TETRA TECH

Enabling Crop Analytics At Scale

ENABLING CROP ANALYTICS AT SCALE (ECAAS)

Next Generation Crop Production Analytics

Smartphone 3D Imaging to Support Crop Analytics

Contents

1

Background

Timely information on crop type, growth, and productivity – collectively called crop analytics – is challenging to generate. Yet crop analytics can provide critical insights for decision-makers. At the institutional level, potential applications of crop analytics include tracking food production, detecting any potential issues early, and intervening to avert or minimize supply disruptions. At the field scale, producers, including smallholder farmers, use the information to monitor crop productivity, manage potential agricultural risks, and help inform farming decisions. Indirectly, farmers can also benefit from private digital agriculture companies that use crop analytics to tailor their services and generate actionable insights at highly granular scales. There is increasing evidence that demonstrates the potential benefits of crop analytics for smallholder farmers, ranging from farm management decision supporting services (e.g., provision of agro-climatic, market trend and prices, and management advisory information) to digital finance and risk management services (e.g., crop insurance and alternative credit ratings).

However, the availability of robust and representative ground-truthing data for model calibration and the validation of estimates primarily constrains the utility of crop analytics. Geospatial analytics based on satellite imagery have illustrated the opportunities to predict crop production at scale, yet the lack of sufficient ground-truthing data impedes the use of remote sensing datasets, especially in the context of smallholder farming where fine spatial resolutions are required.

Here we propose a model to use smartphone 3D imagery and structure from motion approaches to improve yield analytics at spatial scales never achieved before. We first examine existing approaches to improve yield analytics. Next, we highlight how smartphone-based analyses can fill in critical knowledge gaps. Subsequently, we present an overview of the proposed method to use smartphones.

By expediting the crop yield measurement, this method will provide major gains in the number of ground-truthing data with less fieldwork and less time than traditional methods. Further, combined with the Dynamic Area Sampling Frame method developed in the Work Stream #1 of this project, we anticipate that these two complementary approaches can synergistically contribute to the scaling of crop analytics.

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Using smartphone 3D imagery to improve yield estimates

2.1 Why The Approach Is Necessary

Currently, collecting quality ground-truthing data is expensive and slow, requiring lengthy field campaigns. Such campaigns are subject to error due to inconsistent methods and differences in data collection training. In addition, there is a risk that data are not representative beyond the area where the information is collected. The official Crop Cutting Experiment (CCE) guidelines published by the Government of India suggest *in situ* weighings of biomass, grain weight, 1,000 seed weight, georeferenced photographs, and moisture content measurement using solar drying[1]. On average, conducting a CCE takes about two hours per plot and has high associated costs[2] and logistic challenges that hinder scaling the approach.

Against this background, there is an urgent need to develop approaches that provide accurate yield estimates with minimal effort and cost. **We piloted a non-destructive, smartphone-based yield estimation method to expedite the collection of in-field, in-season yield data.** The processing power of smartphone cameras is increasing rapidly, opening unprecedented opportunities to carry out innovative analyses of crop health and performance. Today's smartphones make it possible to convert 2D photos and short video clips into a 3D model using computer vision algorithms such as Structure from Motion (SfM). Smartphone-based SfM analyses have the potential to effectively estimate the weight of field crops with greater accuracy and efficiency than traditional CCE methods, thereby allowing analysis at scale. This new yield estimation approach is expected to increase the number of crop yield data points at a significantly lower cost than traditional methods such as those proposed by the CCE guidelines.

A typical SfM pipeline involves: (1) collecting input images (photos and video clips) by slightly moving the smartphone camera in the field, producing short baseline image pairs from one point to the next; (2) using a SfM algorithm to analyze these images and identify common spectral features (edges and corners) found across images; (3) obtaining a cloud of data points registered in an arbitrary 3D space. The result of the analysis is a 3D reconstruction of the crop (or other feature of interest). This pipeline is further summarized in **Figure 1**.

