Adaptive Deployment for Autonomous Agricultural UAV Swarms

Jayson Boubin
Binghamton University
USA

Zichen Zhang, John Chumley, Christopher Stewart
Ohio State University
USA

Abstract

Unmanned aerial vehicles (UAV) play a critical role in many edge computing deployments and applications. UAV are prized for their maneuverability, low cost, and sensing capacity, facilitating many applications that would otherwise be prohibitively expensive or dangerous without them. UAV are cheaper than alternative aerial analysis methods, but still incur costs from expensive human piloting and workloads which necessitate high-resolution coverage of large areas. Recently, autonomous UAV swarms have emerged to increase the speed of deployments, decrease the cost and scope of human piloting, and improve the quality of autonomous decision-making through data sharing. Autonomous UAV deployments, however, suffer from external factors. UAV are inherently power-constrained, with low onboard battery lives and limited ability to siphon power from the edge systems that support them. Certain environmental conditions, like inclement weather, wind, extreme heat, and low light also affect UAV power consumption, sensed data quality, and ultimately mission success. In this paper, we present an empirically based model for efficient autonomous swarm deployment. We built and deployed a real autonomous UAV swarm to map leaf defoliation in soybeans. Using this deployment, we determined environmental conditions which led to malfunctions, inefficient edge energy usage, and mispredictions. Using these findings, we developed a deployment model for UAV swarms that decreases malfunctions and data irregularities by 4.9X and decreases edge energy consumption by 45%, while increasing deployment times by only 4%.

CCS Concepts: • **Applied computing → Agriculture**; • **Computer systems organization → Distributed architectures**.

SenSys '22, November 6–9, 2022, Boston, MA, USA

ACM ISBN 978-1-4503-9886-2/22/11…$15.00
https://doi.org/10.1145/3560905.3568414

Keywords: unmanned aerial vehicles, edge computing, swarms, agriculture

ACM Reference Format:
Jayson Boubin and Zichen Zhang, John Chumley, Christopher Stewart. 2022. Adaptive Deployment for Autonomous Agricultural UAV Swarms. In *The 20th ACM Conference on Embedded Networked Sensor Systems (SenSys '22), November 6–9, 2022, Boston, MA, USA.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3560905.3568414

1 Introduction

Throughout the past decade, edge computing had IoT have matured from an active area of research among academics to an billion dollar industry. The rise of the internet of things (IoT) and the need for privacy and near-sensor processing has spawned a number of interesting consumer edge computing products, including smart homes and buildings [11], medical devices [1], Unmanned Aerial Vehicles (UAV) and more [6]. UAV, in particular, have formed broad academic, industry, and hobby communities. UAV are fast (moving upwards of 40 miles per hour), highly maneuverable, easy to fly, and can be equipped with high resolution cameras. Their flight can also be automated, making UAV an important tool for any task which requires precise, high resolution sensing that is too dangerous, expensive, or time consuming for humans to perform.

This use-case is common to many edge and IoT-related application areas [16]. UAV have found considerable uses in areas like precision agriculture [27, 28, 30], search and rescue [3], infrastructure inspection [8], and remote sensing in dangerous areas [17]. UAV are particularly useful in agriculture [27] for their maneuverability, low cost, and sensing capacity. Farmers, researchers, and companies use UAV to sense crop diseases, pests, and stressors [18, 29]. UAV deployments can provide analytics to farmers to influence sustainable crop management, or can treat crop health conditions on their own [14].

While UAV are quite useful, they can difficult to use for large or complex deployments. First, UAV have small battery lives. Most UAV have battery lives on the order of tens of minutes [13]. Crop fields are large and often require long deployments, so researchers and companies have recently begun analyzing crops using groups of cooperating UAV (called swarms) to both cover areas faster and mitigate short mission times [21]. Second, the intelligence of each UAV agent affects mission time and capability. UAV can be piloted by humans, operating as an extension of their pilot and her expertise, or flown by software. Human piloting is by far the most common piloting method, but comes with drawbacks. UAV pilots are often licensed and can command high hourly rates, can be scarce or difficult to schedule for long deployments, and can not control multiple UAV at once. UAV flown by software [20] can replace expensive human pilots by either automating UAV flight for pre-defined missions, or autonomously controlling UAV. Automated UAV fly pre-defined routes where the flight path and sensing locations are specified before takeoff. Autonomous UAV sense and respond to their environment [22], accomplishing complex missions using machine learning. Software piloting of UAV both decreases deployment cost from human labor and allows for increased intelligence and response to sensed data.

