Corn Tassel Emergence Identification and Height Mesurment Based on Unmanned Aerial Vehicles

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***Abstract*—In breeding test fields, where tens or even hundreds of thousands of corns are planted, measurements of numerous phenotypic traits—such as plant height, tassel height, stem thickness, fruiting characteristics (e.g., tassel length, tassel width, awnless tip, row number), disease resistance, and lodging resistance—are typically required. Traditional methods rely on pen-and-paper recordings or basic spreadsheets, which are highly inefficient and prone to human errors, including serial mistakes and incorrect data entries. This makes it difficult to ensure data accuracy and quality. To address these challenges, this paper explores the use of Unmanned Aerial Vehicles (UAVs) and deep learning technologies to monitor the entire growth process of corn plants throughout their life cycle and select high-quality seedlings. Using experiments conducted in corn fields in Henan Province as a case study, the research focuses on identifying the growth and development stages of corn plants, as well as monitoring the timing of tassel emergence. A high-quality dataset covering the entire growth and development process is constructed. Based on UAV remote sensing images with Real-Time Kinematic (RTK) coodinates and timestamps, and 3D point cloud coordinates, we employ You Only Look Once (YOLO)v8 to conduct object detection to accurately identify tassel emergence times during growth. We also collect images of mature corn plants and their point clouds to calculate the height of each mature corn. These approachs aim to achieve precise monitoring of corn growth conditions and facilitate the digital and precise management of the corn cultivation process.**

Keywords-Unmanned Aerial Vehicles (UAVs), Real-Time Kinematic (RTK), Deep Learning (DL), You Only Look Once (YOLO).

I. Introduction

The growth and development of corn are critical factors influencing both yield and quality. Currently, crop growth monitoring primarily relies on manual sampling, which struggles to meet the demands of modern agriculture for precision and automation. In recent years, the rapid advancements in UAV remote sensing technology and deep learning have opened new possibilities for breakthroughs in crop growth monitoring [1]. UAVs have a wide range of potential applications in agriculture, including reducing manual labor and enhancing productivity. Drones are extensively used for monitoring crop growth and managing fields. They may also provide early detection of plant diseases, enabling farmers to take preventive measures against costly crop failures [2]. In particular, in scenarios such as seedling cultivation and breeding, it is essential to conduct highly detailed monitoring of each seedling's growth conditions, nutritional status, and pest and disease occurrences.

Drones have become widely used in precision agriculture to capture high-resolution images of crops, offering farmers valuable insights into crop health, growth patterns, nutrient deficiencies, and pest infestations. While several machine learning and deep learning models have been proposed for detecting plant growing status and diseases, their accuracy and computational efficiency still need improvement, especially when working with limited data [3]. The integration of Autonomous Aerial Vehicles (AAVs) has significantly advanced image processing and remote sensing, particularly in the field of precision agriculture [4].

This paper explores how drone technology can be utilized to achieve full-cycle monitoring of corn breeding experimental fields, including detecting and identifying the emergence time of corn tassels and the height of mature corn plants. The goal is to identify corn plants with optimal growth conditions and cultivate superior seeds. The contributions of our work are summarized as follows:

i) RTK point positioning technology is used to accurately analyze and determine the precise location of each corn plant.
ii) A UAV fitted with an H20 camera captures orthographic images of the corn test fields throughout the entire growth period. The pixel coordinates of these images correspond to RTK coordinates, and each image is also time-stamped. We

perform segmentation on these images and use YOLOv8 to detect the tassel (the fluffy structure at the top) status of each plant, along with their positions and emergence times. In our experiments, the identification accuracy reaches 82.5%.

iii) A UAV equipped with an L1 laser camera scans the plot to create a point cloud. The coordinates of the point cloud are then aligned with RTK coordinates in the same projection system. This equipment allows us to capture 3D point clouds and images of mature corn test fields. Based on elevation data from the top point cloud and the root point cloud of a mature corn plant, we can calculate the height of each corn plant.

