# TG-1: Precision Unmanned Aircraft Systems (UAS) System for Soybean Pest Damage Control (PDC)

Submitted by:

## Team Galaxy


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## Eastern Technical High School


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## Executive Summary

Soybean crops play a critical role in the United States agricultural economy with over $115.8 billion of soybeans produced each year! Despite farmers spending over $669.3 million on pest damage control (PDC), there is 1.6% of yield lost to pest damage. One critical problem for PDC is that many pests damage soybean pods beneath the plant canopy, making traditional scouting inefficient, labor-intensive, and costly. The lack of effective early detection methods leads to the fact that current mitigation approaches often rely on blanket pesticide spraying, which increases costs, accelerates resistance, and harms surrounding ecosystems, representing a major pain point for farmers. The objective of this project is to design an affordable, precise, and scalable uncrewed aircraft system (UAS) that enables early pest damage detection and targeted sample collection to support more effective and sustainable PDC.

TG-1, developed by Team Galaxy, is a novel UAS that can scan beneath the soybean canopy for early detection of pest damage, reduce sampling time ~80% (compared with ~5hr manual scouting), save up to 60% in chemical use, and potentially bring farmers annual saving: $10.9M in Maryland and $1.8B nationwide. TG-1 features a modular Vertical Take-off and Landing (VTOL) drone system with interchangeable Imagery Module and Sampling Modules, produced at the cost of approximately $4,667!

Our periscope design enables the RDG-D camera to reach under the canopy of crops to uncover abnormalities that other drones might never reach. The systems are powered by custom fine-tuned AI processors to differentiate pest species to support farmers' individualized PDC strategies. TG-1 also has an industry leading navigation system that promises precise pinpointing of damaged spots. By combining automated surveying with selective human oversight through ground control, the system ensures efficiency and reliability while meeting farmers' needs for actionable, cost-effective solutions through reduced labor costs for scouting, early detection, and improved decision-making for targeted interventions.

The project highlighted the interdisciplinary nature of modern agricultural technology, requiring synergy between engineering, AI, environmental science, and finance. The team has to pivot from single species PDC to manage multiple pests for soybeans, based on the insights of the business assessment and interview with mentors. Repositioning TG-1 from sink bugs to multiple pets, with a properly trained AI/ML model, increases the potential saving from $6.85 per acre to $21.49 per acre. TG-1 can finish the benchmark mission at the operation cost of $67.24 - $71.26 to enable farmers PDC at a reason cost (**~$1,000)**, compared with manual spraying(~$4,600), and regular UAS (~$2,300), creating net gain of thousand dollars!.

Another key lesson was balancing complexity with usability, ensuring advanced sensing and robotics remain intuitive and reliable for real-world farm environments. Throughout TG-1 development, the team gained STEM experience of innovation to address practical problems. The team also recognized the importance of modular architecture, which enables specialized functions while simplifying maintenance, troubleshooting, and future scalability.

Designed with scalability in mind, the platform can be adapted to other crops and agricultural applications beyond soybeans. Through this NASA DwU project, the team demonstrates how integrated engineering, artificial intelligence, and precision agriculture can improve food security, sustainability, and economic efficiency for modern farming.

# Introduction

## 1.1 Local Agricultural Pest

Soybeans were selected by the team as the target crop due to their critical economic impact and massive scale in U.S. agriculture. As a $115.8 billion industry covering 83.4 million acres (second only to corn), soybeans are a cornerstone of the national economy. The sector drives substantial workforce stability, supporting 280,000 jobs and generating $11.6 billion in wages in 2020 alone (National Oilseed Processors Association). “Maryland planted about 495,000 acres of soybeans, and with a value of nearly $200 million to the state’s economy” - U.S. Department of Agriculture 2024 state overview.

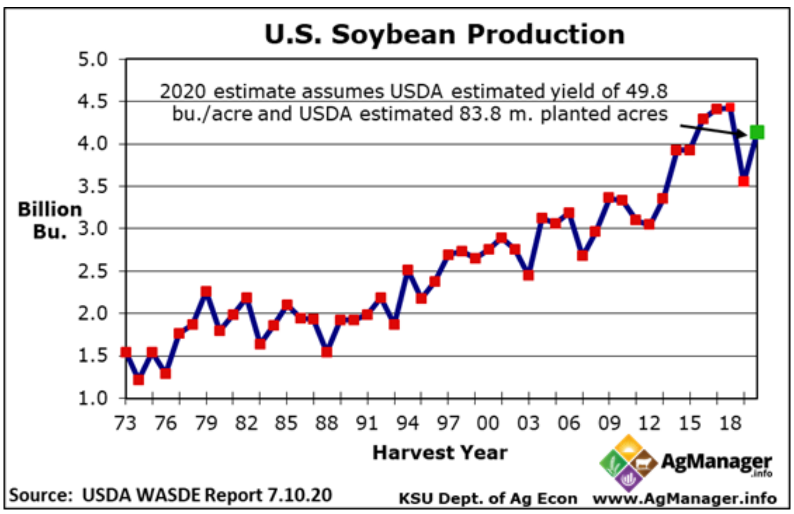



**Figure 1. Graph displaying soybean production in the United States (1973–2018).**

Despite soybean’s economic importance, farmers lack a fast, precise, and cost-effective way to detect and manage pest damage early, resulting in preventable yield loss, excessive chemical use, and hundreds of millions of dollars spent each year on inefficient pest control. A study across 19 major soybean painting states in 2023 show that  invertebrate pests reduced soybean bushels by 1.6 percent of the yield. Additionally, overall management costs (at plant and in-season) were estimated at $669.3 million USD, which includes non-targeted insecticide applications. showing that current management methods are not efficient enough. Quote from USDA:  “even modest reductions in yield caused by pests can translate into serious economic losses for growers.”

In Maryland, Stink bugs reduced yield more than any other invertebrate pest in 2023, followed by corn earworm, soybean looper, bean leaf beetle, and green cloverworm. Table 1 provides numeric yield loss of the top 5 damaging pests.

**Table 1: Top Pests causing most damage**

| **Pests** | **Yield loss (US)** | | **Yield loss (MD)** | |
|---|---|---|---|---|
| Stink bugs | $110,672,614 | $4.31/acre | $413,183 | $6.85/acre |
| Corn Earworm | $108,806,597 | $4.24/acre | $264,095 | $4.38/acre |
| Soybean looper | $37,910,540 | $1.48/acre | $10,481 | $0.17/acre |
| Bean Leef Beetle | $23,684,121 | $0.92/acre | $51,973 | $0.86/acre |
| Green Cloverworm | $10,289,337 | $0.40/acre | $8,726 | $0.14/acre |

Soybean pest damage control is complex. Soybean plants are tightly packed together with small row spacing(can go as low as 7.5 inches) and therefore are harder to distinguish. Many times pest damage in it of itself is hard to detect too, with stinkbugs involving discoloration of such a small pod and spider mites involving discreet white spots on leaves. It is also a low value crop, so farmers can't afford high costs of pest management, which leave some to leave plants untreated

**A**

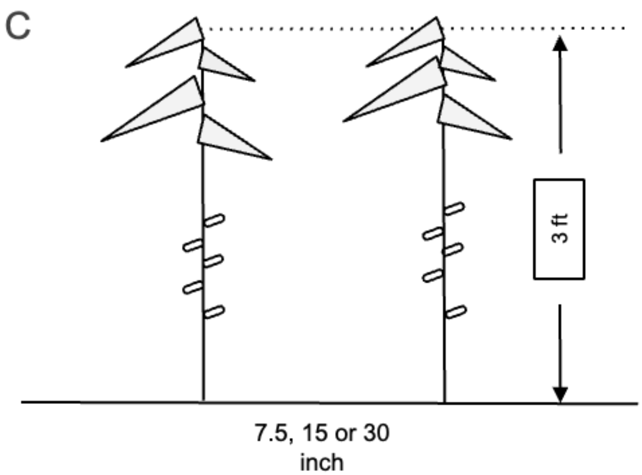




**Figure 2. Images of Soybean Fields and Spacing**

We had a pivoting process when choosing target bugs. Stinkbugs were chosen initially as our target pest as they are the most economically damaging to soybean plants in Maryland according to the Crop Protection Network. After business case analysis and consulting with mentors, we pivoted our invention to include other bugs leveraging our AI capability to meet the marketing viability.

Consequently, the team executed a strategic pivot: expanding the system's scope to address the entire 'Soybean Pest Complex.' By leveraging the scalability of our AI computer vision, we transformed the design from a niche 'bug hunter' into a comprehensive Integrated

Pest Management platform. This pivot maximizes the system's utility for farmers while utilizing the same hardware architecture.

## 1.2 Team Organization

Our team operates under a systems engineering structure, assigning roles based on technical certification and specialized experience.

At the start, the team captain (Lucas Chen) gathered basic information of each team member through a Google Form. Most members had experience with 3D modeling, a few had experience with the building, programming or overall knowledge of drones, one candidate in particular had good skills in programming, having made a weather app online, and one interviewee having experience with mathematics which can contribute to the management of the team finances. However, none of the members had any experience in marketing, so we would have to do further research during the design process.

With the survey completed, Lucas conducted one on one meetings with each team member to go deeper into their skillsets, assigning them more specific roles. No member had particularly deep knowledge in agriculture so we devoted the first few meetings to working together on determining a pest, a crop, and generating a framework on how to properly address the needs of this project. From there, we decided our specific roles.

**Table 2. Team Organization**

| Role | Description |
|---|---|
| Project Leadership | Lucas Chen \| Captain & Systems Lead<br>● Directs project timeline and requirements definition.<br>● Synthesizes mentor research into engineering constraints and manages the interface between technical and business subsystems. |
| Mechanical & Airframe | Skyler Zeng \| Designer<br>● Autodesk Inventor Certified. Leverages advanced CAD skills and VEX Robotics experience to model the airframe and design modular components<br>Samarth Gomatam \| Mechanical & Payload Integration |

| | |
|---|---|
| | ● Designs physical interfaces between the drone frame and agricultural sensors. Ensures payload mounting solutions do not interfere with flight mechanics. |
| Avionics & Flight Operations | Aric Deng \| Avionics & C3<br>● Responsible for Command, Control, and Communications (C3). Applies hands-on drone building experience to component selection (motors, ESCs) and electronics layout.<br>Ruichen Feng \| Flight Dynamics & Mapping<br>● Defines flight paths and operational envelopes. Utilizes experience from the Airborne Robotics Cup (lighter-than-air systems) to optimize stability and control. |
| Systems Analysis & Business Case | Andy Yan \| Systems Analyst (Mass & Cost)<br>● Manages the Mass Budget and Center of Gravity (CG) calculations to ensure flight stability. Conducts cost modeling to verify the economic viability of the solution. |

## 1.3 Acquiring and Engaging Mentors

At the team's formation, they first identified what they lacked for the project. This came in the form of agricultural, programming(computer vision), and business knowledge. We reached out to multiple experts; some responded but many ignored us. But this led to the discovery of the UMD Extension program. The University of Maryland Extension (UME) is a statewide non-formal education system with offices in all 23 Maryland counties and Baltimore City, offering research-based information, 4-H youth development, agriculture, and nutrition programs. Local offices, such as in Harford, Baltimore, and Calvert counties, provide localized workshops, consultations, and resources. It is the perfect match to the scope of the NASA challenges!

We had the privilege to get a response from Erika Crowl, Senior Agriculture Agent at Baltimore county, who were willing to meet us for an interview.  Erika was an expert in agriculture/livestock and most importantly: 5 years of experience with drones in her Extension

Program! With the goal of establishing a foundation for the students in mind, the mentors planned a meeting with Crowl as well as Agricultural Expert Andrew Knees, who mainly works in crop production (mainly grain), disease management and sustainability in crop production. Knees has also worked with stinkbugs, our selected pests for this project.

With their studies they also teach farmers, teach informally through hosting workshops and one-on-one meetings and passively educate through publishing journals and articles. Utilizing these two mentors, the team can collect information for a rough basis and knowledge to design our drone. They can provide us with answers to questions that one would either have a hard time finding on the internet or too specific to find at all.

**Pest Management**

The team started the interview portion by inquiring about unintended consequences of pest management. Crowl noted that there could be issues with wind and other outside factors that can cause pesticides to drift into others' territory and damage plants there. Spraying pesticides can also make pest problems worse as they could kill the pest and their predators, resulting in more yield loss later. There are too many variables to account for, so there's no real estimate on financial damage.

With this in mind, the team proceeded to identify which stinkbug control strategy looked possible on paper but did not work in real-world practice. Crowl stated that stinkbug biology made them more difficult to kill than other pests. Current control products work, however correct application and timing were issues, as contact products do not work on stinksbugs. Damage is also hard to detect as they damage developing seed and seed pods. This process also comes with a cost of $25 per acre, with our area being 160 acres total in a 0.5x0.5 square miles.

**Lab**

The team wanted to know how these agricultural engineers discovered the repellant methods of stinkbugs in the first place. According to Crowl, there are many people working together to fulfill this process including people with degrees in agriculture fields, biologists who study stinkbug life-cycle, entomologists who work in pest management, private manufacturers creating chemicals and testers. This data then goes to farmers and manufacturers to figure out what works and what does not.

Based on the modern search for stinkbug repellants, the team wanted to discover how drones saved money in this process. Crowl stated that imagery drones can find specific places to spray which saves money and resistance. This in theory would lower yield loss. Knees added that drones' versatility makes farm management easier as they can spread fertilizer and pesticides. Adding on to Crowl, imagery drones can target specific areas, which saves chemical costs (restocking, refueling) in the long-run which outweighs the initial expensive cost for the drone itself.

**Financial**

When it came to cost-effective methods of pest management, the answer was quite straightforward. Instead of spraying the whole farm because of a single bug, one would survey the field for damage and only spray areas with damaged plants. When it comes to costs outweighing possible yield losses from neglect, it varies due to inflation as well as resource factors like how much farmland is damaged and any false positives or negatives. With pesticide spraying drones, it costs on average 22-25 dollars per acre not including product, then requiring a truck, trailer, 2 people monitoring, a pilot, and ground support. Imagery drones cost around 10 dollars per acre as they weigh less and therefore use less energy

**Stinkbug Traits**

Signs of stinkbug damage are hard to see.They include small, shriveled up, and smaller than normal seeds. They could also be infected by secondary pathogens and sometimes can be discolored with a smaller pod no bigger than ¼ inch.

Stinkbug management does not typically cause pesticide treadmills (development of resistance to pesticides), they are just hard to kill biologically and because they jump to the bottom of the plant and are covered by the canopies of soybean plants, therefore being harder to detect. Typically, they attack soybean plants in their reproductive stage when the seeds are developing, as they feed on those seeds

**Drone**

Erika directed us to a colleague that was a drone expert, Hemendra Kumar. The team presented the drone to him, and he gave his thoughts. He approved of the innovativeness of the solution, as a big problem with drone surveillance is that the canopies of soybean plants and crops in general cover up all the details of the crop. He paired this claim with actual photos of drone survey results of fields. All were from high above it, which clouds all internal details. Multispectral cameras will pick up signs of damage, but going into the minute details is not feasible. With this information, the team could continue with final touches and complete the innovation.

**Computer Vision**

For the expertise in AI and computer vision, we reached out to Dr Jie Liang, a CV and AI expert teaching at Simon Fraser University in Canada. His research includes Signal Processing, Computer Vision, and Machine Learning, with focuses on Image/Video Compression, and Human Action Recognition for Healthcare. He earned his Ph.D. in Electrical Engineering from The Johns Hopkins University around 2003, focusing on signal processing, video compression, and computer vision.

The team discussed their NASA *Dream With Us* soybean pest detection drone, explaining the system design, sensors, sampling mechanisms, and how damaged pods would be identified and addressed. Jie advised focusing on practical AI tools and tutorials to build workable algorithms within the limited timeline, emphasizing the importance of sensor selection and available data. The group clarified that the NASA deliverable involved both a proposal and a functional drone, and reviewed which sensors—such as RGB-D and multispectral cameras—would best fit the mission requirements.

The conversation then shifted to AI-driven inspection and sampling strategies, including the use of modular imaging and arm systems, coordination between computer vision and mechanical sampling, and whether processing should occur onboard, on the ground, or in the cloud. Jie recommended prioritizing small-area, low-altitude data collection with consumer-grade drones and offline analysis, while maintaining human oversight for simpler control tasks. The team also discussed above-canopy imaging using a periscope-style design, combining multiple images for accuracy, and potentially supplementing drone flights with ground or IoT sensors, ultimately planning to integrate RGB-D sensing and probability-based detection into their first drone iteration.

In the business area, the team consulted Phillipe Duverger, a professor in marketing at Towson University. His specialties include market basket analysis, market sizing, and data-driven segmentation schemes. Building on this guidance, the system is designed to extend beyond soybean pest detection by drawing on international examples such as UAS applications in France for vineyard monitoring and grape harvesting support. This demonstrates strong scalability to other high-value crops and agricultural systems. To evaluate effectiveness, key metrics focus on cost-to-save, separating fixed costs such as hardware, sensors, and AI development from variable costs including maintenance, labor, and mission operations. From a marketing perspective, adoption remains challenging due to farmer inertia, limited incentives, and unfamiliarity with AI and drone technologies. As a result, customer education and clear communication of tangible outcomes such as yield protected, pesticide reduced, and labor saved are essential for successful adoption.

Tao Chen, a professor in marketing, also pitched in, but more so for public affairs. Lucas emailed her questions about how to adapt the value proposition based on early adopters, different ways for social media to be leveraged, and common pitfalls. She advised to gauge the money saved by the innovation, to make sure profit gained with it is more than profit gained without it, and overall that the product should be a net benefit. As for social media, she suggested getting feedback on the product and to better understand any pain points.

**Table 3. Mentor meeting summaries**

| Mentor | Meeting time | Title | Role | Affiliation | Expertise |
|---|---|---|---|---|---|
| Erika Crowl | 12/18/25 | Senior Agent Associate | Agricultural Agent | UMD/Extension Program | Agricultural knowledge |
| Andrew Kness | 12/18/25 | County Extension Director (interim) | Agricultural Agent | UMD/Extension Program | Stinkbugs |
| Jie Liang, Ph.D | 12/26/25 | Professor, Engineering Science; Fellow, Canadian Academy of Engineering | Simon Fraser University Prof. | Simon Fraser University | CV and AI |
| Phillipe Duverger, Ph.D | 1/20/26 | Professor, Department of Marketing | Towson Business Professor | Towson University | Marketing |
| Tao Chen, Ph.D | 1/19/26 | Associate Professor of Practice | Marketing Professor | Johns Hopkins | Marketing; New Product Development |
| Hemendra Kumar, Ph.D | 1/21/26 | Precision Agriculture Specialist | Precision Agriculture Specialist | UMD School of Agriculture | Precision Agriculture w/Drones |

### 1.4 Impact on STEM

Participating in this challenge significantly broadened our perspective on STEM by demonstrating how science, technology, engineering, and mathematics work together to solve real-world problems. Applying engineering principles to a practical agricultural challenge showed us that STEM is not just theoretical, but a powerful tool for creating meaningful, real-world impact. The experience emphasized the importance of systems thinking, data analysis, and interdisciplinary collaboration, reinforcing how technical design decisions directly influence real-world outcomes.

This project also influenced our views on potential career paths by exposing us to fields such as robotics, artificial intelligence, aerospace systems, and agricultural technology. Working through design tradeoffs, cost constraints, and operational challenges helped clarify how engineering and data-driven decision-making can translate into viable careers that combine innovation with social and economic value.

Beyond personal growth, the project increased interest in STEM within our school and organization. By sharing our progress, designs, and results with peers, the challenge sparked curiosity and discussion around drone technology, AI, and sustainable agriculture. The hands-on, problem-solving nature of the project encouraged other students to explore STEM opportunities, demonstrating how applied challenges can inspire broader engagement in STEM education.

