UAV Swarms in Smart Agriculture: Experiences and Opportunities

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***Abstract*—Smart agriculture benefits from unmanned aerial vehicles (UAV), and in-field sensors to collect data used to make responsible crop management decisions which sustainably increase yields. In addition, smart agriculture relies on machine learning algorithms, creative networking solutions, and edge and cloud computing resources to collect, transfer, and process agricultural data. UAV can carry a wide array of sensors, maneuver rapidly throughout the field, apply treatments for some crop health problems, and can be flown by software. UAV, however, have small batteries and limited carrying capacities which keep missions short. In this paper, we provide an overview of state-of-the-art UAV swarm technology for smart agriculture, and present experiences from real-world agricultural UAV swarm case studies. We describe how quick mapping of large areas such as crop fields necessitates multiple UAV missions, potentially using multiple UAV simultaneously as a swarm. We detail how swarms of UAV have added advantages over a single UAV deployment. They can coordinate to map areas in parallel, leverage multiple sensor types, target areas for close inspection, and diagnose and treat problems rapidly. UAV swarms come with additional implementation difficulties beyond single UAV. We list challenges to implementers in terms of Resource allocation, compute orchestration, multi-agent mission planning and swarm goal definition. We also describe recent advances in edge computing, machine learning, and autonomy in orchestration and resource management techniques for swarm deployments. Finally, we conclude with research opportunities that future work can address to improve swarm performance, scale, and adoption for smart agriculture.**

***Index Terms*—UAV swarms, computation offloading, intelligent orchestration, smart agriculture, multi-sensor network**

I. Introduction

Smart agriculture has arisen as a potential mitigating factor to problems that negatively impact crop yields and render some cropland unusable [1]. Smart agriculture uses sensors (satellites, airplanes, Unmanned Aerial Vehicles, and in-field embedded devices), compute resources, and machine learning algorithms to monitor crop growth, diagnose crop health issues, and apply sustainable treatment plans [2]. Farmers and crop breeders rely on frequent monitoring conditions of crops and their growing environments (e.g., soil, water, and weather conditions) to make timely decisions to increasing yield, eliminate pests, and responsibly apply herbicides. The burgeoning smart agriculture industry uses satellite and UAV imagery [3] analyzed in the cloud to generate reports for farmers to aid their crop management practices.

Unmanned Aerial Vehicles (UAV) are particularly useful for smart agriculture. UAV are low cost, equipped with RGB cameras, highly maneuverable, and can be flown with limited training or by software [4]. UAV's highly maneuverable design allow them to shift coverage to areas of interest in-mission, and their small form-factor allows them to fly low over crops, capturing high resolution images which can detect important crop phenomena that satellites and manned aircraft can not. UAV can also be equipped with different sensors, cameras, and actuators to inspect and treat crop health issues online [3].

UAV have various flight modes. UAV can be piloted by humans with remote control devices, or entirely by software. UAVs often are piloted by humans with limited experience. Agricultural scouting UAV are often piloted by professionals who, in some jurisdictions, must be certified and can command high hourly wages. Alternatively, UAV flight can be automated by software. Free software packages and SDKs [5] can automate rudimentary flight actions, fly UAV to GPS waypoints, and capture images using predetermined flight plans. Automated flight removes the need for human piloting for simple missions, but does not exhibit the high-level decision making capabilities of human pilots. Autonomous UAV are UAV flown entirely by software that include decision making capabilities that approximate human ability [6]. Autonomous UAV use machine learning algorithms and onboard or edge compute resources to solve high level goals through sensing and actuation. Often, processed sensed data is provided to reinforcement learning algorithms which evaluate goal performance and select the UAV's next action in order to maximize goal performance or complete a mission. In most cases, reinforcement learning tasks will be offloaded to edge or cloud resources.

In this paper, we describe benefits, challenges and opportunities to show UAV swarms have the potential to revolutionize agriculture. Smart farming, the use of remote sensing techniques backed by data analysis tools, can benefit from the

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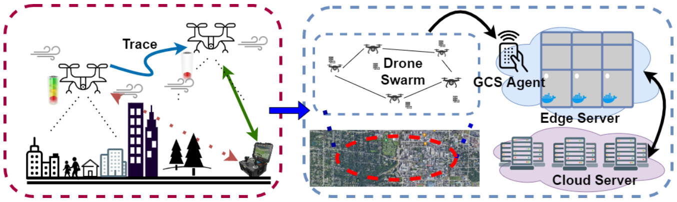

Fig. 1: Evolution from single UAV to UAV swarm architecture.

high maneuverability, sensing proximity, and group dynamics that UAV swarms afford [7] [8]. Despite their advantages, UAV come with serious hurdles to widespread adoption. UAV battery capacities are limited. Thrust to power ratios and battery weight to power scaling limit the maximum flight times of most UAV to below 40 minutes [9]. For many applications this is sufficient, but agriculture provides serious challenges. First, crop fields are large (often $>$100 acres), meaning UAV may fly multiple miles away from their takeoff location to map whole fields. Second, many agricultural monitoring tasks, like disease diagnosis, yield estimation, and phenotyping, require high ground-sample distance images which necessitate low flyover heights and lengthen missions. For these reasons, it is increasingly attractive to use groups of UAV, known as swarms, that cooperate to accomplish tasks in parallel.

UAV swarms leverage parallelism to decrease data collection times across large fields. Firstly, individual drones are energy-constrained vehicles and can only operate, on average, for no more than a few tens of minutes. Thus, handling computation intensive imagery/video data processing on-board and covering surveillance of large geographical areas is not practical unless drone swarms are used. Thus, there is a need to efficiently manage energy usage during execution by e.g., offloading computation-intensive tasks to edge devices or cloud services [10].

