HAFS Think-Tank Ultimatum Final Report

Controlled Environment Agriculture with Autonomous Driving based Farm Managing Drone

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International

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Abstract

We propose a method of collecting vegetation data efficiently even in soil cultivation by the autonomous drone algorithms. The drone manages plant growth in centimeter units, enabling efficient cultivation of large quantities of plants with little human labor and cost. We create drone autonomous driving algorithm by implementing object detection, stereo depth perception mapping, 2D mapping, and 3D modeling technologies. We extracted and used the MultiSpectral Instrument data provided by the European Space Agency to accumulate and learn vegetation data. As a result, multispectral data through satellites cannot be used for automation and efficiency improvement of soil cultivation because the quality of the data is low. If further studies create a high resolution (HD) multispectral data map through Open i Data Collecting Drone (ODCD), it is possible to observe the state of soil cultivation vegetation in detail, and accurately map and data for automation programs of systems such as other drones or tractors.

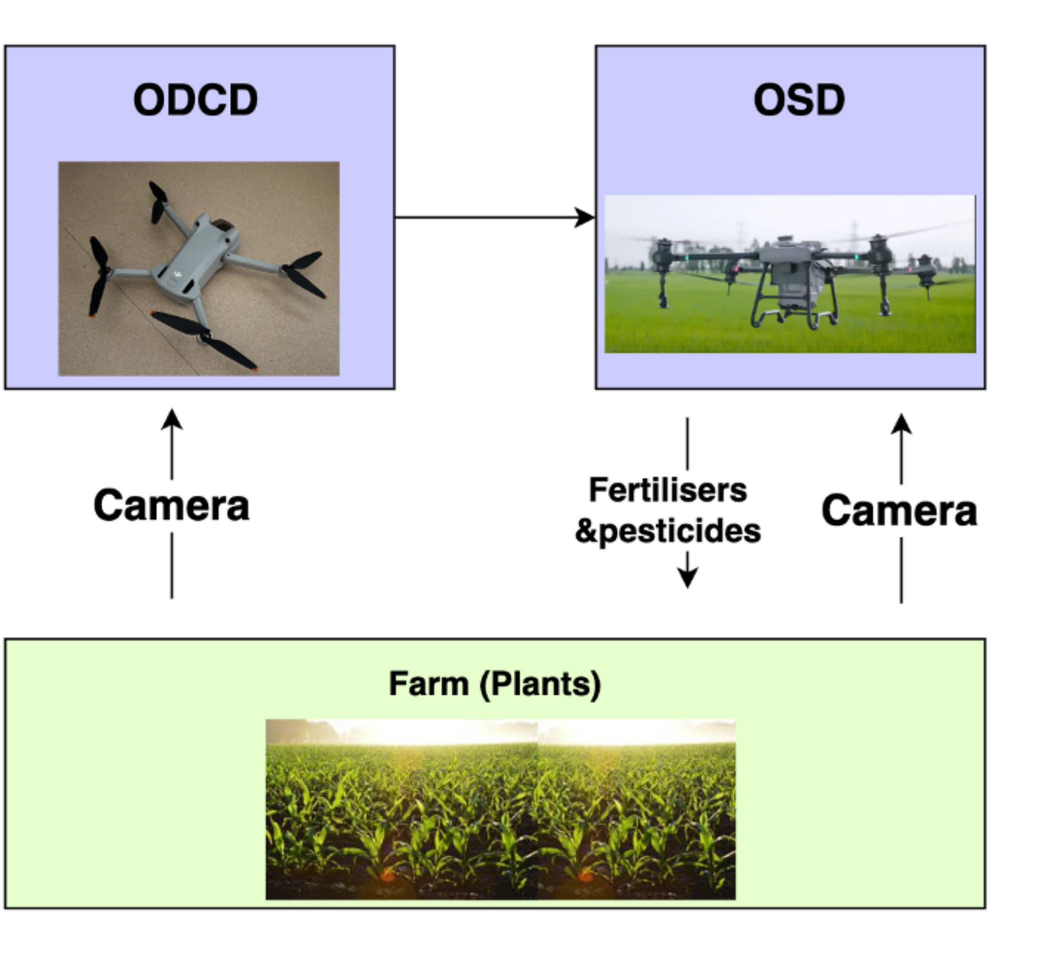
I. Introduction

The chronic decrease in the agricultural labor force due to the underpopulation and aging of rural areas is hindering the sustainability of agricultural management. Due to restrictions on the entry of foreign workers after COVID-19, the imbalance in supply and demand of farming and human resources worldwide has risen to the surface again. [1] Since most of the agriculture laborers are over 60, aging is emerging as a critical issue for decreasing the agricultural labor force. Even worse, the technology of farming or planting has an extremely high entry barrier for the previous generations. Therefore, it is impossible to introduce new technology into agriculture which requires the role of humans.