While autonomy can drastically simplify deployment for UAV applications, deployments must still contend with environmental issues. This is especially true for agriculture. Any outdoor edge or IoT deployment must contend with weatherproofing, but UAV applications are particularly vulnerable. Unlike embedded sensors and edge devices, UAV explore their environments, making them susceptible to failures due to rain, lightning, heat, and other environmental factors. Furthermore, limited UAV battery life and continual recharges can put energy pressure on already constrained edge systems. These issues are compounded again by the remote nature of many agricultural UAV deployments. Crop fields cover large areas with poor provisioning for power and network capabilities. UAV malfunction, data loss, and weather-related misclassification can lead to incorrect results, extension of deployments, or complete mission failure if incorrectly mitigated.

A successful autonomous UAV deployment must contend with these environmental challenges. Prior work has dispatched UAV and duty-cycled edge hardware based on cloud-cover to conserve renewable power [27]. Other viable flight conditions, such as heat, low light, and moderate wind may affect the energy that UAV consume in flight, the odds of UAV malfunction, and model classification results. Researchers have shown that adaptive deployment models, deploying UAV when conditions are conducive to mission success, is a helpful for structural inspection [10] and air pollution monitoring [7]. In this paper, we propose an adaptive deployment mechanism for agriculture.

In this paper, we explore a range of environmental effects that UAV deployments experience and provide an empirical model that reserves edge resource for environmental conditions conducive to UAV flight. We designed a crop scouting UAV swarm that assesses leaf defoliation in soybeans, a globally important crop. We flew over 150 autonomous crop scouting missions in different environmental conditions to measure the effects that environmental conditions have on UAV malfunctions, data quality, and energy consumption. Using this information, we develop and simulate a deployment model for autonomous UAV swarms which saves UAV batteries for conditions where malfunction is least likely, energy consumption is minimized, and data quality is assured. Our simulation results show that this model decreases malfunctions by 4.9X and decreases UAV battery consumption by 45% over the course of a deployment while only increasing total deployment lengths by 4% on average.

This paper is organized as follows. Section 2 covers background information on UAV deployment concerns and prior deployment models. Section 3 describes the design and implementation of our deployment. Section 4 details results from our deployment. Section 5 presents our empirical deployment model for autonomous UAV swarms.

2 Background

Recent UAV work has led to automated and autonomous deployments in a wide range of areas [9, 15, 23, 27]. Particularly in agriculture, UAV have been deployed to scout important crops[9, 28], diagnose diseases and pest infections [2], and apply treatments [14]. Crop scouting and treatment application is a continual process, with best practice suggesting repeated scouting every 7-10 days over the course of a growing season [12]. While researchers (and, increasingly, companies [19]) work to build crop scouting models, techniques are often tested in simulation or through manned flights or short-term deployments.

As the ability to scout and treat crops using swarms of UAV matures, the need for more long-term deployment automation arises. Today's deployments are generally supervised by research teams regardless of the amount of automation or autonomy the UAV have in flight. This expert supervision removes the need to implement a complex deployment model, replacing it with expert human intuition and planning. FarmBeats [27], however, deployed a long-term UAV scouting solution which required some weather awareness, duty-cycling components of their IoT base-station to save solar-generated power. More recent theoretical work has explored the effects that weather can have on package delivery [25, 26] by using optimization to maximize customer satisfaction under different weather conditions. Other work has used adaptive deployment to provide continuity of services in structural inspection [10]. In this paper, we take inspiration from these approaches by deriving a model from long-term deployment experience.

