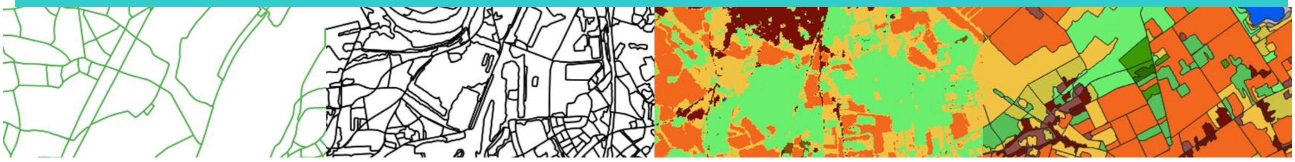
Service contract for the Copernicus Land monitoring services

Crop Mapping for GEOGLAM Country Level Support



Framework contract 939708-2020-IPR

In-season Crop Type Map & Crop Mask

Uganda - short rains season - 2021

Prepared by:

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COLLECTE LOCALISATION SATELLITES

&

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

Issue 1.0 - 25/05/2022

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1.0	25-05-2022	First version submitted to JRC

1 Introduction

This document describes the in-season mapping of the crop type and crop mask for the Area Of Interest (AOI) in Uganda for the short rains season. 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 long rains season. The document also describes the satellite imagery and the ground truth data 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 and implemented during the long rains season.

The current short rains season in Uganda was affected by severe drought impacting the Eastern Africa and consequently the results of the end-of-season mapping.

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.

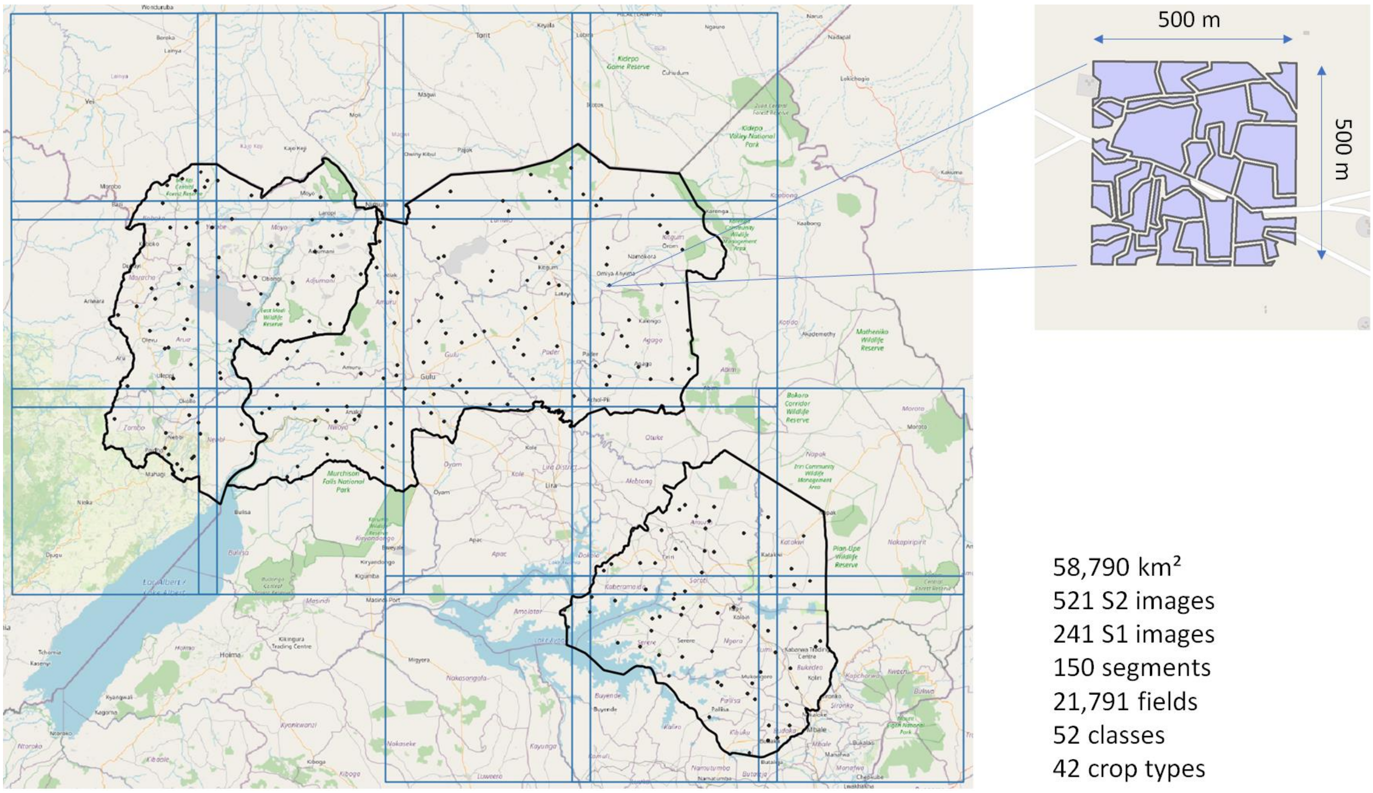


Figure 1. Uganda AOI overlaid with the S2 tile-based grid and the fieldwork segments