# Design

## 2.1 Engineering Design Process

**Conceptual:**

The team first needed to identify the problem they had to tackle and solve. The task at hand was to design an Uncrewed Aircraft System (UAS) that helps to decrease yield loss and save money by detecting pest damage and collecting samples of the damaged plants for further analysis and development of new pest management methods.After identifying the main problem the team needed to solve, they would first identify the stakeholders of the challenge and work their design around them as well as their needs.

**Table 4. Drone stakeholders and type**

| **Type** | **Persona/Stakeholders** | **Notes** |
|---|---|---|
| End user and Payer | Farmers | Pay for these drones in order to maximize their crop yield by monitoring pests. Many do not have the funds to buy a drone, which is the main goal for the team. They want to design a drone that provides the efficiency of high-end drones and a cost-effective one. |
| Industry (Main operators) | Drone Servicer Providers | Team's role: Fly drones and retrieve crop samples for testing. |
| | Drone Manufacturer | |
| | Drone Engineers | |
| | Investors | |
| | Other provider for PDC | Competitors |
| Influencer | Researchers/Educators | Beneficiary |
| Regulator | Government<br>- State<br>- Federal (FAA, USDA, EPA et al) | FAA provides commercial licenses for drones; must comply with regulations |
| General | Public | Beneficiary |

The team then researched how farmers typically grow soybeans in order to retrieve information regarding the soybean crops' maximum vulnerability and when farmers typically apply pesticides. This way, the team can identify environmental factors that may affect the drone design or when the drone is in use. The most vulnerable stage a soybean crop is in is the R3-R6 stage in their development. The team also utilized mentors such as agricultural experts Erika Crowl and Andrew Knees to gain a basic idea and understanding of their pest and crop.

**Table 5. Growth stages of soybeans and month**

| Stage | Month |
|---|---|
| R3 | Late July - Early August |

| | |
|---|---|
| R4 | Early - Mid August |
| R5 | Mid - Late August |
| R6 | Late August - Early September |

Referring back to Crowl's comment on overheating batteries, the team realized the drone would most likely be active in the summer months with scorching temperatures. The team decided a cooling system would also need to be implemented in order to cool down the drone's batteries and prevent them from overheating to continue active use.

**Table 6 the Journey Map: How the UAS is/shall be used for Pest Damage Control**

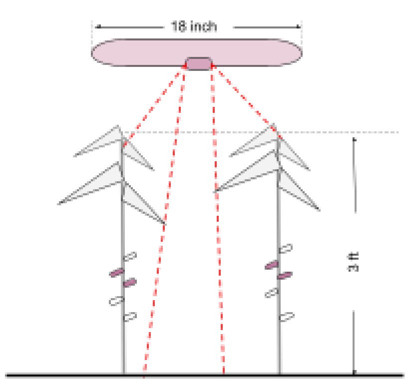
| | **Stage 1** | **Stage 2** | **Stage 3** | **Stage 4** | **Stage 5** |
|---|---|---|---|---|---|
| Stages | Scanning | taking samples | takeoff + spraying | going back + maintenance | assessment |
| Touch Point | In the air | Ground next to a plant | In the air | Wherever the drones are stored | Drone station/cloud |
| Action | Detects pest damage | collects a sample of damaged plant | spraying the target area with pesticide | recharging/refueling the drone | evaluate all system's performance, |
| Pain Point | Could miss damage signs | Complications on how to collect samples: | pesticide costs a lot of money and delivery drones are expensive to fly even w/o chemicals | maintenance could cost a lot during certain seasons like in the summer, higher likelihood of battery overheat | Miscalculations, inaccurate data |
| Emotion/Experience Index | 2/5(?) | 2/5 | 1/5 | 5/5 | 4/5 |
| Emotion/Experience Description | scanning is cheap and can be done for hours; but damage easy to miss; may be inaccurate | actually getting samples using a drone could be difficult to engineer and automate | spraying is easy to do but it costs a lot of money | charging drone is easy, sometimes may cost some money due to system malfunctions | Easy to miss the issues; difficult to mitigate; may cause crew frustration |
| Opportunities | HMW-1 | HMW-2 | HMW-3 | | |

The growing time for soybeans is 100-130 days, which will contain lots of time where the drone is used. Stinkbug damage across multiple species shows the same damage with no distinguishable difference. This will reduce the amount of variables a drone will have to identify in its software which can reduce costs in terms of sensors. After this brief research, the team would research how drones benefit agriculture and how much they generally cost (and what contributes to that cost). Agricultural drones provide benefits such as pest detection, pest research, reduce the use of pesticides/costs and allow concrete precision on where and when to spray pesticides.

Different drone runs cause different costs. Monitoring flights are usually longer in flight time, but use reduced energy and weight which lowers cost. Sampling drones have a shorter flight time, usually costing a medium amount between monitoring drones and pesticide spraying drones. Pesticide spraying drones run in one flight and are the most expensive not even including chemicals used. We can use these cost ranges to identify a price range our design should be in.

Another factor determining the drones' design is the layout of the soybean field. The challenge takes place on a half mile by half mile field, with soybean rows being seven to fifteen inches apart which is very narrow with many drones not being able to fit in that space. Soybean crops in these stages will grow up to three feet. These dimensions would ultimately impact the drone operation decisions. From this research, the team deducted three main issues deriving from the field's layout:

1. If the drone is overhead, leaves would cover the damaged pods which forces the drone or an attachment to go through the rows.
2. If the drone or its attachments are too big, they would not fit.
3. Pods are bunched together on the node of the plant, so precision is imperative.




If a drone were to fly above and survey soybean plants, the leaves in the canopy would block the pods that are damaged, leading to many false negatives. Below is a diagram of that situation.

**Figure 3. Overhead surveillance**

To compensate for the limited space between rows, one solution is to design the drone so that it can fly sideways, and from there, a camera will monitor both sides. Below is a diagram of this method.

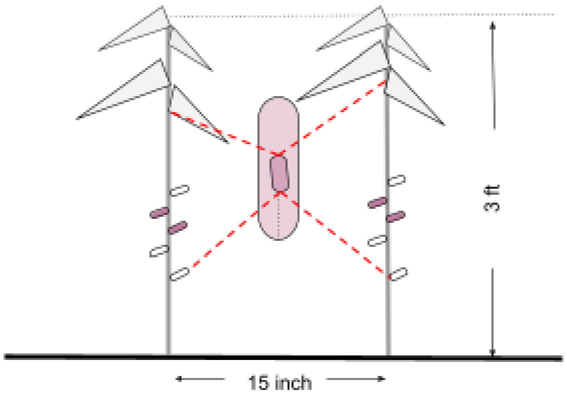



**Figure 4. Sketch of sideways imagery field of view.**

However, this idea still has to operate within a confined space, so there wouldn't be enough space for any attachments to work.

The team's second concept was for the drone to have the main body fly above the soybean rows while its attachments hung below it between the rows of soybean crops. This mitigates the size issue, allowing for attachments such as a 360 camera and a sampling device to work better in a confined space. This became the team's basic blueprint for the drone, as shown below.

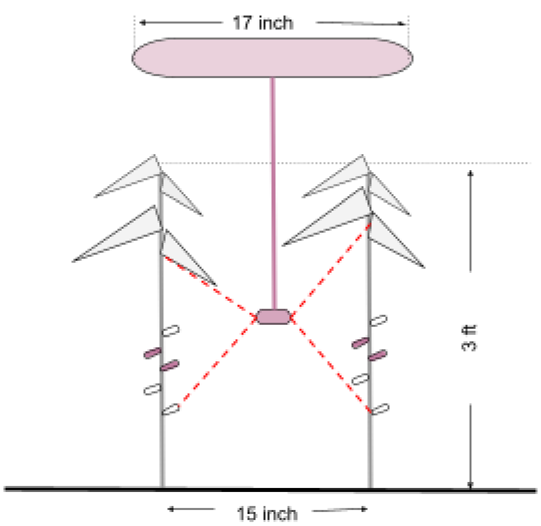



**Figure 5. Sketch of hanging attachment imagery field of view.**

The first concept for the sampling module was to attach a net to the bottom of the drone, which would pick up the entire soybean plant to analyze later. This turned out to be problematic, since it would waste time, create yield loss, and also increase the weight and energy consumption of the drone.

A second idea was to have a box on the bottom of the drone, which would open and cut the pods off of the soybean plant and automatically store them for analysis. This solution was better than the net idea, but still had problems regarding precision (could cut off healthy pods), sorting, and bulkiness.

The team's third idea was to use a bionic arm to grab pods more precisely and place them into a rotating cartridge box, with every slot except the needed one covered by design. This design would be expensive and difficult to engineer. The team ended up choosing the bionic arm design, as its positives outweighed the costs. Below is a basic draft of the drone, showing the main body and both modules along with where they are attached on the main body.

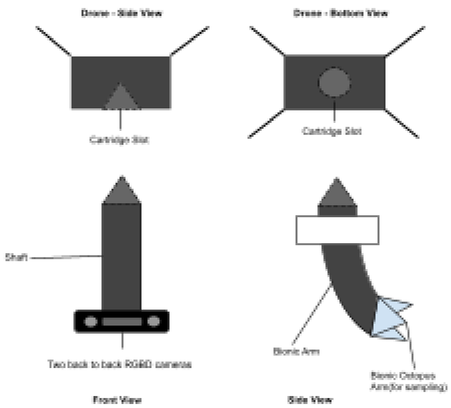



**Figure 6. Rough sketch of interchangeable imagery (left) and sampling (right) modules.**

**Preliminary**

The team laid out a design process plan and a timeline for what to complete during the engineering design process. They would first identify their drone frame, materials and other hardware required in a drone. Next, the team would put these parts together, creating sketches and brainstorming solutions to problems that appear. Finally, the team would put together all their selected components and create a 3D model.

The team began the design process by first selecting their air vehicle design, as it would provide the main basis for the drone. Looking at other agricultural drone designs, most use the quadcopter frames. However the team chose the Vertical Takeoff and Landing (VTOL) frame as it reduces costs needed for a runway, in which the VTOL frame does not need one. However, the only downside is that it would require more energy. The selected material was carbon fiber as most agricultural drones used it for its cost effectiveness, durability and longevity compared to other materials. Carbon fiber propellers were also chosen for the same reason as the frame, as well as the bonus of motor efficiency and type flexibility. The team would put weight and Center of Gravity (COG) for later evaluation as they needed to research software and electronics for the drone to function.

To gain an understanding of drone electronics, the team utilized another mentor named Jie Liang, an AI and CV expert to aid their drone design process and identify what electronics were required. The main takeaway from the interview was the utilization of the RGB-D sensor to identify pest damage.

Support equipment can be done somewhat independently from the drone itself. Erika put the team onto the idea that a drone’s battery could overheat in the summer, so a cooling system was devised. It will maximize airflow within a confined space.

For the sampling system, the team decided to switch to a 6DOF arm to save the thousands of dollars a bionic arm costs. The camera for this attachment will be in the hand of the claw, which will give the sample operator a convenient view to do his/her work. Below is a rough sketch of all of these modules

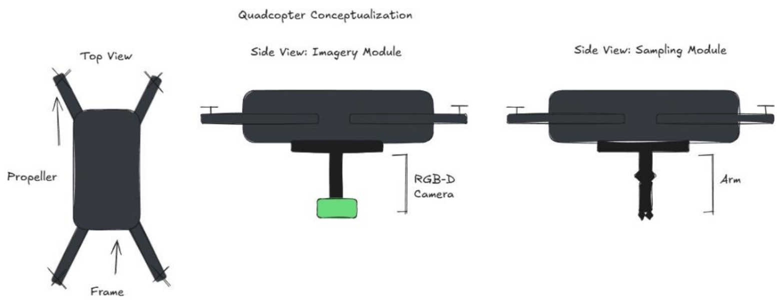



**Figure 7. Rough sketch of imaging and sampling quadcopter drone with respective attachments**

**Detailed**

Over time, the drone's design was clear and the ground station could have a baseline of the requirements it would have. A quick design was to have monitors directly integrated into the container, so that the container could be opened and the components easily accessed. However, this would cost way too much for a bonus that could be done by a simple laptop. We chose an Acer Aspire 14, as it has an AI model that can help a human with detect and avoid. As for communication, we chose a Yagi directional antenna with 915 mhz, and equipped the drone with an antenna of the same type. For controller-drone communication, they were equipped with, once again, 915 mhz happymodel transmitters and receiver.

The cooling system will consist of many components: two vents, two fans, and a centrifugal blower. The vents will allow outside exposure to outside air. The fans actually bring the air in and out. The centrifugal blower will direct airflow onto the batteries. This keeps the drone at a consistent temperature and allows it to complete the mission without any problems.

## 2.2 Project Plan

**Table Gantt Chart of Progress**

| Date Range | Nov (start w/ Thanksgiving) | Nov | Nov - Dec | Dec | Dec | Dec | Dec - Jan | Jan | Jan | Jan |
|---|---|---|---|---|---|---|---|---|---|---|
| Period | | W1- Kickoff | W2 | W3 | W4 | W5 | W6 | W7 | W8 | W9 - Submission |
| Period Ending Date | | 11/30/2025 | 12/07/2025 | 12/14/2025 | 12/21/2025 | 12/28/2025 | 01/04/2026 | 1/11/2026 | 01/18/2026 | 01/25/2026 |
| **Team Building** | COMPLETE | | | | | | | | | |
| - Ideation: LC | done | 11/20 | | | | | | | | |
| - Annoucement: LC | done | 11/20 | | | | | | | | |
| - 1:1 Interview: LC and co | done | 11/24 - 11/26 | | | | | | | | |
| - Kick of Meeting: All | done | | 12/06 zoom | | | | | | | |
| **NASA Registration** | COMPLETE | | | | | | | | | |
| - Team Registration: FA | done | | | 12/8 DDL | | | | | | |
| - Contact NASA: FA | done | | | 12/12 Resolve | | | | | | |
| **Expert/Mentor Engagement** | In Progress | | | | | | | | | |
| - Contact Expert: FA | done | | | ANGR Mentor | | AI/Computer Vision | | Drone&Biz Advisor#1 | Biz Advisor #2 | |
| **-#1 Expt Engagement Prep** | COMPLETE | | | | | | | | | |
| - Meeting the Expert (ANGR) | done | | | | 12/18 Erica/Andy | | | | | |
| - Insight Synthesis | **done** | | | | | | | | | |
| **-#2 Expt Engagement Prep** | COMPLETE | | | | | | | | | |
| - Meeting the Expert (AI&CV) | done | | | | | 12/28 Dr Liang | | | | |
| - Insight Synthesis | done | | | | | | | | | |
| **-#3 Expt Engagement Prep** | COMPLETE | | | | | | | | | |
| - Meeting the Expert (ANGR Drone) | done | | | | | | | | | 1/20 Dr Kumar |
| - Insight Synthesis | TBD | | | | | | | | | |
| **-#4 Expt Engagement Prep** | COMPLETE | | | | | | | | | |
| - Meeting the Expert (Biz#1) | done | | | | | | | | Written review - TC | |
| - Insight Synthesis | done | | | | | | | | | |

| Period | Nov | Nov - Dec | Dec | Dec | Dec | Dec - Jan | Jan | Jan |
|---|---|---|---|---|---|---|---|---|
| Activity | W1-Kickoff ... | W2-Weekly Meeting | W3-Weekly Meeting | W4-Weekly Meeting | Winter BootCamp | W6-Weekly Meeting | W7-Weekly Meeting | W8-Weekly Meeting |
| Team Member | 11/30/2025 | 12/07/2025 | 12/14/2025 | 12/21/2025 | 12/28/2025 - 01/4/2025 | 01/04/2026 | 1/11/2026 | 01/18/2026 |
| Lucas | Y | Y | Y | Y | Y | TBD | TBD | Y |
| Andy | Y | Y | Y | Y | Y | TBD | TBD | Y |
| Skyler | Y | Y | Y | Y | P | TBD | TBD | Y |
| Ruichen | Y | Y | Y | Y | Y | TBD | TBD | Y |
| Aric | Y | N | N | Y | P | TBD | TBD | TBD |
| Samarth | Y | N | N | Y | P | TBD | TBD | TBD |
| Milan | Y | N | N | N | N | TBD | TBD | TBD |

**Fig 6 Project Management Table and Dashboards**

The team started by scanning through the rubric and requirements to see which aspects could be done with the least prior deliberation. This includes all areas besides 1.4 of the introduction and public relations. 1.2 with mentors was a special case as the team would need to gather more and different mentors as time went on. From there, all engineering aspects needed to be done, then concept of operations, then costs, then drawing the final design. Then, costs, logistics, and public affairs can all be done at the same time. This allows for maximum efficiency in working this project. To ensure effective execution, schedule adherence, and technical accountability, the team adopted an integrated Project Management Gantt Chart and Performance Monitoring Dashboard system. This system was designed to track progress across all mission-critical workstreams, including airframe development, payload integration, software development, testing, and business case modeling.

The Gantt Chart serves as the primary scheduling and dependency-mapping tool. All major milestones, such as concept validation, subsystem prototyping, sensor selection, flight testing, and final documentation, are broken into granular tasks with defined start and end dates, assigned team ownership, and inter-task dependencies. This allows the team to identify critical path items, forecast schedule risks, and reallocate effort dynamically when delays occur.

## 2.3 Subsystems

### *2.3.1 Air Vehicle*

**Conceptual**

The team identified the requirements needed in order to decide a specific aircraft frame design as well as the propellers. The drone conceptualized in 2.1 required the ability to hover over the soybean rows, propel itself forward along the path assigned to it and move vertically.

With this in mind, the team began to research specific drone models and frames with specific propeller placements that would aid the design in all of these tasks. The team looked in quadcopters and fixed-wing drones. The team would then compare the pros and cons of each design they researched, to see which drone frame would suit best for the tasks. Fixed-wing drones would be the first idea that came to mind as it had benefits such as being able to save energy and time with its speed; however, it would be less precise because it can not hover.

