Helmets Labeling Crops: Kenya Crop Type Dataset Created via Helmet-Mounted Cameras and Deep Learning

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ABSTRACT

Accurate, up-to-date agricultural monitoring is essential for assessing food production, particularly in countries like Kenya, where recurring climate extremes, including floods and droughts, exacerbate food insecurity challenges. In regions dominated by smallholder farmers, a significant obstacle to effective agricultural monitoring is the limited availability of current, detailed crop-type maps. Creating crop-type maps requires extensive field data. However, the high costs associated with field data collection campaigns often make them impractical, resulting in significant data gaps in regions where crop production information is most needed. This paper presents our inaugural dataset comprising 4,925 validated crop-type data points from Kenya's 2021 and 2022 long-rain seasons. Collaborating with institutional partners and an extensive citizen science network, we collected georeferenced images across Kenya using GoPro cameras. We developed and implemented a deep learning pipeline to process images into crop-type datasets. Our methodology incorporates rigorous quality control measures to ensure the integrity and reliability of the data. The resulting dataset represents a significant contribution to open science and a valuable resource for evidence-based agricultural decision-making.

Background & Summary

Understanding food production patterns is fundamental to Sustainable Development Goal 2 (Zero Hunger), especially in food insecure regions. While Earth Observation (EO) data are increasingly the most cost-effective method of quantifying agricultural production, creating accurate crop-type maps requires significant investment in field surveys for collecting essential in-situ data for training and validating EO-derived maps.[1] Historically, this cost barrier has limited consistent crop mapping primarily to high-income countries with established agricultural monitoring systems, for example, Canada's Annual Crop Inventory[2], USDA's Cropland Data Layer[3], and France's "Registre Parcellaire Graphique"[4]. However, consistent and accurate crop data layers are needed in all countries to help realize Sustainable Development Goal 2: Zero-Hunger. Technological and institutional innovations, including approaches to data collection and modeling frameworks, are needed to address this data gap.[5]

Cropland maps provide spatial information on where crops are growing, while crop-type maps go a step further by specifying the type of crop cultivated in each spatial unit (e.g., maize, wheat, or rice)[6]. These maps are critical for EO-based applications, such as crop yield predictions and crop condition assessments, as they enable analysts to focus on pixels that represent cropland or specific crop types. Given that farmers may change the crops grown in a particular field from season to season, crop-type maps must be updated regularly to maintain accuracy[7]. A fundamental input for creating both cropland extent and crop-type maps is labeled data, which consists of georeferenced points indicating cropland and crop types.

While cropland labels are increasingly derived from satellite image interpretation, making cropland maps more accessible[8–10], crop-type mapping remains a significant challenge. Unlike cropland extent, crop types cannot be determined through