3 Design

Computer system deployments in the wild can be complicated and error-prone, with risk factors increasing for UAV deployments where equipment traverses its environment. We deployed a long-term UAV swarm to study the risks that

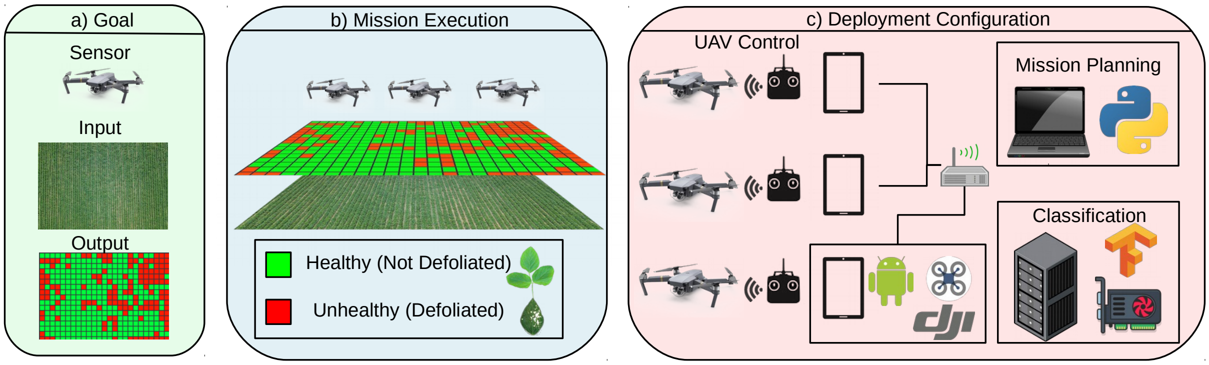

Figure 1. Deployment Overview: UAV scout a crop field to build defoliation maps over time using edge hardware and machine learning software for classification and map generation.

UAV and equipment face in the wild. In this section, we describe this deployment and it's implementation.

UAV Deployment: Our UAV deployment, depicted in figure 1 uses three UAV to regularly scout a crop field. The goal of aerial crop scouting is to turn sensed field images into useful reports for farmers. UAV fly over crop fields periodically and capture images which are then analyzed and compiled into field reports that farmers can use to diagnose and treat pests, disease, environmental stress, and other crop health issues. Our deployment seeks a specific crop health condition: *leaf defoliation*. Leaf defoliation denotes loss of leaf area which occurs naturally as plants mature, but can be caused prematurely by pests, resulting in decreased yield [31]. Premature defoliation in soybeans caused by pests is a common problem experienced by farmers around the world.

To scout soybeans using UAV, we implemented a convolutional neural network (CNN) model, called *DefoNet* [31], to predict the leaf defoliation conditions quickly from aerial images. *DefoNet* is a binary CNN model that classifies soybean leaves into two classes: defoliated or healthy as shown in figure 1. *DefoNet* accepts as input 108x108 pixel soybean leaf images. The main structure contains eight convolutional layers divided into three sections (Three layers in the first section, three layers in the second section, and two in the last). Following each convolutional section are activation and pooling layers. Before the final fully connected layer, we add a dropout layer to avoid model overfitting. In our test cases, *DefoNet* is able to achieve over 92% accuracy on classifying soybean leaf defoliation.

To efficiently and quickly build crop-scouting maps, we relied on prior work to sample crop fields using multi-agent reinforcement learning. We used WholeField-RL [30], a reinforcement learning based sampling technique for crop health modeling, and MARbLE [4], an edge-conscious autonomous swarm deployment architecture to simplify our deployment. Whole-field RL allows our UAV swarm to build accurate crop maps while sampling a subset of the field, using neural networks to extrapolate ground truth samples across unsampled regions. MARbLE provides us an efficient dispatch mechanism which automatically schedules UAV flights, conserves edge resources by duty-cycling edge hardware, and retrains reinforcement learning policies online to improve mapping performance.