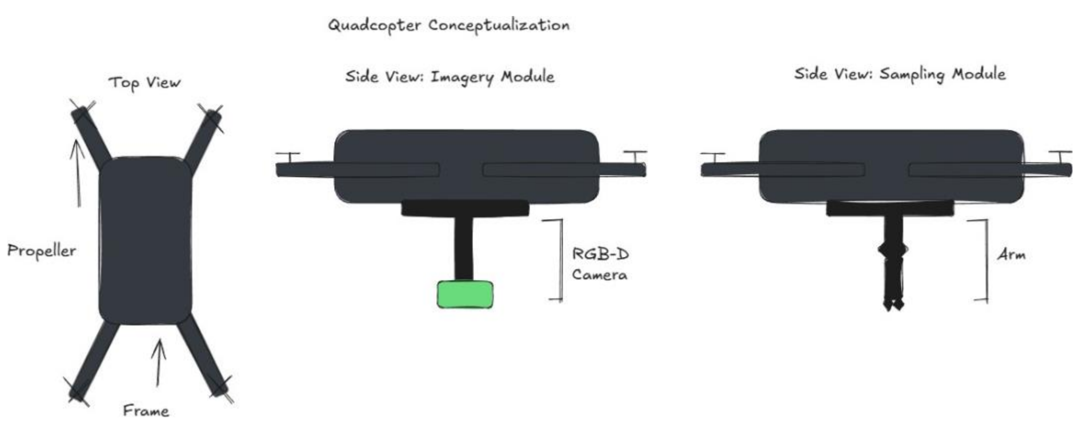



**Figure 7. Rough sketch of imaging and sampling quadcopter drone with respective attachments.**

The team's second idea was to have a similar Vertical Takeoff and Landing (VTOL) drone, with both fixed wings and multirotors. A VTOL design eliminates the need for a runway which reduces costs while also providing efficient flight. However, a VTOL airframe would be more mechanically complex and require more energy than a pure fixed-wing design. (see rough sketch of VTOL drone airframe with RGBD camera attachment and landing gear after figure 8)

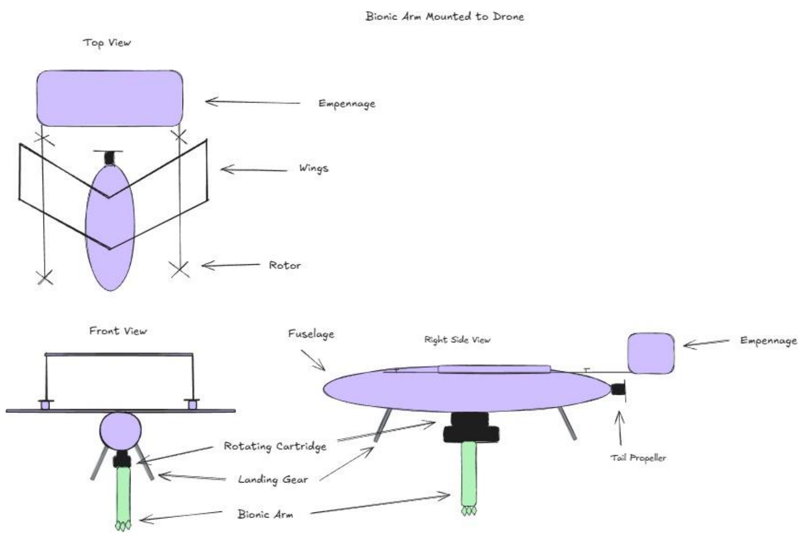



**Figure 8. Rough Sketch of rough VTOL drone airframe with sampling arm attachment.**

| **Drone Frame/Type Research** | | | | |
|---|---|---|---|---|
| Drone | Image | Pros | Cons | Achievements |
| Quadcopter |  | • Increased maneuverability<br>• Can hover | • Limited flight time<br>• More prone to damage<br>• Less energy efficient<br>• Hold less payload | ☑ ~~Vertical Movement~~<br>☑ ~~Can Hover~~<br>☑ ~~Propel Forwards~~ |
| Fixed-Wing |  | • Saves energy<br>• Fast<br>• **Higher payload capacity**<br>• **Can cover large areas** | • Less precise<br>• Cannot hover<br>• Requires a larger takeoff and landing space, increases cost<br>• Expensive<br>• Often hard to control | ☐ Vertical Movement<br>☐ Can Hover<br>☑ ~~Propel Forwards~~ |

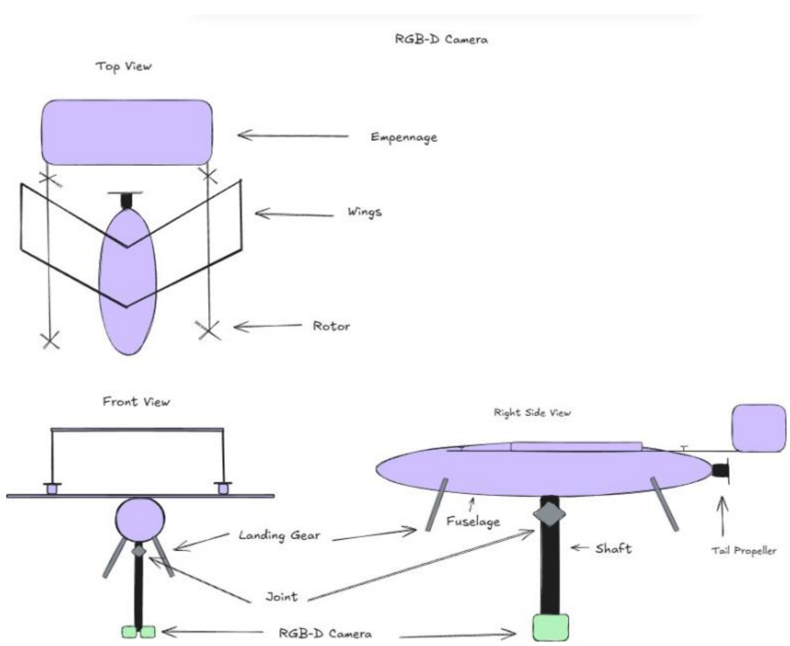
| Drone Frame/Type Research | | | | |
|---|---|---|---|---|
| Vertical Takeoff and Landing |  | • Removes need for runaway, reduces cost<br>• Efficient flight<br>• Can hover<br>• Fly farther than quadcopters<br>• Energy efficient<br>• Hold more payload | • Requires more energy usage | ☑ ~~Vertical Movement~~<br>☑ ~~Can Hover~~<br>☑ ~~Propel Forwards~~ |

**Table 5. Comparison of different drone airframe designs.**

**Preliminary**

The team ended up choosing the VTOL design over fixed-wing and quadcopter drone frames, as fixed-wing drones couldn't meet two of the requirements. Both quadcopters and VTOL drones provided all three requirements, however it is more energy efficient, it can fly farther and hold more payload, which is very important as the team needed to add a sampling collection system.

After sketching figure # above, we realized the modules including both the RGB-D camera and the robotic arm would prevent the UAS from landing due to their length. In response to this issue, we decided to add a joint near the upper portion of the shaft the modules are attached to. This allows the modules to fold upon landing, allowing the landing gear to reach the ground.




For the materials of the drone frame, the team decided to use a carbon fiber frame. Most agricultural drones use the carbon fiber frame due to its strength, durability and its cost-effectiveness.

Other materials such as plastic or composite

**Figure 9. Rough Sketch of rough VTOL drone airframe with RGBD camera attachment.**

fiber is less durable, so the cost of the carbon fiber is worth it. This carbon fiber will cover the fuselage, the bars holding the propellers and the empennage.

For propulsion, the team researched different types of blades and propellers that would be used to keep our aircraft afloat. The team decided on carbon fiber propellers as they are cheap, durable, increased motor efficiency, lasting performance and improved flight dynamics. They also contain multiple mounting types which can allow us to make changes to motor options later in the design process.

As extra precautions, the drone will be equipped with a GPS tracker that a staff member will monitor at ground control, a camera in the nose, and a GPS receiver. The receiver will be used to mark where ground control is on GPS and the tracker will be monitored by the data analyzer to make sure the drone stays on track. The nose camera will be monitored by the data analyzer as well as the AI processor in the Acer Aspire 14. This will function as the Detect and Avoid system.

**Detailed**

The challenge includes a 34 inch by 24 inch by 12.5 inch container that needs to store the drone. The drone frame needs to fit within that domain, so the team would need to decide the dimensions of the model in order to fit in that area with proper function. The drone needs a wingspan of approximately 2 meters in order to successfully be able to fly with all of the electronics and payload and maximize flight time and it needs to have a width of 0.25 m long(10 inches). Due to how large the wingspan of the drone is, it will not be able to fit inside the container, so the drone will be made in a way where the wings can snap off the main body and fold(with hinges) into quarters, making them 0.5 meters(19.68 in) long folded and be able to fit in the container. The battery will be placed towards the rear of the drone and most of the electronics will be placed towards the front in order to maintain the drone’s center of gravity.

Ratios of VTOL drones’ wingspan to fuselage length is 1.6:1, so the fuselage will be 2/1.6 = 1.25 meters or 4.1 feet. The fuselage will be designed so that it can be split into two pieces and put back together. The fuselage’s width will need to decrease drag as much as possible while also fitting the 6DOF arm, which is 3 x 3 inches, so the width will be 4 inches. The wings will be mounted 50% of the way from the nose. The arms holding the rotors will be mounted on the wings 8 inches from the fuselage as they are 6.5 inches in radius. They will extend 8 inches in front of the wing to give the propellers space, and will extend backwards 35 inches to make space for the empennage, which will have a 5 inch depth, vertical fins 7 inches tall, and a horizontal fin 18 inches long for a trapezoidal empennage. Below are the weight calculations

**Table 6. Weights of drone components.**

| Item | Weight | Item | Weight |
|---|---|---|---|
| T-Motor AT3520 Long Shaft Fixed Wing UAV Motor | 221 g | 80A ESC (3–6S, BEC) | 93.4 g |
| Axico Power Distribution Board XT60 (2 pcs) | 32 g | CUAV CAN PMU Lite Power Module | 33.1 g |
| 6S 14,000 mAh (22.2 V) LiPo Battery | 1020 g | ES900RX Receiver | 1.5 g |
| HGLRC M100 PRO GPS (B101 chip) | 7.9 g | TrueRC Bardpole u.fl 915 MHz Antenna | 6.3 g |
| Raspberry Pi 5 (8GB, package weight) | 106.8 g | Adafruit 16-channel PWM/Servo HAT | 14 g |

| | | | |
|---|---|---|---|
| Raspberry Pi Camera Module 3 (autofocus) | ~15 g | MG90S 9g Micro Servo | 9 g |
| WINSINN 50mm Fan 24V 5010 Turbine | 108.86 g | WINSINN 50mm 5015 5V Blower (pack) | 9.07 g |
| **Common subtotal (sum of listed common items)** | **1677.93 g** | | |
| **IMAGERY MODULE ONLY** | | | |
| OAK-D-LITE cameras (6×) | 366 g | Camera Shaft | 300 g |
| **Imagery module subtotal (sum of listed imagery items)** | **666 g** | **Imagery module total (as provided)** | **2369.6 g** |
| **SAMPLING MODULE ONLY** | | | |
| 6DOF Mechanical Arm Claw Kit | 910 g | 55 g Servo Motor | 55 g |
| Rotating Cartridges | 100 g | | |
| **Sampling module subtotal (sum of listed sampling items)** | **1065 g** | **Sampling module total (as provided)** | **2727.6 g** |

| | | | |
|---|---|---|---|
| **AIR VEHICLE STRUCTURE** | | | |
| Fuselage (usable single number) | 950 g | Boom tubes (both, usable single number) | 300 g |
| Empennage (usable single number) | 185 g | | |
| **Structure subtotal (as provided)** | **1435 g** | | |
| **TOTAL SYSTEM WEIGHT** | | | |
| Total system (Imagery) **as provided** | **3778.93 g** | Total system (Sampling) **as provided** | **4177.93** |

## Center of Gravity (COG) Calculations:

For the drone, we calculated the center of gravity for individual subsections (for cleaner math) and then calculated the center of gravity for the overall system.

The point of center of gravity is:

$$y_{COG} = \frac{1677.93g \cdot 25.48\,in. + 1065g \cdot 25.8\,in. + 1435g \cdot 29\,in.}{4177.93g} = 26.77\,in.$$

The center of gravity of the drone is at most 0.68 meters from the nose of the aircraft.

**Table 7. Purposes of different drone components.**

| ID | Component | Purpose |
|---|---|---|

| | | |
|---|---|---|
| 1 | Fuselage | Main structural body of the aircraft; houses battery, avionics, power distribution, and wiring while maintaining aerodynamic shape. |
| 2 | Fixed wings | Generate lift during forward flight, enabling efficient cruise operation. |
| 3 | VTOL motor booms(2) | Provide spacing and clearance for vertical-lift propellers. |
| 4 | VTOL brushless motors(5) | Produce vertical thrust for takeoff, hover, and landing. |
| 5 | VTOL propellers(4) | Convert motor torque into vertical lift. |
| 6 | Fixed-wing propeller | Generates thrust for forward flight efficiency. |
| 7 | Electronic speed controllers (ESCs)(5) | Regulate power delivery and motor speed. |
| 8 | Power distribution board (PDB) | Distributes battery power safely to propulsion and avionics systems. |
| 9 | Flight controller | Controls stabilization, navigation, and VTOL–fixed-wing transition logic. |
| 10 | GPS module | Provides position, altitude, and velocity data for autonomous navigation. |
| 11 | Empennage (tail assembly) | Provides longitudinal and directional stability. |
| 12 | Landing skids / gear(4) | Protect the airframe during ground operations and landing. |
| 13 | Battery (LiPo) | Stores electrical energy for all onboard systems. |
| 14 | Power module | Steps down battery voltage for avionics and peripherals. |
| 15 | Telemetry antenna | Enables real-time communication with the ground station. |

| | | |
|---|---|---|
| 16 | RC receiver | Allows pilot override and safety control. |
| 18 | Wiring(will be assumed to be connecting all components) | Provide electrical and signal connections between components.w |

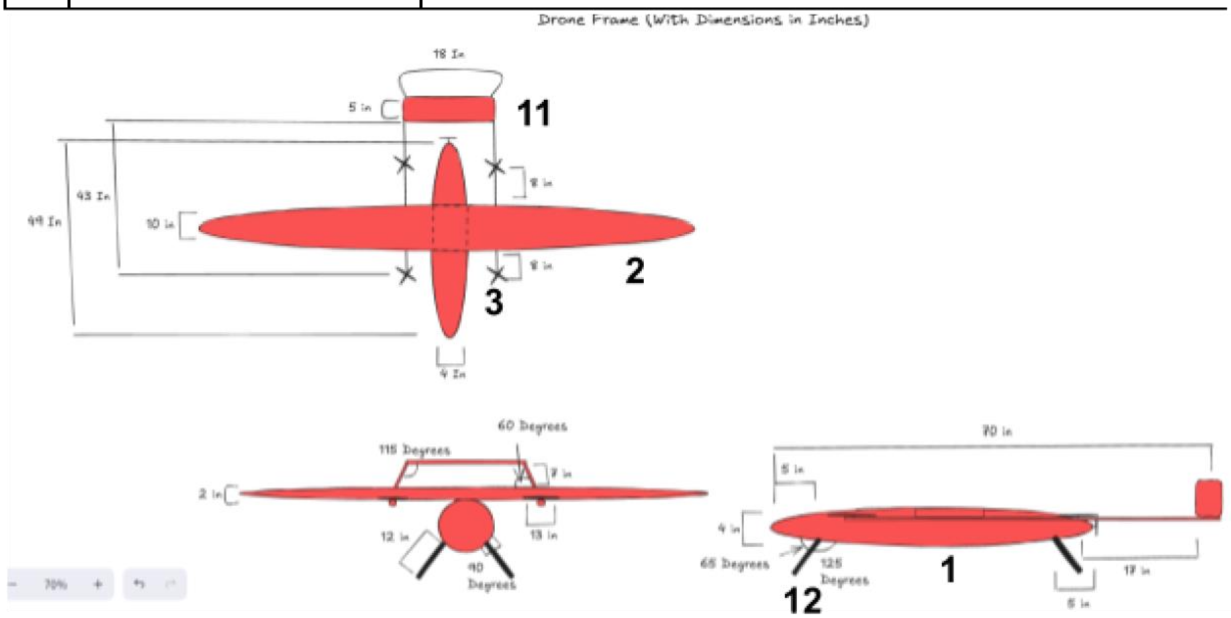


**Figure 10. Final Sketch of VTOL drone airframe**

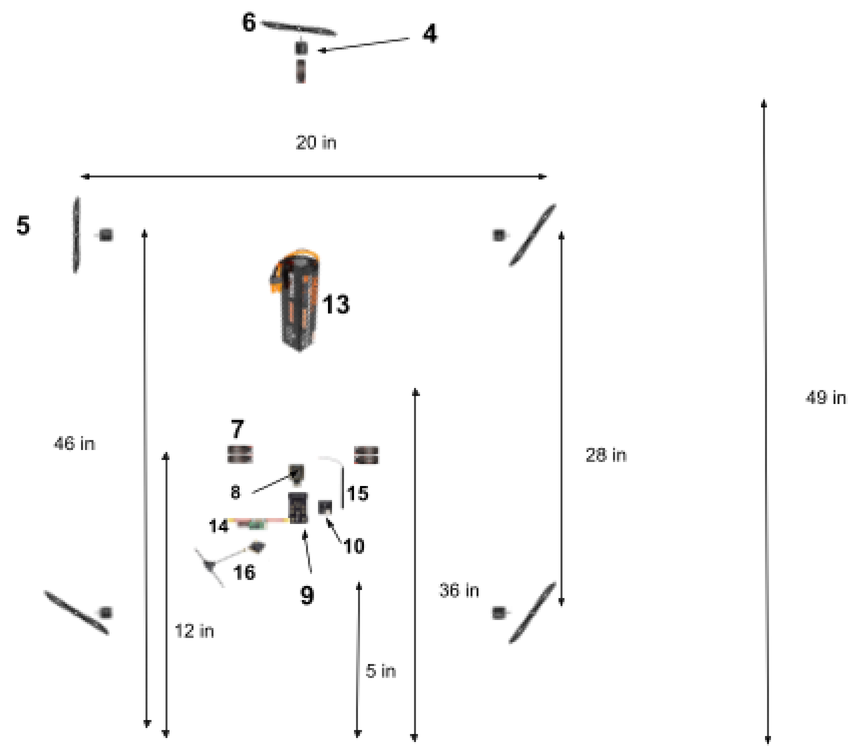



**Figure 11. Final sketch of drone electronics**

### *2.3.2 Command, Control, and Communications (C3)*

**Conceptual**

Looking at the requirements of the challenge, the team needed a way to control the drone, monitor it, establish clear communication through the use of electronics, analyze/override the data it collects, a detect and avoid (DAA) system and a GPS.

For signal transmission (communication), the team selected two Raspberry Pi 5 systems that transmits all sensor data to ground control through. The sampler will be equipped with one as well. The team selected this system due to its high processing power due to both Raspberry Pi 5's controlling the data in the numerous RGB-D cameras. This balances out the workload and reduces overloading in the system. This allows us to use it for communication as well.

For the sampling module, it will follow a waypoint mission based on the coordinates from the surveying module, which allows it to visit each soybean plant with damaged pods to collect samples. The payload operator will then control the 6DOF robotic arm to collect the samples at the waypoint, and when they are done, they can simply send the drone to the next waypoint.

After all waypoints have been visited, the drone can be flown back to ground control for maintenance, unloading of samples, and assessment of the mission.

For the DAA system, there will be a separate camera in the nose monitored by a ground control member coupled with a computer vision algorithm running on its host Raspberry Pi. It will be equipped with a TrueRC Bardpole, u.fl 915 mHz Antenna for Crossfire RX. Once either the staff member or the camera detects an obstacle, a signal will be sent by the pilot to the drone to stop. After the obstacle is taken care of, the drone will continue the mission

If the drone ever loses communication, it will fly to ground control, whose coordinates will be put in the Ardupilot software. The drone will then be checked for repair, maintenance and reinstatement of the mission.

To eliminate the need for extra work, the 34x24x12.5 inch container will be the ground station itself. A monitor mounted to the side of the upper half of the container that will receive data from the sensors and will be constantly watched by a staff member. Antennae will be integrated into the landing gear to save space, and the controllers will have an integrated transmitter for the same purpose. There will be straps to hold down a controller when not in use, and to send out the signal for the DAA, there will be a specialized button on the controller for the staff member to press in the case that the AI doesn’t detect the obstacle. Below is a rough sketch of the ground station.

**Figure 12: Rough Ground station**

The team then decided to attach a GPS tracker to the drone that will be monitored by a staff member. This will be used in 3.3.4 as an additional safety feature. A monitor will be needed for GPS tracking along with sensor data and the DAA camera.

However, this briefcase monitor is bulky, small and is running multiple applications at once as well as taking up most of the space inside the ground control container that the team may need for other equipment. Due to this issue, the team scrapped the idea of compaction and decided to use a standard laptop that runs the same function as the briefcase, but smaller. The laptop will have its own straps to be held in so it doesn’t bounce around. The controller will go in the container for the drone’s equipment.

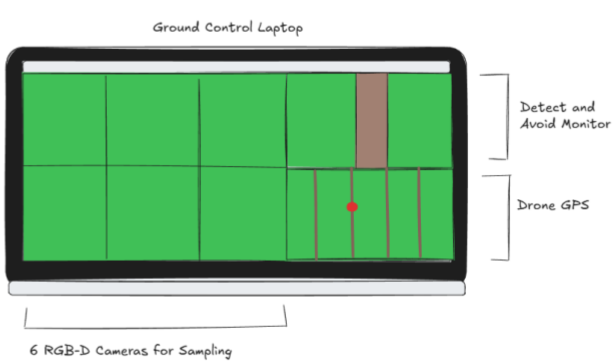


**Figure 12. Sketch of laptop display with camera feeds.**

There will be one controller for the drone's movement and one controller for the robot arm to save space on each and to divide the responsibilities between the pilot and the payload operator. Below are the controllers.