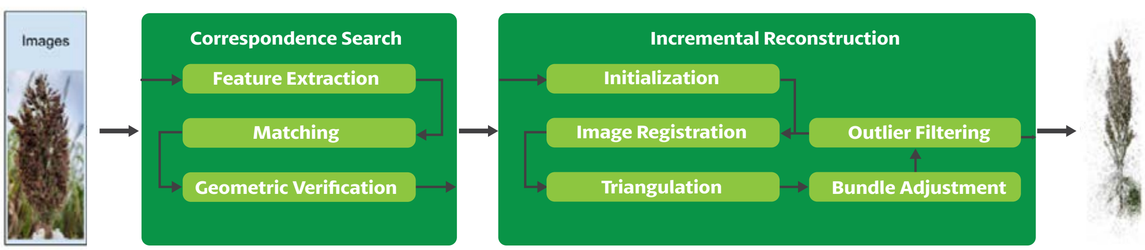
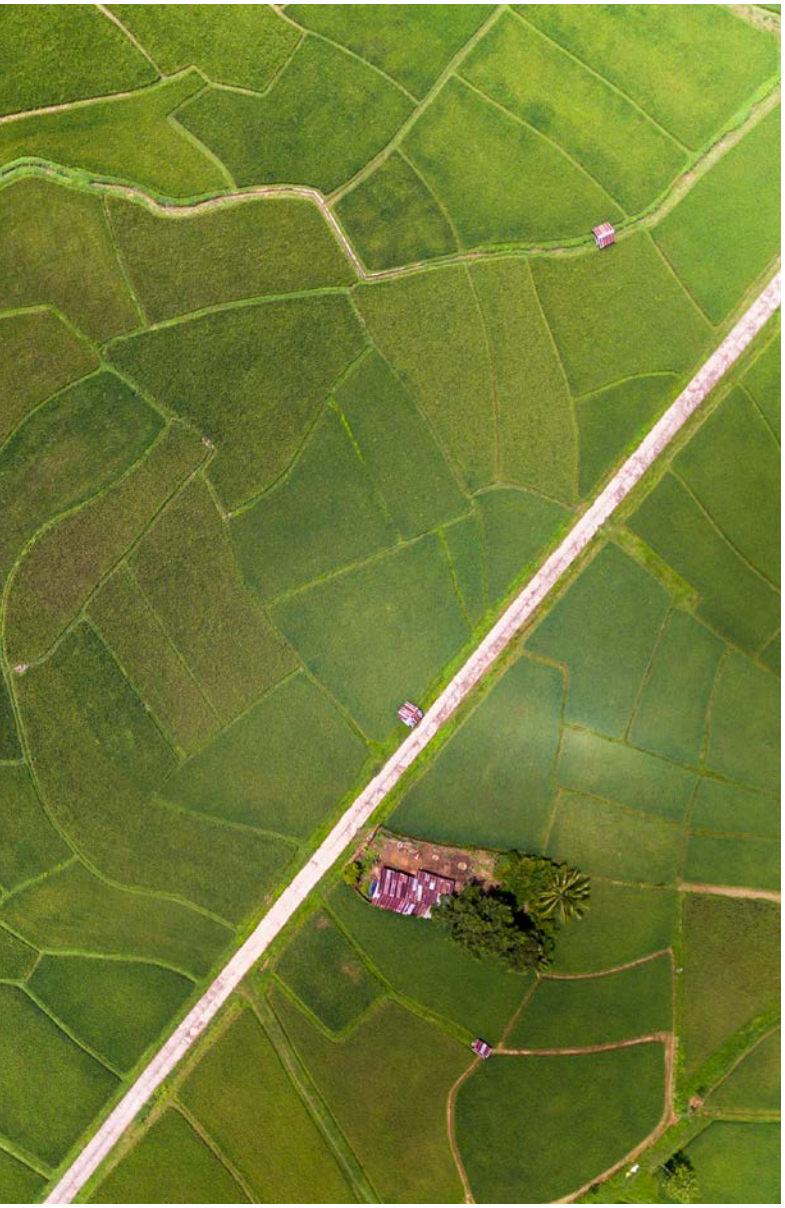


Figure 1:
A structure-from-motion pipeline (Schonberger et al., 2016)

[1] Grains from harvest crops tend to have high moisture content. Solar drying is practiced by leaving the produce in an open area: for instance, in the fields over a plastic cover or on a cemented floor.
[2] At least 2 labourers have to be paid for the time spent to perform the crop cutting experiment in farmers field in an area of 5 x 5 meters square plot. The cost also involves the time for the authorized team to travel and supervise the work, collect a sample of the crop which needs to be dried and then grains should be separated from the Stover to determine the actual yields. All this process is not only cumbersome and costly but also not performed by entities in a responsible way. Hence, the results have limited value.

