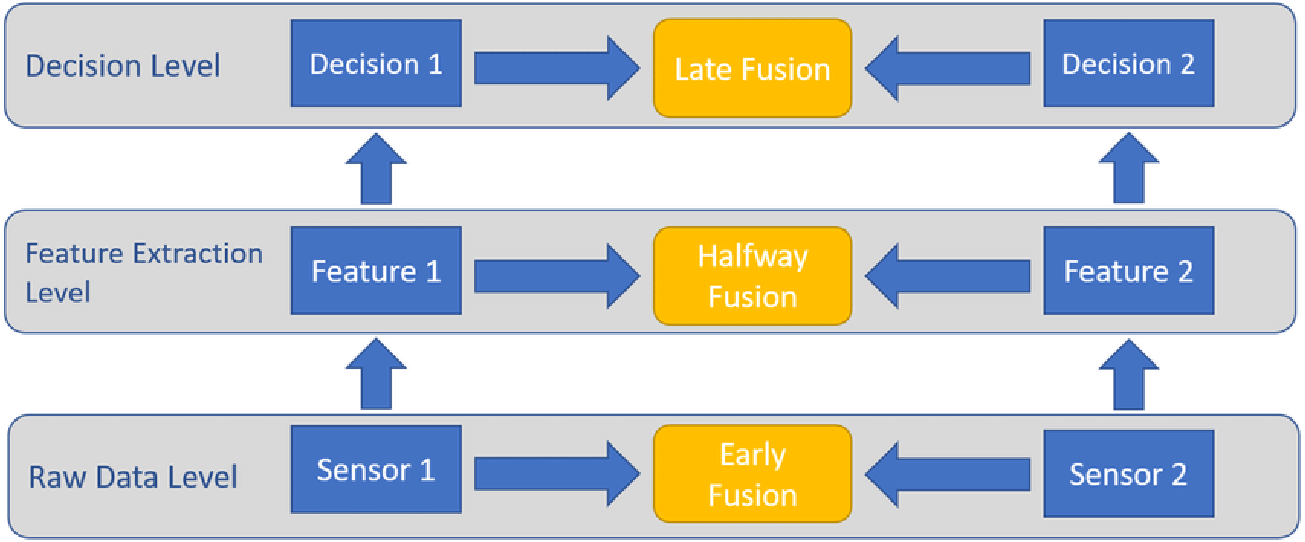
BEYOND
Centre of EO Research
and Satellite Remote Sensing

Data Fusion Methods

(i) Low-level fusion

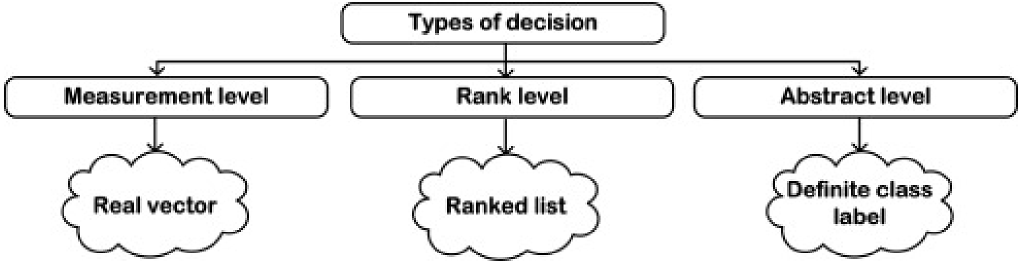
(ii) Medium-level fusion

(iii) High-level fusion



BEYOND
Centre of EO Research and Satellite Remote Sensing

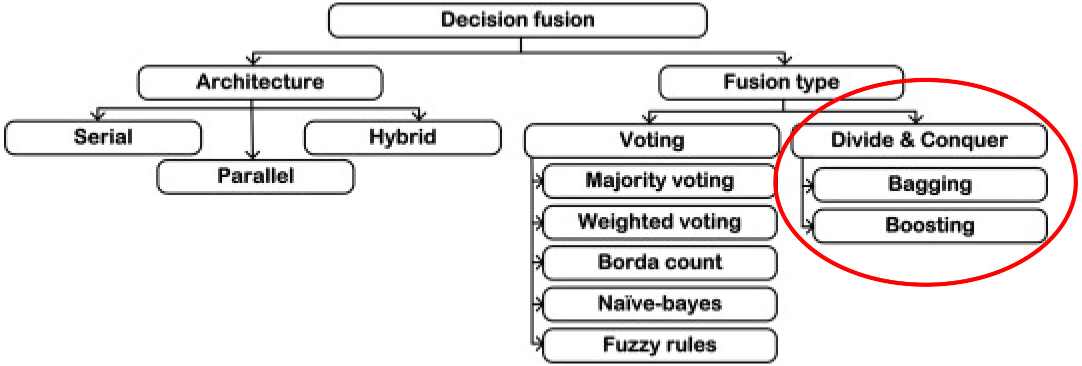
Decision (Late) Level Fusion

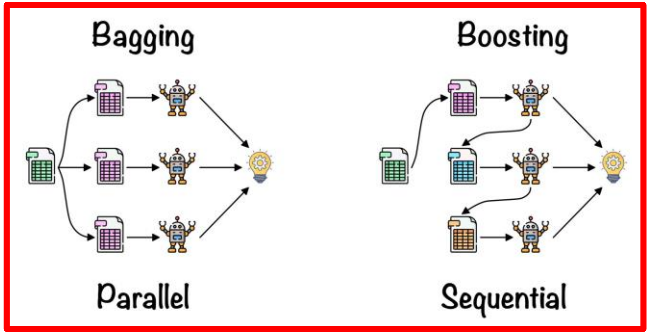


- **measurement level**: this type of decision involves the classifier returning a real valued vector
- **rank level**: this type of decision involves the classifiers to return an ordered sequence of classes
- **abstract level**: this is the most widely applied type of decision where the classifiers return a single class label as the decision

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Decision Level Fusion





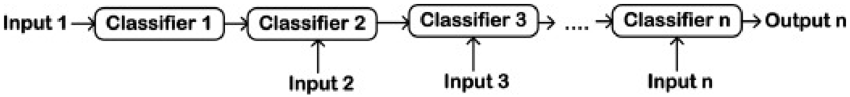
- **Voting-based**: In the voting-based decision fusion techniques, majority voting is the most popular and is widely used. Some of the other techniques include weighted voting in which a weight to each classifier is attached and then decision fusion is performed. Borda count is another technique in which the sums of reverse ranks are calculated to perform decision fusion. Other voting techniques are probability-based, such as fuzzy rules, Naïve-Bayes, Bayesian theory, Dempster-Shafer theory, and so forth .

- **Divide and conquer**: In this decision fusion technique, the dataset is divided into subsets of equal sizes, and then the classification is performed followed by decision fusion on the results of those smaller dataset classifications. These divide and conquer methods include the concepts of bagging and boosting.