As we can observe in Figure 1, individual UAV in the swarm can be dispatched to scout regions of the field depending on swarm needs. Prior work demonstrates that UAV swarms equipped with consumer or professional-grade cameras can be useful as high-throughput field data collection tools for scouting crops at large-scale [11]. Intelligent swarms of autonomous agents can use data collected in-flight to adapt mission plans. Swarms may also contain heterogeneous or specialized agents capable of specialized sensing, manual data harvesting, and treatment.

UAV swarms have been applied to agricultural problems with great success. UAV swarms with infrared thermal cameras that measure canopy and leaf temperature remotely can be useful to quickly identify crop stressors, such as drought, disease and pests across large fields [12]–[14]. Additionally, intelligent UAV swarm management can enable determination of the topography and geography of a field, and provide opportunity for accurate site-specific management. In above cases, UAV swarm management needs to enable real-time information gathering to transform traditional practice of manual data offloading after flights for on-ground processing. Delayed decision-making can impact farm management, especially if large areas need to be treated with effective pest control by timely spraying at the crops/weeds. Figure 2 shows an overview of a multi-sensor, fully connected autonomous hierarchical UAV swarm setup in a soybean area.

TABLE I: List of key acronyms.

Label	Explanation
ANN	Artificial neural network
CNN	Convolutional Neural Network
DefoNet	Learning Body Deformation using GAN
FANET	Flying Ad-hoc Network
GAN	Generative Adversarial Networks
GCS	Ground Control Station
IoT	Internet of Things
LiDAR	Light Detection and Ranging
L-UAV	Location-UAV
NDVI	Normalized Difference Vegetation Index
P-UAV	Precision-UAV
PSNR	Peak Signal-to-Noise Ratio
RL	Reinforcement Learning
RTK	Real-Time Kinematic
RTT	Round-Trip Time
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
WSI	Water Stress Index
WSN	Wireless Sensors Network

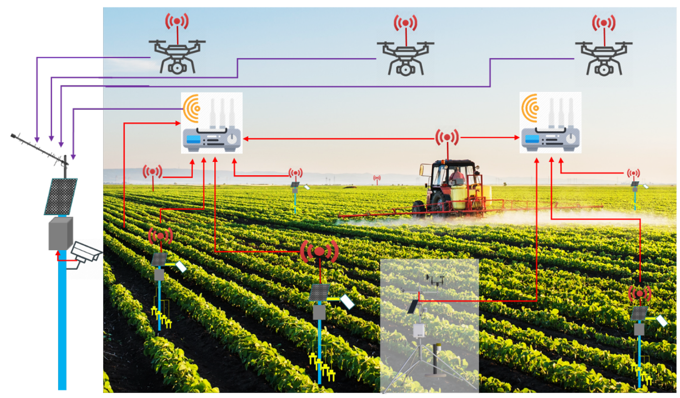

Fig. 2: Overview of a multi-sensor, fully connected autonomous hierarchical UAV swarm setup in a soybean area.

The remainder of this paper is organized as follows: In Section II, we review the state-of-the-art technologies that facilitate UAV swarms in smart agriculture. Through two case studies, Sections III and IV explore how recent advances in machine learning, edge computing, and networking facilitate swarms of complex agents that provide meaningful results to farmers. We detail current methods for swarm resource allocation onboard UAV, at the edge, and in the cloud. In Section V, we discuss deployment findings of recent applications which leveraged UAV swarms to solve agricultural problems. In Section VI, we present future work opportunities and challenges that we hope will inspire further investigation into the design and applications of agricultural UAV swarms. Section VII concludes the paper. Table I presents a list of commonly used acronyms in this paper.

II. Related Work

UAVs have been used as an efficient tool to monitor crop health and detect pesticides by equipping with different optical sensors [11]. Widely used sensors include visible camera

(RGB), multispectral camera, hyperspectral camera, thermal and light detection and ranging (LiDAR) that can quantify plant phenotypes [15]. The major purpose of an UAV imaging system is to quantify the crop development from seedling to maturity and predict yield on a plot scale. UAVs equipped with consumer- or profession-grade cameras have been demonstrated as useful and high-throughput field data collection tools for scouting crops [16], [17].

In another study [18], UAV imagery was used for capturing crop height information of three vegetables (crops eggplant, tomato, and cabbage) with a complex vegetation canopy surface during a complete crop growth cycle to infer biomass. The results of the study showed that - UAV-based RGB imagery can be used to effectively measure vegetable crop biomass in larger areas. Table II lists several widely used cameras (sensors) in agricultural sector that are capable to measure a number of crop traits for quantifying crop development and estimation of yield. It can be seen that an inexpensive RGB camera is able to take measurement of multiple crop characteristics, such as stand count, emergence uniformity, canopy structure and area, plant height, flowing, leaf wilting and senescence, and yield estimation [19]. Meanwhile, a multispectral camera can capture information beyond the range of visible spectrum for the human eye, including crop vegetation indices (e.g., normalized difference vegetation index, or NDVI). Also the study [20] indicates that the multispectral camera is more instructive compared to the other sensing technologies, and has higher sensitivity to the vegetation coverage and accurate NDVI.

Some preliminary work related to the application UAV imaging system includes crop health assessment, nitrogen management, water stress and irrigation management. Commonly used systems in agriculture rely on a single UAV to perform various tasks. However, the introduction of a swarm of UAVs into agriculture can substantially increase work efficiency and decrease operator fatigue. Researchers in [21], [22] have quantitatively evaluated and analyzed several cases of single and multi-UAV systems on a number of performance metrics (total time, setup time, flight time, battery consumption, inaccuracy of land, haptic control effort, and coverage ratio). The performance of the proposed agricultural multi-UAV system is significantly superior to that of the single-UAV system.

