Unmanned Aerial System (UAS) data transfer, processing, and delivery workflow for the Wheat CAP project

Prepared by the Texas A&M AgriLife – Purdue Wheat CAP Group – December 2021

This user manual is based on the experience and efforts of a multi-disciplinary team of scientists at Texas A&M AgriLife to develop Unmanned Aerial System (UAS)-based High Throughput Phenotyping (UAS-HTP) tools for crop breeding and precision crop management. The team has developed and tested standardized protocols for UAS data collection, processing, and analysis to collect high-spatiotemporal phenotypic data on plant morphological traits such as canopy height (CH) (Chang et al., 2017; Hu and Lanzon, 2018), canopy cover (CC) (Ashapure et al, 2019a), canopy volume (CV) (Ashapure et al., 2019b), and several spectral vegetation indices (Yeom et al., 2019). Obtained UAS-based phenotypic traits have been successfully used to (i) assess disease severity (Bhandari et al., 2020) and drought in wheat (Bhandari et al., 2021), (ii) evaluate the effect of tillage management practices on cotton growth and development (Ashapure et al., 2019b), (iii) select high yielding cotton genotypes (Jung et al., 2018), (iii) monitor crop germination (Chen et al., 2018), (iv) estimate plant population/stand count (Oh et al., 2020), (v) model crop growth and estimate yield of cotton (Ashapure et al., 2020) and tomato (Ashapure et al., 2019c; Chang et al., 2021), and (vii) characterize citrus greening disease (Chang et al., 2020).

This user manual is created to standardize Unmanned Aerial System (UAS) data collection, processing, and data sharing procedures among the Wheat CAP breeding programs. Specifically, we discuss the following components that breeders can follow to successfully collect high-quality UAS data and utilize a web-based digital portal to transfer raw/processed data and visualize processed data:

1. Basic protocols and procedures for UAS data collection (RGB and multispectral imagery data)
2. Utilizing UAS data hub/portal (Wheat CAP UAS hub) for data handling

1. Basic protocols and procedures for UAS data collection

1.1. Preplanning

UAS operation in the United States is subject to Federal Aviation Administration (FAA) 14 CFR Part 107 Small UAS rules, available at https://www.faa.gov/uas/. These rules include pilot requirements, aircraft requirements, location requirements, and operating procedures. Pilot requirements are: 1) must possess a valid Remote Pilot Certificate, 2) be at least 16 years old, 3) be able to read, write, speak, and understand English, and 4) be in a physical and mental condition to safely fly a UAS. After studying the FAA Knowledge Test Suggested Study Materials found at https://www.faa.gov/uas/resources/policy_library/#107, the pilot must obtain an FAA Tracking Number (FTN) before the Knowledge Test can be scheduled at an FAA-approved Knowledge Testing Center. Finally, the pilot must Complete FAA Form 8710-13. More details are available at https://www.faa.gov/uas/commercial_operators/. It is up to the pilot to maintain the currency of their Remote Pilot Certificate every two years and keep up to date on changing FAA regulations. Aircraft requirements under Part 107 are as follows: 1) must weigh less than 55 pounds, 2) be registered if over 0.55 pounds at https://faadronezone.faa.gov/#/, and 3) the pilot must undergo a pre-flight check to ensure UAS is in condition for safe operation, Part 107 governs the location of UAS operations, which can be checked with the FAA B4UFLY mobile app. Flights conducted in Class G airspace do not require approval from the FAA. All other airspace levels (Class B, C, D, and E) are restricted and must be approved in advance by the FAA. General operating rules under Part 107 include: 1) must keep the aircraft in sight (visual line-of-sight), 2) remain below 400 feet above ground level, 3) operate during the day, 4) operate below 100 mph, 5) always yield the right of way to manned aircraft, 6) do not operate over people, and 7) the pilot must not operate the UAS from a moving vehicle.

In terms of equipment, the UAVs flown under Part 107 must be registered before operation. A pilot must carry the registration when operating the UAVs. Based on the requirements from FAA, UAV must be available to the FAA for inspection or testing on request, and a pilot must provide any associated records required to be kept under the rule. A pilot also must report any operation that results in serious injury, loss of consciousness, or property damage of at least $500 to the FAA within 10 days (https://www.faa.gov/newsroom/small-unmanned-aircraft-systems-uas-regulations-part-107). Although the UAS mission for agriculture would be conducted in a lonesome region, if an operator is conducting business, flying on behalf of a company/university/institute, or flying for some other kind of non-recreational purpose where another stakeholder might be involved, it might be necessarily needed to purchase a liability drone insurance policy.