Also, the food supply crisis is a critical issue that humans should deal with since the environment on Earth has become less suitable for agriculture due to pollution or climate change. Climate change causes unexpected plant diseases, lack of water, or unexpected insects. Furthermore, Unpredictable global problems such as the Ukraine war complicate the food supply chain, exacerbating the food supply crisis.

Image of various food supply crises (Drought, Unexpected plants Disease, Unexpected Insects)

Recently, a few studies have developed a satellite-based farming system to overcome this limitation. However, most of the studies need more for the accuracy of the detection of the plant. In order to control the farm ideally, it is necessary to scan the plants in a centimeter unit to control the farm. Satellite data are less accurate than required. Also, the applications which can be the tool for the connection of controlled environment and human needs to be developed more.



Flow chart of the proposed Open-i Drone Farm management system

(ODCD- Open-I Data Collecting Drone, OSD- Open-I Spraying Drone)

In this paper, we suggest a novel controlled environment agriculture with autonomous driving drones. The proposed system contains ODCD(Open i Data Collecting Drone), which detects the farm and plants and collects the centimeter unit plants data, and OSD(Open I Spraying Drone), which receives the data from the ODCD and provides plants fertilizers or pesticides. ODCD contains the camera, which is used to collect the RGB data. Overall, the proposed system makes farming fully automatic by ODCD checking the current situation of the plants instead of humans, OSD spraying the essentials for the ideal growth of plants, and the artificial intelligence in both drones, which helps this process done by the machine itself. Through this process, the drones automatically detect the plants' disease that harms plants and give the right chemical that can cure the plant. Also, when the water is lacking, the drone provides the water. The most crucial part is that the administrator can 24-hour monitor the status of plants. Figure 2 shows the overall structure of the Open i system.

II. Related Work

The most traditional controlled environment by monitoring at the top is by satellites. Studies before have used NDVI(Normalized Difference Vegetation Index) to see if the plants are growing well. They checked it by the maps created by satellites which only provide a spatial resolution of 1-10m [2]. However, this low resolution lowers the system's accuracy since the plant is mostly smaller than 1 meter, but the satellite can not see the object as an individual plant. The satellite recognizes 10*10m as 1 pixel.

II-1 Object Detection

Object detection predicts the category and location of the objects in images or videos. The categorization process is conducted the same as image classification. Object localization is often performed by predicting the bounding box surrounding the object.

Object detection can be categorized into one-stage and two-stage methods. One-stage methods usually operate faster than the two-stage methods as they combine the region proposal and region rejection steps. SSD or YOLO are representative one-stage methods. Faster R- CNN is often used for two-stage procedures since it produces more accurate results than the one-stage methods. I consider the plant size estimator as an object localization process in this paper. The proposed system predicts the bounding box of the plant in the inputted image without a categorization score. The detailed procedure is further explained in chapter 3.

III. Methods

III-1 ODCD (Open i Data Collecting Drone)

Open i Data Collecting Drone (ODCD) based on DJI Mini 3 Pro. DJI Mini 3 Pro can record 4K High-Dynamic Range Video, 48Mega pixel RAW Photos, and seven multi-direction surrounding cameras.

4K High-Dynamic Range Video and 48Mega pixel RAW photo can increase our collected data quality. High-resolution videos and pictures make drones fly high and increase coverage area because it can crop and analyze the data.

7 multi-direction surrounding cameras can make Stereo Depth Perception Mapping System. Two cameras are mounted facing up and back, two are mounted facing down, and two are facing forward. The other camera is mounted on the gimbal and can be moved in multiple directions.

This feature is a fitting sensor drone because the gimbal can change direction makes collect more data in the same place. Furthermore, this gimbal can be tilted up to 60 degrees and collect weather or illuminance data.

Open i Data Collecting Drone (ODCD) mapping the whole farm for automized agricultural operations mechanics like autonomous driving drones, autonomous driving tillers, and static data collecting sensor modules. Open i Data Collecting Drone (ODCD) is made to collect full soil cultivation vegetation information. It can collect RGB photo or light data, near-infrared data, 3D depth modeling data, and GPS data.

III-2 OSD (Open i Spraying Drone)

Open i Spraying Drone (OSD) is focused on a payload that can fly with up to 50kg object. The OSD is built automized spraying system, our cloud server calculates ODCD's data find problems and order to OSD. Detailed 2D Maps can increase production by enabling delicate care for each plant.

Open i Spraying Drone (OSD) uses 2D map data which Open i Data Collecting Drone (ODCD) collected. Open i Data Collecting Drone (ODCD) can collect vegetation data in a centimeter unit, monitoring and finding plants' problems with specific coordinate values. When the system reports the problem and solution to Open i Spraying Drone (OSD), it launches from the station, moves to the received coordinate value, and executes the solution.