Furthermore, the use of a swarm of UAVs greatly reduces operational time and costs. However, the transition from single UAV to multi-UAV presents new challenges. One of such challenges is the efficient management of UAV collaboration. One of the crucial applications of the swarm of UAVs is image capturing, the challenge is combining captured images easily. Authors in [23] using Reinforcement Learning (RL) and Artificial Neural Networks (ANNs) techniques designed a system that can obtain a good path for each UAV in the swarm and distribute the flight environment. Another problem is choosing the right protocol for cooperation between UAVs. An extensive review of the Flying Ad-hoc network (FANET) has been presented in [24]. Theoretical analysis has revealed which protocol works best for various agricultural applications (Crop Scouting, Crop Surveying and Mapping, Crop Insurance, Cultivation Planning and Management, Application of Chemicals, and Geofencing).

Phenotypic traits	Sensors (cameras)		
	RGB	Multispectral	Thermal
Stand count, uniformity	5	5	-
Canopy area	5	5	-
Plant height and lodgine	4	4	-
Phenology (e.g., flowering)	3	3	3
Vegetation indices (e.g., NDVI), Water stress indices	5	5	4
Leaf wilting / senescence	4	4	3
Leaf / canopy temperature	-	4	5
Yield estimation	3	4	4

TABLE II: Example of potential cameras and associate crop traits in a typical multi-sensor, fully connected autonomous UAV swarm used in smart farming. Note: number in the table indicates the amount of sensors overall in each drone swarm.

Cooperation of UAVs with wireless sensors networks (WSN) for crop monitoring has been introduced by scientists in the study [25]. They considered designing UAV trajectories for efficient data collection and use consensus aggregate approximation as an important system of UAVs, WSN, and IoT devices proved to be robust and efficient solutions for data collection, control, analysis, and decisions. As mentioned earlier there are quite a wide variety of tasks that could be performed by swarm of UAVs in the agricultural field. This diversity along with decentralized control of UAV swarm result in a problem of sensing and processing resource-intensive data across the nodes. Unequal generation of data by different members of the swarm can lead to under-utilization of available computational resources.

III. Case Study I: Autonomous Soybean Defoliation Modeling

Crop scouting is an important component of digital agriculture. Crop scouting [26] describes the process by which humans, UAV, satellites, or other sensors search crop fields for phenomena. Crop scouting can also be done to assess damage to injured crops [27]. Results from scouting can be used to parsimoniously apply herbicides, pesticides, water, and other resources which may be scarce, expensive, or have environmental impacts when applied too liberally.

Crop scouting is recommended to be performed frequently throughout the growth cycle for best results. Conventionally, humans are used to randomly sample fields. Human scouting is, however, laborious and can be prohibitively expensive for even moderately sized fields [28]. For this reason, much work has been done on crop scouting using UAV [27], [29]–[31]. UAV allow for pilots or software to closely inspect crops without the need for humans to physically explore fields.

In this case study, we will explore an autonomous soybean defoliation modeling application utilizing UAV swarm operation in the field.

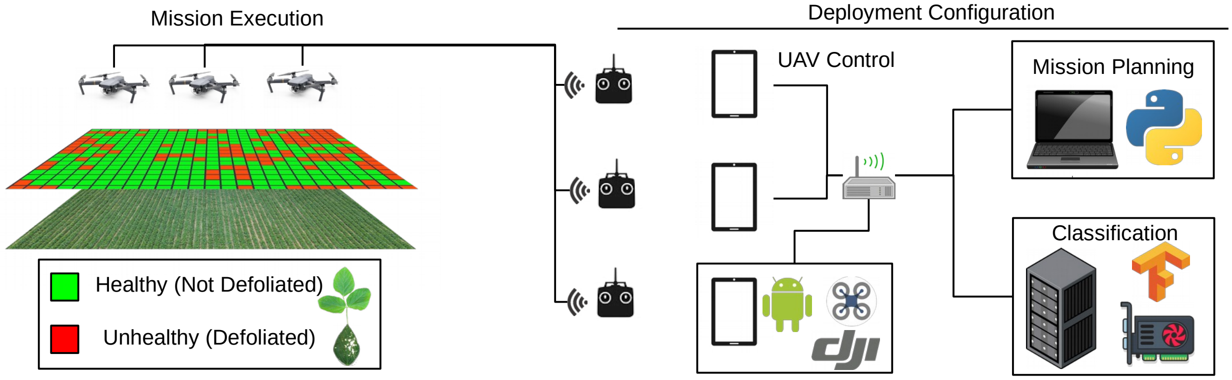

Fig. 3: Experimental design of our soybean defoliation modeling scenario. Devices consist of three DJI Mavic UAV, 3 flight controllers, one ground control station and one compute node.

A. Overview settings of the autonomous modeling application

Automated piloting is easy to implement, but automated swarms may face difficulties when covering large areas. Crop fields often cover great areas. Fields covering hundreds of acres may take days or weeks to map completely at high resolution, meaning sampling approaches are often required. For this reason, autonomous UAV are growing in popularity [27], [32], [33]. Autonomous UAV have been demonstrated to outperform automated approaches in terms of sampling accuracy, mission times, and energy efficiency [34].

This case study revolves around an 80 acre soybean field in Central Ohio, USA. Soybeans are a globally important crop grown by over 500,000 US farmers alone. Soybeans in the United States are threatened by pests like the Japanese Beetle, which contribute to leaf defoliation. Defoliation is the loss of leaves or leaf area from a crop. Leaf defoliation occurs naturally throughout the growing season, but can occur prematurely due to disease and pest infestation. Defoliation in soybeans is a strong predictor of yield, and can be accurately classified by machine learning, making it a strong candidate for autonomous UAV scouting applications.

The goal for our deployment was to scout, as accurately as possible, our 80 acre soybean field once per week throughout the soybean growth stages R3-R6 where pre-mature leaf defoliation most effects yield [35]. Leaf defoliation needs to be scouted at high resolution, meaning flyovers take additional time compared to other high-granularity phenomena like lodging [27]. We determined that scouting of 100% of our field under perfect conditions would take 9.26 days. Ultimately, we implemented an autonomous sampling solution which was capable of generating accurate defoliation maps in under 4 days of scouting.