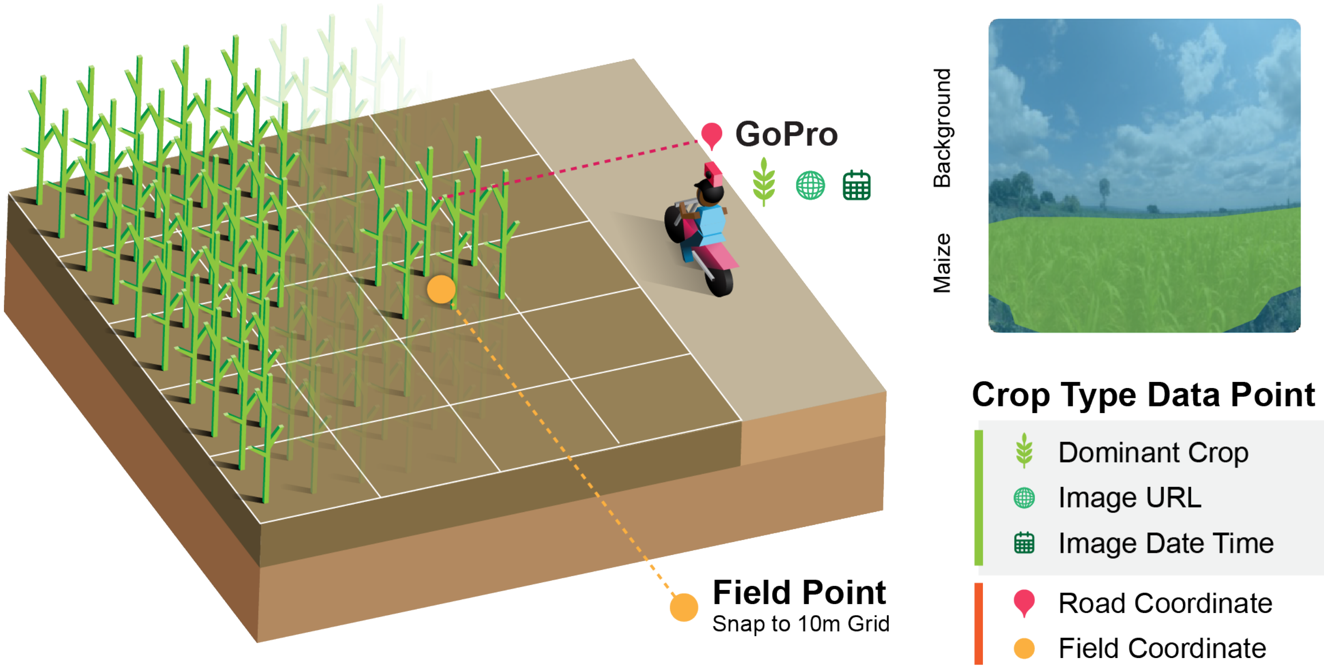

Figure 1. Illustration of crop type data generation pipeline. Steps: 1) Field agent with helmet-mounted GoPro drives along agricultural fields, 2) GoPro captures photo of adjacent field (red dotted line) and road coordinate (red point), 3) field coordinate (orange point) is calculated by moving road coordinate 20 meters into field and snapping to 10 meter grid, 4) GoPro photo is used to predict dominant crop.

image interpretation alone and require extensive field surveys for accurate identification. Traditional methods for collecting crop-type data rely on labor-intensive field visits using GPS devices or smartphone apps, which often result in sparse and unevenly distributed datasets. This is particularly true in low-income regions, where resources for data collection are limited. Consequently, comprehensive crop-type maps with full national coverage or seasonal updates remain scarce, especially in low-income countries where the need for such data is most critical.

Emerging innovations in deep learning and computer vision are transforming in-situ crop type data collection, offering scalable alternatives to traditional methods. Recent studies highlight promising approaches: Paliyam et al. developed Street2Sat, leveraging vehicle-mounted cameras and deep learning to generate georeferenced crop type points in Kenya[11]. Wu et al. introduced the iCrop dataset, based on smartphone-captured roadside imagery in China[12]. Yan and Ryu demonstrated the use of Google Street View and deep learning to produce crop type points and maps in Illinois and California.[13] Similarly, Laguarta et al. applied Google Street View and deep learning to map crop types in smallholder agricultural landscapes in Thailand.[14] d'Andrimont et al. utilized vehicle-mounted cameras to capture multi-temporal imagery, enabling crop phenology tracking for delineated parcels in the Netherlands.[15] Together, these advancements pave the way for overcoming the limitations of traditional data collection methods.

In this paper, we introduce a scalable, low-cost, and effective method for collecting crop-type data in smallholder agricultural landscapes through the Helmets Labeling Crops project. Our approach combines GoPro cameras and deep learning techniques based on the Street2Sat framework[11] to enable rapid and cost-effective field surveys of crop type. We release an open, georeferenced crop-type dataset with associated roadside imagery from 16 counties in Kenya, providing an alternative to proprietary platforms like Google Street View[16] while adhering to FAIR data principles[17]. This initial release will be followed by datasets from additional countries, including Uganda, Tanzania, Zambia, Nigeria, Uruguay, Senegal, India, South Korea, and Bhutan.

Methods

Data Collection

We used 6th Grain's Maize Density Layer[18] and ESA's Global Crop Mask[19] to choose counties to survey to ensure coverage of high, medium, and low-density crop areas across Kenya from 2021-2022. We covered 16 counties across Western, Rift Valley, Central, and Eastern Kenya, selected to capture diverse agro-ecological zones, farming practices, and crop production

Figure 2. Field agent being trained on operating helmet-mounted GoPro for crop type data collection.

intensities covering the counties of Bomet, Bungoma, Homa Bay, Kericho, Kisii, Machakos, Migori, Nakuru, Nandi, Narok, Nyamira, Trans Nzoia, and Uasin Gishu.

In collaboration with the Regional Centre For Mapping Of Resources For Development (RCMRD) and Kenya Ministry of Agriculture, we recruited and trained 25 local agricultural officers as data collectors. These officers received comprehensive training on mounting and operating GoPro cameras to ensure consistent data collection protocols (Figure 2). As part of their regular crop monitoring duties, these officers provided valuable insights into current season crop performance and distribution patterns, which were essential for optimizing data collection routes and timing.