The remainder of the paper is organized as follows. Section II provides a review of representative studies on digital crop management using UAVs and deep learning technologies. In Section III, we present a set of methods for identifying corn tassel emergence and measuring plant height using UAVs. Section IV details the implementation of our experiments. Finally, we conclude our work in Section V.

II. Related Work

Khan et al. [5] proposed an innovative deep learning framework that employs an encoder-decoder architecture to classify each pixel in drone images into categories such as weed, crop, and others. Effective weed control is crucial for enhancing crop yields. Traditionally, weed management relied heavily on herbicide use, but the indiscriminate application of herbicides poses risks to both crop health and productivity. Fortunately, the advent of advanced technologies like UAVs and computer vision has paved the way for automated and efficient weed control solutions. These technologies leverage drone images to detect and identify weeds with a high degree of accuracy.

Gallo et al. [6] created a weed and crop dataset called the Chicory Plant (CP) dataset and tested state-of-the-art deep learning algorithms for object detection. A total of 12,113 bounding box annotations were generated to identify weed targets (Mercurialis annua) from over 3,000 RGB images of chicory plantations, collected using a UAV system at various stages of crop and weed growth. Deep weed object detection was conducted by applying the latest You Only Look Once version 7 (YOLOv7) on both the CP and publicly available datasets, such as the Lincoln Beet (LB) dataset, which previously used an earlier version of YOLO for mapping weeds and crops.

Wu et al. [7] leveraged drone remote sensing data combined with deep object detection models, specifically employing the YOLO-v3 algorithm based on loss function optimization, for the efficient and accurate detection of tree diseases and pests. Utilizing drone-mounted cameras, the study captures insect pest image information in pine forest areas, followed by segmentation, merging, and feature extraction processing. The computing system of airborne embedded devices is designed to ensure detection efficiency and accuracy. The improved YOLO-v3 algorithm combined with the CIoU (Complete Intersection over Union) loss function was used to detect forest pests and diseases. Compared to the traditional IoU loss function, CIoU takes into account the overlap area, the distance between the center of the predicted frame and the actual frame, and the consistency of the aspect ratio.

Deng et al. [8] proposed an end-to-end Global-Local Self-Adaptive Network (GLSAN), in order to address the Object detection from a drone's perspective due to the blurriness of small-scale objects and inefficient detection in areas with uneven or dense object distribution. The key components in their GLSAN include a global-local detection network (GLDN), a simple yet efficient self-adaptive region selecting algorithm (SARSA), and a local super-resolution network (LSRN). They integrate a global-local fusion strategy into a progressive scale-varying network to perform more precise detection, where the local fine detector can adaptively refine the target's bounding boxes detected by the global coarse detector via cropping the original images for higher-resolution detection.

Lan et al. [9] proposed a rice spike detection method that integrates deep learning algorithms with drone-based perspectives. Building on an enhanced version of YOLOv5, the method introduces an Efficient Multiscale Attention (EMA) mechanism, designs a novel neck network structure, and incorporates SCYLLA Intersection over Union (SIoU). The results demonstrate that this approach enables real-time, efficient, and accurate detection and counting of rice spikes in field environments.

Hosseiny et al. [10] proposed an automated and fully unsupervised framework for plant detection in agricultural lands using very high-resolution drone remote sensing imagery. The core idea is to automatically generate an unlimited amount of simulated training data from the input images, which addresses the common limitation of deep learning methods—requiring large amounts of training data. This framework is based on a Faster Regional Convolutional Neural Network (R-CNN) with a ResNet-101 backbone for object detection. The framework's efficiency was evaluated on two different image sets from cornfields, captured using an RGB camera mounted on a drone.

Mota et al. [11] created a database of aerial RGB images of corn crops in weedy conditions to implement and evaluate deep learning algorithms for detecting and counting corn plants.

