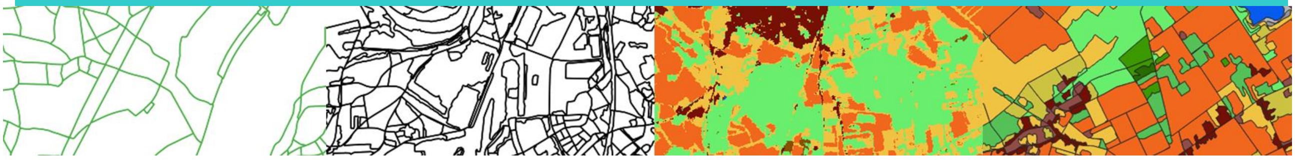
Service contract for the Copernicus Land monitoring services

Crop Mapping for GEOGLAM Country Level Support



Framework contract 939708-2020-IPR

# In-season Crop Type Map & Crop Mask
# Uganda - long rains season - 2021

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Reference : In-season mapping - Uganda - long rains season - 2021

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**Issues :**

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| 1.0 | 01-10-2021 | First version submitted to JRC |
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# 1 Introduction

This document describes the in-season mapping of the crop type and crop mask for the Area Of Interest (AOI) in Uganda. It summarizes the workflow and any methodological change (put in place to obtain the above mentioned products) with respect to what was described in the feasibility study. The document describes also the satellite imagery and the ground truth data actually used for the classification. The document only describes in detail the fieldwork and satellite data pre-, and post-processing as far as they are different from what has been described in detail in the feasibility study for Uganda.

# 2 Summary of data used

The Figure 1 below shows the AOI for Uganda, overlaid with the Sentinel-2 tile-based grid and the fieldwork (500x500m) square segments.

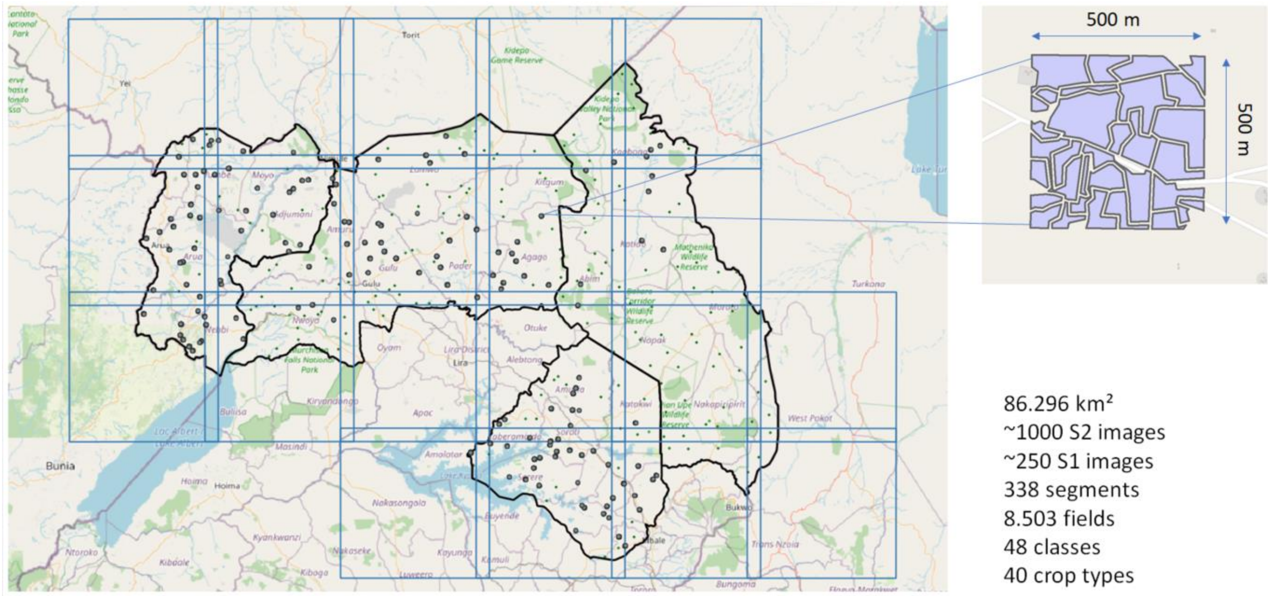



**Figure 1. Uganda AOI overlaid with the S2 tile-based grid and the fieldwork segments**

## 2.1 Satellite data

**Sentinel-2**

In total, approximatively 1,000 Sentinel-2A & B Level-2A images have been acquired covering 20 tiles between 01-01-2021 and 16-09-2021. The Table 1 lists the S2 data used per S2 tile ID.

**Table 1. S2 tiles covering the AOI for Uganda**

| Tile ID | First date | Last date | Number of S2 L2A images |
|---|---|---|---|
| 36NTH | 02/01/2021 | 14/09/2021 | 36 |
| 36NTJ | 02/01/2021 | 14/09/2021 | 35 |
| 36NTK | 02/01/2021 | 14/09/2021 | 34 |
| 36NUH | 02/01/2021 | 16/09/2021 | 64 |
| 36NUJ | 02/01/2021 | 16/09/2021 | 69 |
| 36NUK | 02/01/2021 | 09/09/2021 | 65 |
| 36NVG | 04/01/2021 | 16/09/2021 | 34 |
| 36NVH | 04/01/2021 | 16/09/2021 | 34 |
| 36NVJ | 02/01/2021 | 16/09/2021 | 63 |
| 36NVK | 02/01/2021 | 09/09/2021 | 65 |
| 36NWG | 01/01/2021 | 16/09/2021 | 73 |
| 36NWJ | 04/01/2021 | 16/09/2021 | 37 |
| 36NWK | 04/01/2021 | 27/08/2021 | 36 |
| 36NXG | 01/01/2021 | 13/09/2021 | 77 |
| 36NXH | 01/01/2021 | 16/09/2021 | 69 |
| 36NXJ | 01/01/2021 | 16/09/2021 | 67 |
| 36NXK | 01/01/2021 | 13/09/2021 | 65 |
| 36NYG | 01/01/2020 | 13/09/2021 | 41 |
| 36NYH | 01/01/2021 | 13/09/2021 | 41 |

**Sentinel-1**

In total, approximatively 250 Sentinel-1 images have been used to cover the Ugandan AOI between 01-01-2021 and 29-08-2021 for the in-season mapping. The Figure 2 shows the acquisition dates of the S1 dataset covering the Ugandan AOI. The coverage consists of three descending (southward) orbits, requiring 3 to 4 images per orbit.