2.1 Satellite data

Sentinel-2

In total, approximatively 521 Sentinel-2A & B Level-2A images have been acquired covering 20 tiles between 03-10-2021 and 29-01-2022. 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 Images
36NTH	04/10/2021	27/01/2022	17
36NTJ	09/10/2021	27/01/2022	14
36NTK	09/10/2021	27/01/2022	13
36NUH	04/10/2021	29/01/2022	30
36NUJ	04/10/2021	29/01/2022	32
36NUK	04/10/2021	29/01/2022	33
36NVG	16/10/2021	29/01/2022	18
36NVH	11/10/2021	29/01/2022	18
36NVJ	04/10/2021	29/01/2022	30
36NVK	09/10/2021	29/01/2022	33
36NWG	08/10/2021	29/01/2022	38
36NWH	11/10/2021	29/01/2022	19
36NWJ	11/10/2021	29/01/2022	19
36NWK	11/10/2021	29/01/2022	18
36NXG	03/10/2021	29/01/2022	42
36NXH	03/10/2021	29/01/2022	41
36NXJ	03/10/2021	29/01/2022	36
36NXK	03/10/2021	29/01/2022	28
36NYG	03/10/2021	26/01/2022	22
36NYH	03/10/2021	26/01/2022	20

Sentinel-1

In total, 241 Sentinel-1 images have been used to cover the Ugandan AOI between 01-10-2021 and 30-03-2022 for the in-season mapping of the short rains season. 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.

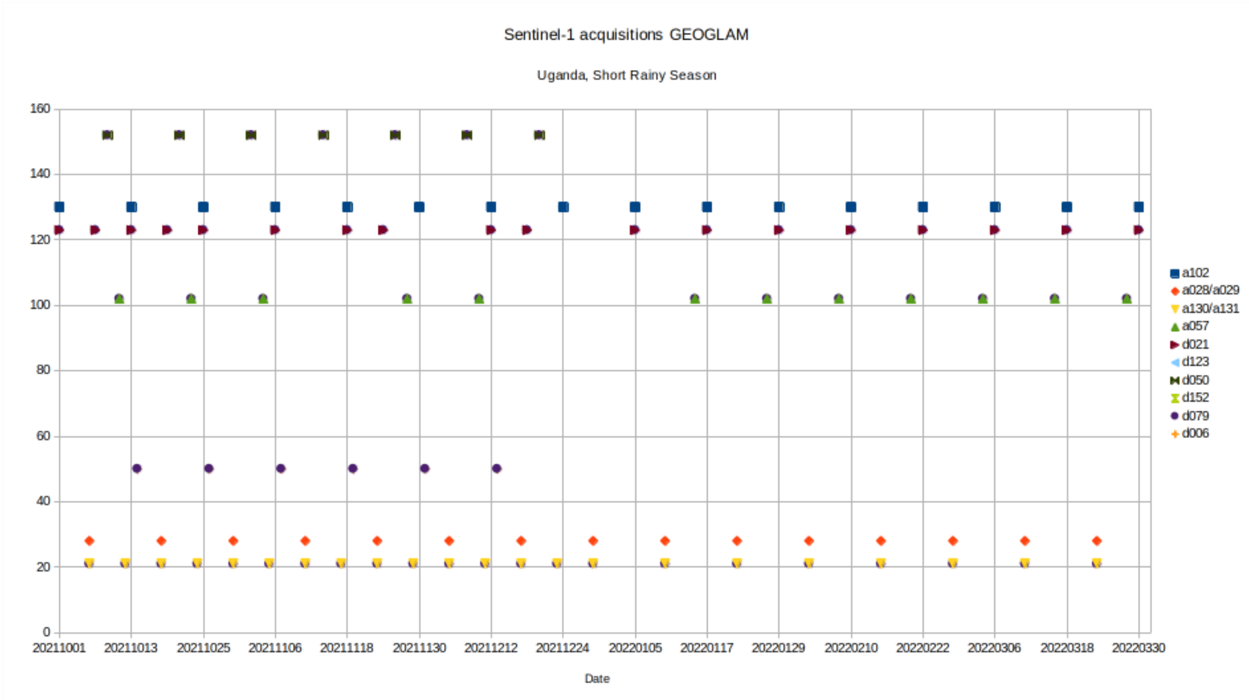


Figure 2. Sentinel-1 acquisition dates over Uganda

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.