Kusumo et al. [12] investigated several image-processing-based features for detecting diseases in corn. They examined various features, such as RGB color, local image features like Scale-Invariant Feature Transform (SIFT), Speeded Up Robust Features (SURF), and Oriented FAST and Rotated BRIEF (ORB), as well as object detectors like Histogram of Oriented Gradients (HOG). They evaluated the performance of these features on several machine learning algorithms, including Support Vector Machines (SVM), Decision Tree (DT), Random Forest (RF), and Naive Bayes (NB). Experimental results indicated that RGB color features were the most informative for this task.

Quan et al. [13] presented an improved Faster R-CNN model for a field robot platform (FRP) designed to automatically extract image features and detect maize seedlings quickly and accurately during different growth stages in complex field environments, with the goal of enabling intelligent inter-tillage in maize fields. The FRP, equipped with five industrial USB cameras, captured a large number of sample images from a 0–90° shooting angle range. These images were used to create a database containing 20,000 images of soil, maize, and weeds. Ten pretrained networks were used to replace the network in the CNN feature-computing component of the classic Faster R-CNN. The proposed method, a Faster R-CNN with VGG19 processed by pretrained networks, was developed for this purpose.

Velumani et al. [14] explored the impact of image ground sampling distance (GSD) on maize plant detection performance at the three-to-five leaf stage using the Faster-RCNN object detection algorithm. The Faster-RCNN model achieved excellent plant detection and counting performance (rRMSE = 0.08) when trained and validated with native high-resolution images. Similarly, good performance (rRMSE = 0.11) was observed when the model was trained on synthetic low-resolution images, obtained by downsampling the native high-resolution images, and applied to synthetic low-resolution validation images. However, poor performance was seen when the model was trained on one spatial resolution and applied to another. Training on a mix of high- and low-resolution images resulted in very good performance on both native high-resolution images (rRMSE = 0.06) and synthetic low-resolution images (rRMSE = 0.10).

Cho et al. [15] proposed a real-time measurement system for obtaining precise target-plant growth information in precision agriculture. They used a smart farm robot that accurately measures plant growth by utilizing object detection, image fusion, and data augmentation with fused images. The system employed image fusion using both RGB and depth images to distinguish the target plant from surrounding plants.

Ahangir et al. [4] addressed the challenge of accurately quantifying corn production by developing an enhanced YOLOv8-based deep learning model, which integrates dynamic and fixed labeling techniques. The model was tested on 810 images and video data for real-time detection.

Daraghmi et al. [3] conducted a comparative analysis of three state-of-the-art object detection deep learning models—YOLOv8, RetinaNet, and Faster R-CNN—and their variants, to identify the model with the best performance for high-resolution crop images. Their study highlighted YOLOv8's robustness, speed, and suitability for real-time aerial crop monitoring, especially in data-constrained environments.

In this paper, we focus on using UAVs and deep learning technology to monitor the entire growth process of each corn plant in an experimental field throughout its life cycle, with the goal of selecting high-quality seedlings. We employ RTK technology to determine the position of each corn plant and use the YOLOv8 model to detect the tassels. By unifying point cloud coordinates with RTK coordinates in the same projection system, we facilitate the calculation of the corn plant's height.

III. Methods

In this section, we will demonstrate the workflows of using drones for corn inspection.

A. Locating the Position of Each Corn Plant with RTK Coordinates

RTK equipment is used to accurately analyze and determine the location of each corn plant. RTK (Real-Time Kinematic) is a global satellite navigation system (GNSS) technology that provides real-time, high-precision positioning. RTK coordinates include two-dimensional positioning data, such as latitude and longitude (e.g., longitude: 113.758619, latitude: 35.445592), offering centimeter- or even millimeter-level accuracy. This technology is widely used in fields like surveying and mapping. In our case, it provides precise coordinate data that serves as a reference for coordinate transformation.

The UAV then captures aerial images of the corn field, which are exported as image files for further analysis.

