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TAKING THE PULSE OF OUR PLANET FROM SPACE

EUMETSAT ECMWF EUSPA

Copernicus4GEOGLAM service: first crop type mapping and area estimates results for strengthening national agricultural monitoring in Kenya, Tanzania and Uganda

Dr. Christophe Sannier | CLS France*, Alexandre Pennec | CLS, Eric van Valkengoed, TerraSphere, Paul van Der Voet | TerraSphere, Dr. Antoine Masse | CLS, Amaury Truffier | CLS, Menno de Vries | TerraSphere, Ir. Rob Verhoeven | TerraSphere, Felix Rembold | Joint Research Center - European Commission, Dr. Michele Meroni | Joint Research Center - European Commission, Dr. Carlos de Wasseige | CLS

*now with IGN FI France

25/05/2022

Copernicus 4 GEOGLAM

Europe's eyes on Earth

Global Agricultural Monitoring

Implemented by:

CLS

TerraSphere

with support from:

Upande

UHURULABS

OpenMap Development Tanzania

End-of-Season Results

Kenya – Tanzania – Uganda 2021

Funded by EU Copernicus program

Managed by EC JRC

European Commission

In collaboration with:

GEOGLAM Global Agricultural Monitoring

Kenya Ministry of Agriculture, Livestock, Fisheries & Cooperatives

The United Republic of Tanzania Ministry of Agriculture

Uganda office of the Prime minister disaster preparedness unit

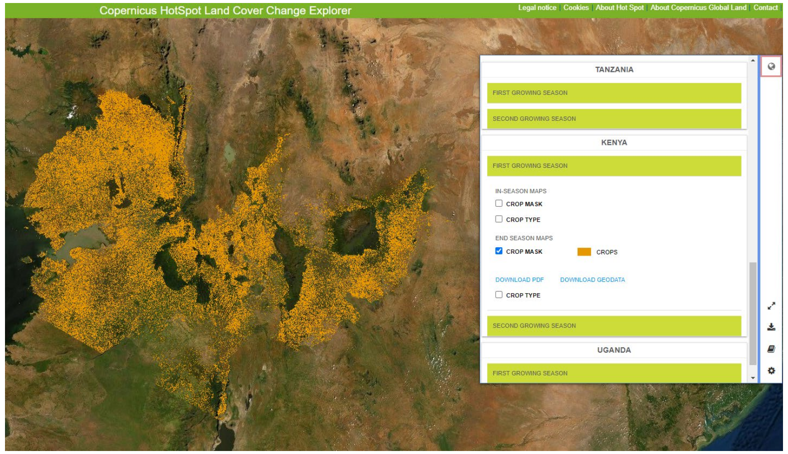
COLLECTE LOCALISATION SATELLITES

TerraSphere

Copernicus 4 GEOGLAM

Europe's eyes on Earth

Global Agricultural Monitoring



- **Mapping service of Copernicus Global Land**
  (https://land.copernicus.eu/global/hsm)
- **Launched in September 2020**
- **Objectives:**

- Strengthening of EU support to GEOGLAM especially in developing countries in Africa with existing national level crop monitoring activities already supported by GEOGLAM such as the national crop monitors in Uganda, Kenya and Tanzania
- Provide ad-hoc baseline crop monitoring info (crop type maps and derived agricultural statistics) with a capacity of 2 to 4 AOIs per year

COLLECTE LOCALISATION SATELLITES

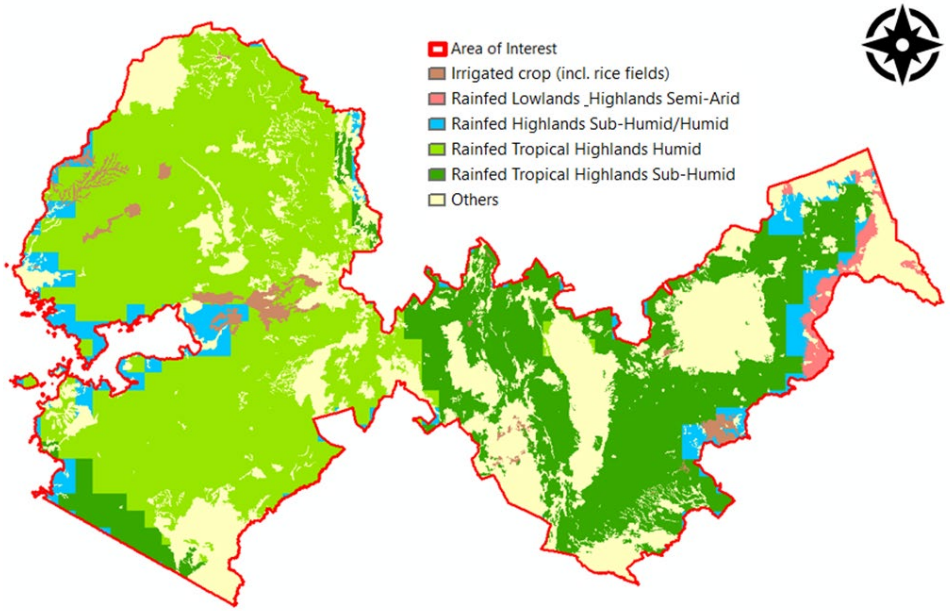
Process and Main Activities

- **Eligibility**: any GEOGLAM partner country can apply
- **Selection**: made by GEOGLAM based on relevance of the request*
- With approved **feasibility study**, the mapping service starts:
  - Field campaign
  - In season mapping / Validation
  - End of season mapping / Validation
- Repeated for a max of 2 growing seasons per solar year
  - Workshop/Handover at country contact premises

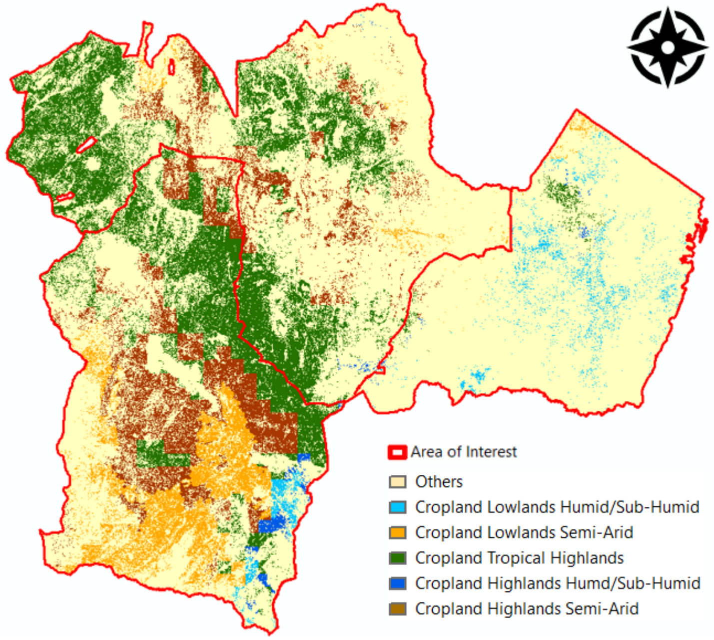
Field Campaign

- **Stratification**: Purpose is to reduce the amount of effort required for the field campaign:
  - Minimise the number of samples necessary to be surveyed
  - Optimise the sample distribution to increase precision of estimates