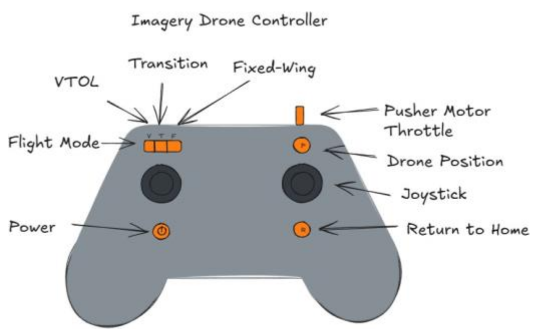



**Figure 13. Sketch of drone flight controller.**


**Detailed**

The specific model of the laptop will be the Acer Aspire 14. It provides sufficient CPU performance, integrated graphics, and memory to run ground control software and telemetry visualization; stable connectivity for radios and

**Figure 14. Sketch of drone sampling arm controller.**

peripherals; adequate local storage for mission logs and maps; and the portability and power efficiency needed for field operations, all at a surprisingly modest cost of $700. It will also be connected to a Yagi directional antenna through an RP-SMA connector. This will allow the laptop to stream the 6 RGB-D camera feeds, the camera in the robotic arm, the DAA camera, and the GPS location of the drone. The Bardpole antenna combined with the Yagi directional antenna at ground control will reliably send information across wide distances.

The drone will be equipped with a Happymodel ExpressLRS 915 Mhz receiver and the controllers will be equipped with a transmitter of the same name. They have a range of 6.2 miles, so range will not be an issue for the average farm in Maryland.

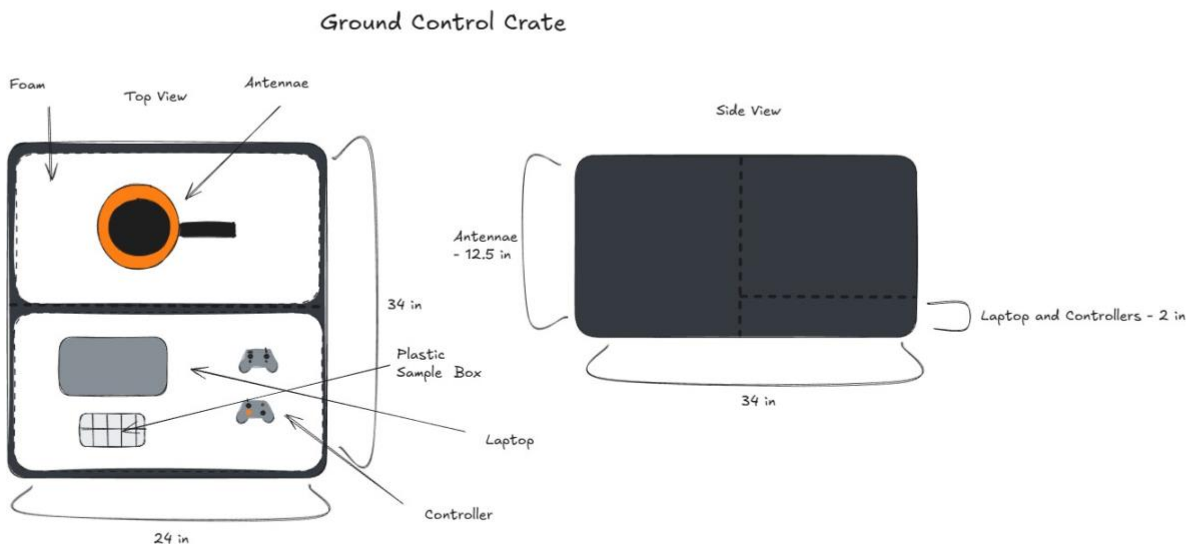



**Figure 15. Sketch of ground control equipment crate and contents.**

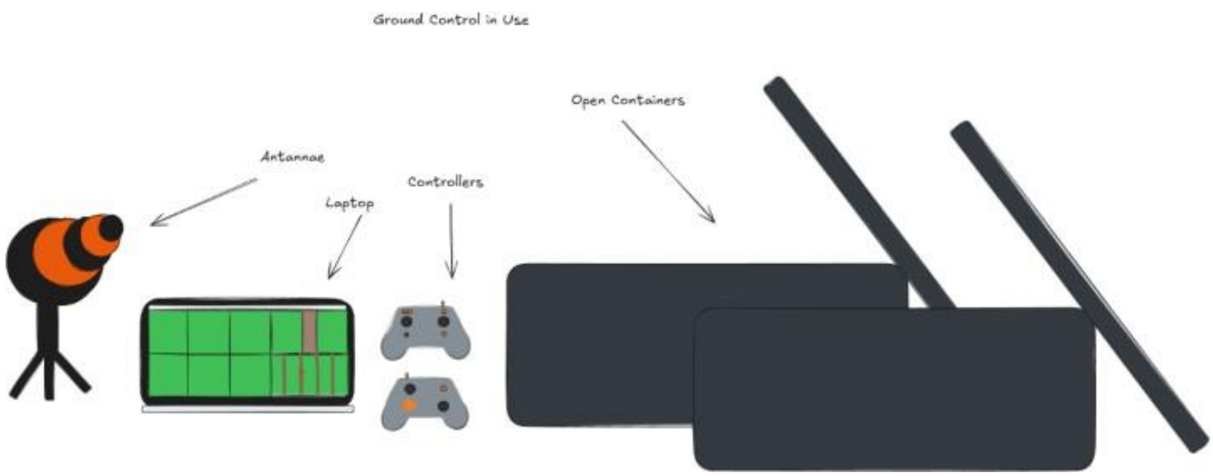



**Figure 16. Sketches of all drone ground control equipment.**

### *2.3.3 Payload – Pest Detection*

**Conceptual**

After doing a quick skim of the challenge this year, the team decided to research the basic subsystems for the payload system in order to attain a good idea of how these drones work. From there, the team can then conceptualize our own design or innovate on one of the already existing systems.

Payload systems are visual/exteroceptive sensors that capture information about the operating environment. It can provide awareness relative to the position and location of the aircraft. The team's ideal sensor needs to detect color differences between healthy and pest-tampered soybean pods as well as be fairly accurate.

Before researching what sensors we needed, the team attended a meeting with the CV and AI Expert Jie Liang. Liang emphasized the need for the RGB-D sensor in our design, which the team took note of in order to use this tip later in the design process. Liang also mentioned the use of CCD/CMOS and multispectral sensors. Using Liang's help, the team did further research on the sensors and if they were going to use them on the design.

From this research, the team discovered the required payloads. The sensor payloads will be used to detect pests and pest damage. This included a camera(s) to monitor the drone's view for the pilot and sensor(s)/camera(s) that can monitor soybean crops. The team decided to select the RGB-D sensor as it met the team's sensor criteria, as its positives outweighed the negatives and accuracy:

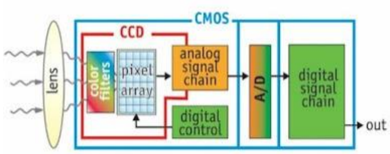
| **Sensor Research** | | | |
|---|---|---|---|
| Sensor | Image | Pros | Cons |
| CCD/CMOS |  | • High image quality, even in bright or dark conditions<br>• **High sensitivity: Detects weak signals** | • Expensive<br>• **Rolling effect for live footage**<br>• Heavier<br>• Uses more power |
| Multispectral |  | • Cost-effective<br>• Fast processing | • More inaccurate, **preventing use in tasks requiring precise data**<br>• **Increased misclassification for data collected** |
| RGB-D |  | • Cost-effective<br>• **Color accurate** | • Does not give information beyond light<br>• Cannot provide sufficient data for precise three dimensional models<br>• **Fairly or reflective light may cause interference** |

**Table 8. Comparison of different drone imaging cameras.**

The RGB-D sensor would detect colors abnormal of the average healthy soybean, using large margins of error of the color to detect stinkbugs themselves or soybean pods damaged by pests. Using this information, the AI will plot a coordinate on the field for the second flight, where sample collection occurs. Eventually, ten samples will be plotted in total.

The original idea for mounting the RGB-D sensor was a 360 degree camera that could capture the surrounding area from all sides. However, none of these have been invented or work well. In response, the team decided they would just place two RGB-D cameras on each side as each soybean row has two rows of crops to scan. The front and back of the drone being captured by the RGB-D sensor is unnecessary. It would prove to be cost effective.

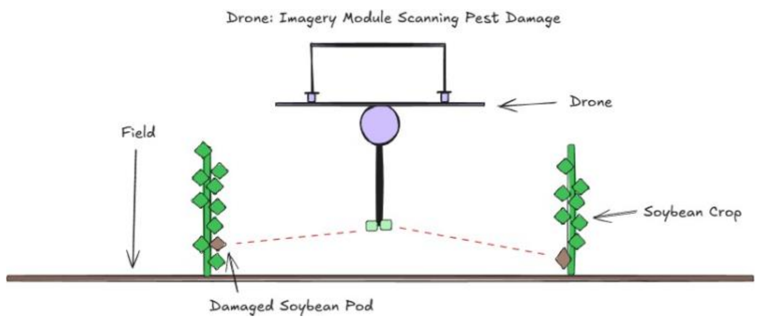



**Figure 17. Rough sketch of drone scanning soybean plants. (not to scale)**

**Preliminary**

The team first decided on using two cameras with RGB-D sensors incorporated as it gives the necessary data and is cost-effective. The sensors' resolution will be 256x256 pixels, and images will be 192 KB in size. The drone will take many pictures, so size and resolution will have to be limited for efficient use of processing power. The only issue is that the field of view (FOV)will not be enough to smoothly fly through the rows and survey everything. If the drone flies between a seven inch (narrow) row, the vertical FOV of the camera will have to be 164 degrees to view the whole plant, shaving off a few as soybean pods most likely would not grow at the complete bottom or top.

The simplest solution would be to get a camera that can view the whole plant, however those cameras do not exist, so we must use six cameras and angle them appropriately while using a wide angle adapter. However, this will be very expensive.

The camera needs to be hooked up to an AI processor in order to function and carry out the path displayed in 3.1.2. The team chose to use the Raspberry Pi 5 as the main AI processor as it is the best performing on a single board. If the team uses a 26 TOPS AI Hat+ AI accelerator, it will be able to run four different RGBD cameras at 30 FPS per camera.

However, RGBD cameras with such FOV's are very expensive, so the team found a camera that costs $149 called Luxonis 392-OAK-D-LITE-AF. If the drone were to use two Raspberry Pis, there will be less room for crashes on each processor. The camera has a vertical FOV of 54 and a horizontal FOV of 69. The team decided to put a Arducam 180 Degree Fisheye 1/2.3" M12 Lens with Lens Adapter for Raspberry Pi High Quality Camera on the camera for a better view, and decided to put two cameras back to back and three cameras stacked on top of each other, all angled appropriately. From there, the AI model will be trained with a massive image library of healthy vs damaged soybean plants, ensuring that the RGB-D sensors will reliably pick up pest damage.

**Calculations for the RGB-D Camera System (Module 1)**:
System uses two Raspberry Pi 5 boards, each paired with a 26 TOPS AI HAT+, processing a total of six RGB-D camera streams
Each Raspberry Pi processes three simultaneous RGB-D camera streams at 256 × 256 pixel resolution
Each RGB frame size is 256 × 256 × 3 bytes = 196,608 bytes ≈ 192 KiB
Each depth frame size is 256 × 256 × 2 bytes = 131,072 bytes ≈ 128 KiB
Total RGB-D frame size per camera is 327,680 bytes ≈ 320 KiB ≈ 0.3125 MiB
Aggregate data rate formula per Raspberry Pi is 0.3125 MiB × 3 cameras × FPS = 0.9375 × FPS MiB/s
At 30 FPS per camera the data rate per Raspberry Pi is approximately 28.1 MiB/s
At 60 FPS per camera the data rate per Raspberry Pi is approximately 56.3 MiB/s
At 120 FPS per camera the data rate per Raspberry Pi is approximately 112.5 MiB/s
The AI accelerator on each Raspberry Pi provides 26 TOPS which equals 26,000 GOP per second using INT8 operations
Estimated model complexity at 256 × 256 resolution is approximately 0.32 GOP per frame
Theoretical compute upper bound per Raspberry Pi is 26,000 GOP/s divided by 0.32 GOP/frame which equals approximately 81,000 FPS
Practical usable compute is significantly lower due to memory transfers preprocessing postprocessing and multi-stream scheduling
Even at 1–5 percent effective utilization the available AI compute on each Raspberry Pi exceeds the required throughput for three camera streams
Each frame set across three cameras is 0.3125 MiB × 3 which equals 0.9375 MiB

PCIe bandwidth between each Raspberry Pi 5 and its AI HAT+ can support hundreds of frame sets per second
PCIe bandwidth does not limit performance at the target frame rates
The primary performance constraint remains Raspberry Pi 5 host-side processing
Host-side processing includes camera ingest synchronization RGB–depth alignment resizing normalization memory copies tensor preparation and postprocessing
Reducing the load from four cameras to three cameras per Raspberry Pi lowers CPU contention and memory pressure
Empirical performance on Raspberry Pi–class systems supports stable operation at approximately 30 FPS per camera under a three-camera load
Aggregate stable throughput target per Raspberry Pi is three cameras times 30 FPS which equals 90 FPS
Total system throughput target is six cameras times 30 FPS which equals 180 FPS
The final design target is six cameras operating at 30 FPS with 256 × 256 RGB-D inputs distributed across two Raspberry Pi 5 systems providing improved stability headroom and fault isolation

One last feature of the imagery model will be part of its landing. The shaft will have a hinge. When the drone is about to land, the shaft will turn at the joint. This way, the module will not interfere with the drone while it tries to land.

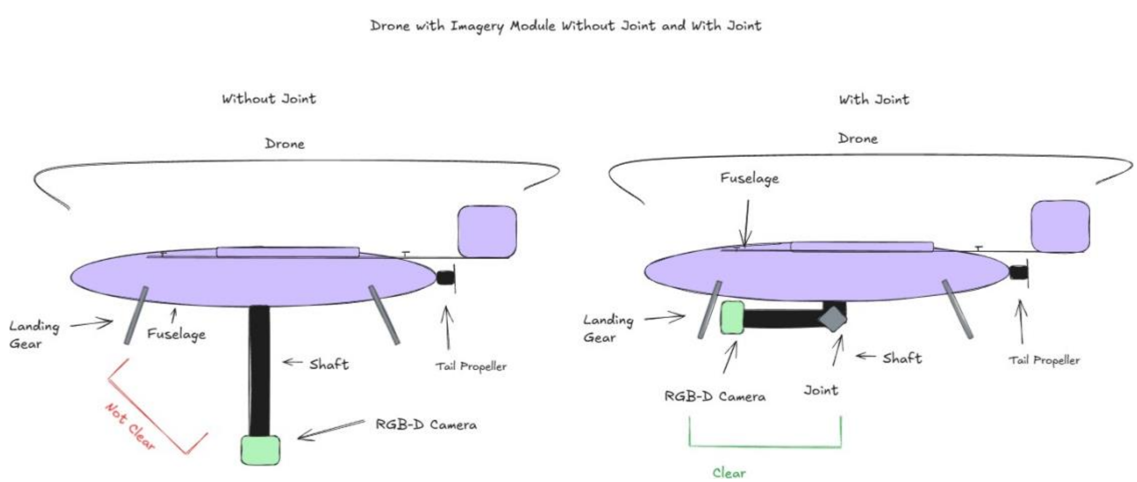



**Figure 18. Drone with imagery module with and without joints.**

**Detailed**

Training will be done with GPU on the cloud and outputs will include accuracy metrics and a final trained model file(AWS specifically). Once training is complete, the cloud computer is shut down to stop costs. The trained model is downloaded and transferred to the onboard system (Raspberry Pi with AI accelerator), where it is used for inference during future flights. All inference and decision-making during missions occur locally on the drone; the cloud is only used between missions for model improvement.

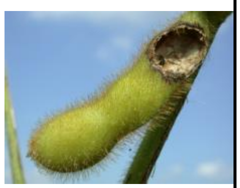
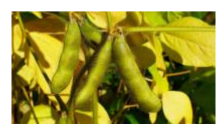
| D (+) | D (+) | D (+) | D (+) | D (+) |
|---|---|---|---|---|
|   |  |   |  |  |
| Damaged soybean pods by Stinkbugs | Damaged soybean pods by **Grasshoppers** | Damaged soybean pods by **Soybean Podworms** | Damaged soybean pods by Stinkbugs(left one)and **Bean Leaf Beetles**(right two) | Damaged soybean pods by **Kudzu Bugs** |
| D(+) | D(-) | D(-) | D(-) | D(-) |
|  |  |  |  |  |
| Damaged soybean leaves by Spider Mites | Healthy soybean | Healthy soybean | Healthy soybean | Healthy soybean |

**Table 9. Various images of damaged and healthy soybeans; used to train drone AI**

Model training is performed using AWS EC2 GPU instances on demand. The AI will be fed different images of pest damage from various pests, such as stinkbugs, grasshoppers, podworms, etc taken from soybean pest damage databases. It will also be fed images of healthy soybeans to prevent false diagnoses. A g4dn.xlarge instance (NVIDIA T4 GPU) is used to balance cost and performance. Training is conducted only between missions, after which the instance is terminated to eliminate recurring cloud expenses.

The imagery module will use six RGB-D Cameras connected to two Raspberry Pi 5 motherboards using USB cables. Due to how simple USB connectors are to attach and disconnect to a source, it will also help with modularity, as the imagery module can be swapped out very quickly. The folding mechanism however will be plugged into the dedicated 3-pin JR connectors, which are most commonly used for servos. All of these connectors means that the modules can be swapped quickly with minimal effort and with a minimal amount of time.

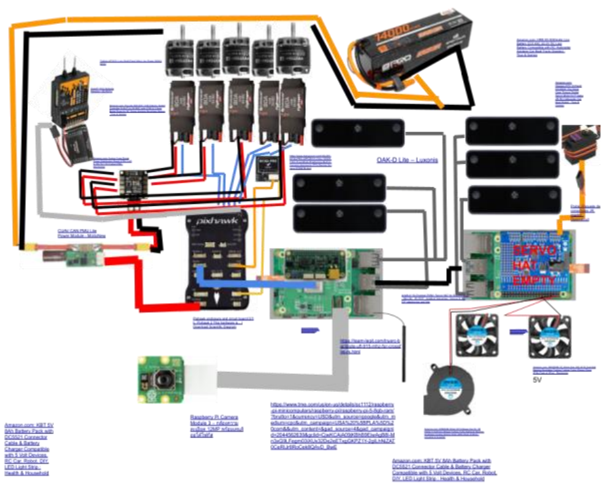



**Figure 19. Schematic of drone electronics.**

The schematic shows the complete inner workings of the drone with the imagery module, which consists of the six black rectangular cameras (OAK-D Lite) and the singular 55g Servo for pivoting the arm.

Soybean plants can grow up to 4 feet tall in the R6 stage. The cameras are 3.58 x 1.1 x 0.69(all inches), so the part of the shaft going straight down from the body will be 2 feet 7 inches long(to give space between drone and canopies) with an extra 1.1 inches for the bottom camera. There will be 6 cameras in total in stacks of 3 on each side. The 3-camera stacks will be angled in a way that makes sure they have no overlap in their field of view. When the drone or the staff member monitoring it senses a damaged soybean plant through the RGB-D sensor, it will send coordinates which can be marked on Ardupilot software running in the Pixhawk. This ensures that when the drone returns to the field with the sampling module, it knows exactly where to go so that the only thing the pilot needs to remote control is retrieving samples.

