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Adaptive autonomous UAV scouting for rice lodging assessment using edge computing with deep learning EDANet

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ABSTRACT

Rice is a globally important crop that will continue to play an essential role in feeding our world as we grapple with climate change and population growth. Lodging is a primary threat to rice production, decreasing rice yield, and quality. Lodging assessment is a tedious task and requires heavy labor and a long duration due to the vast land areas involved. Newly developed autonomous crop scouting techniques have shown promise in mapping crop fields without any human interaction. By combining autonomous scouting and lodged rice detection with edge computing, it is possible to estimate rice lodging faster and at a much lower cost than previous methods. This study presents an adaptive crop scouting mechanism for Autonomous Unmanned Aerial Vehicles (UAV). We simulate UAV crop scouting of rice fields at multiple levels using deep neural networks and real UAV energy profiles, focusing on areas with high lodging. Using the proposed method, we can scout rice fields 36% faster than conventional scouting methods at 99.25% accuracy.

1. Introduction

Rice, *Oryza sativa* L., is an essential staple crop worldwide and has a significant impact on world politics and economics. Under the effects of global climate change and a world population increase by 2 billion persons in the next 30 years (Brown and FuC, 2008; Pison, 2019), maintaining stable rice production is a priority task for many countries to maintain food security. Many studies have shown that rice lodging is the primary factor that weakens rice production. Lodging reduces photosynthesis (Setter et al., 1997), decrease yield (Lang et al., 2012), and significantly diminishes rice quality (Zeng et al., 2017). A large number of studies address rice lodging problems from a cultivation perspective analyzing the mechanisms and the causes of rice lodging (Ookawa et al., 2010; Okuno et al., 2014). In contrast, other studies concentrate on developing effective methods to assess rice lodging (Ogden et al., 2002; Yang et al., 2017; Liu et al., 2018). Traditional rice lodging assessment relies heavily on manual in situ assessment and random sampling (Yang et al., 2017); however, the traditional manual assessment method has significant drawbacks. Typically, a preliminary disaster valuation, a comprehensive investigation, and a review sampling assessment are needed to complete a rice lodging assessment, which may take approximately 1 to 2 months to accomplish in total. Consequently, the rice field cannot be replanted, and the field owner's livelihood is dramatically impacted. Additionally, the delineation of the rice lodging area is performed by officers manually, which is prone to subjectivity and frequently leads to controversies. Lastly, due to the vast land areas involved in natural disasters, the traditional manual assessment faces challenges of high labor cost and efficiency. An effective rice lodging assessment method is urgently needed.

Remote sensing techniques like satellite imagery provide a feasible solution to investigate rice lodging over vast areas of land (Liu et al., 2018). Nonetheless, satellite images are usually limited by their spatial and temporal resolution, as well as their spectral band features (Nelson et al., 2014). Additionally, cloud contamination can limit the usability of optical satellite images as thick clouds can completely occlude target landscapes. In recent years, utilizing unmanned aerial vehicle (UAV)

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technology to obtain timely information on crop lodging has created numerous opportunities due to UAVs ability to fly in cloudy conditions (Zheng et al., 2020). UAVs can be equipped with high-spatial-resolution cameras to collect high spatial aerial red-green-blue (RGB) images for crop lodging assessment. The capability of UAV to obtain high spatial accuracy aerial images is complemented by the benefit of a global positioning system (GPS) and inertial navigation system (INS) technology. Yang et al. (2017) used UAV images combined with a spatial and spectral mixed image classification method, which classified rice lodging at 96.17% accuracy. Based on UAV images, Chu et al., 2017 produced a 3D canopy height model to detect corn lodging severity depending on height percentiles against preset thresholds. Later, Chu et al. (2017) developed a lodging index to automatically reflect the severity of corn lodging and yield after harvesting. Liu et al. (2018) combined thermal infrared images with UAV images to identify lodging rice, which has a false positives rate and a false negative rate of less than 10%.

In the meantime, the development of deep learning techniques has achieved evident results in agriculture applications (Kamilaris and Prenafeta-Boldú, 2018). Chu and Yu (2020) developed an end-to-end prediction model by fusing two back-propagation neural networks (BPNNs) with an independently recurrent neural network (IndRNN) for rice yield prediction. Wang et al. (2020) proposed a deep learning and depth camera combined solution to improve UAV environmental perception and autonomous obstacle avoidance. Zhao et al. (2019) used a deep learning U-shaped Network (UNet) architecture for rice lodging, with results showing that the dice coefficients on the RGB and multispectral datasets reach 0.942 and 0.9284, respectively. Yang et al. (2019) compared vegetation index (VI) with a convolutional neural network (CNN) based approach for rice grain yield estimation at the ripening stage using UAV images. The results show that this CNN based approach performs much better than the VI-based regression model. Yang et al. (2020) applied deep-learning to UAV images to estimate rice lodging in paddies over a large area. The semantic segmentation networks, including FCN-AlexNet and SegNet, are proven to have lower latency, approximately 10 to 15 times faster, and a lower misinterpretation rate than that of the maximum likelihood method. However, the studies, as mentioned earlier, all perform their analysis from an offline approach. Few applications attempt real-time rice lodging assessment. Mardanisamani et al. (2019) presented a deep convolutional neural network (DCNN) architecture using a transfer learning technique for lodging classification, which achieves comparable results while having a substantially lower number of parameters. The author emphasized that DCNN can be deployed on low-cost hardware, which can be suitable for real-time applications.

Recently, the development of edge computing devices and techniques has improved researchers' ability to process large amounts of data in a real-time manner without offloading to the cloud (Satyanarayanan, 2017). The usage of graphical processing units (GPUs) for deep learning and the availability of powerful processors at the edge allow practitioners to analyze data quickly without the cloud. Edge computing has been used to advance many emerging research areas in Computer Science, from the internet of things (IoT) applications (Atzori et al., 2010) to smart homes (Alam et al., 2012) and smart cities (Burange and Misalkar, 2015).

Edge computing has also been applied to agricultural scouting applications. Vasisht et al. (2017) used edge computing techniques to create FarmBeats, a novel precision agriculture platform that gathers data from sensors, cameras, and drones to enable precision agriculture techniques. Instead of transmitting all data to the cloud, a local computer or laptop device is used to process drone imagery data, which corresponds to the concept of edge computation (Yousefpour et al., 2019). As shown in Fig. 1, the connection of edge computing nodes to sensors like UAVs provides advantages, including high mobility, simplicity, interactivity, and responsiveness. Additionally, a simplified ad hoc NN (neural network) can be implemented for a specific purpose/

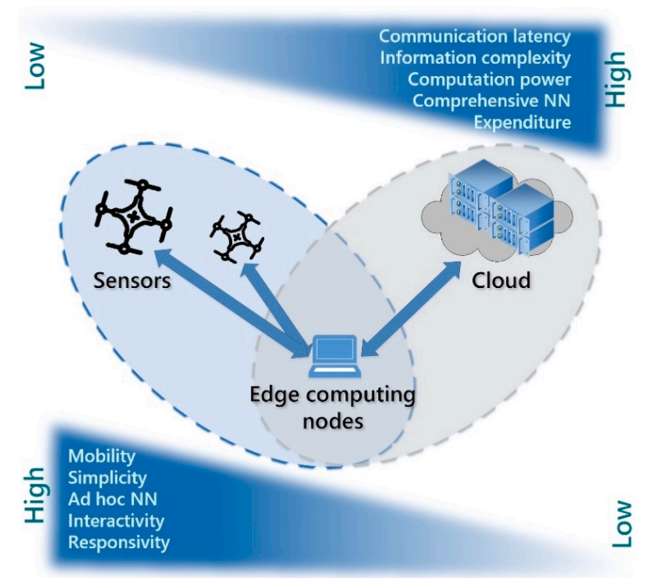

Fig. 1. Comparison of functions of edge computation and cloud-based system.

target. In contrast, several challenges, such as high communication latency and information complexity, need to be considered in the cloud-based system. In the present study, the connection of edge computing nodes to sensors is taken as the primary focus on developing an effective rice lodging assessment method.

