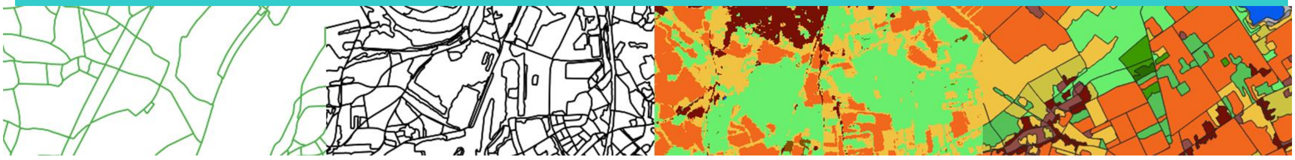
Service contract for the Copernicus Land monitoring services

Crop Mapping for GEOGLAM Country Level Support



Framework contract 939708-2020-IPR

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

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

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Issues :

1.0	10-11-2021	First version submitted to JRC

1 Introduction

This document describes the end-of-season mapping of the crop type and crop mask for the Area Of Interest (AOI) in Kenya. 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 Kenya.

2 Summary of data used

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

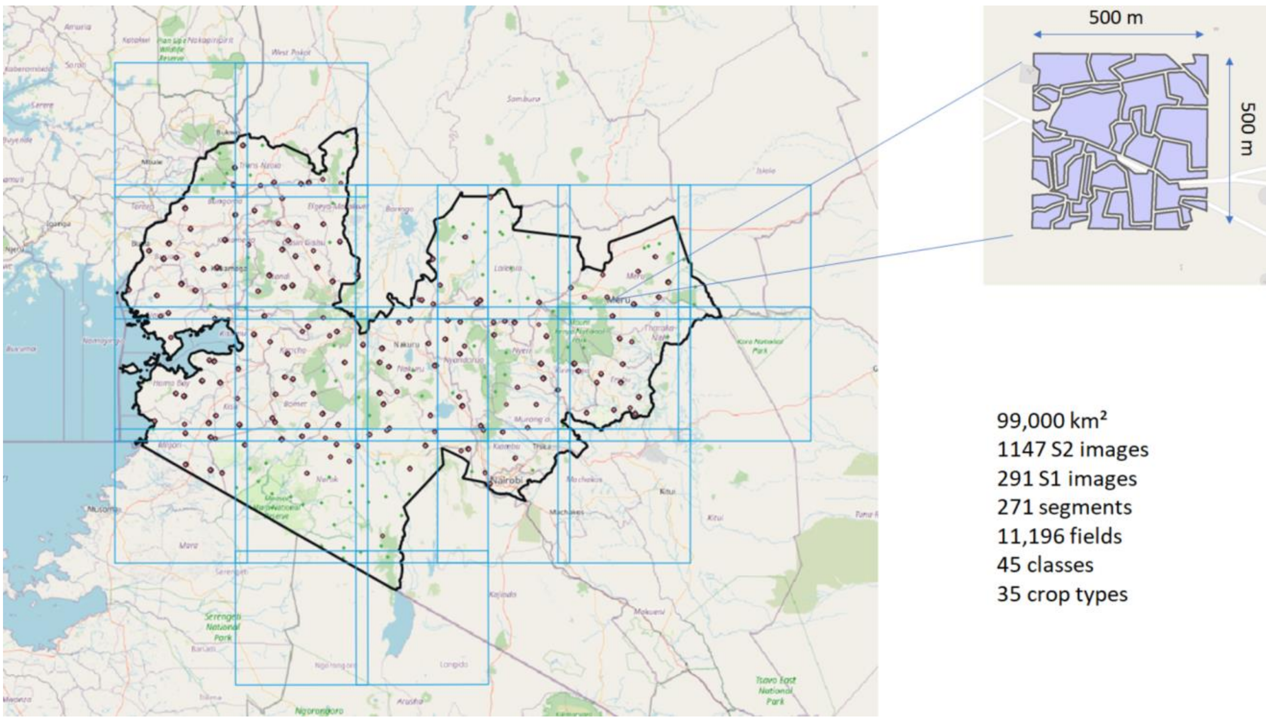


Figure 1. Kenya AOI overlaid with the S2 tile-based grid and the fieldwork segments

2.1 Satellite data

Sentinel-2

In total, 1,147 Sentinel-2A & B Level-2A images have been acquired covering 21 tiles between 01-01-2021 and 15-09-2021 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 Kenya