The data collection strategy utilized Kenya's hierarchical road network classification[20] to maximize coverage efficiency. Primary routes (classes A, B, and C) facilitated movement between counties and major towns, while secondary and tertiary networks (classes D and E) enabled access to local farming communities. Field agents reported that GoPro cameras mounted on motorcycles were particularly effective for village-level data collection, offering superior maneuverability and access to remote agricultural areas compared to vehicle-mounted systems. This mobility advantage resulted in more comprehensive coverage of smallholder farms and diverse agricultural landscapes within each target region.

In Kenya, this method was implemented through a collaboration between the Kenyan Ministry of Agriculture and the Regional Centre for Mapping of Resources for Development (RCMRD), following an initial pilot phase in 2020 with LocateIT. After training 59 agricultural officers and engaging local stakeholders, the team captured 397,190 georeferenced images across all campaigns in Kenya.

To support data collection, we developed a comprehensive Data Collection Toolkit (Figure 3) for each agricultural officer. The toolkit included a manual detailing the contents of the kit, GoPro camera settings for data collection, GoPro mounting instructions, step-by-step guidelines for capturing data, and instructions for uploading data. The toolkit (Figure 3) included a GoPro Hero 8 Black, a magnetic car mount (for capturing data in a car), a motorbike helmet mount (for capturing data on a motorcycle), a 512 GB SD, a USB-C to USB-A cable (to charge the GoPro while collecting data), backup GoPro batteries, and a carrying case to keep all items together. We provided a daily GoPro settings checklist for all data collectors to ensure consistent data collection. The checklist ensured that the GPS was enabled, the battery was charged or plugged in, and sufficient storage space was available on the provided SD card. We added instructions for image capture, including camera settings (**Lens**: Narrow, **Format**: Photo, **Mode**: Time-lapse photo, **Interval**: 0.5 seconds). The short time interval allowed us to capture 3-4 photos every 10 meters at typical rural driving speeds. We chose the short interval to have redundancy in the event of obstructions and poor exposure. In the case of narrow fields which are common in smallholder regions, this ensured there was a photo with the field centered and fully visible.

We also provided a guide for mounting the camera for both cars and motorcycles, as an improperly mounted GoPro meant unusable images. For data collection in Kenya, it was crucial always to mount the camera to point left to optimize the visibility of roadside fields, since Kenya is a left-side drive country. GoPros do not record camera heading, which is critical to determining where the crop is located. By mounting the GoPros to the face left, we determine the camera direction by rotating the driving direction 90 degrees to the left (counter-clockwise, see Figure 4).

We created a Google Cloud Storage bucket and a file structure to store all collected images. We provided detailed instructions to all data collectors to upload collected GoPro images using either the Google Cloud user interface or command line interface (to allow for parallel uploads). We stored the images on Google Cloud Storage to allow for a central repository with managed permissions.

Crop Prediction using Deep Learning

Smallholder fields in Kenya present two challenges to determining the crop from a GoPro image. First, some fields contain multiple crops (inter-cropping); second, the small size of the fields means multiple fields can be visible in a single image. Unlike prior work which formulated the crop recognition task as image classification (one crop label predicted for the entire image), we formulated the crop recognition task as image segmentation. By asking the model to segment the image into crops and background, we measure crop proportion through the number of pixels segmented as each crop type. In addition, we get a fine-grained model output, which can be useful for debugging model failure modes. We experimented with formulating the crop recognition task as object detection (as in Paliyam et al.[11]) but found that labeling and identifying each crop with a bounding box was labor-intensive and difficult to predict with object detection methods.

Table 1. Segmentation dataset distribution and metrics per crop type

Crop Type	Training	Validation	Precision	Recall
Banana	407	55	0.88	0.98
Maize	1272	184	0.85	0.93
Rice	1194	181	0.86	0.96
Soybean	351	48	0.97	0.99
Sugarcane	174	31	0.87	0.98
Sunflower	384	51	0.97	0.98
Tobacco	66	9	0.99	0.99
Wheat	480	72	0.94	0.99
Null (Prevent False Positives)	504	60	0.86	0.93

Crop Segmentation

We trained a Feature Pyramid (FPN) model with an Xception backbone to predict crops within an image. Our model achieved a 92.5% mean average precision on our held-out validation dataset. We also tested a U-net[21] and Linknet[22] architecture but found lower performance.

