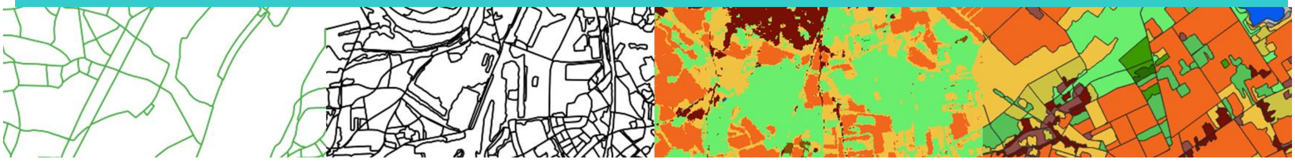
Service contract for the Copernicus Land monitoring services

Crop Mapping for GEOGLAM Country Level Support



Framework contract 939708-2020-IPR

End-of-season Crop Type Map & Crop Mask
Uganda - long rains season - 2021

Prepared by:

CLS

COLLECTE LOCALISATION SATELLITES

&

TerraSphere

Reference: End-of-season mapping - Uganda - long rains season - 2021

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Issues :

1.0	18-11-2021	First version submitted to JRC
1.1	26-11-2021	Correction of minor issues

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1 Introduction

This document describes the end-of-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 and conducted during the in-season mapping. 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.

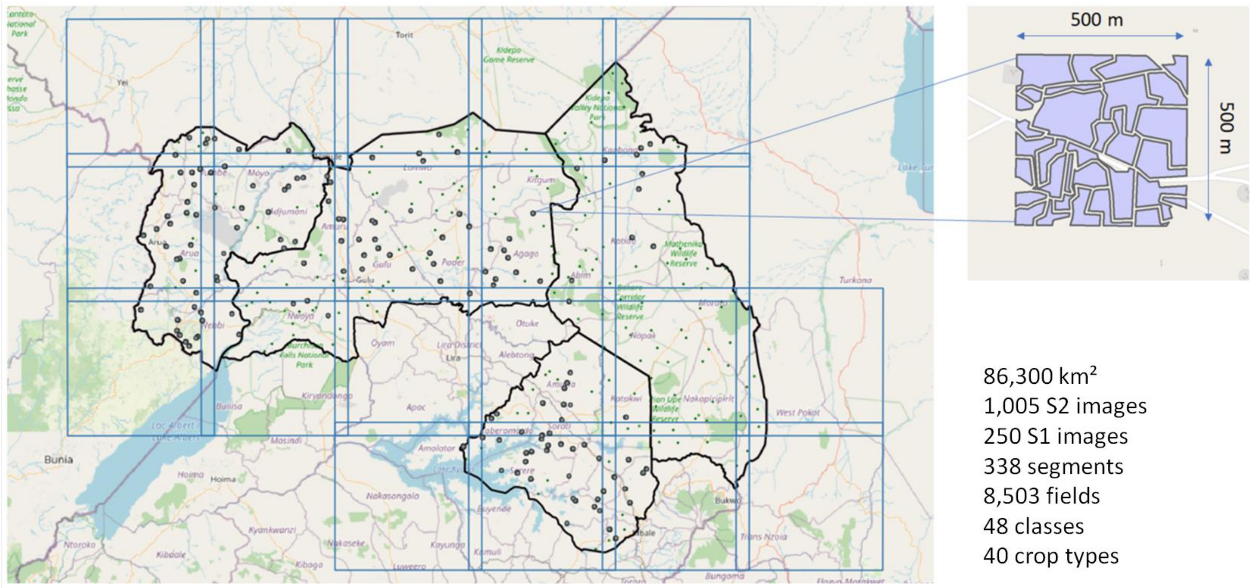

Figure 1. Uganda AOI overlaid with the S2 tile-based grid and the fieldwork segments

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2.1 Satellite data

Sentinel-2

In total, 1,005 Sentinel-2A & B Level-2A images have been acquired covering 20 tiles between 01-01-2021 and 16-09-2021 for the end-of-season mapping. 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 end-of-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.