Precision agriculture techniques like satellite imagery, UAV scanning, and even advanced platforms like FarmBeats are all linked in that they are automated. These approaches perform low-level tasks without human decision-making but require high-level human planning to perform well. Advancements at the edge allow for more complex autonomy policies to be implemented, allowing for autonomous, rather than automated systems to perform agricultural scouting and management tasks. Early attempts at fully autonomous precision agriculture using fully autonomous aerial systems (FAAS) have been implemented (Boubin et al., 2019a; Boubin et al., 2019b), and early fully autonomous precision agriculture software is available (Boubin et al., 2019c). Boubin et al. (2019) presented an open-source software package for FAAS, which includes autonomous UAV routines for agricultural scouting and demonstrates that fully autonomous routines can benefit significantly from correct edge compute architectures and autonomy policies (Boubin et al., 2019a; Boubin et al., 2019b). Simulated approaches to FAAS have also been demonstrated. Boubin et al. (2019b) show that given appropriate pathfinding algorithms and autonomy policies, accurate yield maps of crop fields can be generated by viewing only 40% of a field, saving power, time, and money for the farmer. Combining FAAS techniques with deep learning at the edge may greatly impact future precision agriculture techniques.

In this study, an effective rice lodging assessment method is proposed by combining deep learning and FAAS techniques with UAV images. Notably, the EDANet model was trained to study rice lodging information extracted by conventional digital RGB images. Three UAV scouting approaches, namely 200 m high altitude scouting, 50 m low altitude scouting, and an adaptive fly height, are investigated, and the corresponding energy consumption and rice lodging accuracy are assessed. Specifically, the following contributions of this paper are highlighted as follows.

1. An adaptive autonomous UAV scouting technique utilizing EDANet, a deep learning model, is proposed to assess rice lodging. The adaptive autonomous UAV scouting mechanism is designed based on

a threshold-based rice lodging assessment derived from the EDANet model.

2. Visible spectrum information and three vegetation indices are extracted and calculated from UAV images collected from two real rice lodging occasions in Taiwan. Both visible spectrum information and vegetation indices were used for EDANet model training and testing.
3. The proposed adaptive autonomous UAV scouting approach is compared with the other two approaches - 50 m low altitude scouting and 200 m high altitude scouting - in terms of associated rice lodging identification accuracy and scouting time.
4. The comparison of three approaches is performed in a simulation-based research software SoftwarePilot, in which an autonomy cube data structure (Boubin et al., 2019c) links UAV images with spatial information and an energy profiling using DJI Phantom 4 Pro (P4P) is applied.
5. Through a series of lodged percentage threshold settings for the simulator, our proposed adaptive autonomous UAV scouting approach demonstrates excellent performance in significantly reducing scouting time and preserving relatively high rice lodging identification accuracy.

The remainder of this paper is organized as follows. Section 2 describes our experimental methods, datasets, machine learning process, and adaptive scanning algorithm. Section 3 provides results from experiments. Section 4 discusses the results, their impact, and future work. Section 5 provides conclusions.

2. Materials and methods

Two rice lodging occasions associated with massive rainfall events in June 2017 and May 2019 in the Mozi Shield Park in Wufeng District, Taichung City, Taiwan, were investigated. Visible spectrum information of the field was collected in June 2017 by a fixed-wing UAV and in May 2019 by a rotary-wing UAV for training and testing, respectively. Detailed camera, flight height, area covered, training, and testing dataset information are shown in Table 1. All UAV collected images were mosaicked using Agisoft Metashape software and processed with image tile generating using Python for semantic segmentation model input purposes.

Besides normalized visible spectrum information of *Rn* (normalized red), *Gn* (normalized green) and *Bn* (normalized blue), three vegetation indexes, Excess Green index (*ExG*), Excess Red index (*ExR*), and Excess Green minus Excess Red index (*ExGR*), were calculated for the training and testing datasets (Woebbecke et al., 1995; Meyer and Neto, 2008). Formulas of these three vegetation indices are listed below.

$$E \times G = 2 \times G_n - R_n - B_n$$

$$E \times R = 1.4 \times R_n - G_n$$

$$E \times GR = E \times G - E \times R = 3 \times G_n - 2.4 \times R_n - B_n$$

Table 1
Detail of training and testing datasets.

	Training dataset	Testing dataset	
Camera/Platform	Sony QX-100/SV-1000A	DJI Phantom 4 Pro	
Collection Date	2017 / 06 / 08	2019 / 05 / 21	2019 / 05 /23
Resolution(width*height)	46,343 * 25,658	5472 * 3648	
Flight Height (m)	200	50	200
Area covered (ha)	430	4.4	120
GSD (cm)	5.3	1.3	5.7
Tile resolution(col * row) pixels	480 * 480	1349 * 899	5472 * 3648
# effective tiles	3485	220	65
# tiles in col * row	96 * 53	–	–

2.1. Semantic segmentation model training

We used an implementation of the Efficient Dense modules with Asymmetric convolution network (EDANet) developed by Lo et al. (2019) to detect rice lodging. The network architecture of EDANet is shown in Fig. 2, which is comprised of three major components, including three downsampling blocks, which are adopted from the ENet initial block (Basu and Woodard, 2016), two EDA blocks consist of 5 and 8 EDA modules respectively, and one projection layer. With the special two-branch design of the downsampling layers, module-level dense connectivity inspired by DenseNet (Huang et al., 2017), and a specific dilated asymmetric convolution technique, EDANet outperforms many state-of-art systems with high efficiency at low computational cost and model size (Lo et al. 2019), which makes EDANet a promising network for real-time semantic segmentation.

In the present study, the EDANet was trained using Adam optimizer with weight decay 1e-4, batch size 10, for 50 epochs. As suggested by Lo et al. (2019), the initial learning rate (init_lr) was set to 5e-4, and a polynomial learning rate policy was employed with power 0.9 for the learning rate of each iteration lr_{iter} in formula (4).

$$\mathrm{lr}_{iter} = \mathrm{init\_lr}^{*}(1 - iter/\mathrm{max\_}iter)^{power} \quad (4)$$

The model training environment information is shown in Table 2 below. The EDANet model performance was evaluated using five metrics listed in Table 3: Precision, Recall, Accuracy, Overall accuracy, and F1 score. These metrics are expressed through the calculated *TP* (True Positives), *TN* (True Negatives), *FP* (False Positives), and *FN* (False Negatives) for any given class *c* (Dong et al. 2019; Papadomanolaki et al. 2019).

2.2. UAV scouting

To gain an accurate assessment of rice lodging, fields must be scouted in their entirety to determine the percent of total lodged crops throughout. When scouting an area, operators must concern themselves with a number of factors, of which UAV battery life and image ground sample distance (GSD) are principal. UAV batteries are highly constrained, lasting for flight times between 20 and 40 min depending on the UAV model. We define one UAV flight as one full discharge of the UAV battery by assuming that the UAV takes off with a full battery and ends the flight with an empty battery. Mapping a field of considerable size may require many flights over hours to days, depending on the number of UAVs and batteries available, their recharge time, and GSD. Flight times can be decreased by increasing UAV altitude, which will, in turn, increase GSD.

GSD, and consequently, flight altitude and camera quality, must be considered. Image quality and clarity directly influence the ability of subject matter experts and machine learning algorithms to detect field abnormalities (Yang et al., 2011; Yang et al., 2018). When scouting for lodged rice, it is important to assure that all regions of the field can be accurately classified, and consequently, each image must have a GSD high enough to allow this. Given that raising GSD increases scouting time (independent of camera quality), a tradeoff emerges. Crop scouters must simultaneously balance detection accuracy and total scouting time, which can lead to increased costs, respectively, from unsubsidized lost crops, labor, and equipment.