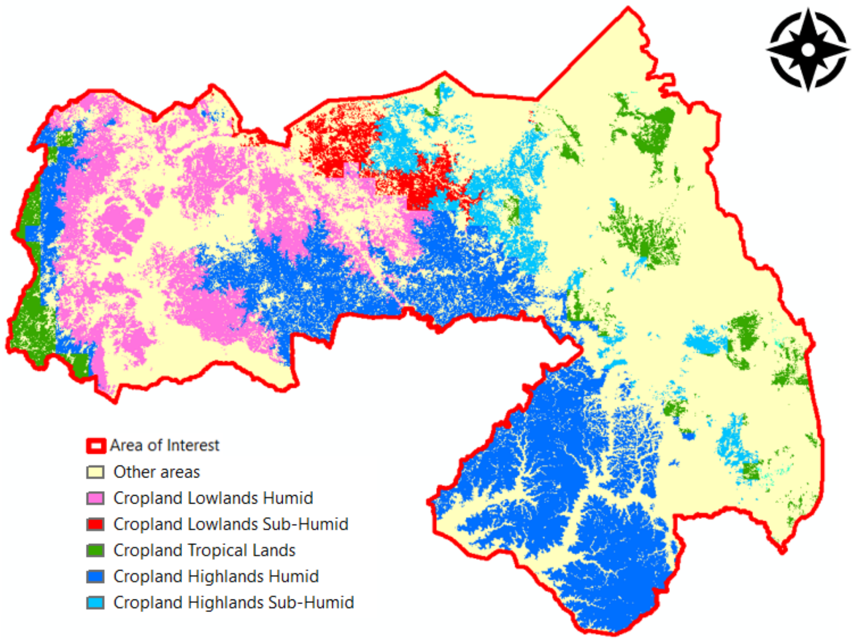
  → based on a combination of physical information (DEM), existing land cover map and agro-climatic conditions (Agro-Ecological Zones)