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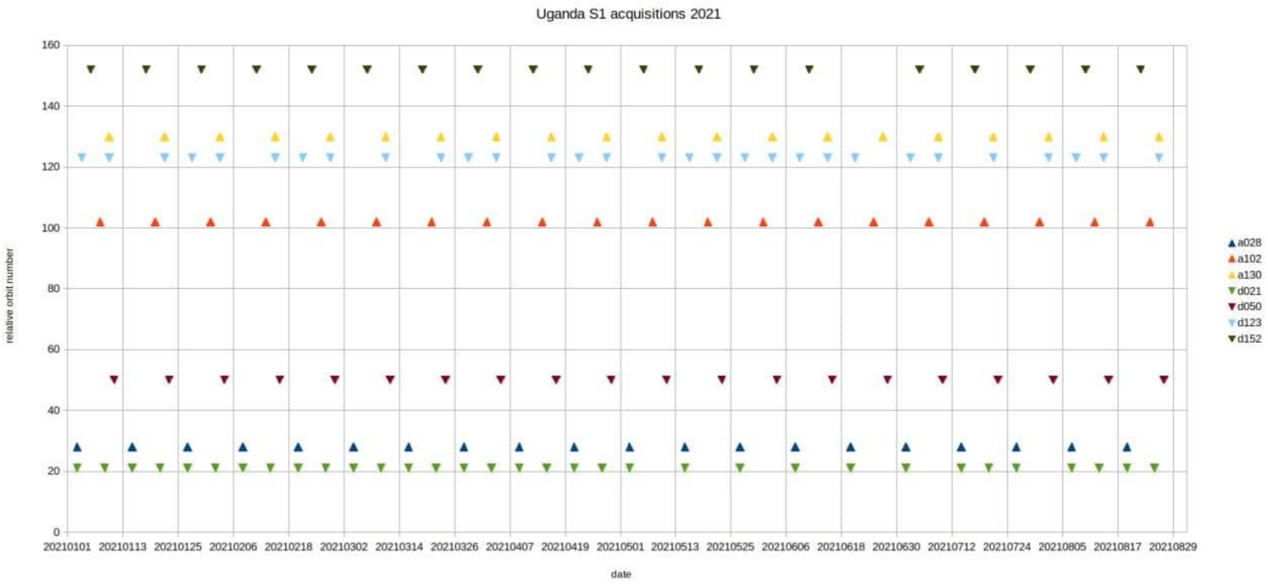

Figure 2. Sentinel-1 acquisition dates over Uganda

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.

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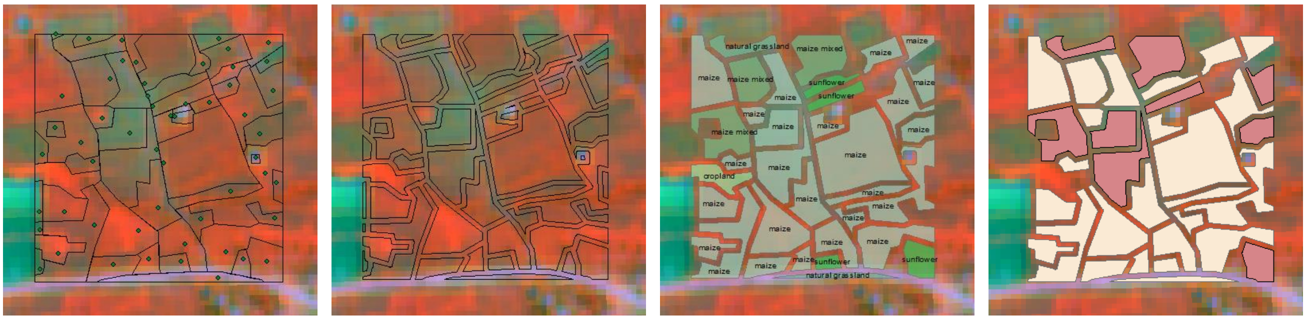
3) The acreage of each buffered polygon is calculated and all polygons smaller than 0.1 ha are deleted. It should be noticed that the threshold of 0.1 ha (approximatively 10 contiguous S2 pixels) is larger than the Minimum Mapping Unit from the technical specifications. Polygons below 0.1 ha are considered spectrally too heterogenous to serve as input into training samples for classification. 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 abovementioned 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, 5,155 polygons, covering approximatively 3,540 ha are available for the classification process. 3,866 are used for training and 1,289 for validation. In total 48 individual classes are distinguished, mostly individual crops (40).

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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.

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

Summary of the deviations from the in-season mapping:
No deviations are to be reported.