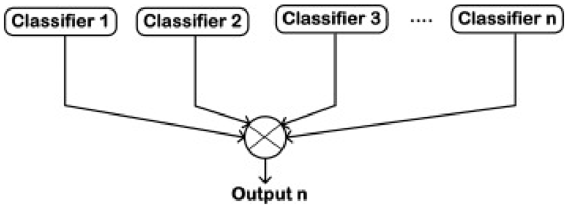
BEYOND
Centre of EO Research
and Satellite Remote Sensing

Decision Level Fusion

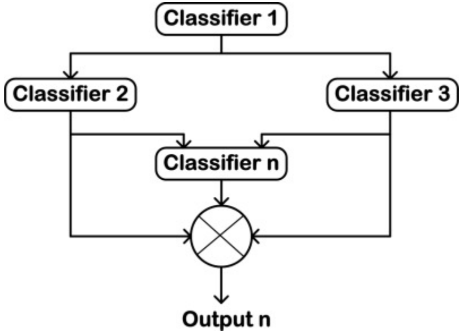
- **Serial decision fusion:** In this architecture, the classifiers are arranged in series; the output of one classifier acts as an input to the next.



- **Parallel decision fusion**: In this, the classifiers are arranged in parallel and the classifiers perform classification simultaneously and then the decision fusion is performed.



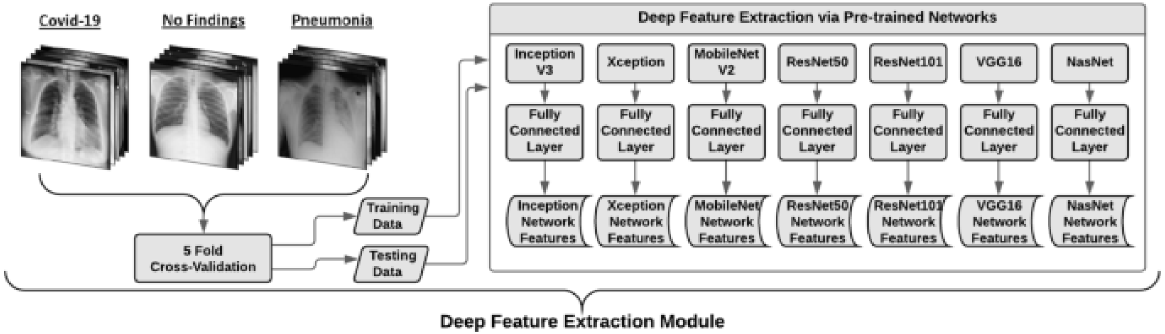
- **Hybrid decision fusion**: This is a hierarchical structure of classifiers.



BEYOND
Centre of EO Research
and Satellite Remote Sensing

Feature Level Fusion

An additional fusion strategy, the feature level fusion, in which various sets of features obtained by different feature extractors are combined, has high potential to achieve better classification performance. Feature level fusion generally consists of the concatenation of various normalized feature subsets resulting in a single feature vector forming a complete representation of different views

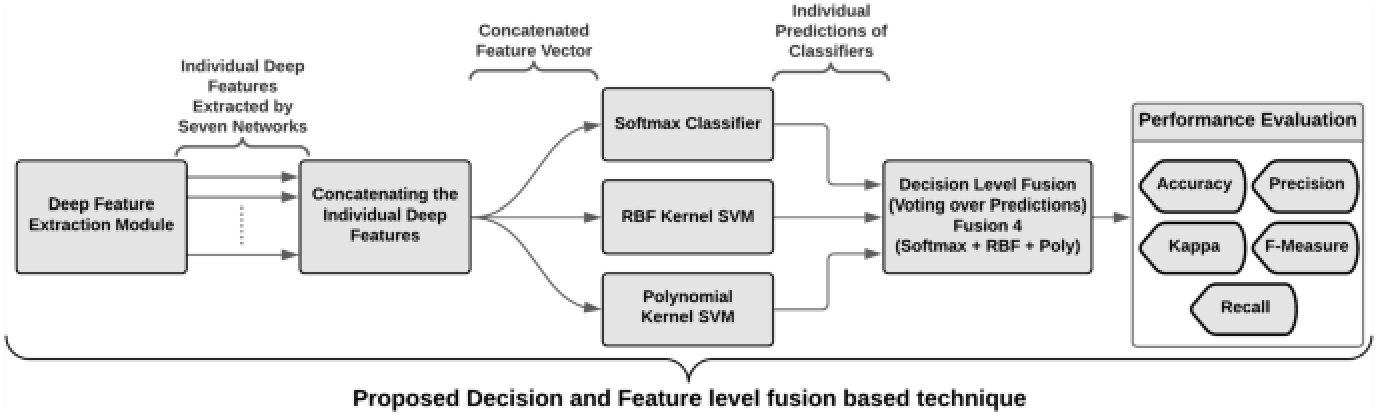


Ilhan, H.O., Serbes, G. & Aydin, N. Decision and feature level fusion of deep features extracted from public COVID-19 data-sets. Appl Intell 52, 8551–8571 (2022). https://doi.org/10.1007/s10489-021-02945-8

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Feature Level Fusion

Simple concatenation: This is the simplest approach, where the features from each source are simply concatenated into a single feature vector. This can be effective if the features from each source are of the same type and have a similar meaning. However, it can also lead to problems with dimensionality and can be computationally expensive.