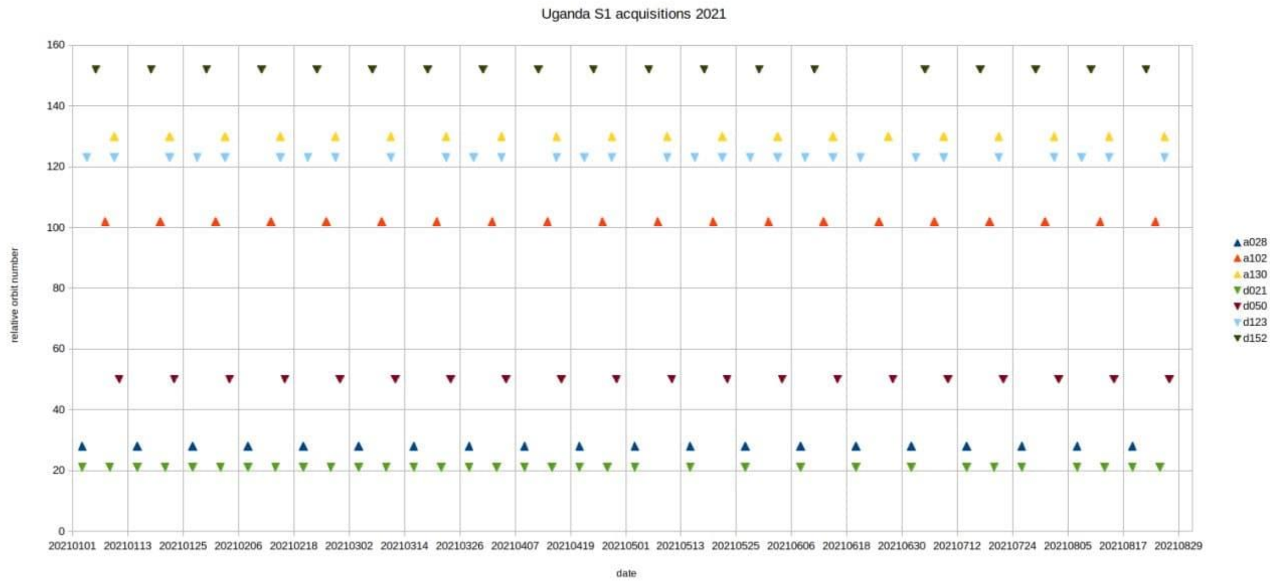



**Figure 2. Sentinel-1 acquisition dates over Uganda**

## 2.2 Fieldwork data

Besides being an autonomous deliverable, the fieldwork data is also used as input into the classification procedure as well as for the validation of the results. To maximise the use of the field data in the classification workflow, the following processing steps are undertaken:

1. Assign point data (actual fieldwork) to pre-digitized polygons;
2. Apply a negative buffer of 5m to allow removal of boundary effects between landcover types;
3. Deletion of polygons smaller than 0.1 ha;
4. Splitting of data between training (75%) & validation (25%) sets;
5. Manual quality check of all training/validation polygons.

In the following, additional details regarding the five steps above are provided.

1) Data on crops and other landcover classes have been acquired in the field on the basis of pre-digitized 500x500m segments (using a combination of the most recent available Very High Resolution (VHR) imagery from Google Earth/Bing Maps, Yandex, Planet and Sentinel-2 imagery from the current season). Points have been gathered for most of digitised segments and landcover classes (amongst others) are recorded. It should be noticed that some segments have not been visited in the field due to the absence of crops or for the safety of the enumerators. To create an input for classification, point data are assigned to the polygons. In the case of no point is recorded (due to e.g. inaccessibility of segment), the land cover class recorded during the first digitising of the segments prior to the field campaign, is automatically assigned. The polygons labelled “cropland” not surveyed (initially supposed to be) are excluded from the fieldwork dataset since the crop type can’t be assigned. In other word, these polygons are excluded from the training dataset for the crop type mapping, from the validation and the area estimates not to bias statistics.

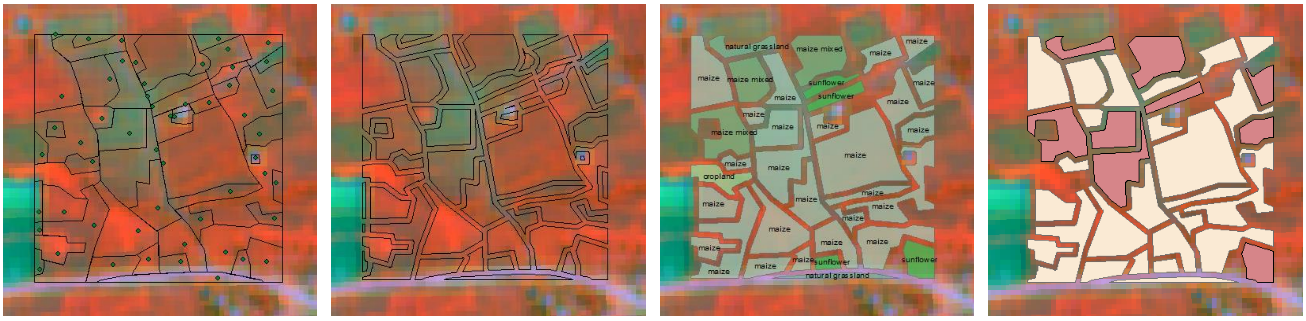
2) A negative buffer of 5 meters is applied to eliminate, or at least minimize, the boundary effects between different classes that will negatively impact the purity of training samples signatures. Consequently, polygons are always separated by 10 meters, which corresponds to the size of 1 Sentinel-2 pixel.