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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) and done during the in-season mapping. For each of the two satellite data types some specific pre-processing steps 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

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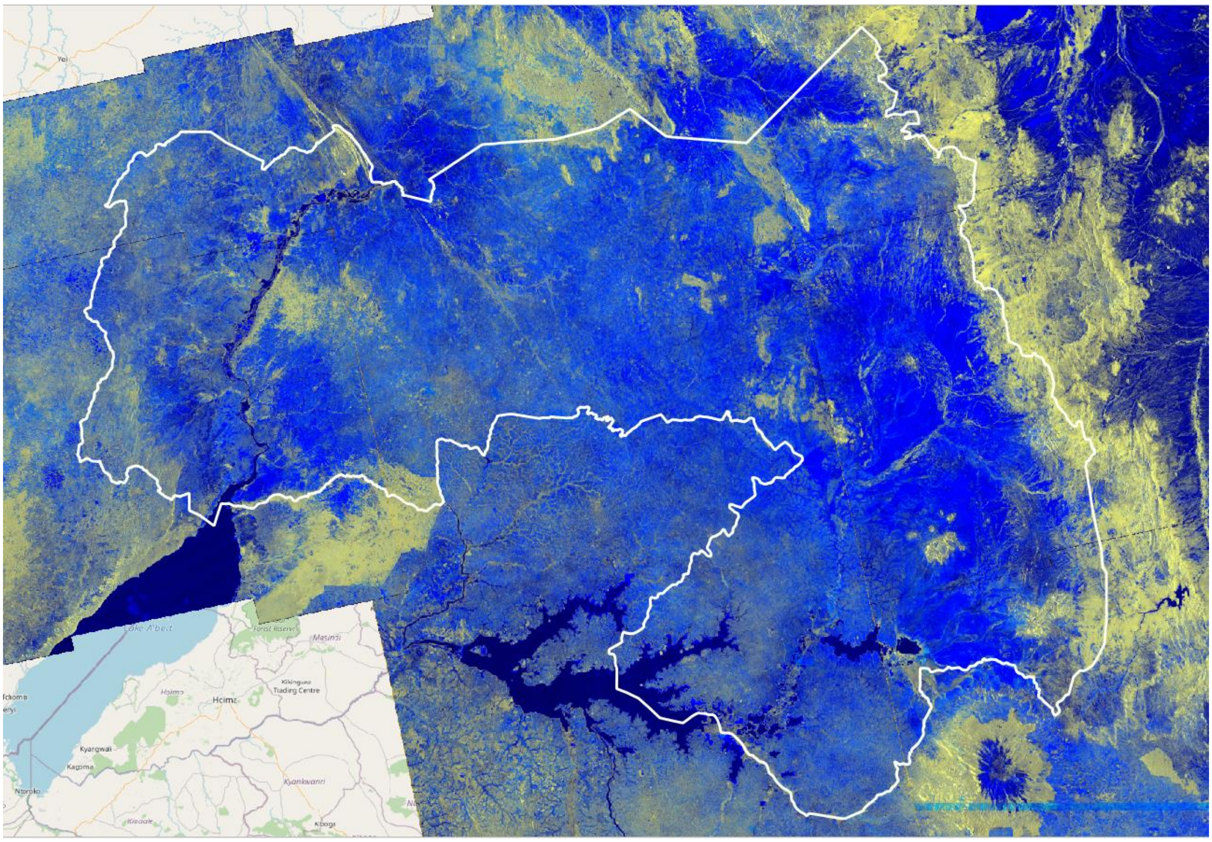

Figure 5. Sentinel-1 synthetic colour composite over the Ugandan AOI (white outline)

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

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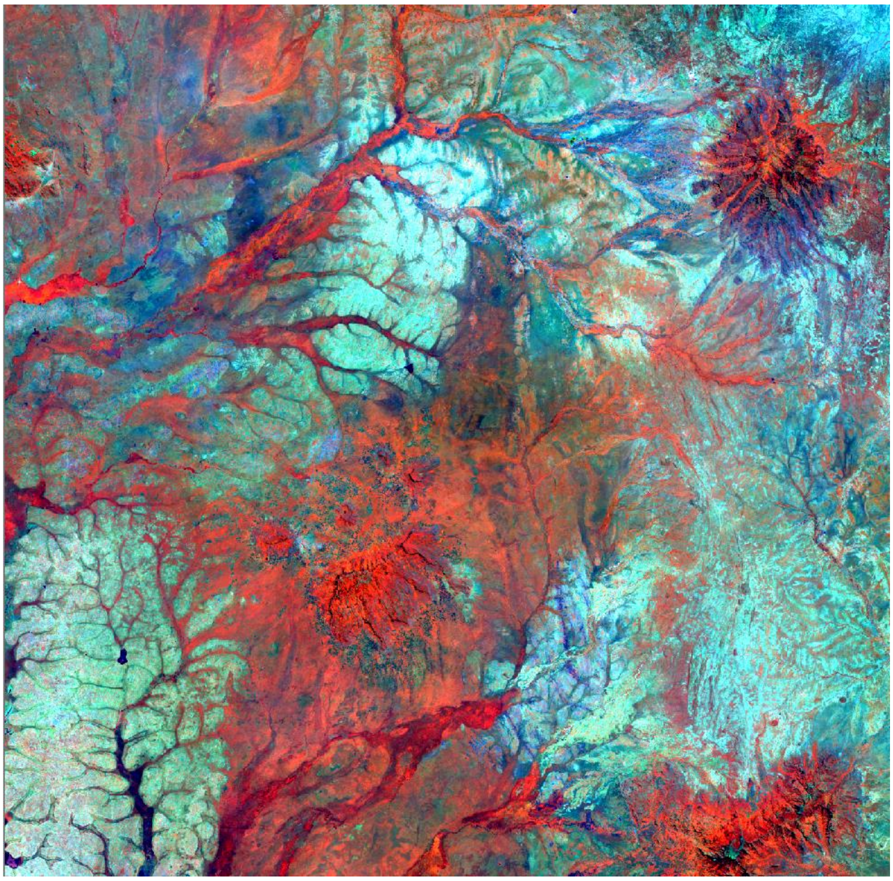