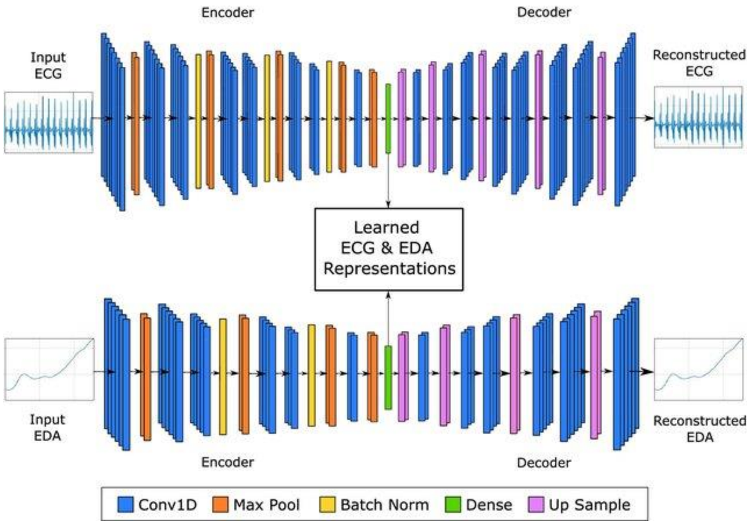


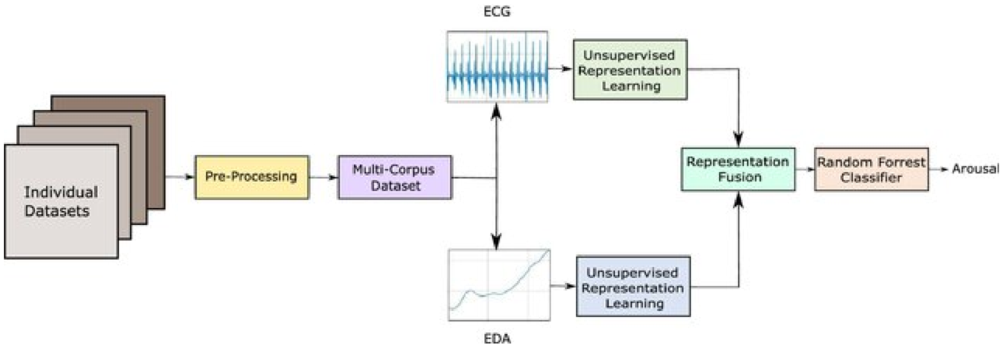
Ilhan, H.O., Serbes, G. & Aydin, N. Decision and feature level fusion of deep features extracted from public COVID-19 data-sets. Appl Intell 52, 8551–8571 (2022). https://doi.org/10.1007/s10489-021-02945-8

BEYOND
Centre of EO Research and Satellite Remote Sensing

Feature Level Fusion

Feature selection: This technique involves selecting a subset of the features from each source that are most informative for the task at hand. This can help to reduce the dimensionality of the data and improve the performance of the fusion algorithm.



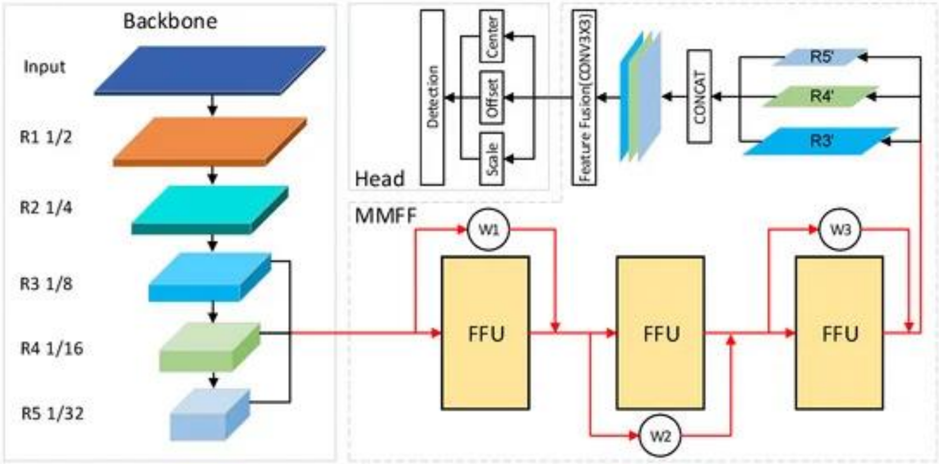


Ross, Kyle & Hungler, P. & Etemad, Ali. (2021). Unsupervised multi-modal representation learning for affective computing with multi-corpus wearable data. Journal of Ambient Intelligence and Humanized Computing. 14. 1-26. https://doi.org/10.1007/s12652-021-03462-9.

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Feature Level Fusion

Feature weighting: This technique assigns weights to the features from each source, based on their importance or reliability. This can be used to give more weight to features that are considered to be more informative or reliable.

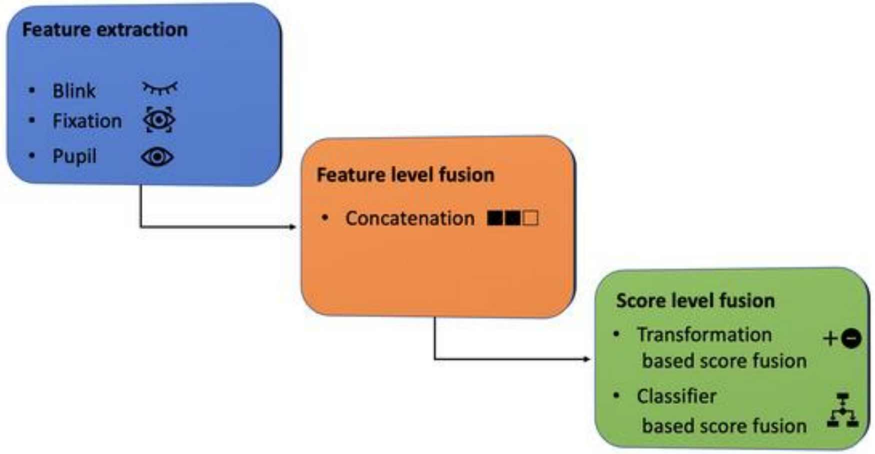


Xu, Y.; Yu, Q. Adaptive Weighted Multi-Level Fusion of Multi-Scale Features: A New Approach to Pedestrian Detection. Future Internet 2021, 13, 38. https://doi.org/10.3390/fi13020038.

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Feature Level Fusion

Feature transformation: This technique involves transforming the features from each source into a new representation that is more suitable for the task at hand. This can be done using techniques such as principal component analysis (PCA) or linear discriminant analysis (LDA).

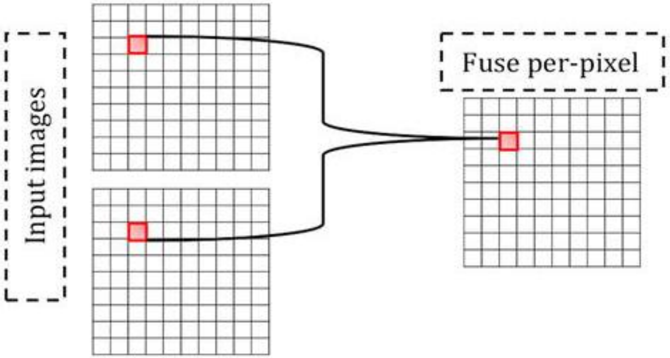


Bisogni, C.; Cascone, L.; Narducci, F. Periocular Data Fusion for Age and Gender Classification. J. Imaging 2022, 8, 307. https://doi.org/10.3390/jimaging8110307.

Raw Level (Early) Fusion

Combines the raw data from multiple sources before any processing or feature extraction occurs. This means the original, unprocessed information from each sensor or modality is directly combined into a single, larger data stream.