3) The acreage of each buffered polygon is calculated and all polygons smaller than 0.1 ha are deleted. It should be noticed that the threshold of 0.1 ha (approximatively 9 contiguous S2 pixels) is larger than the Minimum Mapping Unit from the technical specifications to better consider the observed agricultural practises in Uganda. Indeed, polygons below 0.1 ha are considered spectrally heterogenous and are not deemed fit to serve as input into training samples for classification. Nevertheless, this change is the only deviation from the feasibility study report and the MMU for the classification output is still set to 0.04 ha as required.

4) The resulting dataset from step 1 to 3 is then split into two separate sets to be used for training and validation. 75% of the dataset is used to train the classification while the remaining 25% is used for validation of the classification results. There is no overlap between the training and validation sets to ensure complete independency of the datasets. Splitting is done at a Sentinel-2 tile level to ensure a good representativity of the samples per scene. Indeed, as explained is section 3.3, the classification workflow is applied per S2-based block.

5) All the resulting polygons have been visually checked and manually edited to correct obvious errors.

The Figure 3 shows for a single segment each of the above mentioned processing steps using a Sentinel-2A L3A image from 15-04-2021 as a background.



| Fieldwork points overlaid on digitized polygons | Buffered features, using inside buffer of -5m. | Removal of features < MMU (0.1 ha) | Split between training (yellow) & validation (red) |
|---|---|---|---|

**Figure 3. Preparation of fieldwork data for training and validation**

Resulting from all the described processing steps, 3,657 polygons, covering approximatively 3,540 ha are available for the classification process. 2,724 are used for training and 933 for validation. In total 48 individual classes are distinguished, mostly individual crops (40).

Figure 4 shows some examples of typical fields visited during the campaign including a plot of rice, and two plots with mixed cropping, illustrating the small size of the plots, as well as the heterogeneity of the cultivation.

**Figure 4. Typical cultivation in Uganda with dominantly very small plot size and mixed cropping**

# 3 Workflow

## 3.1 Pre-processing

The pre-processing of the satellite data applied was unchanged from what was proposed in the feasibility study (D1.1). For each of the two satellite data types some specific pre-processing are summarised as follows below.

**Sentinel-1**

Sentinel-1 Gamma0 workflow starts with Sentinel-1 level 1.1 (SLC) data products. The following steps are executed:

1. Querying Sentinel-1 repository for images acquired over area-of-interest;
2. Preparation of CopDEM 30" DEM for area-of-interest;
3. Update of local SNAP Restituted Orbit (RESORB) repository;
4. Reading S1 SLC data product: get image and metadata;
5. Applying restituted orbit file (RESORB), for improved geocoding accuracy, almost as good as Precise Orbits (PREORB) but available just after reception of the image data;
6. Thermal Noise Removal, mostly for suppressing noise patterns over large water bodies;
7. Radiometric Calibration: convert digital numbers to calibrated Gamma0 backscatter intensity values;
8. Multilooking: combine pixels into more or less square pixels and reduce speckle noise;
9. Speckle filtering (Refined Lee) for more reduction of speckle;
10. Terrain Correction: geometric terrain correction and map projection to a 10x10m pixel grid;
11. Radiometric Terrain Correction or Slope Correction and normalization of incidence angle: dedicated script for reducing slope illumination effects using local and global incidence angle information[1];
12. Conversion from intensity values to decibel [dB] values;
13. Export to deflate-compressed geotiff file;
14. Calculation of multi-temporal statistic parameters (e.g. minimum, maximum, mean, standard deviation) over the present growing season or defined period of time;
15. Scaling and output of multi-temporal statistics to 8-bits values;
16. Storing output products in <country>/<rel.orbit>/<product> directory structure;

The Figure 5 shows a colour composite of the Sentinel-1 minimum, mean and standard deviation of images taken between January and August 2021 (ascending orbit). Yellow is seasonal stable medium-high backscatter (e.g. forest, natural shrubs, natural grassland), black is seasonal stable low backscatter (water), blue is seasonal dynamic backscatter (agriculture with the exception of the high mountainous areas which can be easily identified based on ancillary data).

[1] Hoekman, D.,H., Reiche, J. Multi-model radiometric slope correction of SAR images of complex terrain using a two-stage semi-empirical approach, in Remote Sensing of Environment, 2015, doi:10.1016/j.rse.2014.08.037