III-3 Autonomous Driving

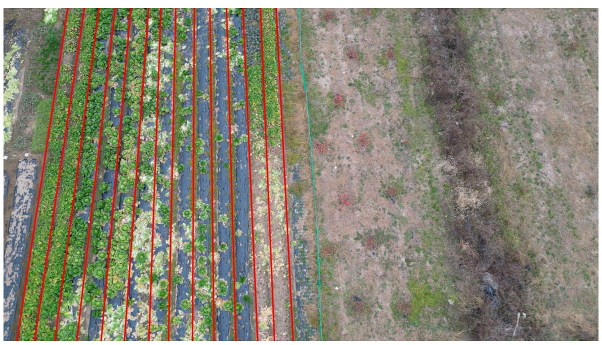
Stereo Depth Perception Mapping demonstrates how to rectify front-facing stereo images, calculate disparity map, and unproject 3D point could using OpenCV and CUDA (Compute Unified Device Architecture). The CMakeLists of this sample will detect if developers have OpenCV or CUDA installed in their system. OpenCV is required for image processing. CUDA is optional and used for accelerating the computation. We use the ximgproc module from the OpenCV control module to post-filter the dispart map.

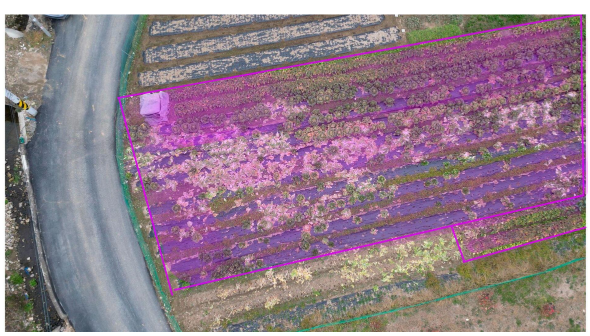
Disparity map post-filtering decreases the error of stereo matching algorithms, especially highly-optimized ones intended for real-time processing on the CPU, which tend to make quite a few errors on challenging sequences. These errors are usually concentrated in uniform texture-less areas, half-occlusions, and regions near depth discontinuities. We use some kind of filtering procedure to align the disparity map edges with those of the source image and to propagate the disparity values from high- to low-confidence regions like half-occlusions.

Import images or videos from multiple angles and develop a 3D model through Stereo Depth Perception Mapping System and surround camera. It can make 3D models of the farm, land, or country map for autonomous driving.

For efficiency, we use a 2D map for autonomous driving. Most of it was made of flat land and no complex structures in the air, so we decided that a 2D map that could be processed with less data capacity and power would be efficient.

The internal video data which detact the lane of field to draq the waypoint automaticaly, and calculate the area for collect data.





III-4 Plant disease classification model

Plant disease classification model is a model that can distinguish whether a plant is healthy or diseased after training the artificial intelligence model with images of a plant's healthy state and diseased state.

Set the batch size, set the size of the image, define the image and define the dropout ratio.

```
batch_size = 8

image_size = 512

input_shape = (image_size, image_size, 3)

dropout_rate = 0.4

classes_to_predict = sorted(training_df.label.unique())
```

After loading and applying the weights of ImageNet, load the efficientnetB0 model.

```
efficientnet = EfficientNetB0(weights="imagenet",

    include_top=False,

    input_shape=input_shape,

    drop_connect_rate=dropout_rate

)
```

```
efficientnet.trainable=True
```

The following are the detailed attribute values of our AI model.

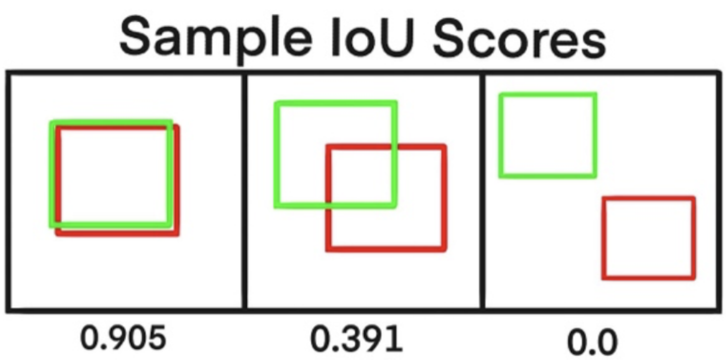
```
model = Sequential()

model.add(Input(shape=input_shape))

model.add(data_augmentation_layers)

model.add(efficientnet)

model.add(layers.GlobalAveragePooling2D())

model.add(layers.Dropout(dropout_rate))

model.add(Dense(len(classes_to_predict), activation="softmax"))

model.summary()
```

```
epochs = 30

decay_steps = int(round(len(training_df)/batch_size))*epochs

cosine_decay = CosineDecay(initial_learning_rate=1e-4, decay_steps=decay_steps,

alpha=0.3)

callbacks = [ModelCheckpoint(filepath='mymodel.h5', monitor='val_loss',

save_best_only=True), EarlyStopping(monitor='val_loss', patience = 5, verbose=1)]

model.compile(loss="sparse_categorical_crossentropy", optimizer=Adam(cosine_decay),

metrics=["accuracy"])
```