B. Method for Identification of Corn Tassel

1) Capturing Images of Corn Fields at Different Growth Stages for Tassel Emergence Identification

The DJI M300 drone, equipped with RTK and the H20 camera, regularly captures orthographic images of the corn fields. By combining these orthographic images with the RTK coordinates provided by the drone, a direct correspondence between the pixel positions in the images and the RTK coordinates is established. A square frame with a side length of 25 cm is placed at the center of each corn plant, within which the tasseling status of the plant is detected, along with its position—specifically, the pixel coordinates of the root and top of the corn plant. It is important to note that these images include both a timestamp and the RTK coordinates of the pixel positions.

2) Identification of Corn Tassels

We construct a high-quality dataset by collecting images from test fields that cover the entire growth and development process of corn plants. Image segmentation and object detection are performed using YOLOv8 to identify the male tassel of corn. YOLOv8 is a hierarchical, multi-scale feature extraction and fusion network. It supports not only object detection but also instance segmentation. Known for its robustness, speed, and suitability for real-time aerial crop monitoring, YOLOv8 is particularly effective in data-constrained environments [3].

First, we perform image segmentation on the collected test field images. We extract the pixels of each corn from an image, which is a square frame with a side length of 25 cm centered on the corn plant's center, and serves as the detection frame of the corn.

Next, YOLOv8 is used to identify the male tassel of the corn. The human visual system employs a selective attention mechanism that automatically focuses on key areas of a scene. Integrating this attention mechanism into a recurrent neural network can significantly enhance image classification performance and improve the model's ability to accurately identify multiple types of targets. Based on this principle, the

Convolution Block Attention Module (CBAM) is integrated into YOLOv8's feature extraction network.

When detecting the male tassel of corn, it is labeled as "tassel" along with a timestamp.

C. Calculation of Corn Plant Height

1) Capturing Images of Corn Field During the Mature Period for Corn Plant Height Calculation

To calculate the height of corn plants, the DJI M300 drone, equipped with a laser radar (L1), captures images of mature corn plants along with point cloud coordinates in local coordinates.

The 3D point cloud coordinates are represented as (x, y, z). Additionally, these images include pixel-to-RTK coordinate correspondence, which helps in locating the position of each corn plant and recording the timestamp when the images are taken.

Two key points need to be marked on each corn plant: the "root" (the base of the stem close to the ground) and the "tip" (the top of the male spike or the highest point of the plant). The pixel coordinates of the tip are crucial for height measurement.

It is particularly important to note that the local point cloud coordinates (x, y, z) must be aligned with the RTK coordinates in the same global coordinate system in order to accurately locate each corn plant and calculate its height. The coordinate conversion method is detailed in the next subsection.

2) Unifying Point Cloud and RTK Coordinates into a Global Coordinate System

First, we unify the point cloud coordinates and RTK coordinates into the same projection coordinate system.

A point cloud is a data set consisting of a large number of points, each containing information such as three-dimensional coordinates (x, y, z) in space. Point clouds can be used to represent the three-dimensional shape and spatial distribution of objects. In this paper, point clouds are utilized to obtain the 3D spatial information of target objects, such as corn plants, for tasks like coordinate transformation and stem height calculation.

The conversion formula, using a seven-parameter model, is employed to convert the local coordinates of the point clouds (x, y, z) into global coordinates (X, Y, Z), as follows:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix}_{\text{global}} = \begin{bmatrix} \Delta X \\ \Delta Y \\ \Delta Z \end{bmatrix} + (1+k) \cdot \boldsymbol{R} \cdot \begin{bmatrix} x \\ y \\ z \end{bmatrix}_{\text{local}}, \tag{1}$$

where $\begin{bmatrix} X & Y & Z \end{bmatrix}^\top$ stands for global coordinates, $\begin{bmatrix} x & y & z \end{bmatrix}^\top$ stands for local coordinates of point cloud, $\begin{bmatrix} \Delta X & \Delta Y & \Delta Z \end{bmatrix}^\top$ is a translation vector, used to represent the position offset transformation model formula for the origin of the local coordinate system in the global coordinate system, k represents the scaling factor, and $\boldsymbol{R}$ represents a rotation matrix:

$$\boldsymbol{R} = \boldsymbol{R}_Z(\omega) \cdot \boldsymbol{R}_Y(\phi) \cdot \boldsymbol{R}_X(\kappa), \tag{2}$$

$$\boldsymbol{R}_X(\kappa) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\kappa & -\sin\kappa \\ 0 & \sin\kappa & \cos\kappa \end{bmatrix}, \tag{3}$$

$$\boldsymbol{R}_Y(\phi) = \begin{bmatrix} \cos\phi & 0 & \sin\phi \\ 0 & 1 & 0 \\ -\sin\phi & 0 & \cos\phi \end{bmatrix}, \tag{4}$$

$$\boldsymbol{R}_Z(\omega) = \begin{bmatrix} \cos\omega & -\sin\omega & 0 \\ \sin\omega & \cos\omega & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{5}$$

3) Method for Calculating Corn Height

Plant height refers to the vertical distance from the root to the top of a corn plant. At the center of each corn plant, a square frame with a side length of 25 cm is placed. The highest point in the point cloud within this frame is detected as the center elevation of the plant, which corresponds to the "tip"—the top of the male spike or the highest point of the plant. The base of the stem, close to the ground, is defined as the "root." Therefore, the height of the corn plant is calculated as the difference between the global coordinates of the tip and the root.

The formula for calculating the actual height of the corn plant is as follows:

$$\boldsymbol{Height} = \boldsymbol{Z}_{tip} - \boldsymbol{Z}_{root}, \tag{6}$$

where Z_{tip} represents the elevation of the tip's coordinates of the corn in the global coordinate system, and Z_{root} represents the elevation of the root's coordinates of the corn in the global coordinate system.

IV. Implementation and Case Study

In this section, we describe our experiments conducted in corn breeding test fields in Xinxiang, Henan Province, using the DJI M300 drone equipped with various devices and cameras to capture images for different purposes.

A. Locating Corn Plants with RTK

RTK equipment is used to accurately analyze and determine the location of each corn plant in the test fields of Xinxiang, Henan Province.

For example, Figure 1 (a) and (b) show two corn seedlings, each marked with their respective RTK coordinates.

B. Identification of Corn Tassel

The DJI M300 drone, equipped with the H20 camera, captures orthographic images of cornfields. By combining these orthographic images with the RTK coordinates, a correspondence between the pixel positions in the images and the RTK coordinates is established.

We collected 1,000 images taken in corn test fields in Xinxiang, Henan Province, at fixed intervals (i.e., every three days) throughout the entire growth period, using the DJI M300 drone. A correspondence between the pixel positions in the images and the RTK coordinates is established. These images, captured by the drone, are marked with both RTK coordinates and time stamps.

At the center of each corn plant, a square frame with a side length of 25 cm is placed, and the tasseling status of each