2.2 Lidar And Sfm: Two Approaches To Enhance Crop Yield Estimates

Two types of sensors are currently promoted as tools to generate three-dimensional models of objects that can then be used to assess crop yield. (1) LiDAR sensors are considered the gold standard that natively generates dense point cloud structure data (Damkjer and Foroosh, 2020). (2) Image-based structure from motion is an emerging approach that relies on computer vision algorithms to analyze multiple two-dimensional images and provide a three-dimensional virtual estimate of the point cloud (de Souza et al., 2017). These two approaches are reviewed below.



1. Terrestrial LiDAR Scanner System

Terrestrial LiDAR provides highly accurate 3D models with a high density of points (Lim et al., 2013). In addition, LiDAR systems can process data at high speed and provide (near-) instantaneous results. LiDAR has been widely used to develop 3D models of infrastructure and real-time navigation of autonomous vehicles (Vicari et al., 2019; Dong et al., 2020). In agriculture and plant science disciplines, LiDAR is commonly used to measure tree height and phenotype crops (Lin, 2015). ICRISAT is equipped with a LiDAR scanning platform, LeasyScan, which projects lasers at a fixed wavelength on top of the canopy. The light reflections are captured at a high rate to generate dense 3D point clouds.

Despite the appeal, LiDAR observations have major limitations. Because of their low mobility, LiDAR scanners cannot be used to generate 3D models of small objects in complex environments like fields. New, portable LiDAR scanners have become available and can rapidly develop a 3D model at a low cost, yet their resulting point cloud density is low and unsuitable for small objects, such as crops. Especially for objects like panicles, the LiDAR captures data immediately surrounding it and not the object of interest, making it challenging to make models. In order to produce a complete 3D model of an object using portable LiDAR, the sensor needs to be placed at different locations around the object. Once the data are collected, the scans can be stitched together to get the 3D model of the object.

2. Structure-from-Motion (SfM) approach

In recent years, the Structure from Motion (SfM) approach has been promoted as an effective method to recreate the three-dimensional structures from a collection of two-dimensional images via estimation of camera motion corresponding to these images. Incremental SfM is an overall strategy for 3D reconstruction from unordered image collections. These techniques produce a sparse set of points in 3D that are then used to reconstruct ordinary objects such as buildings and furniture. Generally, these simple objects are well-defined by a set of vertices. However, complex objects, such as plants, require a dense set of 3D points to sample their surfaces with sufficient spatial resolution (Schonberger and Frahm, 2016).

Marzulli et al. (2020) demonstrated the utility of the SfM approach by capturing images with a smartphone camera to calculate dense point clouds of a forest plot. In order to estimate diameter at breast height (d.b.h.) and stem volumes, the authors automated a method to extract the stems from the point cloud and then model these stems as cylinders. The results show that the image scale is the most influential parameter in identifying and extracting trees from the point clouds. The best performance with cylinder modeling from point clouds compared to field data had an RMSE of 1.9 cm and 0.094 m3, for d.b.h. and volume, respectively.

In a different study, estimates of canopy height and above-ground carbon density derived using SfM are compared with those from an airborne laser scanning (also known as LiDAR) benchmark (Swinfield et al., 2019). Measurements obtained from SfM analysis systematically underestimated the canopy height with a mean bias of approximately 5 m. However, the model based on SfM analysis was able to predict the field-measured heights when the approach was applied to an independent survey in a different location with relatively high accuracy (R2 = 67% and RMSE = 1.85 m). The inclusion of ground control points was important in accurately registering SfM measurements in space. However, at the scale of several hectares, the top-of-canopy height and above-ground carbon density estimates from SfM and LiDAR were very similar even without ground control points. The ability to produce accurate top-of-canopy height and carbon stock measurements from SfM holds great promise for forest managers and restoration practitioners. It provides the means to make rapid, low-cost surveys over hundreds of hectares without the need for LiDAR.

In the case of LiDAR, a single terrestrial scan cannot create a dense 3D model of panicles associated with crops such as oat or rice. LiDAR scans the environment immediately surrounding it and only captures the front of the object exposed to the scanner. When modeling a panicle for volumetric analysis, the model should capture all possible angles of a given panicle. One way to tackle this is to collect data by placing the scanner at different positions around the panicle. Then all the scans should be carefully registered and segmented to get the 3D model of the panicle.

Unlike LiDAR-based approaches, the SfM method can be carried out using readily available technology such as smartphones, cameras, tablets, and computers. The user can effortlessly move around the panicle, capture images, and use them as an input for 3D reconstruction. SfM photogrammetry shows high potential for practitioners and researchers. However, constraints linked to the fundamental principles of SfM photogrammetry — such as geometry, lighting, and the availability of static — remain. Researchers should pay attention to these issues before investing in a SfM exercise.