Figure 6: Sentinel-2 monthly synthesis composite (false colour RGB composition), 15/06/2021, tile 36NXHG

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 end-of-season mapping as enough Sentinel-2 data with higher resolution was available thanks to the L3A processing.

No deviations from the in-season mapping.

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

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3.2 Classification

Crop Type – It was decided to take profit of the run already conducted for the in-season mapping to select the classification algorithm in Uganda for the end-of-season. Various algorithms were tested, including supervised (maximum likelihood) classification, TempCNN and Random Forest (RF) algorithms. Based on the validation results, it was decided to use the RF classification as final method for the Ugandan end-of-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.

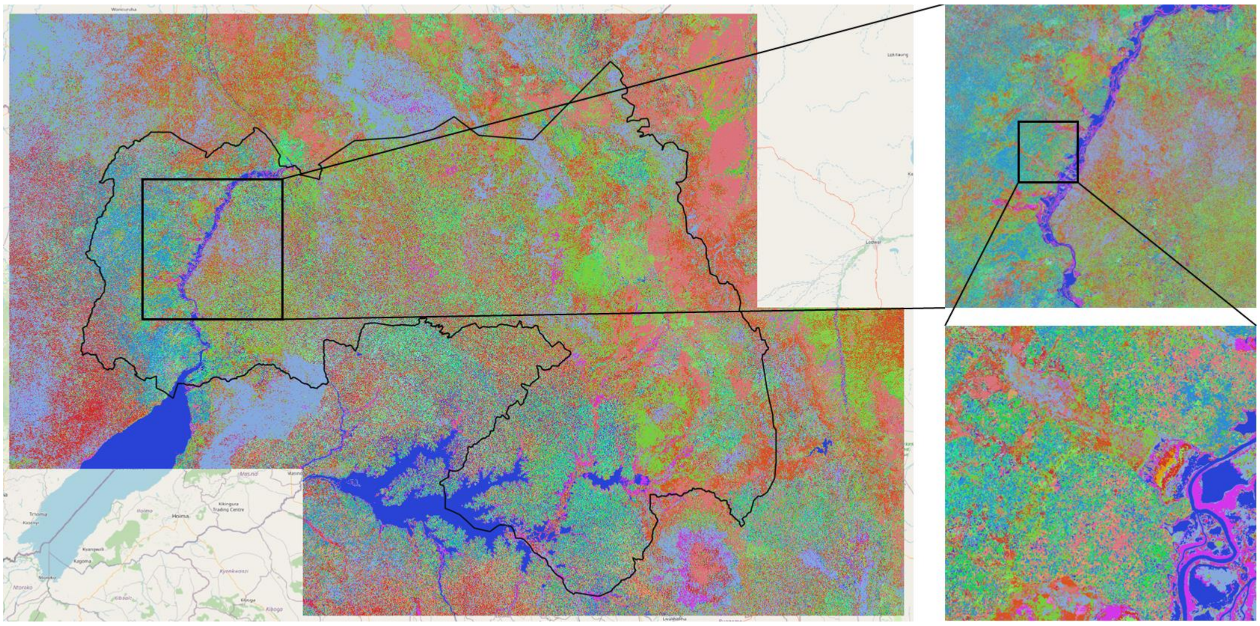

Figure 7. Raw classification output end-of-season crop type map Uganda

For the end-of-season mapping, a test was performed on a single tile (36MYA, located in Tanzania), using 3 different datasets: 1) monthly synthesis Sentinal-1 data, 2) Sentinel-2 images (L3A) and 3) a combination of S1 and S2 datasets. Classifications were being tested to produce the crop type map as well as the crop mask. Both classifications based on S1 (F1-score Crop class 55%) and based on a combination of S1 and S2 (F1-score 65%) did not yield better results than solely S2 data (F1-score 65%). It was therefore decided at this point to only use S2 L3A data as is done for the in-season mapping.