Implementation: Using this design, we built and deployed a UAV swarm to track soybean defoliation at a local private soybean farm. Our swarm was deployed for three weeks from August 27th to September 16th 2021, running more than 150 missions over that time. Our swarm consisted of three DJI Mavic Pro UAV with six interchangeable UAV batteries. UAV were controlled by SoftwarePilot [5] running on three android tablets as shown in Figure 1c. Each tablet was connected via USB to a Mavic RC Controller via 5GHz WiFi to a MARbLE cluster.

Our MARbLE cluster consists of two Lenovo T470 Thinkpad laptops and one Dell precision 7920 workstation. Each Lenovo had an Intel i7 CPU and ran Ubuntu 18.04. One Lenovo laptop was used as the head node of MARbLE as well as the master node of the MARbLE kubernetes cluster, controlling all UAV communication. This machine was provisioned with 24 GB of RAM. The second Lenovo laptop was used for UAV control and retraining offloading, and was provisioned with 8GB of RAM. The Dell workstation had one Intel Xeon 6258R CPU, 64 GB of RAM, and one NVIDIA RTX 2080 Ti GPU. This machine was used for *DefoNet* classification and as the primary node for reinforcement learning retraining.

Each swarm mission was managed by MARbLE but was manually dispatched by one of two on-site researchers. Missions covered 0.4 hectares of soybeans per UAV, taking between 5 and 20 minutes depending on the actual coverage rate of the 0.4 hectares. To determine the effects of environmental conditions on UAV swarms, we executed missions in varying degrees of heat, wind, humidity, lighting, and cloud cover. We refrained, however, from executing missions in hazardous conditions with winds higher than 15mph, rain, or

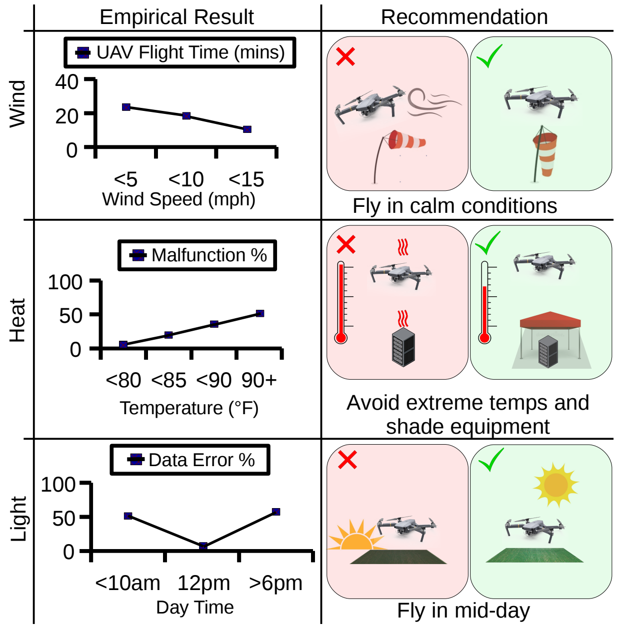

Figure 2. high winds, extreme heat, and low light all contribute to malfunctions. We recommend flying in calm conditions, avoiding extreme temperatures, and flying when the sun is high for best results.

storms. We sought specifically to find the effects that seemingly reasonable flight conditions could have on UAV swarm performance.

4 Deployment Results

Throughout our deployment, we collected data on UAV and battery drain, system malfunctions and causes, machine learning mispredictions, and flight times for certain weather conditions. Our analysis shows that three key conditions (wind, temperature, and lighting) have serious effects on mission performance. Shown in Figure 2, wind speeds greatly affect flight times. We found that average single-UAV mission times degraded as 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 GPS waypoints. Wind can be helpful if it blows in the direction the UAV is traveling [27], 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 2.

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 and 30 minutes after sunset in a day, low light and long shadows from a low solar angle contributed to increased mispredictions from DefoNet. We found via manual inspection of predictions 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.

