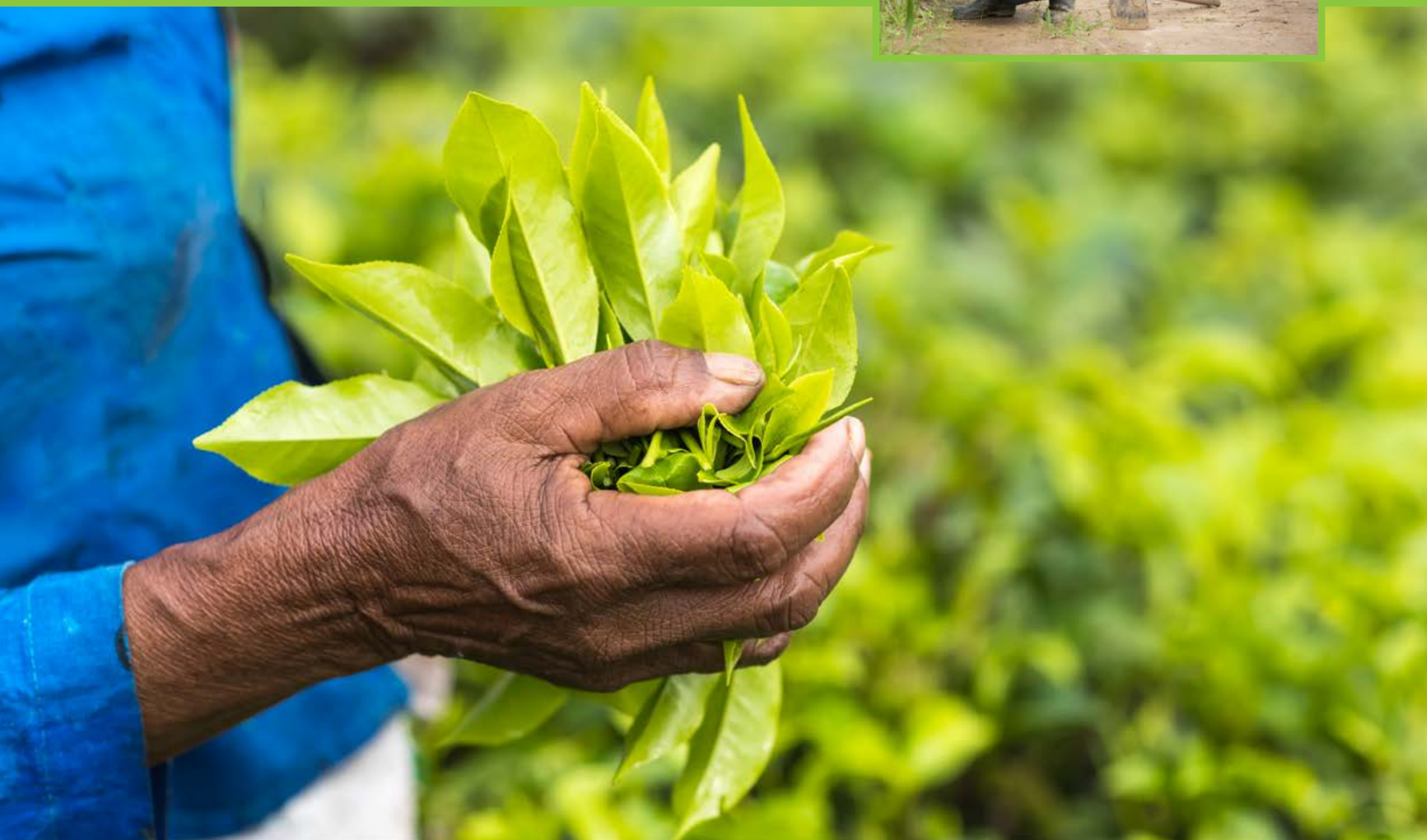
TETRA TECH

Enabling Crop Analytics At Scale

ENABLING CROP ANALYTICS AT SCALE (ECAAS)

State of the Science

Ground Truthing in Crop Analytics for Smallholder Farmers



Contents

Introduction

The number of people experiencing food insecurity has increased for the third consecutive year, a worrying reversal of progress since the 1990s (FAO, 2020). Addressing food insecurity and achieving the United Nations' second sustainable development goal to eradicate hunger by 2030 will require more timely and accurate information on agricultural yield, food availability, and land use, with data that are relevant for the most vulnerable populations. Special attention should focus on smallholder farming, which continues to dominate the agricultural landscape of sub-Saharan Africa, Asia, Latin America, and the Middle East. While the definitions of a "smallholder farm" differ, as of 2018, 475 million out of 580 million farms worldwide were smaller than two hectares in size and that more than 500 million were family-operated (Lowder et al., 2018). These farms are often intercropped, used primarily for home consumption, and operated by a single household or family.

Ensuring better availability and access to actionable data can be empowering and transformational for smallholder farmers. For example, timely advisory information can help drastically improve productivity and facilitate more efficient harvesting, processing, and marketing of crops (Chew et al., 2020). Identifying regions where agricultural planting or crop development is delayed allows for the informed allocation of resources and mitigation of potential food insecurity (Brown and Funk, 2009). However, in many low-income countries where the need for crop analytics is greatest, agricultural data are unavailable or lack the accuracy, centralization, structure, and consistency required for farmers and stakeholders to achieve timely and informed decision-making (Weersink et al., 2018).

The advent of small unmanned aerial vehicles (UAVs) and remote sensing products with increasingly fine spatial resolutions has transformed the capabilities for crop analytics, offering an unprecedented opportunity to collect and provide better information to benefit smallholder farmers. However, remotely sensed data alone are not sufficient, either because the data do not have the required spatial or temporal resolution, or because the data are not sufficiently accurate for a given location. Ground-truth data can fill in a key gap by providing key variables for informed crop analytics to overcome this issue. To date, acquiring timely and accurate field data in areas of smallholder agriculture has been challenging due to a lack of technical and economic resources, the large number of small plots, intense intercropping, and a high diversity of crop types within those plots. (Chew et al., 2020). While the challenges are many, progress in the development of remote sensing technologies over the last decade offers new and existing approaches to advance crop analytics in smallholder settings. New technologies and analytical approaches provide unprecedented access to data, both in time and space.

In this report, we review the state of the science in the use and collection of ground truth observations to enable crop analytics for smallholder agriculture. The report has four chapters in addition to the Introduction — each focusing on a key crop variable. The second chapter provides a review of approaches to mapping **crop field boundaries**. In the subsequent chapter, we review data and techniques used to map **crop types**. The fourth chapter concerns **yield estimation**, arguably one of the most critical and challenging agricultural indicators. The final section concludes with a set of **recommendations** for advancing the agenda of crop analytics for smallholder farmers.

[1] While the term ground truthing is often used in the crop analytics literature, ensuring that the ground truth has been observed at selected locations, even if observing in situ, is not always feasible. Hence, the term reference observation is preferred in the literature. A reference observation is the most accurate available assessment of the true condition of the land surface (Stehman and Czaplewski, 1998). Here, ground truth and reference observation are synonymous.

2

Ground truth data for field boundary mapping

Accurate knowledge of field boundaries' location and geographic extent are critical for a wide variety of decisions and crop analytics applications, including improved crop type mapping and yield estimations (Wagner and Oppelt, 2020). Most field boundary maps have typically relied on labor-intensive field campaigns or existing administrative maps, which are often outdated or inaccurate. The increasing availability of high-resolution imagery drones, phones with integrated GPS (global positioning system) capabilities, and handheld devices have opened new opportunities to improve the availability and reliability of field boundary ground-truthing.