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 end-of-season map. The rule to produce the current end-of-season crop mask is as follows:

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

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

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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 has 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_EndOfSeason_LongRainy_2021.tif & Uganda_CropMask_EndOfSeason_LongRainy_2021.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	
11	potatoes	including mixed cropping with potatoes as dominant crop
12	rice	
16	groundnut	
17	Sesame (simsim)	
9	other crops	all other monoculture crops and mixed cropping
10	other landcover	Forest, water, natural shrubs, natural grassland, urban, bare, aquatic vegetation, wetlands

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 and they were of course preserved in the final map. As a final step a majority filtering have been applied using a moving window of 3x3 pixels, as well as a sieve function, removing all pixel clusters below 4 pixels (MMU = 0.04 ha). All maps are presented in UTM, zone 36 North.

Deviations from feasibility study proposal and the in-season mapping:

There's been no substantial deviations from what has been described in the feasibility study and done for the in-season mapping.

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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 end-of-season Crop Mask and Crop Type map for Uganda.

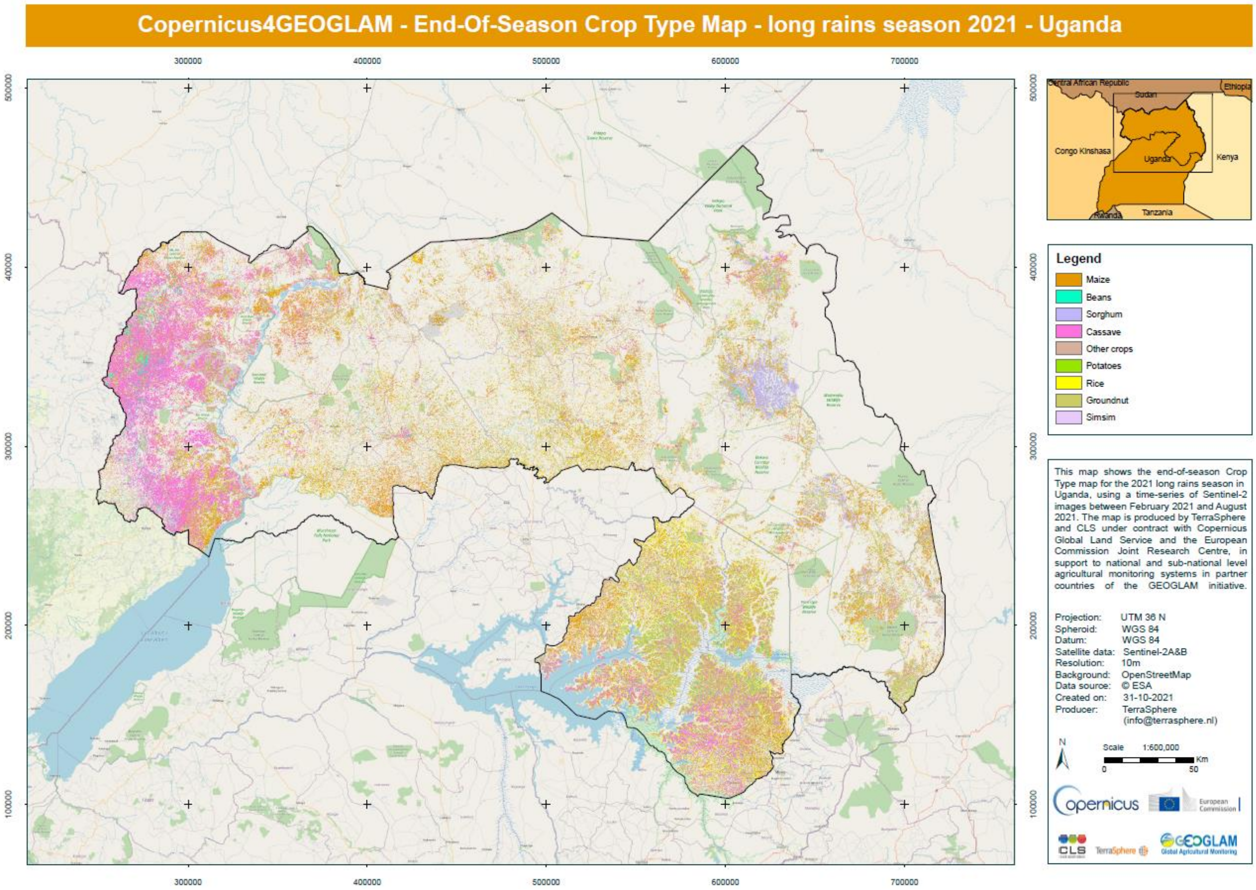

Figure 8. End-of-season Crop Mask for Uganda 2021.