Table 1 Key differences between LiDAR and SfM approaches (adapted from Wilkinson et al., 2016)

	LiDar	**Structure from Motion**
Cost	High (>50K USD)	Low (<1K USD)
Weight	High (fixed platform; 50 kg)	Low (2 kg)
Immediate results in the field	Yes (No Post Processing)	No (Post Processing required)
Precision	High (for stationary objects) Low (for moving objects)	High (image quality and amount dependent)
Processing time	Low (minutes to hours)	High (hours to days)
Performance under wind	Low	Moderate
Performance under direct sunlinght	High (Light does not effect)	Low (Light effects)
Short-range (>1m)	Low (Low quality at very short range)	High (High quality if the object is close to the camera)
Long-range (>300m)	High (Good density for distant objects)	Low (Distant objects cannot be focused)

3

Approach

In the last two decades, methods that enable 3D reconstructions of objects from images taken from different viewpoints with multiple cameras have been developed (Seitz et al., 2006). These tools allow the use of extensive image collections to create 3D models of points of interest automatically. Furthermore, due to the development of camera features, smartphones have become standard devices for image acquisition.

Initially, we anticipated using the LeasyScan LiDAR scanner to create the densest quality point clouds of the harvestable yield elements of focus crops to estimate yields accurately. However, due to the static configuration of the platform and storm damage (in February 2021), we were unable to acquire high-quality point cloud data of yield components from LeasyScan before the harvest period. An initial analysis revealed that LeasyScanned sorghum panicles generated sparser point cloud data than expected, and, therefore, were ineffective for yield estimates (**Figure 2**). Given these challenges, we opted to use a technique-based SfM reconstruction to estimate yield.

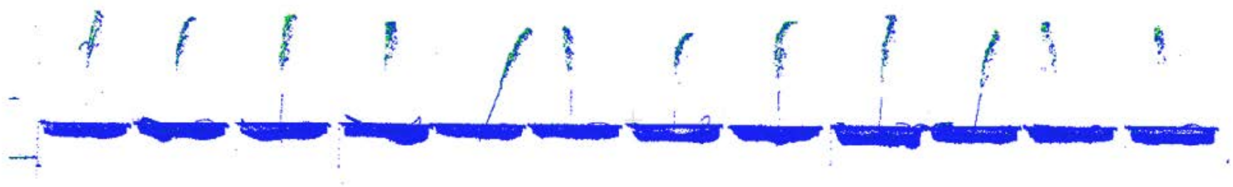


Figure 2:
LeasyScan outputs (sparse 3D point cloud) from sorghum panicles

The possibility to reconstruct reliable 3D models by using low-cost consumer devices represented a transformative opportunity (Newcombe and Davison, 2010; Vogiatzis and Hernández, 2011). Smartphones are used worldwide and offer the possibility to access various applications to accomplish many tasks, including assessing yields (or other crop metrics) with greater accuracy, efficiency, and scale. For instance, crop data can easily be captured and computed into useful crop analysis, as demonstrated in **Figure 3**.

Figure 3:
A set of 2D images of sorghum panicles captured using a smartphone camera

Using the technique-based SfM method, we ran a feature-matching algorithm to identify similarities between images after extracting features from all images (Lowe, 2005; Bay et al., 2008). We then used a mapper algorithm to reconstruct a 3D model. The 3D reconstruction mapping of the dataset using hierarchical SfM occurs after performing feature extraction and matching. This order parallelizes the reconstruction process by partitioning the scene into overlapping sub-models and then reconstructing each sub-model independently. Finally, the overlapping sub-models are merged into a single reconstruction. Using a sparse model, we then compute the dimensions of the panicles (**Figure 4**).