These technologies, together with affordable high spatial and temporal resolution data collected by satellite constellations such PlanetScope and high-quality continuous missions with free data policies such as the Landsat and Sentinel families, are all valuable assets for crop management that were not readily available just a few years ago. Data collected by UAVs or very high resolution (VHR) satellites have a spatial resolution that allows for the collection of reference observations that can augment or even replace observations collected on the ground. Table 1 below highlights different remote sensing technologies that have augmented crop analytic opportunities.

Table 1:

Overview of the remote sensing data sources mentioned in this chapter.

Platform or Sensor	Historical Availability	Spatial res. [m]	Spectral res. [bands]	Temp-oral res. [days]	Examples in Crop Analytics	Comments
MODIS	Continuously from 2000 onwards	250, 500 and 1,000	32	1	Most examples use the ET product; e.g., Tang et al. (2009)	Very coarse resolution limits relevance for smallholder agriculture
Landsat 4-8	From 1984 onwards but with gaps during the 90s in certain parts of the world	30	L4,5: 7 L7: 8 L8: 11	16	Roy and Yan (2020)	Long time series allows for monitoring change; 30 m is too coarse for many smallholder applications
Sentinel 2	Continuously from 2017 onwards	10 (B, G, R, NIR); 20 (SWIR)	4 at 10 m; 6 at 20 m	5	Immitzer et al. (2016)	10m resolution, free data policy, and growing time series will make S-2 increasingly relevant for smallholder crop analytics

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Table 1.
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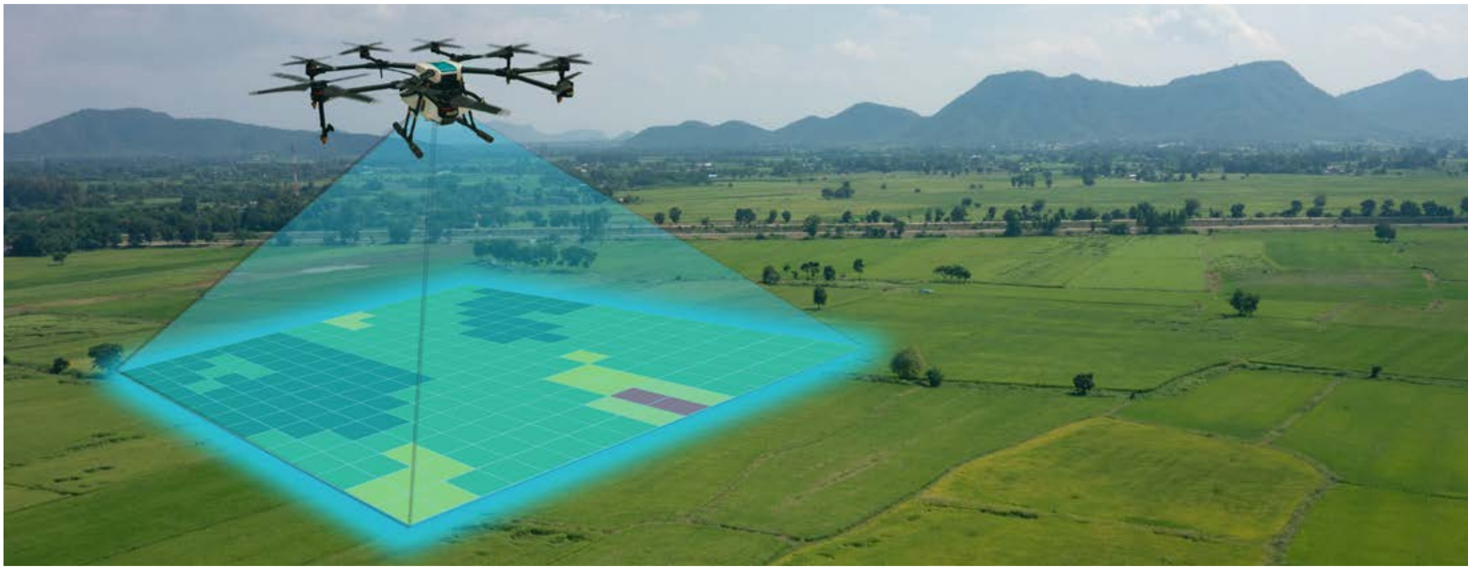
Platform or Sensor	Historical Availability	Spatial res. [m]	Spectral res. [bands]	Temp-oral res. [days]	Examples in Crop Analytics	Comments
PlanetScope	Continuously from 2016 onwards	< 5	4 (B, G, R, NIR)	1	Kpienbaareh et al. (2021)	Data is not free other than in the tropics through the NICFI program; high potential data source for smallholder agriculture due to spatial resolution
Miscellaneous VHR satellites	IKONOS at 1 m res. from 1999	Down to 0.4	Varies but often B, G, R, NIR	Varies	Du et al. (2019)	Often expensive and temporal resolution can be limited. But very high spatial resolution makes these products highly useful for smallholder applications
UAVs	–	Down to a few cm	Varies but often B, G, R, NIR	–	Hegarty-Craver et al. (2020)	Extremely high resolution with high potential, especially in crop health but across a smaller area than satellite imagery



2.1 Mapping of Field Boundaries: Review of different approaches

Boundaries of agricultural fields are important for a wide range of applications, but collecting, mapping, and maintaining boundary information is often costly and difficult. Further, a uniform definition of a *boundary* is complicated as fence lines, ownership, different crops in the same field, different crop parcels, different management practices, and other factors all constitute relevant boundaries. Rydberg and Borgefors (2001) define boundaries of crop fields as the locations "where a change in crop type takes place or where two similar crops are separated by a natural disruption in the landscape, like a ditch or a road." North et al. (2019) suggest a broader definition that includes differences in crop management while arguing that methods for boundary mapping must apply to large areas with the ability to keep boundary information up to date. For this paper, we define field boundaries according to the characterization proposed by North et al. (2019).

The development and expanded use of smartphones, or handheld devices that combine cellular and computing functionality, significantly enables the scaling of crop analytics. Crucially, smartphones are affordable, and their use is widespread, including in low-income countries. The combination of accessibility, computing, and remote sensors have made smartphones an important tool for many farmers; for example, 98% of the farmers in smallholder farming communities in Kenya own a cellphone (not necessarily a smartphone), and 25% make use of the device in farming activities (Krell et al., 2020). Of particular interest is the use of smartphones for collecting data on the ground to delineate boundaries and to calculate the area and perimeter of crops fields. With built-in GPS in tablets and smartphones, the user can collect coordinates along the boundaries of fields, or by automatically collecting coordinates when moving along field boundaries. The GPS receivers in today's tablets and smartphones achieve a horizontal positional error of 5 m (this is spatially finer than the 10 m resolution that Sentinel-2 imagery offers). If higher accuracy is required, an external GPS receiver connected to the smartphone will achieve real-time positioning within a few centimeters.

Several smartphone applications are used for field boundary delineation (Figure 1 shows an example of screenshots from the GPS Fields Area Measure application by Farmis; http://farmis.lt). The interface for collecting coordinates on the ground shows the user's location and recorded coordinates on top of high-resolution data from Google Earth. While the use of smartphones with built-in GPS technologies is generally appealing for field boundary mapping, the accuracy of the mapping outputs largely depends on the degree to which the data collection platform is user-friendly. Without clear instructions or prior mapping experience, users may end up collecting incorrect data.

Figure 1:
The GPS Fields Area Measure application for collecting coordinates for field boundary delineation.

