

# StatE0

5-7 May 2026 | ESA-ESRIN | Frascati (Rome), Italy

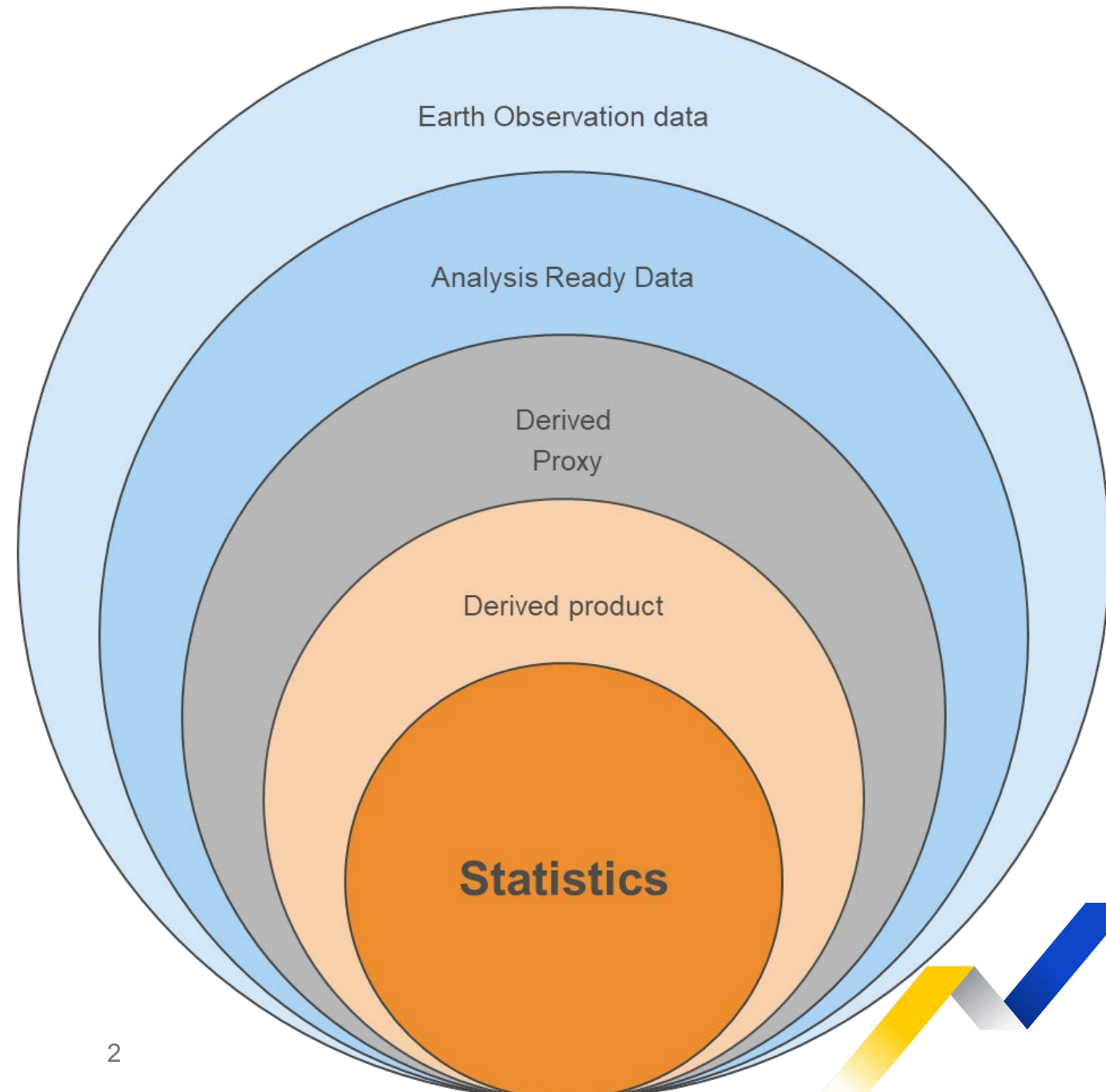


## Earth Observation for Agriculture Statistics (technical)

Zacharias Kandylakis, Carla Martins, Hannes Reuter, EUROSTAT E.4

# Main principles

- **Statisticians should not be processing raw EO data**
- **EO products need to adhere to certain standards**
- **Traceability of accuracy enables bias alleviation**