Kenya



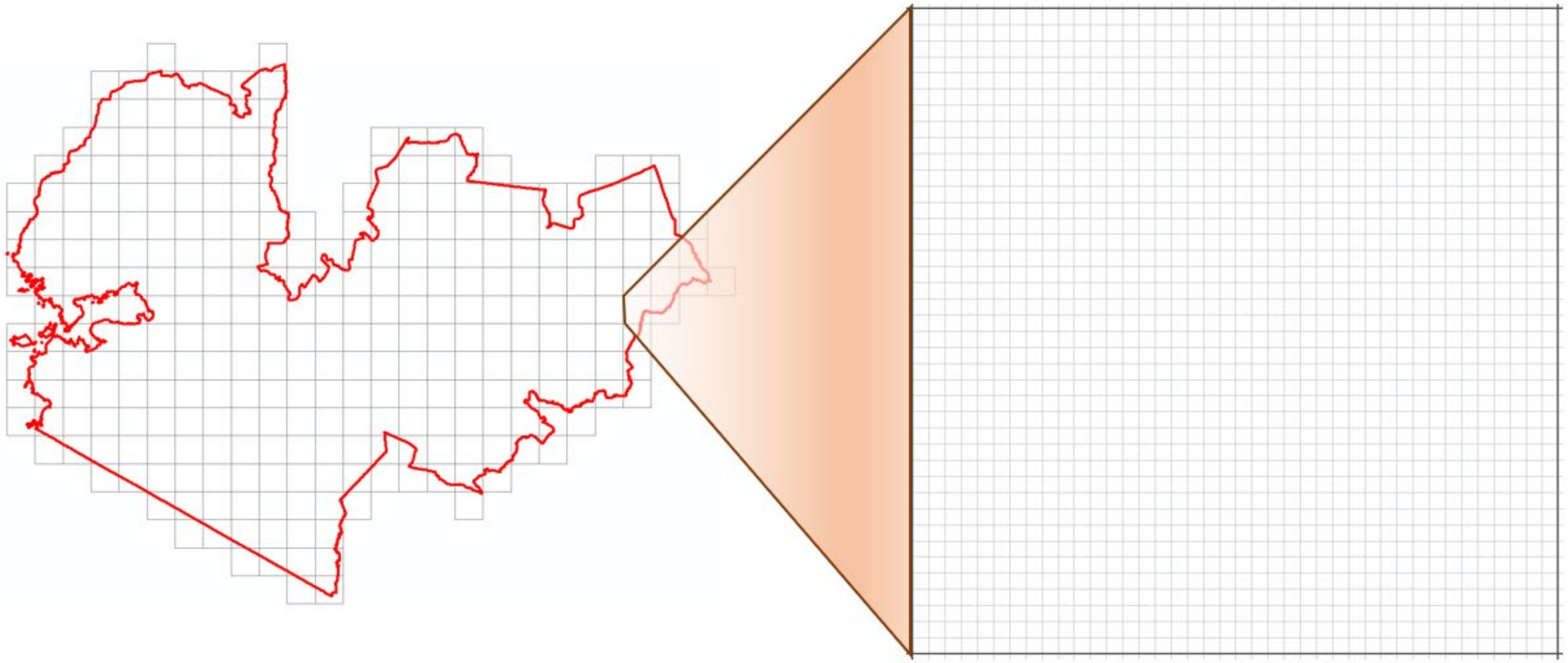
Tanzania



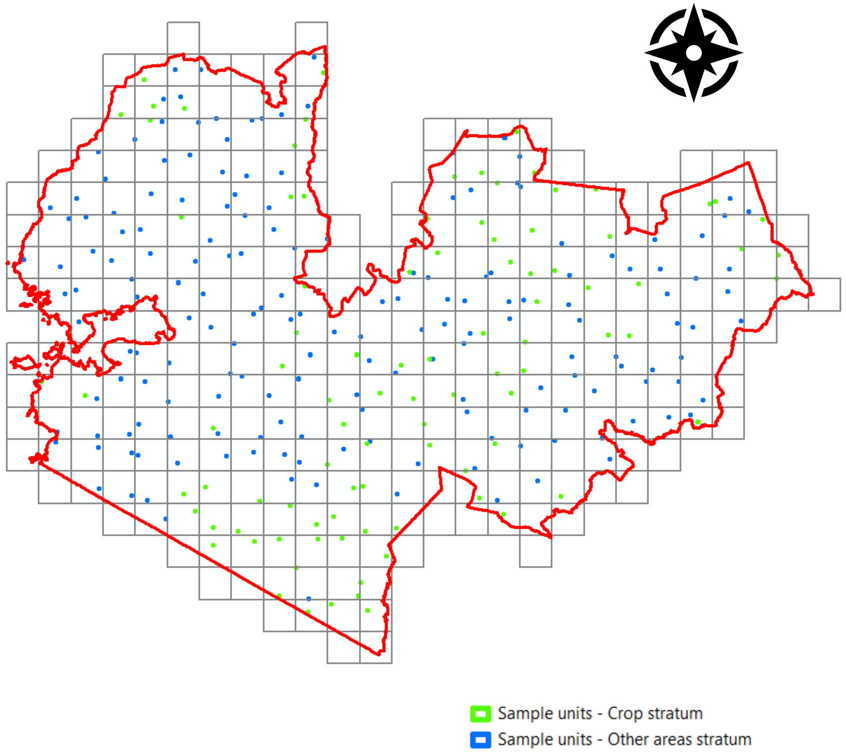
Uganda

Field Campaign

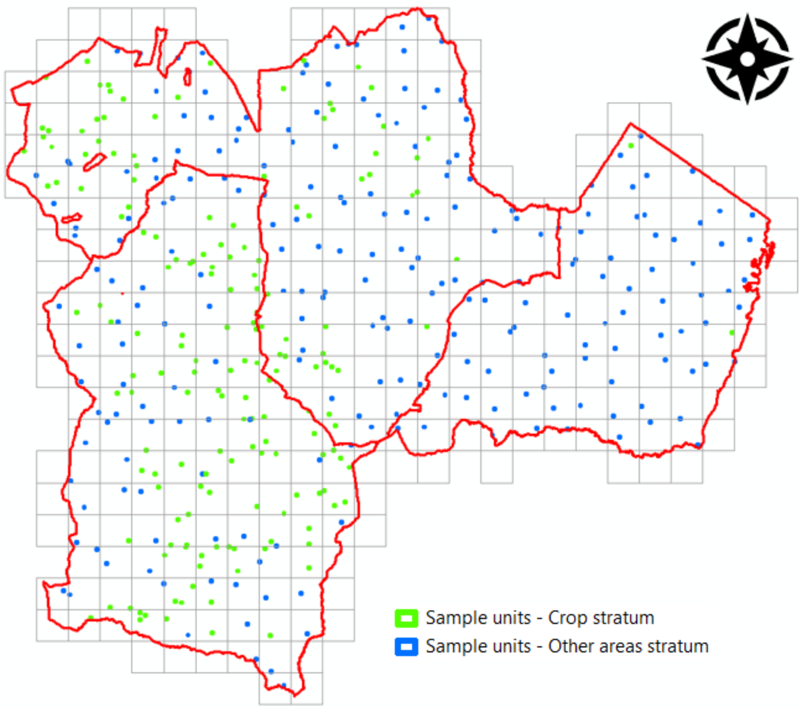
- **<u>Sampling design</u>**: stratified random sampling based on a two-stage approach within each strata:
  - First stage implemented by applying a 20 x 20 km grid over the AOI.
  - In a second stage, sample units were still randomly selected in sequence for each grid cell based on the 500 x 500 m sub-grid