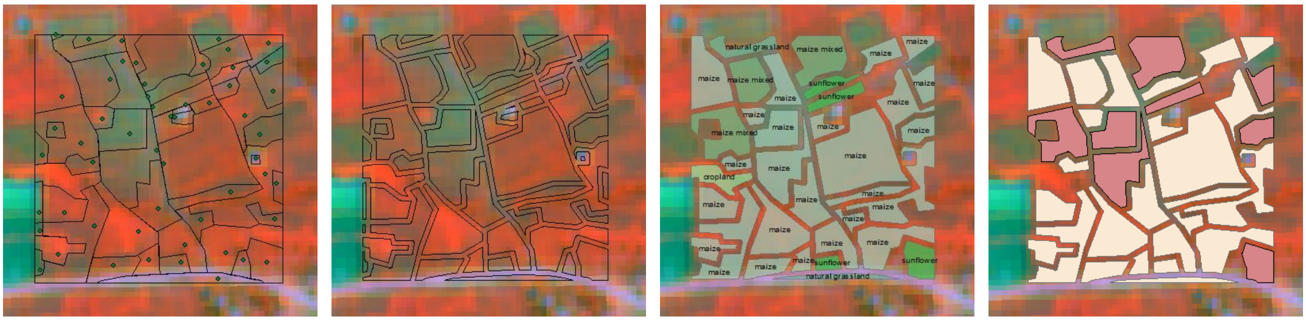
2) A negative buffer of 5 meters is applied to eliminate, or at least minimize, the boundary effects between different classes that will negatively impact the purity of training samples signatures. Consequently, polygons are always separated by 10 meters, which corresponds to the size of 1 Sentinel-2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

3) The acreage of each buffered polygon is calculated and all polygons smaller than 0.1 ha are deleted. Based on the long rains mapping experience, 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) All the resulting polygons have been visually checked and manually edited to correct obvious errors.

5) The resulting dataset from step 1 to 4 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 0, the classification workflow is applied per S2-based block.

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, 7,282 polygons, covering approximatively 3,366 ha are available for the classification process. 5,462 are used for training and 1,820 for validation. In total 52 individual classes are distinguished, mostly individual crops (42).

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;

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

[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

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

“centre-date” are used to build a cloud-free image. The Figure 5 shows an example for tile 36NVJ, with a centre-date of 15-01-2022. For this synthesis, the algorithm considers all images +/- 45 days from 15-01-2022, and takes the cloud-free pixel closest to the centre date.

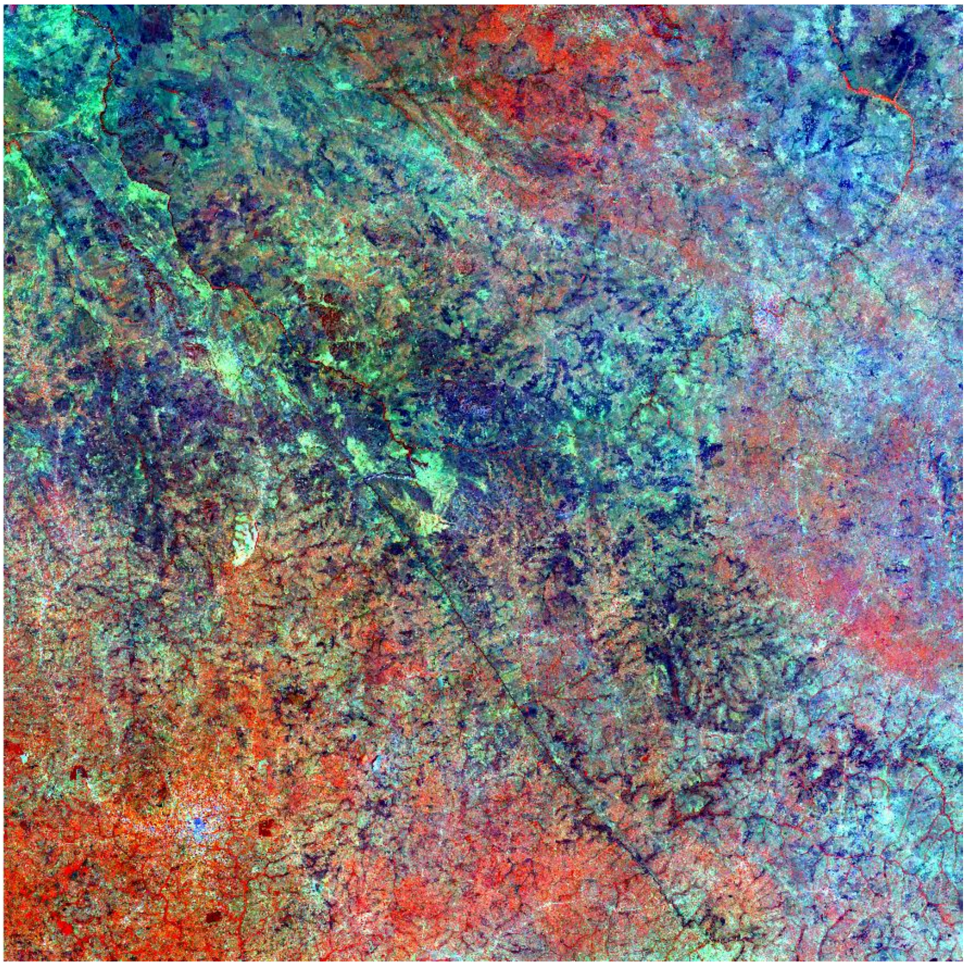


Figure 5: Sentinel-2 monthly synthesis composite (false colour RGB composition), 15/01/2022, tile 36NVJ

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.