Efficient data collection begins with planning the nursery field layout. Global Positioning System (GPS) guidance and auto-trip capability on the planting tractor and planting equipment are vital in laying out a uniform boundary of plots. Plots with consistent size and shape are necessary for automated data processing. Grouping germplasm or trials for UAS data collection together in the field will maximize the efficiency of data collection. Permanent, semi-permanent, or temporary ***Ground control points (GCPs)*** should be installed and surveyed by a survey grade RTK (Real Time Kinematic) GPS devices in the field for precision georeferencing to conduct successful UAS-HTP over the whole cropping season. It is strongly recommended to distribute GCPs well around and in the middle of the study area (***Figure 1***). We also recommend using chess-board pattern GCPs (square or circle) with about 1×1 foot (the size could be determined by the flight altitude) (*Figure 2*).

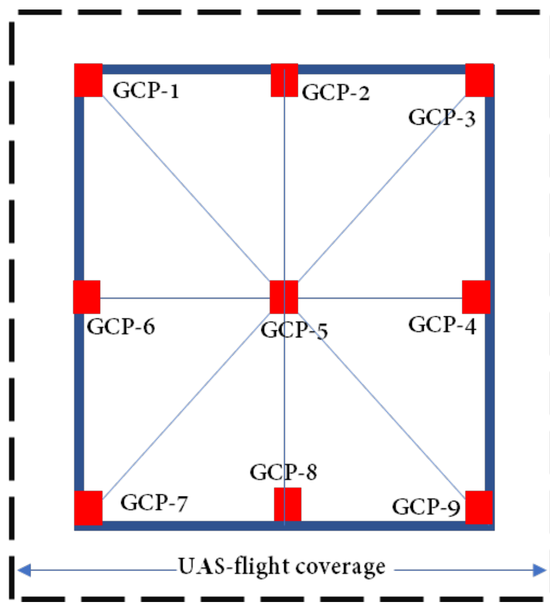

Figure 1. Ground Control Point (GCP) distribution

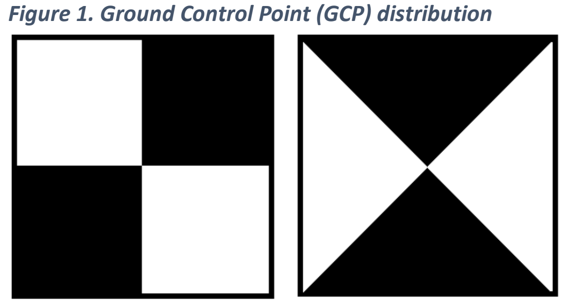

Figure 2. Pattern examples of GCPs)

As the accuracy of GPS measurements affects the quality of UAS-based products, the coordinate of all GCPs should be measured by Differential GPS (DGPS), which provides improved location accuracy (< 2~3 cm). Most quadcopter batteries offer less than 20~25 minutes of flight time; therefore, multiple batteries are required to collect data for larger areas. To collect high spatial resolution images, low-altitude-flights will be required with high image overlap and multiple battery changes restricted to a portion of the entire nursery. In contrast, lower spatial resolution images require less intensive image overlap, and flights may be conducted at higher altitudes and with fewer battery changes. Other factors to consider are obstructions such as trees or utility transmission lines, interference from other GPS guidance systems, and Wi-Fi/cellular data service for the aircraft and controller.

1.3. Equipment

Our wheat breeding program adopted DJI platforms (SZ DJI Technology Co., Ltd., Shenzhen, China) equipped with RGB (DJI Phantom 4 RTK) and multispectral sensors (DJI Phantom 4 Multispectral) in 2018-2021 (Bhandari et al., 2020; Bhandari et al., 2021). DJI Phantom 4 and Mavic 2 Pro series equipped with RGB cameras and DJI Matrice 100 with a SlantRange 3P multispectral camera (SlantRange, San Diego, CA, USA) were used for RGB and multispectral imagery data collection.