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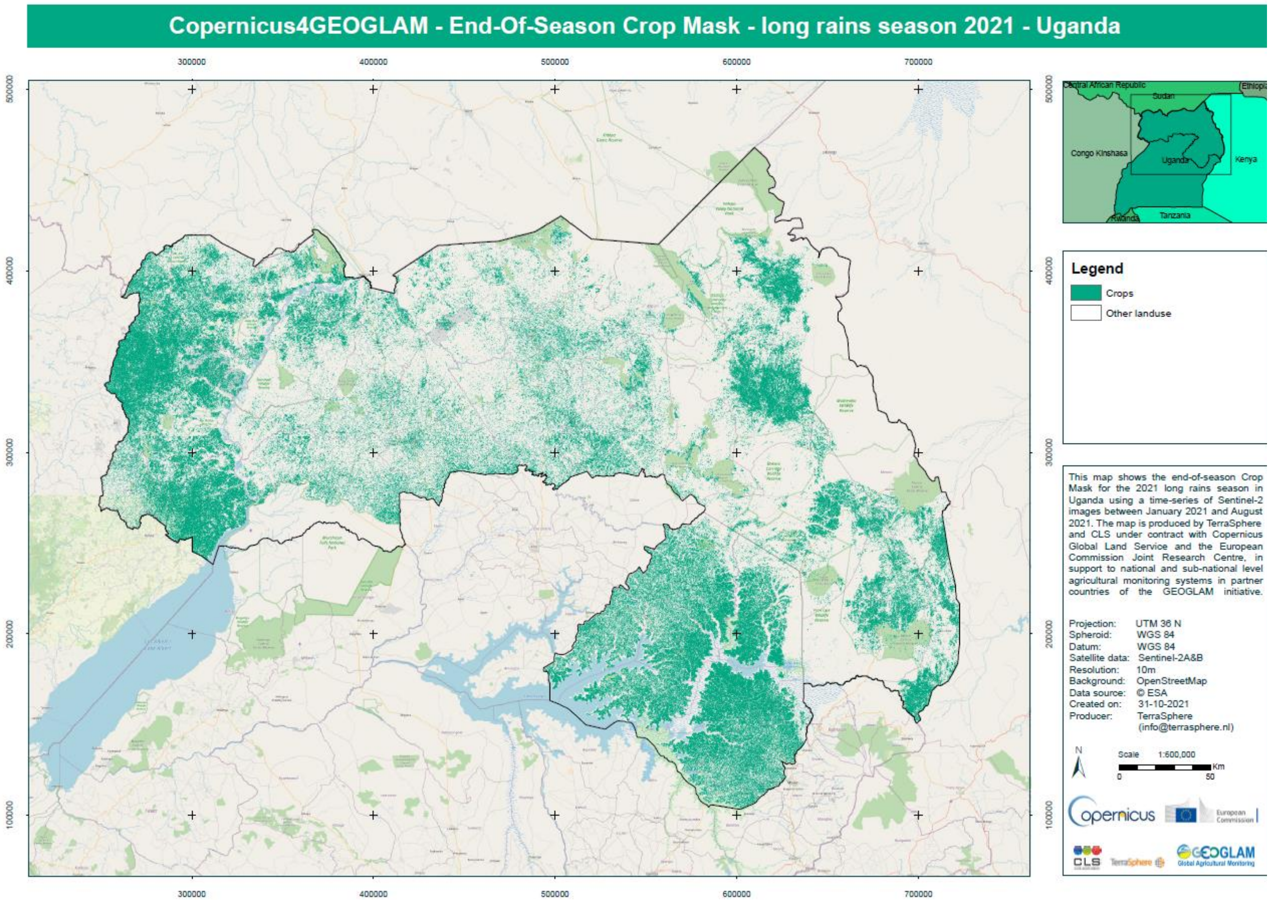

Figure 9. End-of-season Crop Type map for Uganda 2021.

Deviations from feasibility study proposal and the in-season mapping:

There's been no substantial deviations from what has been described in the feasibility study and done for the in-season mapping.

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.