**Updated version (after speaking with Dr Liang)**

| | Remote Sensing (Liang) | Conventional | Aerial Scouting (Eric, Andy) | IoT (Liang) |
|---|---|---|---|---|
| Device/Method | Satelite | Manual | UAS | IoT |
| Early Detection | No | Yes | No | No |
| Effiency | Yes | No | Yes | Yes |
| Labor demand | Low | High | Low | Low |
| Cost | High | High | Low | Low |
| Verdict | Only detect macroscopic level damage | Easy to miss for Soybean, Low efficiency, Labor intensive | Fast, reduced labor but easy to miss for Soybean | Not applicable for Soybeans |

**Table 10. Comparisons of different damage detection strategies**

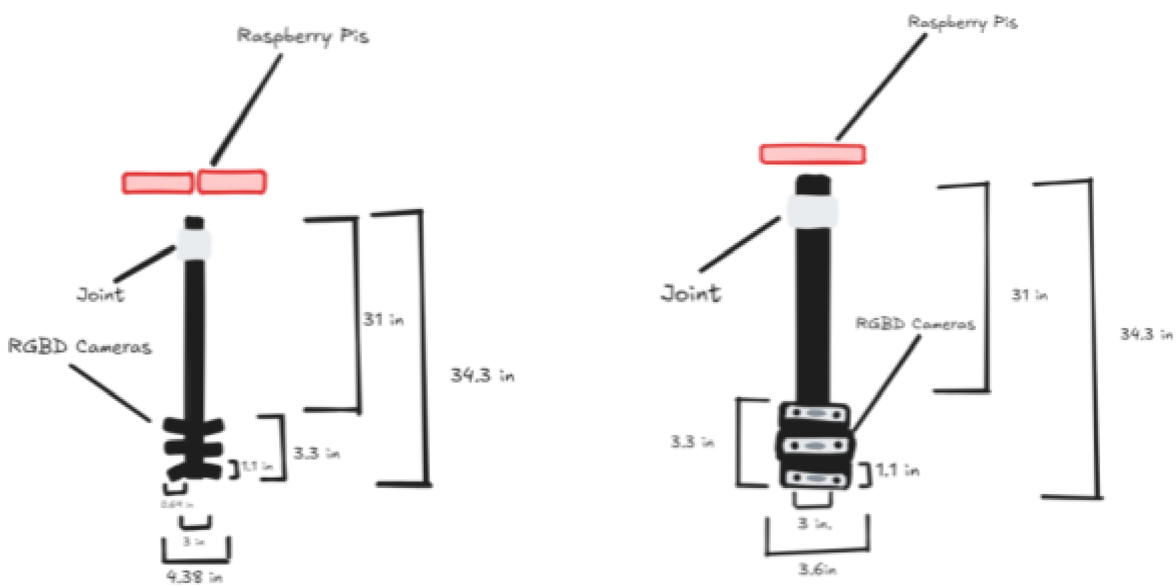
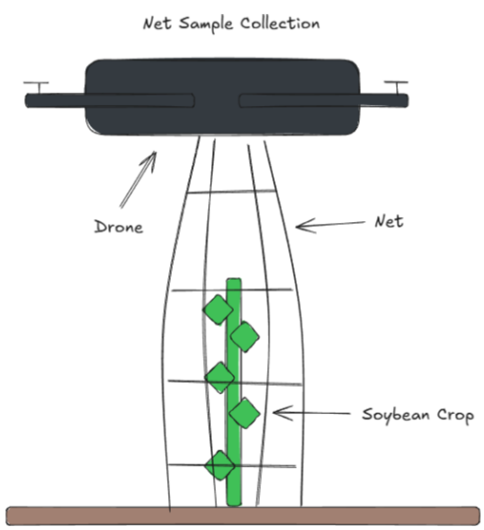



**Figure 20. Drone Imagery Module Front and Side View**

### *2.3.4 Payload – Sample Gathering*

**Conceptual**

The challenge requirements for the sampling payload system includes the retrieval of ten samples from the field. This payload system would also need to fit within the 34 inch by 24 inch by 12.5 inch container along with the imagery model and other equipment. However it would need to be lengthy as the drone hovers over the crops. This caused the team to design a model that would be foldable for packaging purposes.




The team's first idea for a sampling drone was to have a net take the entire soybean plant out of the ground for analysis. However, this idea was flawed in many ways. This included the insane amount of weight the drone would have to carry, yield loss, increased energy use, inefficient movement and an unnecessary amount of space. It may also interfere with cameras, sensors and communication.

**Figure 21. Sketch of drone with net sample collector.**

The team's second idea was to have a rotating storage box with a bionic octopus arm along with two blades to cut off the soybean pod for analysis. The arm would then bend and rotate to store the sample into a single slot stored inside the box. This allows easy storage, increased accuracy, decreased yield loss and overall flexibility. However, a bionic arm would be very costly, usually costing a few thousand dollars.

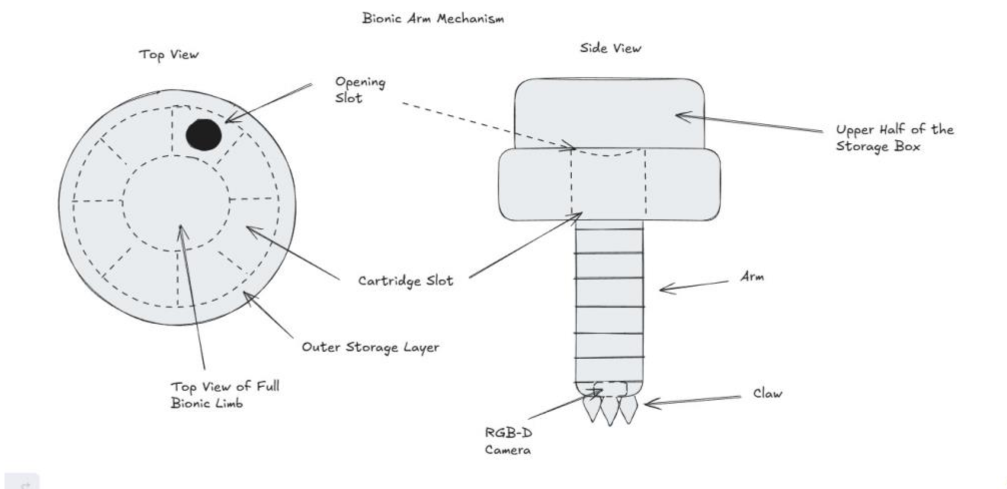



**Figure 22. Sketch of sampling container mechanism.**

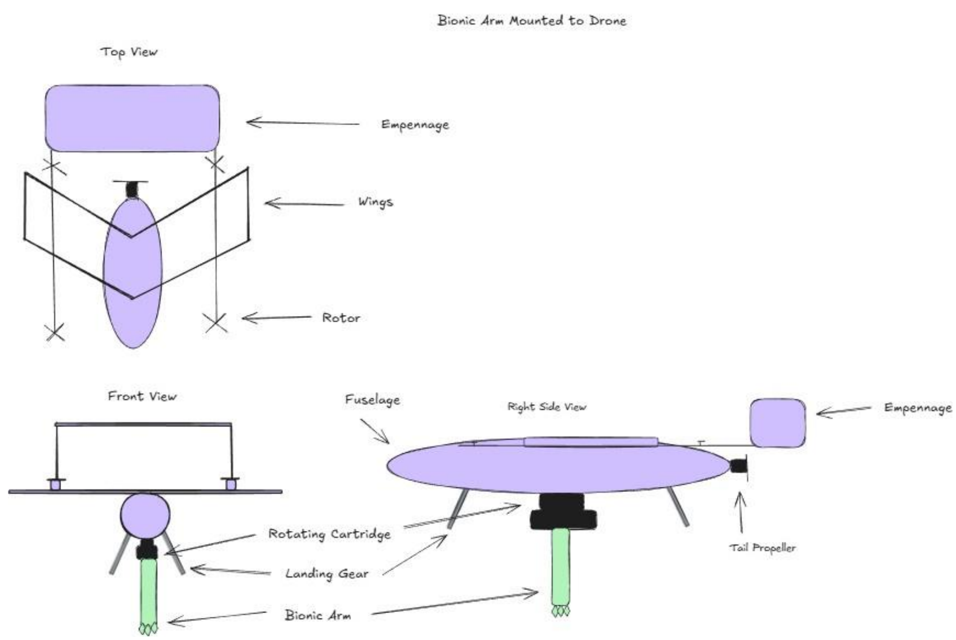



**Figure 23. Sketch of drone with mounted bionic arm sample collector.**

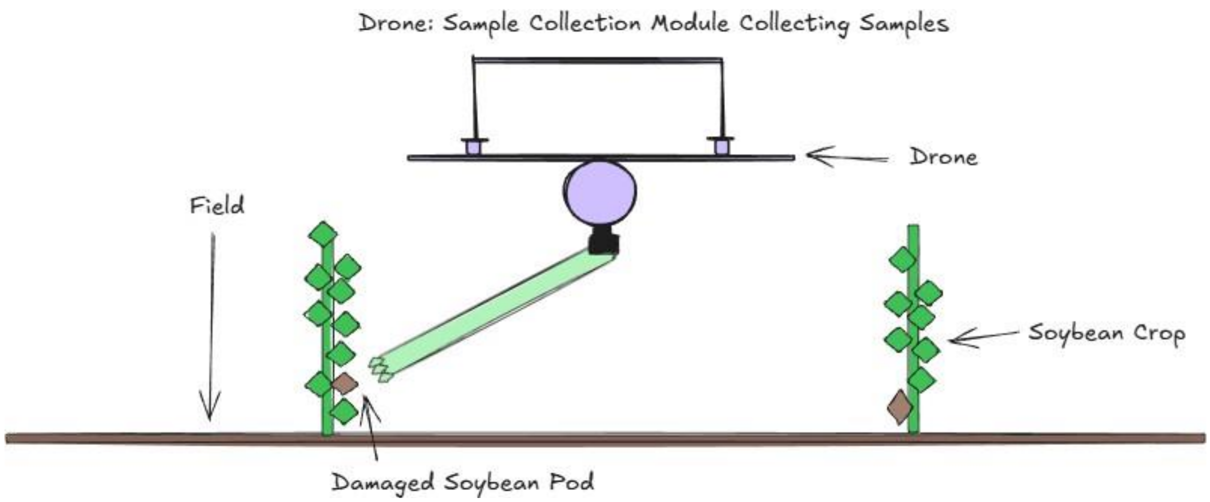



**Figure 24. A rough visualization of the sampling arm mechanism.**

Due to the insane cost of such an arm as well as it requiring some pneumatic systems that overcomplicates its function, the team would ditch the idea in search of a cheaper and equally effective option. The team would stumble upon the 6 degrees-of-freedom robotic arm, a cheaper alternative that provided flexibility, was foldable and provided the same function as the octopus arm. Pairing this with the rotation cartridge box, this would be the design the team picked. The arm itself was made of shafts mounted on multiple joints controlled by electronics paired with a two-pronged claw for gripping.

However, many of the models seen on other machinery are small, short and contain a two-prong claw. The team decided to make modifications accustomed to the drone’s function, including the elongation of the shafts for length to reach the soybean pods and a four-prong claw to better grip the sample to collect it. In order to see the sample it's collecting, there will also be a camera inside the arm as it is collected.

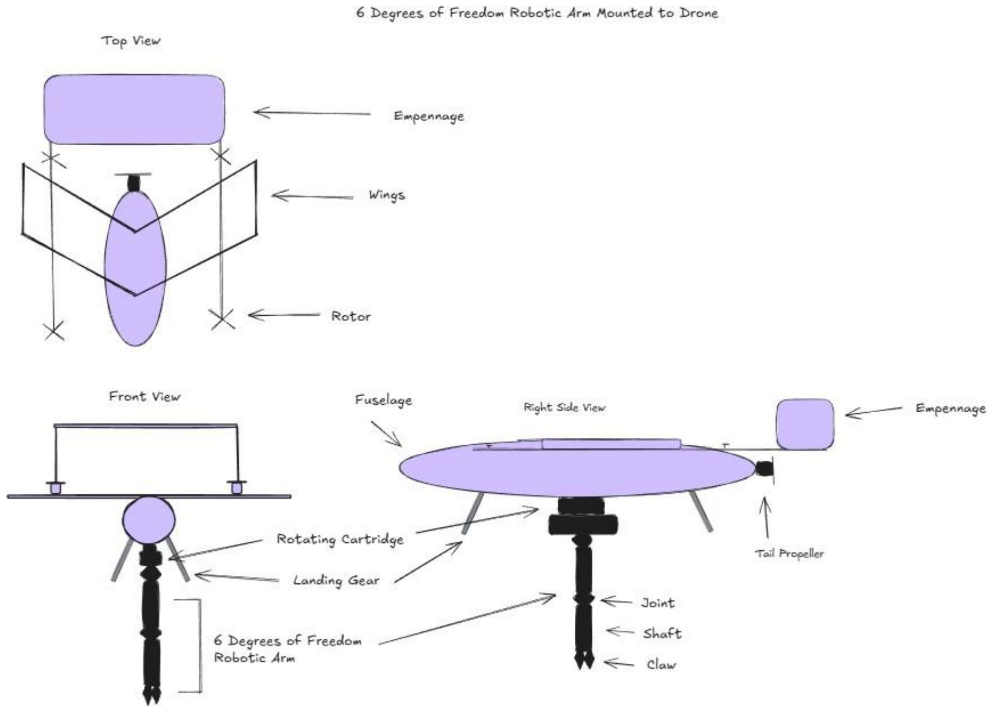



**Figure 25. Rough 3 view-sketch of 6 degree of freedom arm mounted to drone.**

**Preliminary**

The box portion of the system is split into two parts. One inner circular compartment with multiple storage slots for multiple samples and an outer circular frame equipped with a single opening for the arm to drop off samples into a single slot at a time on top of the storage box, while the other slots would be blocked off with a solid barrier. The outer barrier rotates to match the opening with an empty storage slot for the arm to then transfer a pod into, which prevents the pod from falling out of the side from inertia of the drone. This increases our storage space by one if we were to place the opening on the side of the box. This mechanism itself allows the system to be very organized and allow few failures such as two pods in one slot, pods falling out and convenient placement relative to the arm.

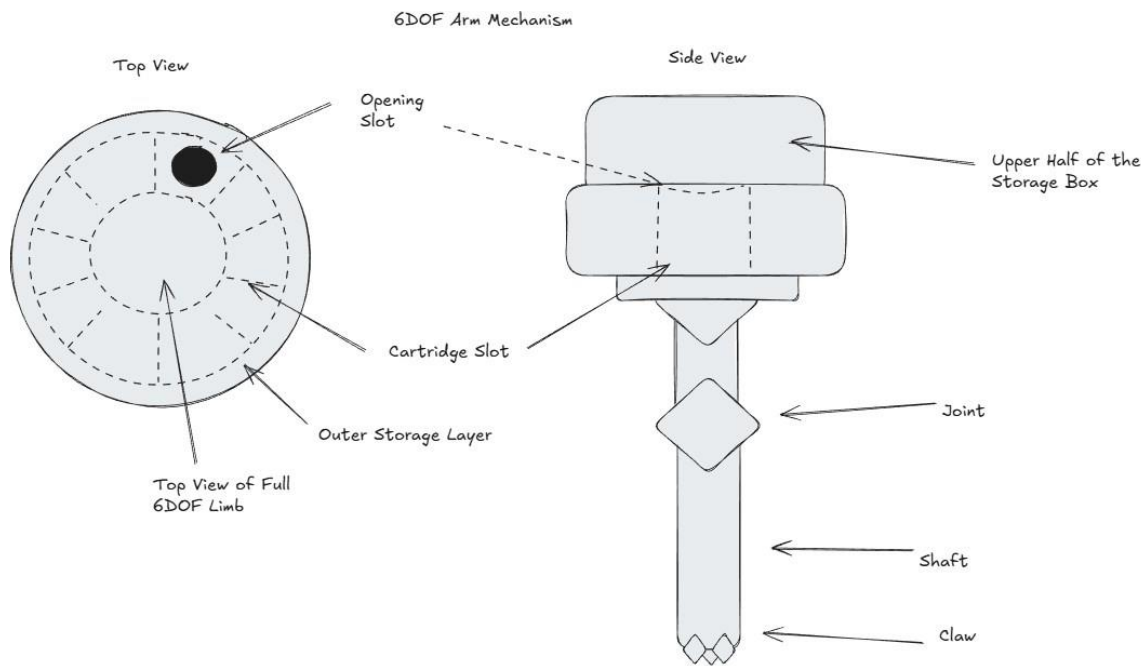



**Figure 26. Rough 2-view sketch of arm mechanism.**

In order to get the samples out, the upper half of the storage box would act as a screw-on lid connected to the actual storage compartment. With the detachment of the arm module and the removal of this lid, it allows easy access to the samples for the consumers. This prevents inconvenient or time consuming removal.

**Detailed**

The final schematic for the sampling module is mostly the same as the imagery module. The only difference is that the cameras are gone and that there are now six 55g servos, two 9g servos, and one continuous rotation servo connected to the Raspberry Pi.

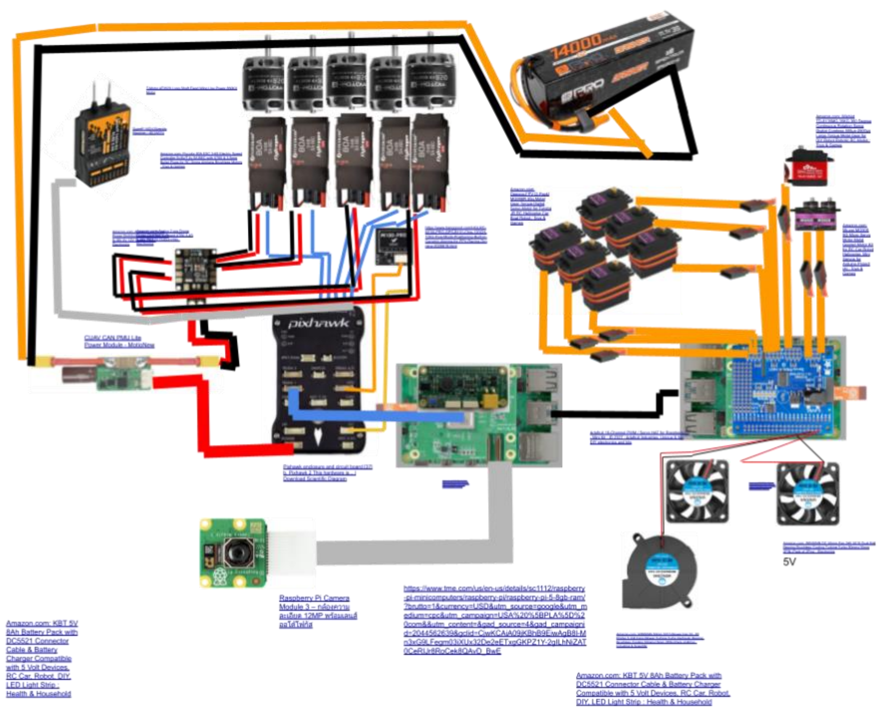



**Figure 27. Enlarged map of drone electronics.**

The arm itself will be 3 feet long independent of the rotating cartridge, with its 3 joints starting at the claw and the other 2 one foot and two feet up the arm. The bar holding the rotating cartridge will be 6 inches, holding a 2.5 inch tall 4 inch radius cylinder. The width across the board for both shafts(cartridge holder and arm) will be 3 inches.