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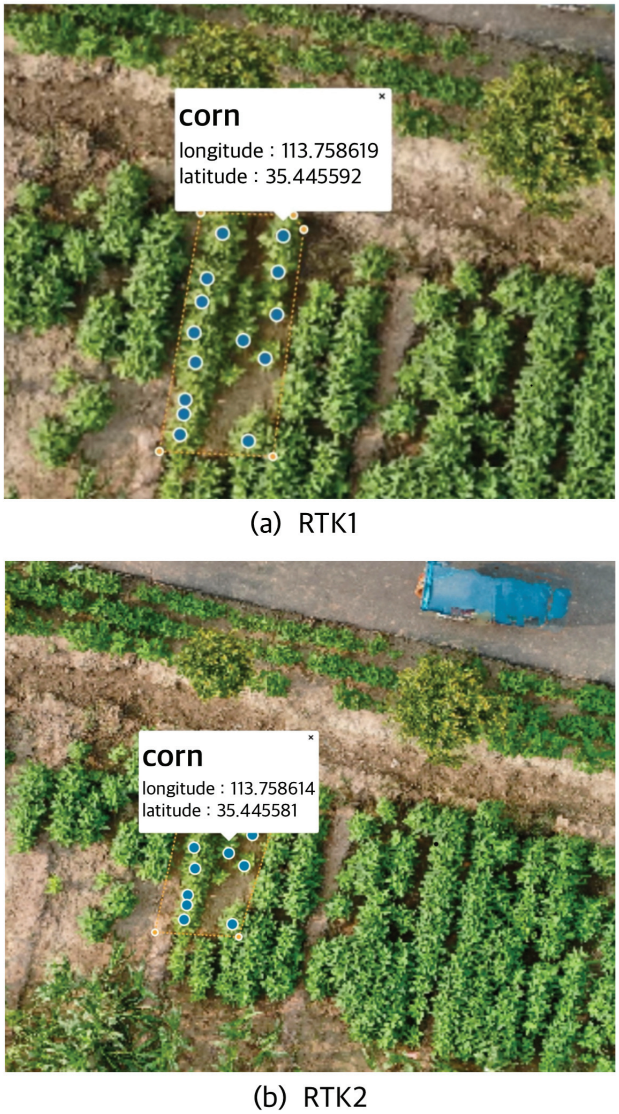

Figure 1: Corn plants with RTK coordinates.

plant within the frame is detected, along with their positions and timestamps.

Figure 2 shows a corn plant with its male tassel spike emerging. The image clearly reveals the main axis of the male spikelet and several male spikelet branches.

The detection model we used is the deep learning-based YOLOv8 (medium) network, which is applied to these images to identify the corn tassels.

First, we perform image segmentation on the collected test field images. We extract the pixels of each corn from an image, defining a square frame with a side length of 25 cm centered on the middle of each corn plant, which serves as the detection frame for the plant.

We used 810 images for the training set and 190 images for the test set. The corn tassel at each plant position within the detection frame is detected. The test results show that the accuracy rate can reach 82.5%. This demonstrates the effectiveness of YOLOv8 in capturing fine plant features under real field conditions, while also indicating that further optimization of parameters and training data could yield even higher detection performance.

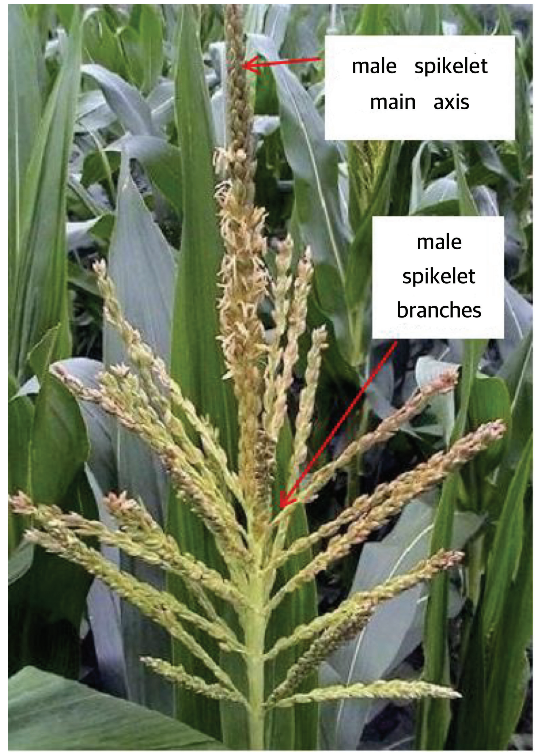

Figure 2: Photo of corn plants.

C. Calculatiion Corn Height

The DJI M300 drone is equipped with an L1 laser camera that scans the plot to generate a 3D point cloud. The point cloud coordinates are then aligned with the RTK coordinates within the same projection coordinate system. At the center of each corn plant, a square frame with a side length of 25 cm is placed, within which the highest point cloud elevation is detected, serving as the plant's center elevation.