5 Adaptive Deployment Model

UAV deployments are, at heart, a resource allocation problem. UAV and edge devices require power which can be drawn from electric grids, stored in batteries, or supplied by renewable sources. Conventional UAV rely entirely on batteries which must be recharged between short missions. Flights generally last less than 40 minutes, while battery recharge periods can extend to over 90 minutes, incensing the importance of both parallel execution of UAV flights in the form

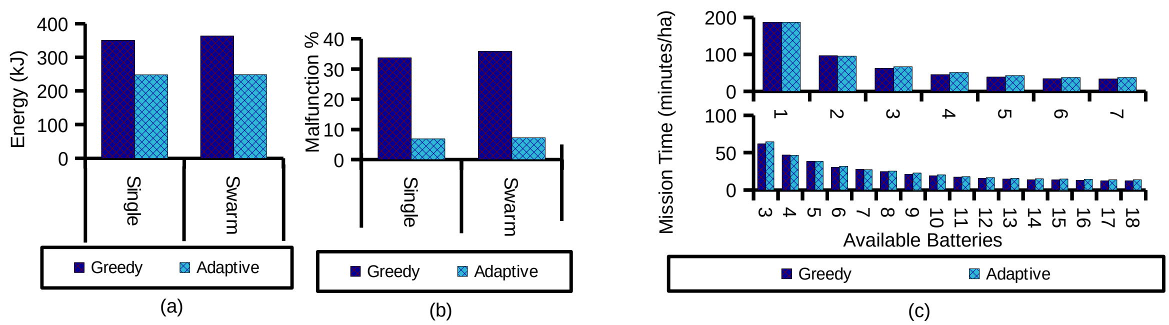

Figure 3. Simulation Results: a) greedy dispatching uses more energy that adaptive dispatching, b) adaptive dispatching encounters less malfunctions, c) adaptive dispatching saves energy without significantly impacting mission time.

of swarms and over-provisioning of batteries. Swarm deployment workflows are cyclical, with periods of UAV flight, battery interchange, and downtime where all batteries are depleted or recharging.

Based on our deployment results, we designed a simple adaptive deployment model to dispatch UAV flights based on environmental factors. Our goal is to implicitly leverage the flight and charging cycle to charge batteries in unfavorable conditions to maximize flight times in favorable conditions. Specifically, our goals are to minimize the following three quantities: 1) total mission time for aerial coverage of a target region, 2) total UAV energy consumption by avoiding re-scouting due to malfunctions, and 3) re-scouting of areas deemed mispredictions.

$$T = < T_t, T_{ds}, T_{de}, T_w > = < 85, 10{:}00, 18{:}00, 10 > \quad (1)$$

Model Definition: Our model explicitly schedules UAV flights for periods where conditions are favorable, and keeps UAV grounded while conditions are deemed unfavorable regardless of battery availability. Favorable conditions are determined via user-provided threshold vector T set based on deployment type, risks, and empirical experience. T, shown as an example in Equation 1, holds thresholds for the three unfavorable environmental conditions we determined from our experiments: temperature (T_t), appropriate start and end flight times (T_{ds} and T_{de}), and wind speed (T_w).

$$Dispatch(T) = \begin{cases} True & if \quad t \leq T_t, T_{ds} \leq dt \leq T_{de}, w \leq T_w \\ False & \end{cases} \quad (2)$$

Equation 2 shows the dispatch equation which determines whether waiting UAV with charged batteries should begin their mission or wait until conditions improve. This simple method charges and conserves batteries through unfavorable conditions, assuring longer flights and less malfunctions. It may, however, lead to underutilization of UAV resources and greatly increased total mission times if unfavorable conditions persist for too long. To test the effectiveness of our model under a variety of conditions, we tested it in a simulated version of our deployment.

Simulation and Results: Our simulator was created using SoftwarePilot [5], the same UAV control platform used to build our original deployment. We simulated UAV flight over a 50-hectare field similar in size to our deployment field. The field was cut into 10,000 individual management zones for UAV sampling. Our simulated UAV flight characteristics were based on data from our deployment, maintaining similar mission times, battery discharge rates, and sampling rates.

