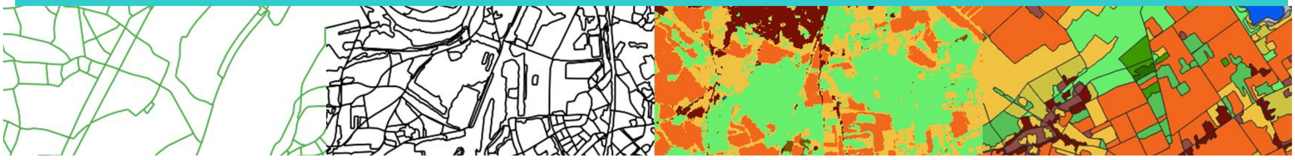
Service contract for the Copernicus Land monitoring services

Crop Mapping for GEOGLAM Country Level Support



Framework contract 939708-2020-IPR

End-of-season Crop Type Map & Crop Mask

Kenya - short rains season - 2021

Prepared by:

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

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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 Kenya 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 mapping. 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 Kenya and implemented for the in-season mapping.

The current short rains season in Kenya was affected by severe drought[1], impacting the North of the country but also the Eastern parts of the AOI and consequently the results of the end-of-season mapping. The drought has affected crop growth in the beginning of the season, reduced the availability of water and pasture for livestock. Several media have reported decimated crops and high livestock death; some of them mentioning failed rainy season[2].

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.

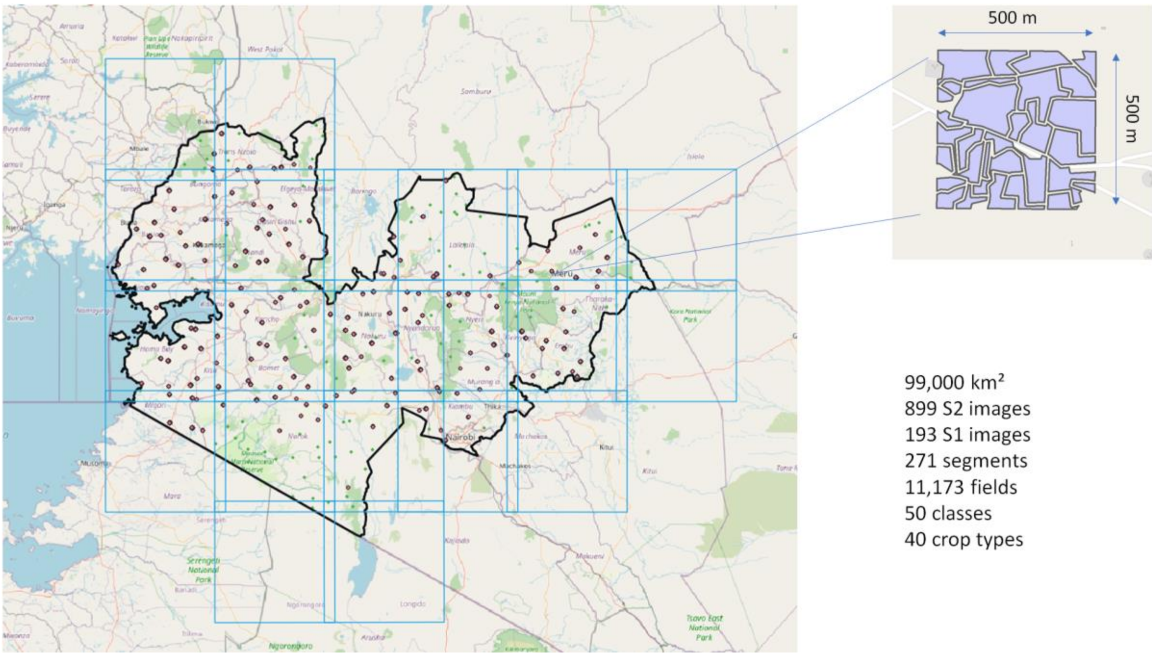


Figure 1. Kenya AOI overlaid with the S2 tile-based grid and the fieldwork segments

[1] https://mars.jrc.ec.europa.eu/asap/country.php?cntry=257

[2] https://news.un.org/en/story/2022/02/1111472

2.1 Satellite data

Sentinel-2

In total, 899 Sentinel-2A & B Level-2A images have been acquired covering 21 tiles between 03-10-2021 and 29-03-2022 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 Images
37MCU	05/10/2021	24/03/2022	19
37MBV	03/10/2021	27/03/2022	51
37MCV	05/10/2021	29/03/2022	24
36NXG	03/10/2021	30/03/2022	65
36NYG	03/10/2021	27/03/2022	31
36MXE	03/10/2021	27/03/2022	25
36MZE	03/10/2021	29/03/2022	64
36MYE	03/10/2021	27/03/2022	25
36NXF	08/10/2021	30/03/2022	50
36NYF	03/10/2021	27/03/2022	30
36NZF	03/10/2021	29/03/2022	64
37MDV	02/10/2021	29/03/2022	43
37NBA	03/10/2021	29/03/2022	62
37NCA	05/10/2021	29/03/2022	32
37NDA	02/10/2021	29/03/2022	58
36MYC	03/10/2021	29/03/2022	60
36MZC	03/10/2021	29/03/2022	61
36MXD	03/10/2021	27/03/2022	26
36MYD	03/10/2021	22/03/2022	27
36MZD	03/10/2021	29/03/2022	56
37MBU	05/10/2021	29/03/2022	26

Sentinel-1

In total, 120 Sentinel-1 images have been used to cover the Kenyan AOI between 01-10-2021 and 30-03-2022 for the end-of-season mapping of the short rains season. 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.