Tile ID	First date	Last date	Number of S2 L2A images
36MXD	01/01/2021	13/09/2021	42
36MYC	01/01/2021	13/09/2021	81
36MYD	01/01/2021	13/09/2021	41
36MYE	01/01/2021	13/09/2021	36
36MZC	01/01/2021	15/09/2021	74
36MZD	01/01/2021	15/09/2021	67
36MZE	01/01/2021	15/09/2021	77
36NXF	01/01/2021	29/08/2021	71
36NXG	01/01/2021	13/09/2021	77
36NYF	01/01/2021	29/08/2021	34
36NYG	01/01/2021	13/09/2021	41
36NZF	01/01/2021	29/08/2021	73
37MBU	03/01/2021	15/09/2021	27
37MBV	01/01/2021	15/09/2021	67
37MCU	03/01/2021	15/09/2021	22
37MCV	03/01/2021	15/09/2021	32
37MDV	03/01/2021	15/09/2021	50
37NBA	01/01/2021	31/08/2021	66
37NBB	01/01/2021	10/07/2021	66
37NCA	03/01/2021	31/08/2021	43
37NDA	03/01/2021	31/08/2021	60

Sentinel-1

In total, 291 Sentinel-1 images have been used to cover the Kenyan AOI between 01-02-2021 and 31-08-2020 for the end-of-season mapping. The Figure 2 shows the acquisition dates of the S1 dataset covering the Kenyan AOI. The coverage consists of three descending (southward) orbits, requiring 3 to 4 images per orbit.

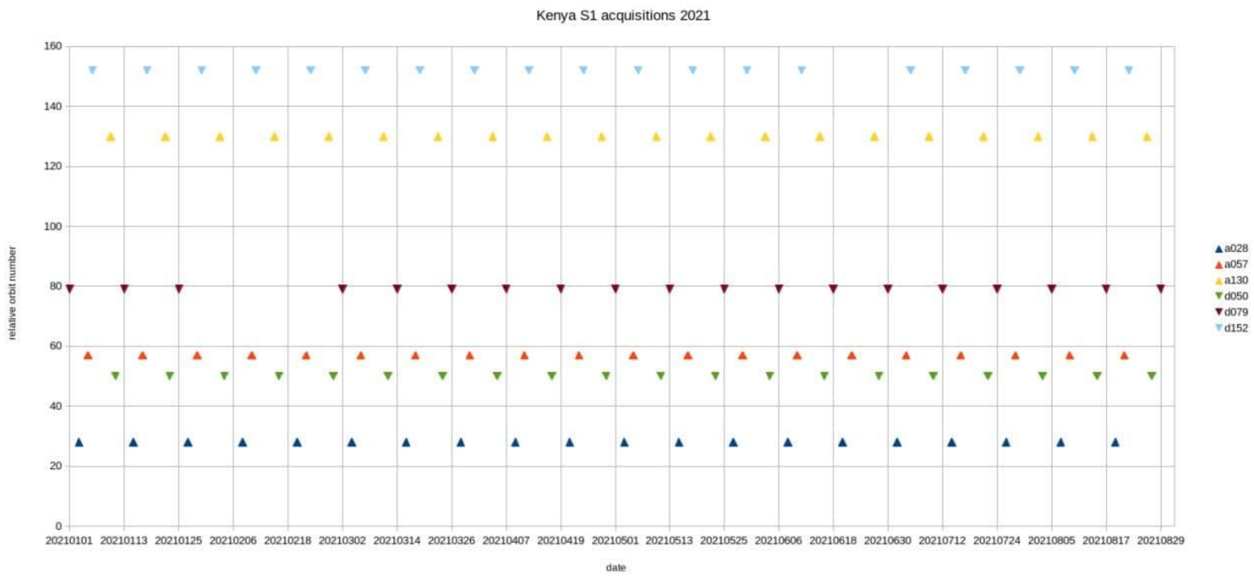


Figure 2. Sentinel-1 acquisition dates over Kenya.

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 0.2 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.