- Simple concatenation
- Feature engineering
- Dimensionality reduction techniques
- Other statistical fusion techniques



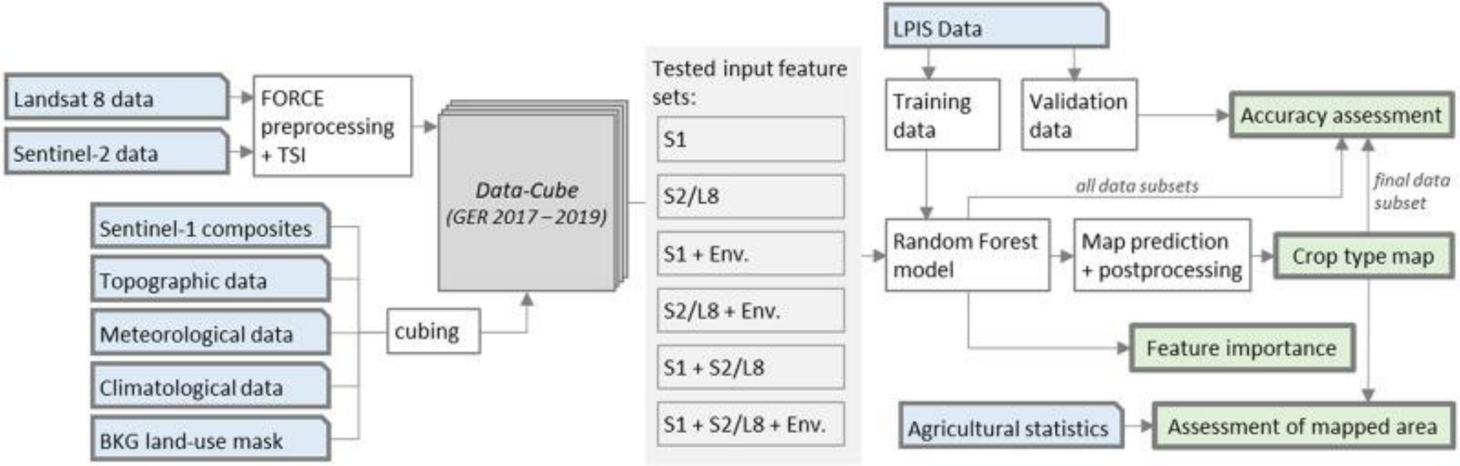
<u>Challenges:</u>

- **Data Preprocessing**: Ensuring proper alignment, normalization, and synchronization of data from diverse sources can be complex and computationally expensive.
- **High Dimensionality**: Combining raw data can lead to high-dimensional features, potentially causing difficulties in training models and increasing computational costs.
- **Limited Interpretability**: Understanding how the model utilizes the fused data becomes challenging as the raw information is directly combined, making it difficult to pinpoint the specific contributions of each source.

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Data Fusion in EO

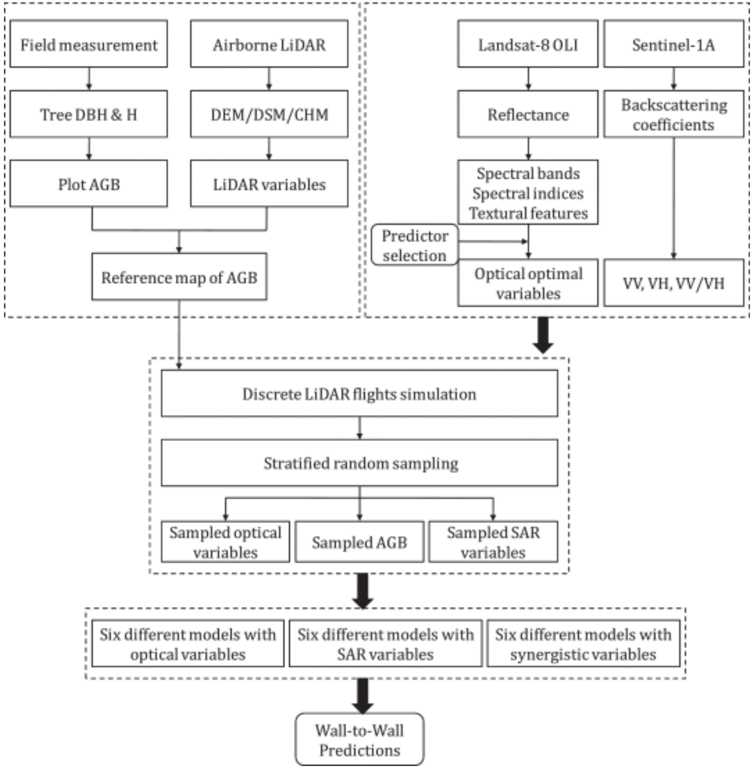
How does the combination of multispectral time series, SAR data, and environmental data influence classification accuracy in large-area crop type mapping?



Blickensdörfer, Lukas, et al. "Mapping of crop types and crop sequences with combined time series of Sentinel-1, Sentinel-2 and Landsat 8 data for Germany." Remote sensing of environment 269 (2022): 112831. https://doi.org/10.1016/j.rse.2021.112831.

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Data Fusion in EO



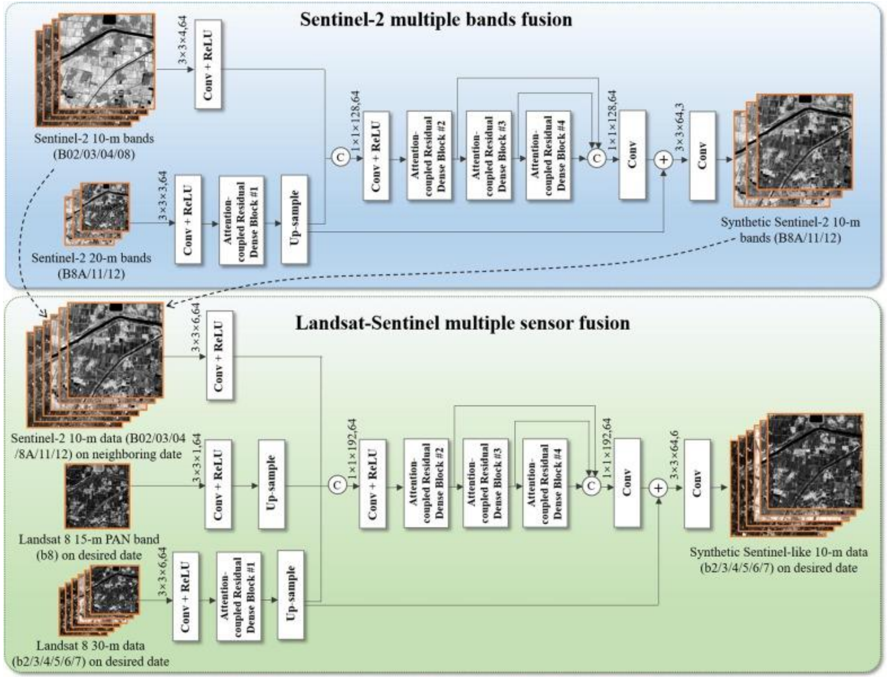
Integrate the LiDAR-derived AGB with the synergy of satellite optical (Landsat 8 OLI) and SAR (Sentinel-1A) data for mapping forest AGB using the DL technology for the forests in the northeast region of Conghua in the central Guangdong province, China.