In terms of multispectral sensors, radiometric calibration is an important component to convert pixel values in raw images to spectral reflectance to see accurate crop traits such as vegetation indices. Traditionally, radiometric calibration is conducted through the relationship between actual reflectance values and pixel values in images of various reflectance panels (Sapkota et al., 2020). Recently, multispectral cameras for UAV provide two different ways of radiometric calibration: 1) using the images including a reflectance panel taken before and after flights (Chang et al., 2021), and 2) using upward-light sensor recording illumination condition (Change et al., 2020).

During the last four years of our work on UAS-HTP development, we found the following basic equipment features for smooth and efficient UAS data collection: 1) a stable and uniform UAS with the autonomous mode is needed to collect high-quality UAS data over a cropping season consistently, 2) UAS that can measure light conditions such as the Ambient Illumination Sensor (AIS) on SlantRange sensors or has calibrated reflectance panel (CRP) that comes with MicaSense RedEdge sensors (AgEagle Aerial Systems Inc., Seattle, WA, USA) can be used for radiometric calibration of multispectral images and avoid the need to add calibration panels in the field during data collection.

For those programs that can purchase DJI platforms, below are some of the recommendations with respect to UAS platforms and associated sensors (costs listed here might be different currently):

<u>*Option #1 (1 multi-spectral platform)*</u>

1. DJI Phantom 4 RTK Multispectral (6 bands) with Ground Station: $9,100
2. Reach RS2 base/rover: $6,000 (rover and base is around $5,000 but you will need survey rods for each, so it will be around $6,000 for everything)
3. Reflectance Tarps (optional): $1,200

<u>*Option #2 (1 multi-spectral platform)*</u>

1. DJI Matrice M200 V2: $6,000
2. SlantRange 4P+ (6 bands): $6,000 or MicaSense RedEdge MX (5 bands): $6,300
3. Reach RS2 base/rover: $6,000 (rover and base is around $5,000 but you will need survey rods for each, so it will be around $6,000 for everything)
4. Reflectance Tarps (optional): $1,200

<u>*Option #3 (1 RGB and 1 multi-spectral platform)*</u>

1. DJI Phantom 4 RTK with Ground Station: $8,500
2. DJI Phantom 4 RTK Multispectral (6 bands): $6,500

3. Reach RS2 base/rover: $6,000 (rover and base is around $5,000 but you will need survey rods for each, so it will be around $6,000 for everything)
4. Reflectance Tarps (optional): $1,200

<u>*Option #4*</u>

1. DJI Matrice 300 RTK: ~ $10,000
2. DJI ZenMuse P1 (45MP full frame RGB): $6,800
3. Reach RS2 base/rover: $6,000 (rover and base is around $5,000 but you will need survey rods for each, so it will be around $6,000 for everything)
4. DJI Phantom 4 Multispectral: $6,500 or you should be able to use SlantRange 4P+ with M300 as well.

1.2. UAS campaign preparation and mission planning

To prepare the UAS campaign for agriculture fields, weather conditions and flight parameters should be carefully considered based on the targeted field. Those can strongly affect actual flight time, mainly the battery life of the platform. Although the battery life could be varied with the specifications of UAV platforms and sensors, the battery can drain more quickly to balance its position under high wind speed. In addition, the overheating battery and sensor may not work properly under high temperatures in the summer. In terms of flight parameters for the imaging campaigns, there is a trade-off among flight altitude, image over-lap, and field size. With the same image overlap, high flight altitude can cover a larger area, while lower flight altitude yields high spatial image resolution for smaller areas. Therefore, an operator must seek optimum weather and flight conditions when planning a UAS mission (de Lima et al., 2021). Based on our experience of UAS missions under various conditions, we have established best practices for mission planning: 1) preparing sufficient fully-charged batteries including one or two extra, 2) setting up the optimum flight altitude and overlap according to required image resolution and field size, 3) conducting UAS missions under low wind speed (< 15 mph) and clear sky and no ice/water droplets on plants, and 4) selecting bright-colored platforms and sensors, if possible, to avoid overheating.