To train the image segmentation model we labeled a dataset of 2302 images with 8 different classes (Table 1): maize, banana, rice, soybean, sugarcane, sunflower, tobacco, and wheat. These crops (particularly maize, banana, rice, and wheat) were selected for their importance to food security in East Africa and their high likelihood for cultivation in the 16 counties surveyed. Maize, for instance, is a vital food security crop, contributing 36% of caloric intake in Kenya alone[26]. Similarly, rice, wheat, and bananas are integral to regional diets and have significant nutritional and economic impacts[27]. Collectively, these crops provide a solid foundation for evaluating agricultural patterns and enhancing food security across the region.

Table 2. Data distribution by source

Source	Training	Validation	Total
Tanzania	3027	422	3449
Kenya	87	16	103
Uganda	486	76	562
USA	369	50	419
Kaggle[23]	369	52	421
Kaggle[24]	314	47	361
FlevoVision[25]	180	28	208
Total	**4832**	**691**	**5523**

We gathered training images from previous field campaigns and existing datasets of crop images (Table 2). We manually labeled a segmentation mask in each image using the Roboflow annotation tool. We allocated 30% of the crop images for validation.

We applied several augmentation techniques (rotation: ± 5 degrees, contrast: $\pm 5\%$, horizontal flip, and exposure: $\pm 3\%$) to increase the size of the training set to 4832 images. We resized all images to 800×800 pixels. We applied adaptive gamma correction[28] after observing that lighting conditions significantly affected model performance. The full segmentation dataset is publicly available on Roboflow: https://app.roboflow.com/ivan-zvonkov/street2sat-segmentation/overview.

Filtering images that contain crops

We found that a significant amount of collected images contained no crops. Rather than running the relatively computationally heavy segmentation model on all images, we decided to train a lightweight binary crop classification model to filter out images that did not contain any crops before feeding crop images to the segmentation model. We call this the CropNop (crop or not crop) model. We trained a variant of the SqueezeNet model[29], known for its computational efficiency. In addition, the simpler task allowed us to use smaller images (300*x*300 pixels) which further reduced computation requirements.

We created a training dataset using pseudolabels from the segmentation model predictions: if an image was segmented as more than 75% background, the image was labeled non-crop. If the image was segmented as less than 25% background, the image was labeled crop. We gathered crop and non-crop images from Kenya, Uganda, the USA, and Tanzania for a total of 8439 images (Train: 6957 [crop: 3711, non-crop: 3246], and Test: 1482 [crop: 400, non-crop: 1082]). We used the same image preprocessing as for the crop segmentation model. Our model achieved 99% accuracy on the test dataset.

Road to Field Coordinate

For each image, we extracted the GPS coordinates, date, and time from the image's EXIF-formatted metadata. We then projected the coordinates from WGS84 into the Universal Transverse Mercator (UTM) system to enable calculations in meters. We then used the image's coordinates and metadata on the road to compute the coordinates of the crop field captured in each image.

Next, we computed the vehicle's driving direction to determine the GoPro camera's field-facing direction. For each coordinate, we selected the prior coordinate and calculated the difference between the two coordinates to determine the Northing and Easting components of the driving direction. Since Kenya is a left-hand-drive country and the GoPro cameras are mounted on the passenger side, the field-facing direction is obtained by rotating the driving direction 90 degrees to the left.

We applied a 20-meter offset along the field-facing direction from the GoPro's position to estimate the field coordinates. This offset was chosen to minimize overshooting smallholder fields while accounting for GPS error and field buffer zones. At this stage, crop-type data points may form clusters, with consecutive field points spaced only a few meters apart. To ensure compatibility with moderate-resolution Earth observation data, such as Sentinel-2, we snapped all points to the centroid of a 10-meter pixel grid (Figure 4). If multiple points fell within the same 10-meter pixel, we retained the photo with the highest percentage of crops and discarded the rest.

End-to-End Automated Pipeline

In total, we ran our automated pipeline on 32,804 GoPro images in the focus counties. Of these, we progressively eliminated 28,580 images that were not fit to be transformed into crop type points. We eliminated 5.7% of the photos captured in Kenya due to invalid EXIF data (coordinate metadata). Next, we ran the CropNop model on the photos with valid EXIF data, resulting in the removal of 73.9% images that did not contain crops according to the classifier. We ran the segmentation model on the remaining photos. We used a segmentation proportion threshold for the dominant crop to eliminate photos where the segmented area was very small. We set the default threshold to 5%, meaning only photos with a dominant crop covering at least 5% of the image are kept. We adjusted this threshold for some dataset subsets. Finally, we snapped our GoPro field coordinates to a grid and deduplicated points in the same grid. The deduplication step eliminated 53% of the remaining photos. We packaged the remaining 4,224 points into Google Earth Pro KMZ files, on which we performed further manual verification (see Technical Validation).