IV. Experimental Results

IV-1 Quantitative Evaluation (object detection)

For the quantitative evaluation metric for the proposed object localization network, I used the IoU (Intersection over Union), which is often used for the object detection problem



IOU is the score value that is measured between 0 to 1. The overlap part of the answer and the predicted would be divided by the union area of both parts. Higher overlap with less union indicates that the predicted part is close to the solution. Therefore, 0 is the poorest score it can have, and 1 is the best score it can have. IoU value is calculated by Equation 1.

Example of an equation that can be cited later in the article text:

$$IoU = Plant_{area} \cap GroundTruth_{area} \; / \; Plant_{area} \cup GroundTruth_{area}$$

Where, $Plant_{area}$ is the prediction area of the model, and $GroundTruth_{area}$ is the answer area in training. The area of the green box in Fig 8 is the $Plant_{area}$, and the red box is the $GroundTruth_{area}$.

IoU evaluation comparison with state-of-the-art method

	IoU
SSD	0.6972
Faster R-CNN	0.7459
Ours	0.7871

Table 1 compares the IoU evaluation results with the state-of-the-art methods. I choose SSD and Faster R-CNN for the comparison methods, which generally show comparable performance in object detection problems.

The proposed method achieves an IoU of 0.7871, while the SSD and Faster R-CNN achieve an IoU of 0.6972 and 0.7459, respectively. Compared with SSD, the proposed method's score is 0.0899 higher, and compared with Faster R-CNN, the proposed method's score is 0.0412 higher. The proposed method extracts richer features than SSD and Faster R-CNN, leading to higher IoU results.

Actual size error comparison

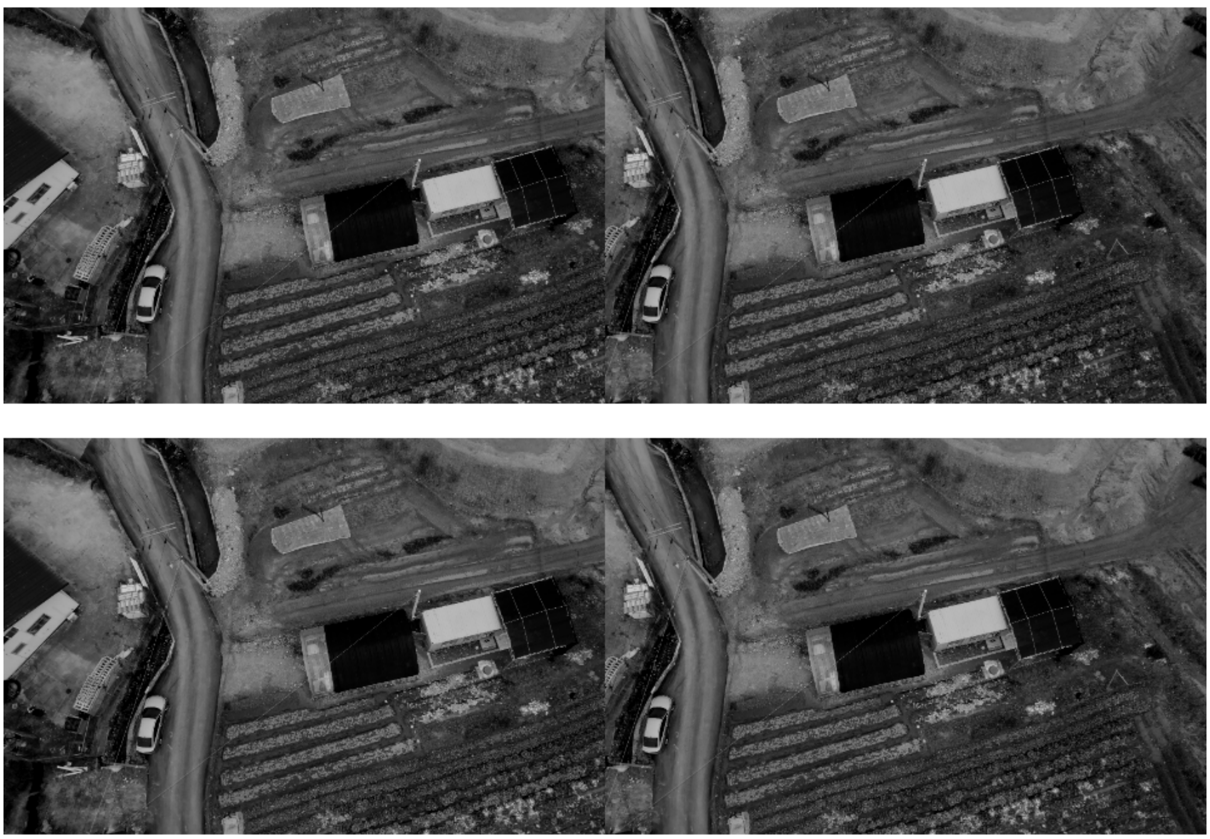
	Average error (width)	Average error (height)
SSD	16.7 cm	14.5 cm
Faster R-CNN	8.8 cm	10.1 cm
Ours	7.4 cm	8.2 cm