Figure 3 shows the architecture of our swarm. Our swarm used 3 DJI Mavic UAV, each of which searched independent regions of the crop field. Each UAV was controlled by an android tablet running SoftwarePilot which managed all flight control and data transfer. Tablets were connected via a 1GB/s router to our ground station. Our ground station, a Lenovo Thinkpad T470 running Ubuntu 18.04, was used to plan each mission, dispatch swarm members, and aggregate swarm results. We also provisioned a custom desktop PC with an Intel Xeon processor and Nvidia 2070TI GPU for reinforcement learning and defoliation classification.

We classified all soybean defoliation using DefoNet [36], a neural network designed specifically to classify leaf defoliation. We used a Whole-filed RL [34], a Q-learning method for autonomous crop scouting, to control UAV in field. We also used the Fleet Computer [37], a software architecture for building and training multi-agent reinforcement learning models, deploying them across edge systems, and retraining them online to garner better results over the course of our deployment. By combining Whole-Field-RL and the fleet computer, we were able to minimize the amount of UAV flight coverage we required to build accurate maps.

B. Preliminary results on learning based defoliation modeling

We used 120 acres of prior aerial soybean images to build our reinforcement learning sampling approach. Figure 4(a) shows the performance of our model on a patch of soybeans compared to a naive lawnmower method and whole-field RL without fleet computer training. The goal of our procedure was to capture accurate field maps through sampling with as little coverage as possible. Sampling accuracy was determined by binning regions into one of four overall defoliation categories based on the DefoNet prediction percentage. To minimize the coverage required, we determined that 80% accurate defoliation maps were sufficient inform treatment considering our field and swarm sizes. As seen in Figure 4 (a), lawnmower scouting can generate an 80% accurate defoliation map with 70% coverage and extrapolation. Qualitatively, this map unevenly samples the field, leaving a large region in the south of the field unsampled. While whole-field-RL performs better, requiring only 65% coverage to generate an 80% accurate map, it still leaves large parts of the western region of the field unsampled. The fleet computer model, however, more evenly samples the field, resulting in a map that only requires 43% coverage to meet accuracy goals and is also qualitatively much closer to ground-truth.

Using this deployment architecture and machine learning model, we flew 150 autonomous UAV swarm missions between August and September of 2021. We wanted to: (i)

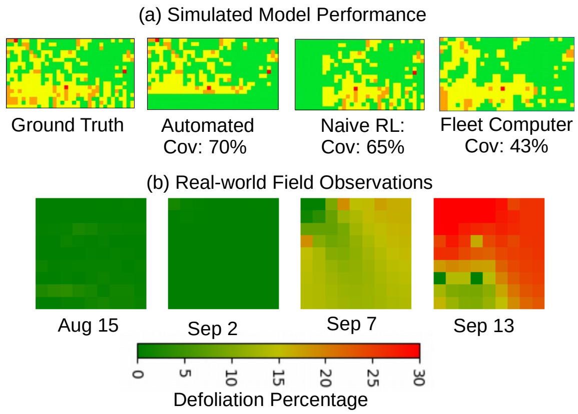

Fig. 4: Reinforcement learning performance and in-field observations for soybean defoliation modeling.

collect accurate soybean defoliation maps to better guide treatment strategies, and (ii) analyze the effects that normal weather patterns and environmental conditions had on agricultural UAV swarm performance and failures. Figure 4(b) shows a sampling of maps we captured throughout the scouting process. These maps show how our deployment was able to capture the same region of field naturally defoliating toward the end of the growing season. Our first two maps, collected August 15th and September 2nd, shows no defoliation. Between August 15th and September 2nd, the soybeans were in stages R3-R6, where defoliation should be limited. Defoliation in these stages would indicate potential yield impacts and would require additional treatment. Our third map, taken when the Soybeans were entering stage R7 shows spreading defoliation across the field, which is a natural part of the soybean life cycle. Finally, our last map shows increased defoliation as soybeans naturally enter the end of their growing cycle where defoliation is high. Overall, these maps represent the healthy growing cycle of a soybean field.

IV. Case Study II: Hierarchical Multi-UAV Single-UGV Crop Monitoring Video Analytics

In this case study, we present a hierarchical multi-UAV single-UGV (Unmanned Ground Vehicle) scenario for precision agriculture in terms of learning-based trajectory prediction. Coordination of UAVs can be performed through connectivity via FANETs as well. Under this circumstances, FANETs involve a group of UAVs communicating with each other and with the edge server through a wireless connection (e.g., Wi-Fi connection). UAV swarm operation can be performed in a centralized or decentralized manner. In a decentralized setting, the UAVs need to explicitly cooperate at different levels to exchange information, share tasks and make decisions in order to achieve the system goals under limited edge resources [38]. Under this setting, even if the connection from one of the UAVs to the GCS is interrupted, inter-UAV communication is still possible. To this end, UAV swarm applications have the potential to augment communication and operation through the integration of UAV, edge computing, and even cloud services [39].