Data Records

Our resulting dataset consists of a CSV file representing the crop type points and a zipped folder of roadside images associated with each crop type point. We also host the roadside images on a public Google Cloud Storage bucket for accessibility without the need to download all images. We make the dataset public on Zenodo with the CC BY 4.0 license: https://zenodo.org/records/15133324. In total, we present 4,925 crop type points collected across 16 counties in Kenya during 2021 and 2022. Maize is the staple crop in Kenya and our collected data reflects that fact with 4,351 maize, 301 sugarcane, 140 banana, 106 wheat, 10 tea, 5 beans, 4 sunflower, 2 rice, 2 soybean, 2 cassava, and 1 kale point. In 2022, the dataset contains points from Nakuru (653) and Machakos (14). In 2021, the dataset contains points from Nakuru (764), Trans Nzoia (550), Nandi (528), Kericho (516), Busia (493), Bungoma (370), Narok (236), Homa Bay (204), Uasin Gishu (170), Kisii (124), Migori (117), Vihiga (84), Bomet (40), Kakamega (34), Nyamira (28).

We chose to store the crop type points in a CSV file because it is human-readable, easy to open on any computer, and can be easily used in common GIS software (e.g., Google Earth Engine, Google Earth Pro, QGIS) when **latitude** and **longitude** columns are included. We include the road coordinates as a separate row in our CSV so future researchers can use them as non-crop points when training a cropland classifier. Each row of our CSV has the following attributes:

- **latitude** [number]: Field latitude snapped to 10m UTM grid.
- **longitude** [number]: Field longitude snapped to 10m UTM grid.
- **is_crop**: [number]: 1 if field coordinate, 0 if road coordinate.
- **crop_type** [string]: The dominant crop in the image.
- **capture_info** [string]: ID for each image.
- **capture_time** [string]: Date and time of image capture.
- **adm1** [string]: Admin Level 1 from GADM.
- **adm2** [string]: Admin Level 2 from GADM.
- **image_path** [string]: The path of the roadside image inside the provided image folder.
- **image_url** [string]: The URL of the roadside image hosted on our Google Cloud.

Technical Validation

Quality Assessment

We performed quality assessment on all classified crop type data points to verify the dominant crop prediction and whether the point fell inside a field. We packaged the crop type points into a Google Earth Pro KMZ file which allows viewing the points on top of high resolution satellite imagery. We used Google Earth Pro to select the temporally closest available satellite imagery to the given point. The quality assessment was conducted as a process of elimination. We eliminated any point that did not fall within a field, any point where the photo contained no crops, and any point where a human was present in the given photo. We also corrected misclassified dominant crops at this stage of the assessment. The interface for point assessment is shown in Figure 7. All KMZ files were checked by a minimum of two people. We reviewed difficult points with representatives from Kenya's Ministry of Agriculture and Livestock Development. We then converted approved KMZ files into a single CSV file.

Point Assessment Challenges

One of the most frequent obstacles during our point analysis occurred when a capture point was situated ahead of or beyond a field's boundaries. While the 20-meter offset was determined to be the ideal capture point distance when considering the average field, farmers in different regions establish their field boundaries at varying distances from the road. At times, the off-target capture distance caused a point to land beyond field boundaries or on buffer crops. While buffer crops serve the function of creating a boundary between the roadside and the main crops, the model would classify these points as buffer crops, leading to the point being discarded (see Figure 6b). In other cases, buffer crops like maize obstructed our view of the main crop, again resulting in the point being discarded. Additionally, the model faced challenges in classifying intercropped fields. Many smallholder farmers in these regions practice intercropping, which can resemble banana trees sparsely planted in a field of maize or bean crops to provide shade. However, this often led the model to classify the entire field as a banana crop. Since this does not accurately represent a banana crop, these points were relabeled as the primary cultivated crop (Figure 6a).

Maize Mapping

We further validated the points by using them to create a maize map over Kenya's Nakuru county. Nakuru county covers an area of 7496.5 square kilometres and is an important agricultural center in Kenya.[30] We chose to map maize in Nakuru county because that is by far the most dominant crop grown in the region.