# Main goal

**Develop methodologies to calculate unbiased statistics at NUTS2 level for:**

- 1. Crop area**
- 2. Grassland main area**
- 3. Grassland main area by age**
- 4. Wind turbines on agricultural holdings**



# Available resources

- Raw satellite data (Sentinel-1, Sentinel-2, etc.)
- Earth Observation products (Copernicus, JRC, etc.)
- Reference data (LUCAS points, ACS, member state data)
- Nomenclatures (ACS, IFS, LUCAS)
  
- In-house experts (limited)
- EO4S Taskforce
- IT infrastructure (CDSE Jupyterlab, CREODIAS)



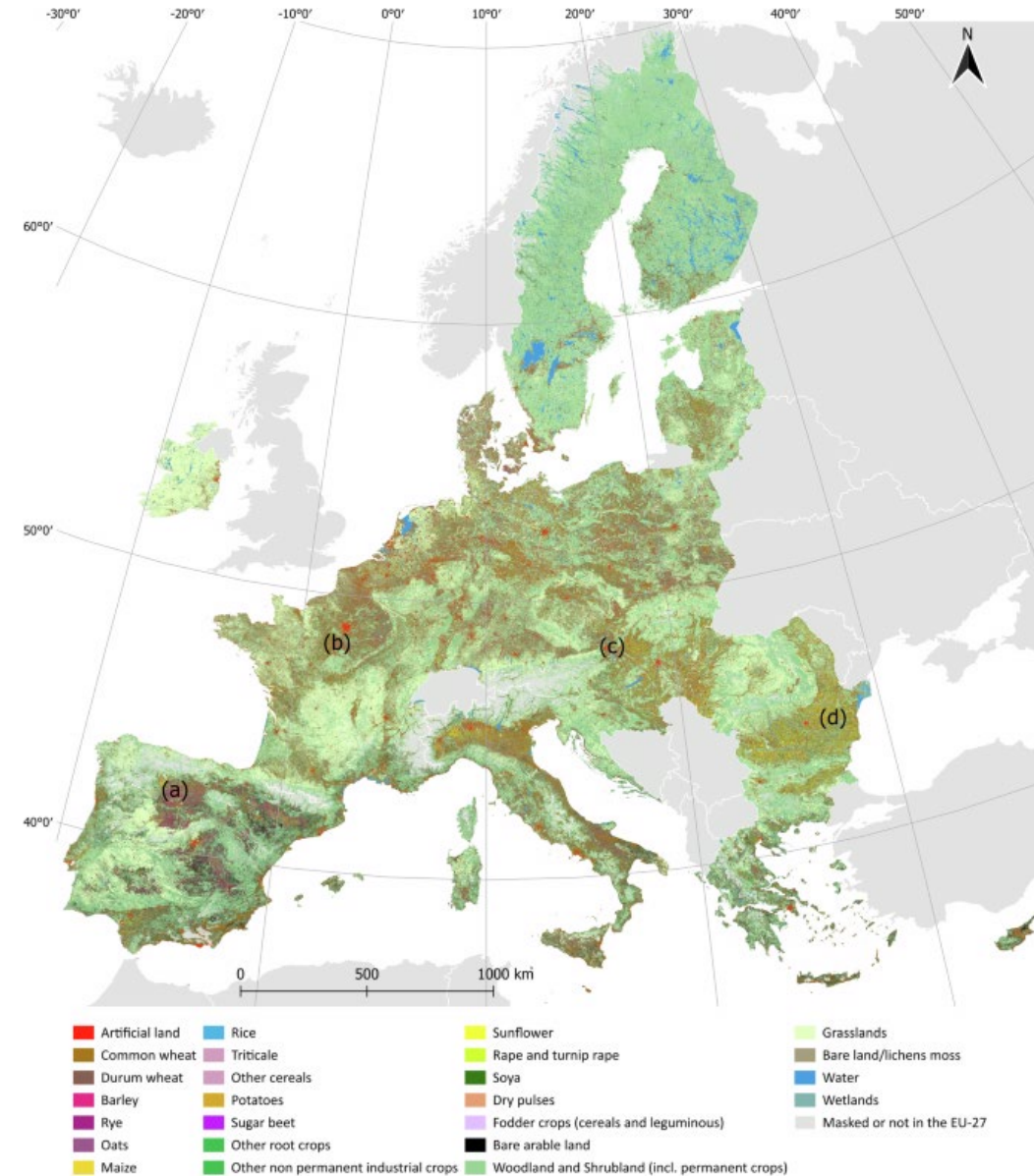
# Case 1: Crop & Grassland area statistics