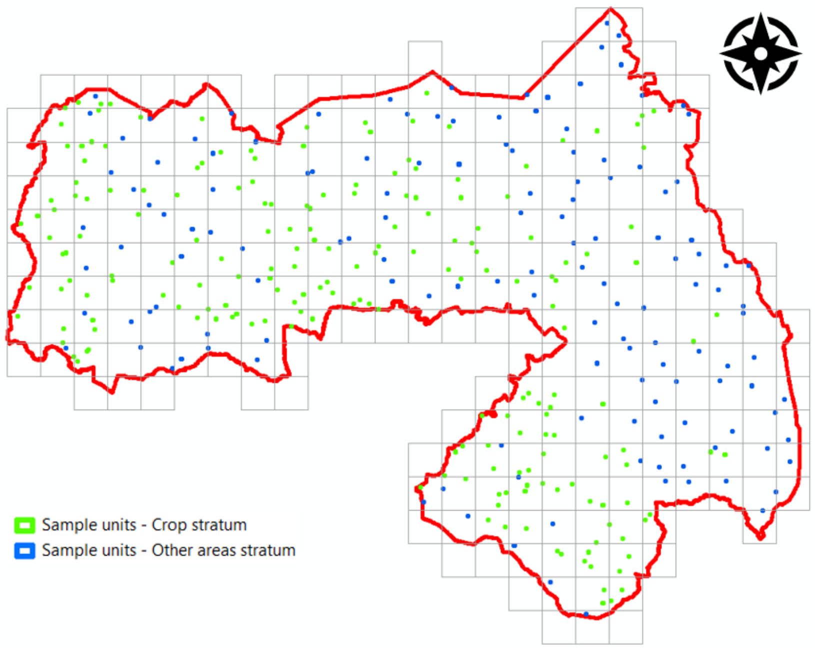
Field Campaign



Kenya - Spatial distribution of the 271 segments

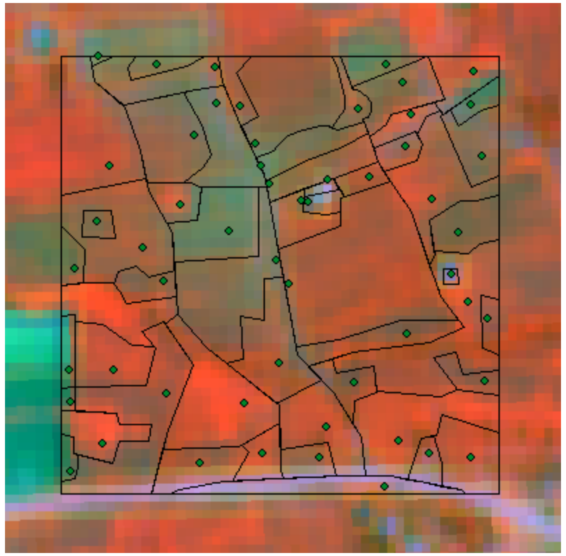


Tanzania - Spatial distribution of the 400 segments

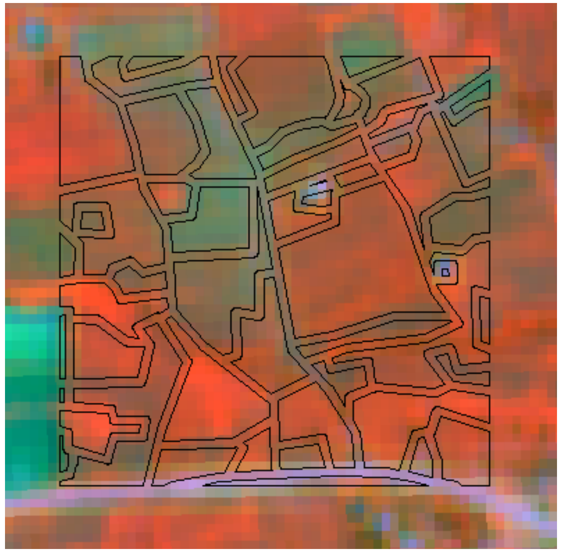


Uganda - Spatial distribution of the 338 segments

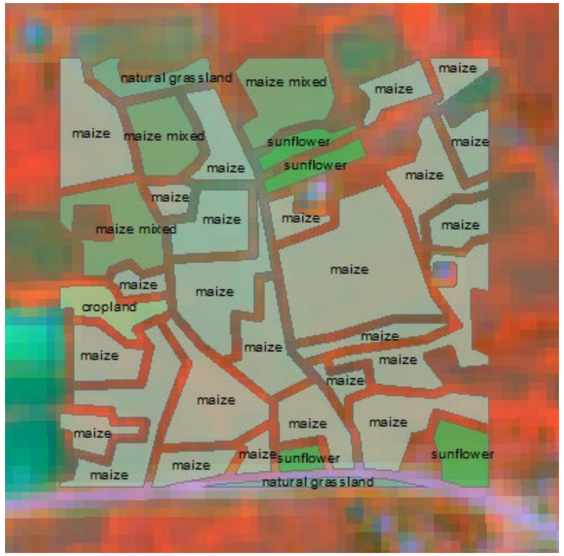
Training data preparation



Collected fieldwork points with labels



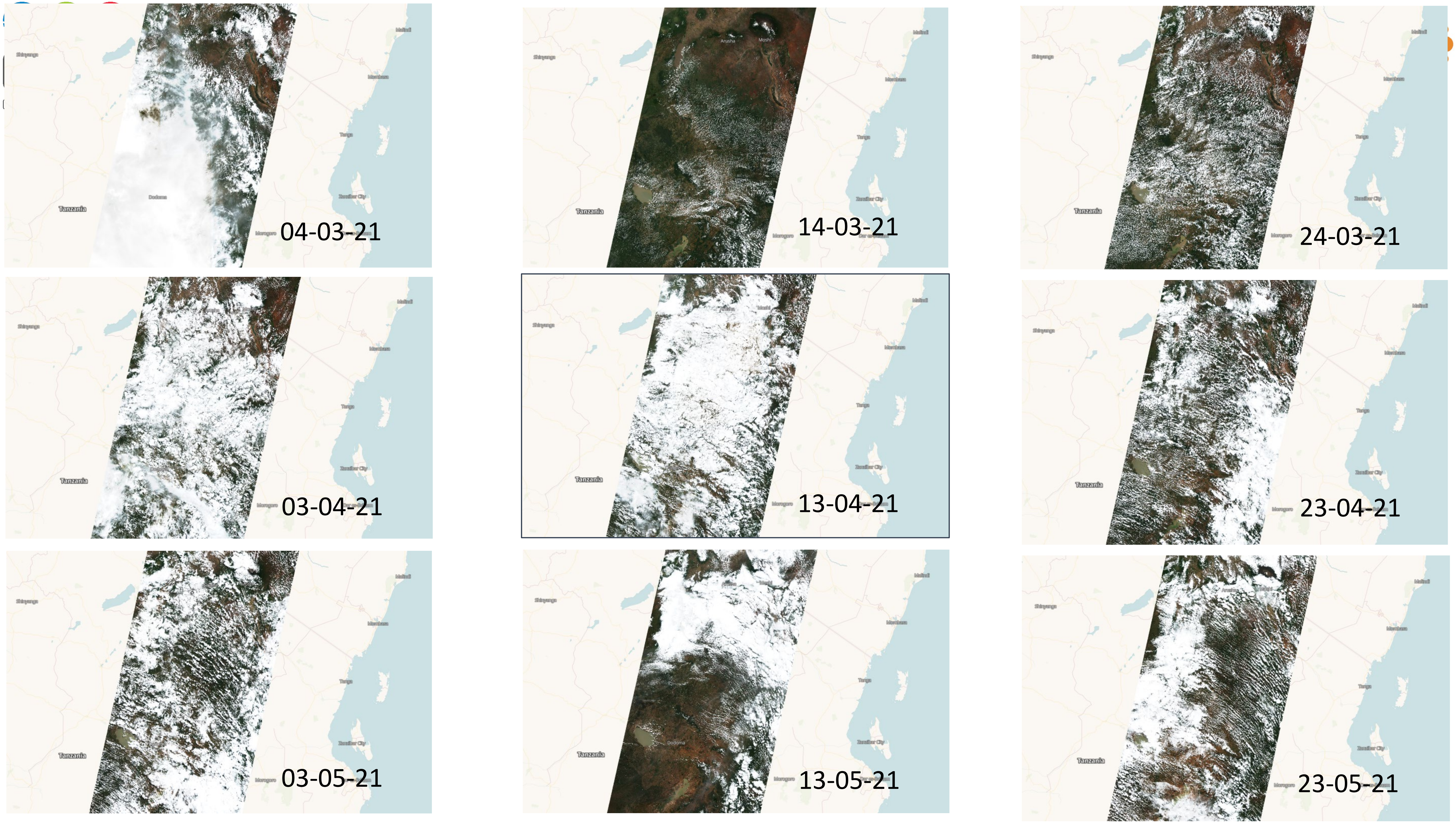
Buffering polygon features (-5m)



Filtering features < 0.1/0.2ha (MMU)

Splitting 75/25 training / validation

End-of-season adaptation: deletion of polygons smaller than 0.5/1.0 ha to better fit the agricultural practices.


04-03-21
14-03-21
24-03-21
03-04-21
13-04-21
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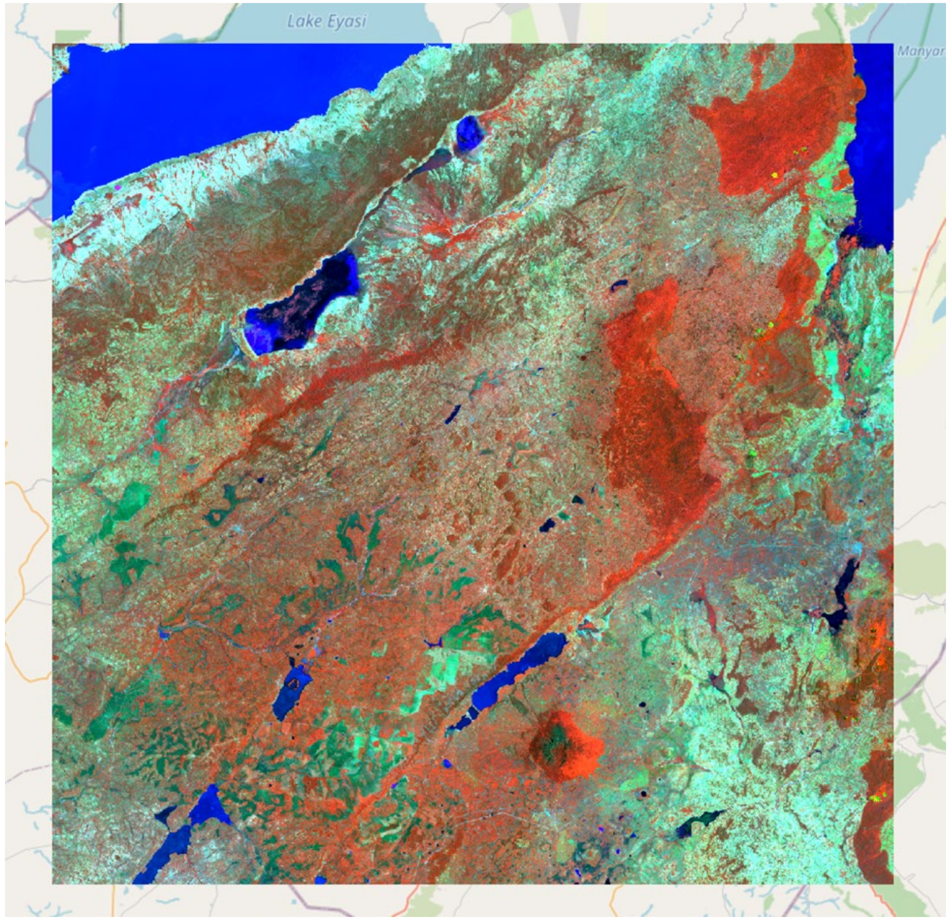
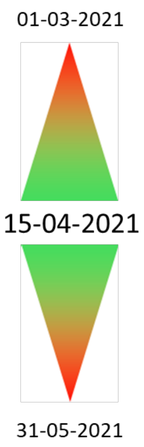
03-05-21
13-05-21
23-05-21