Satellite Data

We used Sentinel-2 L2A data as the input data source for our maize mapping workflow. We queried images in the area of interest from April 1, 2021 to December 1, 2021 to cover the entire growing season. We used the S2 Cloudless collection to mask out pixels with over 30% cloud cover. We then composited the images into 2 month median composites (April-May, June-July, August-September, October-November). For each median composite, we computed the Normalized Difference Vegetation Index (NDVI). We selected the following bands from each composite: B2, B3, B4, B8, B8A, B9, B11, NDVI.

Crop Type Data

We used all crop type points in Nakuru county generated through our pipeline (a total of 1528 points consisting of 764 field points, and 764 corresponding road points). Of the 764 field points, 760 were maize. We increased the amount of non-maize crop points by sampling additional points within the fields of our non-maize crop points. Specifically, we drew field polygons for a sample of non-maize crop points, then applied a 5 meter buffer to the field polygons to remove border effects and sampled exhaustively every 10 meters within the field polygon. This process resulted in 1102 non-maize crop points. Additionally, after an initial round of classification we added 41 maize points. For a total of 801 maize points and 1870 non-maize points to be used for classification.

Classification

We used a two step approach to maize classification, first masking out obvious non-crop pixels and then training a random forest classifier to classify remaining pixels as maize or non-maize. To mask out obvious non-crop pixels such as water bodies, we used the WorldCover 2021 land cover map.[31] We masked out all classes except crops, tree cover, and grassland, as we found that the latter two classes in the WorldCover map sometimes contained crop fields. We trained a random forest classifier (with 50 trees) on Google Earth Engine using the satellite data and crop type data described above.

Map Validation

We evaluated the created maize map using the Copernicus4GEOGLAM[32] polygons available in the Nakuru region. The Copernicus4GEOGLAM polygons were gathered by by visiting the fields in-person and therefore could be used as high quality ground truth data. We used only each polygon's centroid to avoid spatial auto-correlation at the field level. Our maize mask achieves an overall accuracy of 71.1%, a user accuracy of 45.7%, and a producer accuracy of 58.2%.

Code availability

We share all the code for the crop type pipeline through the helmets-kenya repository: https://github.com/nasaharvest/helmets-kenya/tree/main. Highly relevant files include:

- notebooks/GoPro2CropKMZ.ipynb for processing the GoPro images into crop type points,
- notebooks/CropKMZtoCSV.ipynb for converting analyzed and approved KMZ files into a single CSV file.

Our collected crop-type points can be used to train machine learning models and create crop-type maps. We recommend using Google Earth Engine with our data points because Earth Engine makes it straightforward to analyze crop-type coordinates in conjunction with remote sensing data. We share code for an example maize mapping use case in Nakuru county on Google Earth Engine: https://code.earthengine.google.com/?accept_repo=users/izvonkov/helmets-kenya-public.

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Author contributions statement

C.N., H.K, and I.Z. conceived the study and experiment(s), C.N., K.M., J.K. led the data collection effort, I.Z., K.M., J.K., B.T., K.J, conducted the experiments, I.Z., C.N., D.B.F., J.K., A.P., I.S., C.A.W., A.M.T., S.J, P.M.L. analyzed the results. The manuscript was written by C.N. and I.Z. All authors reviewed the manuscript and provided input on results and experiments.

Competing interests

The authors declare no competing interests.

Figures & Tables

Figure 3. Data Collection Toolkit Content.