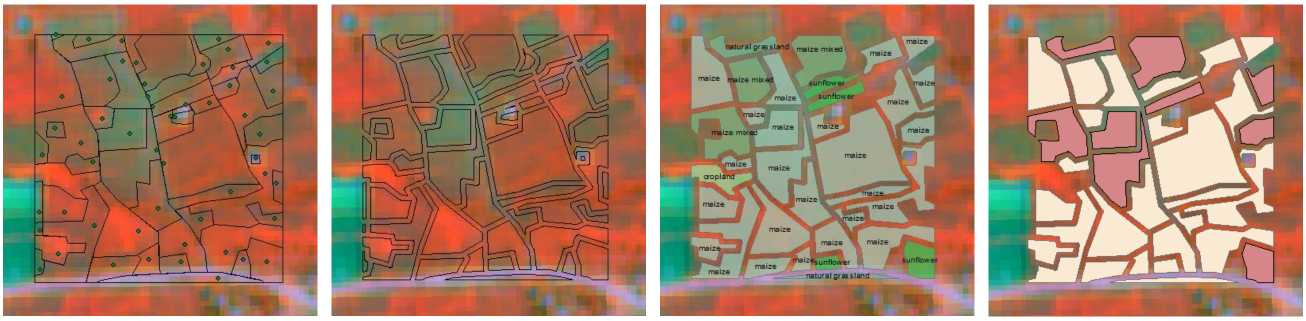
2) A negative buffer of 5 meters is applied to eliminate, or at least minimize, the boundary effects between different classes that will negatively impact the purity of training samples signatures. Consequently, polygons are always separated by 10 meters, which corresponds to the size of 1 Sentinel-2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

3) The acreage of each buffered polygon is calculated and all polygons smaller than 0.2 ha are deleted. It should be noticed that the threshold of 0.2 ha (approximatively 18 contiguous S2 pixels) is larger than the Minimum Mapping Unit from the technical specifications and the MMU applied for the in-season mapping for the step 3 to better consider the observed agricultural practises in Kenya. Indeed, based on the in-season mapping experience, polygons below 0.2 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 0, 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 (0.2 ha)

Split between training (yellow) & validation (red)

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

Resulting from all the described processing steps, 3,593 polygons, covering approximatively 3,950 ha are available for the classification process. 2,695 are used for training and 898 for validation. In total 38 individual classes are distinguished, mostly individual crops (32).

Figure 4 shows an example of a typical field visited during the campaign, highlighting the small size of the plots, as well as the heterogeneity of the cultivation.

Figure 4. Typical cultivation in Kenya with small plot size and multiple crops (beans and maize)

Summary of the deviations from the in-season mapping:

- Deletion of polygons smaller than 0.2 ha (0.1 ha during the in-season mapping).

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 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. 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).