To examine the effectiveness of the proposed size estimation in a real-world scenario, I also conducted an additional experiment that can verify that the proposed method is more effective for measurement. I have divided the experiment into two categories: the error of width and length. I averaged the error of length and width of 30 photos of crops such as apples, cucumbers, bananas, and other plants.

The error of the proposed size estimation was 7.4 and 8.2 cm for the width and height. SSD has 16.7 cm in width and 14.5 cm in height. Faster R-CNN achieves 8.8 cm in width and 10.1 cm in height. The result shows that the proposed size estimation has a lower error compared to SSD and Faster R-CNN. Compared to SSD, the proposed method has a 9.3 cm lower width error and a 6.3 cm lower height error. Similarly, compared to Faster R-CNN, the proposed method achieves a 1.4 cm lower width error and 1.9 lower height error compared to Faster R-CNN. This result shows that the proposed model is not only superior for the prediction of the bounding box but also for the real-life size estimation.

IV-2 Autonomous driving algorithm

Firstly, the Stereo Depth Perception Mapping System display rectified stereo images to compare their phase difference. Next, build a model for a disparity map with corrected stereo images. We set the disparity range to 64, and the block size is 13.

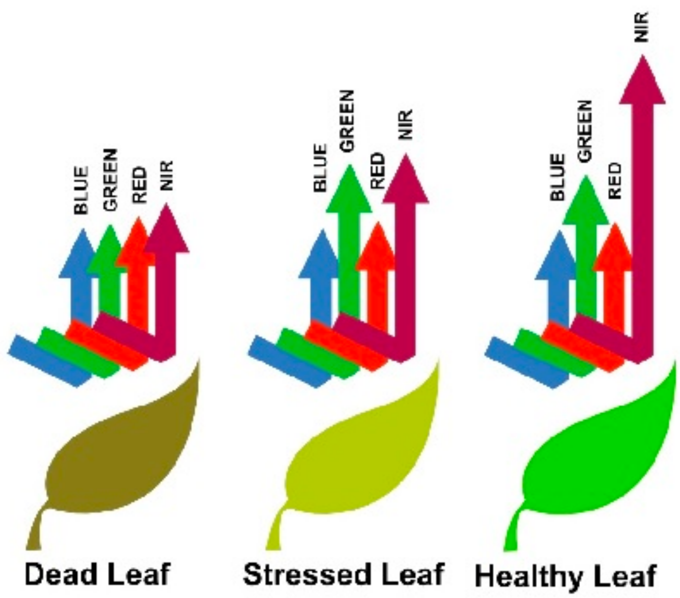


Finally, we obtain 3D information on each pixel with a disparity map and camera parameters to generate a point cloud. Finally, we obtain 3D information on each pixel with a disparity map and camera parameters to generate a point cloud.