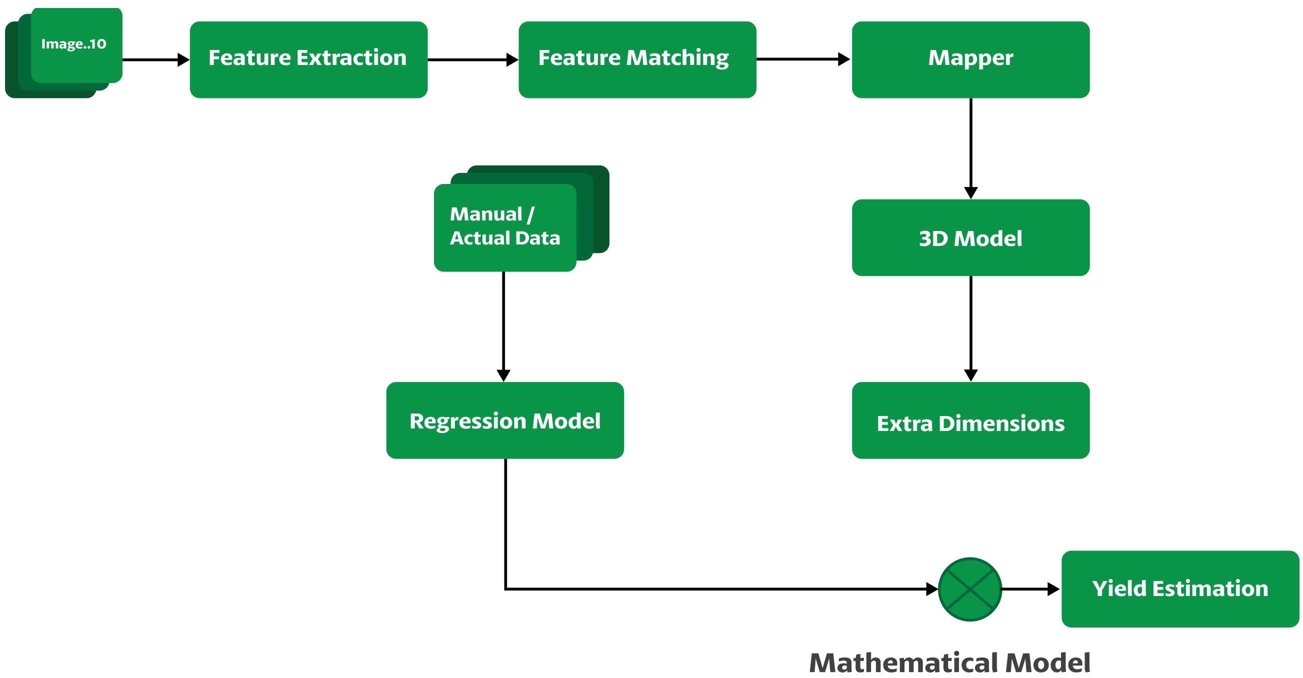


Figure 4:
A process flow from 2D image sourcing to the yield estimation

For our anlaysis, we used the COLMAP algorithm (Schonberger and Frahm, 2016; Schönberger et al., 2016) to carry out the 3D reconstruction of crop panicles (**Figure 5**). The library serves as a processing pipeline for reconstructing camera poses and 3D scenes from multiple images. It consists of basic modules for Structure from Motion, focusing on building a robust and scalable reconstruction pipeline. The final SfM point clouds also possess RGB values, which enables rendering in full color, thereby facilitating the interpretation of SfM clouds.

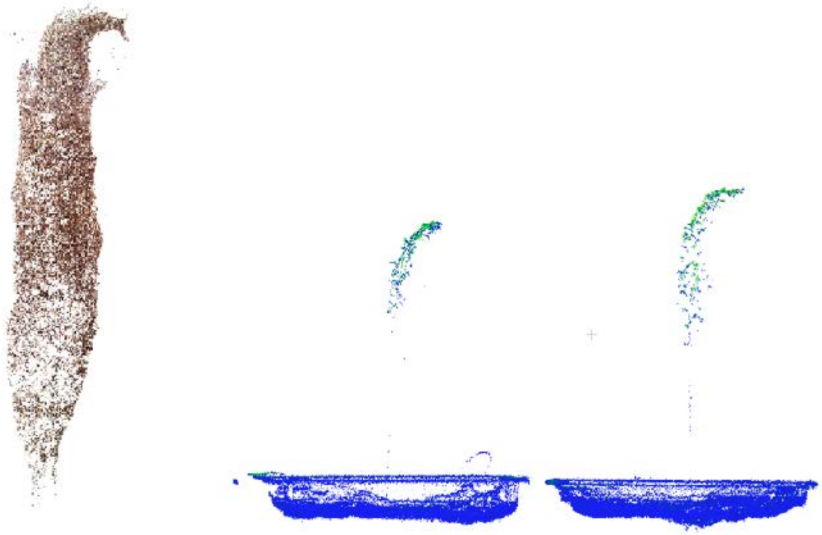


Figure 5:
An SfM-reconstructed 3D model vs. the close-up view from LeasyScan of a sorghum panicle.