A. *Pre-flight Based Setups and Devices Settings*

A multi-UAV, single-UGV crop monitoring video analytics scenario with the cycle of precision agriculture in soybean area is shown in Figure 6. The map corresponds to a smart farm, where the UGV, UAV, sensors, and field are identified. In this smart farm area, one depot interacts with two UGVs that are communicating at the same time with different monitoring UAVs. These UAVs are categorized with two types, one with lower-resolution camera but high flight time (location UAV (L-UAV)), one with high-resolution camera(s) but limited with flight time (precision UAV (P-UAV)). Those two types of UAVs are assigned with tasks for crop monitoring purposes in a hierarchical way. For example, one UGV is equipped with four L-UAVs and one P-UAV. L-UAV will take flight first to scan the farm area by capturing videos of the soybean field, and transmit the video stream into the ground. After ground server receives the video, video analytics algorithms will be applied and a group of suspicious areas will be point out and record on UGV. After UGV finish analyzing all the video, the P-UAV will take off and fly to these suspicious areas one by one with lower flight height and transmit higher resolution images to the UGV. During the time when L-UAV and P-UAV is processing precision crop status monitoring, UGV will also take its own tasks with a pre-assigned route. To this end, we formulate a multi-UAV single-UGV crop monitoring video analytics problem which include establishing high throughput end-to-end communication link from UAV-to-UGV while optimizing the overall UAV 'on-the-air' energy usage.

In this case-study, we utilize a group of open-source and commercial quad-copters with various embedded cameras to process crop monitor tasks in an soybean field in central Missouri, USA. Four L-UAVs and two P-UAVs are used to process. We assembled each L-UAVs utilizing open-source Ardupilot supported devices to control the UAV. More specifically, we use CubePilot ecosystem provided by the Cube [40]. The Cube autopilot is a further evolution of the Pixhawk autopilot [41]. It is designed for commercial systems and manufacturers who wish to fully integrate a autopilot into multi-UAV system. To further save energy usage of the L-UAV, we use Raspberry Pi (RPi) camera with a 720p resolution (1080*720) to capture the aerial video. RPi camera is installed on one NVidia Jetson Nano device which is also embedded on-board on L-UAV. Since Jetson Nano provides computation resources for simple inference abilities, we run pre-processing functions (e.g., gray scale) on Nano itself before further transmission process to the UGV. The video analytics application pipeline based on containers and transmission model logic can be found in [39].

In terms of the P-UAV design, we use a combination of commercial UAV device and high standard cameras to achieve more accurate and comprehensive video analytics. To be specific, The P-UAV we used in the experiments consists of a commercial UAV platform (DJI Matrice 600), a multispectral camera RedEdge (Micasense), a RGB camera (Sony a6300)

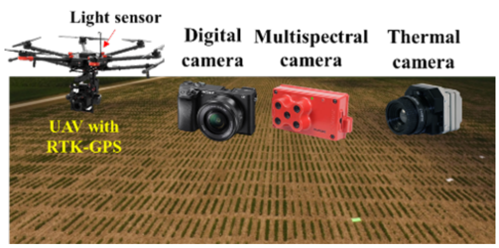

Fig. 5: Basic setups for one precision UAV consists of three different camera for the purpose of generate.

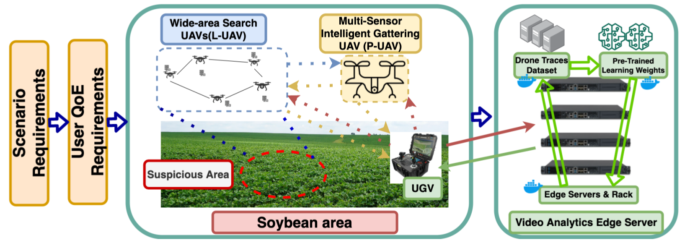

Fig. 6: Overview of multi-UAV single-UGV crop monitoring vidoe analytics process in a example soybean area.

and a thermal image ICI 8640P (ICI company), a high-performance Real-Time Kinematic (RTK)-GPS receiver and a light sensor (As shown in Figure 5). The multispectral camera includes five factory-calibrated narrow-band images of blue, green, red, red edge and near-infrared (NIR). Each of the narrow-band images outputs a 12-bit image with a resolution of 1280×1024 pixels. The thermal image has a pixel resolution of 640×512 with a measurement accuracy of $\pm 1°C$, which is used to record canopy temperature.

In the following, we describe the common settings and assumptions for both types of UAVs. First, in terms of the flight speed of P-UAV and L-UAV, we assume that both are set before the mission by the UGV to allow the images/video collected to have sufficient overlap. Second, a Downwelling light sensor (DLS) is used on both types of UAVs to measure the real-time irradiance to correct the change of light conditions in each image captured. Meanwhile, the RTK-GPS system (REACH RS+ and M+) is integrated into the imaging system to allow accurate geo-referencing of all the images. The geo-referenced images are potentially used to directly extract each soybean information without stitching images to increase the image processing efficiency, and reduce the information loss due to the stitching process. Finally, the camera gimbal system is applied to reduce the variation of the cameras' orientation during flight. The cameras for both UAVs are set facing downwards straightly for all flights by default.

Imagery data which captured by P-UAV is processed through the pipeline used in other similar research [4], [42], including building mosaic images and 3D point cloud points using commercial software packages, e.g., Pix4D or Agisoft. The mosaic images are used to extract image features of each crop row for quantifying crop morphological, physiological and chemical characteristics. Image features derived from the RGB, multispectral and thermal cameras will include canopy area, canopy color, vegetation indices (e.g., NDVI, green NDVI – GNDVI, normalized difference red-edge – NDRE), canopy temperature and water stress index (WSI). In addition, 3D point cloud data is used to calculate the 3D architecture of plants for extracting plant height and volume information.

B. Application case study description and preliminary results

We integrate the UAV scouting and video analytics in an multi-sensor IPM-based soybean management smart farming system, as shown in Figure 6. In this system, UAVs are used in crop scouting (stand count, inventory, density), diagnosis (pests, disease, nitrogen, droughts), and yield estimation by taking imagery of crop fields. Imagery data are processed following the pipelines described in the previous section to extract features, quantify crop morphological, physiological and chemical characteristics, and make decisions on spraying pesticides/fertilizer, as well as planting cover crops.