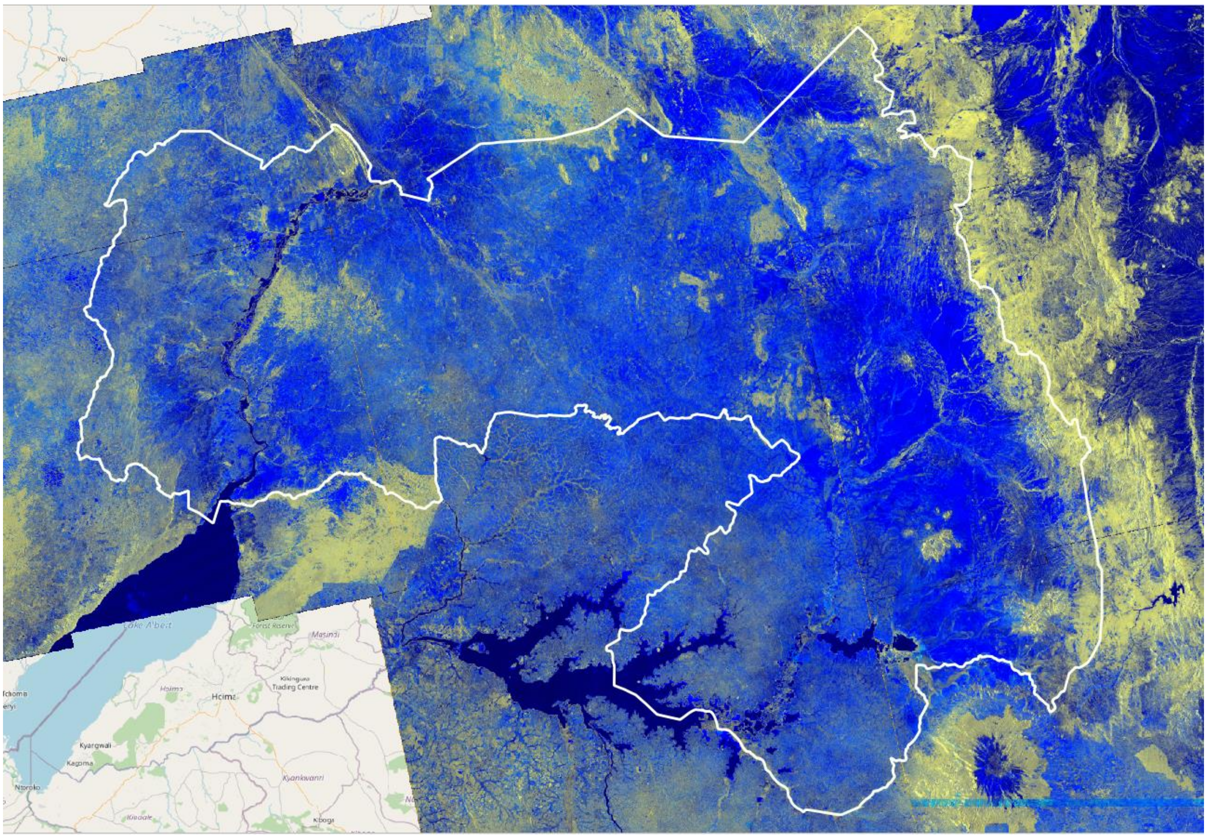



**Figure 5. Sentinel-1 synthetic colour composite over the Ugandan AOI (white outline; false colour RGB composition = Minimum, Mean, Standard Deviation)**

### Sentinel-2

Based on the Sentinel-2 L2A data, we reprocessed the cloud masks using S2cloudless and Fmask algorithms for detailed removal of clouds and cloud shadows. Monthly synthesis are then processed using the WASP algorithm (open-source solution developed by CNES[2]). For each pixel and each band (10 and 20m bands), the WASP algorithm computes the monthly synthesis using a weighted average of the cloud free surface reflectance's gathered during a synthesis period of 91 days. Cloud-free pixels as close as possible to the "centre-date" are used to build a cloud-free image. The Figure 6 shows an example for tile 36NXH, with a centre-date of 15-06-2021. For this synthesis, the algorithm considers all images +/- 45 days from 15-06-2021, and takes the cloud-free pixel closest to the centre date.

[2] https://doi.org/10.5281/zenodo.1401360

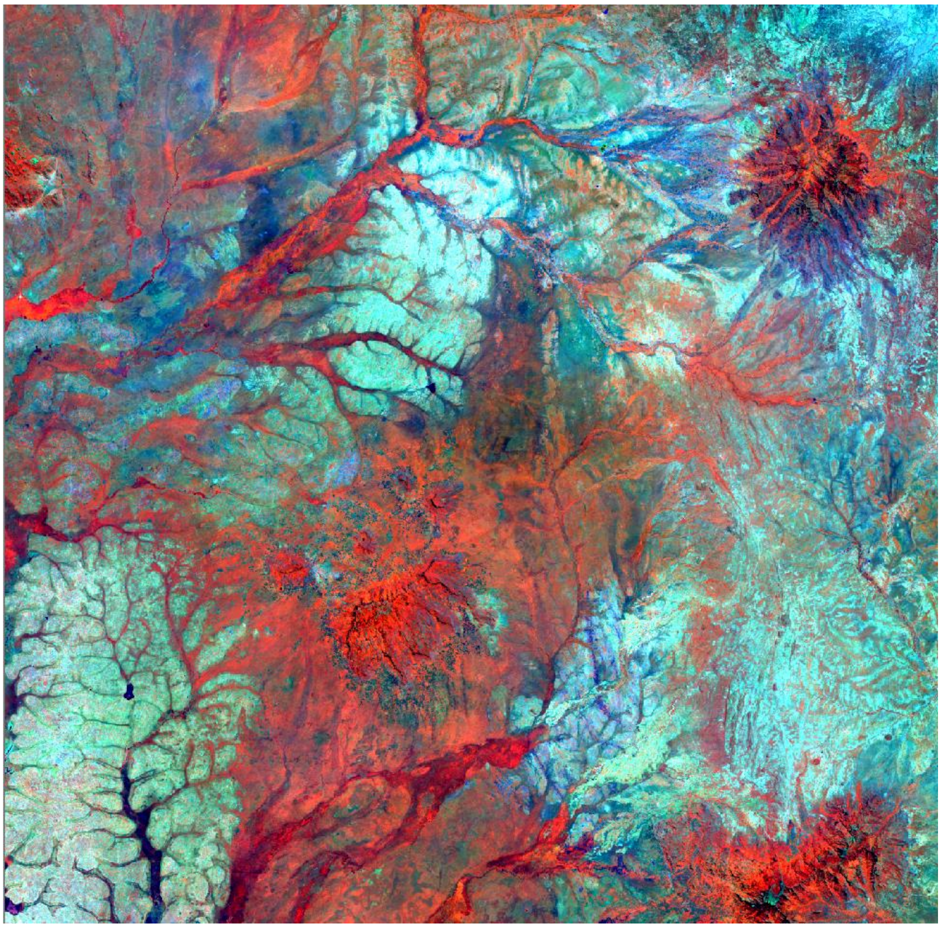


**Figure 6: Sentinel-2 monthly synthesis composite (false colour RGB composition), 15/06/2021, tile 36NXHG**

Based on these monthly synthesis, four spectral indices are computed: the Weighted Difference Vegetation Index (WDVI[3]), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Brightness Index (BI). All layers are used as input in the classification algorithm.

**Landsat-8**

The use of the Landsat-8 dataset was not considered as relevant since the L3A monthly synthesis images using Sentinel-2 were successfully generated. Moreover, the coarse spatial resolution of the Landsat-8 data (30m) was considered not very suitable in case of Uganda when reviewing the size of the agricultural fields.