Three mapping strategies are shown in Fig. 3 to demonstrate these differences. For a small section of a field (requiring 36 images to fully map at low altitude and four at high altitude), we outline three mapping strategies: high altitude, low altitude, and adaptive scouting. Low altitude and high altitude scouting exhibit the two principal differences previously described. Low altitude scouting requires significantly more energy and time to complete its task, requiring a second UAV mission in

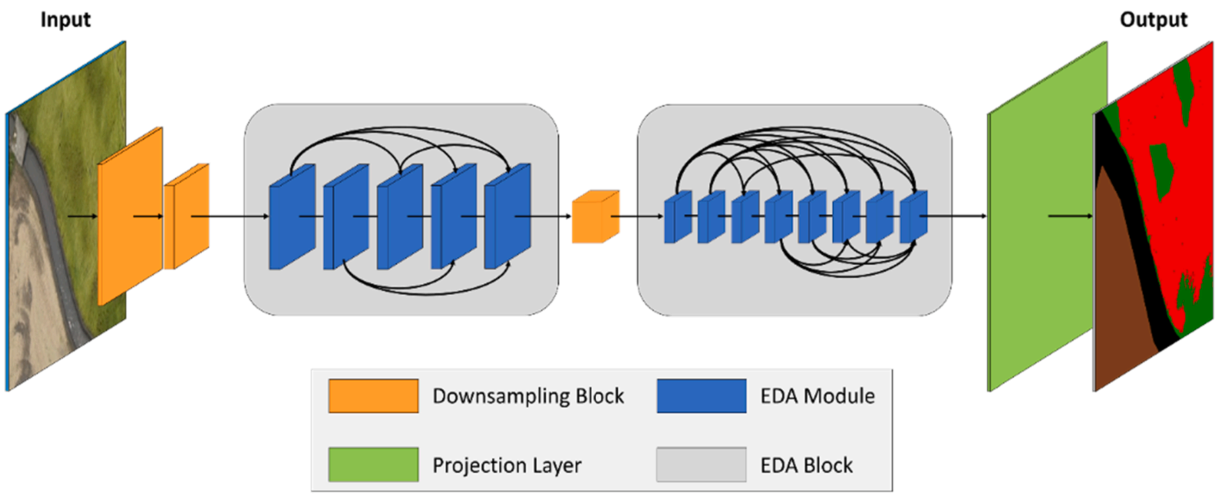

Fig. 2. EDANet architecture. (Figure adapted from Lo et al. (2019)).

Table 2
Model training environment information.

CPU	Intel Xeon Gold 6154 @3.00 GHz (4 cores/GPU node)
RAM	90 GB/GPU node
Accelerator	NVIDIA Tesla V100 GB SMX2/GPU node
Image	TensorFlow-1.0py3
Libraries	Python 3.6.8, NumPy 1.14.5, scikit-image 0.16.1, Keras 2.3.2, TensorFlow-GPU 1.14, Jupiter notebook, CUDA 10.1

Table 3
Model performance evaluation metrics.

Evaluation Metrics	Formula
Precision	$\text{precision}_c = \frac{TP_c}{TP_c + FP_c}$
Recall	$\text{recall}_c = \frac{TP_c}{TP_c + FN_c}$
Accuracy	$\text{accuracy}_c = \frac{TP_c + TN_c}{TP_c + TN_c + FP_c + FN_c}$
Overall accuracy	$\text{OA} = \sum_{c=1}^{n} \frac{TP_c}{TP_c + TN_c + FP_c + FN_c}$
F_1 score	$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$
Notes	*TP* (True Positives), *TN* (True Negatives), *FP* (False Positives) and *FN* (False Negatives)

this scenario to take each picture. In contrast, high altitude scouting is capable of capturing the entire section of the field in only four images.

The tradeoff, however, is that high altitude scouting is less capable of predicting lodging. It can not properly guarantee the correctness of its predictions at its decreased GSD. We can see in Fig. 3 that high altitude scouting mispredicts lodging in a number of regions. Given the high GSD of low altitude scouting, we can accept its lodging predictions as credible. A strategy that combines the high accuracy of low altitude scouting and the low energy costs of high altitude scouting could be dominant. In this paper, we present an autonomous scouting procedure that uses high altitude scouting to inform selective low altitude scouting.

2.3. Autonomous scouting

Autonomous scouting allows UAVs to make decisions on where to scan for high GSD images based on potentially inaccurate, but informative predictions from low GSD scouts at high altitude. In short, UAVs scout the field at high altitude first. An edge system analyzes these images in situ, then uses machine learning to determine positions to investigate at low altitudes based on classification accuracy and certainty.

Fig. 4 shows how autonomous scouting can help balance the accuracy of low altitude scouting with the energy efficiency of high altitude scouting. The UAV first performs a high altitude scan and predicts lodging in each region of the field at the edge. Once lodged areas are classified at the high altitude, the UAV investigates all lodged areas at the low altitude. In this example scenario, the UAV can gain a 100% accurate picture of lodging in the field subsection by using half the energy of low-altitude scouting.

Autonomous scouting does, however, include a substantive hardware addition to the above requirements for both high and low altitude automated scouting procedures. Automated scouting can be done by a pilot or lightweight edge system. Images do not need to be processed locally, so simple systems are sufficient. Autonomous scouting, however, requires an edge system capable of controlling the UAV and executing simplified machine learning algorithms within a reasonable time-frame, which would require a hardware accelerator such as a GPU.

Fig. 4 describes the autonomous scouting algorithm in detail. For this scenario, we define the high altitude scouting height as 200 m, and the low altitude scouting height as 50 m. There are six key steps to complete an entire mission.

1. UAV must map at least one high altitude section of the field. This entails the UAV flying to a GPS waypoint at the center of the 200 m region being mapped and capturing an image.
2. Once the edge system downloads images of at least one region, machine learning is used to predict rice lodging in regions of high altitude images. Each image is decomposed into subsections that correspond to a possible 50 m image (i.e., a 200 m image decomposes into 16 50 m subsections). Each region is then given a certain lodged percentage (i.e., the percentage of pixels in that region represents lodged rice). Regions are then marked as uncertain if their lodged percentage is above a user-provided threshold. Uncertain regions are regions that must be explored further to accurately gauge lodging.
3. Once all regions are predicted, our system finds the most efficient route in which a UAV can fly to visit all uncertain regions. To do this, the edge system calculates the least cost Hamiltonian path between a fully connected graph whose vertices include the UAV's current position and all uncertain regions. This Hamiltonian path is then remapped to a UAV flight path, such that the UAV flies to each uncertain region once (Gurevich and Shelah 1987).
4. The UAV descends from its 200 m height and flies to the next region in the Hamiltonian path at 50 m altitude.
5. The UAV then captures a 50 m image of each uncertain region, flying along the prescribed Hamiltonian flight path.

	Step						
	1	6	12	18	24	30	36
1) Low Altitude Scouting							
UAV Mission 1 Battery %	95	77	59	41	23	5	7
UAV Mission 2 Battery %	100	100	100	100	100	100	95
Scouting %	4	20	36	52	68	84	100
Current Zone	F0	A0	F1	A2	F3	A4	F5
2) High Altitude Scouting							
UAV Mission 1 Battery %	95	77					
Scouting %	25	100					
Current Zone	E2	Fin					
3) Adaptive Scouting							
UAV Mission 1 Battery %	95	77	59	41			
Scouting %	8	38	69	100			
Current Zone	D2	C1	E3	Fin			

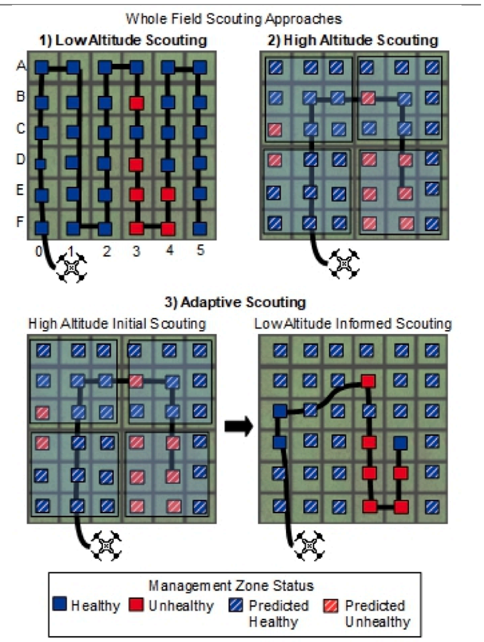

Fig. 3. Three scouting methods over a small area of cropland: 1) Low altitude scouting, 2) high altitude scouting, and 3) adaptive scouting. For each scouting method, scouting is tracked at 4 step intervals, logging battery of each necessary UAV mission, scouting completion percentage, and position.