The collection of ground data to delineate field boundaries using handheld devices is straightforward and effective for small areas, but manual ground data collection might not be feasible for delineating field boundaries over larger areas. In those instances, analysis of high-resolution imagery obtained from remote sensing instruments might be more adequate.

The spatial resolution of satellite data is often too coarse for crop analytics purposes, especially for smallholder farmers. ESA's Sentinel-2 has bands with a higher spatial resolution of 10 m, and has been used successfully for boundary delineation (e.g., Masoud et al., 2020). However, for some applications, very high resolution (VHR) data (<5 m) are required. While VHR data are typically not free of charge, the spatial resolution is often finer than the positional error of a smartphone GPS and allows for delineation of crop boundaries in smallholder settings. The most basic approach to boundary mapping is manual delineation directly in the imagery through digitization in GIS software. Using QuickBird imagery (0.6m), North et al. (2019) delineated 273 crop fields by digitizing agricultural holdings (Figure 2). As with ground-based boundary mapping, manual delineation techniques rely on the user's knowledge of the location of the boundaries and can be potentially time-consuming.

Figure 2:
Manual delineation of crop field boundaries using QuickBird satellite image (North et al., 2019).

An alternative to the manual digitization of boundaries is automatic classification, in which a small sample of ground truth data are used to train an algorithm that identifies features of interest in the imagery. Such approaches are particularly useful when the features of interest have spectral properties that remote sensors can measure (For example, satellite-derived indices can measure crop type, land cover, and vegetation condition). For mapping field boundaries, the most widely used methods rely on edge detection and segmentation (North et al., 2019). An edge detector is a filter that moves across the imagery in a rectangular window and does not usually require any training or ground truth data. More relevant to smallholder crop analytics is segmentation and object-based image classification. Both are processes in which objects on the land's surface composed of pixels are identified and classified in the imagery (Blaschke, 2010). Object-based image classification takes advantage of the high spatial resolution of the data while not being hampered by the lack of spectral information. Classifying objects instead of pixels have been shown to yield more accurate maps of crop fields (Duro et al., 2012; Li and Shao, 2014), and is the recommended approach for extracting thematic information from high-resolution data.

Access to object-based image classification has been hindered by the high costs associated with data inputs (high-resolution satellite imagery) and software (e.g., Trimble eCognition and ENVI Crop Science). In recent years, however, open-source software alternatives have emerged. The Orfeo Toolbox (https://www.orfeo-toolbox.org/) contains a segmentation algorithm that creates segments or objects corresponding to features on the land surface based on spectral and spatial properties, as well as machine learning classifiers such as Random Forest.

A new and promising technique uses more advanced machine learning methods such as deep learning. The TensorFlow Development in Google Earth Engine, for instance, is an open-source machine learning platform that supports such methods, providing access to both advanced processing methods and a range of satellite data. Saraiva et al. (2020), who mapped center pivot irrigation systems in Brazil, illustrates how these resources can be leveraged for field boundary mapping. The pivots vary greatly in size, and the spatial resolution of Landsat or Sentinel-2 would be insufficient. Instead, the authors created mosaics of PlanetScope data (3 m resolution) and collected training, validation, and testing data in the imagery. The authors then developed a model based on a neural network architecture (U-Net, initially developed for segmenting images in medical applications). The entire analysis and model were built using the TensorFlow framework in Google Earth Engine (Figure 3).

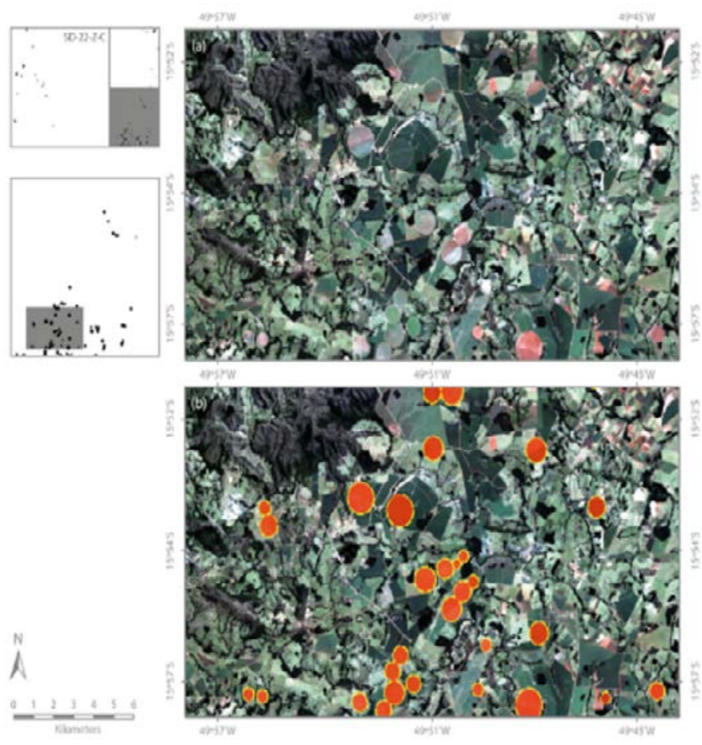


Figure 3:

From Saraiva et al. (2020): pivots in Brazil identified in PlanetScope data by a deep learning model based on the TensorFlow framework.

2.2 The use of unmanned aerial vehicles in ground-truthing

Ground truth data are essential for calibrating and interpreting the results of remotely -sensed analyses, especially in areas where there is limited prior knowledge about the reality on the ground. The use of unmanned aerial vehicles (UAVs) has been promoted to rapidly collect large amounts of ground truth data at a lower cost than field campaigns. UAVs are unique in that they can provide data at extremely high resolution within a small study area (less than 100 ha). Because of the small area covered by UAVs and because the operator must be physically present when the aircraft is operating, UAV data do not replace satellite data; instead, UAV data are suitable for assisting in the collection of ground-truth observations . In the discussion above, a distinction was made between observations of ground-truth conditions collected *in situ* and observations collected in remotely sensed imagery. UAV data erase that distinction by being a remote sensing instrument and providing visual information close to what an observer on the ground would see. Hegarty-Craver et al. (2020) present an application of UAVs for ground truth data collection in Rwanda: the researchers collected a large dataset consisting of observations of mono-cropped fields, small intercropped fields, and natural vegetation in smallholder farms which was used to train and test a machine learning model for classification of crop fields in Sentinel-1 and -2 data, achieving accuracy rates of 83% and 91% respectively.

[2] UAVs are primarily tools for reference data collection; the topic is revisited in the Appendix.