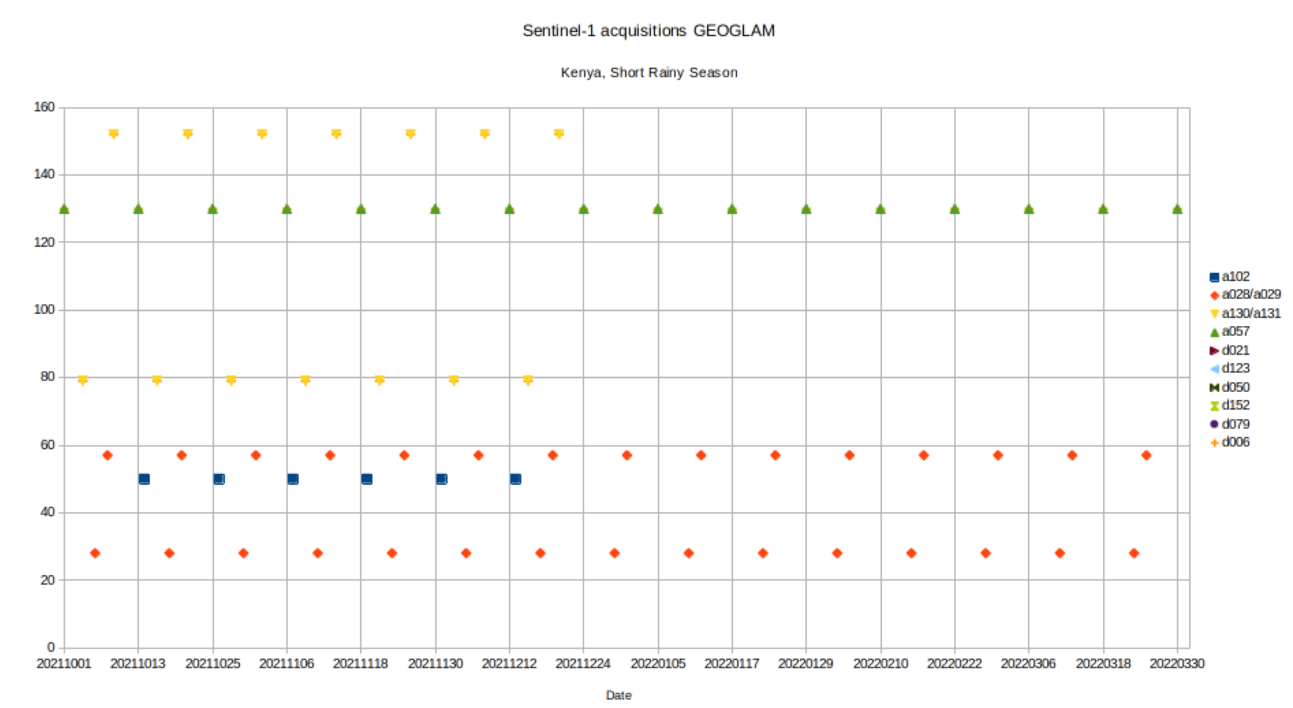


Figure 2. Sentinel-1 acquisition dates over Kenya.

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. Manual quality check of all training/validation polygons.
5. Splitting of data between training (75%) & validation (25%) sets;

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.

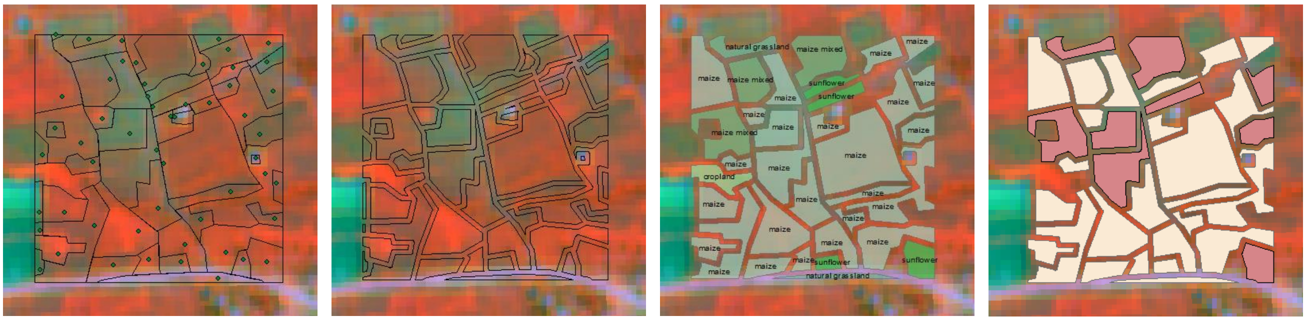
2) A negative buffer of 5 meters is applied to eliminate, or at least minimize, the boundary effects between different classes that will negatively impact the purity of training samples signatures. Consequently, polygons are always separated by 10 meters, which corresponds to the size of 1 Sentinel-2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

3) The acreage of each buffered polygon is calculated and all polygons smaller than 0.2 ha are deleted. Based on the long rains season 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) 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, the classification workflow is applied per S2-based block (see section 3.2).