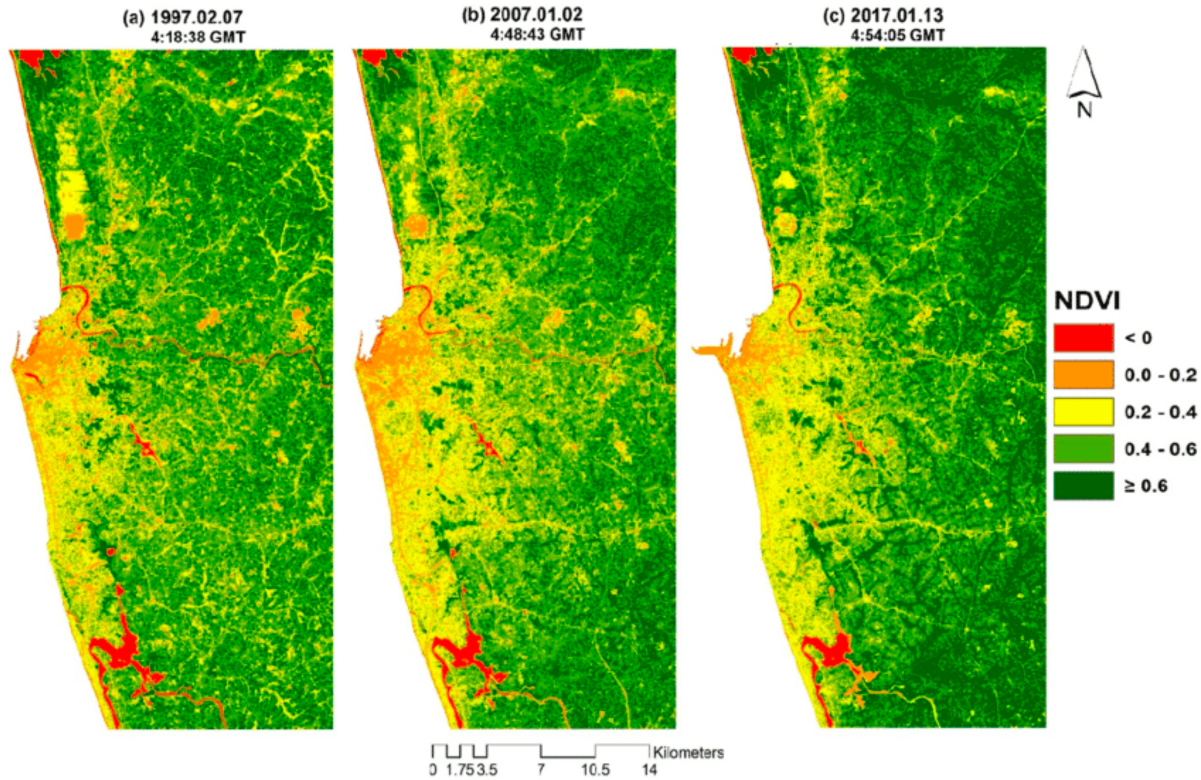
We mapped the whole farm with Stereo Depth Perception Mapping System. It can target the waypoint that drones can map and collect vegetation data. It can collect multispectral vegetation data to centimeter units.

IV-4 Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) quantifies vegetation by measuring near-infrared and red light data. Almost all of the data is collected by satellites. However, the multispectral camera mounted on the satellites has low-resolution data. It is fine to analyze by country or continent scale, but more is needed to analyze each farm in centimeter units.



Healthy vegetation (chlorophyll) reflects near-infrared (NIR), and green light compared to other wavelengths and absorbs more red light. This is why healthy plants appear green to our eyes. Chlorophyll strongly absorbs visible light. The cellular structure of the leaf strongly reflects near-infrared light. If the plant is diseased or sick, the cellular layer deforms and does not reflect near-infrared light and absorbs more of it. Therefore, if we observe the change in near-infrared compared to red light, we accurately display chlorophyll status to allow an analysis of plant health.



NDVI (Normalized Difference Vegetation Index) is obtained by the formula below.

NDVI =

It is calculated from a number between -1 and 1, with a higher NDVI value indicating a healthier plant. Negative values usually represent clouds, water, and snow, while values close to 0 primarily represent rocks and dirt. Primarily 0.2-0.3 represents shrubs and grasslands, and 0.6-0.8 represents temperate, tropical forests. NDVI value of 0 indicates no green vegetation, and values close to +1 (0.8–0.9) indicate the highest possible green leaf density.

We use Google Earth Engine to provide multispectrum data from a satellite of farmland. Google Earth Engine can browse planetary scale Earth science data and analysis. It is designed to quickly access and analyzes over 600 remote sensing data sets, including satellite imagery from the 1970s to today. Since we do not have NDVI or a large amount of data to calculate it, we used GEE to accumulate all of the past data for AI learning.

We use Sentinel-2 MSI: Multispectral Instrument Data for calculating NDVI. The Sentinels are a constellation of satellites developed by ESA to operationalize the Copernicus program, which includes high-resolution optical images from Sentinel-2A and 2B. Sentinel-2 is a wide-swath, high-resolution, multi-spectral imaging mission supporting Copernicus Land Monitoring studies, including monitoring vegetation, soil and water cover, and observation of inland waterways and coastal areas.

We made Open i NDVI Map with Google Earth Engine API. The below calculates NDVI around Hankuk Academy of Foreign Studies by Open i NDVI Map. We were setting Hankuk Academy of Foreign Studies' coordinates were set at 37.329 degrees north latitude and 127.2528 degrees east longitude.

```
Map.setCenter(127.2528, 37.329, 15)

point = ee.Geometry.Point(127.2528, 37.329)
```

Open i NDVI Map use CLOUD_PIXEL_PERCENTAGE image properties to collect granule-specific cloudy pixel percentage taken from the original metadata by double data type.

```
data =
```

```
ee.ImageCollection("COPERNICUS/S2").filterBounds(point).filterMetadata('CLOUDY_PIXEL_PERCEN
AGE', 'less_than', 10)
```

The table below summarizes the wavelengths that Sentinels-2 can collect.