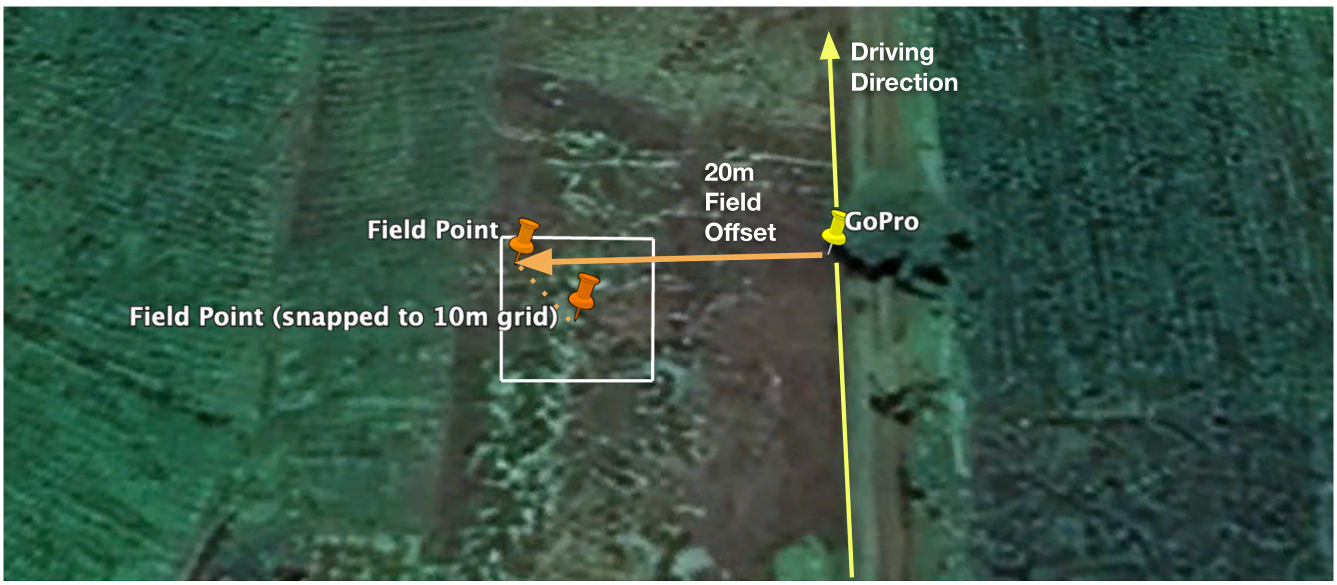

Figure 4. Field Offset Algorithm Example.

