

Drones, Data, and Artificial Intelligence: A Multidisciplinary Model for Experiential Learning in Agriculture (Work-in-Progress)

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Modern farming presents complex, real-world challenges that cannot be solved from a single disciplinary perspective. At York College of Pennsylvania, we developed a project-based learning initiative that integrates engineering, horticulture, computer science, and environmental sciences with the use of drones, artificial intelligence (AI), multispectral imaging, and field-based testing. Students learn to operate drones under FAA licensing requirements, program autonomous flight missions, and process multispectral imagery using specialized software. These skills are coupled with soil and tissue sampling, laboratory analysis, and the study of farm-specific environmental stressors such as pests, fungi, and weather conditions.

The program was made possible through external grant funding, which allowed us to compensate students for their research contributions and thereby deepen their engagement with local farms of varying types and scales. Faculty across departments collaborated to connect student teams with farmers, who provided authentic problems ranging from disease detection to yield prediction. Early measures of success include more than doubling student participation for the upcoming planting season, the creation of actionable reports for partner farms, and strong qualitative feedback from both students and community stakeholders. At its core, the program is structured around five integrated components: (1) drone-based multispectral data acquisition; (2) integration of aerial imagery with ground-truth soil and tissue sampling; (3) AI-enabled image and yield analysis; (4) multidisciplinary student teams; and (5) farmer-facing reporting that creates authentic accountability.

This paper describes the pedagogical structure of the program, with emphasis on how external funding shaped student motivation and project outcomes. We present examples of student–farmer collaborations, outline strategies for coordinating multidisciplinary faculty teams, and share testimonial evidence that highlights both the educational impact and the practical value for participating farms. By documenting this experience, we aim to offer a replicable model of grant-supported, multidisciplinary, experiential learning that benefits students, faculty, and community partners alike.

1. Introduction

Experiential and project-based learning (PBL) are now widely recognized as high-impact practices in engineering and STEM education. Over the past three decades, engineering programs have adopted laboratories, design projects, service-learning, and community-engaged research experiences to help students connect theoretical content to authentic problems and professional practice [1]. Systematic reviews of experiential learning in engineering report that such activities can enhance students' technical skills, teamwork, communication, and professional identity, while also strengthening connections among self, school, and community [1]. Within the broader education literature, experiential learning has been linked to increased motivation, classroom engagement, and long-term student success [2, 3].

This shift toward experiential pedagogies has coincided with calls for greater methodological diversity in engineering education research. Borrego, Douglas, and Amelink argue that quantitative, qualitative, and mixed methods each play an essential role in building evidence about student learning, and that no single approach should be considered inherently more rigorous than the others [4]. Kelly and Bowe similarly highlight the value of qualitative methods, such as interviews, focus groups, and reflective writing, for capturing how students experience complex learning environments, particularly when programs span multiple disciplines and stakeholder groups [5]. Recent reviews of experiential learning in engineering show a landscape that includes exam scores and surveys alongside rich qualitative analyses of student reflections and stakeholder narratives [1]. This methodological pluralism is especially important for early-stage programs where sample sizes are small, contexts are highly local, and much of the impact is affective, relational, or identity-based.

Drones, remote sensing, and data-driven agriculture provide a compelling context for experiential learning at the intersection of engineering, computer science, and the applied life sciences. Prior work has used unmanned aerial vehicles (UAVs) as a platform for teaching STEM concepts, demonstrating gains in student engagement and perceived relevance of course material [6]. In agricultural settings, project-based experiences with multispectral imagery and on-farm data collection have been used to connect classroom content to real production challenges such as disease detection and yield monitoring [7, 8]. These studies suggest that working with authentic agricultural data can help students see the societal value of their technical skills while simultaneously delivering actionable information to community partners.

Another strand of research emphasizes the role of paid undergraduate research and experiential opportunities in shaping student participation and learning. Compensation is increasingly recognized as an equity issue: unpaid research positions disproportionately exclude students who must work for pay, particularly those from low-income and underrepresented backgrounds [8, 9]. Reviews of diversity-focused undergraduate research programs highlight stipends, structured mentoring, and authentic research tasks as key design features that promote persistence and a sense of belonging in STEM [10]. Côté further argues that paying undergraduate researchers is pedagogically meaningful because it allows students to devote sustained time to complex projects, deepens accountability to partners, and positions students as legitimate contributors rather than volunteers [8]. Taken together, this literature suggests that funding models are not merely logistical details but central components of the learning environment.

The work reported in this paper is situated at the intersection of these lines of inquiry. At York College of Pennsylvania, we developed a grant-supported, multidisciplinary program in which students from engineering, horticulture, computer science, and environmental science collaborated with local farmers to address real farm problems using drones, multispectral imaging, artificial intelligence (AI), and field-based testing. Building on prior PBL initiatives involving drone-based multispectral analysis of crops [10] and related efforts in sustainable robotic agriculture [7], the program intentionally compensated undergraduate students for their research contributions. Our early assessment data consist primarily of qualitative evidence: written testimonials from students, reflections from faculty mentors, and feedback from partner farms regarding the perceived value of the collaboration.