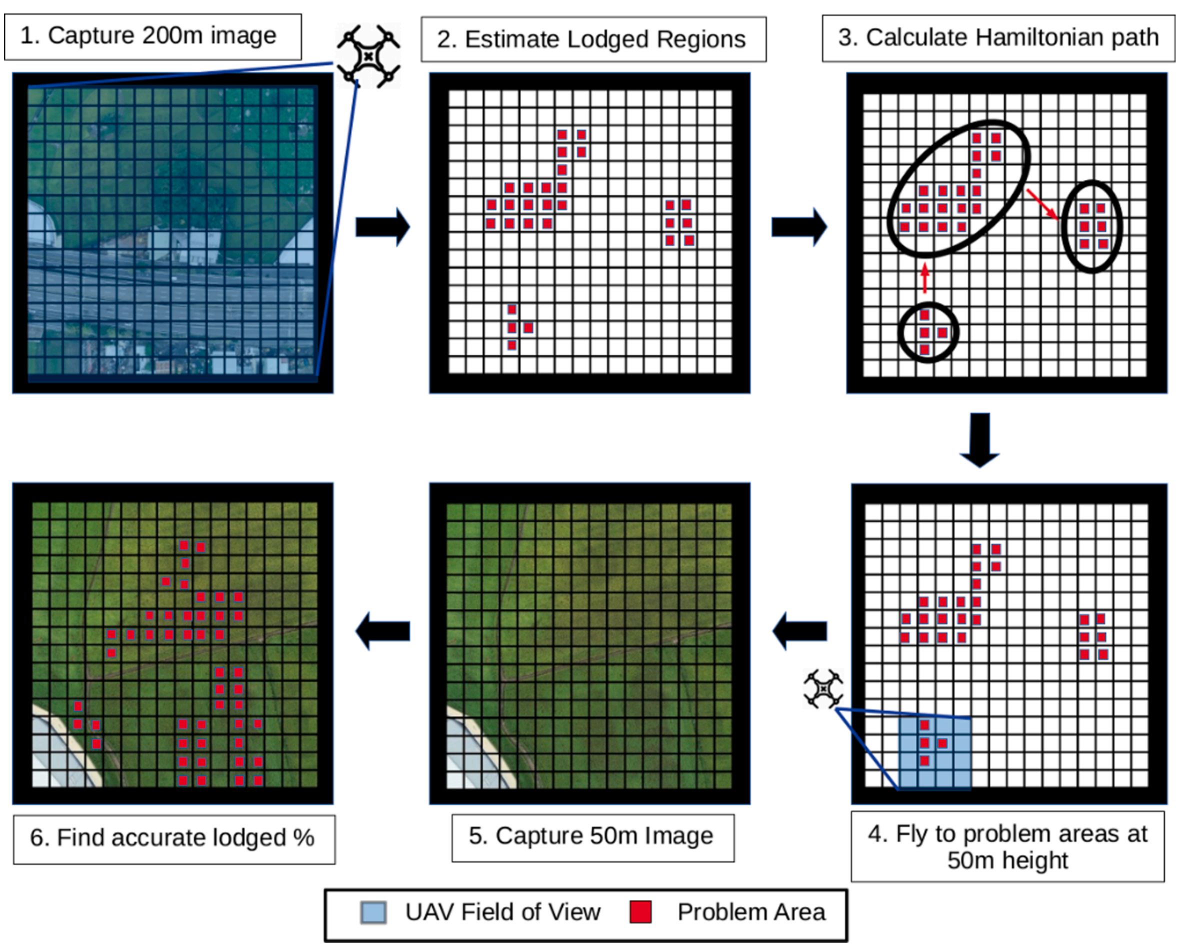

Fig. 4. A visual depiction of the autonomous scouting algorithm for 200 m and 50 m altitudes.

6. Once all images are captured, the edge system downloads each image. It calculates its lodged percentage using the high GSD 50 m images, thus gaining a more accurate picture of actual rice lodging.

2.4. Scouting in simulation

Crop scouting with autonomous UAV requires considerable infrastructural support, including software construction, testing, and regulation compliance. Furthermore, rice lodging on a large scale may happen more often with the increasing severity of typhoons or storms caused by global climate change. Therefore, an efficient crop scouting method is urgently needed for the challenge of rice lodging assessment, and careful testing and evaluating are also needed to ensure practicality. For these reasons, we chose to simulate our scouting algorithms using the lodged rice data sets mentioned earlier in this section. Crop scouting and autonomous UAV simulation mechanisms have been tested and validated in prior work (Boubin et al., 2019a; Boubin et al., 2019b). Using these methods, we were able to construct valid simulations and gather results for our scouting techniques.

2.4.1. Autonomy profiling

Autonomous systems must have the ability to fully navigate dynamic environments. For UAV, this implies the ability to fly to any point within some two-dimensional or three-dimensional space relevant to the problem at hand. When scouting a crop field for lodged rice, an autonomous UAV must have the ability to fly to and sense data at any point within the three-dimensional region where sensed data would be relevant to the field being scouted. When planning a crop scout, however, certain components of this bounding region can be abstracted to obtain similar results. For instance, the UAV may only fly at one altitude, presumably selected to balance image GSD and flight time.

Similarly, UAVs are usually only required to fly to a subset of points within the space, such that the subset of points allows the UAV to fully observe the crop field. Crop scouting and UAV mission plans in this respect are usually represented by a set of GPS waypoints and altitudes read by mission planning software that pilots the UAV automatically. Unlike automatic flight, autonomous systems make high-level decisions, like which waypoint to fly to next, in flight.

Given both the amount of possible sensed data by an autonomous crop scouting UAV and its ability to choose which data is sensed at runtime, profiling autonomous UAV for simulation can be difficult. To simulate lodged rice crop scouting, we used the autonomy cube, a data structure specifically created to aid in autonomous vehicle simulation (Boubin et al., 2019a). Autonomy cubes are data structures that combine sensed data (e.g., images, videos, other sensor readings) with spatial information (e.g., altitude, GPS locations). Each piece of data in an autonomous cube is linked to both an altitude and GPS location. As shown in Fig. 5, data also have links to surrounding data points based on possible flight actions. A flight action is defined as any movement or process that the UAV can undertake to solve its autonomy goal (e.g., takeoff, land, fly up 150 m, fly west 10 m, capture an image, hover). Flight actions are combined to create a complete UAV flight. Missions generally consist of UAV takeoff and landing combined with some series of UAV translation actions (e.g., fly left, fly up) and data sensing (e.g., capture images). For our simulation, we have created a set of standard flight actions that can be used for aerial scouting.

For every possible flight action of the UAV being modeled that displaces the UAV, a link will exist to data sensed at that position. These links allow simulated UAV to navigate virtual environments easily, accessing sensed data from real UAV missions. To construct autonomous cubes, a considerable amount of profile data is required. We sensed lodged rice data from Mozi Shield Park in Wufeng District in Taichung City, which we built into autonomy cubes using available research software (Boubin et al., 2019c).

2.4.2. Energy profiling

To properly evaluate the performance of a simulated UAV flight, the energy expenditure of each possible flight action for both UAV and