Environmental characteristics and their effects were simulated using prior work and empirical information. Sunrise and Sunset were set at 7:00 am and 8:03 pm respectively, the corresponding sunrise and sunset for September 1st 2021 in the rural town when and where our experiments were performed. Temperature was simulated based on the actual seasonal weather data from the experiment site obtained from the United States National Weather Service [24]. It was modeled using a sinusoidal curve with each given day being given a random temperature within the range of two standard deviations of local seasonal weather data. Temperatures experienced in flight by simulated UAV were between 60F and 93F. Wind was modeled by selecting a random wind value at the beginning of every simulated day and randomly increasing or decreasing it by up to 3mph (between 0 and 15mph) twice per simulated hour. Each simulated configuration was executed 100 times until the field was completely mapped without mispredictions. We simulated configurations with both single-UAV flights and swarms of 3 UAV as performed in our deployment, and with between 1 and 18 interchangeable batteries shared between UAV. For each configuration, our deployment model was compared against a naive greedy model which dispatches UAV missions whenever sufficient batteries are available.

Figure 3 shows results from our simulations. Figure 3 (a) shows total energy expenditure for both swarms and single UAV using both greedy and adaptive deployment models. Total energy expenditure is 41.4% less for single UAV and

45.8% less for swarms when dispatched adaptively. This decrease is due to multiple factors. First, These UAV do not operate in windy conditions, which degrade batteries 19% faster than calm conditions, but this accounts for only part of the decrease. The main decrease comes from repeated scouting of areas that were mispredicted or where data was lost or missions were cut short due to malfunction. Flying back to these potentially remote areas of the field for partial missions cuts other missions short and overall wastes energy compared to flying missions at opportune times.

Figure 3 (b) dives deeper into the malfunctions that both deployment models experience. Both single UAV and swarms experience about 4.9X less malfunctions when dispatched using our adaptive model compared to the greedy method. Malfunctions in this case, include any region that has to be re-sampled due to a hardware malfunction or data misprediction. For greedy dispatching, 33-35% of all zones must be sampled more than once due to malfunction as opposed to 6% with adaptive dispatching. This decrease in resample is the primary driver for energy savings in Figure 3 (a).

Figure 3 (c) shows total mapping times for single UAV and swarm mapping using both greedy and adaptive dispatching with varying numbers of available batteries. One concern with adaptive dispatching is that UAV idle while they could be sampling the field which should lead to commensurately increased mapping times. Contrary to this supposition, figure 3 (c) shows that adaptive dispatching does not significantly impact overall deployment times. Across all simulations, deployment times were increased by only 4% when using our adaptive strategy, with the largest increases (11-12%) shown when sufficient batteries are available to eliminate UAV wait-time for battery recharging (7 batteries for single UAV, 18 for swarm). Adaptive dispatching performs best when batteries are scarce and UAV wait-times are long, but maintains effectiveness even when batteries are plenty due to aforementioned decreases in malfunction-based remapping.

6 Limitations and Future Work

In our experiments, we measured many environmental effects, but only identified three (wind, temperature, and light) that significantly impacted mission performance. Only these three factors, therefore, are considered in our adaptive deployment model. Other environmental factors that did not effect our missions may impact missions with different characteristics. Similarly, UAV who fly longer missions, fly at higher altitudes, or operate in different climates may experience weather effects differently than our low-flying agricultural UAV. We believe that our adaptive deployment model will hold for low-flying UAV in common agricultural settings, but UAV that fly at higher altitudes, for instance, may experience different magnitudes of effect from temperature, lighting, and wind. Furthermore, misprediction rates due to lighting and their effects are model-specific. Some models are more robust to lighting differences than others, but our adaptive deployment model is meant to provide guidelines for flight that guarantees the best chances to capture quality data. Future work should address these shortfalls of our adaptive model. Researchers should test the effects that environmental factors have on UAV who fly different mission types, and in different application areas.