Z. Shao, L. Zhang and L. Wang, "Stacked Sparse Autoencoder Modeling Using the Synergy of Airborne LiDAR and Satellite Optical and SAR Data to Map Forest Above-Ground Biomass," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 10, no. 12, pp. 5569-5582, Dec. 2017. https://doi.org/10.1109/JSTARS.2017.2748341.

BEYOND
Centre of EO Research and Satellite Remote Sensing

Data Fusion in EO

A novel deep network is proposed for Landsat 8 and Sentinel-2 data fusion

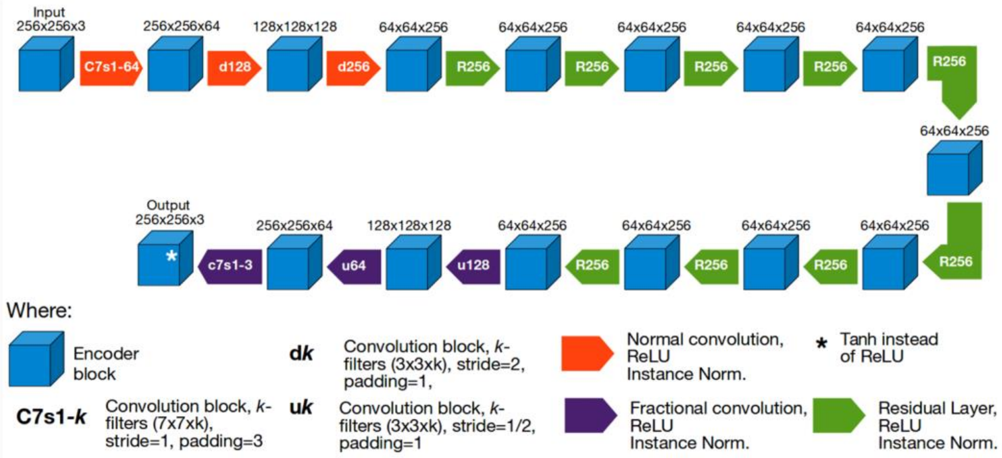


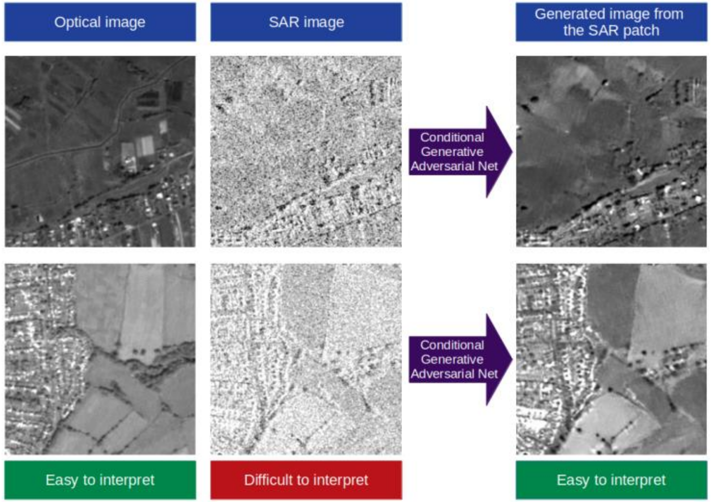
Wu, Jingan, et al. "Fusing Landsat 8 and Sentinel-2 data for 10-m dense time-series imagery using a degradation-term constrained deep network." International Journal of Applied Earth Observation and Geoinformation 108 (2022): 102738. https://doi.org/10.1016/j.jag.2022.102738.

BEYOND Centre of EO Research and Satellite Remote Sensing

Data Fusion in EO

SAR to Optical using GANs



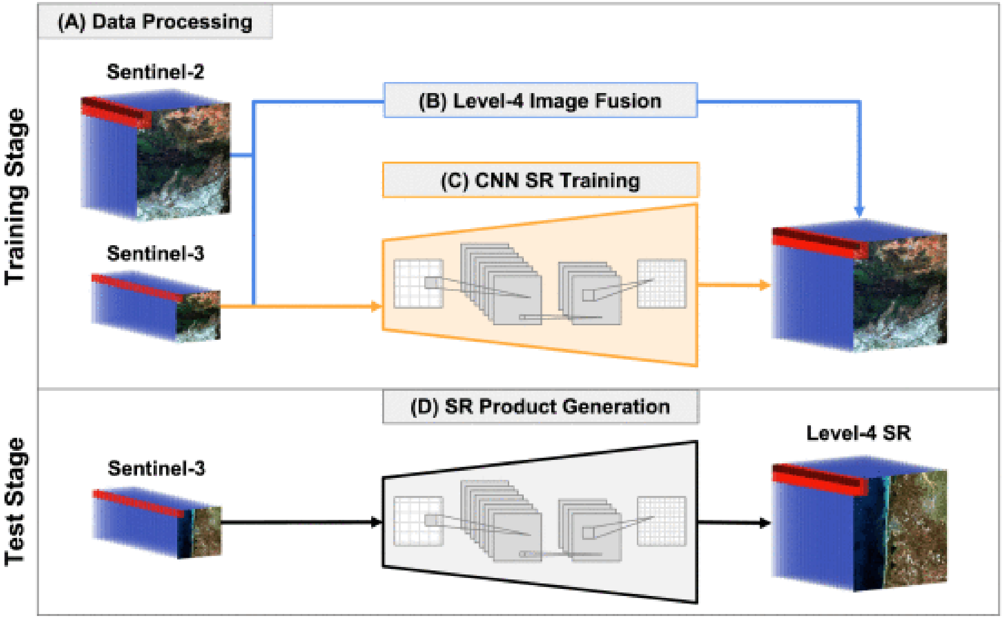


Fuentes Reyes, M.; Auer, S.; Merkle, N.; Henry, C.; Schmitt, M. SAR-to-Optical Image Translation Based on Conditional Generative Adversarial Networks—Optimization, Opportunities and Limits. Remote Sens. 2019, 11, 2067. https://doi.org/10.3390/rs11172067.