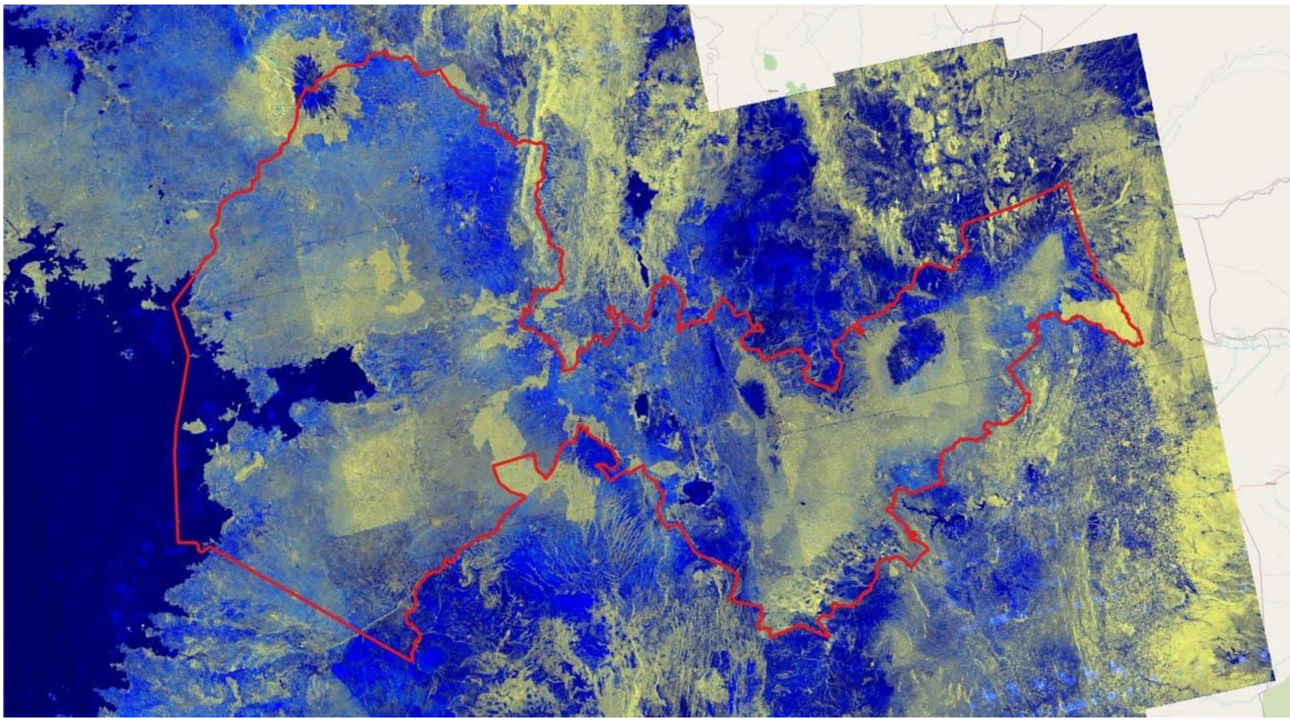


Figure 5. Sentinel-1 synthetic colour composite over the Kenyan AOI (red outline).

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

[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

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 below shows an example for tile 36MZU, with a centre-date of 15-03-2021. For this synthesis, the algorithm considers all images +/- 45 days from 15-03-2021, and takes the cloud-free pixel closest to the centre date.

Figure 6: Sentinel-2 monthly synthesis composite (true colour RGB composition), 15/03/2021, tile 36MZU.

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 Kenya when reviewing the size of the agricultural fields.

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

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

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.

3.2 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 Kenya 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 Kenyan 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 38 classes (of which 32 crop types). The Figure 7 shows the result of the raw classification output, before post-processing.

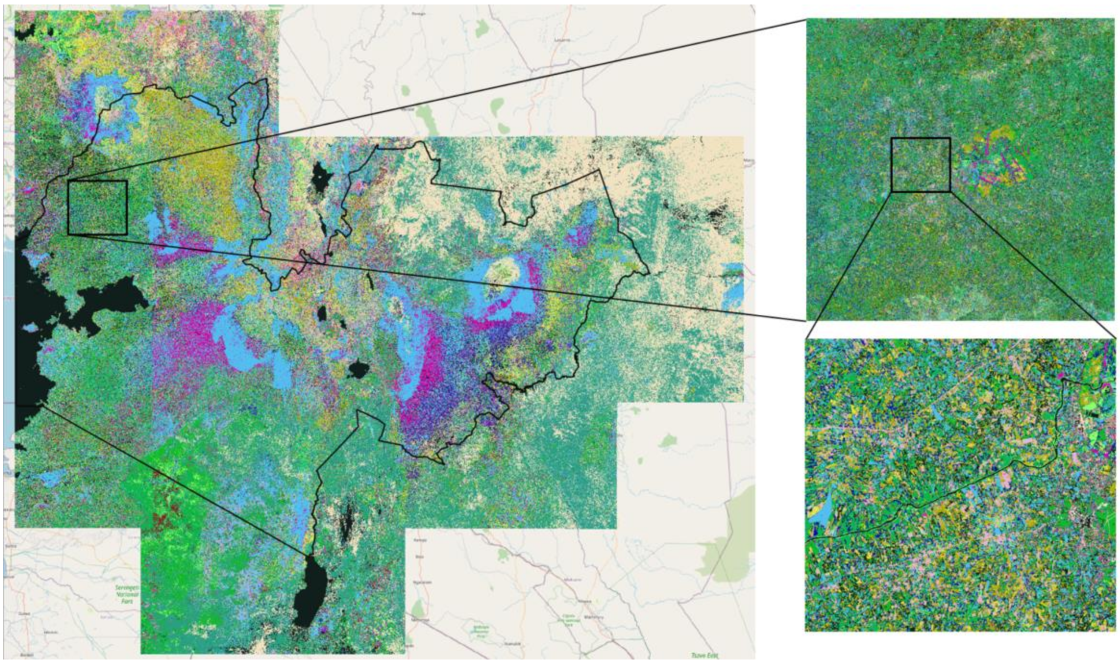


Figure 7. Raw classification output end-of-season crop type map Tanzania.

For the end-of-season mapping, a test is being performed on using S1 monthly synthesis data (as well as a combination of S1 and S2) on a single tile (36MYA). Based on monthly synthesis Sentinel-2 images (L3A) and monthly Sentinal-1 data, the RF and TempCNN classifier are being tested to produce the crop type map [*at the time of writing this report, the results are not available yet, but will be reported in a new version of the document*].