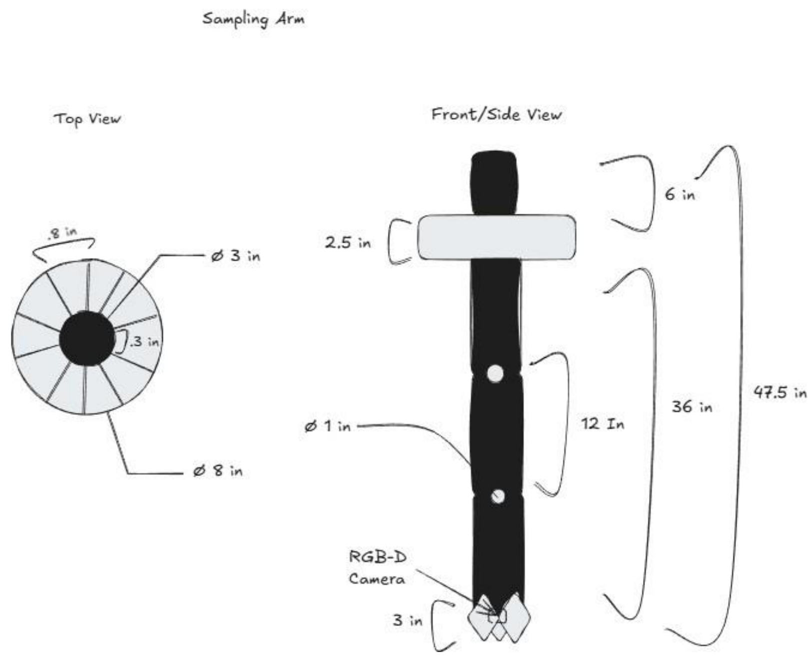



**Figure 28: Final Sampling Module with 1 rotating cartridge holder, a 6DOF robotic arm, and 3 joints**

### *2.3.5 Ground/Support Equipment*

**Conceptual**

After some research about drone ground control and the components of our own design, the team deducted what was necessary on the ground control. Since the drone was running on an AI processor, there is always a possibility for machine error, which needs to be backed up by human intervention. This would require monitoring screens by staff members looking through the lens of the cameras on the drone, including the safety and RGB-D cameras along with the location of the drone on the field from the GPS. This ensures proper data, manual override for safety purposes (objects such as humans or other aircraft in the way or wrong path) and overall surveillance for the mission to perform correctly.

Outside of the general task that can be solved with other components, Crowl noted that a drone's batteries can overheat in the summer and must be kept refrigerated. Many ground control stations contain a battery fridge to cool down batteries used, but if the drone had a cooling system on the drone these concerns wouldn't need to be a concern. Possible concepts include the use of fans, vents, and some sort of insulation within the frame. This would allow extra space for the ground control container with the size of 34 inch by 24 inch by 12.5 inch container teams are limited to for this challenge.

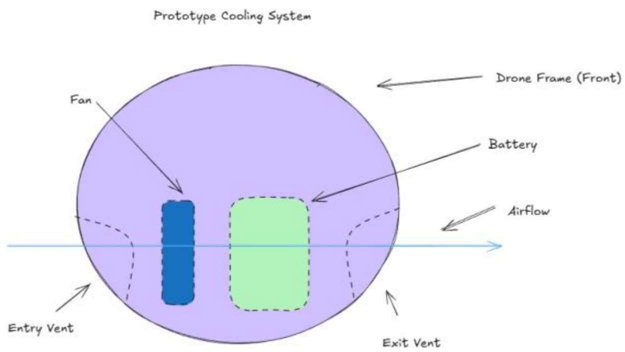



**Figure 29. Rough sketch of prototype cooling system.**

The team researched already existing on-drone cooling systems. However, many ended up being bulky and pricy, so the team needed a cooling system that was cheaper and effective. After doing research on cooling equipment, the team discovered the minimal equipment required was a centrifugal blower, two fans and two vents. With this in mind, the team would later craft their own system in the preliminary stage of the ground support design process.

**Preliminary**

The cooling device will be made up of an entry vent, an entry fan, the centrifugal blower, an exit fan and an exit vent inside a carved out tunnel in the drone. Air will enter through the entry vent, blown into the drone through the entry fan and into the centrifugal blower. The centrifugal blower would then redirect air flow onto the batteries which will cool them down. The warm air would then exit through the exit fan and exit vent into the surrounding environment.

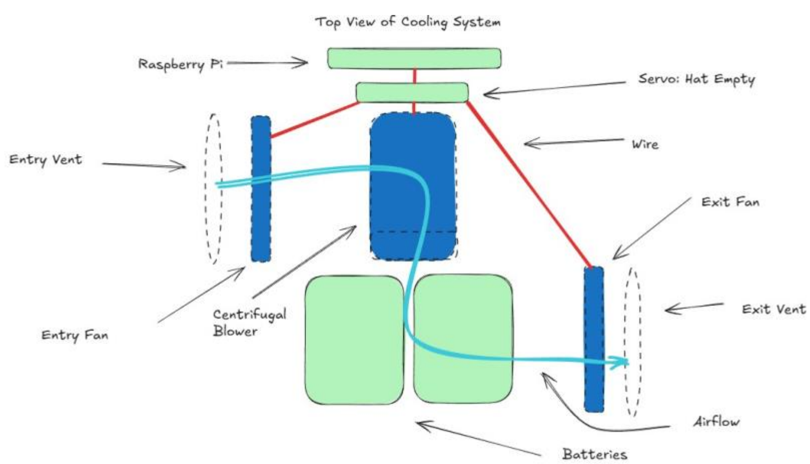



**Figure 30. Top-view sketch of drone cooling system.**

This will cool down the batteries when temperatures are high, especially in the summer when soybean crops are at their most vulnerable growth stage. This allows the drone to function despite the harsh weather conditions, elongating time on the field and any emergency steps that may require extra energy.

**Detailed**


The spacing of the air vehicle is convenient for the arrangement of the cooling system, as the electronics are small and can snugly fit in a 4 inch space. The vents will be staggered on the edges of the fuselage to let air flow through, and the two fans will be placed directly in front, one facing inwards for air intake and one facing outwards for exhaust. The centrifugal blower will be placed perpendicular to the airflow of the intake fan, and the battery will be placed along its length so that the centrifugal blower will directly blow on the batteries. The exhaust fan will be placed just beyond the batteries and will take the air out. Below is a diagram of that arrangement assuming the nose is pointing down.

**Figure 31. Top-view map of drone cooling system electronics**

## 2.4 Lessons Learned

Throughout the design process, several key lessons were learned. One of the most important lessons was clearly defining the real problem before designing a solution. Initially, the team wanted to focus on a single pest, such as stinkbugs. However, this would severely limit the system's market potential and its potential to make an impact on the environment. Expanding the platform to detect and analyze signs of multiple pests damage was necessary to improve efficiency, customer value, and overall profitability. Designing the platform with a modular architecture proved essential, as it allowed the same system to do both imaging and physical sampling without redesigning the airframe.

The project also reinforced the need to integrate business considerations directly into engineering decisions. Evaluating both costs and benefits early on highlighted that the true metric of success was not just hardware cost, but the total cost of service required to complete a mission, including labor, preparation time, and operational expenses. This holistic perspective influenced design choices such as modularity, automation, and a rental-based deployment model, ensuring the system was both technically viable and economically sustainable.

Finally, the team learned the importance of iteration and pivoting throughout the innovation process. As technical constraints, cost limitations, and market realities emerged, the system was refined through multiple design cycles. Each iteration improved efficiency, expanded capability, and strengthened the business case, demonstrating that flexibility and continuous improvement are essential to developing a scalable and impactful technology solution.

## 2.5 Final Design Drawings

The following, Figure 32, depicts the three-view of the final unmanned system design.

[ADD FIGURE-CENTERED]

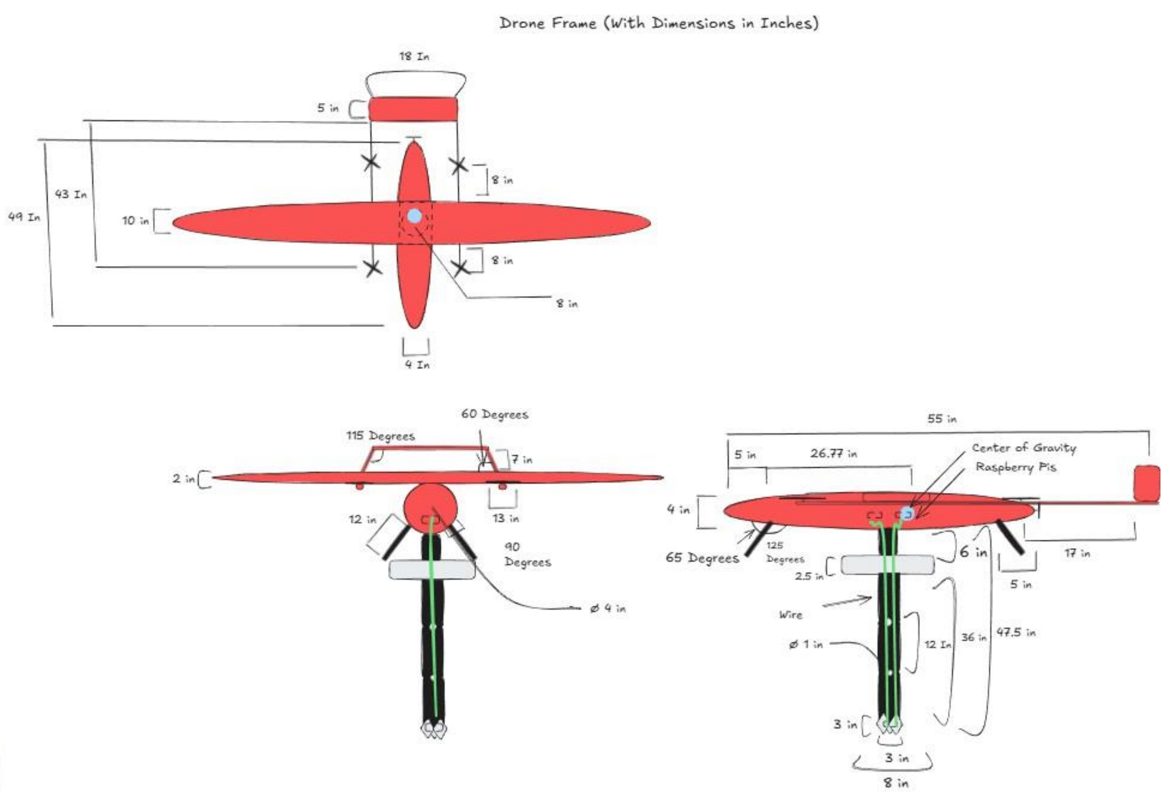


**Figure 32. Three-view sketch of final uncrewed system design.**

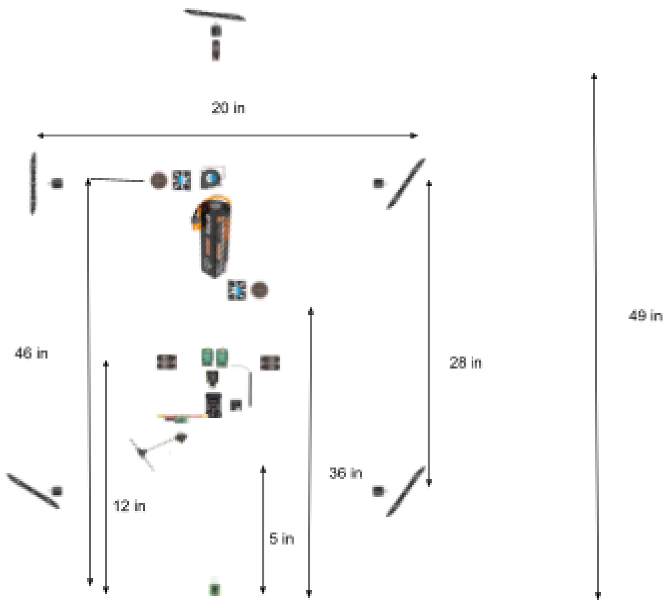


**Figure 33. Top-view sketch of final electronics map.**

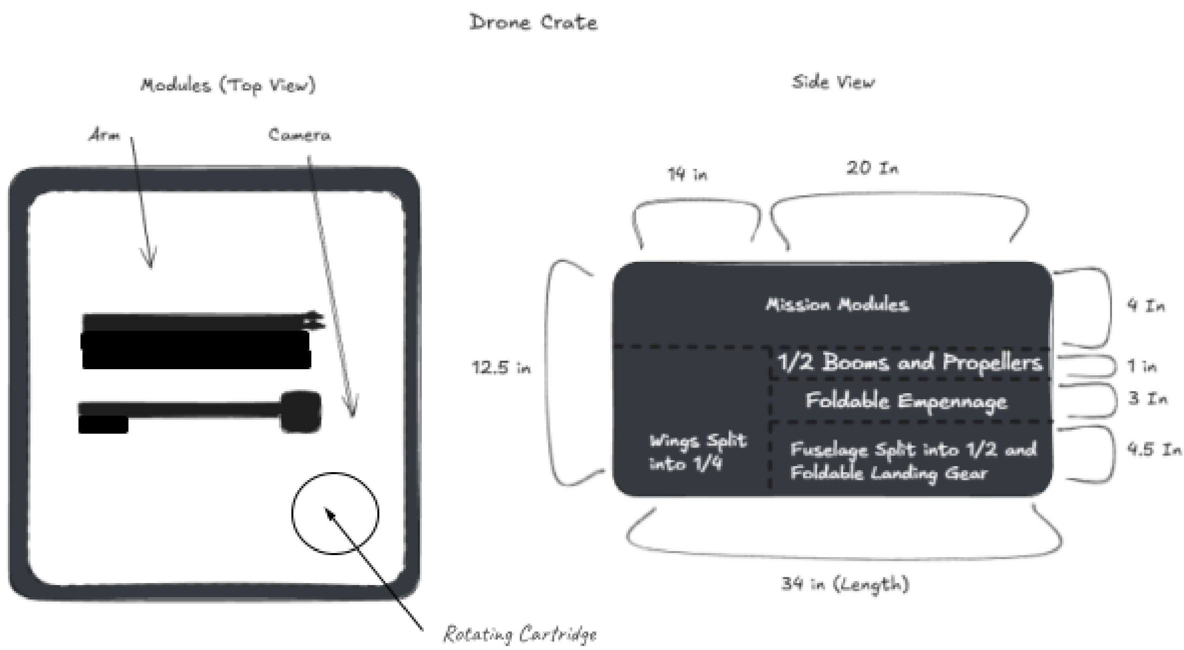



**Figure 34. 2-view sketch of drone storage crate.**

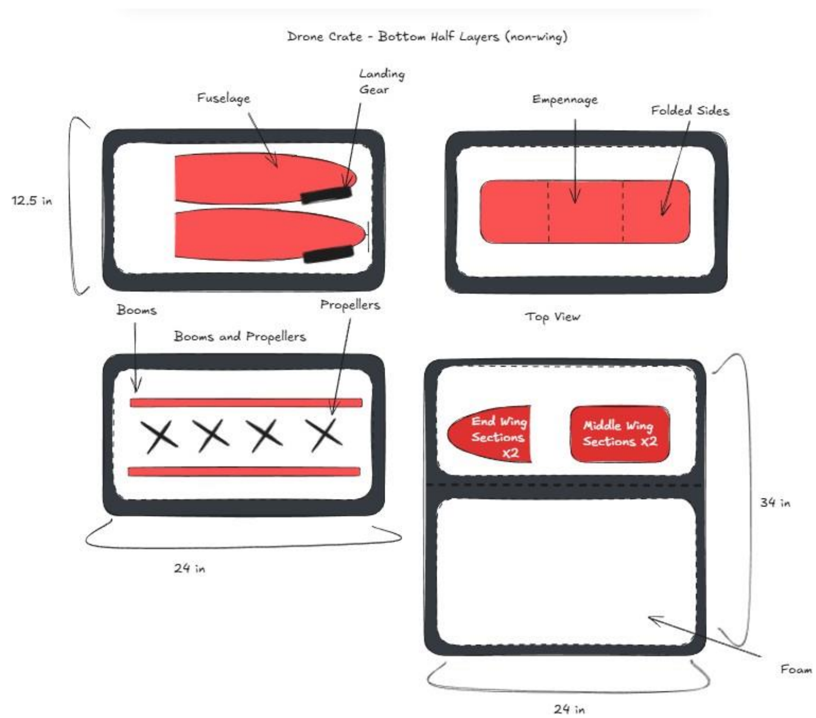



**Figure 35. 2-view sketch of stored components of the bottom half of the drone.**

# Mission Discussion

## 3.1 Concept of Operations

### *3.1.1 Preparation*

The mission begins with the drone team moving to a designated location along the edge of the soybean field. Ideally, this location will provide minimal obstacle interference and provide a clear life of sight of the drone. It should also be clear from any farm workers, equipment or vehicles. The drone pilot then powers on the laptop and flight control software, verifies communication links, confirms live video feeds from all sensors, and checks GPS connectivity. Emergency procedures such as return-to-home and lost-link protocols are also verified before flight. The cooling system will also be made sure to be working.

At the same time, the drone pilot prepares the aircraft in a designated takeoff area. The pilot inspects the airframe, propellers, and landing gear, installs fully charged batteries, and confirms battery temperature and cooling system operation. The aircraft is powered on and all onboard systems are checked for proper initialization.

Once the aircraft is ready, the drone pilot will upload and review the drone's flight path. A final check of the surroundings and weather in order for the drone to perform optimally will also be done by the entire team. Finally, all crew members will move a safe distance (around 15 meters) away from the drone as it begins flight.

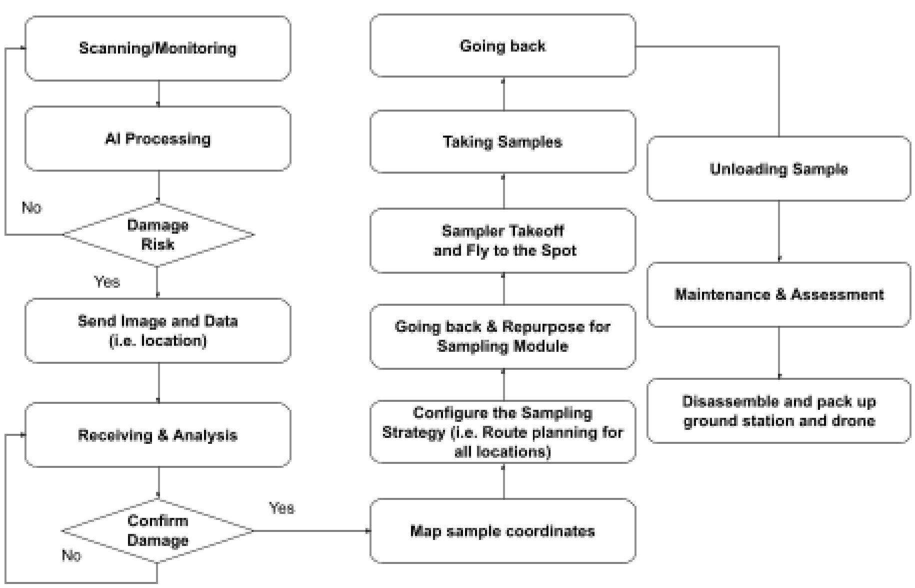



**Figure 36. Full Mission Flowchart**

### *3.1.2 Pest Detection*

The UAS will first go through one lap of the field in a zig zag formation. This routine is used to scan for pests or signs of pest damage. These include the stinkbugs being on the plant, dark brown spots on the pods, shriveled up or flattened pods, and discoloration. It allows the full scanning of the field through the six RGB-D cameras, mapping pest infested or infected spots in the Ardupilot software forming a pathway where the next flight routine will follow.

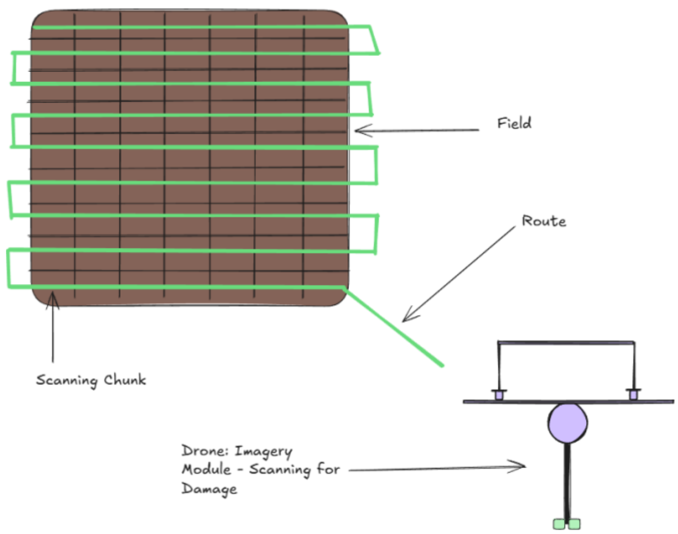



**Figure 37. A rough sketch of the module 1 (imagery) flight path. Module 1 moves through each row in the entire field detecting pest damage.**

The sensor data will constantly be exchanged between the drone and the ground control station. Ideally, the AI model will automatically detect pests or pest damage. However, if the AI fails to see damage but the staff member notices it, the pilot will press a button to map the spot where the staff member saw the damaged plants.