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, 3,147 polygons, covering approximatively 4,309 ha are available for the classification process. 2,360 are used for training and 787 for validation. In total 50 individual classes are distinguished, mostly individual crops (40).

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 short rains in-season mapping:
The only deviation from what has been done for the in-season mapping concerns the MMU used for deleting the polygons. During the in-season mapping, all polygons smaller than 0.1 ha were deleted. For the end-of-season mapping, we used 0.2 ha to keep the polygons considered spectrally homogeneous.

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[3];
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[4]). 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 36MXD, with

[3] 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

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

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.

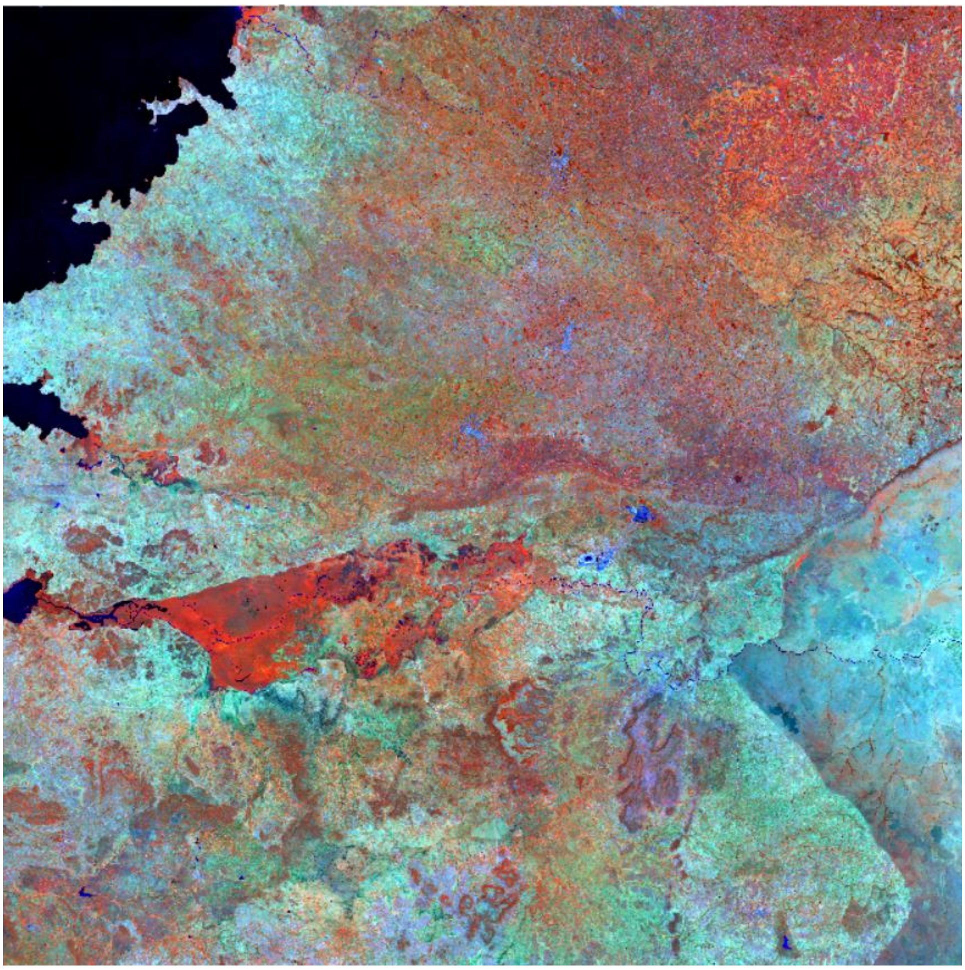


Figure 5: Sentinel-2 monthly synthesis composite (true colour RGB composition), 15/01/2022, tile 36MXD.

Based on these monthly synthesis, four spectral indices are computed: the Weighted Difference Vegetation Index (WDVI[5]), 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.

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.

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

- 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.

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 algorithms were tested during the previous long rains season, including supervised (maximum likelihood) classification, TempCNN and Random Forest (RF). Similar to the long rains season, it was decided to use the RF classification as final method for the Kenyan 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 50 classes (of which 40 crop types). The Figure 6 shows the result of the raw classification output, before post-processing.