2.3 Using existing datasets

Data collection in situ may not always be feasible, either because it is prohibitively expensive or because of security issues. Global public data can fill this gap: several open-access large-scale datasets contain agricultural information, and this trend is expected to continue. Some of the most popular publicly available products include:

- GFSAD30 (Global Food Security Analysis-Support Data at 30 Meters; https://www.croplands.org), provides global maps of cropland products at 30 m resolution (Thenkabail et al., 2012; Teluguntla et al., 2015). The datasets are based on Landsat data and provide maps of croplands globally, including irrigated and rainfed croplands for South Asia, Iran, Afghanistan and Australia.
- The GLanCE project (Global Land Cover Mapping and Estimation; http://sites.bu.edu/measures/). If land-use change either to or from cropland is of interest to users, this product should be highly relevant. The GLanCE datasets are not yet available for all continents, but tools for using the data and datasets for South and North America are accessible at: https://code.earthengine.google.com/?scriptPath=projects%2FGLANCE%3AAPPS
- The newly released iSDAsoil dataset provides soil properties and agronomy maps at 30 m resolution across Africa (https://www.isda-africa.com/isdasoil). The datasets contain predictions based on 130,000 soil samples for various chemical, physical, and agronomic soil properties.
- A global land cover product at 10 m spatial resolution -- The Esri 2020 Land Cover — based on Sentinel-2 data was released in 2021. The data is available through the ArcGIS Living Atlas of the World (https://www.arcgis.com/apps/instant/media/index.html?appid=fc92d38533d440078f17678ebc20e8e2). The product has Crops class in addition Water, Trees, Grass, Flooded Vegetation, Scrub/Shrub, Built Area, Bare Ground, Snow/Ice, and Clouds.
- Another 10 m map of global land cover, titled Dynamic World, is being produced by World Resources Institute, National Geographic, and Google. If successful, the product is likely to be of high relevance for the smallholder agriculture; it has three tiers of a hierarchical cropland class: Crops (Tier I), Row/Paddy/Other (Tier II), Maize/Soy/Wheat/Rice/Other (Tier II). The product is scheduled for 2021: https://drive.google.com/file/d/1JW9Egg05I0gGHC6a6hHR1Hzbh55DARCM/view; https://www.youtube.com/watch?v=VuALyQ6eoq4&ab_channel=GoogleEarth
- The Global Hyperspectral Imaging Spectral-library of Agricultural Crops (GHISA) is a library of spectral signatures for wheat, rice, corn, alfalfa, and cotton in different growth stages for Asia and the United States (Aneece and Thenkabail, 2018). USGS maintains the data and are available via Google Earth Engine and the LP DAAC. While these data are not maps, a library of spectral signatures is needed for splitting the cropland classes in the GFSAD30 and GLanCE datasets into different crop types.
- The Copernicus Global Land Service from ESA provides annual maps of global land cover at 100 m resolution, including stable cropland and expansion of croplands on behalf of other land covers: https://land.copernicus.eu/global/products/lc
- The Global Cropland Extent product (https://glad.umd.edu/dataset/gce/global-cropland-extent) is generated using MODIS data at 250 m spatial resolution but has the advantage of providing pixel-level probability of the presence of cropland probability layer (Pittman et al., 2010). In addition to the continuous probability, the product is a discrete cropland/non-cropland indicator.
- Radiant MLHub (https://www.mlhub.earth/) provides a growing suite of labels based on machine learning applications on Earth observation products. MLHub was initially developed to train geospatial data as well as hosting machine learning models, and is becoming an increasingly useful library for public labels.

2.4 Summary and recommendations

Field boundary mapping is one of the most basic yet important indicators for crop analytics, enabling various decisions and further analysis. Relevant techniques for field boundary mapping range from handheld devices to global satellite systems. The most suitable tool depends on the objective of the application. Global satellite systems are relevant if changes in crop field size, land use conversions, crop types, etc. that occur over time and space are of primary interest. Time series-based approaches still rely largely on Landsat data, which have a relatively coarse resolution of 30 m and are therefore of lesser relevance for smallholders. As the record of Sentinel-2 data at 10 m spatial resolution continues to expand, time series-based monitoring of croplands at high resolution will grow in importance.

If small field boundaries and crop type are of interest, data with a spatial resolution finer than 5 m might be necessary. New products such as PlanetScope data with a resolution of about 3 m are freely available from 2016 onwards in the tropics, offering exciting opportunities to improve field boundary mapping. With the exponential increase in smartphone accessibility and processing power, it is likely that mobile computing in ground-truthing will greatly impact smallholder farming in the future. Finally, deep learning techniques and the increasing use of UAVs to reduce the effort required to collect ground truth data are auspicious developments that will revolutionize crop analytics in the coming years.

3

Crop Type Mapping

Smallholder agriculture is of global significance, but data on the type, location, and production of smallholder crops are often scarce. The lack of crop type data makes it challenging to track smallholder yield progress, understand land cover change, analyze farm management strategies, and design targeted agricultural policies (Wang et al., 2020). If properly leveraged, technological developments in mobile solutions and remote sensing could potentially close or mitigate the data gap. Specifically, these advances can help ground truth data collection. Observations of crop type can either be used as training data in subsequent analyses to make maps, or be collected at locations selected by probability sampling to make area estimates (see Appendix).

3.1 Crop type mapping: Review of different approaches

Accurate detection and mapping of crop types in smallholder farms are particularly challenging given that holdings are rarely homogeneous in space and time, with intercropping and crop rotation practices providing an additional source of complexity. Supervised classification techniques using high spatial and temporal resolution imagery like Sentinel-1 can provide accurate seasonal crop type maps (Kenduiywo et al., 2017). However, recent work by Peter et al. (2020) suggests that to be operational, data should have a spatial resolution similar to the scale of the crop being studied (e.g., in the case of corn, the appropriate resolution is ~14–27 cm). The implication is that even high-resolution satellite data such as Sentinel-1 and -2 at ~10m, SPOT 6 at ~6 m, Planet at 3 m, and Pléiades at 2 m, – are too coarse to inform on crop health in smallholder agriculture. To overcome this challenge, smartphones and UAVs have been proposed as useful technologies.

Smartphone use among smallholder farmers is often limited to location information enabled using GPS (e.g., delineating field boundaries) or to retrieve basic information; more advanced use of smartphones in crop analytics is still rare (Mendes et al., 2020). Still, the ever-increasing accessibility, computing, and hardware capabilities of handheld devices suggest that the importance of smartphones in crop analytics will continue to grow. In a review of recent advances in the field of smartphone-based agricultural technologies, Mendes et al. (2020) list several applications that use image recognition, machine learning, and artificial intelligence to support crop-related activities. Most applications involve the user collecting data using smartphone sensors (either built-in or attached), which are then converted to information using mobile machine learning and artificial intelligence algorithms together with databases of training data. The result is an almost instant acquisition of important variables; current applications support, in addition to crop type mapping, crop protection and diagnosis, crop nutrition and fertilization, crop irrigation, crop growth, and canopy management, and crop productivity and yield (Mendes et al., 2020; see Figure 4).

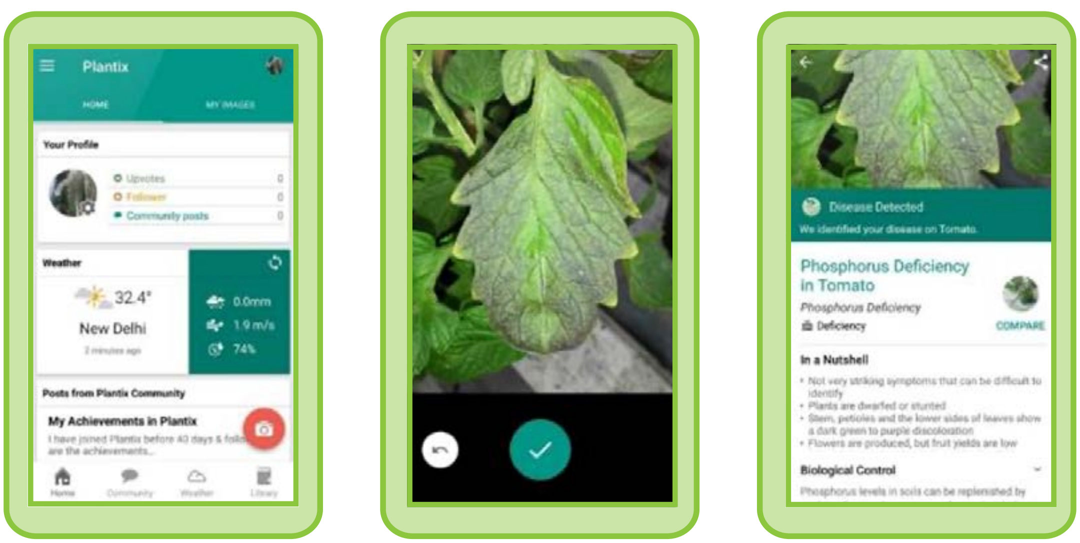


Figure 4:
The Plantix application by PEAT GmbH (https://plantix.net/en/) on a smartphone; the application identifies crop type and makes diagnoses of pest damages, plant diseases, and nutrient deficiencies by processing photos of crops using mobile machine learning and a database of training data.