## EUCROPMAP 2022 (JRC, BOKU)

- S1&S2 data, LUCAS points
- Random forest, 19 crop types

## Exploratory phase

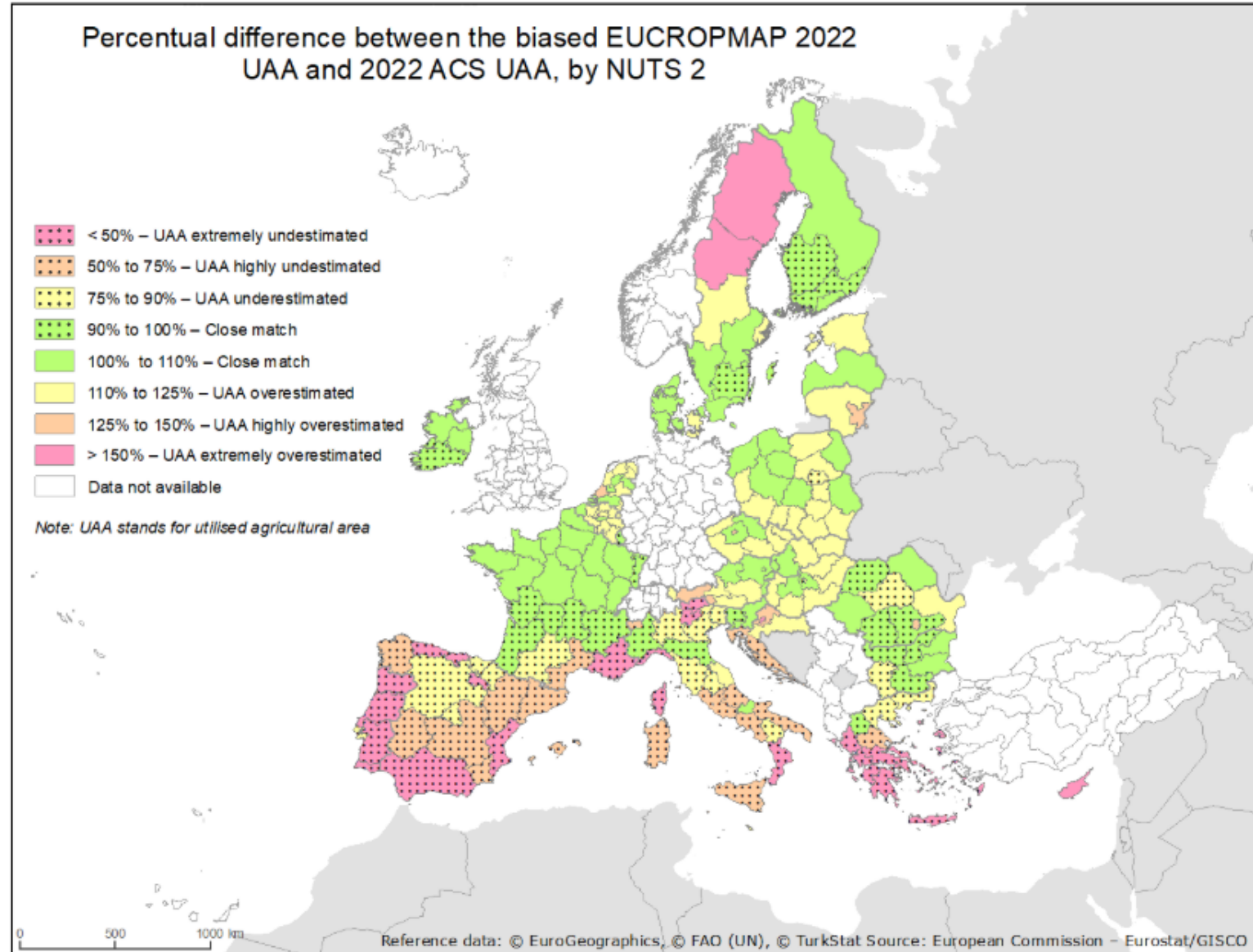
- Alignment of different nomenclatures (ACS, IFS, LUCAS, EURCROPMAP)
- Re-production in CDSE for certain areas
- EBLUP (Empirical Best Linear Unbiased Prediction) (access to test data, no access to probabilities)
- Aggregation to NUTS2, comparison with ACS for both biased and unbiased modalities