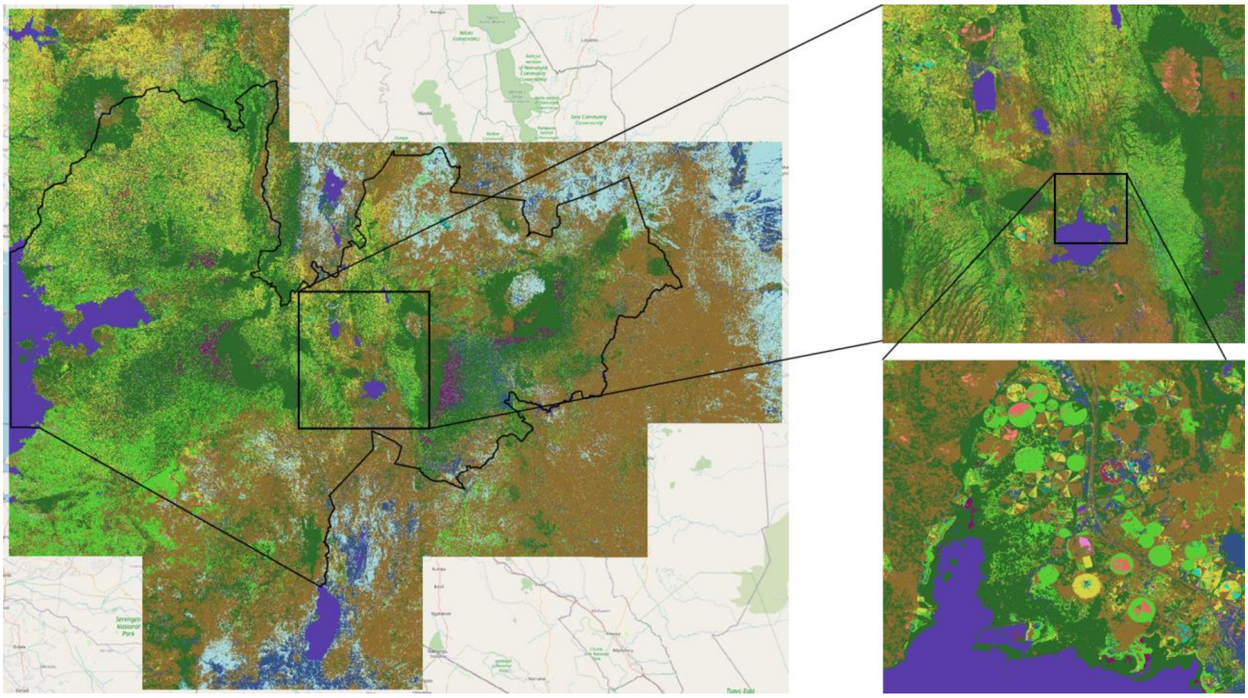


Figure 6. Raw classification output end-of-season crop type map Kenya

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 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>

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_ShortRains_2021.tif & Kenya_CropMask_EndOfSeason_ShortRains_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 (>50% coverage)
4	beans	including mixed cropping with beans as dominant crop (>50% coverage)
11	potatoes	including mixed cropping with potatoes as dominant crop (>50% coverage)
13	wheat	including mixed cropping with wheat as dominant crop (>50% coverage)
14	sugarcane	including mixed cropping with sugarcane as dominant crop (>50% coverage)
15	tea	including mixed cropping with tea as dominant crop (>50% coverage)
20	Elephant grass	including mixed cropping with elephant grass as dominant crop (>50% coverage)
21	Banana	including mixed cropping with banana 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 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 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, millet, beans, potatoes, wheat, sugarcane, tea and rice.

Deviations from feasibility study proposal and the short rains 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.