Name	Scale	Pixel Size	Wavelength	Description
B1	0.0001	60 meters	443.9nm (S2A) / 442.3nm (S2B)	Aerosols
B2	0.0001	10 meters	496.6nm (S2A) / 492.1nm (S2B)	Blue
B3	0.0001	10 meters	560nm (S2A) / 559nm (S2B)	Green
B4	0.0001	10 meters	664.5nm (S2A) / 665nm (S2B)	Red
B5	0.0001	20 meters	703.9nm (S2A) / 703.8nm (S2B)	Red Edge 1
B6	0.0001	20 meters	740.2nm (S2A) / 739.1nm (S2B)	Red Edge 2
B7	0.0001	20 meters	782.5nm (S2A) / 779.7nm (S2B)	Red Edge 3
B8	0.0001	10 meters	835.1nm (S2A) / 833nm (S2B)	NIR
B8A	0.0001	20 meters	864.8nm (S2A) / 864nm (S2B)	Red Edge 4
B9	0.0001	60 meters	945nm (S2A) / 943.2nm (S2B)	Water vapor
B10	0.0001	60 meters	1373.5nm (S2A) / 1376.9nm (S2B)	cirrus
B11	0.0001	20 meters	1613.7nm (S2A) / 1610.4nm (S2B)	SWIR1
B12	0.0001	20 meters	2202.4nm (S2A) / 2185.7nm (S2B)	SWIR2
QA10		10 meters		
QA20		20 meters		
QA60		60 meters		Cloud mask

We use B4 and B8 bands data for calculating NDVI. B4 band's wavelength range is 664.5nm (S2A) /

665nm (S2B), which is applicable Red light range. B8 band’s wavelength range is 835.1nm (S2A) / 833nm (S2B), which applies to Near-infrared light.

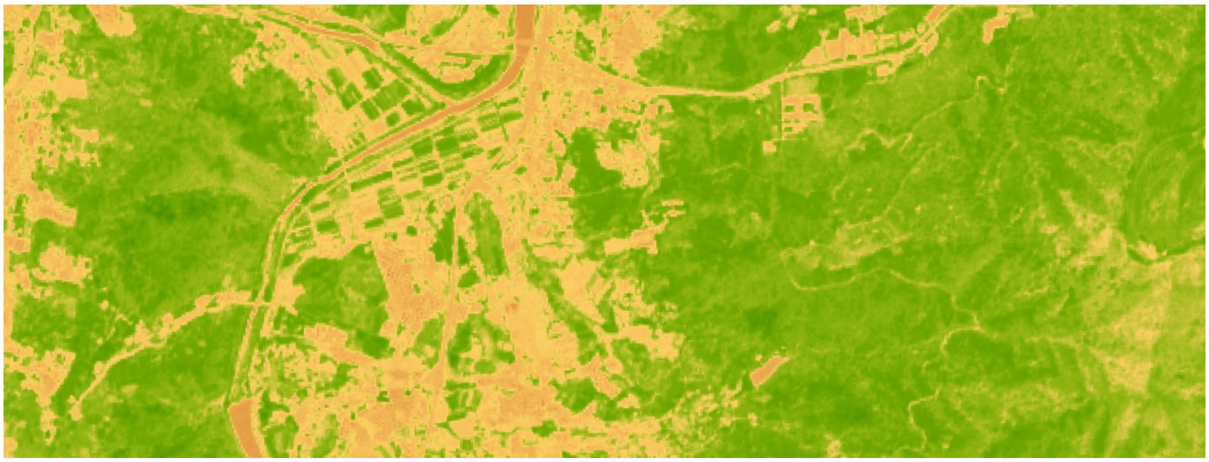
```
image =
ee.Image(data.filterDate("2022-06-01","2022-09-30").sort("CLOUD_COVERAGE_ASSESSMENT
.first())
```

```
ndvi = image.expression("(NIR - RED) / (NIR + RED)",
{"NIR":image.select("B8"),"RED":image.select("B4")})
```

We set the range of NDVI displayed map feature, limit the range of NDVI -0.2 to 1 because of optimizing the features and visualization of the place. Looking at the surrounding environment of the sample location, the drone can see that only mountains, fields, buildings, and roads exist. Since very low NDVIs like water do not exist, we limit the minimum range to -0.2.