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 32 individual crop types or mixed cropping): Crops

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

The results of the test to use a combination of S1 and S2 data as described above for mapping crop types will also be used to analyse if we can further increase Crop Mask 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 38 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 (Kenya_CropType_EndOfSeason_LongRains_2021.tif & Kenya_CropMask_EndOfSeason_LongRains_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
3	millet	
4	beans	
11	potatoes	including mixed cropping with potatoes as dominant crop
13	wheat	
14	sugarcane	
15	tea	
16	rice	
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 manual recoding has been done along edges of tiles to eliminate hard boundaries between different classes. Some obvious classification errors have been recoded, e.g. the presence of crop 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 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.

3.3 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 Kenya.

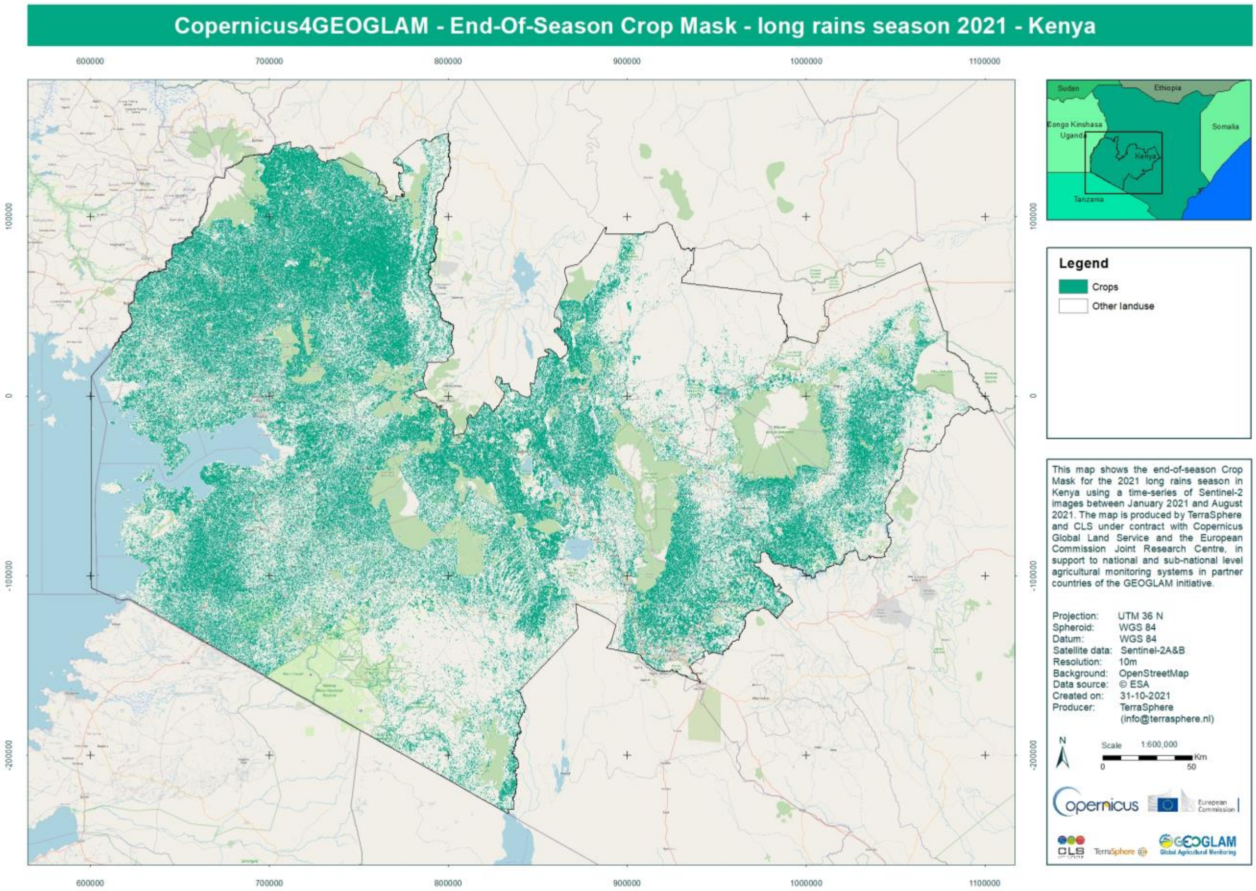


Figure 8. End-of-season Crop Mask for Kenya 2021.