Users can use DJI GO 4/DJI GS Pro/Pix4D capture apps (or CrystalSky for the latest platforms) to plan flight missions and control the drones for aerial mapping for DJI Phantom and Mavic series with an RGB camera. The software supports most DJI platforms and flight parameters depending on the UAS models and camera specifications. DJI Matric 100 with SlantRange 3P camera can be operated by DroneDeploy with an additional plug-in to set up flight conditions for the multi-spectral camera. Based on the previous experience and research on UAS data collection for breeding programs, we came up with flight specifications on image overlap, flight altitude, and flight pattern to design UAS missions. For example, *the RGB platform was flown at 20-30m altitude with 80~85% forward and side overlap to obtain sub-centimeter (0.5-1 cm/pixel) Ground Sampling Distance (GSD) orthomosaics (Bhandari et al., 2021; Yeom et al., 2018). As the multi-spectral camera has a narrower field of view (FOV), a multi-spectral platform was flown over the study area at a higher altitude (>50m) with lower overlap (70~75%) than the RGB platform. 1.2–1.7 cm/pixel GSD orthomosaic images were obtained from DJI Matric 100 with SlantRange 3P camera when flown at 30–35 m with a 70–75% overlap (Bhandari et al., 2021; Yeom et al., 2018).*

2. Utilizing UAS data portal/hub for data handling

A UAS data hub/portal was created specifically for the Wheat CAP project in the Oracle cloud system. Below is the link to access the Wheat CAP UASHub (***Figure 2***).
https://wheatcap.uashubs.com/
Users can access the hub by submitting an email address and password. The hub is equipped with data sharing, visualization, and analysis features. A project for each individual breeding program will be created.

Figure 2. Wheat CAP UASHub Dashboard

2.1. Uploading raw UAS data:

The general rule before uploading raw UAS data:

1. Create a folder for a specific flight date. The format of the folder name is: YYYYMMDD_location (two letters) crop name_experimental condition (if any)_flight altitude(meters)_overlap. Example for Amarillo datasets: 20220124_ar_wheat_dryland_30m_75.
2. Create a sub-folder inside this folder for RGB and multi-spectral sensors separately. Name of subfolders depend on platform used. Example for Mavic 2 Pro and SlantRange 3p (respectively):
   m2p, s3p.
   Note: Do not rename images or folders from the platform. Copy them from the memory and paste them as they are into the new folder.
3. **Include GCP information in this folder as well.**
4. Zip it to reduce the file size and upload it in the UAS hub (.zip format) using the Upload Raw UAS Data tool .

Hover the mouse on Manage data > Upload Raw UAS Data > Select a project, a platform, a sensor, a date, and a flight (if not included, please click on the "Add Flight" button (Figure 3)). To add a flight, fill out the input fields and click on the "Add" button > Click on the 'Upload' button and select the file to upload (Figure 4).

Notes:

- **Flight name is YYYYMMDD**
- **Use only numbers when filling out flight altitude, overlap, and name.**
- **Upload only ONE .zip file at the time. Once uploading has been completed, change flight details as needed and upload the next .zip file.**