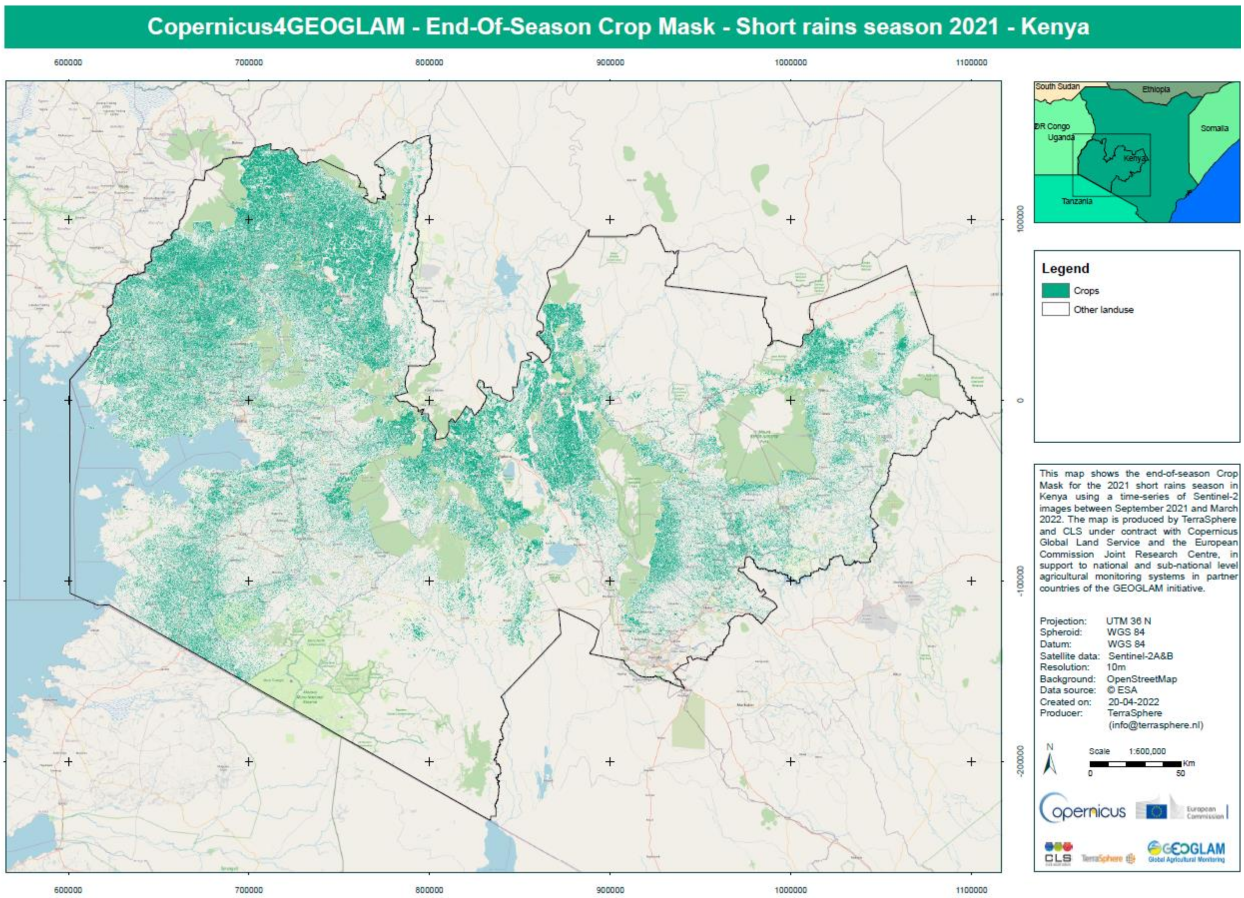


Figure 7. End-of-season Crop Mask for the short rains season 2021 in Kenya

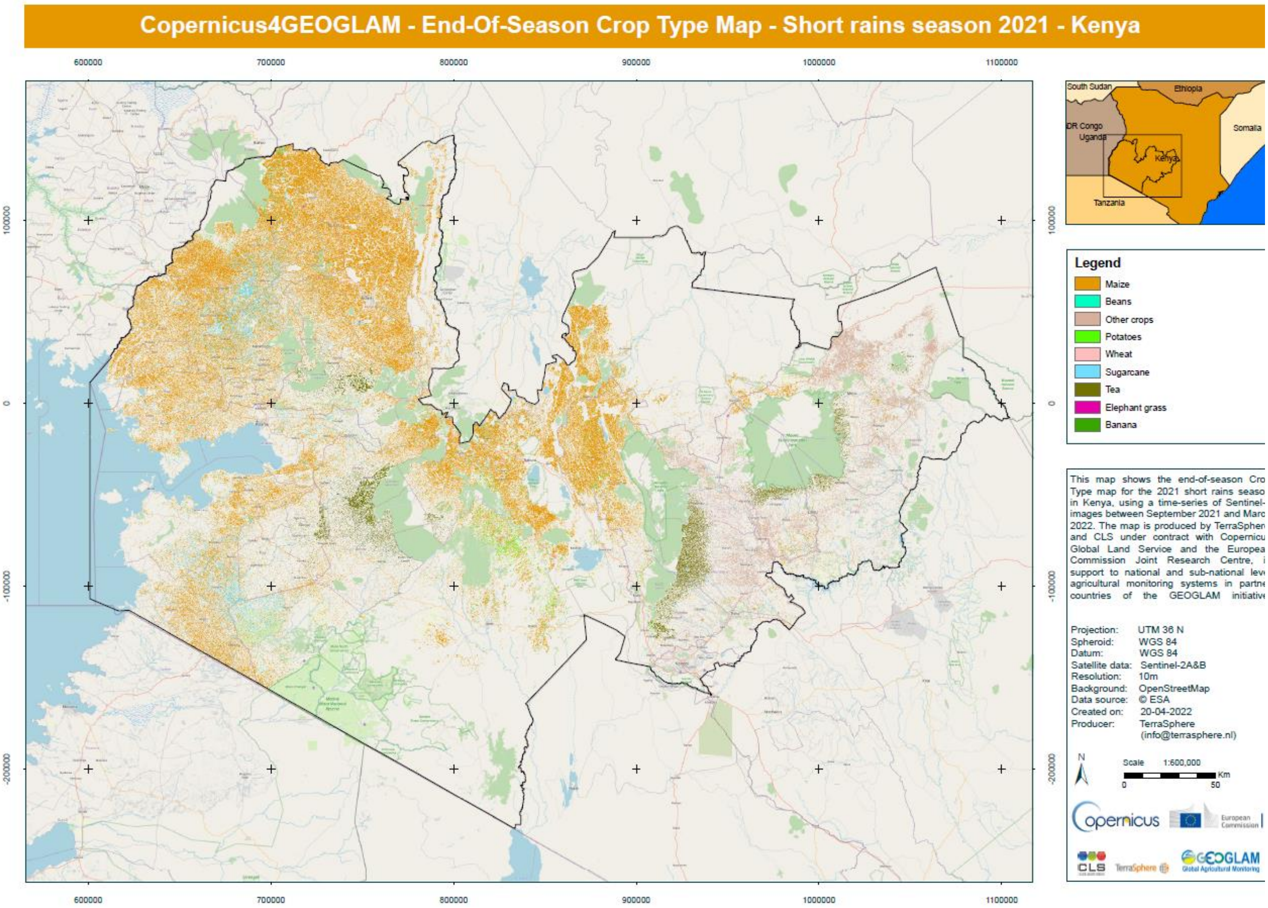


Figure 8. End-of-season Crop Type map for the short rains season 2021 in Kenya

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 (Short rains)

Map \ Reference	Maize	Beans	Potatoes	Wheat	Sugarcane	Tea	Napier grass	Other crops	Other landcover	Total	User Accuracy	F-Score
Maize	**1300**	30	158	9	67		19	15	706	**2304**	0,56	0,55
Beans	3	**60**					22	6		**91**	0,66	0,40
Potatoes			**79**	3				34	117	**233**	0,34	0,30
Wheat	7			**28**				2		**37**	0,76	0,32
Sugarcane	27				**142**			6	24	**199**	0,71	0,39
Tea						**118**			15	**133**	0,89	0,60
Napier grass									9	**9**	0,00	N/A
Other crops	70	9	5					**177**	71	**332**	0,53	0,40
Other landcover	988	111	50	100	326	140	50	319	**19261**	**21345**	0,90	0,93
Total	**2395**	**210**	**292**	**140**	**535**	**258**	**91**	**559**	**20203**	**24683**		
Producer accuracy	0,54	0,29	0,27	0,20	0,27	0,46	0,00	0,32	0,95			

Overall accuracy	0,86
Crop Type User accuracy	0,57
Crop Type Producer accuracy	0,43

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

Cropland mask end-of-season mapping for Kanya (Short Rains Season)

Map \ Reference	Non-crop	Crop	Total	User Accuracy	F-Score
Non-crop	**19261**	2084	**21345**	0,90	0,93
Crop	942	**2396**	**3338**	0,72	0,61
Total	**20203**	**4480**	**24683**		
Producer accuracy	0,95	0,53			

Overall accuracy	**0,88**

Figure 10. Confusion matrix for end-of-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 86% and 88%, 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 user accuracy of the crop class (72%) with 28% commission errors. The producer accuracy of the crop class presents low results (53%) with 47% omission errors. Large decrease of the producer accuracy is to be noted compared to the end-of-season mapping for the long rains season (a decrease of 28%).

With the addition of end-of-season satellite imagery, the results for the end-of-season mapping are slightly better than the in-season. Indeed, even if the overall accuracy both crop type map and crop mask remains almost identical (small increase or decrease of 1-4%), the results at crop type level are better for the end-of-season mapping. Indeed, the validation exercise shows an increase of the F1-Score. In details:

- F1-Score for the "Maize" class is identical (0.55) and remains encouraging,