The pilot will be ready to take over the drone at any time. If the drone loses partial communication or an obstacle is detected by a staff member or the ground control AI model senses an obstacle, the pilot will flip a switch to send a signal and take control of the drone to reset and continue the mission.

### *3.1.3 Sample Gathering*

Using the information from the first routine scanning of the field to mark a pathway of pest infected samples for the drone to travel to (sample to sample). This is through the use of the RGB-D sensor marking differences in the color between healthy and pest-tampered soybean pods. If there is a pest-tampered soybean pod, the drone will send a signal to the monitor to mark that location on the grid map. If there is an error in the detection, the human monitor on the drone crew can look at the footage from the RGB-D cameras to see if a sample was incorrectly marked. The pilot can then override the pathway depending on the results.

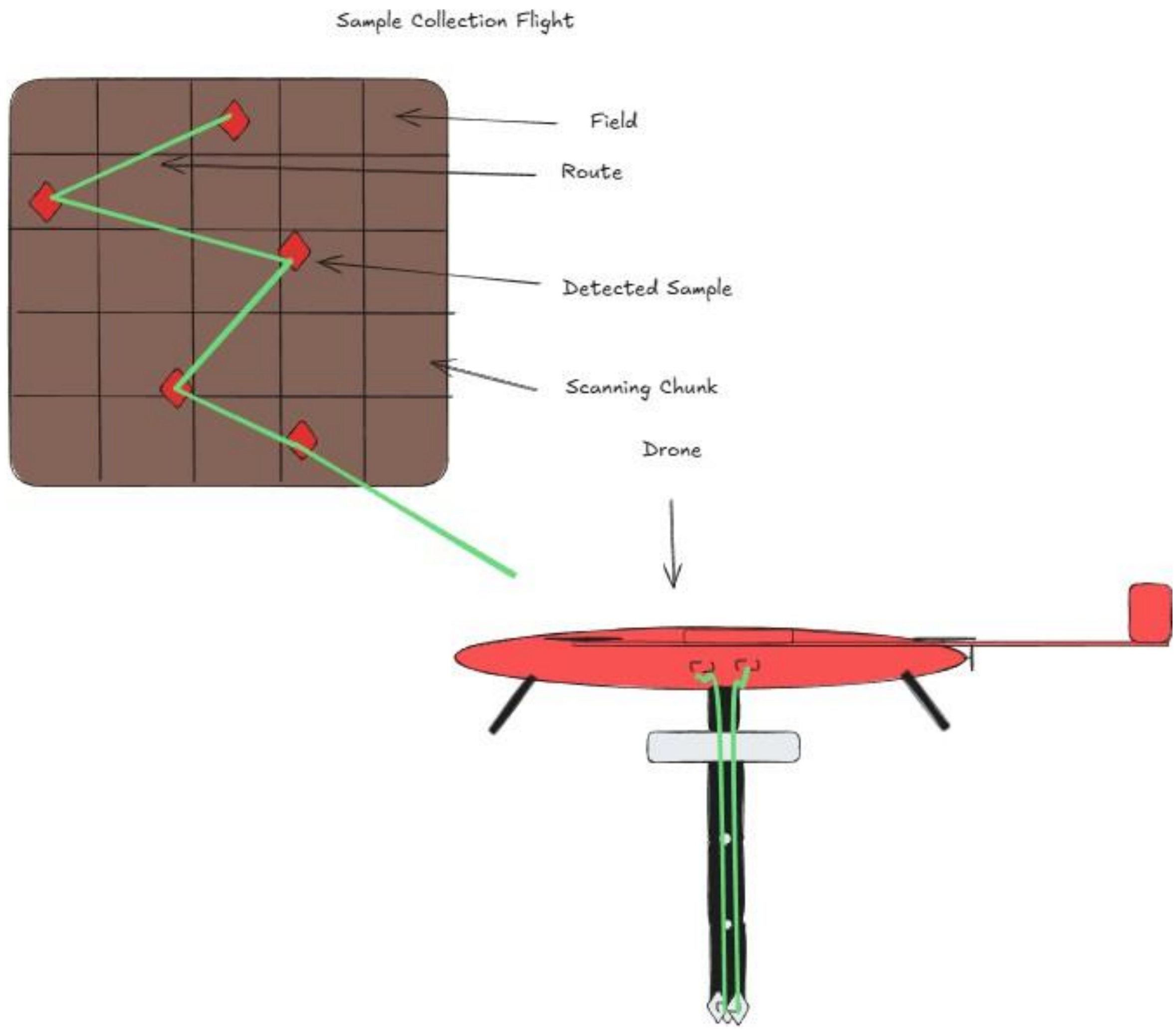



**Figure 38. A rough sketch of the module 2 (sample collection) flight path. Module 2 takes the shortest path to the areas with pest damage to collect samples.**

Through the AI processor on the drone using Ardupilot software, it will follow the shortest pathway possible, (using past flight data to avoid suboptimal detours) stopping at each sample. The drone pilot will then use buttons on the controller to maneuver the 6 DOF arm to collect the sample and deposit it into the rotating storage box. The drone monitor will direct the drone pilot on how to move the arm in order to ensure successful collection. Then, the pilot will press a button to signal the drone to move to the next sample.

In the storage box itself, the camera on the end of the 6 DOF arm will ensure the sample has been successfully deposited into the box. The drone monitor will signal the pilot the transfer was a success, initiating the pilot to press a button on the controller to signal the rotating cartridge box to rotate to the next empty slot through motor rotation. In total, there are 10 slots inside the box. After 10 samples are collected, the drone will fly back to the ground control station to retrieve the samples.

Communication necessary between the drone and the drone crew during sample collection includes the control of the arm from the drone pilot, pathway monitoring on the laptop, analysis of the sample itself through the camera on the 6 DOF arm and sample storage maintenance.

### *3.1.4 Post-Mission*

Once every sample is collected and the drone flies back, the staff members will turn the cartridge many times to take out all samples collected and be put in a separate container. Then, they will detach the sampling module and put both it and the imagery module in their respective holders. The drone will be checked for any signs of damage, including visual cues like scratches, dents, or pieces not being there and signs of electronic malfunctions and overheating of hardware. Then, it will be disassembled and its parts strapped down to its area. Finally, the waypoints will be gathered up and brought back to ground control to be stored. The samples will be sent off to a lab for analysis. As for the ground control equipment, the laptop will simply be closed and it and the controller will be strapped down to their respective areas, the briefcase will be sealed up, and the job will be done.

## 3.2 Benchmark Mission

Below are the calculations for maximum speed to capture reliable data with its usable HFOV being 120 before distortion warps data, paired with a diagram:

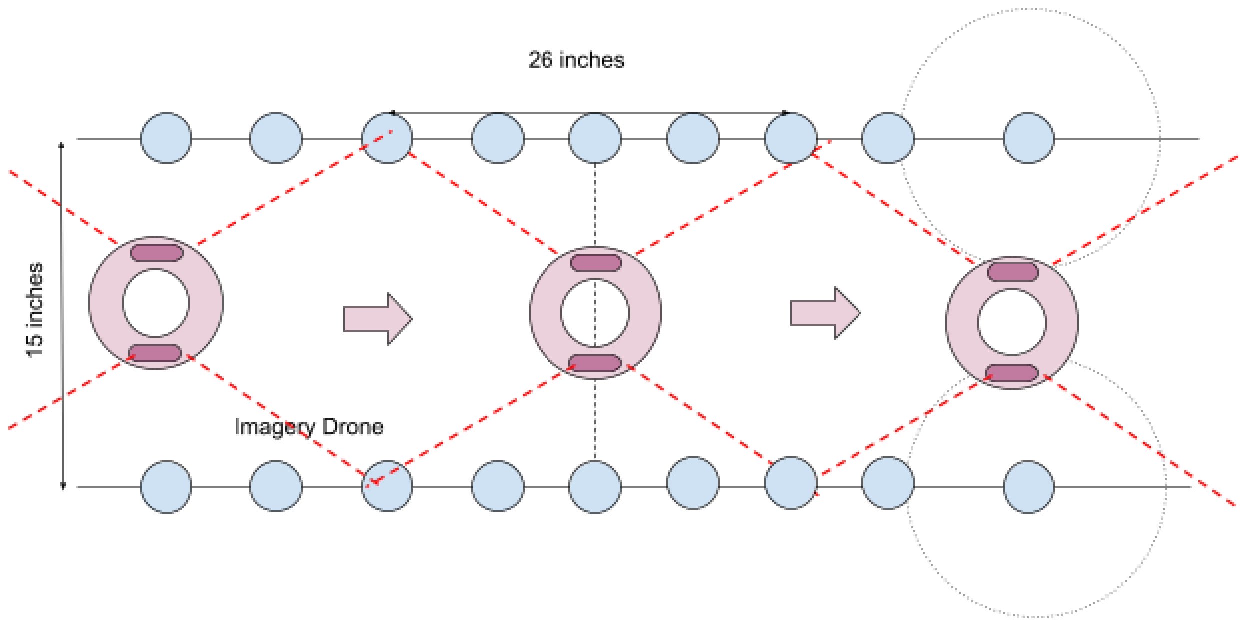



**Figure 39. Sketch of drone FOV.**

Assume usable HFOV = 120°

tan(HFOV/2) = tan(60°) = 1.732

Distance from camera to each row (camera centered)

d = (row spacing)/2

Usable row-length covered per frame

L = 2 d tan(60°) = 3.464

d = 1.732 × (row spacing)

FPS = 30

Max speed (no overlap)

v = L × FPS = 1.732 × (row spacing) × 30

v = 51.96 × (row spacing) inches/second

Convert inches/second to mph

1 mph = 17.6 inches/second

v(mph) = (51.96 / 17.6) × (row spacing) = 2.952 × (row spacing)

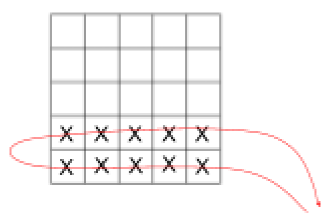
Row spacing 15 inches

L = 1.732 × 15 = 25.980 inches/frame

v = 2.952 × 15 = 44.3 mph

Case 1 — shortest sampling route

| Mission segment | Explanation | Calculation | Time |
|---|---|---|---|
| Pre-mission setup | The drone is taken out of its container and assembled. The Acer Aspire 14 AI laptop is powered on. The imagery module is attached, and the analyst confirms the live feeds of the six RGB-D cameras, the DAA camera, and GPS. This process should take no longer than five minutes. | Given | 5:00 |
| Imagery flight (in-field) | The drone flies between the center rows of each benchmark square to map all sample coordinates. With 15-inch row spacing, the calculated maximum flight speed is 44.3 mph. The total in-field flight distance is 2.9 miles. | 2.9/44.3 hr = 0.0655 hr = 3.93 min | 3:56 |
| Imagery flight (transit) | After surveying the field, the drone returns to ground control. The total round-trip distance between the field and ground control is 6.7 miles at 70 mph. | 6.7/70 hr = 0.0957 hr = 5.74 min | 5:45 |
| Imagery flight total | Total imagery flight time includes in-field surveying and transit to and from ground control. | 3:56 + 5:45 = 9:40 | 9:40 |

| | | | |
|---|---|---|---|
| Module replacement | After imagery collection, the imagery module is removed and replaced with the sampling module. This process should take no longer than five minutes. | Given | 5:00 |
| Sampling operations | At each sampling location, the drone hovers while the 6-DOF robotic arm retrieves the correct pod and places it into the rotating cartridge. Hovering, alignment, grabbing, depositing, and climbing back to flight altitude are estimated at 40 seconds per sample.  | 40 s × 10 = 400 s = 6.67 min | 6:40 |
| Sampling flight (shortest route) | The AI processor calculates the shortest route between sampling coordinates. The drone flies at 45 mph. | 7.1/45 hr = 0.1578 hr = 9.47 min | 9:28 |
| Sampling total | Total sampling time includes handling time and shortest-route travel time. | 6:40 + 9:28 = 16:08 | 16:08 |
| Post-mission teardown | After completing the mission, the drone and laptop are disassembled and returned to their containers. This process should take no longer than five minutes. | Given | 5:00 |

| | | | |
|---|---|---|---|
| Total mission time (Case 1) | Total benchmark mission time for the shortest sampling route. | 5:00 + 9:40 + 5:00 + 16:08 + 5:00 = 40:48 | 40:48 |

**Table 11. Mission stages timings and explanation for the shortest flight route**

Case 2 — longest sampling route

| Mission segment | Explanation | Calculation | Time |
|---|---|---|---|
| Pre-mission setup | The drone is assembled and all sensor feeds are verified prior to flight. | Given | 5:00 |
| Imagery flight total | Imagery mission includes in-field surveying and transit between the field and ground control. | 3:56 + 5:45 = 9:40 | 9:40 |
| Module replacement | The imagery module is replaced with the sampling module before the second flight. This process should take no longer than five minutes. | Given | 5:00 |
| Sampling operations | Ten total samples are collected, with 40 seconds required per sampling event. | 40 s × 10 = 400 s = 6.67 min | 6:40 |

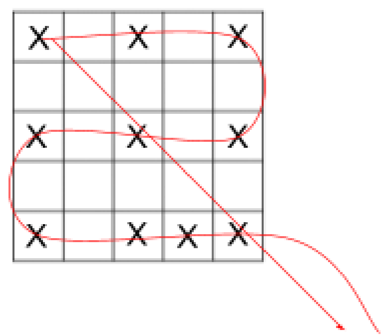
| | | | |
|---|---|---|---|
| Sampling flight (longest route) | In the worst-case configuration, sampling points are spread across the field. The drone flies the entire route at 45 mph.  | (3 + 3.7 + 1.5 + 0.2 + 0.2) mi = 8.6 mi → 8.6 / 45 hr = 0.191 hr = 11.47 min | 11:28 |
| Sampling total | Total sampling time includes handling time and longest-route travel time. | 6:40 + 11:28 = 18:08 | 18:08 |
| Post-mission teardown | The drone and laptop are disassembled and returned to storage. This process should take no longer than five minutes. | Given | 5:00 |
| Total mission time (Case 2) | Total benchmark mission time for the longest sampling route. | 5:00 + 9:40 + 5:00 + 18:08 + 5:00 = 42:48 | 42:48 |

**Table 12. Mission stages timings and explanation for the longest flight route**

The system retains communication by running a Happymodel ExpressLRS 915 MHz receiver on the drone with matching ground transmitters (documented 6.2-mile control/telemetry range) and then boosting the ground-station link budget by feeding the Acer Aspire 14 through a directional Yagi (RP-SMA) that's explicitly intended to maintain and receive the 6 RGB-D feeds, the robotic-arm camera, the DAA camera, and GPS across distance. A 6S 14,000 mAh (22.2 V, 14 Ah) pack stores about 311 Wh of energy (22.2×14). Using a conservative 80% usable budget to keep a landing reserve gives about 250 Wh usable. Sustained fixed-wing cruise for a ~4.5 kg aircraft is realistically in the ~400–600 W electrical range (because drag rises fast with speed and all onboard compute + cooling is continuous load), so endurance is ~250 Wh ÷ 600 W ≈ 25 min on the high-power end and ~250 Wh ÷ 400 W ≈ 38 min on the efficient end. That time window is the engineering basis for "battery can sustain the full benchmark mission" (and it's what gets validated by the flight log showing end-of-mission reserve rather than hitting low-voltage cutoff). Peak power events (takeoff/transition/climb) are not the limiting case because they are short-duration compared to cruise; the limiting case is always the average power over the whole mission, which is exactly what the voltage/current log captures.

## 3.3 Safety Requirements

### *3.3.1 Detect and Avoid*

The location of the decision making process is at the ground control station as the drone crew consisting of the pilot and the drone monitor can easily relay information to one another in close proximity. The monitor withholds the information regarding the drone's view and position, which is vital when making decisions such as maneuvering around objects. The drone's view will be implemented through a camera embedded in the nose of the drone frame.

This camera is being powered by the dual Raspberry Pi system, connected to the ground control station, with a staff member (with an AI model's help at ground control) watching it carefully so as to not waste processing power of the two Raspberry Pis. If the visual observer or the AI model sees an obstacle 40 feet away (to account for the flying distance in the transition to hovering), the pilot will flip a switch to send a signal to and take control over the drone. If the obstacle is cooperative, the drone will wait for it to pass, and if un-cooperative, he/she will fly around it. From there, the pilot will move the drone back into the rows safely and continue monitoring or taking samples.

### *3.3.2 Lost Link Protocol*

If there is any level of loss of communication, a pilot will take over the AI with the press of a button(sending a signal) and stop the drone midair. He/she will fly the drone slightly farther to test the connection, and if it still holds, the mission will continue. If communications get worse, the pilot will bring the drone all the way back to ground control for maintenance and assessment for any level of damage. If there are any pedestrians, objects or other aircraft in the way, the pilot will manually fly around it.

Protocol in the case of total loss of communication is much simpler. The drone will have the coordinates of ground control saved in its Ardupilot software, and when communication is lost, it will automatically fly directly to those coordinates. Then, maintenance and resetting will be done on the drone.

#### *3.3.3 Integration with Manned Aircraft and Other Aircraft*

The requirements to intricate UAS successfully and safely into flight with other aircraft in the area is through coordination with cropdusters and pesticide-spraying UAS. While the sampler is flying through the field collecting samples, a separate crew can operate any sort of pesticide spraying aircraft and spray the general vicinity of the sampled plant. This wildly reduces chemical and labor costs and makes pest management more environmentally friendly.

#### *3.3.4 Additional Safety*

The team discussed the addition of a GPS tracker on the drone and support equipment in the form of waypoints. A drone crew member will monitor the GPS at all times. If the drone ever veers off course or flies off the field entirely, another staff member will press a button on the controller to send a signal to the drone to stop and go to the nearest waypoint. The drone will fly to the waypoint, land, and wait for maintenance. If there are people or other aircraft in the way, the drone pilot will manually override the AI by pressing a button on the controller that sends signals to the drone to have it stop moving forwards. The pilot will then manually drive the drone to the waypoint around the objects. Then, it will reset and continue the mission.

# Business Case

## 4.1 Cost Analysis

#### *4.1.1 Operating Costs*

Below is a table of all operating costs for the benchmark mission.