In this use case, the fundamental requirement is real-time UAV-to-UAV, UAV-to-UGV communication to allow: (i) *location awareness* to provide current location information of UAVs to avoid collision while being able to cover the entire crop field; and (ii) *cross calibration and validation* of imagery data, which are affected by factors, such as ambient light condition, wind speed and camera setup. Real-time communication between UAVs will allow images collected at similar time to be cross checked and validated for quality. Another important requirement is timely and efficient data analytics for decision-making. This requires development of deep learning models (e.g., CNN or R-CNN) that will be trained with ground truth data collected by P-UAV, e.g., spatial and temporal maps of plant properties, vegetation indices, flowering and maturity date, and water stress index. Transferring and analysis of all these data requires a highly available network setup with access to edge computing resources to meet decision-making time constraints. To this end, we provide an energy-efficient and trajectory-awareness algorithm to optimize the network performance in terms of the UAV-to-UAV link and UAV-to-UGV link during the flight. Heuristic algorithms and reinforcement learning algorithms are introduced to provide network routing decisions among links.

TABLE III: Experiment settings for soybean monitoring.

Application Settings		Network Settings	
Collect Period:	2 days a week	Trans. protocol:	RUDP
Monitoring Area:	10-15 miles	App. Bit rate:	6 Mbps
Mosaic Img. size:	Avg. 30*20 m	Tx power:	32-48 dBm
Radio range:	250 m	Tx/Rx gain:	3 dB
UAV dist.:	Euclidean	Prop. model:	TWO RAY
UGV dist.:	Rectilinear	Max. msg. size:	4000 bit
Experiment time:	7000-8000 s	WIFI protocol	802.11s
Avg. L-UAV speed:	25 mph	Modulation:	OFDM
P-UAV Flight Time:	max. 30 mins	Data rate:	65 Mbps

To run the experiments in a reproducible and reliable testbed, we fist use a trace-based UAV-UGV emulation platform that we developed on top of ns-3 [43]. Table III shows the basic setting of the emulator. This platform integrates emulation on both UAV and networking sides, and provides flexibility in adding plugins for UAVs and ground nodes to e.g., change the mobility model on the UAVs and UGVs, adding multi-sensor emulations and applying realistic map interfaces. We apply various supervised learning methods to better predict the communication performance as well as the video transmission results. After traces generated from the emulator, we apply the experiments into the actual soybean field. To test the accuracy of the machine learning model predictions, we use 95% confidence interval range of accuracy on correctly categorized data. In addition, to evaluate the overall video quality, we use peak signal-to-noise ratio (PSNR) as a performance metric based on our investigation [44]–[46]. Here, we assume that impairments in the video can be rectified effectively if the PSNR is less than or equal to a fixed threshold ($\leq$30%). We measure network performance (in terms of the average goodput and RTT) as well as transmitted video quality (in terms of the PSNR) for communications between UAV to UGV. The comparison of our predicted metrics with the real experiments test results in terms of the network as well as video quality performance can be seen in Table IV[1] . Although we can observe some of the algorithms (i.e., RFR) provide better performance, it is not achievable in real-world tests based on our data collection. We conclude that: (a) SVR-RBF gives more accuracy on networking performance prediction in terms of the goodput. However, the video after transmission is unstable compared with other approaches; and (b) GPR can generate more reliable results with a stable range of PSNR, although the communication throughput performance is slightly greater than the realistic experiments.

TABLE IV: Real-world experiments and various machine learning prediction (KRR, SVR-RBF, GPR, and RFR) results.

Model Type	Goodput (Mbps) 95% CI	RTT (ms) 95% CI	PSNR
Real-world	**3.7 ± 0.98**	**45 ± 1.82**	**(36.41, 37.26)**
KRR	4.9 ± 0.39	60 ± 1.37	(39.86, 46.93)
SVR-RBF	**3.5 ± 0.37**	35 ± 1.08	(33.59, 46.93)
GPR	4.15 ± 0.98	**39 ± 0.33**	**(32.26, 39.86)**
RFR	2.5 ± 0.46	26 ± 1.13	(32.26, 49.37)

V. Deployment Findings

Throughout our deployment, we also collected data on UAV and edge battery drain, system malfunctions and causes, machine learning mispredictions, and flight times for certain weather conditions. Our analysis shows that 3 key conditions (wind, temperature, and lighting) have serious effects on mission performance. We observe that the performance has no difference between UAV swarms or a single UAV in terms of the environmental features since each UAV takes its own flight individually to generate a swarm. As shown in Figure 7, wind speeds greatly affect flight times. We found that average single-UAV mission times degraded as the wind speed increased. Our data shows that UAV in calm conditions (wind less than 5mph) had 19% longer battery lives than UAV flown in conditions where wind was on average faster than 10mph. Wind affects the power required for our UAV to fly between

[1]Algorithms used: Kernel-Ridge Regression (KRR), SVR-RBF (Radial Basis Function kernel SVM), Gaussian-Process Regression (GPR), and Random Forest Regression (RFR)

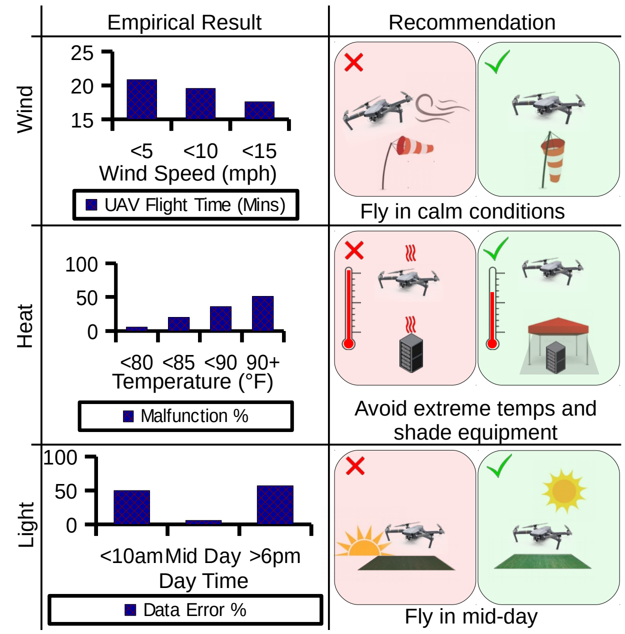

Fig. 7: A comparison of piloted, automated and autonomous swarms in terms of the consideration on wind, heat and light.