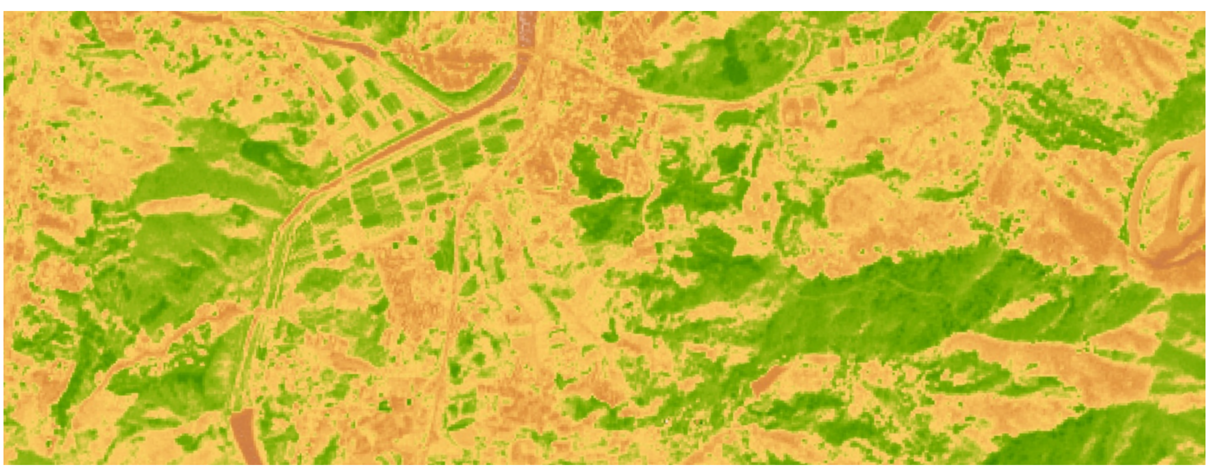
```
display = {
    "min":-0.2,
    "max":1,
    "palette":['FFFFFF', 'CE7E45', 'DF923D', 'F1B555', 'FCD163', '99B718', '74A901', '66A000',
'529400', '3E8601', '207401', '056201', '004C00', '023B01', '012E01', '011D01', '011301']
}
```

We setting three symbolic periods, which represent when vegetation is the most active when vegetation activity is the least, and one year. When vegetation is the most active period, spring and summer show the highest NDVI distribution.

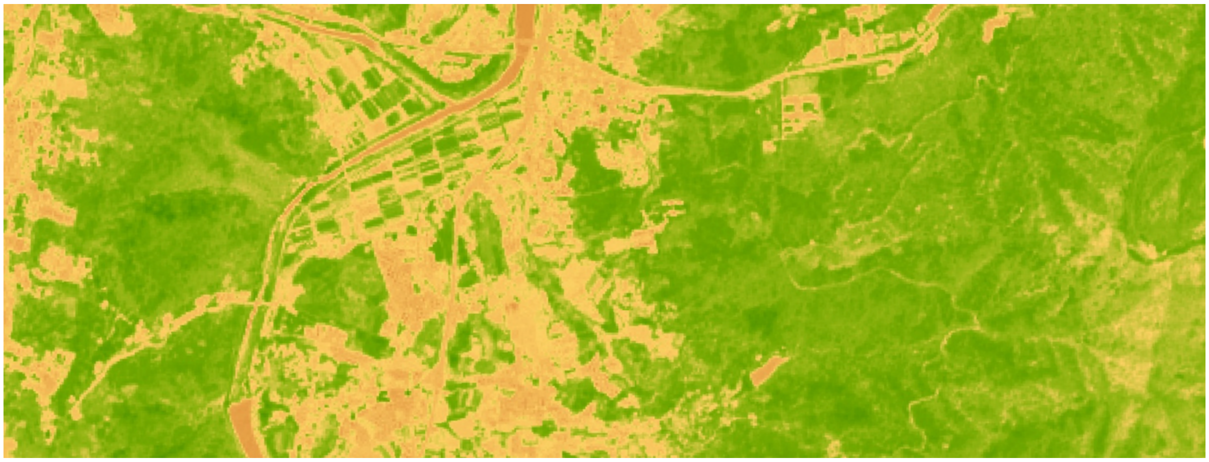


2022-03-01 ~ 2022-09-30

Winter, when vegetation activity is the least shows the lowest NDVI distribution.



2021-12-01 ~ 2022-02-28



2021-11-20 ~ 2022-11-20

V. Conclusion

We propose a system that can solve the food crisis humanity is facing. This study is on how to efficiently collect vegetation data from native cultivation and manage plant growth in centimeters through the development of autonomous drone algorithms so that large amounts of plants can be cultivated efficiently with less human labor and cost. For the study, drone autonomous driving algorithms were created by implementing Object detection, Stereo Depth Perception Mapping, 2D Mapping, and 3D Modeling technologies, and some of the MultiSpectral Instrument data provided by the European Space Agency were extracted and utilized to accumulate and learn vegetation data. As a result, Multispectral data through satellites cannot be used to automate and increase the efficiency of terrestrial cultivation because of the low image quality of the data. By creating a High Resolution (HD) Multispectral data map through Open i Data Collection Drone (ODCD), you can observe the state of native cultivation in detail and provide accurate maps and data for automated programs of systems such as other drones and tractors.