Ground observations of crop type, collected and processed in smartphones using the Plantix application, can be used to make detailed maps of crop types in smallholder agriculture. In their analysis, Wang et al. (2020) used a total of 2 million geolocated photos with crop type labels collected by local farmers in two Indian states from 2017-2019 using the Plantix application. The photos were combined with time-series data from Sentinel-2 to a train neural network to map rice, cotton, and other crops at 0.3 m resolution. In this example, only photos of crops were collected by farmers. The crop type labels were identified by machine learning using a large database of reference crop photos.

Similar approaches combining ground truth observations of crop type and machine learning algorithms have been successfully used to map crop types in Malawi (Kpienbaareh et al., 2021). In this case, ground truth observations of crop type were collected by visual inspection instead of using deep learning to determine crop type (cf. Wang et al., 2020). In the Kpienbaareh et al. (2021) analysis, ground truth observations at 1,170 locations were used for training.

A third approach for collecting ground truth data relies on RGB drone images and transfer learning techniques, as recently tested in Malawi and Mozambique (Nowakowski et al., 2021). The protocol developed by Nowakowski et al. (2021) included a data collection campaign using drone imagery, a field validation campaign whereby enumerators collected information on crop types (among other variables), and then the use of transfer learning to reduce the amount of reference data required to generate a model. The reference observations were collected at 1,000 locations — comparable to the sample used by Kpienbaareh et al. (2021) but considerably lower than in the Wang et al. (2020) analysis — highlighting the challenge of determining how much data should be collected on the ground. The map accuracies in the three studies were reportedly high, at 75-90%. Importantly, Nowakowski et al. (2021) showed the potential to use transfer learning approaches to reduce the amount of ground truth data required for crop type mapping.

The diverging amount and types of data and analytical approaches used in these studies highlight the difficulty of providing concrete recommendations when mapping crop types in smallholder systems. Further research, facilitated by the increasing availability of methods and technologies, will likely help resolve these questions. Below are key comments and overarching recommendations about the use of ground truth data for map type mapping:

1. Compared to parametric classifiers such as maximum likelihood, an essential aspect of advanced machine learning methods is that the results are not negatively impacted by having "too much" training data. However, it is difficult to provide general recommendations on the amount of data needed. The availability of satellite data of sufficient resolution for collection of ground truth observation in the imagery has increased in recent years, which has greatly reduced the time and cost associated with ground truth collection (note that ground truth observations collected in imagery instead of *in situ* are often referred to as reference observation). Further, the availability of crowd-sourced ground truth data collected and processed using smartphones and which can be used as training data continues to improve (Wang et al., 2020).

2. A portion of ground truth data is often used for validation. Note that validation data cannot be used to make point estimates of population parameters such as areas and map accuracy unless the ground truth data were collected under a probability design (see Appendix).

3. Deciding which imagery to use will depend on the situation. A general recommendation is to use imagery of a spatial resolution sufficient to observe ground truth conditions in the imagery (i.e., being able to delineate crop fields and identity crop type). For smallholder farms, very high-resolution data are required. PlanetScope data are becoming increasingly important, and are now provided free of charge for the pantropic region from 2015 onwards through Norway's International Climate & Forests Initiative (Figure 6). However, at a resolution of ~3.7 m, PlanetScope data may only be useful for identifying field boundaries rather than specific crop types. Higher-resolution data (~1 m) would be needed to clearly delineate crops. Still, open access, high-resolution data offer an opportunity to obtain training data in non-traditional ways as well as potentially collecting reference observations throughout the cropping cycle. Such observations can augment or even replace data collected on the ground, and be used to train machine learning algorithms for crop type mapping.

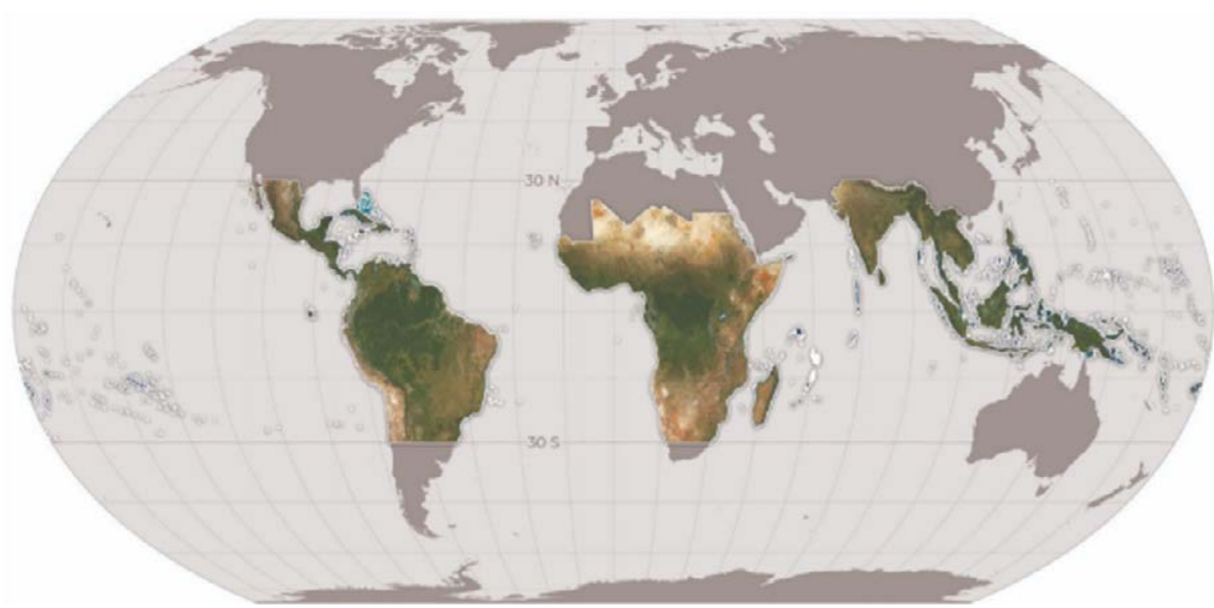


Figure 5:
Areas for which free Planet data are provided through Norway's International Climate & Forests Initiative (from https://www.planet.com/nicfi/).

Unfortunately, data with areas that are too large to be mapped by VHR data, that change over time, or data with longer historical availability often have coarser spatial resolutions. The Landsat missions, which started in 1972, provide imagery at a 30 m resolution, and these datasets are often used for time-series analysis given the availability of a 50-year dataset. The move away from analysis based on individual imagery to time series analysis significantly shifted the paradigm in remote sensitive science over the last decade.

Time series-based algorithms operate on pixel-level time series, which tend to be rather data-intensive. However, implementation on computing platforms such as Google Earth Engine has alleviated previous bottlenecks of storage capacity and computing power required to run the algorithm. Users can now focus on collecting relevant training data for the classification of the time series segments.