- The class "Tea" shows a lower F1-Score for the end-of-season mapping (0.60) but results are still very satisfying.
- The classes "Beans", "Potatoes", "Wheat" and Sugarcane" shows a better F1-Score for the end-of-season mapping (respectively 0.40, 0.30, 0.32 and 0.39) with large increase of both omission and commission errors.

The large improvements of the results between the in-season and the end-of-season can be explained by the drought that affected the beginning on the growing season in Eastern Africa as explained in the crop mapping report of the in-season (D3.4). The addition of images up to late March permits increasing the accuracies with the biomass increasing.

Indeed the current short rains season in Northern and Eastern districts in Kenya was influenced by anomalous weather conditions late 2021. Very dry conditions throughout Eastern part of the AOI results in very late planting and failed crops. It has been observed during our fieldwork campaign many fields during the anticipated height of the growing season were still being prepared (waiting for rains). The field campaign report (D2.1) also showed that the agricultural activities in Kenya were preponderant during the first season. The preliminary area estimates showed a decrease of the areas covered by cropland between the two rainy seasons (from 33,822 to 28,389 km²) and an increase of the areas covered by bare soils. Areas covered by bare land with crops planted or fields in preparation stage have increased and represent one of the most dominant classes surveyed during the second field campaign. The situation is confirmed on the EU ASAP service, where biomass and water balance red alerts were issued from October 2021 onwards (see Figure 11).

Due to the dry circumstances in the first part of the growing season (mainly in in the Eastern districts), the in-season mapping resulted in erroneous data because some fields showed only very few biomasses up to now resulting in confusion between bare land and cropland.

Nevertheless, the situation improved slightly during the last few weeks with the arrival of rain. Consequently, end-of-season mapping results improve as well as biomass is increasing rapidly now as observed on the latest S2 images (March 2022).

Following these considerations, improvements of the accuracies were achieved for the end-of-season mapping through the addition of end-of-season satellite imagery.