GPS waypoints. Wind can be helpful if it blows in the direction the UAV is traveling, but more often UAV must fight the wind to traverse the field and stabilize while capturing images and waiting for instructions, leading to increased battery drain.

Heat also has negative effects on equipment. Throughout our deployment, we ran missions in various temperatures between 60F and 95F. We found that 5% of missions run in temperatures below 80F experiencing a malfunction due to equipment failure, while 51% of missions run at temperatures over 90F experienced malfunctions. Equipment malfunctions included communication errors between UAV and remotes, network errors, equipment overheating, and heat-based UAV battery malfunctions. Not all errors were caused directly by overheating, but many were compounded by high temperatures as suggested in Figure 7.

Lighting was another major contributor to mission errors. Lighting, in this case sunlight, affects the quality of images that UAV capture. While all missions were flown within United States FAA regulated flight periods (between 30 minutes before sunrise to 30 minutes after sunset), low light and long shadows from a low solar angle contributed to increased mispredictions from DefoNet. We found that 50% of missions flown between sunrise and 10:00am and 57% of missions flown between 6:00pm and sunset contained mispredictions, while only 6% of missions flown between 10:00am and 6:00pm contained mispredictions. Mispredictions were generally false-negatives (predicting defoliated crop regions as healthy) due to DefoNet's inability to discern holes in leaves obscured by shadow.

Using these identified failure points for UAV missions, we provide recommendations for UAV deployments to avoid failures and unnecessary energy consumption. First, we recommend flying in conditions where sustained winds do not exceed 10 mph. While UAV can fly safely in winds higher than 10mph, we recommend conserving UAV battery for periods where weather is calm to maximize mission lengths, especially for deployments where power is scarce, harvested from compute resources, or generated by renewable sources. Second, we suggest avoiding flights during extreme temperatures, and always providing ample shade for equipment. High temperatures (over 90F) greatly increased incidence of equipment failure from UAV, edge, and networking hardware. For UAV, failures were limited mainly to battery malfunctions from short-term exposure to sun and high temperatures while flying which can be mitigated by conserving UAV batteries for cooler periods of the day. Furthermore, edge equipment malfunctions were often due to overheating from direct sun exposure. We suggest shading equipment from direct sunlight and potentially moving throughout the day as shade shifts with solar angle. Lastly, lighting effects on mispredictions can be mitigated by flying UAV when the sun is high, especially when areas are obscured in shadow at dawn or dusk.

VI. Challenges, Opportunities and Future Work

UAV swarm research is by no means new, but translation to agriculture has been slow. As previously expressed, UAV are flown manually in the majority of extant agricultural implementations, which all but precludes swarms. Prior work and our case studies, however, show that early agricultural UAV swarms are here and provide considerable benefits. Swarms can cover wide areas, analyze crops live in the field, and learn from one another to improve their performance. Much work must still be done, however, to reach a world where agricultural UAV swarms are effective, inexpensive, and pervasive enough to improve agricultural production globally. In this section, we outline 3 key trajectories that scientists and engineers can continue to explore to facilitate pervasive agricultural UAV swarms. These directions, as shown in Figure 8 are intelligence, deployment infrastructure, and hardware.

A. Intelligence

One key benefit of agricultural UAV swarms is their sensing and compute capacity. UAV can use captured images and video in combination with onboard or edge hardware to identify, report, and potentially treat crop phenomenon online. UAV analysis can be used to detect crop diseases, pests, health conditions, growth stages, phenotypes, and other important field qualities [47]–[49], but problems persist.

First, the number and importance of crop phenomena that farmers and subject matter experts can detect in crop fields are many. Unlike other complex applied machine learning problems such as autonomous driving, agriculture relies on deep expert knowledge that is difficult to translate into a single model. Farmers and researchers can identify and treat hundreds of stressors, pests, and diseases whose effects range in severity depending on field qualities like crop stage. Machine learning research has applied some of this knowledge to UAV applications [50], but normally only one phenomenon at a time.

We identify 3 AI developments that would further advance the state of the art: 1) the introduction of an agricultural model or data-commons, 2) improvements to few-shot learning in agriculture, and 3) the development of many-class models for agricultural phenomena. Model and data aggregation led directly to the deep learning revolution [51]. Data aggregation services like ImageNet and widely distributed many-class models like AlexNet and ResNet [52], [53] greatly improved access to and development of deep learning models for a broad range of subjects including agriculture. Many research groups, companies, and independent farmers have crop data, but sharing and access remain limited mostly to independent datasets and paid services with limited raw-data access. The emergence of an open aggregation service or repository for agricultural data would greatly improve the possibilities for UAV swarms.

Conversely, the emergence of few-shot learning approaches [54] have shown that well-trained initial models can learn new classes via experience. Agriculture is an excellent application domain for few-shot learning, as classes are many, phenomena are often rare [27], and data is expensive to collect and often not readily available. Few-shot learning could be used to boost the efficacy of early many-class agricultural models or to add rare phenomena.

Finally, we suggest research into heterogeneous agricultural swarms. Swarms as a learning problem are well-understood [55]. From a learning perspective, swarms are regularly reduced to cooperative Markov games. While this model has been explored deeply, it has not been convincingly adapted to agriculture. Extant agricultural swarm deployments focus on cooperative Markov games where swarm members are homogeneous and effect global utility similarly as in Case Study I (see Section III). Swarm and reinforcement learning literature, however, have rigorous models for heterogeneous swarms where members fill different roles [56], [57]. Heterogeneous agricultural swarms where separate members sense, treat, plant, and harvest hold deep technical challenges and should be explored.