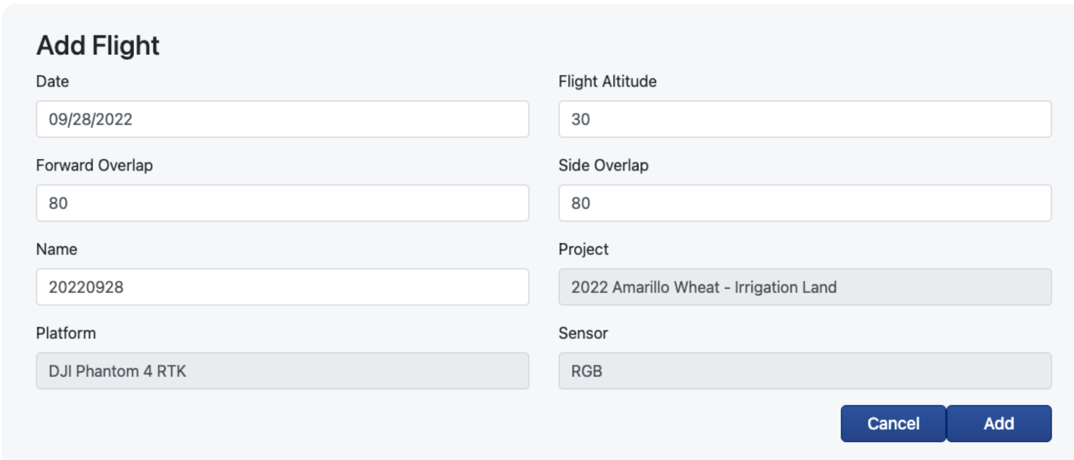

Figure 3. Add Flight

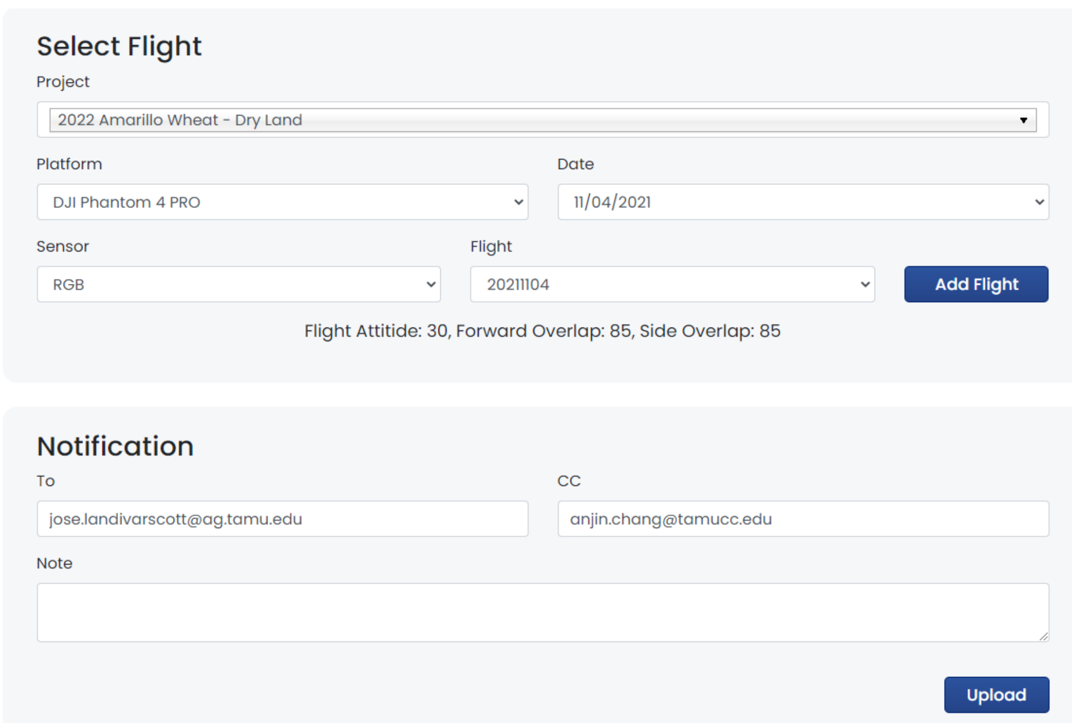

Figure 4. Upload Raw UAS Data tool

2.2. Uploading excel sheet with field layout and plot identifiers

The field layout and plot identifiers should be uploaded with the first .zip file (File containing raw images). The field layout should look something similar to Figure 5. The plot identifier worksheet should contain information as shown in Table 1. This file is expected to be in excel format (.xlsx or .csv).