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

- 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.

Deviations from the long rains season mapping:
For the long rains season, Sentinel-1 monthly synthesis images based on the S2 tiling grid were produced parallel to the S2 L3A data. The objective was to perform test for the crop type classification using S1 scenes or a combination between S1 and S2 images. The tests showed that a combination of S1 and S2 did not yield better results. So, for the short rains season, the monthly synthesis Sentinal-1 data were not produced.

3.2 Classification

Crop Type – Various classification algorithms were tested during the previous long rains season, including supervised (maximum likelihood), TempCNN and Random Forest (RF). Similar to the long rains season, it was decided to use the RF classification for the Ugandan short rains season mapping. 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 52 classes (of which 42 crop types). The Figure 6 shows the result of the raw classification output, before post-processing.

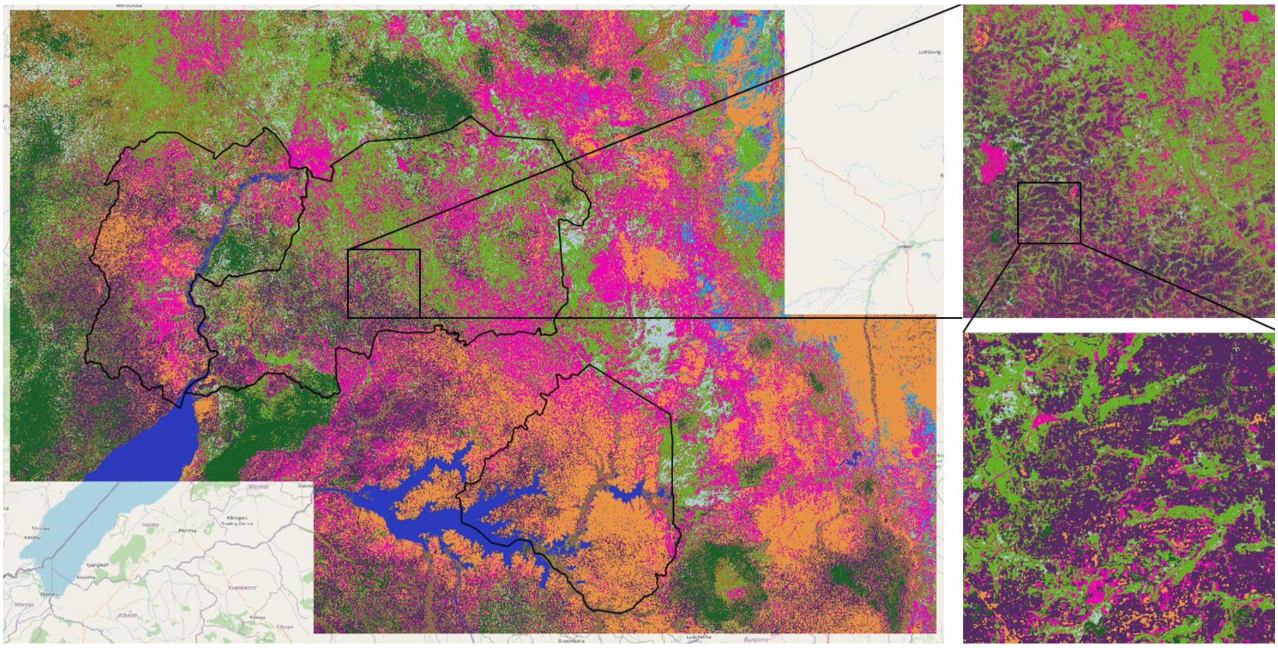


Figure 6. Raw classification output in-season crop type map Uganda

Crop Mask – For the crop mask, the aggregated results from the S2-derived crop type map have been used. The rule to produce the current in-season crop mask is as follows:

Crop Type S2 map = (1 of 42 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>

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_ShortRains_2021_V1.tif & Uganda_CropMask_InSeason_ShortRains_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 (> 50% coverage)
5	sorghum	including mixed cropping with sorhum as dominant crop (> 50% coverage)
8	cassava	including mixed cropping with cassava as dominant crop (> 50% coverage)
11	potatoes	including mixed cropping with potatoes as dominant crop (> 50% coverage)
12	rice	including mixed cropping with rice as dominant crop (> 50% coverage)
16	groundnut	including mixed cropping with groundnut as dominant crop (> 50% coverage)
17	sesame	including mixed cropping with sesame as dominant crop (> 50% coverage)
19	peas	including mixed cropping with peas as dominant crop (> 50% coverage)
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 (rare) and they were of course preserved in the final map. As a final step a sieve operation has been applied whereby all pixel clusters of 4 pixels and below (0.04 ha = approximate MMU for S2) are recoded to the majority surrounding class. All maps are presented in UTM, zone 36 North.