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Data Fusion in EO

The proposed approach gathers a multi-spectral data fusion scheme together with a CNN-based mapping function to project the OLCI sensor (300m) onto its corresponding synthetic spatial ground-truth generated by the OLCI/MSI fusion

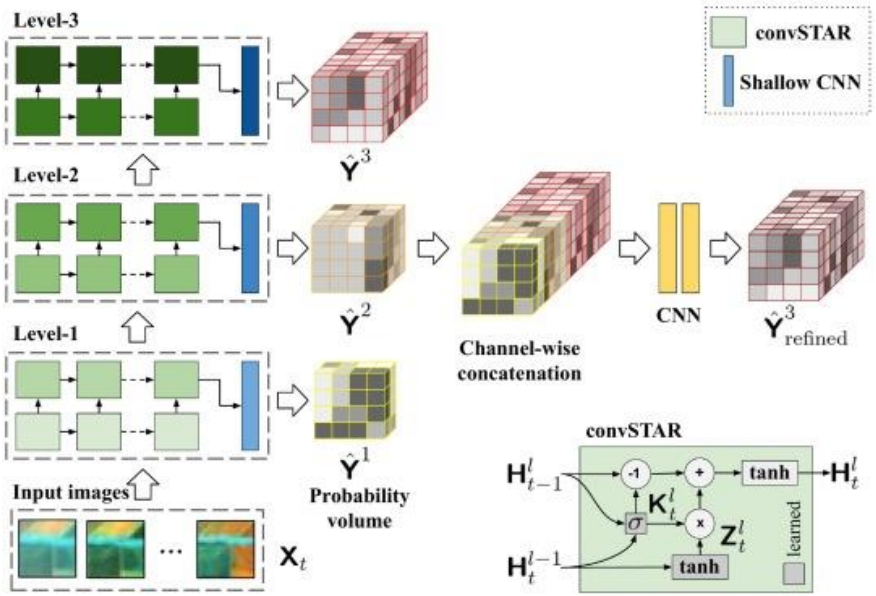


R. Fernandez, R. Fernandez-Beltran and F. Pla, "Sentinel-3 Image Super-Resolution Using Data Fusion and Convolutional Neural Networks," 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, 2021, pp. 2867-2870. https://doi.org/10.1109/IGARSS47720.2021.9554826.

BEYOND Centre of EO Research and Satellite Remote Sensing

Data Fusion in EO

Hierarchical convolutional recurrent network

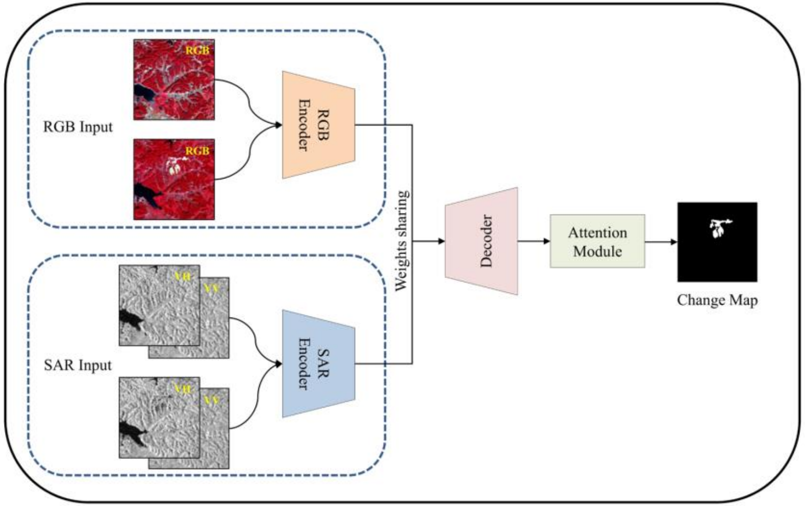


Turkoglu, Mehmet Ozgur, et al. "Crop mapping from image time series: Deep learning with multi-scale label hierarchies." Remote Sensing of Environment 264 (2021): 112603. https://doi.org/10.1016/j.rse.2021.112603.

BEYOND Centre of EO Research and Satellite Remote Sensing

Data Fusion in EO

A Siamese network model named DSNUNet was designed to achieve accurate forest change detection by combining optical and SAR images.

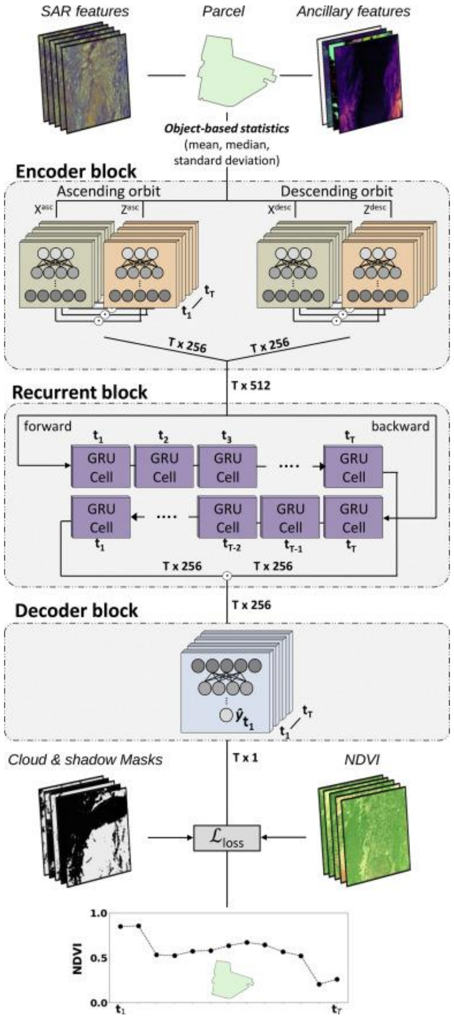


Jiang, J.; Xing, Y.; Wei, W.; Yan, E.; Xiang, J.; Mo, D. DSNUNet: An Improved Forest Change Detection Network by Combining Sentinel-1 and Sentinel-2 Images. Remote Sens. 2022, 14, 5046. https://doi.org/10.3390/rs14195046.

Data Fusion in EO

SenRVM model overview. It targets to regress SAR and associated ancillary data into optical-like vegetation index (here NDVI)

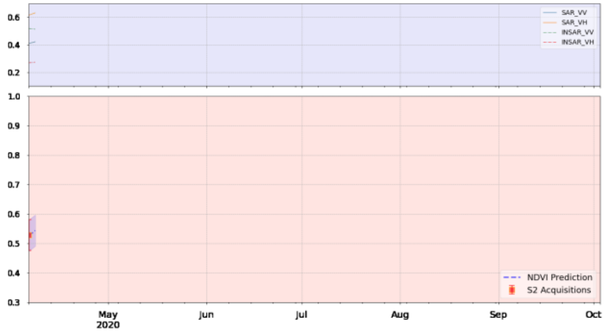
Garioud, Anatol, et al. "Recurrent-based regression of Sentinel time series for continuous vegetation monitoring." Remote Sensing of Environment 263 (2021): 112419. https://doi.org/10.1016/j.rse.2021.112419.