# Case 1: Crop & Grassland area statistics

## Key findings:

- Fairly good results for several countries at NUTS0
- Mediterranean regions performed worse
- EBLUP method did not perform as expected
- Classification probabilities necessary for better results



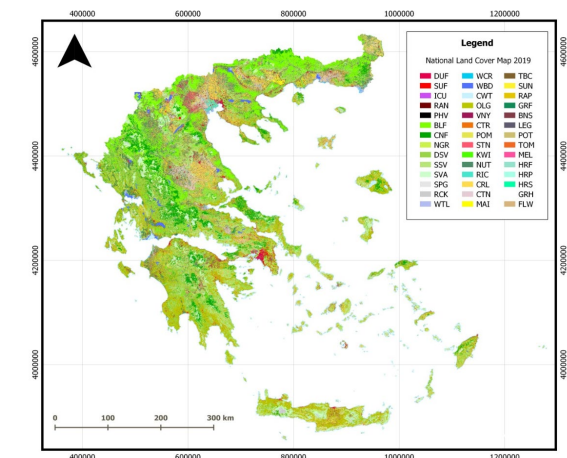
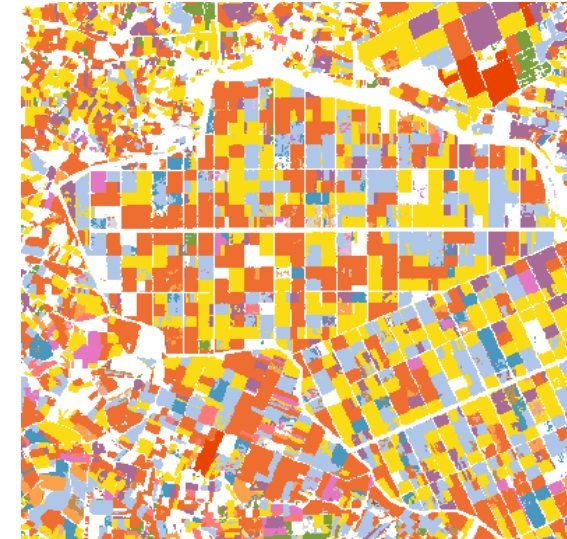
# Case 2: Crop area statistics

## HRL VLCC CTY 2017-2023 (EEA, VITO)

- S1 & S2 data, LPIS and LUCAS points
- Vision transformer methodology trained over a 5-year period 2017-2021
- Classification probabilities made available for 4 NUTS2 areas (in PL, PT)
- 17 crop types, for EEA38

## ELMAP 2019 (NTUA)

- S2 data, LPIS
- 25 crop types, tailored to Greek landscape
- Random forest trained on singular year