Deviations from the long rains season mapping:

The only deviation concerns the 8 individual crop types mapped. In fact, the largest crop types are based on the crop area estimates and depending on the rainy season, agricultural practices vary. For the long rains season, the 8 largest individual crop types were: maize, beans, sorghum, cassava, potatoes, rice, groundnut and sesame.

Deviations from feasibility study proposal:

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

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.

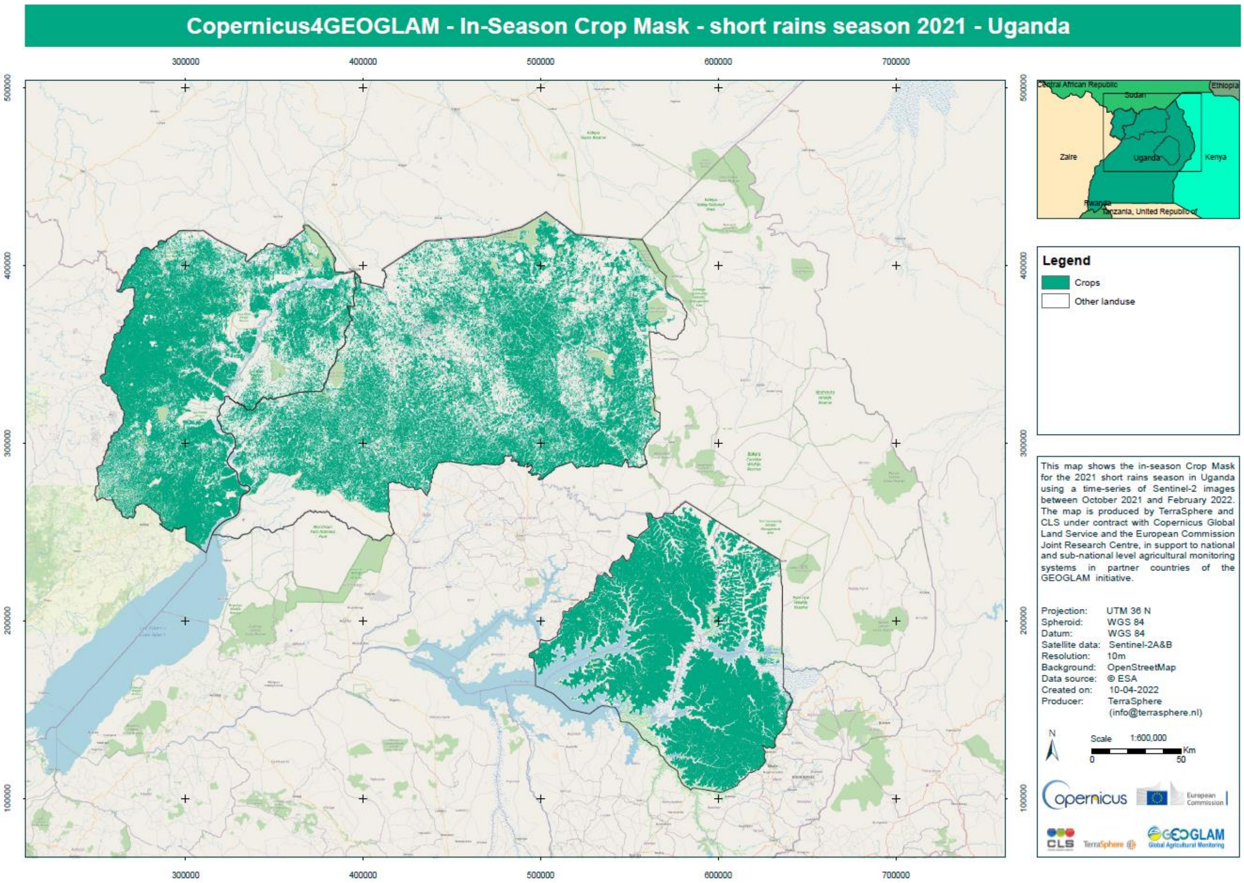


Figure 7. In-season Crop Mask for the short rains season 2021 in Uganda

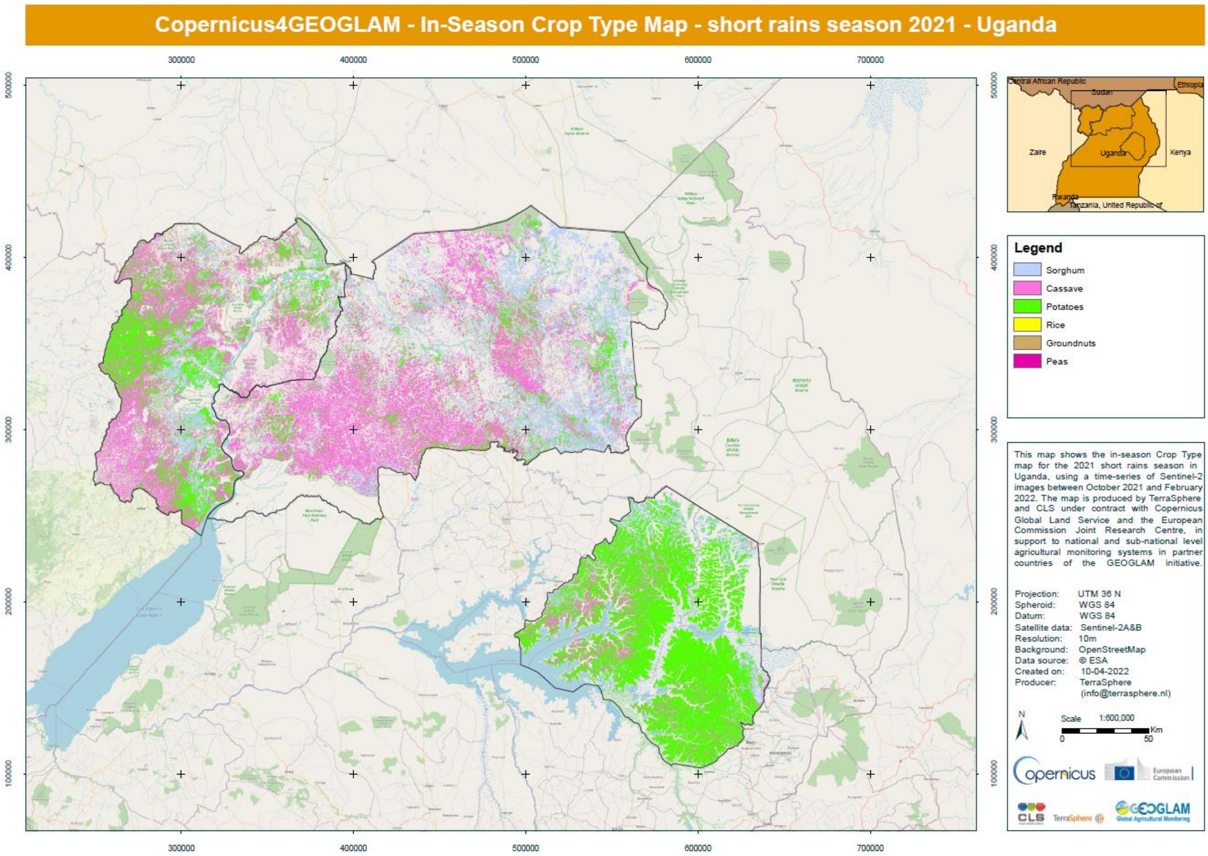


Figure 8. In-season Crop Type map for the short rains season 2021 in Uganda

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 (short rains)	Reference												
Map	Maize	Sorghum	Cassava	Potatoes	Rice	Groundnuts	Sesame	Peas	Other crops	Other landcover	Total	User Accuracy	F-Score
Maize												N/A	N/A
Sorghum	132	**1546**	586	17	64	20	153	89	70	5179	**7856**	0,20	0,25
Cassava	721	1177	**1553**	28	122	172	67	159	603	3373	**7975**	0,19	0,25
Potatoes	394	700	1928	**480**	82	57	121	144	550	1640	**6096**	0,08	0,14
Rice					**3**						**3**	1,00	0,02