Based on the results, we developed a mathematical model using panicle volume and weight, which in turn was computed using the water displacement technique (**Figure 6**). The volume of displaced fluid is equivalent to the volume of an object fully immersed in a fluid or to that fraction of the volume below the surface for an object partially submerged in a liquid (Kireš, 2007). The dataset is then split into training and test datasets. The test dataset provides an unbiased evaluation of a model fit on the training dataset while tuning the model hyperparameters. The output panicle weight is fed as input into a second mathematical model that estimates the panicle's grain weight and its yield.

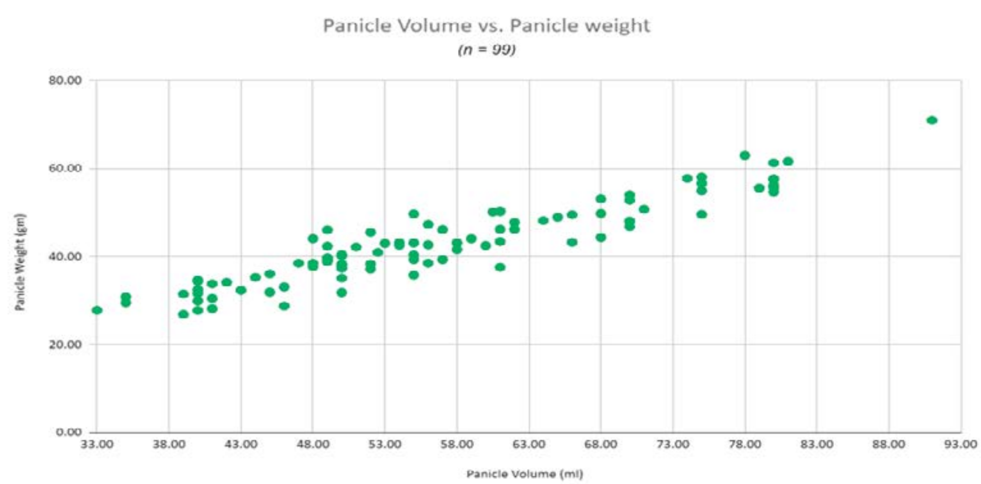


Figure 6:
Volume vs. weight plot of sorghum panicle

In situ data were collected in Odisha during the Kharif season (June–October) for finger millet and during the Rabi season (November–April) for finger millet (**Figure 7**).

Figure 7:
Spots indicate the source of finger millet (n=213) in Odisha (right cluster) and Sorghum (n=103) in Telangana (left cluster; ICRISAT campus)

The model's output is a weight matrix that estimates the weight of the panicle based on its volume. We estimated the volume of the panicle by constructing a convex hull (**Figure 8**). The process consisted of inputting the volume data into a model that provides an estimate of the weight of the panicle; this value is then used to compute the grain weight of the panicle. Finally, the weight estimate is used to estimate crop yield, given the total area and density of the field. The accuracy of the model relies on the data used for training the model.

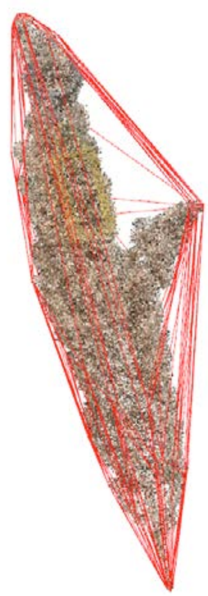


Figure 8:
A 3D-approximation of sorghum panicle using a convex hull modeling method.

A major problem that affects the accuracy of monocular SFM, however, is scale ambiguity. The monocular camera cannot compute the length of translational movement from feature correspondences only, as the distance between the camera and the features cannot be estimated by triangulation directly. The inherent scale ambiguity of the reconstructed 3D structure from a set of images taken by a monocular camera can be addressed by using markers (**Figure 9**). We placed a marker of know dimension in the scene and used it to compute the scaling factor.

Figure 9:
A key chain of known dimension is used as a marker

Qhull: A web application to calculate the volume of an irregular-shaped object

Qhull Deomonstartion video

Calculating the volume of an irregular-shaped object, such as a crop panicle is a key challenge in quantifying crop yields. The most widely used approach is to mesh the surface of the reconstructed panicle as a convex hull and compute the volume of the hull (**Figure 8**). The convex hull of a set I of points in Euclidean space is the smallest convex set that contains *I* (Andrew, 1979). We use *Qhull*, which implements the Quickhull (Barber et al., 1993) algorithm for computing the convex hull. This volume of the hull is the input to our app-based model.