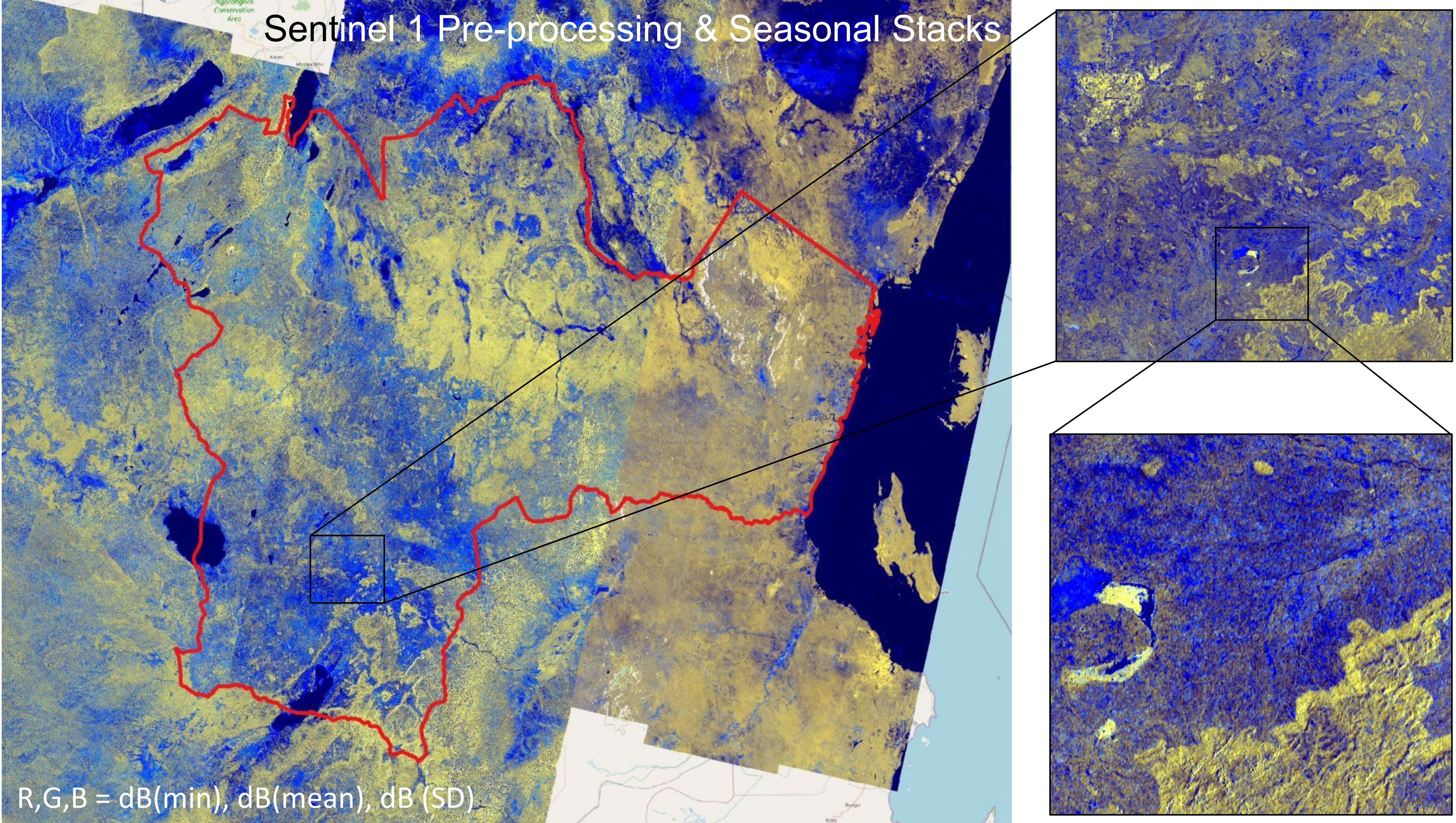
Sentinel-2 pre-processing

- **Acquisition** of S2 Imagery dataset (Sentinel data hub): full growing season S2 tiles = ~1,000 scenes
- **Pre-processing** approach for the end-of-season:
  - L2A -> L3A: +/- 45 days monthly cloud-free synthesis per tile
  - Advanced cloud/shadow masking





S2 L3A RGB=B8,B12,B4


Sentinel 1 Pre-processing & Seasonal Stacks
R,G,B = dB(min), dB(mean), dB (SD)

Crop Type & Mask Classification

Crop Type Map

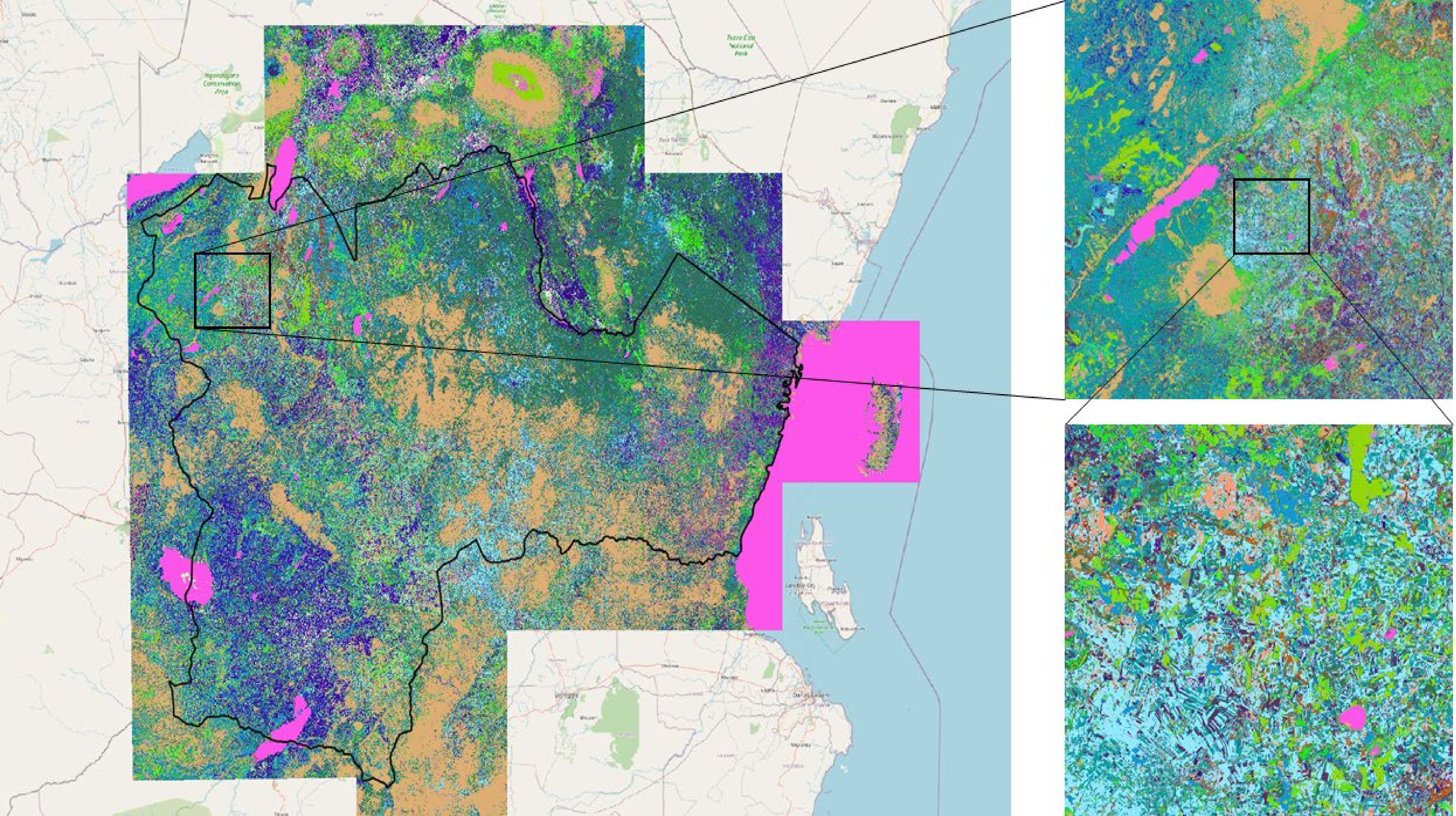
- Tests on classification algorithms:
  - 1) IOTA-2 Random Forest
  - 2) TempCNN

- Tests on various satellite data sources:
  - 1) S2 L3A
  - 2) S1 monthly synthesis
  - 3) S1 & S2 combination
- Random Forest (IOTA2) + S2 L3A dataset yielded best results

Crop Mask Map

- Tests on method:
  - Directly derived from Crop Type map
  - Based on Sentinel-1
  - Combination of S2 and S1