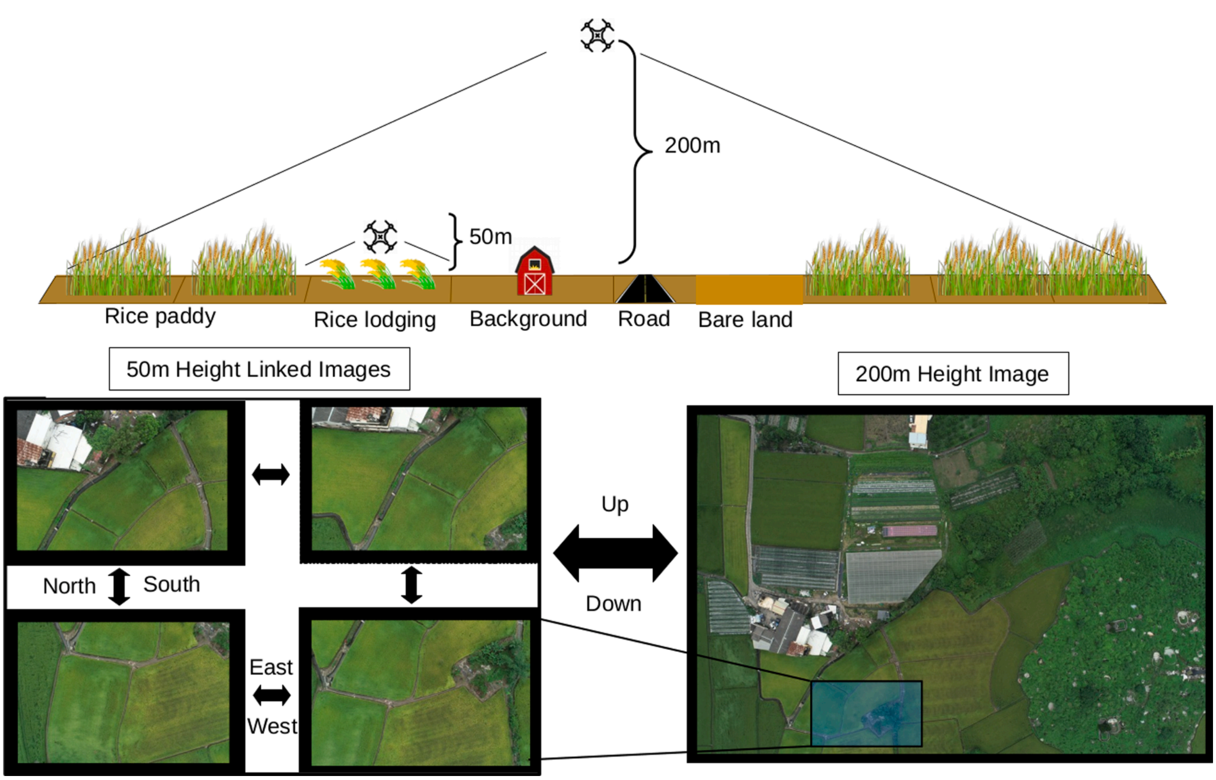

Fig. 5. Autonomy cubes capture both sensed data and spatial information. Sensed data points are spatially linked by flight action. In this figure, sensed data is liked by both cardinal direction and altitude.

compute must be known. To construct valid simulations, we created energy profiles for both UAV and compute. We define an energy profile as the execution time in seconds and energy expenditure in joules for every action available to a given system. In this context, an aircraft's energy profile would include energy and execution time information for each flight action. For a base station, this would include energy and execution time information for each flight control, classification, or data movement task.

To obtain this information, we used methods from prior work (Boubin et al., 2019b). We performed each compute and flight action 100 times, fitting the execution time to normal distributions and recording energy expenditure in watts to construct energy profiles. We gathered energy and execution time information from UAV and edge systems using SoftwarePilot (Boubin et al., 2019c). Flight actions were profiled at Glacier Ridge Metropark in Dublin, Ohio (Fig. 6), using a DJI Phantom 4 Pro (P4P).

Table 4 shows the results of the profiling with the P4P. Flight actions include translation at 2 m/s, data capture and transfer, hovering, and takeoff/landing. The simulated UAV translates at 2 m/s in all directions for consistency. At the height of 50 m, the UAV must move 10 m along one of its horizontal axes to see a different image in our dataset, and similarly, at 200 m, the UAV must move 35 m. For this reason, we profiled each movement along the horizontal axis (left, right, forward, and backward) at both 10 m and 35 m. Vertical translations (fly up, down, takeoff/landing) were also profiled. We combined takeoff and landing into one action per prior work (Boubin et al., 2019b), and profiled translation between the 50 m and 200 m heights at 2 m/s. Lastly, we profiled interactions with edge systems. The Sense Data action includes capturing an image with the UAV camera and transferring it to the edge system. The hover action is used when the UAV idles, awaiting commands from the edge system during the adaptive approach.

2.4.3. Simulated scouting

Using autonomy cubes and energy profiles, we constructed software to simulate the three whole field mapping strategies detailed earlier in this section. Fig. 7 shows how to construct the simulator. Inputs include workload settings (e.g., machine learning models, flightpath type), the autonomy goal (i.e., to estimate the lodged percentage of the crop field), and autonomy cubes. Based on the flightpath type, potentially sensed data and model outputs, flight paths for the UAV are generated. Once a flightpath is generated, it can be used to determine the number of each flight and compute the actions required. We sample the normal distributions of these actions latency, which are used to calculate energy expenditure in joules.

Table 4
Simulated flight actions and their energy cost as profiled with a DJI Phantom 4 Pro (P4P).

UAV	Flight Action	Energy (J)	Battery Consumption (%)	Time (sec)
P4P	Takeoff/Land	249	0.95	14
	Left 10 m	558	0.76	5
	Left 35 m	558	2.65	17.5
	Right 10 m	558	0.76	5
	Right 35 m	558	2.65	17.5
	Forward 10 m	661	0.89	5
	Forward 35 m	661	3.14	17.5
	Backward 10 m	514	0.69	5
	Backward 35 m	514	2.44	17.5
	Fly Up 150 m	560	2.28	15
	Fly Down 150 m	519	2.11	15
	Sense Data	367	0.05	5
	Hover	257	0.07	1

Adaptive scouting in the simulation was principally compared to low and high altitude scouting, which both scout the entire field using EDANet to predict lodging at 50 m and 200 m respectively after the flight. All three methods were simulated with UAV starting at one of 4 corners of the waypoint grid and moving first in either of the two possible directions from the start point in a lawnmower fashion for a total of 8 possible traversals of the grid. Simulations were run on a Lenovo Thinkpad T470 laptop with an Intel 7500U CPU and 24 GB of RAM running Ubuntu Linux 18.04. The simulator was written in Python 3.6 and was given pre-segmented images from our EDANet model.

3. Results

To develop the proposed adaptive crop scouting mechanism, we carefully trained EDANet, the semantic segmentation model, to ensure model capability for lodging assessment. Additionally, we simulated UAV crop scouting of rice fields at multiple levels using EDANet and real UAV energy profiles. Hence, accuracy and scouting time were compared between the proposed adaptive crop scouting, 50 m scouting, and 200 m

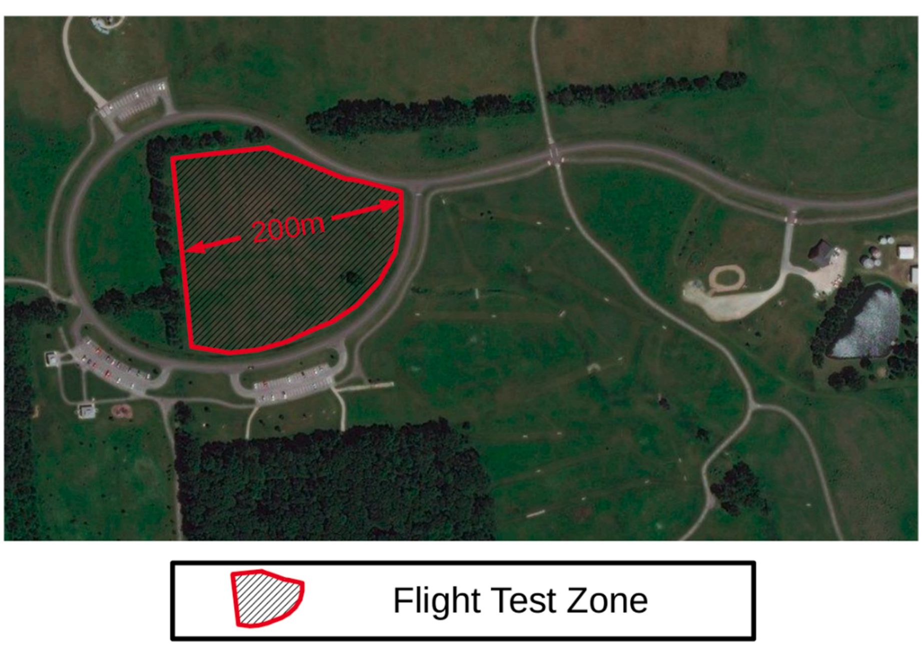

Fig. 6. Aerial view of Glacier Ridge Metropark in Dublin, Ohio, where the flight action profiling was performed.

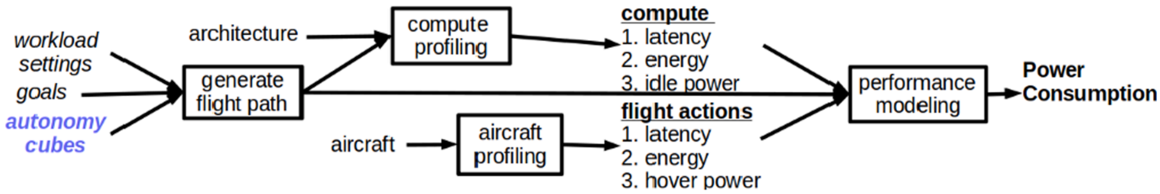

Fig. 7. Workload settings, goals, autonomy cubes, and energy profiles are taken as inputs to the simulation. These inputs are used to generate flight paths and determine the overall power consumption and execution time of UAV missions.

scouting. Furthermore, overlap and cost considerations of UAV scouting were also investigated.