Time series-based algorithms are data-agnostic but continue to rely on Landsat data, primarily because of the long and consistent data record. Landsat imagery has been used to assess within-field variations (edaphic, crop treatment, crop disease, drainage, etc.) across the U.S. (Roy and Yan, 2020). Of importance to crop mapping is the ability of these algorithms to use both spectral and temporal information to classify land surface features. Certain crop types have similar spectral signatures, which makes them hard to separate in a single image classification. However, if their phenology, rotation cycle, and spectral temporal behavior are different, the time series data analysis is likely to allow the different types to be discerned.

Judging by the lack of examples in the literature, the spatial resolution of Landsat is too coarse for studying smallholder agriculture. Sentinel-2 at 10 m spatial resolution has been used successfully in object-based approaches to crop species classification (e.g., Immitzer et al., 2016), but because of the relatively limited length of the time series (since 2015 with Sentinel-2A; 2017 with both Sentinel-2A and -2B) the experience of using Sentinel-2 data with time series-based algorithms is limited. Soon, however, time series-based algorithms with 10 m Sentinel-2 data will likely provide information and products of high relevance for crop management.

The role of ground truth/reference data is equally important in time series-based approaches as in previously mentioned approaches. The main role of the reference data is to train a classifier to map features on the ground over time. Time series data serve another important role in ground-truthing by providing a temporal dimension to observations not available when collecting observation in situ or in-field imagery. If reference observations of ground conditions over time are of interest, it is recommendable to study time series of reflectance data in addition to *in situ* observations or imagery interpretation.

3.2 Summary and recommendations

Crop type mapping is a key variable in crop analytics, providing useful insights on farm management and crop dynamics, and can ultimately help provide tailored information at the farm level. Crop type mapping generally requires information at extremely fine spatial resolutions, often in the range of tens of centimeters, which satellite remote sensing cannot offer at scale. The advent of handheld devices (primarily smartphones with built-in cameras and GPS) and unmanned aerial vehicles (UAV), offer an opportunity to collect data at the fine scales required for crop mapping. Evidence suggests that data collected through smartphones and UAVs can help detect crop types with relatively high accuracy in diverse geographies. Machine learning, deep learning, and transfer learning techniques have helped augment the capabilities of ground-truthing by reducing the amount of data required to create crop-type accurate maps.

However, a key question remains: How much data is enough? It is hard to provide robust recommendations for how much training data to collect, and users often resort to trial and error. Finding the minimum amount of data that provides optimal model accuracy will enable better decisions about how much time and resources to spend on field campaigns. Analysis in Ethiopia and Malawi suggests that model performance varies depending on geolocation strategies: peak performance is achieved with 2,500 plots when utilizing “boundary points”; 4,000 plots if relying on “convex hull”, “hull mean”, “plot points”, and “plot mean”; and around 4,500 plots when using “corner” and “centroid” approaches. After these points, models stop learning and additional data only provide marginal improvements in model accuracy (Azzari et al., 2021). Additional work is still required to understand whether these findings can be applied universally.

Crop type mapping is made more difficult by the nature of inter-and intra-seasonal crop changes within a plot. Understanding how crop patterns have changed over the last decades is critically important for some crop analytics applications—for example, understanding the impact of climate change on smallholder agriculture to inform climate change adaptation strategies. Few datasets currently exist to help answer this question, and the default product is still Landsat. With new satellite products becoming increasingly available, the possibility to conduct more detailed time-series analysis will only increase, but it may be a few years before substantial work in this direction can be carried out.

4

Yield Estimation

One of the most important goals of crop analytics is yield estimation. While considered the most critical indicator, directly relevant for food security and livelihood measures, crop yield is a challenging indicator to measure, especially in smallholder farms. Crop yield, or land productivity, is computed as the ratio of the total mass of harvestable components (e.g., grains for cereal crops) to the farm area. The crop cut method is the most commonly used approach for yield estimation – it is considered to be the most reliable and objective approach for estimating yields (FAO, 2017). Unfortunately, the process can be highly labor-intensive and time-consuming.

In India, for example, a typical crop-cut yield measurement takes about two hours per plot, which poses significant challenges for scaling across large areas (S. Rupavatharam, personal communication, October 15, 2020; Figure 6). To overcome these logistical challenges, remote sensing-based yield estimation pilots are used. These methods leverage an empirical relationship between field-level crop yield and satellite remote sensing data, either using a vegetation index as a proxy of crop growth or a data assimilation technique with model-estimated crop growth and yield. However, most of these methods are developed in largely homogeneous landscapes often found in the U.S. and China (e.g., Lobell et al., 2015). Largely unsolved challenges remain to apply these methods to smallholders farming systems in developing countries, where agricultural land uses are heterogeneous, farm sizes are smaller and mixed- and inter-cropping systems are commonly practiced.

Figure 6:
Crop-cut yield measurement steps at a paddy rice field in India. Source: CropIn

The rapid development of remote sensing technologies, especially improvements in spatial and temporal resolution, makes satellite remote sensing data suitable to monitor dynamics in crop productivity in a precise and timely manner at scale. Analytical models can also play a significant role, describing the complex physical processes that underlie crop growth, transpiration, and senescence to provide high-resolution estimates and forecasts of crop production and yields. When historical crop production data are available, models are often based on statistical regression (Challinor et al., 2014). Whether "process-based" or "statistical," these models provide a robust basis for evidence-driven agricultural decision-making. Yield estimates can be used to evaluate and compare proposed management, policy, and investment alternatives, predict year-to-year risks to food security due to droughts and floods.

4.1 Yield estimation: Review of different approaches

Remote sensing-based yield estimation methods use an empirical relationship between field-level crop growth and yield and the satellite-measured reflectance data. Existing literature can be roughly classified into two approaches that estimate yield from 1) a post-harvest empirical relationship between vegetation indices and yield, 2) a within-season statistical modeling framework that assimilates remote sensing estimates with the model-estimated yields.

4.1.1 Empirical modeling approach (post-harvest)

An empirical modeling approach estimates crop yield based on the statistical relationship between satellite remote sensing-derived vegetation indices with crop growth and yield. This approach is, by far, more common than within-season statistical models. The method has been tested in Canada, where Mkhabela et al. (2010) tested the performance of yield estimates from MODIS-derived 10-day composite of NDVI data throughout the growing season of four crops (barley, canola, field peas, and spring wheat) across 40 Census Agricultural Regions in the Canadian Prairies. Regression models using the running average of NDVI from one to two months before harvest estimated yields within ±10% of the actual reported data. In the U.S., Sakamoto et al. (2013) used MODIS-derived WDRVI (Wide Dynamic Range Vegetation Index) and crop phenology data to develop a statistical maize yield estimation model. The WDRVI data around the silking stage showed the best correlation with maize yields at multiple scales from field to county levels. Sakamoto et al. (2014) further developed the model to incorporate a bias correction algorithm to address region-dependent yield prediction errors.

Similarly, in the U.S., Bolton & Friedl (2013) used MODIS-derived EVI2 (2-band Enhanced Vegetation Index) and crop phenology information to improve yield forecasting performance for maize and soybean. Lobell et al. (2015) developed a more sophisticated approach incorporating a process-based crop model in the analytical framework. Using the APSIM model (Agricultural Production Systems Simulator; https://www.apsim.info), they first emulated reflectance values from the model-estimated crop growth and yield. The emulated pseudo-observation data was used to train empirical models to predict yields. Finally, they applied the empirical model to the Landsat-measured real-reflectance values with gridded monthly weather data to estimate yields across the region. The approach is called SCYM (Scalable satellite-based Crop Yield Mapper), developed in Google Earth Engine and tested for maize and soybean in the Midwestern U.S.