On the launch page, the web-based application asks for the video files/set of images as a major input (Figure 10). In addition, the user can provide other inputs like plant density (number of plants per sq m) and the field area (Ha). A small video file (10-12 seconds) taken around the panicle can also be uploaded and used for 3-D reconstruction. Once the conversion is complete, the application will direct the user to a viewer output of the data points (**Figure 11**).

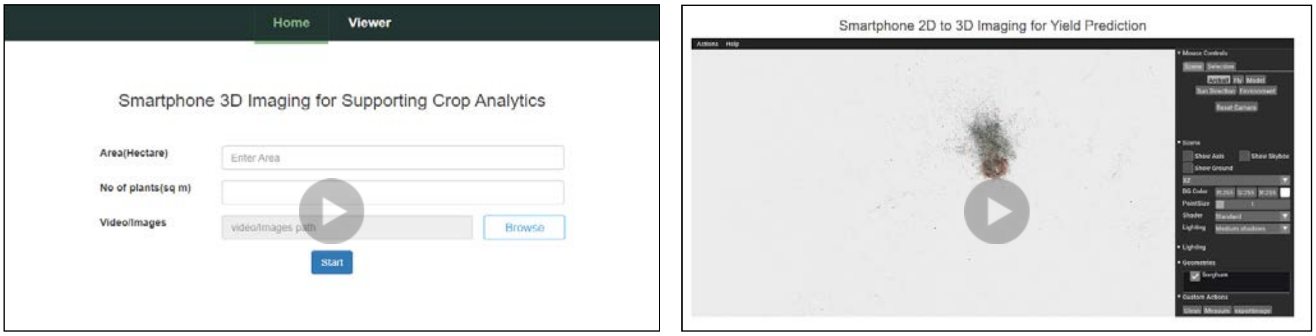


Figure 10 & 11:
Launch Page & Viewer - Qhull demonstration video

However, when utilizing 2D data collected from scanning devices or images, the resulting point cloud in the 3D conversion tends to contain noise (**Figure 12, left**). This excessive noise can lead to inaccurate results, so filtering the data before computing the convex hull is highly recommended. The 3D viewer application provides the option to clean and filter the data.

Radius Outlier Filter is a simple filter that removes outliers if the number of neighbors in a specific search radius is smaller than a given K. This filter iterates through the entire input once, and for each point, retrieves the number of neighbors within a certain radius. Thus, the point is considered an outlier if it has too few neighbors. Only the inliers are kept, and the outliers are discarded as noise (**Figure 12, right**).

Figure 12:
Reconstructed Data – Unfiltered (left) and filtered (right)

After filtering the data, the user selects two corner points on the marker in order to measure the size of the panicle (**Figure 14)**. Our method uses the measurements from the model and actual dimensions of the marker to compute the scale. Once the scale is computed, we transform the volume to a weight estimate and translate the area (in hectares) and density of planting (plants per square meter) to calculate the yield (tons/ ha).

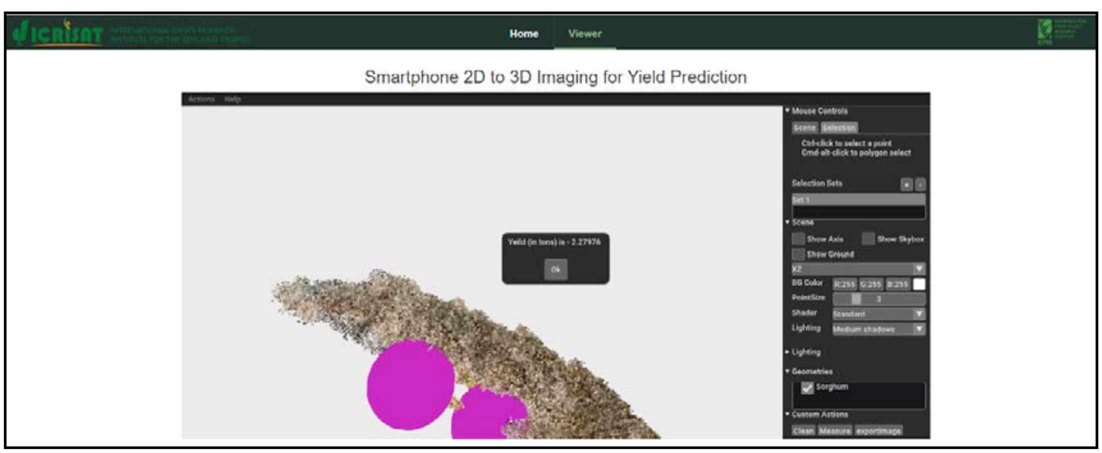


Figure 13:
Reconstructed Data – Unfiltered (left) and filtered (right)