3.1. Semantic segmentation model training and testing

Due to the limited space, only the F1 score and overall accuracy (OA) among the six metrics are reported for the training results. As shown in Table 5, the highest OA reaches 94.87% when RGB information is used. For these five classes (rice paddy, rice lodging, road, bare land, and background), the associated F1 scores are quite stable for each class. The bare land class has the highest F1 score of 96.97%, whereas the road class shows the lowest F1 score of 80.26%.

Table 6 shows the testing results for the 2017 and 2019 datasets. Based on the testing results, the entire testing process can be performed in around one minute, which is the most compelling evidence demonstrating the real-time capability of EDANet. Fig. 8 represents testing results from a subset of the 2019 field dataset. As shown in Fig. 8, EDANet performs well in capturing rice lodging, rice paddy, and other classes. Based on the results of the 2019 dataset, EDANet using RGB + ExG + ExGR information illustrations the highest value in recall (85.22%), accuracy (92.83%), and F1 score (78.51%). Therefore, the EDANet using RGB + ExG + ExGR information is the final model that has been applied in this study for further investigation in UAV scouting simulation.

3.2. Scouting in simulation

The adaptive scouting process was evaluated in simulation using autonomy cubes, a DJI P4P UAV profile, and a series of lodged percentage thresholds. Autonomy cubes were constructed from the Wufeng rice crop dataset using the SoftwarePilot autonomy cube builder (Boubin et al., 2019c). Autonomy cubes were created for images captured at both 200 m and 50 m heights. Out of 215 Wufeng crop images captured at 50 m, 73 contained no rice or exclusively rice that could be seen from other waypoints, so the simulated UAV did not capture data at those waypoints. The 200 m autonomy cube contained 12 images that were able to encompass all 215 50 m images. An energy profile was created for the P4P by profiling each simulated movement under real-world conditions using SoftwarePilot. Ten lodged percentage thresholds were also assigned for the simulator, denoting what estimated lodged percentage a region must have at 200 m in simulation to be investigated at 50 m, meaning that a 5% lodged threshold would only scout 50 m regions showing 5% or greater lodging at 200 m. The lodged percentages were chosen between 2.5% and 25% at intervals of 2.5%. The simulator used EDANet to estimate lodged percentages.

Fig. 9 shows example results from one simulation comparing the three methods where all methods begin on the same path, at the southwest corner of the grid, and move immediately north. The number of each flight action, total discharges, and lodged percentage prediction of each method are reported. Note that the adaptive method's Hamiltonian path is not included as a flight action. Fig. 9 also shows the route taken by the adaptive approach. The adaptive approach originally follows the same route as the 200 m approach, sensing data at each 200 m waypoint. Once all data is sensed, uncertain sections are found, and the best possible waypoints are determined to explore them. A Hamiltonian path between those waypoints is determined and is explored at 50 m by the UAV.

Table 6
Model testing results for the 2017 and 2019 datasets (the highest value is marked in bold).

Year	Information	Precision (%)	Recall (%)	Accuracy (%)	F1-score (%)	Time (sec)
2017	RGB	84.03	82.19	94.26	83.10	56
	RGB + ExG	**86.16**	84.19	**94.96**	**85.16**	58
	RGB + ExGR	84.42	85.77	94.84	85.09	61
	RGB + ExG + ExGR	83.34	**86.99**	94.78	85.13	64
2019	RGB	72.71	38.27	88.30	50.15	55
	RGB + ExG	**93.46**	56.45	92.70	70.39	59
	RGB + ExGR	82.24	52.72	90.98	64.25	60
	RGB + ExG + ExGR	72.78	**85.22**	**92.83**	**78.51**	65

3.3. Accuracy and scouting time comparison

The principal comparison points between the three approaches are accuracy and time in Fig. 10. Fig. 10a compares a normalized accuracy between 200 m and the adaptive scouting as they compare to 50 m scouting. 200 m scouting has a normalized error of 24.2%, meaning that an overall field scout at 200 m differs in predicted lodged percentage by 24.2% from a 50 m scout.

Adaptive scouting differs between 0.75% and 16.73% depending on the lodged threshold, steadily increasing as the lodged threshold increases. Until the lodged threshold exceeds 12.5%, the normalized error between 50 m scouting and the adaptive scouting does not exceed 2%. Higher lodged percentages, however, increase a normalized error by 5.03% to 16.73% due to their higher frequency to ignore largely lodged regions of the field due to inaccuracies in the 200 m scout.

Fig. 10b shows the differences in UAV missions required to scout the field between 50 m, 200 m, and the adaptive scouting. In the analysis, a P4P would have access to extra batteries, and when the battery depletes,

Table 5
EDANet model training results of F1 score and overall accuracy (OA) (the highest value is marked in bold).

Information	Rice paddy (%)	Rice lodging (%)	Road(%)	Bareland (%)	Background (%)	OA (%)
RGB	**95.28**	**86.17**	**83.02**	**96.97**	**96.94**	**94.87**
RGB + ExG	**95.28**	85.99	81.10	96.86	96.58	94.60
RGB + ExGR	95.24	85.87	81.80	96.48	96.55	94.54
RGB + ExG + ExGR	95.19	86.03	80.26	96.51	96.46	94.45

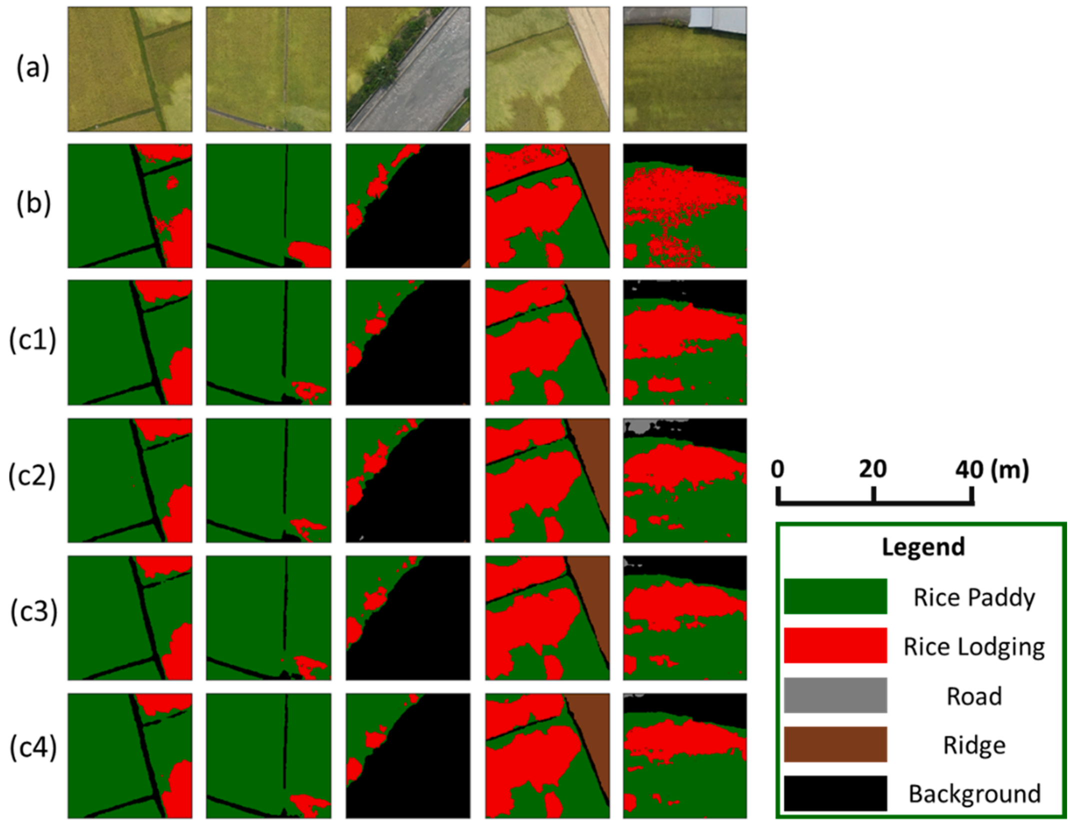

Fig. 8. Model testing results demonstration. (a)original image, (b)ground truth, and (c1-c4) represent EDANet with RGB, RGB + ExG, RGB + ExGR, and RGB + ExG + ExGR information, respectively. (Red represents rice lodging, green represents rice paddy, and black represents other classes). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the UAV battery would be changed, and scouting would resume. 200 m scouting is considerably faster than either adaptive or 50 m scouting, taking only 0.34 flights (at least one flight) to map the field. 50 m scouting, on the other hand, took 2.43 total (at least three flights) flights to map the entire field. The adaptive scouting was able to map the field in between 1.6 and 1.27 (at least two flights) flights depending on the lodged threshold, saving one recharge period and mapping the field in 65%-52% the total time required by 50 m scouting.