7 Conclusion

UAV deployments are complicated, requiring environmental considerations beyond those of normal edge and IoT deployments. While extreme weather will clearly impact UAV flights, some viable flight conditions like excessive heat, moderate winds, and low lighting can cause malfunctions and waste UAV energy. In this paper, we use data from over 150 missions of a long-term autonomous crop scouting UAV swarm to inform UAV deployment scheduling. In simulation, our empirical model decreases machine learning mispredictions by 4.9X, decreases overall swarm energy consumption by 45%, and increases total deployment times by only 4%.

Acknowledgments: This work was funded by NSF Grant OAC-2112606 and the Ohio Soybean Council.

References

[1] A. A. Abdellatif, A. Mohamed, C. F. Chiasserini, M. Tlili, and A. Erbad. Edge computing for smart health: Context-aware approaches, opportunities, and challenges. *IEEE Network*, 33(3):196–203, 2019.

[2] J. Abdulridha, Y. Ampatzidis, S. C. Kakarla, and P. Roberts. Detection of target spot and bacterial spot diseases in tomato using uav-based and benchtop-based hyperspectral imaging techniques. *Precision Agriculture*, 21(5):955–978, 2020.

[3] E. T. Alotaibi, S. S. Alqefari, and A. Koubaa. Lsar: Multi-uav collaboration for search and rescue missions. *IEEE Access*, 7:55817–55832, 2019.

[4] J. Boubin, C. Burley, P. Han, B. Li, B. Porter, and C. Stewart. Marble: Multi-agent reinforcement learning at the edge for digital agriculture. In *Proceedings of the 7th ACM/IEEE Symposium on Edge Computing*, 2022.

[5] J. Boubin and C. Stewart. Softwarepilot: Fully autonomous aerial systems made easier. In *2020 IEEE International Conference on Autonomic Computing and Self-Organizing Systems Companion (ACSOS-C)*, pages 250–251. IEEE, 2020.

[6] J. G. Boubin, N. T. Babu, C. Stewart, J. Chumley, and S. Zhang. Managing edge resources for fully autonomous aerial systems. In *Proceedings of the 4th ACM/IEEE Symposium on Edge Computing*, pages 74–87. ACM, 2019.

[7] A. Boubrima and E. W. Knightly. Robust mission planning of uav networks for environmental sensing. In *Proceedings of the 6th ACM Workshop on Micro Aerial Vehicle Networks, Systems, and Applications*, pages 1–6, 2020.

[8] S. Chen, D. F. Laefer, E. Mangina, S. I. Zolanvari, and J. Byrne. Uav bridge inspection through evaluated 3d reconstructions. *Journal of Bridge Engineering*, 24(4):05019001, 2019.

[9] S. W. Chen, S. S. Shivakumar, S. Dcunha, J. Das, E. Okon, C. Qu, C. J. Taylor, and V. Kumar. Counting apples and oranges with deep learning: A data-driven approach. *IEEE Robotics and Automation Letters*, 2(2):781–788, 2017.

[10] M. Erdelj, O. Saif, E. Natalizio, and I. Fantoni. Uavs that fly forever: Uninterrupted structural inspection through automatic uav replacement.

Ad Hoc Networks, 94:101612, 2019.

[11] F.-J. Ferrández-Pastor, H. Mora, A. Jimeno-Morenilla, and B. Volckaert. Deployment of iot edge and fog computing technologies to develop smart building services. *Sustainability*, 10(11):3832, 2018.

[12] F. Fishel, W. C. Bailey, M. L. Boyd, W. G. Johnson, M. H. O'Day, L. Sweets, and W. J. Wiebold. Introduction to crop scouting. *Extension publications (MU)*, 2009.

[13] B. Galkin, J. Kibilda, and L. A. DaSilva. Uavs as mobile infrastructure: Addressing battery lifetime. *IEEE Communications Magazine*, 57(6):132–137, 2019.

[14] D. Giles and R. Billing. Deployment and performance of a uav for crop spraying. *Chemical engineering transactions*, 44:307–312, 2015.

[15] J. Hu, A. Bruno, B. Ritchken, B. Jackson, M. Espinosa, A. Shah, and C. Delimitrou. Hivemind: A scalable and serverless coordination control platform for uav swarms. *arXiv preprint arXiv:2002.01419*, 2020.