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Crop type end-of-season mapping for Uganda

Map \ Reference	Maize	Beans	Sorghum	Cassava	Potatoes	Rice	Groundnut	Simsim	Other crops	Other landcover	Total	User Accuracy	F-Score
Maize	**2 050**	30	227	119	3	62	119	9	211	1 948	**4 778**	0,43	0,42
Beans	106	**87**	6	143	1		11			163	**517**	0,17	0,19
Sorghum	119		**237**	3		34	19		9	400	**821**	0,29	0,26
Cassava	336	24	47	**1 941**	27		124	38	49	3 208	**5 794**	0,34	0,42
Potatoes	135	10	37	217	**21**	3	60	21	27	546	**1 077**	0,02	0,04
Rice	178		30	11		**172**	2		6	169	**568**	0,30	0,38
Groundnut	467	51	62	171	4	11	**366**	**21**	49	3 099	**4 301**	0,09	0,13
Simsim	57		29	12			**15**	**16**	7	345	**481**	0,03	0,05
Other crops	101	97	19	98	1		39	15	**105**	380	**855**	0,12	0,13
Other landcover	1 431	109	308	789	35	48	403	30	260	**63 400**	**66 813**	0,95	0,90
Total	**4 980**	**408**	**1 002**	**3 504**	**92**	**330**	**1 158**	**150**	**723**	**73 658**	**86 005**		
Producer accuracy	0,41	0,21	0,24	0,55	0,23	0,52	0,32	0,11	0,15	0,86			

Overall accuracy	0,80
Crop Type - User accuracy	0,26
Crop Type - Producer accuracy	0,40

Figure 10. Confusion matrix for end-of-season Crop Type map

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Cropland mask end-of-season mapping for Uganda

Reference (columns) / Map (rows)

Map	Non-crop	Crop	Total	User Accuracy	F-Score
Non-crop	**63400**	3413	**66813**	0,95	0,90
Crop	10258	**8934**	**19192**	0,47	0,57
Total	**73658**	**12347**	**86005**		
Producer accuracy	0,86	0,72			

Overall accuracy	**0,84**

Figure 11. Confusion matrix for end-of-season Crop Mask

Figure 10 and Figure 11 show that the overall accuracy for the Crop Type map and Crop Mask is respectively reaching 80% and 84%, which is greater than the specifications mentioned in the feasibility study report (D1.1) (65% & 65%). The crop mask for the end-of-season shows very satisfying results for the overall accuracy (84%) but both user and producer accuracies for the crop class are relatively low with respectively 53% and 28% commission and omission errors (Commission = 100% - User Accuracy, Omission = 100% - Producer Accuracy). The crop mask for the end-of-season mapping presents better results than the in-season mapping for the overall accuracy but lower results for the user and producer accuracies of the crop class. Indeed, a decrease of both user and producer accuracies can be observed, respectively from 49% to 47%, and 75% to 72%.

Despite the addition of end-of-season satellite imagery, the results for the end-of-season mapping are not better than the in-season. Indeed, the results for individual crops remain weak and show lower accuracies as reported in the confusion matrix. The classes “Maize” and “Cassava” show the best individual results with F1-Score around 0.42. The lower results are obtained for the classes “Potatoes” and “Simsim (Sesame)” with a F-Score lower than 0.05.

Deviations from feasibility study proposal:

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

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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 end-of-season map alone;
3. Regression estimators: area estimates derived from field data combined with end-of-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.

Some deviations have been applied compared to the in-season mapping to better consider the mixed cropping practice. For the in-season area estimates, only the dominant crop was considered for the mixed cropping parcels whereas for the end-of-season mapping, all the crop surveyed in the field were taking into account for the estimates, contributing equally to the total area of the field. Figure 12illustrates the change with one example.