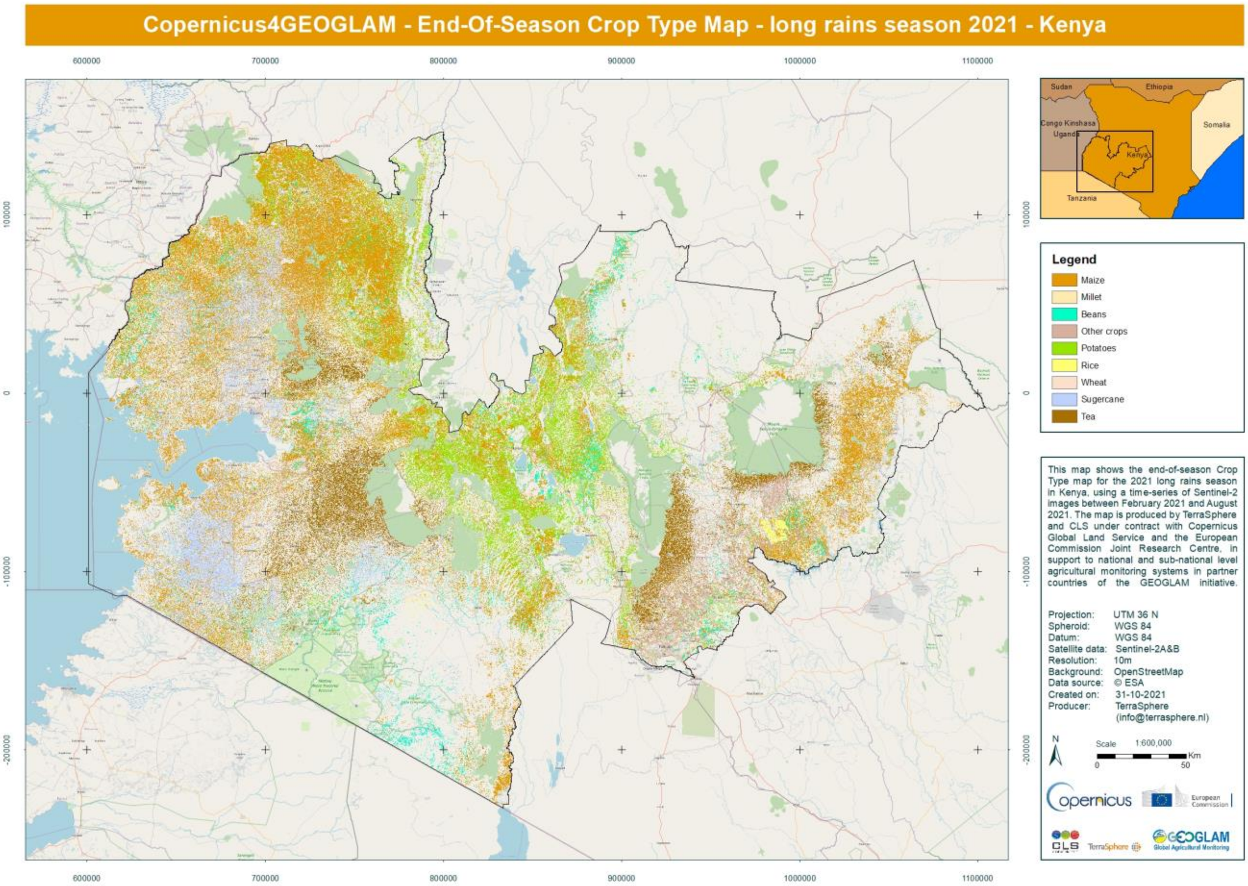


Figure 9. End-of-season Crop Type map for Kenya 2021.