Groundnuts	29	764	52				31		2	1793	**2671**	0,00	N/A
Sesame												N/A	N/A
Peas												N/A	N/A
Other crops												N/A	N/A
Other landcover	43	475	216		63	35	93		164	**21785**	**22874**	0,95	0,77
Total	**1319**	**4662**	**4335**	**525**	**334**	**284**	**465**	**392**	**1389**	**33770**	**47475**		
Producer accuracy	0,00	0,33	0,36	0,91	0,01	0,00	0,00	0,00	0,00	0,65			

Overall accuracy	0,53
Crop Type - User accuracy	0,15
Crop Type - Producer accuracy	0,26

Figure 9. Confusion matrix for in-season Crop Type map for the short rains season 2021

Cropland mask in-season mapping for Uganda (short rains)		Reference				
		Non-crop	Crop	Total	User Accuracy	F-Score
Map	Non-crop	**21785**	1089	**22874**	0,95	0,77
	Crop	11985	**12616**	**24601**	0,51	0,66
	Total	**33770**	**13705**	**47475**		
	Producer accuracy	0,65	0,92		Overall accuracy	**0,72**

Figure 10. Confusion matrix for in-season Crop Mask for the short rains season 2021

Figure 9 and Figure 10 show that the overall accuracy for the Crop Type map and Crop Mask is respectively reaching 53% and 72%, which is greater than the specifications mentioned in the feasibility study report (D1.1) only for the Crop Mask (65% & 65%). The Crop Type map failed reaching the requirements.