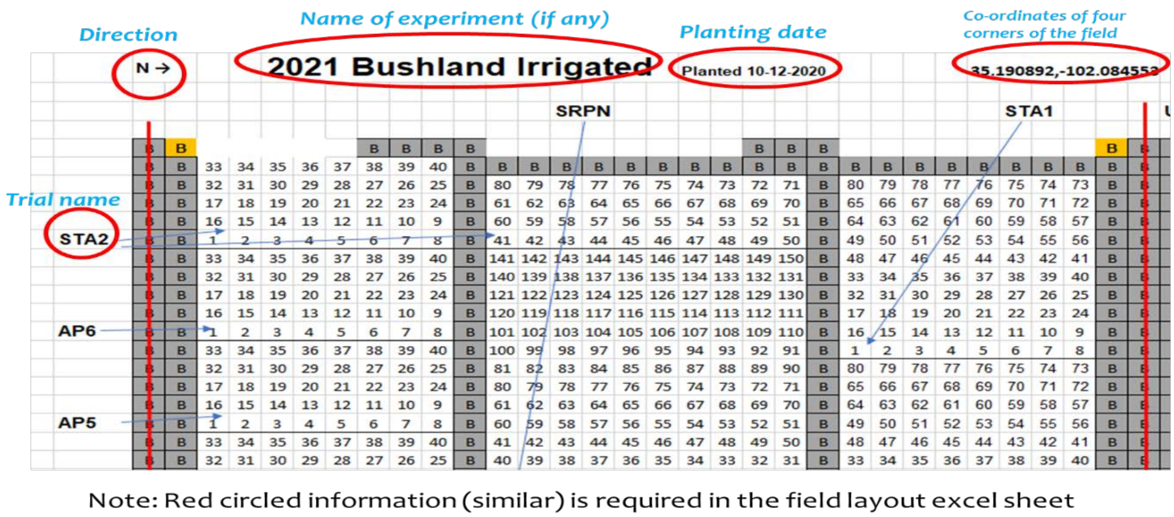

Figure 5. Field layout template

Table 1: Sample of plot identifier information

Year	EXPT	TEST_N	PLOT_ID	PLOT	BLOC	ENTRY	NAME
2021	BI	DEMO	202112039001	1	1	1	Tascosa
2021	BI	DEMO	202112039002	2	1	2	Sturdy
2021	BI	DEMO	202112039003	3	1	3	Caprock
2021	BI	DEMO	202112039004	4	1	4	TAM W-101
2021	BI	DEMO	202112039005	5	1	5	TAM 105
2021	BI	DEMO	202112039006	6	1	6	TAM-107

2.3. Data processing pipeline (Figure 6) and data product visualization

The image processing workflow starts with the collection of raw images (Level 0 data product from different sensors and platforms) (Figure 6). The Level 0 data is then processed using the Structure from Motion (SfM) algorithm to generate Level 1 geospatial data products such as Digital Elevation Models (DEM), orthomosaic images, and 3D point cloud data. The Level 2 data products (obtained from Level 1 data) include crop features such as canopy height (CH), canopy cover (CC), canopy volume (CV), Normalized Difference Vegetation Index (NDVI), Normalized Difference Red-edge Index (NDRE) and Excessive Greenness Index (ExG). Plot-level phenotypic features are extracted using plot boundaries. *Level 1 data product (Orthomosaic-RGB) can be visualized using a visualization tool in the UAS hub. Extracted plot level phenotypic data (in excel file) will be either shared as an online excel spreadsheet or be available to download from T3-Database.*