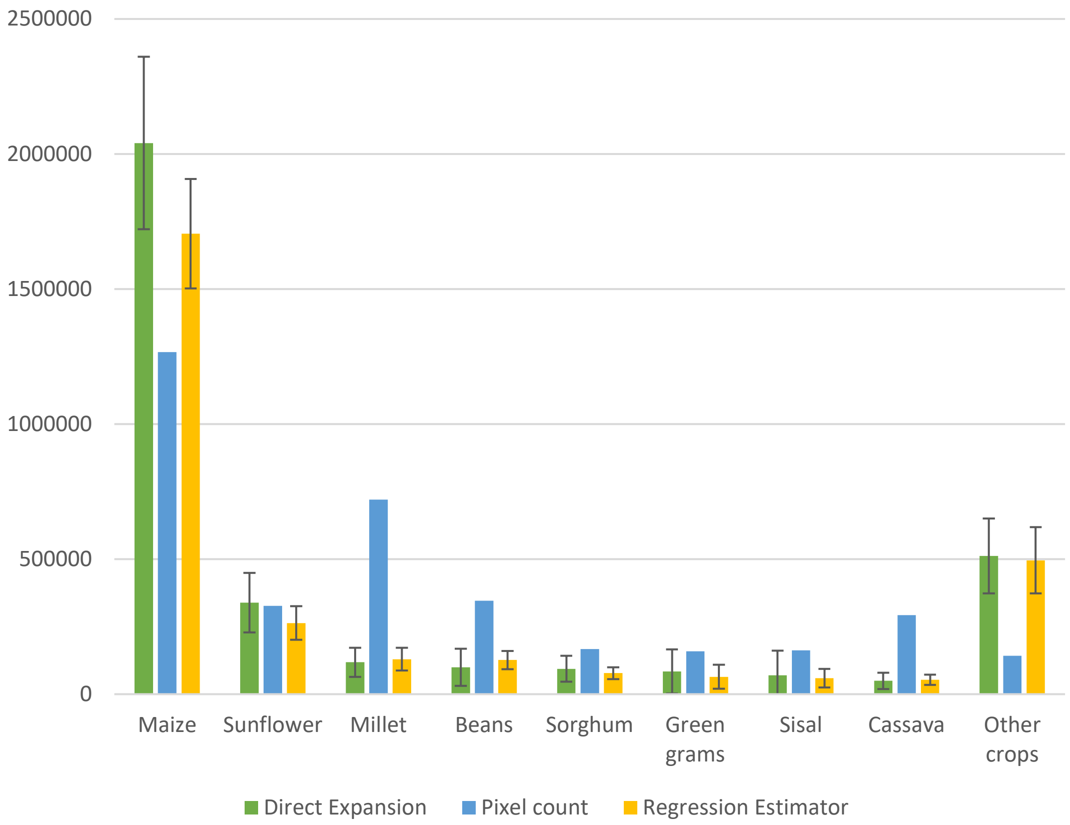
  - All methods similar results, Crop Mask for the in-season & end-of-season Crop Masks will be derived directly from S2 Crop Type map.



Crop Area Estimates

- **Objective**: provide area estimates per crop type

- Three approaches applied:
  - **<u>Direct expansion estimates</u>**: area estimates from the field data alone
  - **<u>Pixel count</u>**: areas measured from the map alone, but likely to be biased
  - **<u>Regression estimators</u>**: area estimates derived from field data combined with map based on linear regression



Crop Area Estimates

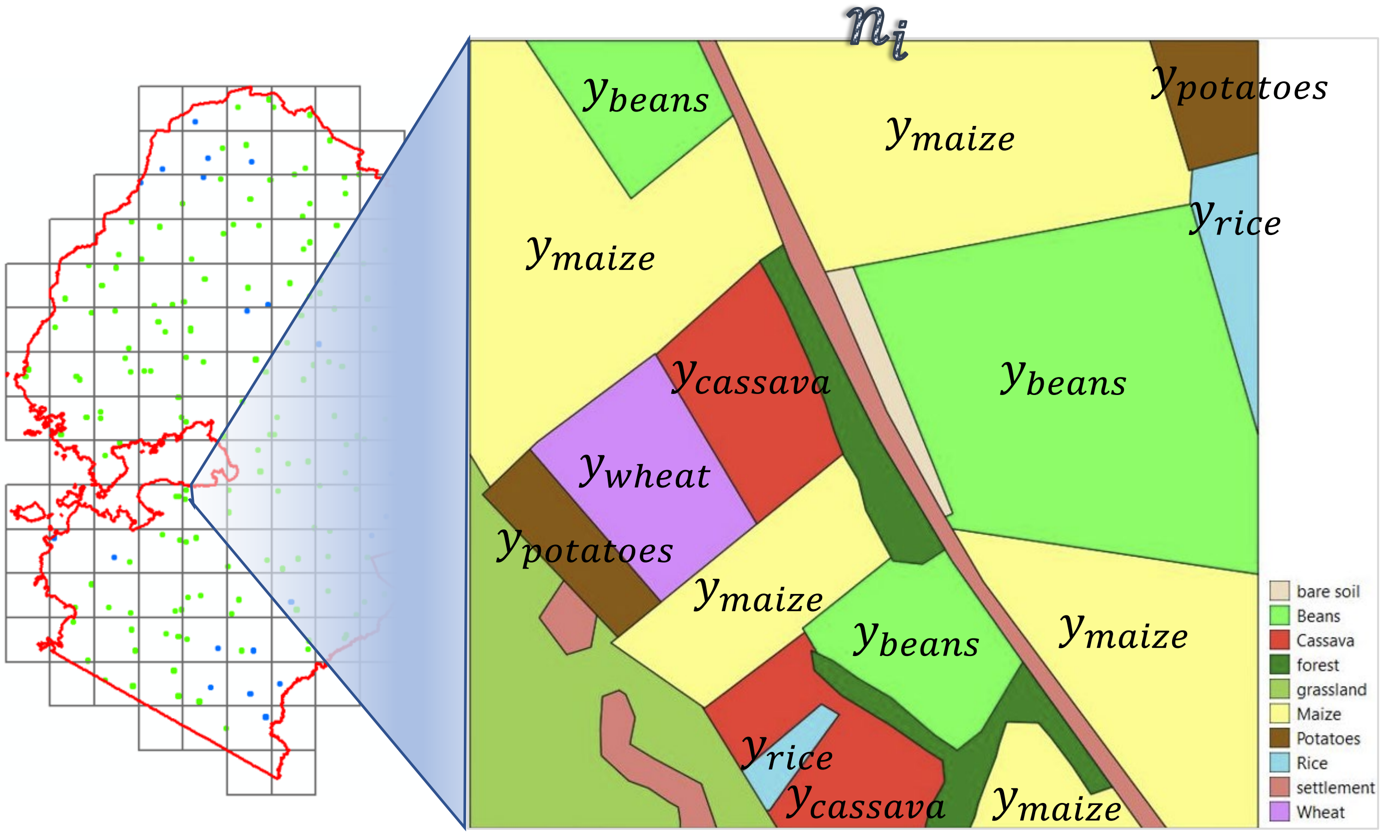
- **Direct expansion estimates**: Direct crop area estimates can be produced from field survey alone right after the field campaign. Estimate of proportion (y) of class (c) and its variance are given by:

$$\bar{y}_c = \sum_{i=1}^{n} \frac{1}{n} y_i$$

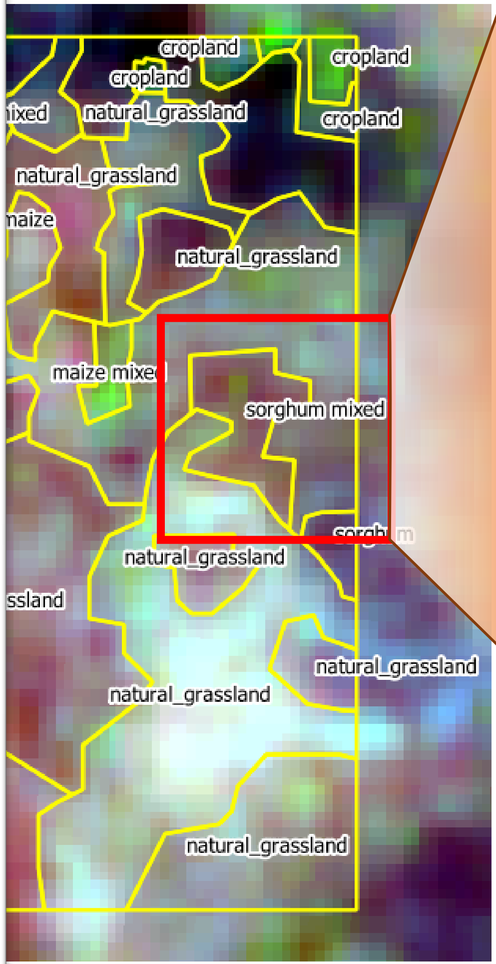
$$var(\bar{y}_c) = \left(1 - \frac{n}{N}\right) \frac{1}{n(n-1)} \sum_{i=1}^{n} (y_i - \bar{y}_c)^2$$

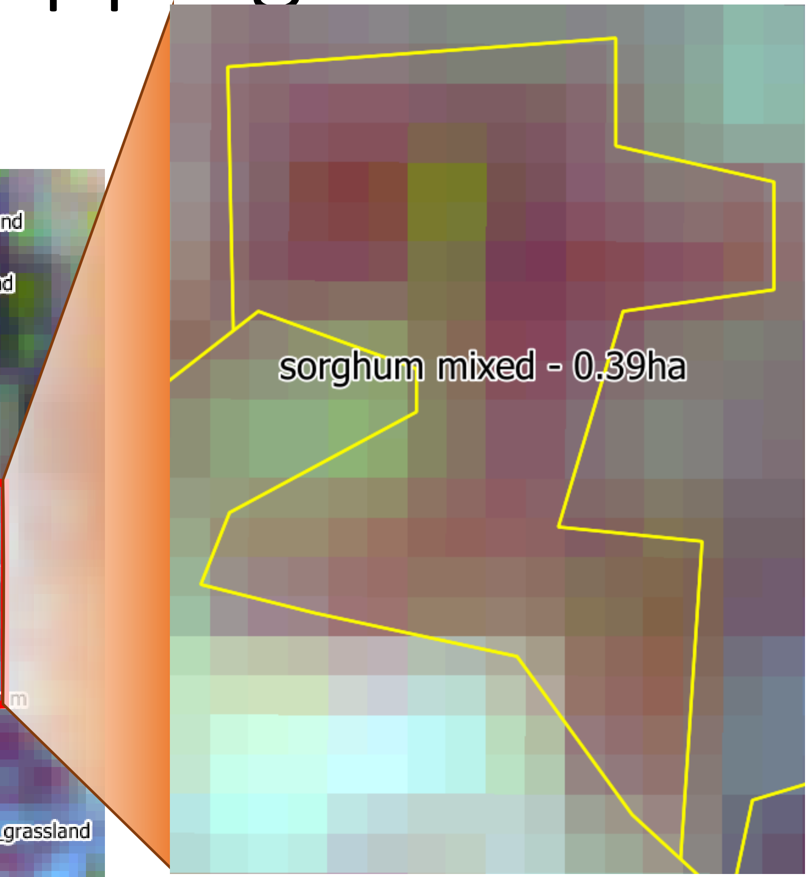
where:

- *y_i is the proportion of segment i covered by class c,*
- *N is total number of segments in the region,*
- *n is number of segments in the sample*



Mixed Cropping Pattern





1) Sorghum dominant 50% of the area considered:
Sorghum = 0.20 ha
Sesame = 0.10 ha
Pumpkin = 0.10 ha

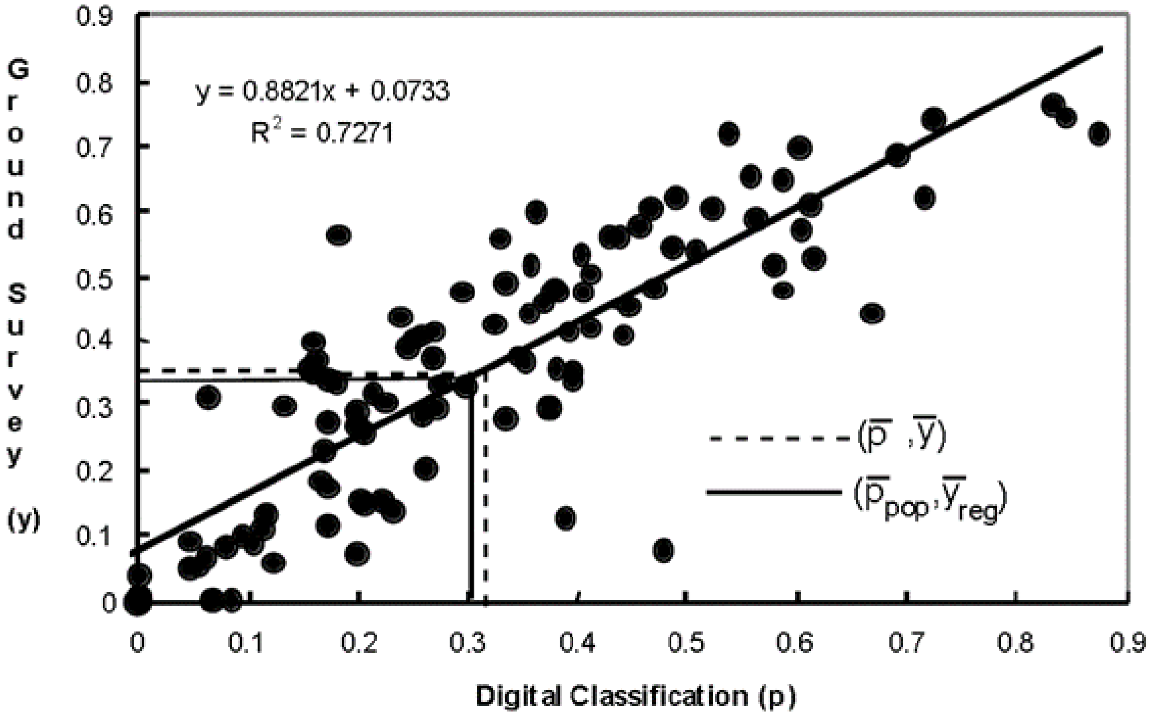
2) If no dominant crop:
Sorghum = 0.13 ha
Sesame = 0.13 ha
Pumpkin = 0.13 ha

Crop Area Estimates

Regression estimator:

- To improve the precision of the crop area estimates, field data can be combined with classified satellite imagery