The crop mask for the in-season shows very satisfying results for the producer accuracy with 8% omission errors but a low user accuracy with 49% omission errors.

Both user and producer results for individual crops show very lower accuracies as reported in the confusion matrix. The classes “Sorghum” and “Cassava” show the best individual results with F1-Score around 0.25. The lower results are obtained for the class “Rice” with F1-Score around 0.02.

The very low results can be partly explained by the high presence of bare soils during the second field campaign resulting in a decrease of valid training samples for the classification algorithm. In fact, the preliminary results presented in the field campaign report (D2.1) showed a huge decrease of the areas covered by crops in monoculture and mixed cropping from the long rains to the short rains season (respectively from 15,481 to 9,865 km² and 10,363 to 3,713 km²) and also showed that approximatively 60% of the cropland was characterized with bare soil. The preliminary tendency is confirmed by the crop area estimates showing that bare soils represent approximatively 2,442 km² (+/-1,226) which is the 6th most dominant class surveyed during the fieldwork (regarding the crop types, only the classes “Cassava” and “Sorghum” are larger). The presence of bare soils can be explained by the drought that affected the Eastern Africa during the short rains season confirmed by the field team.

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. To better consider the mixed cropping practice, adaptations were implemented during the short rains season. Previously, only the dominant crop was considered for the mixed cropping parcels but now, all the crop surveyed in the field were taking into account for the estimates:

1) contributing equally to the total area of the field if no dominant crop was declared or,
2) the dominant crop contributing to half of the total area and the other crops surveyed contributing equally to the second half of the total.

Figure 11 illustrates the change with one example.

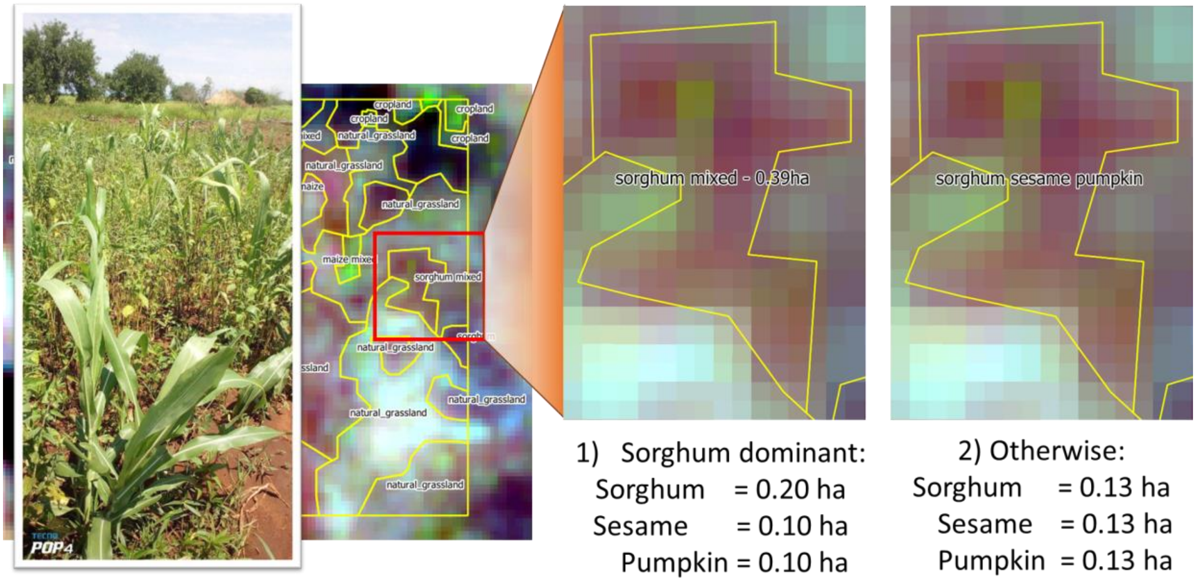


Figure 11: Mixed cropping fields and crop area estimates (non-dominant crop study case)

(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 for the in-season for the short rains season. Relative efficiencies for the short rains are lower than relative efficiency obtained for the long rains season with figures lower 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. The regression estimates fail to improve the crop area estimates as high as for the long rains season because the accuracy of the crop type mapping is low for the short rains season. Indeed, (Taylor et al. 1997[4]) showed that a producer accuracy greater than 30% and a coefficient of determination r^2 greater than 0.3 are mandatory to ensure sufficient number of well classified pixels. Such level of precision is not reached for the short rains season. Moreover, (Taylor et al. 1997) recommends that each regression should have at least 30 observations on its own and a sufficient number of non-zero points in the regression well distributed across the range to ensure high quality. The preliminary results presented in the field campaign report (D2.1) showed a huge decrease of the areas covered by crops in monoculture and mixed cropping from the long rains to the short rains season (respectively from 15,481 to 9,865 km² and 10,363 to 3,713 km²) and also showed that approximatively 60% of the cropland was characterized with bare soil. The crop area estimates show that bare soils represent approximatively 2,442 km² (+/-1,226). Even if the drought that heavily impacted the Eastern regions of Africa late 2021 is not clearly established on the ASAP (Anomaly hotSpots of Agricultural Production) system, field teams during the campaign reported dry conditions.