**Summary of the deviations from the feasibility study report:**

- Sentinel-2 data has been processed to monthly L3A synthesis images covering +/-45 days whereby mostly cloud-free monthly data has been obtained.
- Sentinel-1 data has been processed to synthetic channels of minimum, mean and standard deviation (Sigma nought, Db) of a seasonal stack of VH images.
- No Landsat-8 data was used for the in-season mapping as enough Sentinel-2 data with higher resolution was available thanks to the L3A processing.

[3] https://www.sciencedirect.com/science/article/abs/pii/092427169190005G

## 3.2 Classification

**Crop Type –** It was decided to take profit of the test already conducted for the Tanzanian in-season mapping, as well as an operational run for the Kenya AOI to select the classification algorithm in Uganda. Various algorithms were tested on a single tile (36MYA) for the Tanzanian AOI, including supervised (maximum likelihood) classification, TempCCN and Random Forest (RF) algorithms. Based on the validation results for Tanzania, it was decided to use the RF classification as final method for the Ugandan in-season mapping too. The algorithm is characterized by relatively simple parameterization, a good computation efficiency, and highest accuracy. Based on monthly synthesis Sentinel-2 images (L3A), precomputed features and ground truth from fieldwork (75% for training, 25% for validation), the RF classifier has been applied on all the tiles to produce the crop type map. The initial classification output contains 48 classes (of which 40 crop types). The Figure 7 shows the result of the raw classification output, before post-processing.

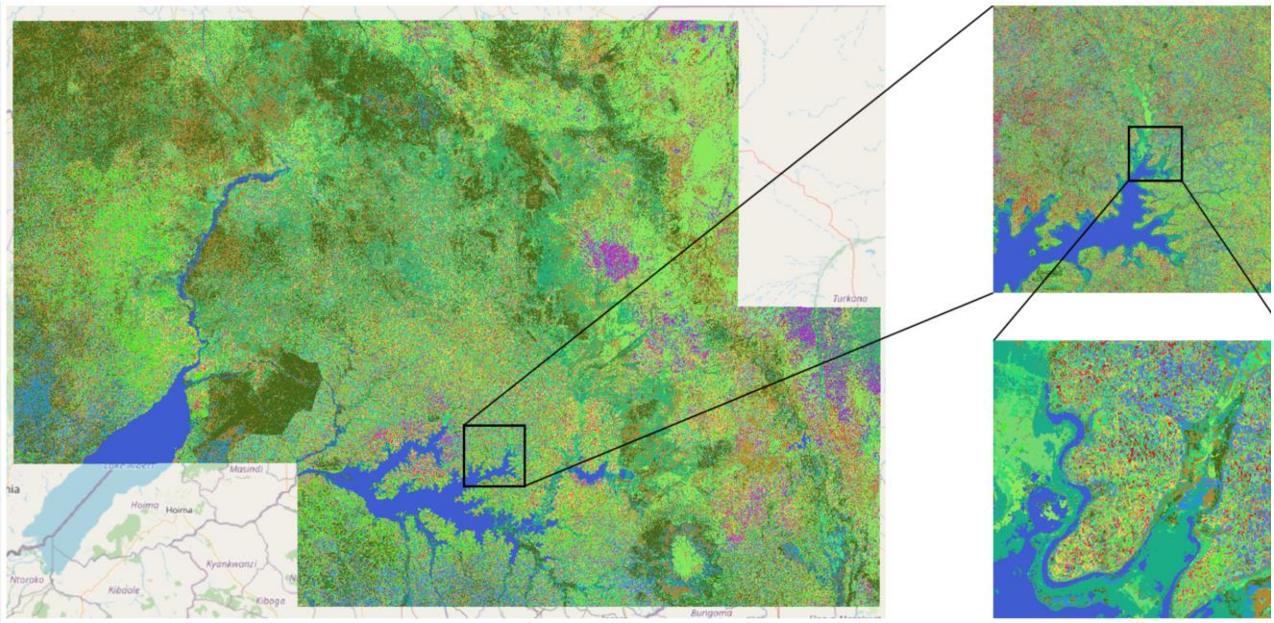


**Figure 7. Raw classification output in-season crop type map Uganda**

**Crop Mask** – For the crop mask, different methods using both S2 and S1 data have been tested. A full crop mask using only Sentinel-1 data has been generated, and in parallel a full crop mask using the aggregated results from the S2-derived crop type map has been produced. Both methods yielded good results (70% for S1; 82% for S2), but since the accuracy of the S2-derived map was significantly higher, it was decided to use the S2-based product as the final Crop Mask for the in-season map. The rule to produce the current in-season crop mask is as follows:

Crop Type S2 map = (1 of 40 individual crop types or mixed cropping): Crops

Crop Type S2 map = (forest, natural shrubs, natural grassland, bare, urban, aquatic vegetation, water, wetlands): Other landcover

Tests for the end-of-season mapping will be conducted whether combining S1 and S2 results to quantify the potential increase of the overall accuracy. The nomenclature for the Crop Mask can be found in the Table 2.

**Table 2. Nomenclature for Crop Mask**

| Code | Class | Description |
|---|---|---|
| 1 | Crops | All monoculture and mixed cropping |
| 2 | Other landcover | Forest, water, natural shrubs, natural grassland, urban, bare, aquatic vegetation, wetlands |

Post-processing of the classification results have been carried out by merging and clipping all tiles into a seamless mosaic covering the entire AOI for both Crop Type and Crop Mask. The 48 classes from the raw crop type classification are merged into 10 final classes for the final map, including the 8 largest individual crops types according to fieldwork statistics. The Table 3 lists the final classes for the Crop Type map and number coding as found in the final GeoTiff files (Uganda_CropType_InSeason_LongRainy_2021_V1.tif & Uganda_CropMask_InSeason_LongRainy_2021_V1.tif). The nomenclature can be viewed by opening the accompanying *.lyr files provided with the above-mentioned GeoTiff files.