- A Regression estimator model can be applied



Crop Area Estimates

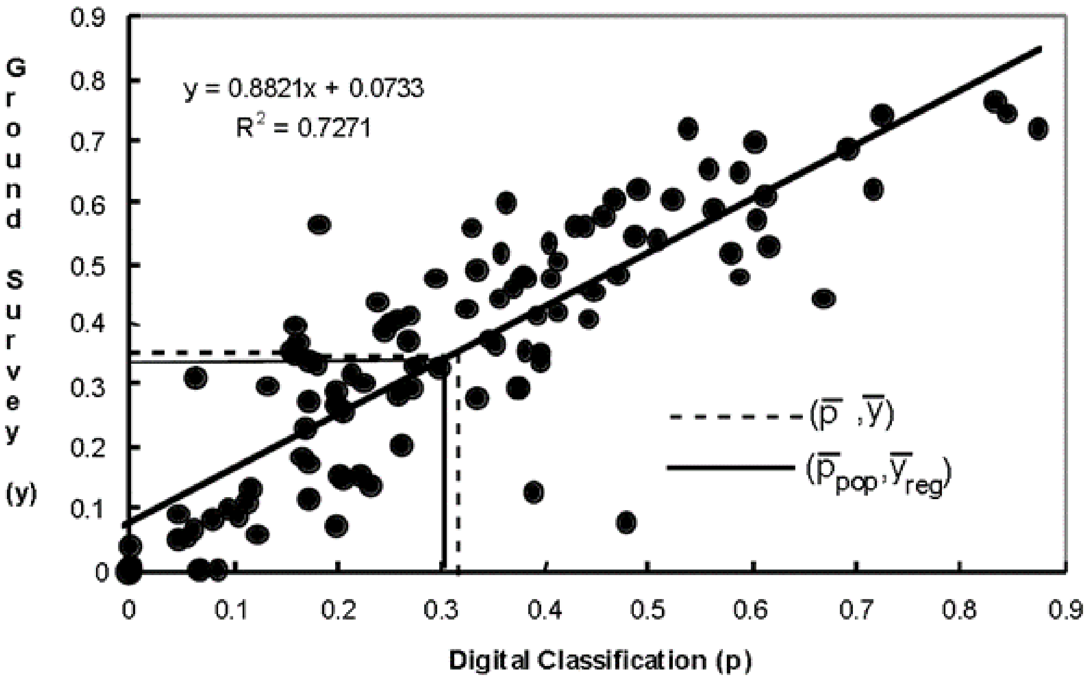
- **<u>Regression estimators</u>**
- Rely on the combination of area estimates made at the segment level for both field data and classified satellite imagery. The observation is paired, and a regression analysis is performed

- The regression estimator y_{reg} is calculated based on:

$$y_{reg} = \bar{y} + b * (\bar{p}_{pop} - \bar{p})$$

Where:

- $\bar{y}$ *is the mean field data sample value,*
- *b is the slope of the regression line,*
- $\bar{p}_{pop}$ *is the proportion of pixels classified as the crop in the whole of the region of interest and*
- $\bar{p}$ *is the classified image mean sample value.*



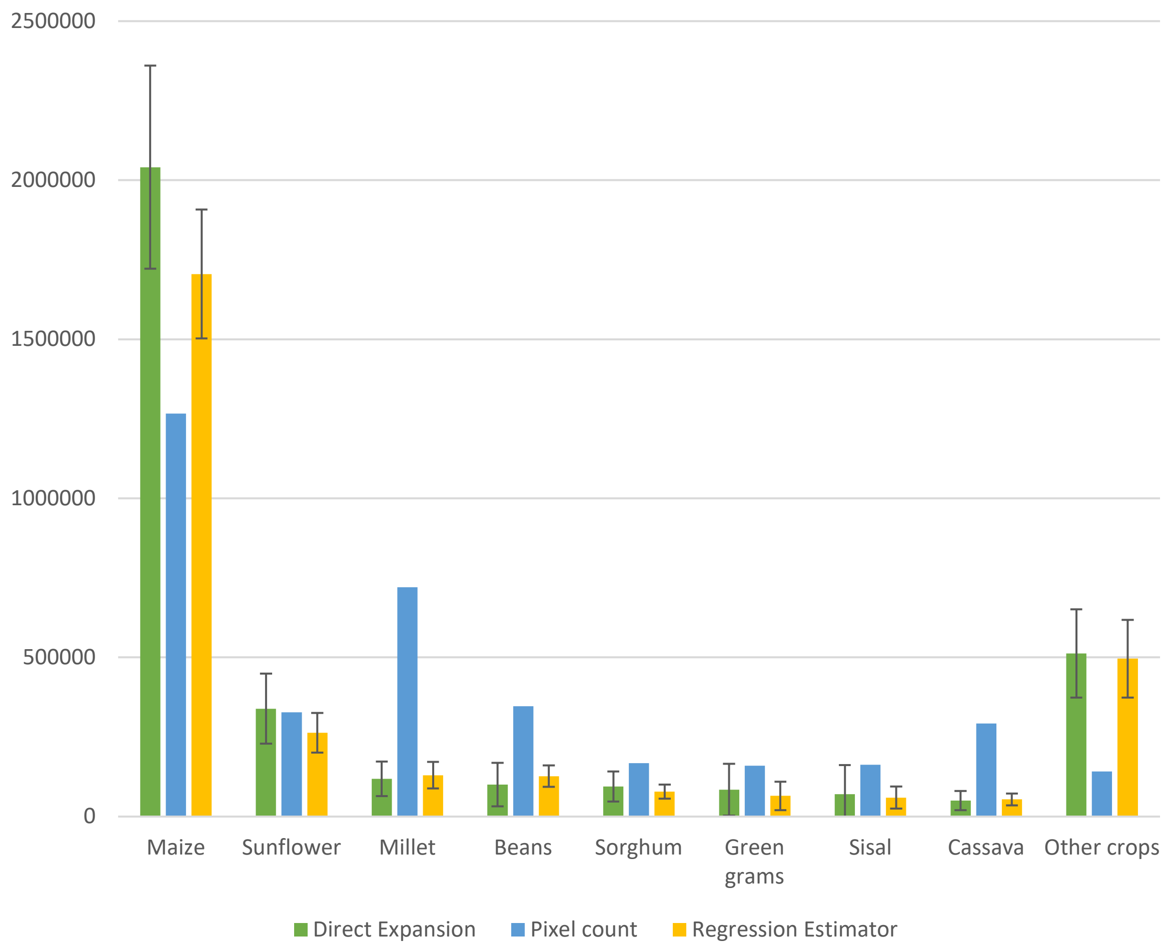
Crop Area Estimates

- **Relative efficiency:**
- Level of improvement brought in by the combination of field with image classification data
- Relative efficiencies of 2 to 5 achieved for the main crops in all 3 countries, i.e. field sample size would need to be increased by the same factor to achieve the same precision
- The Relative efficiency n_{reg} is calculated based on :

$$n_{reg} = \frac{1}{1 - r_{py}^2}$$

Where:

- r_{py}^2 *is the coefficient of determination*



Conclusions

- **<u>Dataset</u>**:
  - Low availability S2 (clouds) in growing season
  - S2 L3A 45-day synthesis yields good results
- **<u>Crop type & Mask Classification:</u>**
  - High overall accuracy for Crop Mask (from 84 to 87%) & Crop Type map(from 80% to 81%)
  - Significant improvements compared to the in-season mapping (+5% crop mask & +10% crop type)
  - Non substantial improvement with use of S1 data for crop type identification so far
  - Need to better characterize the mixed cropping farming practices
- **<u>Crop area estimates:</u>**
  - Fieldwork good basis for Crop Type area estimates
  - Crop Type Area estimates much improved with regression estimates combining field and satellite-based classification
  - Improvement of the relative efficiencies for the end-of-season
- **<u>Data access:</u>**
  - All map data freely available on: https://data.jrc.ec.europa.eu/collection/id-00356
  - Following GEOGLAM in situ data workshop, field data to become soon available on ML platform