While showing promising performances, the majority of analyses have been conducted in rather homogeneous fields in large-scale agriculture. For smallholders' agriculture, Burke and Lobell (2017) developed an empirical model using the GCVI (green chlorophyll vegetation index) derived from TerraBella imagery (1 meter). They compared it with field-measured maize yield survey data in western Kenya. The model showed a promising performance (R2 up to 0.4) when the field area is precise and larger. They demonstrated the comparable accuracy and value of using high-resolution satellite imagery to estimate smallholder farms' crop yield, even with minimal or no field training data.

For smallholders' maize farms in eastern Uganda, Lobell et al. (2019) applied the SCYM approach (Lobell et al., 2015) using five types of Sentinel-2-derived vegetation indices (i.e., NDVI, GCVI, MTCI, NDVI705, and NDVI740). They then compared the yield estimates with three types of ground-based yield measures (e.g., self-reported, sub-plot crop cutting, and full-plot crop cutting). They found that, compared to the full-plot crop cutting, which was considered the gold standard, satellite-based yield estimates explain as much, or more, yield variations across fields (Figure 8). Further, crop-cut and satellite-based yield estimates showed similar associations with field management factors, indicating the potential applicability of satellite-based yield estimates in smallholders' crop production systems. SCYM approaches use a synthetic yield estimate generated from a process-model as the target variable in developing the relationship with satellite variable. In that sense, the approach does not require observed yield data (except for validation) but requires a well-calibrated crop model.

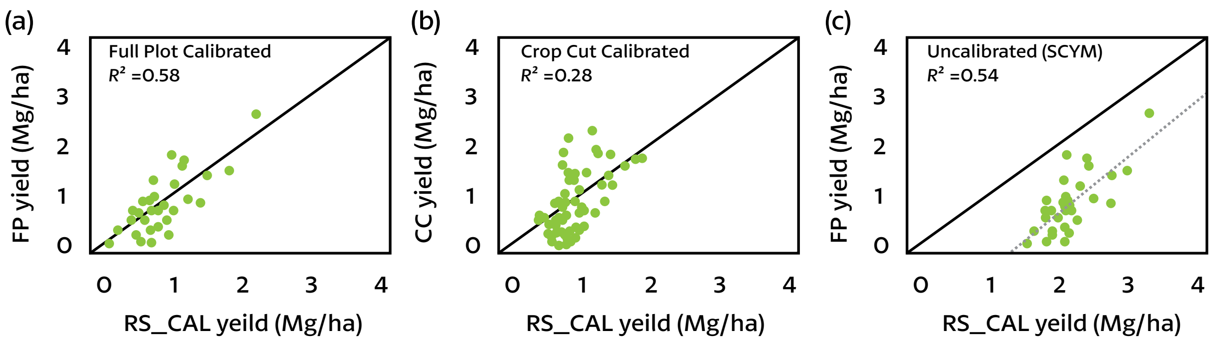


Figure 7:

Comparison of (a) full plot yields vs. predictions from a remote sensing model calibrated to full plot yields, (b) crop cut yields vs. predictions from a remote sensing model calibrated to crop cut yields, and (c) full plot yields vs. "uncalibrated" remote sensing yield estimates, which are based on calibration to crop model simulations. All panels show results for pure stand maize plots at least 0.1 ha in size, which is the subset of plots used to calibrate the models in (a) and (b) (Lobell et al. 2019).

4.1.2 Data assimilation approach (within-season)

Crop growth and yield estimates from process-based crop models can be assimilated with satellite remote sensing-estimated leaf area index (LAI). This assimilation process effectively calibrates the crop model and, over time, reduces the uncertainty of model-estimated yields. For example, Huang et al. (2015) assimilated Landsat-derived LAI with the WOFOST crop model using the ensemble Kalman Filter approach to improving winter wheat yield estimations. NASA Harvest's GEOCIF (Global Earth Observation Crop Yield and Condition Forecasting) approach uses a machine learning-based yield prediction approach. The GEOCIF approach uses an ensemble-based machine learning model to estimate in-season crop yield, based on multiple globally available earth observation datasets (e.g., crop-specific crop masks, NDVI, LAI, temperature, precipitation, soil moisture, and evaporative stress index). GEOCIF reliably forecasted crop yields 2-3 months before harvest, with errors in the range of 1.5-5% in previous studies (Figure 8).

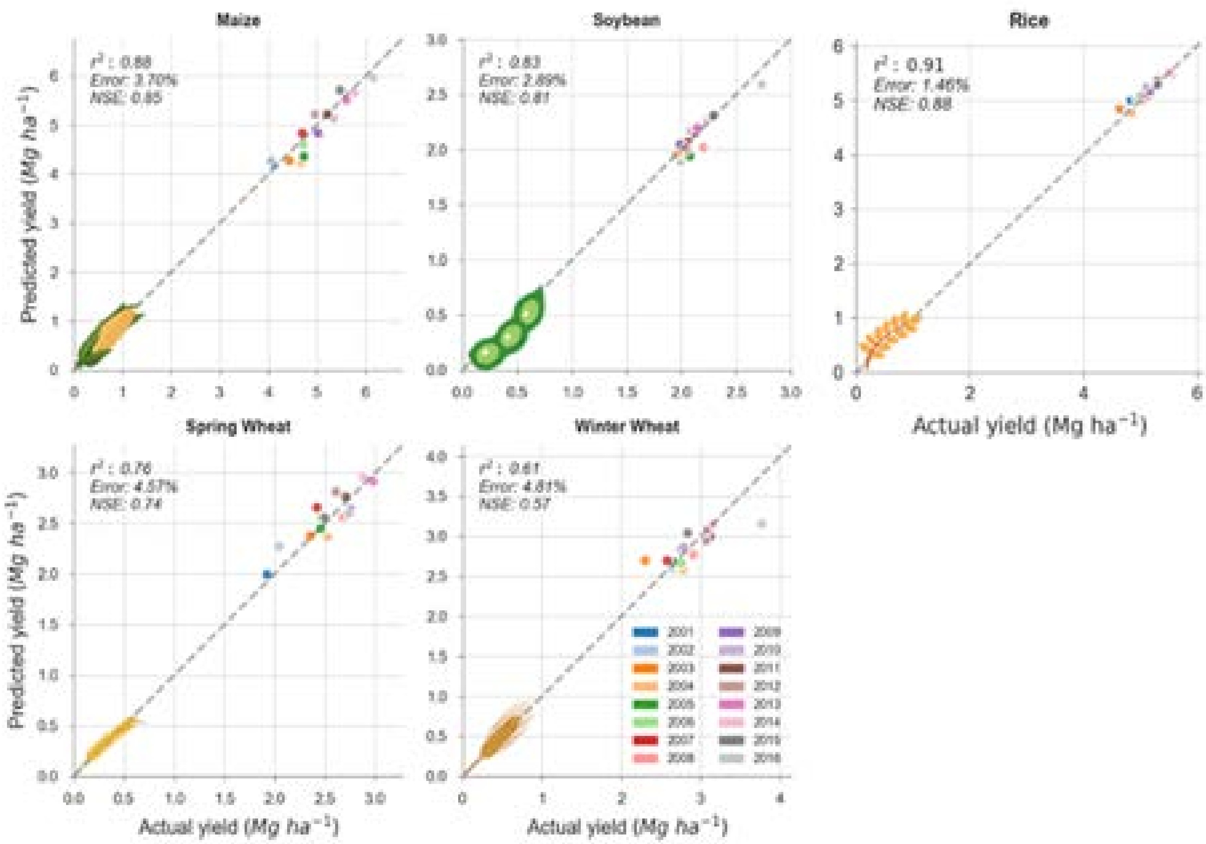


Figure 8:

Comparison of GEOCIF simulated and actual crop yields for five crops across multiple commodity crop-producing regions. Source: Sahajpal (2020).