Deviations from feasibility study proposal and the long rains season mapping:

Following the feedback from the end users, some improvements have been applied compared to the long rains season, mapping to better consider the mixed cropping practice.

For the short rains season, in order to improve the classification results and the crop area estimates, the surveyors indicated if a dominant crop was visible in the field in case of mixed cropping (with more than 50% coverage). Now all the crops surveyed in a parcel are considering for the crop area estimates, the contribution depending on the dominant crop declaration:

1) All the crops surveyed contributing equally to the total area of the field if no dominant crop was declared or,
2) The dominant crop surveyed contributing to half of the total area and the other crops contributing equally to the second half of the total of the field.

[4] Taylor, C., 1997. Regional crop inventories in Europe assisted by remote sensing : 1988-1993 : synthesis report of the MARS Project - action 1 - Kings Norton Library (No. EUR 17319 EN). JRC, European Commission.

Table 4: Area estimates for the in-season mapping

AOI Area (ha)	5 878 193,22

		Maize	Beans	Sorghum	Cassava	Potatoes	Rice	Groundnut	Simsim	Other crops	Other landcover
Direct Expansion	Estimate of proportion	0,03	0,05	0,07	0,02	0,01	0,01	0,01	0,02	0,03	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	0,00	0,01	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,02
	95% Confidence Interval	0,01	0,02	0,01	0,01	0,00	0,00	0,01	0,00	0,01	0,03
	Estimate of the class area	**147 189,90**	**289 319,67**	**438 195,81**	**93 961,10**	**46 020,58**	**69 817,97**	**78 209,69**	**93 356,47**	**176 841,46**	**4 445 280,57**
	Variance	272 862 661,51	2 072 004 317,28	1 696 229 970,45	253 758 276,31	95 520 030,59	118 524 298,40	249 714 328,57	200 706 501,06	308 331 102,08	10 297 465 715,51
	Standard Error	16 518,56	45 519,27	41 185,31	15 929,79	9 773,43	10 886,89	15 802,35	14 167,09	17 559,36	101 476,43
	95% Confidence Interval	32 376,37	89 217,78	80 723,21	31 222,39	19 155,93	21 338,30	30 972,61	27 767,50	34 416,34	198 893,80
Pixel count	Map (ha)	**-**	**824 011,04**	**1 205 426,65**	**1 236 176,84**	**1 685,15**	**121 070,15**	**-**	**9,45**	**-**	**2 489 813,94**
	Map (%)	-	0,14	0,21	0,21	0,00	0,02	-	0,00	-	0,42
Regression Estimator	Regression estimate	N/A	0,05	0,07	0,02	0,01	0,01	N/A	N/A	N/A	0,77
	Variance	N/A	0,00	0,00	0,00	0,00	0,00	N/A	N/A	N/A	0,00
	Standard Error	N/A	0,01	0,01	0,00	0,00	0,00	N/A	N/A	N/A	0,02
	95% Confidence Interval	N/A	0,01	0,01	0,00	0,00	0,00	N/A	N/A	N/A	0,03
	Regression estimate of the class area	**N/A**	**272 299**	**435 382**	**90 563**	**37 545**	**55 958**	**N/A**	**N/A**	**N/A**	**4 542 034**
	Variance	N/A	1 952 443 826	1 676 089 326	202 969 652	52 407 192	91 024 078	N/A	N/A	N/A	8 298 910 685
	Standard Error	N/A	44 186	40 940	14 247	7 239	9 541	N/A	N/A	N/A	91 098
	95% Confidence Interval	N/A	86 605	80 243	27 924	14 189	18 700	N/A	N/A	N/A	178 553
Efficiency	Regression Estimator	**N/A**	**1,06**	**1,01**	**1,25**	**1,82**	**1,30**	**N/A**	**N/A**	**N/A**	**1,24**

4 Conclusions

The results for the short rains season have been affected by the severe drought, impacting the Eastern Africa. The overall accuracy for the in-season Crop Type map is 53% and the in-season Crop Mask 72%. Only the Crop Mask reaches the requirements mentioned in the feasibility study (both 65%). For all individual crops, lower accuracies are reported. Relative efficiencies for the short rains are lower than relative efficiency obtained for the long rains season with figures lower than 2. The regression estimates fail to improve the crop area estimates as high as for the long rains season because the accuracy of the crop type mapping is low for the short rains season.