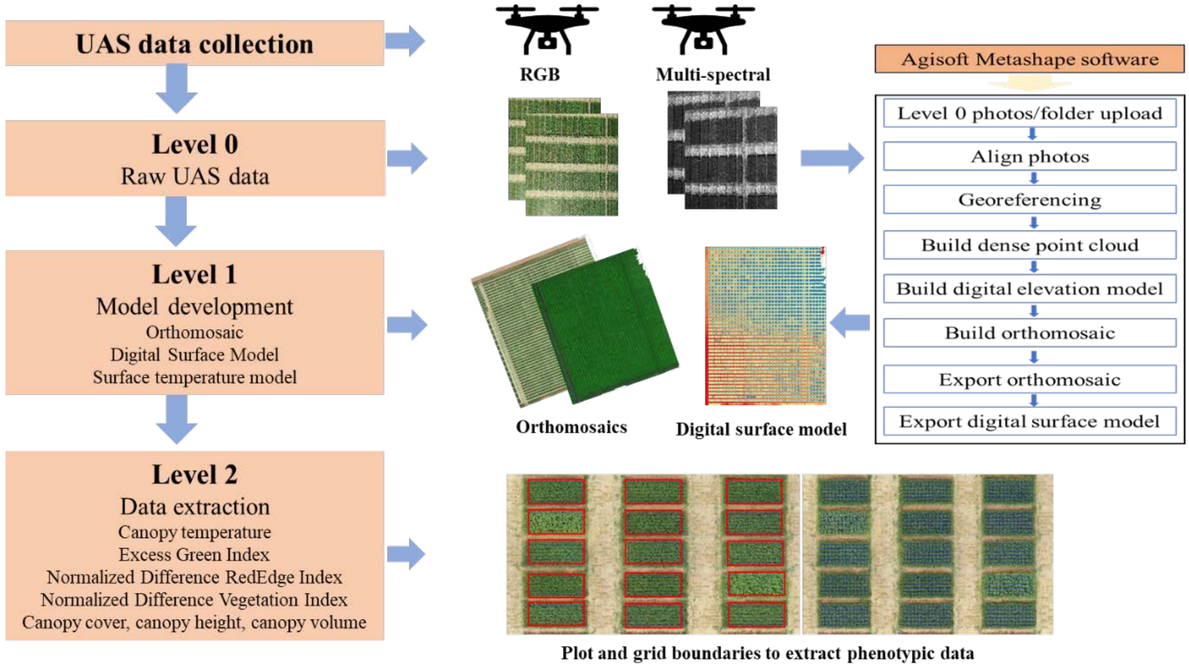

Figure 6. Data processing pipeline

2.3. Downloading UAS data products (Orthomosaic):

Hover the mouse on Manage data > Download UAS Data > Data Product > Select a project, a platform, a sensor, and type. Click on Search > Download file by clicking on blue icon next to desired orthomosaic (Figure 7).

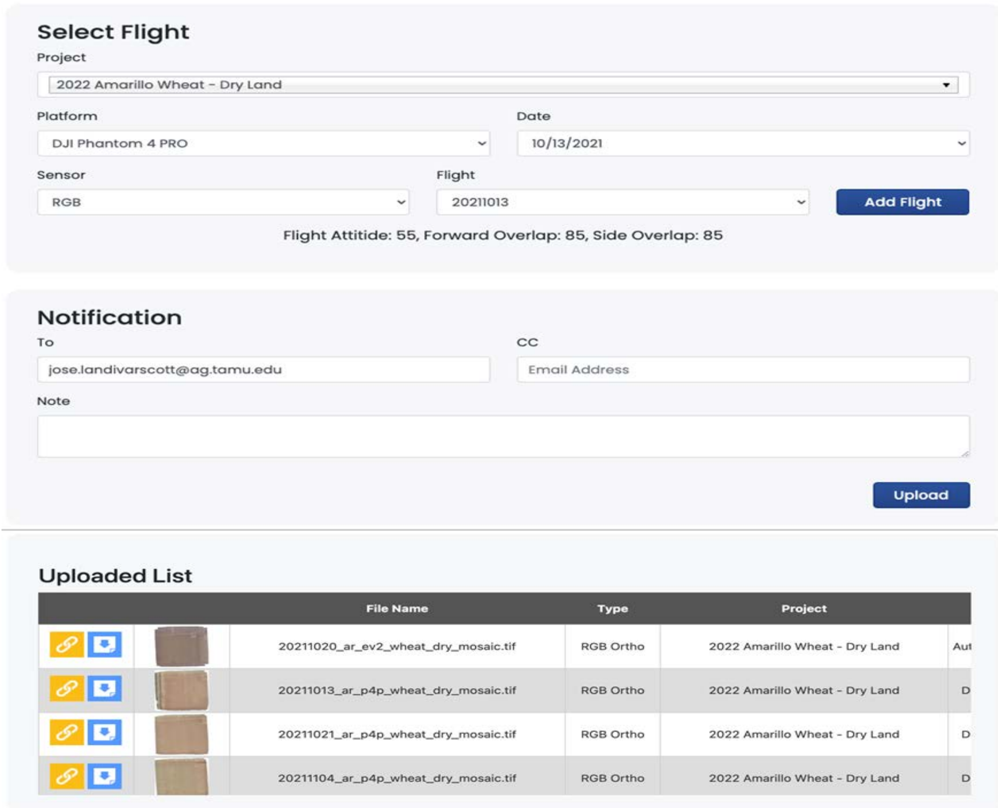

Figure 7. UAS data product (orthomosaic) list

Integrating Wheat CAP UAShub with T3 database:
We will work on integrating the current Wheat CAP UAShub to T3 database and make it Breedbase complaint in the first year of Wheat CAP project.

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