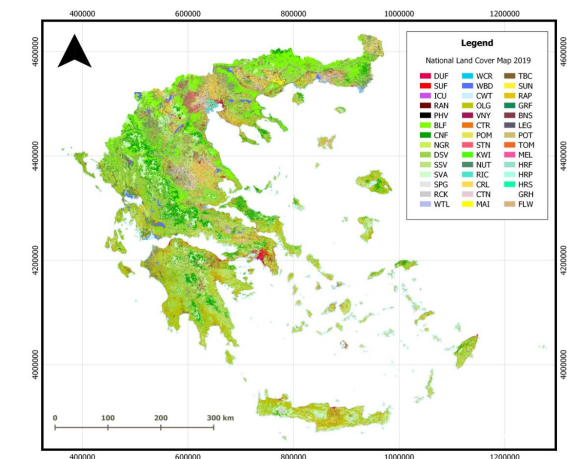
# Case 2: Crop area statistics

## Comparisons between:

- HRL VLCC CTY & ACS (2017-2023)
- HRL VLCC CTY & ELMAP (2019)
- ELMAP & ACS (2019)

## Focusing on HRL VLCC CTY (2017-2023):

- Extensive comparison with ACS over the whole extent (per country, per crop)
- Focused study over 4 NUTS2 areas
- Bias alleviation using unit-level Multinomial Logit Mixed Model (MLMM)
- At which point during the pipeline is it best to perform bias alleviation?



# Case 2: Crop area statistics

- **UAA average WAPE values** across all years, **at NUTS0 level:**
  - Most countries between 1-10%
  - 10-15% for SI, DE, LU, EL
  - 25-40% for AL, FI, IS, PT, XK
  - CY, MT notably bad
- **Per crop average WAPE values** across all years, **at EEA38 level**
  - 10-15% for Maize, Rapeseed, Wheat, Barley
  - 15-25% for Sunflower, Permanent Crops, Natural Fibers, Rice, Soya
  - 25-40% for Potatoes, Sugar beet, Dry Pulses, Vegetables
  - Worst performance for Other Cereals (WAPE  $\approx$  68.5%)

# Case 2: Crop area statistics

## Key findings:

- Bias alleviation inconclusive, 4 NUTS2 regions too limited in scope
- Results relevantly consistent across 2017-2023
- Great results for UAA at NUTS0 for most of the EEA38
- Certain crops are underperforming
- HRL VLCC CTY is more aligned with ACS than ELMAP
- Advantages of using a regional model are overshadowed by continental models using modern methodologies (transformers)
- **Next steps:**
  - Classification probabilities over the entire spatial extent
  - More detailed investigation of NUTS2 results