Simulation Attribute		50m	200m	Adaptive (T=2.5%)
Flight Actions	Takeoff/Land	1	1	1
	Left 10m	0	NA	NA
	Left 35m	NA	0	0
	Right 10m	9	NA	NA
	Right 35m	NA	1	1
	Forward 10m	103	NA	NA
	Forward 35m	NA	5	5
	Backward 10m	102	NA	NA
	Backward 35m	NA	4	4
	Fly Up 150m	NA	1	1
	Fly Down 150m	NA	1	1
	Sense Data	142	11	29
	Hover	NA	NA	29
UAV Discharges		2.34	0.32	1.60
Predicted Lodged Percentage		26.1	32.4	25.9

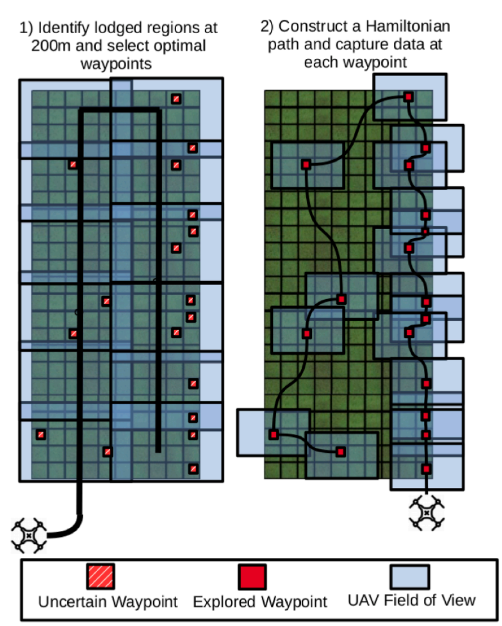

Fig. 9. Sample simulation results with the adaptive lodged threshold (T) set to 2.5%. Depicted is the simulated FAAS path for the adaptive approach at both 200 m and 50 m.

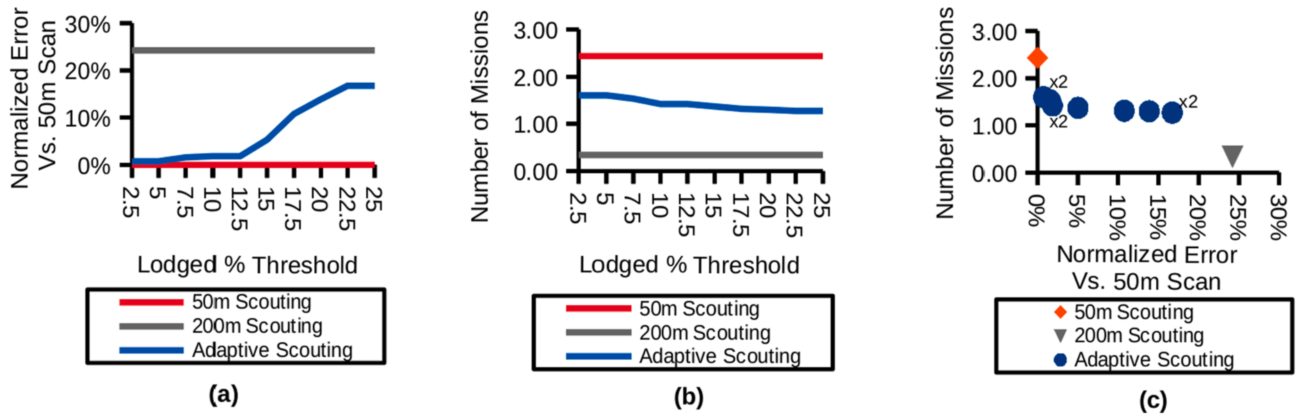

Fig. 10. a) Adaptive scouting is up to 99.25% accuracy compared to 50 m scouting, while 200 m scouting alone is 75.8% accuracy. b) Adaptive scouting takes at most 35% less missions to completely scout the field as compared to 50 m scouting. c) Adaptive scouting balances the high speed of 200 m scouting with the accuracy of 50 m scouting, sacrificing little accuracy for significant speed gains.

Fig. 10c shows the relationship between time and accuracy experienced by each scouting method. Of all approaches, 200 m scouting is by far the fastest but suffers from accuracy issues. On the other hand, 50 m scouting is highly accurate but requires considerable execution time. The adaptive scouting at low thresholds experiences less than 1% normalized error compared to 50 m scouting but completes in 36% less execution time. The adaptive scouting approach is able to decrease scouting time and preserve accuracy due to the correlation between 200 m and 50 m lodged predictions.

As shown in Fig. 11, predicted lodging at 200 m and 50 m for highly lodged regions are correlated, with a bias toward higher prediction rates at 200 m. By following the overall correlation, we are able to scout at 200 m and successfully predict which regions contain lodging, but not accurately predict the amount. By then scouting only those regions at 50 m, the adaptive approach can improve on total mission time without losing significant accuracy.

The largest differences between 200 m and 50 m scouting predictions can be found at low levels of lodging, where 200 m scouts predict lodging where there is none or predict no lodging where there is some at 50 m. Many of these points are regions which contain smaller amounts of rice crop, in lieu of buildings and roadways. 200 m scouting could mispredict these regions as lodged or healthy rice to the detriment of the overall scout, requiring either the scouting of unlodged regions or the skipping of lodged regions. While these outlier points may be mispredicted as highly lodged or healthy, they generally encompass only a small percentage of the overall field. They, therefore, have little effect on the overall performance of the adaptive scouting model, as demonstrated by the results presented in Fig. 10. Handling outlier cases such as these, however, should be addressed by future work.

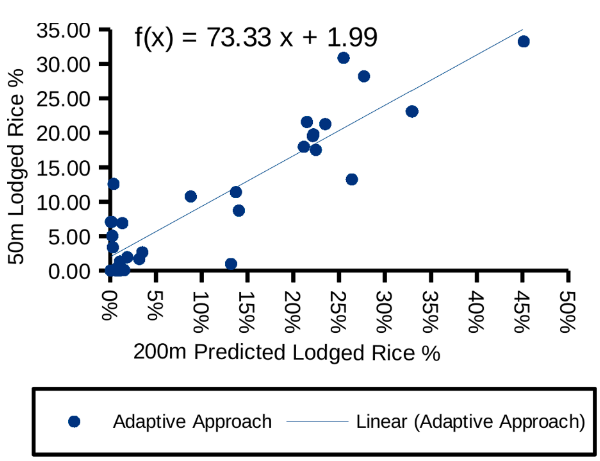

Fig. 11. Lodged rice predictions at 200 m correlate with observed values at 50 m but are inaccurate enough to yield valuable results alone. By informing 50 m scouting using 200 m results, high accuracy can be achieved while decreasing scout times.