Figure 3 shows three corn plants in a field, with the global coordinates of their respective 3D point clouds. The points marked in the figure represent the highest point of each corn plant's point cloud, enclosed by the 25 cm frame.

For example, Figure 4 shows an image of a mature corn test field, highlighting a corn plant with the global coordinates of its tip and root, represented by three-dimensional point clouds.

As shown in the figure, the tip and root of a mature corn plant share the same longitude and latitude coordinates, but their elevation coordinates differ. The elevation coordinates of the tip and root are 66.911 m and 64.602 m, respectively, with the unit defaulted to the international standard of meters.

Based on the coordinate values marked in Figure 4, and using Eq. (6) from Section III-C3, we can calculate the height of this corn plant as follows: 66.911 - 64.602 = 2.309 m.

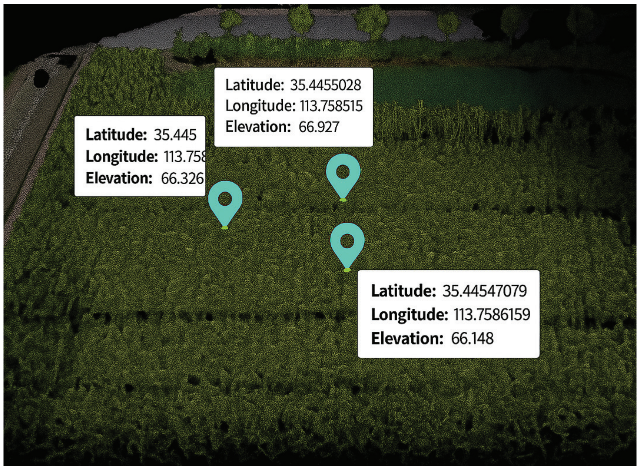

Figure 3: Photo with three global point cloud coordinates.

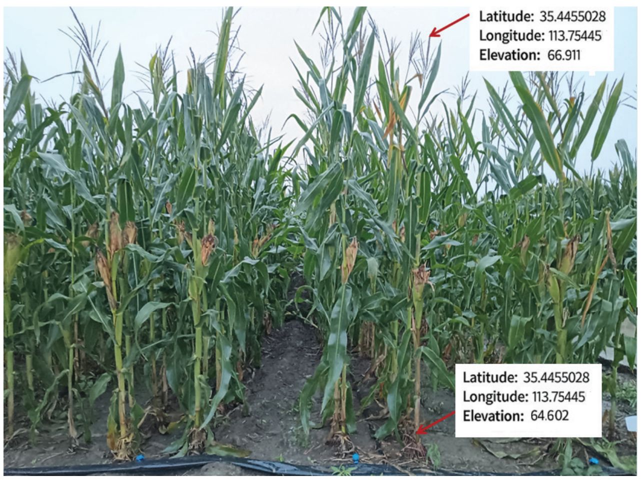

Figure 4: Photo with tip and root point cloud coordinates of corn plants.

This straightforward calculation confirms the vertical growth measurement method and provides a reliable reference for evaluating plant height across the test field.

V. Conclusion And Future Work

In this study, we proposed and validated an integrated framework that combines UAV imagery and deep learning techniques to monitor tassel emergence timing and plant height in corn breeding fields. By leveraging high-resolution drone images, precise RTK positioning, YOLOv8-based tassel detection, and 3D point cloud analysis, we achieved accurate and automated extraction of critical agronomic traits at the single-plant level. This approach not only reduces the labor intensity and potential errors associated with manual measurements but also provides efficient data support for large-scale breeding trials, thereby improving the efficiency of high-quality germplasm selection.

However, the relatively small dataset may limit generalizability, and the evaluation relied mainly on accuracy; future work should include precision, recall, and F1 score for a more complete assessment. We also plan to expand monitoring to traits such as tassel height, stem thickness, and fruiting characteristics, and to integrate multi-source data with advanced models to enhance robustness. Overall, this work provides a practical foundation for UAV-based phenotyping and highlights directions for future improvement.

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