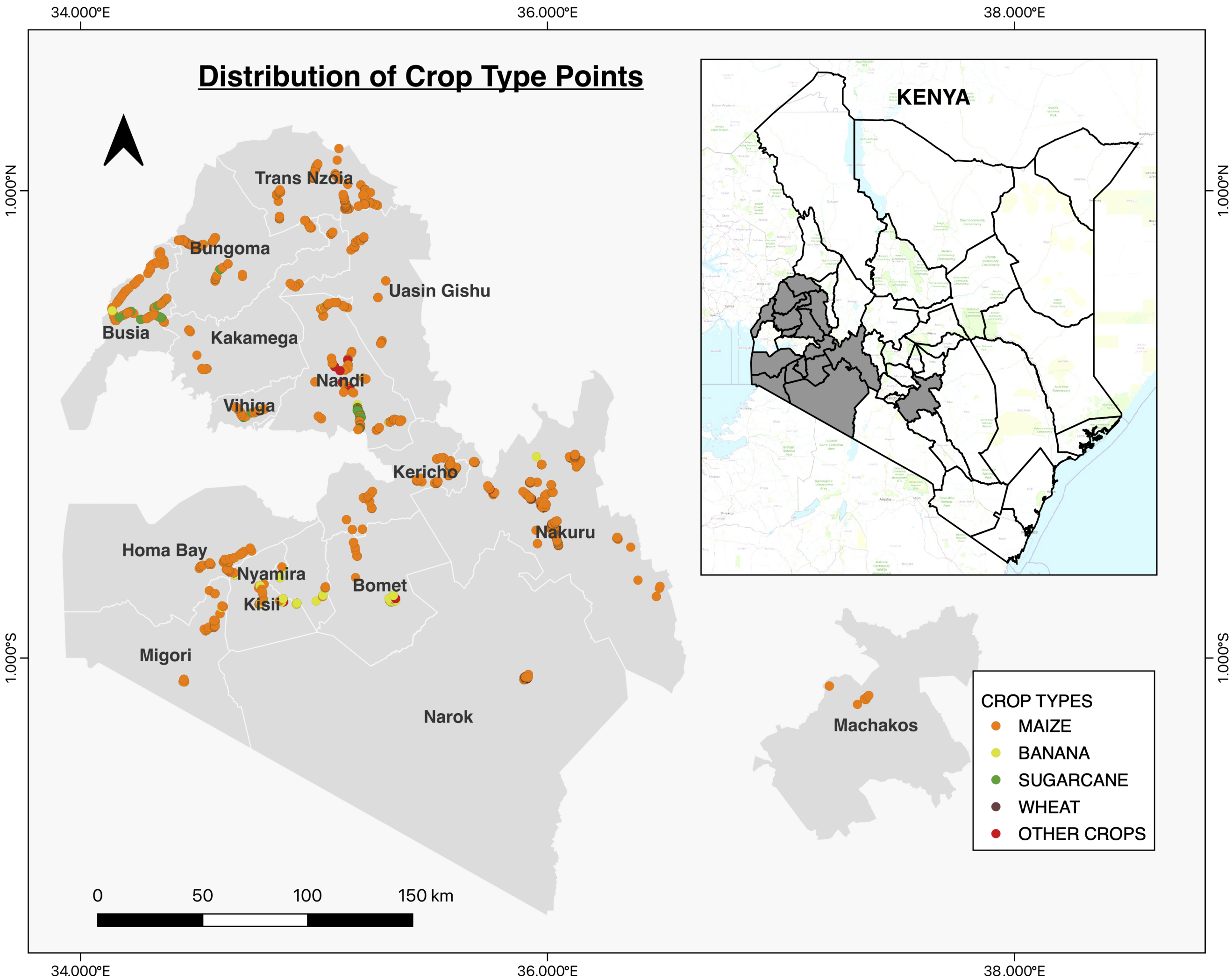

Figure 5. Distribution of crop type points in Google Earth Engine.

Figure 6. (a) Intercropped banana and beans farmland and (b) A buffer plant occasionally misclassified as a crop

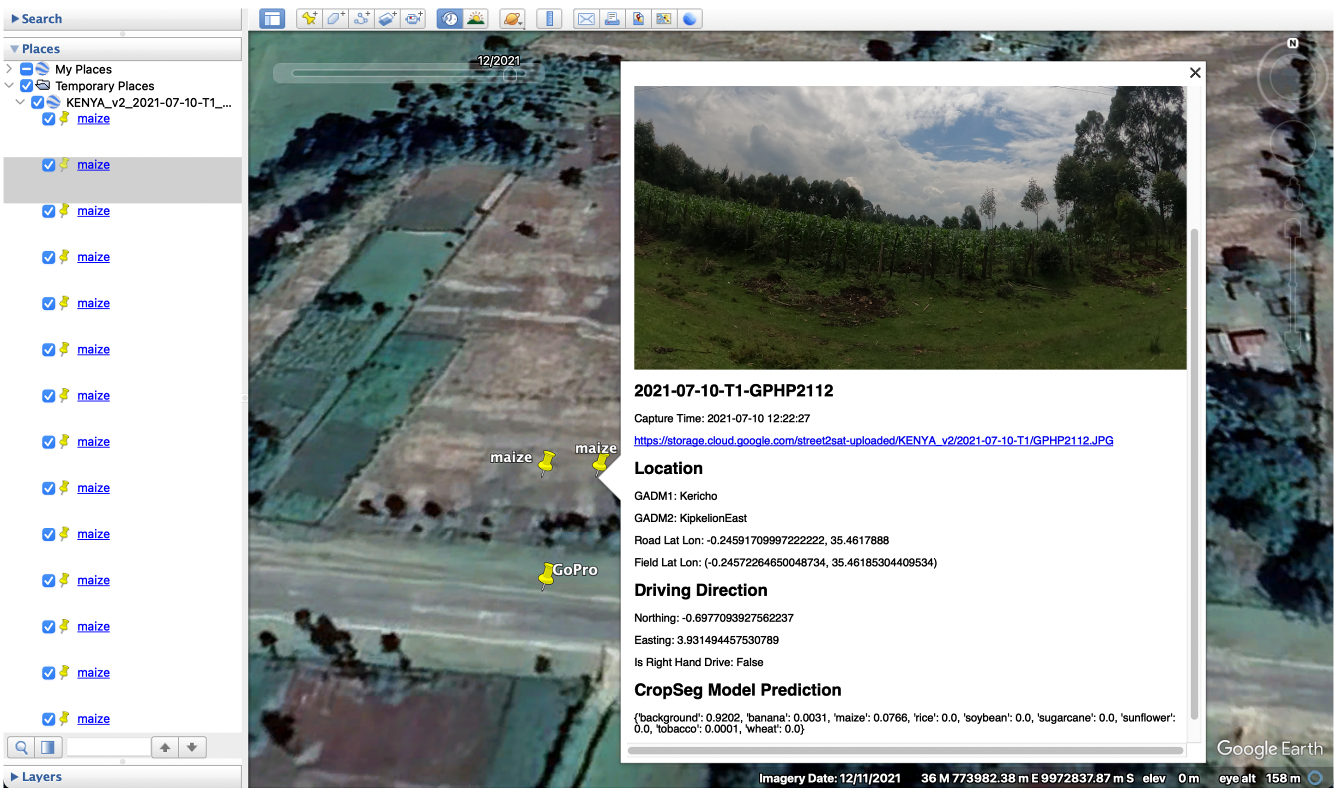

Figure 7. Interface for quality assessment.