3.4. Overlap and cost considerations of UAV scouting

A flight plan must be specifically made before executing the UAV mission, and consists of parameter setting, including the required spatial resolution of the photography, the camera focal length, the film format size, (forward) overlap, sidelap, the flying height above the ground, the ground speed of UAV, and the time interval between exposures. The purpose of photography is a major consideration in the flight plan. In this study, the overlap and the sidelap are required only for image mosaic in the 200 m scouting. In the 50 m flight mission, a higher overlap, larger than 67% of overlap and sidelap so that one feature point and its corresponding points appear on at least three successive photos, is required for image-based modeling. To increase robustness and accuracy, the redundancy should be afforded with a large number of mutually overlapping photos simultaneously, so-called multi-ray photogrammetry, which requires a very high overlap (80%-90%) and sidelap (up to 60%) (Lillesand et al., 2015). The overlap and the sidelap are 85% and 85%, as well as 80% and 60% for 200 m and 50 m scouts, respectively. Moreover, the total number of exposures necessary for a mission should be computed prior. Each photo has an incremental area, A, as

$$A = (1-p)^{*}h/S^{*}(1-q)^{*}w/S = (1-p)^{*}(1-q)^{*}h^{*}w^{*}S^{-2} \tag{5}$$

p is the overlap, q is the sidelap, h is the height of the photo, w is the width of photo, and S is the scale and shows an inverse relationship with the flying height above the ground using the same focal length.

As the setting overlap in the previous flight plan, the ratio of the numbers of total photos at 50 m scouting over 200 m scouting is 35 for a designated area. Furthermore, the overlap can be reduced to 60% for a 200 m scouting that can increase the ratio of the total photos up to 71.

The cost of 50 m, 200 m, and adaptive scoutings varying with the scouting area can be illustrated in Fig. 12. Based on a preliminary market survey of crop scouting and DJI P4P flight statistics, we estimate that 50 m and 200 m crop scouting cost \$100USD and \$500USD respectively in Taiwan. According to the regulation of Taiwan Civil Aviation Law, an out-of-sight flight that 200 m scouting may encounter needs an extra supervisor standing at commanding heights, who is responsible for connecting the nearby airport controlling center in case of emergency, beside a UAV operator. Thus, the extra supervisor results in a different initial cost between 50 m and 200 m scouting. In general, the cost of 50 m and 200 m scouting increases with area coverage.

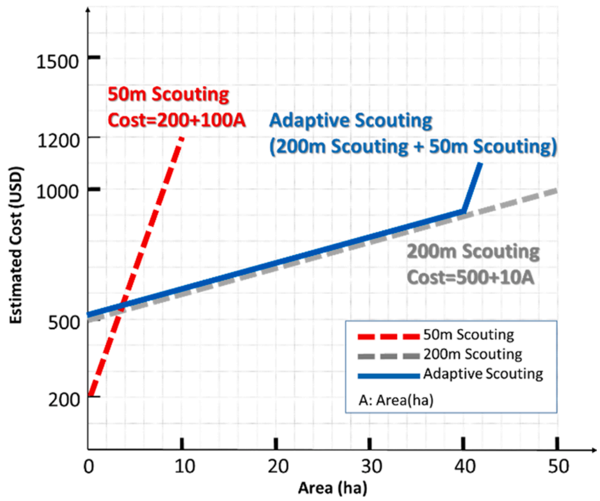

Fig. 12. The estimated cost of 50 m, 200 m, and adaptive scoutings varying with the scouting area.

Adaptive scouting combines the cost estimation at 200 m and 50 m and depends on the area of fine and coarse coverages. In this case study, the adaptive scouting combines one 200 m fight and two 50 m fights as one mission to efficiently reduce the total cost and achieve the goal of lodging identification, as shown in Fig. 12.

4. Discussion

As demonstrated in the results, we are able to construct a deep neural network for lodged rice detection that outperforms prior work using SegNet and FCN-AlexNet (Yang et al. 2020). The EDANet approach classifies rice paddy at 95.28% accuracy using RGB, as compared to SegNet at 91.49 and FCN-AlexNet at 92.77%. EDANet classifies lodged rice at 86.17% accuracy compared to SegNet at 70% and FCN-AlexNet at 77.91%. Even with more information in the form of vegetation indices, the best performance from prior work was garnered using FCN-Alexnet yielding 93% rice paddy accuracy and 80.08% lodged rice accuracy.

The adaptive algorithm was able to maintain this newfound accuracy. The adaptive approach scouts at two levels, first estimating highly lodged regions at high altitude, then confirming lodging at low altitude at only those highly lodged areas as efficiently as possible. We were able to maintain 99.25% accuracy using EDANet as compared to a complete scout of the entire field by simply avoiding regions that showed less than 2.5% lodging at high altitude.

The adaptive approach allows for a considerable time and costs savings compared to a complete scout of the crop field. Adaptive scouting at optimal accuracy takes 35% less flight time to achieve and saves precious UAV battery life. Flight time is important from a number of perspectives, including urgency, resource savings, and labor costs. Crop scouting for lodged rice is particularly sensitive to these factors. Rice lodging generally only occurs in reasonable quantities during periods of high flooding and heavy rainfall, which often coincide with other effects like power loss or limited labor availability and assessment time, which make aerial scouting difficult. Furthermore, lodging must be determined quickly to allow farmers to remove lodged rice or replant crops and promptly receive government subsidies (Yang et al., 2017) so that aerial scouting resources will be in high demand during these periods. This double effect of high demand and low resources makes the time and energy savings of the proposed approach much more consequential.

Scouting approaches also commonly utilize skilled independent pilots or aerial photography companies to survey cropland and locate lodging, which can be expensive. In a period of high volume for aerial scouting, demand for pilots may also increase, raising prices or delaying scouts. The proposed approach is fully autonomous, requiring only compute resources, UAVs, and labor for setting up and taking down systems. This process could be done easily by farmers, especially if they already use UAVs on the farm and own a reasonably powerful computer. Because the proposed approach does not require human piloting, it costs considerably less over time.

There are many available avenues for future work to improve our neural network and approach. First and foremost, increased data collection of lodged rice fields is imperative. Rice lodging, though devastating, is not an everyday situation, so gathering lodging datasets is difficult. Increasing the number of samples available will increase the ability of machine learning techniques to accurately detect lodging, like the proposed EDANet approach. Techniques to increase the accuracy of the proposed approach or other approaches with higher lodged rice detection accuracy are also valuable directions for future work.

The adaptive approach is not simply useful for rice lodging, but for finding and counting any anomaly that can be detected using aerial image analysis. Possible applications could include finding other crop diseases or estimating crop yield but is also applicable to other areas of aerial photography like infrastructure inspection or battlefield surveillance. Applying this technique to other domains may yield superior results compared to simply scouting entire areas at low altitudes, as shown here.

The most pressing avenue for future work is to take the proposed approach out of the simulation and test it on an actual rice lodging scenario. Additionally, many newly developed embedded edge computing devices are lightweight and portable, such as Nvidia Jetson TX2, AGX Xavier, or Xavier NX. These devices are suitable for real-time onboard computing power on small drones with restricted space (Burger et al., 2020), which can be useful to empower our approach. We plan to address this in future work by using the SoftwarePilot framework for fully autonomous aerial systems (Boubin et al., 2019c) and our EDANet for lodged rice detection to implement the proposed approach to scout crop fields in real-time.

5. Conclusions

Rice is a globally important crop that will be a necessary component of the earth's food supply for the foreseeable future. Rice lodging is a threat to rice production, hurting yield and diminishing farmers' income. Assessing rice lodging should be more efficient because current methods rely primarily on random manual sampling. This paper presents an autonomous scouting approach to estimate rice lodging using machine learning and UAVs. The machine learning model using EDANet is capable of identifying rice at 95.28% accuracy and lodging at 86.17%, improving in prior work by 2.51% and 8.26%, respectively. The adaptive scouting approach, which scouts rice at multiple altitudes to target lodged regions, in particular, maintained 99.25% lodged prediction accuracy compared to a complete scan of the field at low altitude while taking 35% less time. The adaptive scouting approach saves considerable money and time and provides a great opportunity to enhance rice lodging assessment over a large area using deep learning techniques on UAV images. The adaptive scouting approach is ready to be implemented in lodging assessments to provide low-cost and in-time digital maps. In the future, edge computing will be integrated into adaptive scouting to identify field anomalies in real-time and complete multi-scale imaging tasks in one flight.

CRediT authorship contribution statement

Ming-Der Yang: Conceptualization, Methodology, Supervision, Formal analysis, Funding acquisition. **Jayson G. Boubin:** Methodology, Software, Formal analysis, Writing - original draft. **Hui Ping Tsai:** Conceptualization, Formal analysis, Methodology, Writing - original draft, Writing - review & editing. **Hsin-Hung Tseng:** Conceptualization, Methodology, Software, Visualization. **Yu-Chun Hsu:**

Conceptualization, Methodology. **Christopher C. Stewart:** Conceptualization, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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