4

Learnings

4.1 CHALLENGES

Data collection: Training is needed to ensure consistency in data collection. Average users may capture images from incorrect positions, limiting the final model's accuracy and completeness. For instance, unfocused subjects and low lighting can lead to failure in the reconstruction process. Even image overlap needs to be considered when collecting the data. 85-90 % overlap would generate a denser model with good texture. To overcome this challenge, we have asked users to record 12-second-long videos as they move around the panicle while ensuring that the panicle is in focus and in the center of the video. The remaining challenge will be to continuously communicate clear directions for data capture to new users to avoid the common pitfalls mentioned above.

Markers: The markers were introduced as control points to estimate the scale of a panicle, but selecting the corner points on the markers can be challenging. Sometimes the marker is not clearly visible in the reconstructed model due to noise. The marker should be placed in an obvious location to ensure that it can be more easily identified, even in a noisy version of a reconstructed model.

Challenges of SfM: Low image overlap might yield mismatches during the initial step of the SfM pipeline and generate discontinuities in the reconstructed sparse point cloud. This, in turn, can destabilize the bundle adjustment solution. Lighting differences caused by either wrong in-camera exposure settings or variations in lighting during data capturing can generate errors in the final model. Overexposing bright areas or under-exposing dark areas can alter the properties of surface features, thereby adversely affecting tie point detection.

Processing time: The processing time depends upon the computational power of the individual system that is being used for processing. It can be reduced after down sampling the original high resolution of input imagery. On average, the data processing will take 2-3 minutes per 12-second video (with a resolution of 1920 x 1080) on an i7 CPU with 16 GB memory. The same process will take less than one minute if 10-12 images are uploaded instead of the video.

4.2 FUTURE WORK

Dataset: The quality and availability of data are the most critical factors determining the ability to predict crop yield from a panicle. A greater amount of data would yield more accurate models. The current model was trained on a dataset containing 68 sorghum panicles. Additional data should be collected to enhance the model. This will require further retraining and re-deploying as well as re-running the entire existing pipeline with new data. Moving forward, data should be collected from at least 200 panicles from the field to increase the robustness of the proposed model.

Automating data noise removal: Noise removal is a key step in the process to compute the volume of the panicle; excessive noise can create inaccurate results. We provide visual feedback to the user through a 3D viewer application and expect input from the user to clean the generated 3D model. As our next step, we would like to automate this by developing models that can effectively remove noise from the reconstructed model automatically with minimal human intervention (Wolff et al., 2016). This is a critical step to move forward in the 3-D reconstruction process.

Identifying markers: In the current model, the user needs to explicitly select two corner points on the marker to address the scale ambiguity. We will work to automate this by first detecting the marker in the generated point cloud data and computing its dimensions without any human intervention.

Data validation using LiDAR: The inherent scale ambiguity in photogrammetry is a drawback for SfM approaches. To address this, we used a marker to compute the scale of the generated 3D model and used the scale value to compute the dimensions of the panicle. To validate our approach in future research, we will compare the dimensions of the panicle captured using the SfM approach with measurements obtained from a LiDAR system. LiDAR measurements provide the dimensions of a panicle at high accuracy — on the scale of centimeters — allowing for a comparison with SfM models, which are equally accurate in the scale of centimeters. The calculated volumes, using the data generated by the LiDAR system and reconstructed data, will help calibrate the model to achieve more accurate results that better represent ground-truth values.

5

Conclusion

Here, we presented an approach to estimate yield from images and videos collected with a smartphone. We calculated yield estimates by reconstructing a 3D model of crop panicles using 2D images and computing their volume. This volume is then used to predict grain weights and estimate yields. The key advantage of the SfM approach is that data collection is relatively straightforward and can be conducted by a wide variety of stakeholders – not only trained officials. With smartphones and very low barriers to operation, the structure from motion technique can become an operational tool for local agencies and organizations to improve the collection of crop yield data at scales that are relevant for decision-making.

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Enabling Crop Analytics At Scale

Smartphone 3D Imaging for Supporting Crop Analytics

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.

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Final report

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Final Report for Workstream 2: Smartphone 3D Imaging

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