4.2 Summary and recommendations

Timely and reliable crop yield estimates are vital at multiple levels, from achieving smallholder farmers' resilient livelihood to making policies for ensuring food security and economic growth. Given the challenges of ground-level yield measurement at scale, the potential of using satellite remote sensing-derived information to estimate crop yields across large-area is highly appealing. Many examples of empirical modeling approaches exist, yet not all the approaches may apply to smallholders' farming systems in low and middle-income countries. Inherently smaller fields and uneven management practices have proven to pose significant challenges. To address the challenges, the resolution of imagery should be sufficiently high, both spatially and temporally. Regarding spatial resolution, Burket and Lobell (2017) reported that, compared to the *very* high 1-meter resolution imagery from TerraBella, 3.7-meter (e.g., PlanetScope), 10-meter (e.g., Sentinel) and 30-meter (e.g., Landsat) data loses the explanatory power of maize yields in western Kenya by 25% and 50%, respectively. The temporal resolution, or the imagery acquisition frequency, is especially important in rainfed agriculture, where the rainy season (i.e., clouds) coincides with major crop seasons. Multiple images acquired throughout the season provide the possibility of cloud-masking.

In addition to the availability of (*very*-) high-resolution satellite remote sensing data, smallholder farmers' management practice data will be important to improve yield estimates' accuracy and applicability. These data, such as the adoption and application of fertilizer, high-yielding variety, supplementary irrigation, and soil fertility management practices, are significant factors for determining yield levels yet are largely not observable from remote sensing. Soil properties (e.g., soil texture, acidity levels, rooting depth) and conditions (e.g., moisture contents, fertility levels) are also important factors often highly associated with yield levels, especially in smallholders' farming systems. Hyper-local weather data over the growing season will also increase the explanatory power of empirical models. Lastly, coordinated efforts to measure ground-based yield data should continue, ideally collected using a standardized protocol at strategically identified locations that improve the representativeness of data from smallholder farming systems. More research is also needed to expedite the field-level yield data collection with an improved level of accuracy. Through these collective efforts, more yield estimating research pilots will continue, spur innovations, and achieve the impacts.

5

Path Forward

Thanks to the increasing availability of technologies that help collect critical information on field boundaries, crop types, and crop yield, significant advances have been made in crop analytics for smallholders. Still, challenges remain that inhibit the ability to increase smallholder yield and improve management strategies. There remain several questions and challenges that required further insight before they can be fully resolved. These largely depend on the emergence of new technologies and methods that can help improve the accuracy of crop analytics products. Below we identify five key knowledge gaps that should be addressed to advance the field of crop analytics.

1. What are the most promising technologies to enable crop analytics at scale with high accuracy?

Today it is possible to collect ground truth data for crop analytics, including crop type, field boundaries, crop diseases, and deficiencies, using handheld devices with built-in GPS and camera. With the development of attachable sensors that enable measurements of temperature, humidity, pressure, illuminance and photosynthetically active radiation in the field, the range of applications is likely to increase (Saiz-Rubio and Rovira-Más, 2020), as is the accuracy of measurements. Regarding remote sensing data, much of the data available for free today are too coarse for smallholder crop analytics while data of sufficient resolution are often prohibitively costly. But the cost, frequency, and resolutions of data collected by CubeSats are improving steadily; this development is likely to create data streams of high relevance for smallholder agriculture.

2. What is the minimum amount of ground-truth data required to enable crop analytics at scale?

Traditional analyses have relied on supervised and unsupervised classification techniques to train and test the model's accuracy. With such techniques, excess data can compromise the quality of models — so caution must be exercised when designing the model. In recent years, machine learning, deep learning, and transfer learning approaches have been promoted as methods to generate highly accurate crop analytics products with fewer data than (un)supervised classification models. The question of how much data is needed to train the algorithms is still unanswered. Initial work in this direction has already started (e.g., Azzari et al., 2021) but additional studies are needed. This question is not trivial as determining the minimum amount of ground-truth data required can help design an effective study while reducing operational costs.

3. What are the minimum required types and accuracy of datasets to improve crop analytics in smallholdings?

Specifying a minimum required accuracy or precision of maps and estimates is complicated. A precision requirement suggests that if a threshold needs to be reached for the data to be valid or used in subsequent analyses — this is rarely the case. Instead, users should try to estimate and correct for bias, and quantify and reduce uncertainty as far as practicable. The communication of such information is often invaluable for using datasets, measurement, and estimates in decision-making or subsequent analyses. Moving forward, the community should thus pay attention to approaches to achieve unbiasedness and uncertainty quantification and how to communicate and use such information in crop analytics.

4. What methods, other than field assessments, are available to obtain ground-truthed data?

As the cost and resolution of remote sensing data improve, collecting imagery observations is becoming increasingly feasible. Observing reference conditions in imagery for training or sampling-based estimation is done routinely in studies of land cover change, deforestation, and other large-scale landscape processes. The resolution of imagery in such studies is too coarse for smallholder agriculture but as mentioned, the situation is changing. Also, the use of mobile applications for the collection of ground-truth observations is increasing. The data collected are stored in cloud computing platforms and can be made available to the public, and used for crop analytics. While it can be challenging to assess the quality of such data, the sheer quantity makes the data attractive for application using machine learning and artificial intelligence. For example, Wang et al. (2020) used 2 million crowd-sourced ground-truth observations collected by farmers using the app Plantix to map crop types.

5. What are the advantages and disadvantages of different machine learning/artificial intelligence algorithms used for crop analytics?

Machine learning algorithms offer opportunities to process unprecedented quantities of data to obtain data on crop boundaries, types and yield. Similarly, ever-growing datasets of crowd-sourced observations are already available to the public. Such datasets are helpful when training a machine learning algorithm. The combination of cloud computing, machine learning, large ground truth datasets for training, and free satellite imagery at high resolution has made it easier than ever to generate valuable information for smallholder crop analytics over large areas. The drawback is the technical know-how required to perform such analyses. As crop analytics require more advanced technologies, a critical path forward will incorporate technology into devices that are readily available to smallholder farmers.

Undoubtedly, the increasing availability of very high-resolution data from various sources (satellites, handheld devices, smartphones, and UAVs) and new analytical approaches based on machine learning algorithms will offer opportunities to answer these questions. The crop analytics community is in an unprecedented position to advance solutions to these five critical questions in the coming years, and enable crop analytics at scale to benefit smallholder farmers.

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Enabling Crop Analytics At Scale

State of the Science

Ground Truthing in Crop Analytics for Smallholder Farmers

The Enabling Satellite-based Crop Analytics at Scale (ECAAS) Initiative is a multi-phase project that aims to catalyze the development, availability, and uptake of agricultural remote-sensing data and subsequent applications in smallholder farming systems. The initiative is funded by The Bill & Melinda Gates Foundation and implemented by Tetra Tech.

info.ecaas@tetratech.com
cropanalytics.net

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Authors

P. Olofsson: ORCID iD (0000-0002-8406-4719).
J. Koo: ORCID iD (0000-0003-3424-9229).
A. Ghosh: ORCID iD (0000-0003-3667-8019).
P. K. Krishnamurthy: ORCID iD (0000-0002-0320-8523).

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