B. Deployment Infrastructure

Infrastructure is another major roadblock for agricultural swarms. Swarm applications require power, networking, and compute resources that are not readily provisioned in rural settings even in the wealthiest nations. Societal infrastructure investment is, however, not always possible. Scientific and engineering problems to bypass the limitations of rural infrastructure should therefore be a research focus. Edge computing research for example, could focus on efficient resource allocation, scheduling, and cloud offloading for the types of sensor and machine learning workloads that UAV swarms embody [37], [58]. Networking research should expand on prior agricultural work relying on unused wireless spectra [32], LoRa [59], and other technologies to facilitate long-range communication across fields with limited cellular network access. Furthermore, more advanced scientific solutions to

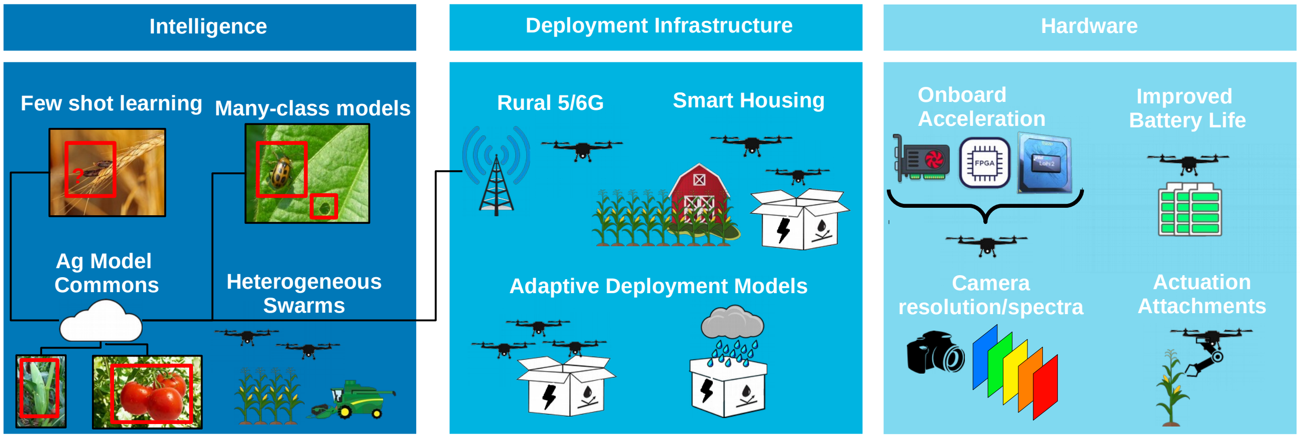

Fig. 8: Challenges and opportunities for autonomous UAV swarm research in agriculture and beyond. Three aspects are considered: intelligence, deployment infrastructure, and hardware.

bandwidth limitation in rural settings should continue to be explored.

UAV swarms face long-term deployment problems other than networking which are direct results of their rural operational environments. Current agricultural swarm deployments rely on research teams to judge the conditions under which to fly, and to set up and take down equipment. Rain, high winds, and heat all contribute to UAV loss and malfunction and must be considered. To facilitate long-term deployment, researchers should focus on technologies that can keep UAV safe and charged in or near-field. Furthermore, weather-aware deployment models [32] should determine when conditions are safe enough for missions to begin or continue.

C. Hardware

The breakdown of Dennard scaling, limited onboard power, and takeoff weight restrictions of UAV make onboard compute provisioning complex. Advances in hardware acceleration have improved prospects and generated products [60]–[62], but complete onboard hardware platforms for UAV are still lacking. Improvements in low size weight and power hardware acceleration focused on machine learning and network communication could greatly benefit UAV swarm research. Furthermore, any significant advances in battery capacity to weight ratio or better implementations of hydrogen fuel-cells in aerial applications could revolutionize the adoption of UAV swarms. Battery power is the greatest limiting factor to most aerial swarm applications, so improvements to battery life will improve most other aspects of swarm deployment.

Increases in camera resolution requirements is a major limiter for the agricultural UAV applications, necessitating low-altitude flight for applications with high resolution requirements like in Case Study I. Increases in camera resolution allow UAV to fly higher and cover more ground with similar flight times, but would necessitate more onboard or edge processing power and memory. Multi-spectral and near infrared cameras [63], [64] are also widely used in aerial imaging applications, but due to their expense, they can be difficult to apply to swarms. This could be rectified by reductions in camera cost, improved RGB camera models, or heterogeneous swarm models. Beyond cameras, the ability for UAV to manipulate its environment via attachments could facilitate new applications. Some UAV can spray and water crops [65], but the widespread use of these technologies has not materialized. Intelligent application of water, pesticides, and herbicides through machine learning and heterogeneous swarms may be one avenue to investigate. Additional manipulation such as sample collection could also be of great value for some crops.

VII. Conclusion

In this paper, we described how UAV swarms can be applied in smart agriculture applications. We detailed the benefits of utilizing a swarms of UAVs in two different case studies and evaluated the performance in terms of the computation and communication gains compared with the scenario when no UAV-aided or single UAV situations are considered. Further, we widely discussed existing challenges, opportunities and future research directions for the intelligent orchestration on UAV swarm guided smart agriculture management. Three aspects in terms of intelligence, deployment infrastructure and hardware were used to provide a broad overview of future research opportunities. We concluded that UAV swarms have the potential to revolutionize agriculture. In addition, we showed that the usage of the state-of-the-art techniques on UAV swarms such as machine learning/reinforcement learning, edge computing and advanced network facilities can widely improve the smart farming involving e.g., field observation, spraying, crop monitoring, and defoliation modeling.

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