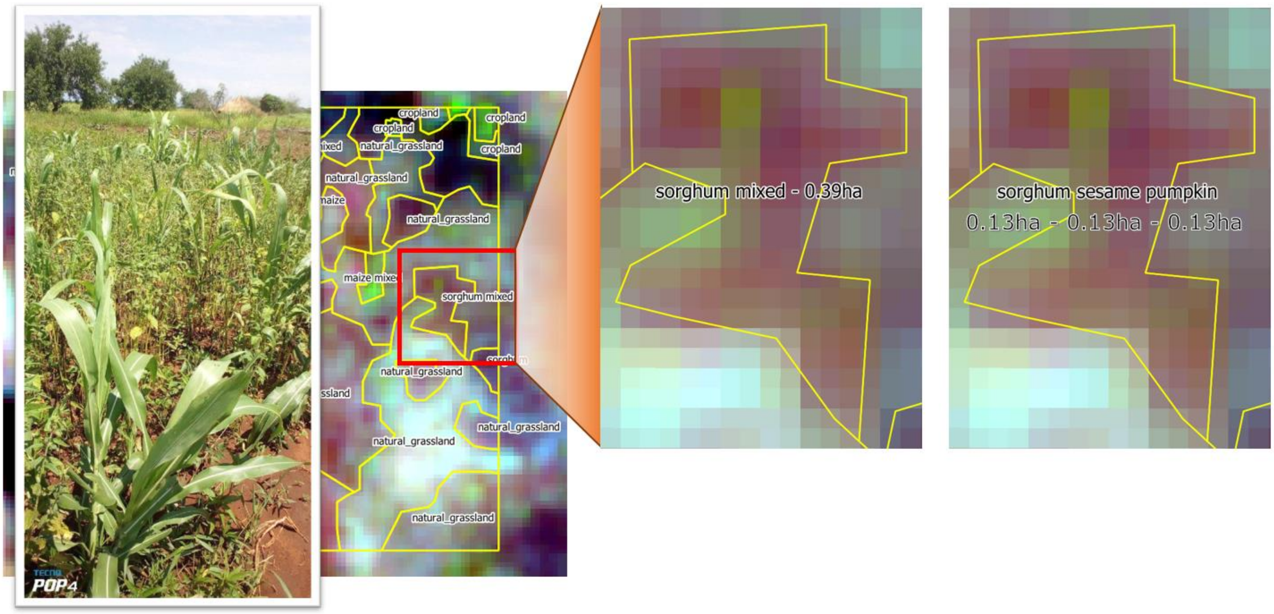

Figure 12: Mixed cropping fields and crop area estimates

(2) Crop area estimates can be derived directly from the end-of-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.

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

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Table 4: Area estimates for the end-of-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	0,07	0,01	0,02	0,07	0,01	0,01	0,03	0,00	0,04	0,76
	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
	Estimate of the class area	**585 097,98**	**82 633,97**	**158 774,64**	**596 562,53**	**44 931,74**	**57 058,43**	**239 587,36**	**30 389,71**	**309 067,23**	**6 520 236,95**
	Variance	3 981 372 365,35	165 024 629,86	969 573 227,26	6 192 622 115,74	125 511 559,56	266 171 763,15	971 309 756,42	84 980 897,05	1 209 626 832,92	31 680 043 937,01
	Standard Error	63 098,12	12 846,19	31 137,97	78 693,22	11 203,19	16 314,77	31 165,84	9 218,51	34 779,69	177 988,89
	95% Confidence Interval	123 672,31	25 178,53	61 030,42	154 238,70	21 958,26	31 976,95	61 085,05	18 068,28	68 168,19	348 858,22
Pixel count	Map (ha)	**618 825,15**	**55 641,37**	**117 615,60**	**595 879,39**	**125 762,80**	**132 549,98**	**526 791,34**	**88 319,23**	**135 249,70**	**6 227 705,97**
	Map (%)	0,07	0,01	0,01	0,07	0,01	0,02	0,06	0,01	0,02	0,72
Regression Estimator	Regression estimate	0,06	0,01	0,02	0,06	0,00	0,01	0,03	0,00	0,03	0,80
	Variance	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Standard Error	0,00	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	**488 061,18**	**74 730,84**	**152 605,96**	**480 916,20**	**30 317,90**	**53 963,16**	**230 784,87**	**36 438,90**	**276 797,52**	**6 920 289,79**
	Variance	1 522 696 969,00	111 366 862,24	359 004 291,63	2 704 577 274,33	61 956 231,14	62 684 804,22	583 655 393,09	74 132 393,43	980 815 006,38	11 118 904 119,42
	Standard Error	39 021,75	10 553,05	18 947,41	52 005,55	7 871,23	7 917,37	24 158,96	8 610,02	31 317,97	105 446,21
	95% Confidence Interval	76 482,63	20 683,98	37 136,92	101 930,88	15 427,61	15 518,05	47 351,56	16 875,63	61 383,21	206 674,58
Efficiency	Regression Estimator	**2,61**	**1,48**	**2,70**	**2,29**	**2,03**	**4,25**	**1,66**	**1,15**	**1,23**	**2,85**

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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 have been tested of which RF yields the best results so far. The overall accuracy for the in-season Crop Type map is 80% and the in-season Crop Mask 84%, which is better than what was mentioned in the feasibility study (both 65%). For some individual crops though (e.g. potatoes or simsim), lower accuracies are reported.

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