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 end-of-season mapping for Kenya	Reference												
Map	Maize	Millet	Beans	Potatoes	Wheat	Sugarcane	Tea	Rice	Other crops	Other landcover	Total	User Accuracy	F-Score
Maize	9376		62	79	45	118	28		266	4073	14047	0,67	0,64
Millet	118	504	45		212	23			1	157	1060	0,48	0,64
Beans	281		212			24			18	2100	2635	0,08	0,13
Potatoes	805		106	854	142	3			77	1475	3462	0,25	0,38
Wheat	87	3			148	6				29	273	0,54	0,36
Sugarcane	1487					941			86	1891	4405	0,21	0,32
Tea	82						505		49	1114	1750	0,29	0,42
Rice								0			0	N/A	N/A
Other crops	115				4		7		246	244	616	0,40	0,26
Other landcover	2953	15	83	126	7	280	122		519	67765	71870	0,94	0,90
Total	15304	522	508	1059	558	1395	662	0	1262	78848	100118		
Producer accuracy	0,61	0,97	0,42	0,81	0,27	0,67	0,76	N/A	0,19	0,86			

Overall accuracy	0,80
Crop Type User accuracy	0,45
Crop Type Producer accuracy	0,60

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

Cropland mask end-of-season mapping for Kenya		Reference				
		Non-crop	Crop	Total	User Accuracy	F-Score
Map	Non-crop	67765	4105	71870	0,94	0,90
	Crop	11083	17165	28248	0,61	0,69
	Total	78848	21270	100118		
	Producer accuracy	0,86	0,81		Overall accuracy	0,85

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 85%, 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 both user and producer accuracies for the crop class with respectively 29% and 19% commission and omission errors.

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, even if a slight improvement of the overall accuracy both crop type mapping and crop mask (small increase of 1-2%) should be noted, the results at crop type level are heterogeneous. Indeed, the validation exercise shows a decrease of the omission errors (better producer accuracies) but an increase of the commission errors (lower user accuracies). In details:

- F-Scores for the “Maize” class are identical (0.64) but an increase of the commission errors and a decrease of the omissions should be noticed for the end-of-season.
- The classes “Millet” and “Wheat” shows a better F-Score for the end-of-season mapping (respectively 0.64 and 0.36) with a decrease of the commission errors but an increase of the omission errors.
- The classes “Beans”, “Sugarcane” and “Tea” show a lower F-Score (respectively 0.13, 0.32 and 0.42) for the end-of-season mapping with an increase of both omission and commission errors.
- “Potatoes” is the only class that shows a better F-Score (0.38) for the end-of-season mapping with both better user and producer accuracies.

The classes “Maize” and “Millet” show the best individual results with F1-Score of 0.64. The lower results are obtained for the class “Beans”.

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.

3.5 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.

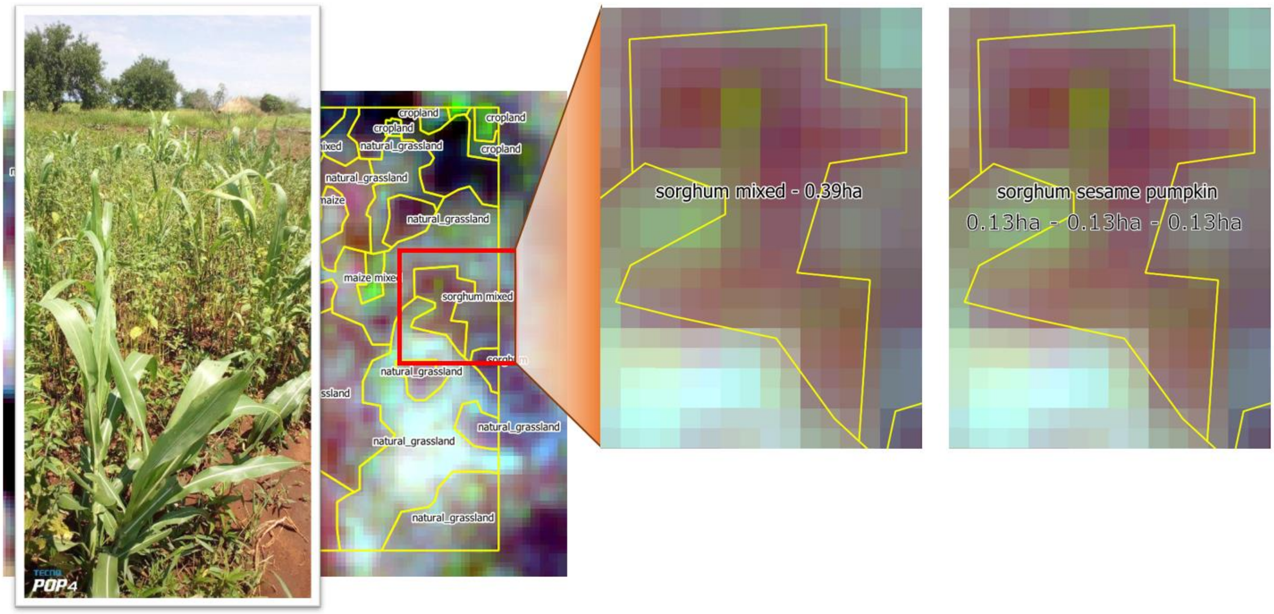


Figure 12: Mixed cropping fields and crop area estimates

(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.