**kTable 13. Personnel and operating costs.**

| Cost item | Case 1 (shortest route) | Case 2 (longest route) | Notes |
|---|---|---|---|
| Mission total time | 40:48 | 42:48 | Used for operator + pilot time (whole mission) |

| | | | |
|---|---|---|---|
| Operator pay | $34.00 | $35.67 | $50/hr × (mission hours) |
| Pilot pay | $23.80 | $24.97 | $35/hr × (mission hours) |
| Payload operator pay | $9.41 | $10.58 | $35/hr × (second-flight time = sampling total) |
| Total personnel cost | $67.21 | $71.22 | |
| Total flight time (battery-used time) | 25:48 | 27:48 | Flight time = imagery flight (9:40) + sampling total (16:08 or 18:08) |
| Energy used (Wh) | 172–258 Wh | 185–278 Wh | Energy = power × flight time, using 400–600 W cruise range |
| Electricity cost (at $0.16/kWh) | $0.03–$0.04 | $0.03–$0.04 | Cost = (Wh/1000) × $/kWh. |
| Total operating cost (personnel + electricity) | $67.24–$67.25 | $71.25–$71.26 | Electricity is tiny vs labor. |

### *4.1.2 Fixed Costs*

Below is a table of all the fixed costs of the drone

| System Category | Component | Quantity | Estimated Unit Cost (USD) | Subtotal (USD) | Justification |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| **Air Vehicle** | Carbon fiber fuselage (custom fabricated) | 1 | $180 | $180 | Primary structural body required to support wings, modules, and electronics |
| | Carbon fiber wings (2 m total, foldable) | 1 set | $220 | $220 | Required for efficient fixed-wing forward flight during benchmark mission |
| | Carbon fiber booms (43 in × 2) | 2 | $40 | $80 | Supports empennage and rear propulsion system |
| | Empennage (horizontal + vertical fins) | 1 | $60 | $60 | Provides pitch and yaw stability during cruise |
| | Landing gear + hinges | 1 set | $45 | $45 | Required for safe takeoff, landing, and container stowage |
| **Air Vehicle Subtotal** | | | | **$585** | |
| **Propulsion & Power** | T-Motor AT3520 motor | 5 | $70 | $350 | Main propulsion for VTOL/fixed-wing hybrid flight |
| | ESC 80A | 1 | $45 | $45 | Motor control |
| | Speed controller | 5 | $37 | $185 | Augments the speed of motors |

| | | | | | |
|---|---|---|---|---|---|
| | Carbon fiber propellers | 5 | $20 | $100 | Efficient thrust and durability |
| | 6S 14,000 mAh (22.2 V) LiPo battery | 1 | $207 | $207 | Provides sufficient endurance for benchmark mission |
| | Power modules & PDB | 1 set | $50 | $50 | Safe power distribution to avionics |
| | 2 vents, 2 fans, centrifugal blower | 1 | $156 | $156 | Regulates temperature to prevent overheating |
| **Propulsion Subtotal** | | | | **$1113** | |
| **Payload – Imagery Module** | OAK-D-Lite RGB-D cameras | 6 | $149 | $894 | Required to detect soybean pod damage across multiple rows |
| | Model Training | | $50 | $50 | Backbone of damage detection |
| | Raspberry Pi 5 (8 GB) | 2 | $80 | $160 | Onboard AI processing |
| | AI HAT+ (26 TOPS) | 2 | $70 | $140 | Enables real-time CV inference |
| | Camera shafts, mounts, servos | 1 set | $120 | $120 | Positions cameras between crop rows |

| | | | | | |
|---|---|---|---|---|---|
| **Imagery Payload Subtotal** | | | | **$1,314** | |
| **Payload – Sampling Module** | 6-DOF robotic arm | 1 | $180 | $180 | Required to retrieve soybean pod samples |
| | Arm camera | 1 | $35 | $35 | Visual confirmation during sample collection |
| | Rotating cartridge storage | 1 | $60 | $60 | Stores ten samples securely |
| | Servos and control electronics | 1 set | $90 | $90 | Enables precision movement |
| **Sampling Payload Subtotal** | | | | **$365** | |
| **C3 (Command, Control, Communication)** | Pixhawk flight controller | 1 | $120 | $120 | Executes autonomous and assisted flight |
| | ExpressLRS 915 MHz receiver | 1 | $35 | $35 | Long-range control and telemetry |
| | ExpressLRS transmitter | 2 | $160 | $160 | Pilot/payload command input |
| | GPS module (HGLRC M100 Pro) | 1 | $25 | $25 | Navigation and return-to-home |

| | | | | | |
|---|---|---|---|---|---|
| | Antennas (Bardpole + cabling) | 1 set | $40 | $40 | Reliable communication |
| **C3 Subtotal** | | | | **$380** | |
| **Ground Equipment** | Acer Aspire 14 laptop | 1 | $700 | $700 | Ground control station and data visualization |
| | Directional Yagi antenna | 1 | $60 | $60 | Maintains long-range communication |
| | Controllers (pilot + payload) | 2 | $60 | $120 | Required human-in-the-loop operation |
| | Ground container & mounting | 1 | $50 | $50 | Transport and mission setup |
| **Ground Equipment Subtotal** | | | | **$930** | |

**Table 14. Fixed costs of drone parts.**

**Total Fixed System Cost**

**≈ $4,667**

## 4.2 Logistics Details

The drone team will consist of three people.The first will be the pilot, who will fly the drone and be responsible for all of its movement. This includes hovering and aligning the drone during sampling and operating the drone in the DAA and lost link protocol. All other movements will be autonomous.

The second will be the data analyst, who watches the feeds from the RGB-D and DAA cameras. On the off chance the AI processor does not catch a damaged plant, the analyst will notify the pilot to press a button that will map the spot in the Ardupilot software. If the Acer Aspire AI model does not catch an obstacle in the distance, he/she will tell the pilot to stop the drone and act on the DAA protocol.

The third will be the payload operator, who operates the 6DOF arm during sampling. Once the pilot hovers over and aligns the drone on a plant, the payload operator will use the controller to precisely grab the sample, whether it be a leaf or a pod, put it in the rotating cartridge, rotate the cartridge for the next sample, and let the AI continue its wayfinding mission.

## 4.3 Economic Impact

Below is the table of pesticide use cost for different methods(the team's method is done after the samples are taken so that the spraying drone will know exactly where to spray)

**Table 15. Cost comparison of different pesticide spraying strategies**

| Metric | No mitigation | Manual spraying | UAS full-field spray (100%) | Team Galaxy targeted spray (40%) |
|---|---|---|---|---|
| Baseline crop loss (all pests, Maryland) | 160 × 21.49 = $3,438.40 | same | same | same |
| Crop loss avoided (economic benefit) | $0.00 | $3,438.40 | $3,438.40 | $3,438.40 |
| Acres sprayed | 0 | 160 | 160 | 64 |
| Pesticide reduction vs full-field | — | 0% | 0% | 60% less pesticide |
| Pesticide cost per acre | — | $14 | $14 | $14 |
| Chemical cost | $0 | $2,240 | $2,240 | $896 |
| Labor method | none | manual backpack/ tractor | UAS crew | UAS crew |
| Labor time (hours) | 0 | 160.0 hr | 0.640 hr | 0.524 hr |

| | | | | |
|---|---|---|---|---|
| Labor cost | $0 | $2,400 | $54.40 | $115.79-$115.80( TG-1 + separate targeted spray) |
| Electricity used | 0 | 0 | 256–384 Wh | 210–314 Wh |
| Electricity cost | $0 | $0 | $0.04–$0.06 | $0.03–$0.05 |
| Total mitigation cost (chemical + labor + electricity) | $0 | $4,640 | $2,294.44–$2,294.46 | $1,011.82–$1,011.85 |
| Net economic impact (profit gained) | –$3,438.40 | –$1,201.60 | $1,143.94–$1,143.96 | $2,426.55–$2,426.58 |
| Additional gain vs manual spraying | — | — | +$2,345.55 | +$3,628.15–$3,628.18 |

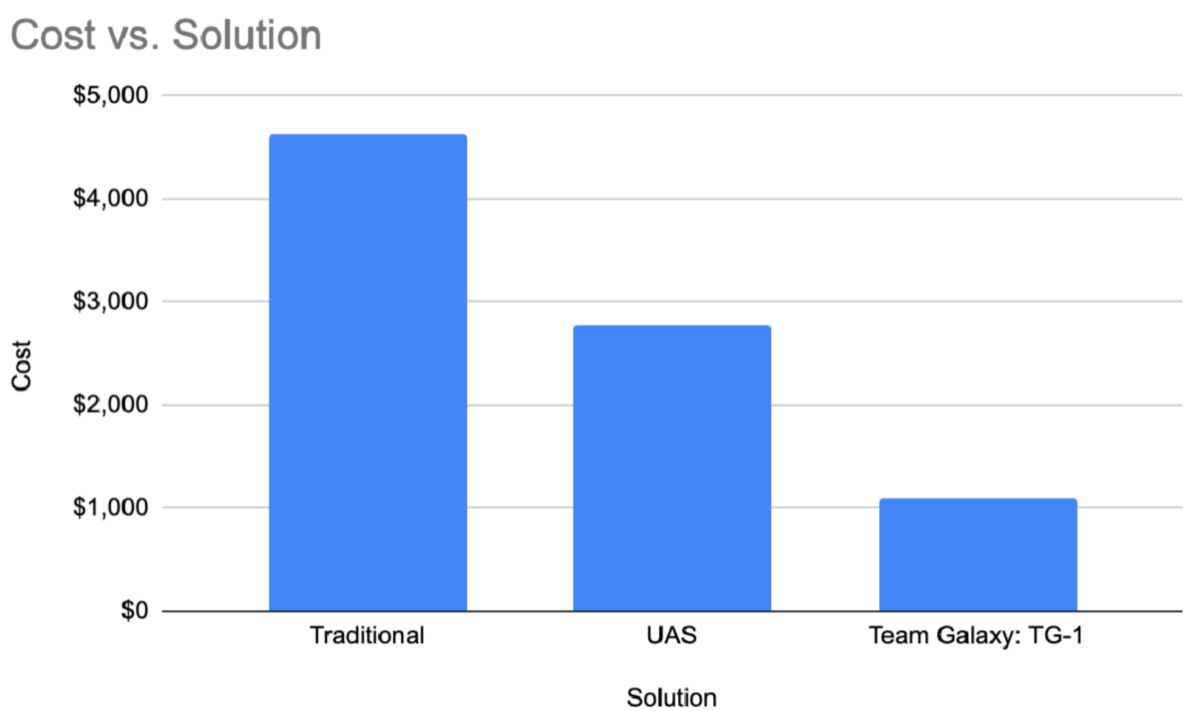



**Figure 40. Comparison of pest management methods**

This system improves farm economics in three ways: it reduces crop loss by finding pest damage early enough to take action, it reduces mitigation inputs by spraying only the damaged areas instead of the entire field, and it reduces labor by replacing slow, manual scouting and spraying with a single UAS mission. The targeted approach also saves resources because less chemical is applied, which lowers material use and reduces unnecessary exposure to beneficial insects and non-damaged plants. It saves around $3600 per farm per year, then with 12,000 soybean farms, it saves $4320000 per year. Operationally, the mission is short and repeatable, so labor becomes a small part of the workflow compared to manual methods that require many hours per field. Overall, the economic impact comes from turning the same loss-avoidance benefit into a lower-cost response by minimizing pesticide use and minimizing human time required to detect and treat damage.

# Public Affairs/Communications Plan

## 5.1 Public Relations Strategy Template

### *5.1.1 Background and Purpose*

The design challenge was to design an autonomous drone, capable of detecting signs of pest damage and taking samples from damaged plants to use for analysis and targeted pesticide spraying. Pests, stinkbugs and corn earworms being the worst, cause significant yield loss by feeding on soybean pods, most often before damage is visible from the ground. Early detection is critical for farmers to respond quickly, reduce pesticide overuse, and protect crop yields. The challenge matters because traditional scouting methods are time-consuming, labor-intensive, and often miss early-stage damage across large fields. The drone must integrate computer vision, RGB-D imaging, precise navigation, and an efficient airframe while operating reliably in outdoor agricultural environments. The design also must be affordable, easy to use, and safe. Solving this problem supports sustainable agriculture by improving efficiency, reducing chemical inputs, and improving food safety.

The team's public relations strategy focuses on framing the drone as a farmer-focused, sustainable solution rather than just a piece of technology. Messaging will emphasize real-world benefits such as early pest detection, cost saving, reduced pesticide use, and greater crop yields. The team plans to demonstrate the drone's capabilities at agricultural expos, form partnerships with local farms, and share clear visual data from test flights to build credibility and trust. Other online content, such as short videos, infographics and case studies will be used to show how the drone works in simple, easy-to-understand terms and show measurable results from trials. This transparency will be crucial for communication with farmers, investors, and other audiences.

A public relation strategy in this scenario is critical since agricultural drones already face skepticism regarding cost, durability, and regulatory concerns. Even a perfect product could fail if stakeholders don't trust it. Public relations helps translate complex engineering into clear value propositions, ensuring that investors will see the drone as a practical tool rather than something experimental.

Besides engineering challenges, gaining support could be difficult due to skepticism, farmer resistance to new technology, concerns on return on investment, and fears of job displacement. Data privacy and limited awareness about precision agricultural tools may also create hesitation. Addressing these issues through proactive communication, education, and transparency is essential for building long-term support for the project.

By identifying exactly where pest damage is occurring, caused by what species, and assess how severe the damage is not and will be, the system allows farmers to reduce unnecessary pesticide application and lower labor costs. This targeted approach protects crop yield and quality while improving overall return on investment and supporting more sustainable farming practices.

### *5.1.2 Audience and Messaging*

The team's primary audience includes farmers, drone crews and researchers (see table 2 and 3), with the team trying to connect with farmers as they are the producers of the soybean crop, which has a massive effect on the US and even an effect on our local economy. The team also connected with pest management personnel as they spent their lives researching ways for more efficient pest management in order to contribute to the economic stability and soybean production.

However, these groups are plagued with a buildup of pesticide use which is very expensive. With that, the team wanted to design a drone of their own that not only contributes to pest management through monitoring the behaviors of stinkbugs but also collects samples for research. This way, scientists and biologists can continue to discover ways to minimize pest damage and discover new, effective methods to increase crop yield through pest removal.

The team's secondary audience includes drone engineers and drone service providers. They want to connect with these groups as they have indirectly contributed to the design process of the team's aircraft and informed the team of how drone service is typically performed. The team wants to design a drone that can be actively innovated upon and actually used in the future for its intended purpose.

The final audience is the government, who are responsible for regulations. For an industrial grade drone like this, we'll need to pass certification exams and background checks. From there, the stakeholder is satisfied and we'll be allowed to fly.

Overall, the team is striving for a taste of real-world contribution. Whether its pest research or drone designing, the team connected with these groups in order to achieve that goal. Hopefully, this design will allow those goals to take shape.

## 5.2 Products to be Created

Live demonstration of drone use through popular social media platforms (TikTok, Twitter, Youtube, Instagram)
Calculations of money saved on chemicals, yield loss, and listing of all benefits non-economic(less damage to environment, researchers devising better pest management methods like stronger pesticides)

Below is a flyer to be made and posted on social media


**Figure 41: Flyer of Drone and benefits**

## 5.3 Distribution Plan

We will first build a corporation website as a flagship platform to demonstrate our unique value proposition. The team will post live demonstrations, break down costs and profits, collect evaluations from experts and farmers alike, and show improvement. We will have a comprehensive plan for distribution, combining special channels (Extension programs), Expo (conventions) and digital channels (social media) to build an effective user acquisition funnel.

A cornerstone of this strategy is collaboration with land-grant university extension programs. These programs maintain trusted advisory relationships with farmers, agribusinesses, and local cooperatives, making them uniquely positioned to serve as both technical validators and distribution amplifiers. We've built relationships through our mentors at

UMD Extension who are very supportive to help engage with farmers. We will begin with UMD Extension and expand to parallel Extension networks nationwide. By integrating the drone system into Extension-led demonstration trials, field days, and pest management workshops, the product gains immediate credibility while reaching highly targeted end-users at the point of need.

Agricultural expos will be leveraged to for the messaging and media products go out to farmers and researchers through. The team would go to every major expo in Maryland, such as Maryland State Fair, Great Frederick Fair, Washington County Ag Expo and Montgomery County Agricultural Fair.

In addition, demonstrations of the drone will be posted on major social media platforms, such as Youtube, Instagram, Facebook, and Twitter. This spreads the drone to a wider audience and will help to configure improvements.

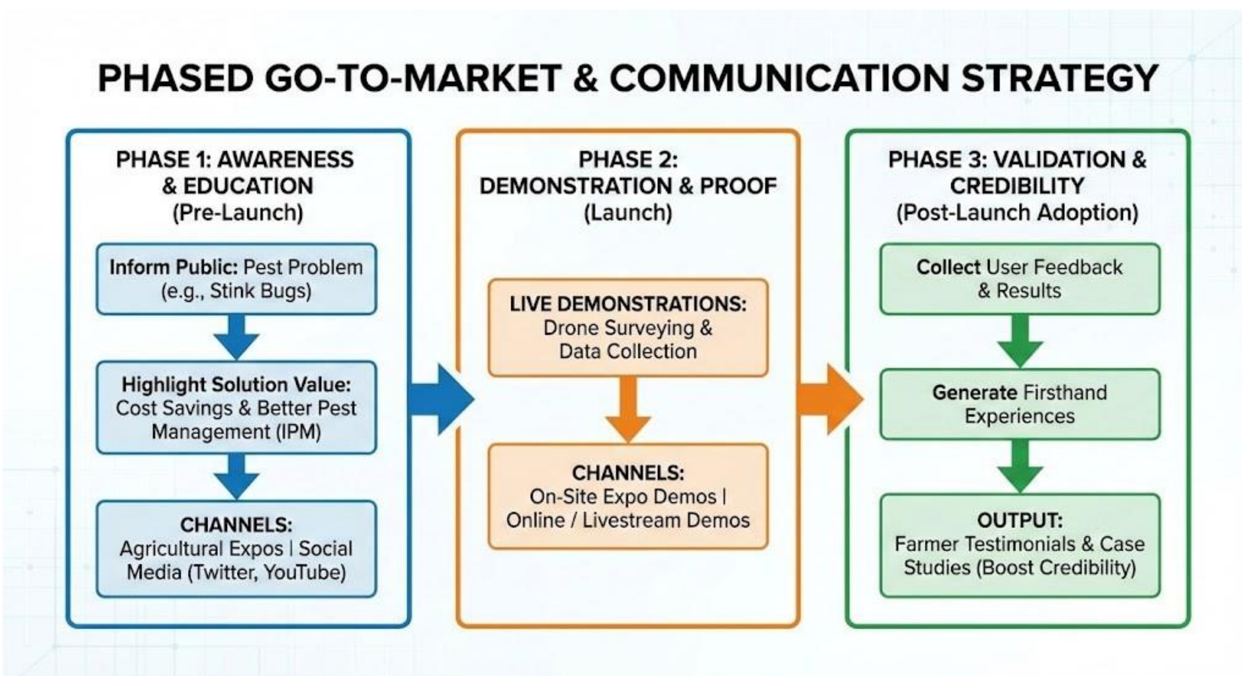



**Figure 42: Action Plan**

The media will be distributed through a phased action plan. The first step is to inform the public of the pest problem, such as the stink bugs, and show in full how the drone will save money and help develop better pest management methods. These tasks will be done at both expos and posted on social media(Twitter, Youtube). After it launches, the team will do live demonstrations at expos and online of how it surveys farmland and collects samples. Finally, when it starts to catch on and get used, the team will collect farmer testimonials about the drone and its results, which will provide firsthand experiences that boost its credibility.

Farmers are quite weary of high up front costs. However, from Tao Chen's advice, if benefits increase from the product's use, people will use it. UAS are already used to spray pesticides over fields, and our product reduces costs on said chemicals, and that combined with saving on time and labor costs will give them no reason to refuse. From there, the testimonials will convince more farmers to adopt the product.

# Conclusion

Team Galaxy applied engineering innovation to address real agricultural problems.  Our periscope design reaches under the canopy of crops to detect abnormalities that other drones might never reach. The systems are powered by high-end AI processors and we also have an industry leading navigation system that promises precise pinpointing of damaged crops. These two aspects combined with our VTOL airframe allows us to solve an unbounded amount of pest control issues and also helps us to solve them more quickly and efficiently.

By identifying exactly where pest damage is occurring, TG-1 is the only agricultural drone that allows farmers to reduce unnecessary pesticide application by 60% and lower labor costs, achieving a net gain of around $3,500 from manual spraying. This targeted approach protects crop yield($10.9 million in Maryland and $1.8 billion in US) and quality while improving overall return on investment and supporting more sustainable farming practices.

The NASA Dream With Us Challenge provided a unique opportunity to build systems-level thinking, strengthen interdisciplinary STEM skills, and prepare team members for future careers in science, engineering, and innovation. Through this project, Team Galaxy experienced the full innovation management process — from problem discovery and field research, to engineering design, economic validation, and strategic pivoting. By combining engineering creativity, agricultural insight, and economic reasoning, the team transformed an initial idea into a solution grounded in real-world feasibility.

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