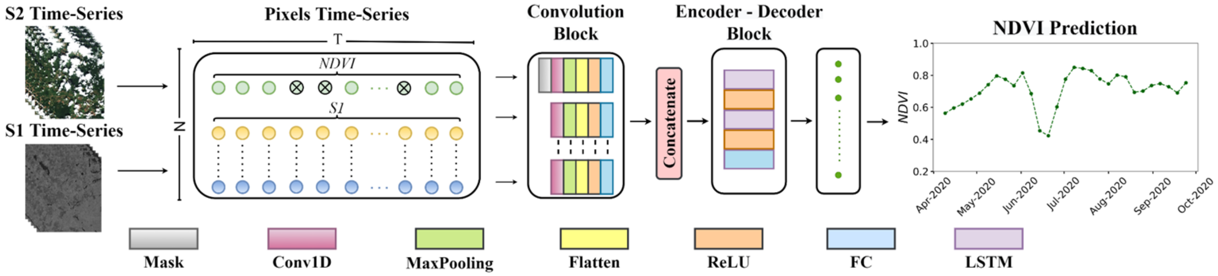


BEYOND Centre of EO Research and Satellite Remote Sensing

Data Fusion in EO

Reconstructing continuous NDVI grassland time series with a fixed 6-day time step using SAR data and the available NDVI values.



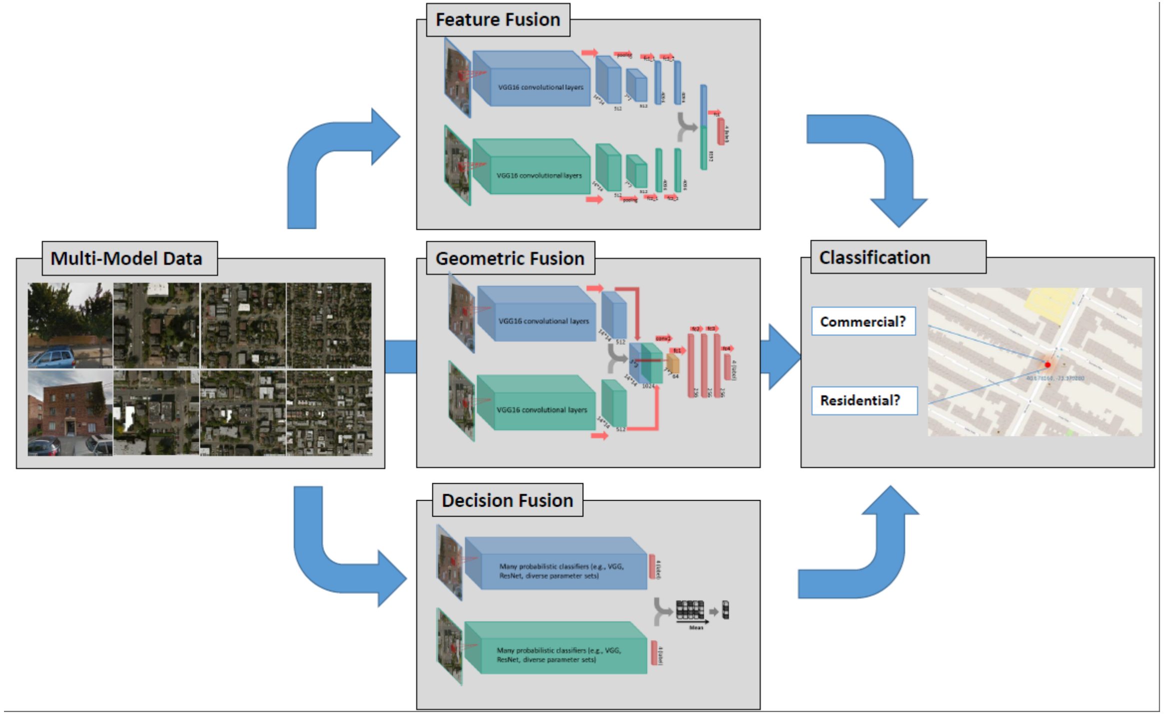


Tsardanidis, et al. "Cloud gap-filling with deep learning for improved grassland monitoring." Computers and Electronics in Agriculture (Under Review)

BEYOND
Centre of EO Research
and Satellite Remote Sensing

Data Fusion in EO

Two different strategies—geometric feature fusion, and decision-level fusion—for fusing ground-level street view images and nadir-view remote sensing images with the application of building functions' classification.

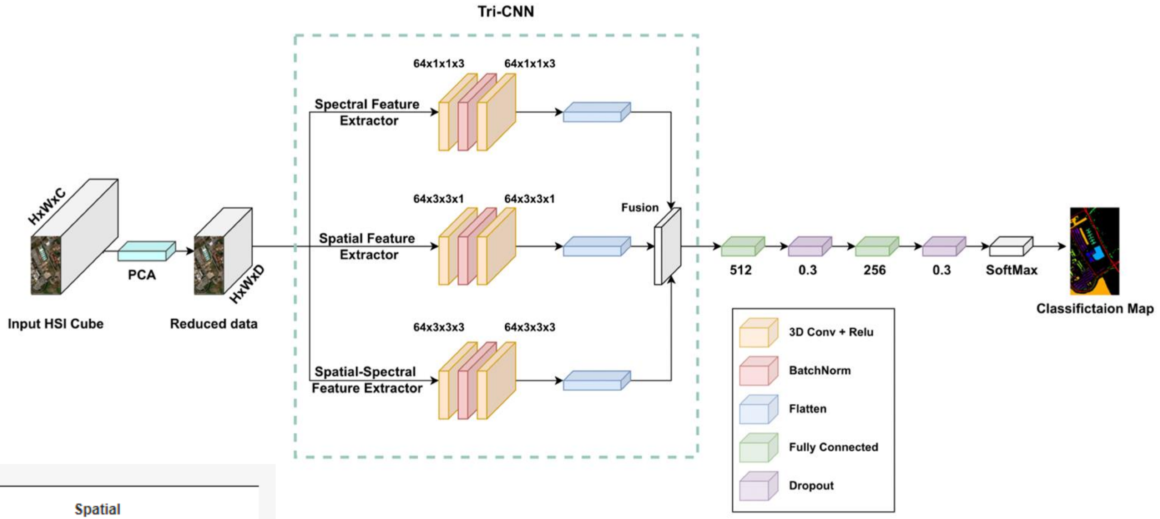


Hoffmann, E.J.; Wang, Y.; Werner, M.; Kang, J.; Zhu, X.X. Model Fusion for Building Type Classification from Aerial and Street View Images. Remote Sens. 2019, 11, 1259. https://doi.org/10.3390/rs11111259.