Table 4 shows the results of the crop area estimates for Kenya. It is interesting to notice the very good relative efficiencies for most of the crop types with figures greater than 2. For example, for millet, the same reduction in variance would have been achieved by increasing the size of the field survey sample by 17.

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

Following the feedback from the end users, some deviations have been applied compared to the in-season mapping to better consider the mixed cropping practice. For the end-of-season mapping, all the crops surveyed in a parcel are now considering for the crop area estimates, contributing equally to the total area of the parcel. Previously, only the dominant crop was considered for the associated parcel.

Table 4: Area estimates for the end-of-season mapping

AOI Area (ha)	9 868 656,42	**Maize**	**Millet**	**Beans**	**Potatoes**	**Wheat**	**Sugarcane**	**Tea**	**Rice**	**Other crops**	**Other landcover**
Direct Expansion	Estimate of proportion	0,12	0,00	0,03	0,02	0,00	0,02	0,01	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	**1 232 677,92**	**47 106,41**	**303 800,81**	**183 905,02**	**33 680,26**	**179 329,85**	**145 596,34**	**421,80**	**464 767,35**	**7 277 370,67**
	Variance	8 174 650 115,29	560 924 791,93	1 253 280 425,48	1 343 994 411,46	238 307 741,79	2 154 078 564,90	1 671 343 068,61	177 914,26	3 286 745 903,26	20 271 223 188,07
	Standard Error	90 413,77	23 683,85	35 401,70	36 660,53	15 437,22	46 412,05	40 882,06	421,80	57 330,15	142 377,05
	95% Confidence Interval	177 210,99	46 420,35	69 387,33	71 854,64	30 256,95	90 967,62	80 128,84	826,73	112 367,09	279 059,01
Pixel count	Map (ha)	**1 397 928,47**	**36 823,51**	**225 630,34**	**501 070,80**	**37 440,26**	**479 510,98**	**390 476,96**	**8 018,95**	**189 516,52**	**6 602 239,64**
	Map (%)	0,14	0,00	0,02	0,05	0,00	0,05	0,04	0,00	0,02	0,67
Regression Estimator	Regression estimate	0,12	0,00	0,03	0,02	0,00	0,02	0,02	N/A	0,05	0,73
	Variance	0,00	0,00	0,00	0,00	0,00	0,00	0,00	N/A	0,00	0,00
	Standard Error	0,01	0,00	0,00	0,00	0,00	0,00	0,00	N/A	0,00	0,00
	95% Confidence Interval	0,01	0,00	0,00	0,00	0,00	0,00	0,00	N/A	0,00	0,00
	Regression estimate of the class area	**1 198 857,36**	**14 558,62**	**320 201,81**	**196 603,17**	**17 783,52**	**177 286,03**	**168 132,78**	**N/A**	**501 552,97**	**7 201 855,13**
	Variance	3 461 374 440,30	32 898 104,24	1 070 179 496,92	569 126 520,44	107 084 525,39	463 169 819,68	444 858 315,45	N/A	2 734 232 929,08	8 310 499 500,55
	Standard Error	58 833,45	5 735,69	32 713,60	23 856,37	10 348,17	21 521,38	21 091,66	N/A	52 289,89	91 161,94
	95% Confidence Interval	115 313,56	11 241,95	64 118,65	46 758,49	20 282,40	42 181,91	41 339,66	N/A	102 488,19	178 677,40
Efficiency	Regression Estimator	**2,36**	**17,05**	**1,17**	**2,36**	**2,23**	**4,65**	**3,76**	**N/A**	**1,20**	**2,44**

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 using IOTA2 yields the best results so far. The overall accuracy for the end-of-season Crop Type map is 80% and the end-of-season Crop Mask 85%, which is better than what was mentioned in the feasibility study (both 65%) and slightly better than the in-season mapping (better producer accuracy but lower user accuracy). For some individual crops though (e.g. beans), lower accuracies are reported. Tests using a combination of S1 and S2 are conducted to improve the end-of-season mapping by including SAR data in the classification algorithm [*results not available at the time of writing the version 1.0 of the report*].