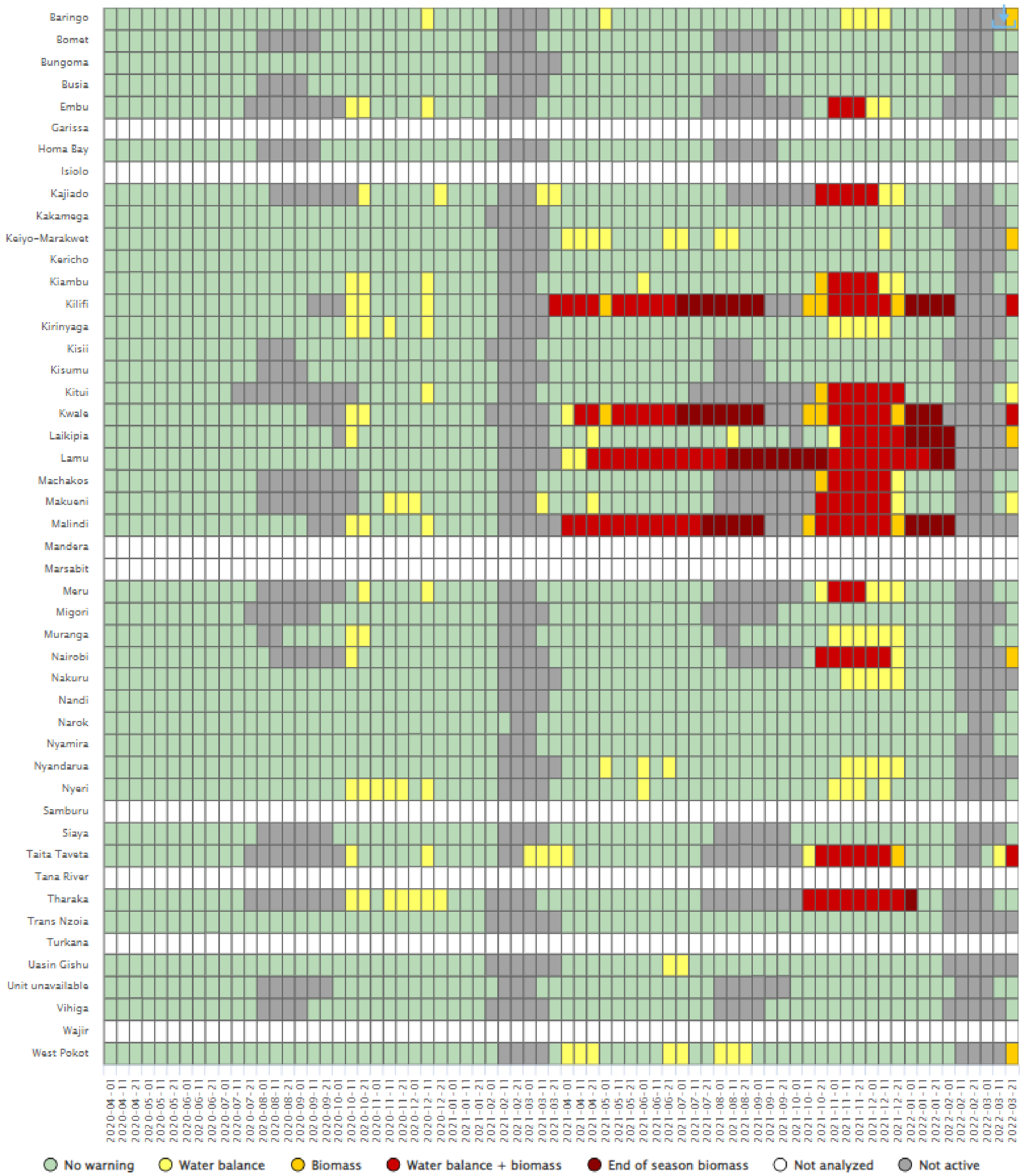


Figure 11: Biomass and water balance red alerts (source: EU ASAP service)

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 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.

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 12 illustrates the change with one example.