BEYOND Centre of EO Research and Satellite Remote Sensing

Data Fusion in EO

A model that incorporates feature extraction at different filter scales is proposed



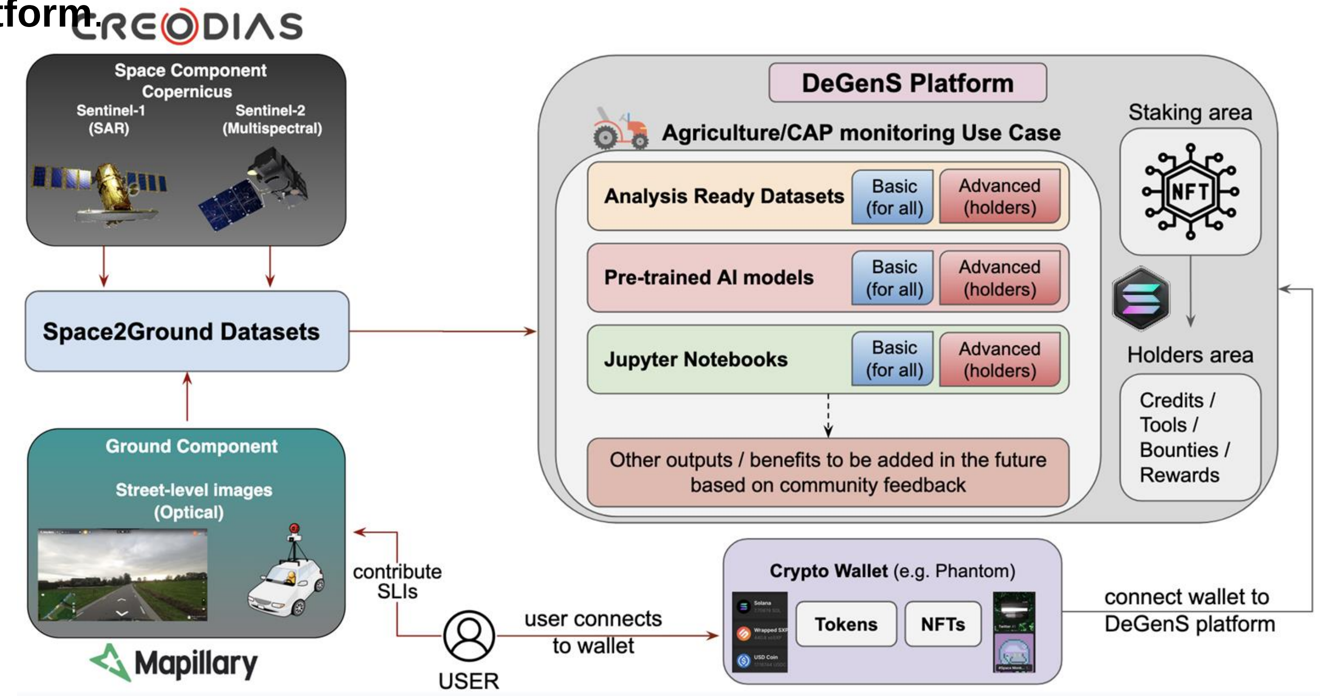
Method	Spectral Only	Spatial Only	Spectral–Spatial Only	Spectral + Spatial	Spectral + Spectral–Spatial	Spatial + Spectral–Spatial	Proposed
Overall Accuracy (%)	85.63 ± 4.42	89.45 ± 2.58	91.43 ± 1.93	90.88 ± 3.74	91.41 ± 1.57	91.51 ± 2.18	**92.96 ± 1.05**
Average Accuracy (%)	82.44 ± 3.28	85.21 ± 3.30	88.23 ± 2.32	87.70 ± 2.55	88.67 ± 2.84	89.48 ± 3.90	**89.53 ± 1.39**
Kappa × 100	79.31 ± 4.28	87.90 ± 2.40	89.26 ± 2.43	88.89 ± 3.74	90.06 ± 1.13	90.16 ± 1.23	**90.56 ± 2.53**

Alkhatib, M.Q.; Al-Saad, M.; Aburaed, N.; Almansoori, S.; Zabalza, J.; Marshall, S.; Al-Ahmad, H. Tri-CNN: A Three Branch Model for Hyperspectral Image Classification. Remote Sens. 2023, 15, 316. https://doi.org/10.3390/rs15020316.

BEYOND Centre of EO Research and Satellite Remote Sensing

DeGenS Platform (Best IDEA Award)

- Incentivizing Crowdsourcing with Blockchain Technologies → a blockchain-based rewarding mechanism using NFTs built on the **Solana** blockchain.
- Space2Ground Data Availability & AI Framework → analysis-ready datasets, together with relevant AI code implementations and examples, **will be accessible through a user-friendly platform**.



References

- Karagiannopoulou, A.; Tsertou, A.; Tsimiklis, G.; Amditis, A. Data Fusion in Earth Observation and the Role of Citizen as a Sensor: A Scoping Review of Applications, Methods and Future Trends. Remote Sens. 2022, 14, 1263. https://doi.org/10.3390/rs14051263.
- D’Andrimont, R., Yordanov, M., Martinez-Sanchez, L., van der Velde, M., 2022.Monitoring crop phenology with street-level imagery using computer vision.Comput. Electron. Agric. 196, 106866. https://doi.org/10.1016/j.compag.2022.106866.
- D’Andrimont, R.; Lemoine, G.; Van der Velde, M. Targeted Grassland Monitoring at Parcel Level Using Sentinels, Street-Level Images and Field Observations. Remote Sens. 2018, 10, 1300. https://doi.org/10.3390/rs10081300.
- D'Andrimont, R.; Yordanov, M.; Lemoine, G.; Yoong, J.; Nikel, K.; Van der Velde, M. Crowdsourced Street-Level Imagery as a Potential Source of In-Situ Data for Crop Monitoring. Land 2018, 7, 127. https://doi.org/10.3390/land7040127.
- Choumos G., Koukos A., Sitokonstantinou V. and Kontoes C. (2022). Towards Space-to-Ground Data Availability for Agriculture Monitoring. 2022 IEEE 14th Image, Video, and Multidimensional Signal Processing Workshop (IVMSP 2022), 26-29 June 2022, Nafplio, Greece. https://doi.org/10.1109/IVMSP54334.2022.9816335.
- L. See et al., "Supporting Earth-Observation Calibration and Validation: A new generation of tools for crowdsourcing and citizen science," in IEEE Geoscience and Remote Sensing Magazine, vol. 4, no. 3, pp. 38-50, Sept. 2016. https://doi.org/10.1109/MGRS.2015.2498840.
- F. Dell’Acqua and D. De Vecchi, "Potentials of Active and Passive Geospatial Crowdsourcing in Complementing Sentinel Data and Supporting Copernicus Service Portfolio," in Proceedings of the IEEE, vol. 105, no. 10, pp. 1913-1925, Oct. 2017. https://doi.org/10.1109/JPROC.2017.2727284.
- A. Mittal, A. K. Moorthy and A. C. Bovik, "No-Reference Image Quality Assessment in the Spatial Domain," in IEEE Transactions on Image Processing, vol. 21, no. 12, pp. 4695-4708, Dec. 2012. https://doi.org/10.1109/TIP.2012.2214050.
- Lin, Kwan-Yee, and Guanxiang Wang. "Hallucinated-IQA: No-reference image quality assessment via adversarial learning." Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.
- Chandola, Yashvi, et al. Deep Learning for Chest Radiographs: Computer-Aided Classification. Elsevier, 2021.

BEYOND
Centre of EO Research
and Satellite Remote Sensing