**Table 3. Nomenclature for Crop Type map**

| Code | Class | Description |
|---|---|---|
| 1 | maize | including mixed cropping with maize as dominant crop |
| 4 | beans | |
| 5 | sorghum | |
| 8 | cassave | |
| 9 | other crops | all other monoculture crops and mixed cropping |
| 10 | other landcover | Forest, water, natural shrubs, natural grassland, urban, bare, aquatic vegetation, wetlands |
| 11 | potatoes | including mixed cropping with potatoes as dominant crop |
| 12 | rice | |
| 16 | groundnut | |
| 17 | simsim | |

Some obvious classification errors have been recoded, e.g. the presence of crops in large water bodies. A shapefile on protected area boundaries was used to recode erroneous cropland to other landcover, as no agriculture is legally supposed to be taking place in these areas. However, agricultural encroachment may sometimes take place in these protected areas (rare) and they were of course preserved in the final map. As a final step a majority filtering have been applied using a moving box-size of 3x3 pixels (= approximate MMU for S2). All maps are presented in UTM, zone 36 North.

**Deviations from feasibility study proposal**:

There’s been no substantial deviations from what has been described in the feasibility study.

## 3.3 Map production

Both the Crop Type map & Crop Mask are presented in A0 printable PDF map with layout including legend, north arrow, metadata, grid (UTM 36, North), relevant client and contractor logo's and scale bar. The maps are presented on 1:600.000 scale, the largest possible scale to fit the entire AOI on A0 format. The figures below show the in-season Crop Mask and Crop Type map for Uganda.