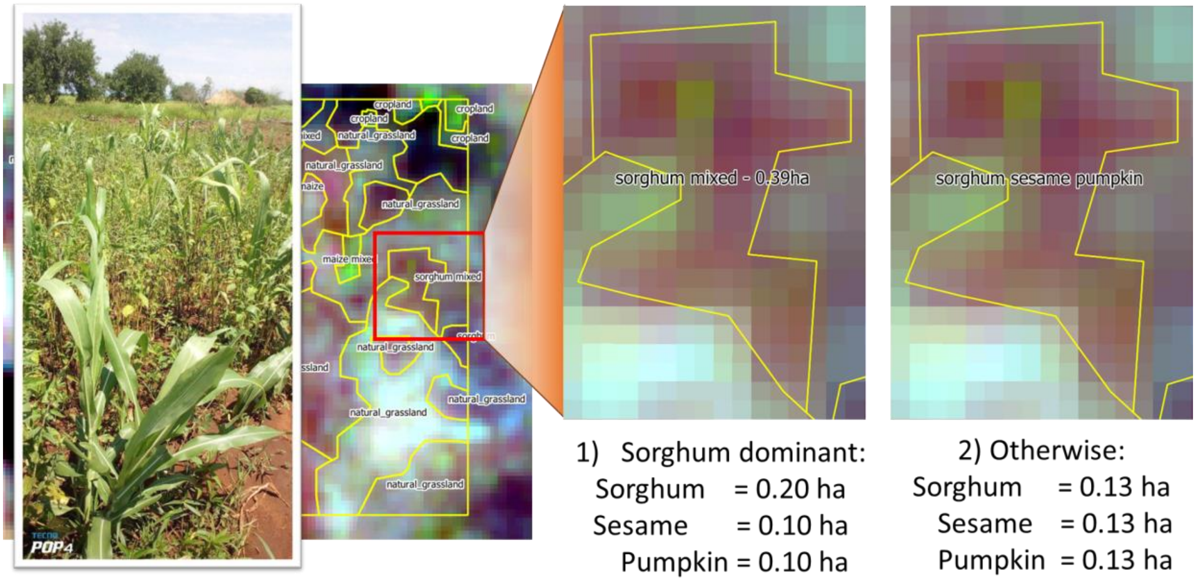


Figure 12: Mixed cropping fields and crop area estimates

(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 for the end-of-season of the short rains season. It is interesting to notice the very good relative efficiencies for most of the crop types with figures greater than 2. For example, for sugarcane, the same reduction in variance would have been achieved by increasing the size of the field survey sample by 7.

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.

Table 4: Area estimates for the end-of-season mapping of the short rains season 2021 in Kenya

AOI Area (ha)	9 868 656,42	Maize	Beans	Potatoes	Wheat	Sugarcane	Tea	Napier grass	Banana	Other crops	Other landcover
Direct Expansion	Estimate of proportion	0,10	0,01	0,01	0,00	0,02	0,01	0,01	0,00	0,04	0,79
	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	**948 005,14**	**144 158,03**	**108 906,31**	**43 400,44**	**193 610,72**	**133 165,41**	**71 414,05**	**42 513,34**	**380 497,50**	**7 802 985,50**
	Variance	7 241 740 919,08	587 969 752,61	574 294 250,04	447 784 654,42	2 022 105 408,29	1 578 388 780,50	125 258 343,46	68 474 887,85	2 310 966 131,61	16 463 395 643,30
	Standard Error	85 098,42	24 248,09	23 964,44	21 160,92	44 967,83	39 728,94	11 191,89	8 274,96	48 072,51	128 309,76
	95% Confidence Interval	166 792,90	47 526,25	46 970,30	41 475,41	88 136,94	77 868,73	21 936,10	16 218,91	94 222,12	251 487,14
Pixel count	Map (ha)	**1 219 789,50**	**17 999,20**	**22 928,17**	**10 235,19**	**90 895,39**	**105 246,76**	**938,46**	**-**	**206 891,59**	**8 193 732,15**
	Map (%)	0,12	0,00	0,00	0,00	0,01	0,01	0,00	-	0,02	0,83
Regression Estimator	Regression estimate	0,09	0,01	0,01	0,00	0,01	0,01	0,01	N/A	0,03	0,82
	Variance	0,00	0,00	0,00	0,00	0,00	0,00	0,00	N/A	-	0,00
	Standard Error	0,01	0,00	0,00	0,00	0,00	0,00	0,00	N/A	-	0,00
	95% Confidence Interval	0,01	0,00	0,00	0,00	0,00	0,00	0,00	N/A	-	0,00
	Regression estimate of the class area	**908 044,60**	**94 661,94**	**69 788,34**	**15 698,13**	**134 983,89**	**122 016,43**	**52 676,42**	**N/A**	**343 103,50**	**8 046 990,93**
	Variance	3 291 933 527,79	156 037 532,76	153 247 814,00	9 827 221,73	288 869 612,37	418 325 895,66	72 451 426,10	N/A	1 444 709 112,82	7 032 375 812,63
	Standard Error	57 375,37	12 491,50	12 379,33	3 134,84	16 996,16	20 453,02	8 511,84	N/A	38 009,33	83 859,26
	95% Confidence Interval	112 455,73	24 483,34	24 263,49	6 144,29	33 312,48	40 087,91	16 683,21	N/A	74 498,29	164 364,15
Efficiency	Regression Estimator	**2,20**	**3,77**	**3,75**	**45,57**	**7,00**	**3,77**	**1,73**	**N/A**	**1,60**	**2,34**

4 Conclusions

The results for the short rains season have been affected by the severe drought, impacting the North of the country but also the Eastern parts of the AOI. Very dry conditions result in very late planting, failed crops. The overall accuracy for the end-of-season Crop Type map is 86% and the end-of-season Crop Mask 86%, which is better than what was mentioned in the feasibility study (both 65%) and slightly better than the in-season mapping at individual crop level (better for both producer and user accuracies) but lower than the long rains season mapping. Some classes such as maize and tea show satisfying and encouraging results. Very good relative efficiencies of 2 to 45 have been achieved for the main crops.