[16] N. Islam, M. M. Rashid, F. Pasandideh, B. Ray, S. Moore, and R. Kadel. A review of applications and communication technologies for internet of things (iot) and unmanned aerial vehicle (uav) based sustainable smart farming. *Sustainability*, 13(4):1821, 2021.

[17] K. D. Julian and M. J. Kochenderfer. Distributed wildfire surveillance with autonomous aircraft using deep reinforcement learning. *Journal of Guidance, Control, and Dynamics*, 42(8):1768–1778, 2019.

[18] S. Khanal, J. Fulton, and S. Shearer. An overview of current and potential applications of thermal remote sensing in precision agriculture. *Computers and Electronics in Agriculture*, 139:22–32, 2017.

[19] M. Kummerow. Fly the farm. http://www.flythefarm.com.au/, 2018.

[20] L. Meier, P. Tanskanen, L. Heng, G. H. Lee, F. Fraundorfer, and M. Pollefeys. Pixhawk: A micro aerial vehicle design for autonomous flight using onboard computer vision. *Autonomous Robots*, 33(1-2), 2012.

[21] C. Qu, J. Boubin, D. Gafurov, J. Zhou, N. Aloysius, H. Nguyen, and P. Calyam. Uav swarms in smart agriculture: Experiences and opportunities. In *2022 IEEE International Conference on eScience*. IEEE, 2022.

[22] J. L. Sanchez-Lopez, R. A. S. Fernández, H. Bavle, C. Sampedro, M. Molina, J. Pestana, and P. Campoy. Aerostack: An architecture and open-source software framework for aerial robotics. In *International Conference on Unmanned Aircraft Systems*, 2016.

[23] J. Scherer, S. Yahyanejad, S. Hayat, E. Yanmaz, T. Andre, A. Khan, V. Vukadinovic, C. Bettstetter, H. Hellwagner, and B. Rinner. An autonomous multi-uav system for search and rescue. In *Proceedings of the First Workshop on Micro Aerial Vehicle Networks, Systems, and Applications for Civilian Use*, pages 33–38, 2015.

[24] N. W. Service. Noaa's online weather data (nowdata). https://www.weather.gov/wrh/Climate?wfo=iln.

[25] A. Thibbotuwawa, G. Bocewicz, G. Radzki, P. Nielsen, and Z. Banaszak. Uav mission planning resistant to weather uncertainty. *Sensors*, 20(2):515, 2020.

[26] A. Thibbotuwawa, G. Bocewicz, B. Zbigniew, and P. Nielsen. A solution approach for uav fleet mission planning in changing weather conditions. *Applied Sciences*, 9(19):3972, 2019.

[27] D. Vasisht, Z. Kapetanovic, J. Won, . R. Chandra, A. Kapoor, S. Sinha, M. Sudarshan, and S. Strãtman. Farmbeats: An iot platform for data-driven agriculture. In *NSDI*, 2017.

[28] M.-D. Yang, J. G. Boubin, H. P. Tsai, H.-H. Tseng, Y.-C. Hsu, and C. C. Stewart. Adaptive autonomous uav scouting for rice lodging assessment using edge computing with deep learning edanet. *Computers and Electronics in Agriculture*, 179:105817, 2020.

[29] L. Yubin, D. Xiaoling, and Z. Guoliang. Advances in diagnosis of crop diseases, pests and weeds by uav remote sensing. *Smart Agriculture*, 1(2):1, 2019.

[30] Z. Zhang, J. Boubin, C. Stewart, and S. Khanal. Whole-field reinforcement learning: A fully autonomous aerial scouting method for precision agriculture. *Sensors*, 20(22):6585, 2020.

[31] Z. Zhang, S. Khanal, A. Raudenbush, K. Tilmon, and C. Stewart. Assessing the efficacy of machine learning techniques to characterize soybean defoliation from unmanned aerial vehicles. *Computers and Electronics in Agriculture*, 193:106682, 2022.