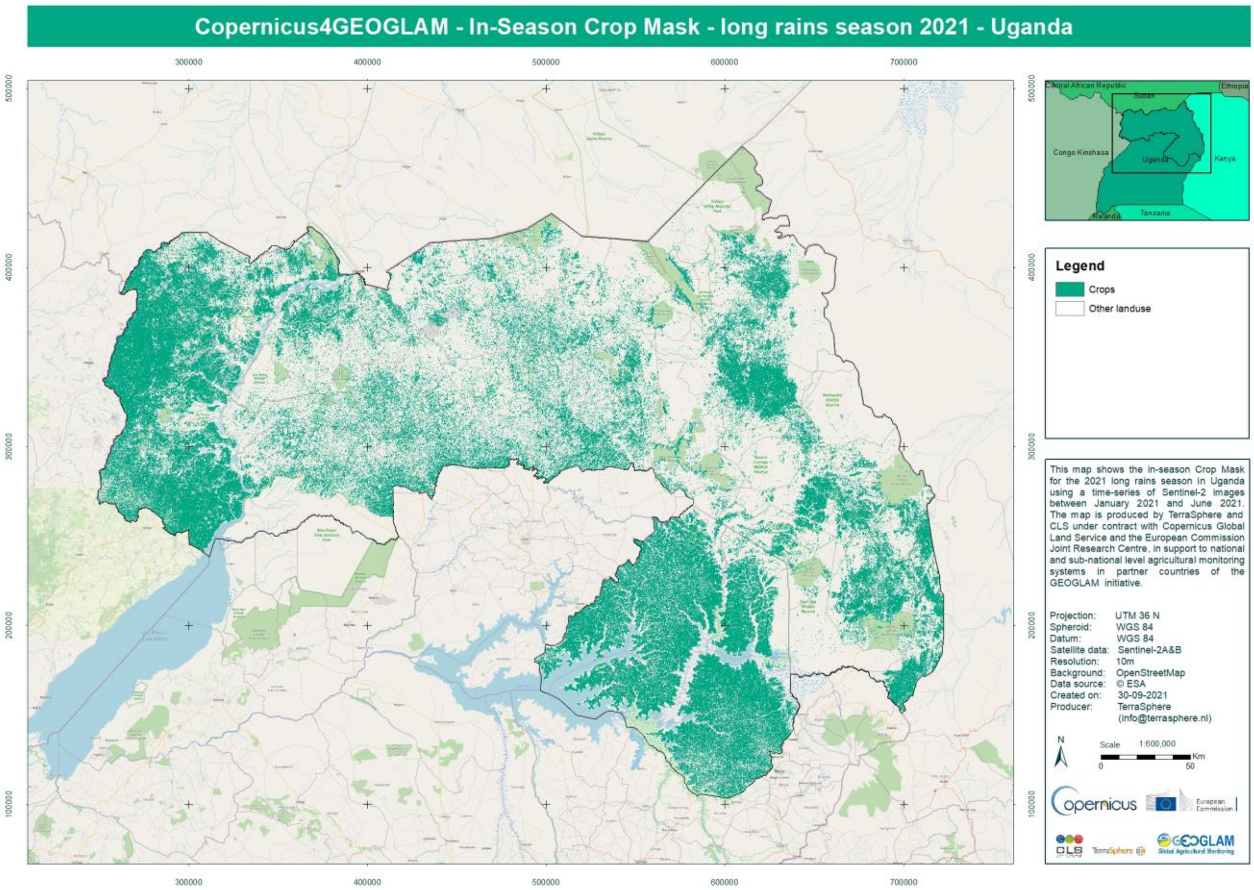



**Figure 8. In-season Crop Mask for Uganda 2021**

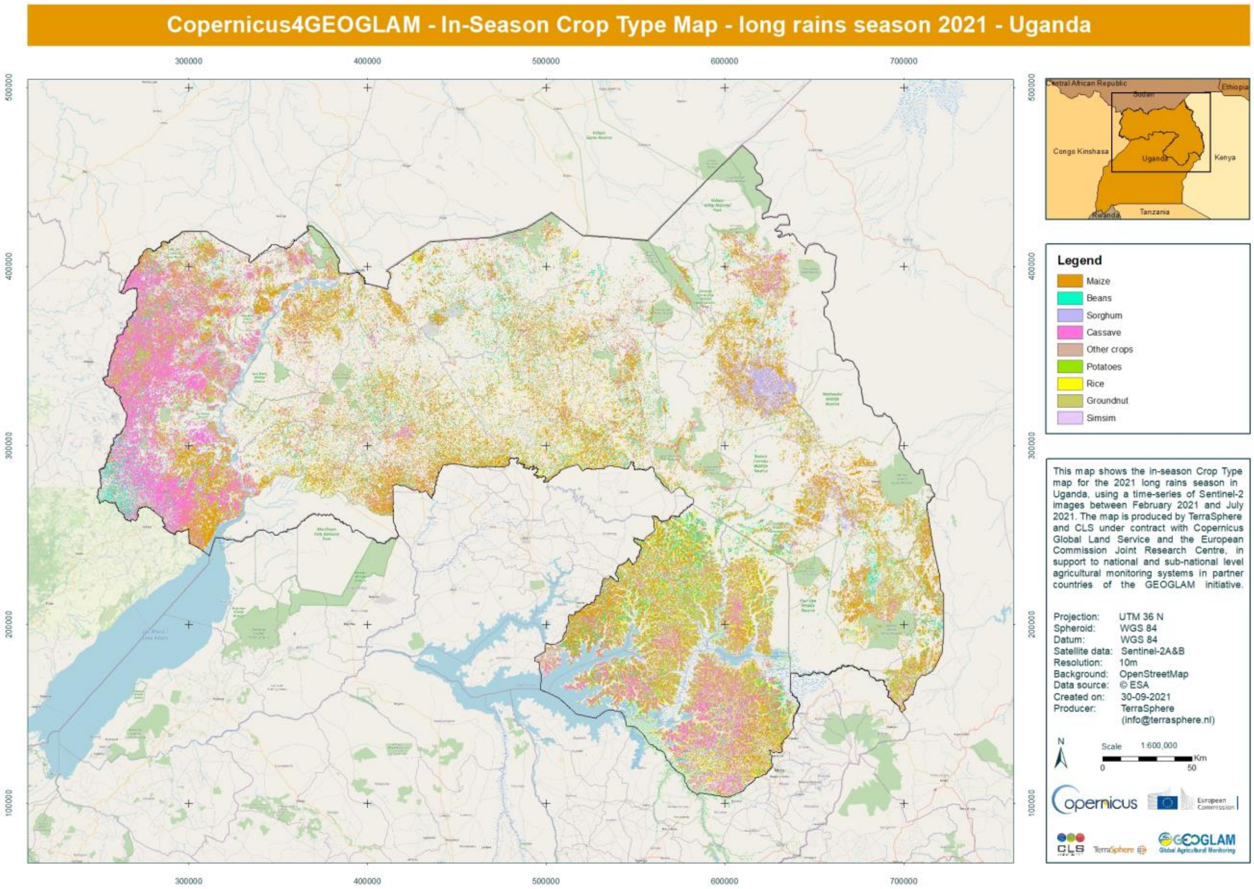



**Figure 9. In-season Crop Type map for Uganda 2021**

**Deviations from feasibility study proposal:**

There's been no substantial deviations from what has been described in the feasibility study.

## 3.4 Validation

For both the Crop Mask and Crop Type map, 25% of processed fieldwork data (that is not used for training) is used for validation. Confusion matrices are produced and F1 score per class have been calculated, and can be found in the figures below. The procedures for validation were carried out as described in the technical offer. There was no need to apply correction factors because an equal sampling intensity was applied to each stratum.

Crop type in-season mapping for Uganda

| Map \ Reference | Maize | Beans | Sorghum | Cassava | Potatoes | Rice | Groundnut | Simsim | Other crops | Other landcover | Total | User Accuracy | F-Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Maize | **4281** | 86 | 390 | 735 | 30 | 111 | 253 | 98 | 101 | 4604 | **10689** | 0,40 | 0,41 |
| Beans | 438 | **68** | 22 | 93 | 2 | | 82 | | 15 | 1754 | **2474** | 0,03 | 0,05 |
| Sorghum | 107 | 8 | **709** | 7 | | 8 | | | 11 | 471 | **1321** | 0,54 | 0,43 |
| Cassava | 1357 | 86 | 193 | **2739** | 17 | | 143 | 48 | 106 | 4154 | **8843** | 0,31 | 0,37 |
| Potatoes | 237 | 1 | 92 | 232 | **112** | 17 | 101 | 37 | 14 | 326 | **1169** | 0,10 | 0,16 |
| Rice | 205 | 18 | | 77 | | **80** | 2 | 12 | | 291 | **685** | 0,12 | 0,16 |
| Groundnut | 597 | 15 | 155 | 273 | 10 | 13 | **321** | **52** | 78 | 4546 | **6060** | 0,05 | 0,08 |
| Simsim | 43 | | 20 | 18 | | 22 | | **42** | 4 | 323 | **472** | 0,09 | 0,11 |
| Other crops | 1121 | 187 | 120 | 741 | 27 | 2 | 242 | | **141** | 1967 | **4548** | 0,03 | 0,04 |
| Other landcover | 1771 | 64 | 300 | 1057 | 14 | 48 | 359 | 27 | 2276 | **79515** | **85431** | 0,93 | 0,87 |
| Total | **10157** | **533** | **2001** | **5972** | **212** | **301** | **1503** | **316** | **2746** | **97951** | **121692** | | |
| Producer accuracy | 0,42 | 0,13 | 0,35 | 0,46 | 0,53 | 0,27 | 0,21 | 0,13 | 0,05 | 0,81 | | | |

| | |
|---|---|
| Overall accuracy | 0,72 |
| Crop Type - Overall accuracy | 0,23 |

**Figure 10. Confusion matrix for in-season Crop Type map**

Cropland mask in-season mapping for Uganda

| Map \ Reference | Non-crop | Crop | Total | User Accuracy | F-Score |
|---|---|---|---|---|---|
| Non-crop | 79515 | 5916 | 85431 | 0,93 | 0,87 |
| Crop | 18436 | 17825 | 36261 | 0,49 | 0,59 |
| Total | 97951 | 23741 | 121692 | | |
| Producer accuracy | 0,81 | 0,75 | | | |

| | |
|---|---|
| Overall accuracy | 0,80 |

**Figure 11. Confusion matrix for in-season Crop Mask**

Figure 10 and Figure 11 show that the overall accuracy for the Crop Type map and Crop Mask is respectively reaching 72% and 80%, which is greater than the specifications mentioned in the feasibility study report (D1.1) (65% & 65%). Nevertheless, going beyond the requirements, the overall accuracy focused on the crop type remains weak, reaching 23%. Both user and producer results for individual crops show lower accuracies as reported in the confusion matrix. The classes “Maize” and “Sorghum” show the best individual results with F1-Score around 0.4. The lower results are obtained for the classes “Bean” and “Groundnuts” but improvements of the accuracies are expected for the end-of-season mapping through:

- Addition of end-of-season satellite imagery
- Further selection of training polygons (e.g. >1 ha)
- Add Sentinel-1 (SAR) data for Crop Mask & Crop Type classification

**Deviations from feasibility study proposal:**

There’s been no substantial deviations from what has been described in the feasibility study.