# Case 3: Grassland main area, area by age

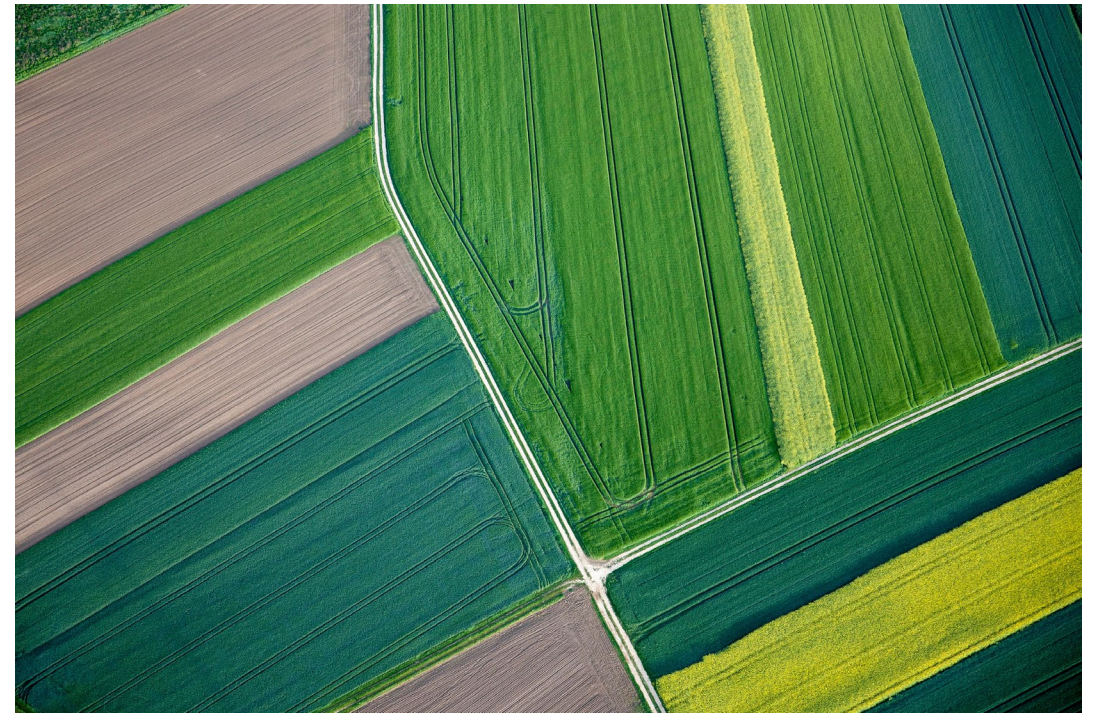
## Cross-reference between

- Reporting requirements for reference year 2026
- Available EO data & products

## QtM contract focusing on Grassland

Explore **HRL VLCC GRA, PLOUGH, TCD** etc., for the ability to detect:

- Grassland main area
- Grassland age groups 1-2, 3-5, 6-10 years
- Grassland trees/shrubs cover



# Case 3: Grassland main area, area by age

- NUTS 0 and NUTS 2 scope
- Several other requirements will be explored (e.g., grassland types, for more see Table 4 of [Report on Earth Observation capabilities for grassland statistics.pdf](#))
- In collaboration with E1 (Agriculture statistics)
- Limited ground truth data available for CH, FR, PL, SI



# Wind turbine detection

- Wind turbine locations
- Spatial accuracy needed?
- What data are available at national and EU-27 scale?
- Different backgrounds require different solutions
- Solved for Off-shore Wind Turbines ([link](#))



# Wind turbine detection in agricultural areas

## Two-fold problem:

- Wind turbine locations ( EO, Registers )
- Agricultural areas ( EO, LPIS/GSAA, Cadastre, Land Use Maps )

## Motivation:

- Reporting requirement in agriculture statistics
- Pan-European solution, also useful for energystatistics



# Wind turbine detection using Earth Observation

## Methodologies studied:

1. Satellite single scene a-contrario framework
2. Satellite multitemporal.  
Performed well in AT, DE. Developed for ESA and available at a cost. Unreliable for forest areas.
3. Ortho-imagery machine-learning.  
Explored in cooperation with INE PT, for study areas in PT and PL. Had a lot of false-positives.



# Wind turbine detection using Earth Observation

## Issues faced:

- Artifacts, miss-detections of other industrial installations.
- Varied accuracy depending on background (agriculture, forest, sea etc.)
- Sentinel imagery (10m) resolution not enough

## Solution proposed:

- Use of registers, geospatial approach
- Example for Brittany, France



# Use of registers, LPIS and cadastre

- Dedicated cadastre parcels for wind turbines (not always available).
- Agricultural parcel data should not include wind turbines (subsidies)
- Use of agricultural holdings is better if available
- Buffers around the wind turbine are also helpful
- Buffer size? Percentage of overlap between buffered wind turbine locations, agricultural parcels, cadastral parcels?
- Parameter values should be based on the specific country conditions (infrastructure, legislation, etc.)



# Thank you!

Images:

PT GEOS 2023 presentation (Buildings)

CDSE <https://dataspace.copernicus.eu/explore-data/data-collections/sentinel-data>

Stock Images

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