## 3.5 Area estimates

As described in the feasibility study report (D1.1), crop area statistics are also provided, including:

1. Direct expansion estimates: area estimates from the field data alone;
2. Pixel count: areas measured from the in-season map alone;
3. Regression estimators: area estimates derived from field data combined with in- season map based on linear regression..

In the following, additional details regarding the three estimates are provided.

(1) Crop area estimates can be derived directly from the field data alone using the so-called direct expansion method since the data has been collected based on a probabilistic sample. Nevertheless, the confidence interval of the estimates derived from direct expansion is relatively large.

(2) Crop area estimates can be derived directly from the in-season map alone. Areas measured from digital classification have no sampling errors because they are based on pixel counts covering the whole of the AOI but they are biased because of mis-classification.

(3) To improve the precision of the estimates, field segment data (1) can be combined with classified satellite imagery (2). In this latter case, a Regression Estimator model can be applied which is more reliable than any other area estimation methodology as it provides both an area estimation per cover type together with an indication of its uncertainty. In brief, Regression Estimator relies on the combination of area estimates made at the segment level for both ground data and classified satellite imagery. The observations are paired, and a regression analysis is performed.

Table 4 shows the results of the crop area estimates for Uganda. It is interesting to notice the good relative efficiencies for Sorghum, cassava, potatoes or rice with figures greater than 2. For example for cassava, the same reduction in variance would have been achieved by increasing the size of the field survey sample by nearly 3.

**Table 4: Area estimates for the in-season mapping**

| AOI Area (ha) | 8 624 340,54 | Maize | Beans | Sorghum | Cassava | Potatoes | Rice | Groundnut | Simsim | Other crops | Other landcover |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Direct Expansion | Estimate of proportion | 0,10 | 0,01 | 0,01 | 0,05 | 0,00 | 0,01 | 0,02 | 0,00 | 0,05 | 0,74 |
| | Variance | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| | Standard Error | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| | 95% Confidence Interval | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| | Estimate of the class area | **904 186,06** | **66 476,09** | **123 395,64** | **469 138,52** | **36 834,09** | **48 494,38** | **142 734,14** | **17 524,02** | **410 283,20** | **6 405 274,40** |
| | Variance | 7 964 822 241,34 | 170 551 762,61 | 860 800 456,23 | 4 413 909 819,61 | 113 122 747,00 | 202 669 632,46 | 544 930 619,34 | 31 790 826,18 | 2 206 022 961,77 | 33 934 092 847,69 |
| | Standard Error | 89 245,85 | 13 059,55 | 29 339,40 | 66 437,26 | 10 635,92 | 14 236,21 | 23 343,75 | 5 638,34 | 46 968,32 | 184 212,09 |
| | 95% Confidence Interval | 174 921,87 | 25 596,71 | 57 505,23 | 130 217,03 | 20 846,40 | 27 902,97 | 45 753,75 | 11 051,14 | 92 057,90 | 361 055,69 |
| Pixel count | Map (ha) | **937 916,85** | **248 108,93** | **101 744,29** | **646 486,74** | **120 251,76** | **123 653,49** | **481 826,33** | **69 043,92** | **233 433,88** | **5 661 874,35** |
| | Map (%) | 0,11 | 0,03 | 0,01 | 0,07 | 0,01 | 0,01 | 0,06 | 0,01 | 0,03 | 0,66 |
| Regression Estimator | Regression estimate | 0,10 | 0,01 | 0,01 | 0,04 | 0,00 | 0,01 | 0,02 | 0,00 | 0,04 | 0,78 |
| | Variance | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| | Standard Error | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| | 95% Confidence Interval | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| | Regression estimate of the class area | **854 131,81** | **75 760,81** | **116 937,23** | **340 371,93** | **24 230,14** | **47 209,06** | **144 684,40** | **21 726,61** | **361 154,51** | **6 753 702,05** |
| | Variance | 4 227 921 025,41 | 144 769 172,57 | 328 577 890,23 | 1 566 359 201,87 | 51 278 732,88 | 60 271 702,22 | 345 109 829,89 | 21 500 524,10 | 1 935 759 317,23 | 12 522 725 404,94 |
| | Standard Error | 65 022,47 | 12 032,01 | 18 126,72 | 39 577,26 | 7 160,92 | 7 763,49 | 18 577,13 | 4 636,87 | 43 997,26 | 111 904,98 |
| | 95% Confidence Interval | 127 444,03 | 23 582,73 | 35 528,37 | 77 571,42 | 14 035,40 | 15 216,43 | 36 411,18 | 9 088,26 | 86 234,64 | 219 333,77 |
| Efficiency | Regression Estimator | **1,88** | **1,18** | **2,62** | **2,82** | **2,21** | **3,36** | **1,58** | **1,48** | **1,14** | **2,71** |

# 4 Conclusions

The availability of cloud-free Sentinel-2 data over the AOI was lower than expected during the feasibility study based on 5-yearly cloud statistics. However the processing to L3A 45-day synthesis yields very good results and creates monthly nearly cloud-free data tiles with which crop classification is feasible. Various crop type classification methods has been tested of which RF using IOTA2 yields the best results so far. The overall accuracy for the in-season Crop Type map is 72% and the in-season Crop Mask 80%, which is better than what was mentioned in the feasibility study (both 65%). For some individual crops though (e.g. beans or groundnuts), lower accuracies are reported, which we hope to be able to improve upon for the end-of-season map by including more satellite data and apply stricter training polygon rules.