Guided by the literature above, we treat these narratives not as anecdotal add-ons but as central data for understanding how a paid, multidisciplinary, community-engaged research experience shapes student learning and motivation [1–5]. Specifically, this paper (1) describes the pedagogical structure of the program and the role of external funding in enabling sustained student participation; (2) presents qualitative evidence of student learning, identity development, and motivation drawn from testimonials and reflections; and (3) documents how farmers and community partners perceive the practical value of student-generated reports and analyses. By doing so, we aim to contribute a replicable model of grant-supported experiential learning that leverages drones and AI in agriculture while foregrounding the importance of both qualitative assessment and student compensation.

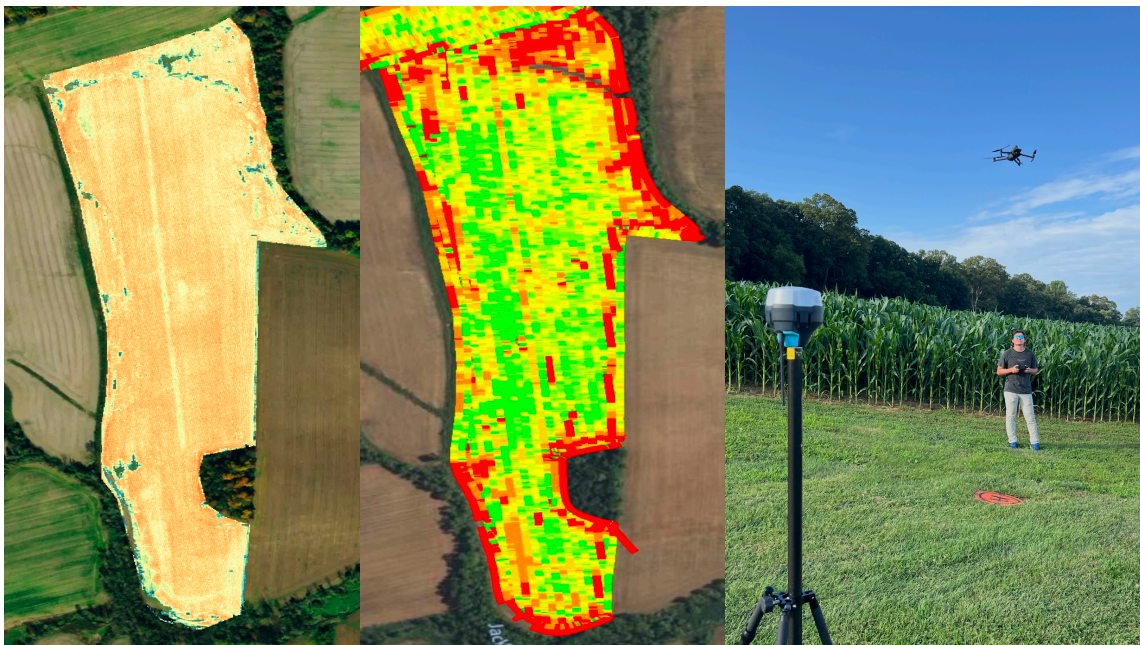
While prior work has examined UAV-based STEM instruction [6] and project-based agricultural analysis [7,10], the present initiative differs in three important respects. First, students engage in a full end-to-end workflow that integrates aerial sensing, harvester yield data, laboratory sampling, and farmer-facing reporting. Second, the program is intentionally structured as paid undergraduate research to promote sustained engagement and accountability to community partners. Third, artificial intelligence and analytics are integrated not as isolated technical exercises, but as tools embedded within real farm decision contexts. Together, these elements create a model that extends beyond traditional PBL by coupling multidisciplinary technical integration with authentic stakeholder impact.

In response to the literature on experiential learning, methodological pluralism, and compensated undergraduate research, the drones–data–AI initiative was intentionally structured to operationalize these principles within a real agricultural context. The following section describes how these theoretical commitments were translated into concrete program design, multidisciplinary implementation, and community-engaged workflows.

2. Program Context and Design

York College of Pennsylvania is a primarily undergraduate institution located in a region with a strong agricultural presence, including small family-owned farms and mid-sized commercial operations. In recent years, local growers have expressed interest in using drone-based imaging and data analytics but have lacked the time, equipment, or technical background to implement these tools on their own. This context provided a natural opportunity to connect undergraduate STEM education with real community needs.

The work students conduct in this program is inherently multidisciplinary. On the engineering side, students plan and fly missions with multispectral drones, then download and merge hundreds of overlapping images into a single georeferenced mosaic (GeoTIFF). Using software such as Pix4D, they compute vegetation indices, most commonly NDVI, to visualize spatial variation in crop vigor and potential stress across a field (Figure 1). Students also analyze yield and moisture maps generated by tractor-mounted harvesters and yield monitors (Figure 2), learning how ground-based sensing complements aerial imagery when interpreting field performance. (Figure 3) shows the student landing the aircraft after the flight. These tasks require not only familiarity with drone hardware and image-processing tools, but also a working understanding of coordinate systems, file formats, and data management. One might note the similarity between the drone image and the harvest data; this correlation is routinely observed in corn and soybean fields and will be the focus of a future technical publication.



Figures 1-3. NDVI, Harvester and Flight Respectively

Equally important are the agronomic and environmental dimensions of the work. To interpret the patterns observed in NDVI¹ or yield maps, students must engage with basic farming practices, including soil testing, plant tissue analysis, and pest and disease scouting. During field days, they collect soil cores and leaf samples from specific zones identified in the imagery, label and prepare these samples for laboratory analysis, and record metadata needed to connect lab results back to field locations Figures 4-6. Putting these pieces together, drone imagery, harvester data, field work, lab reports, and farmer knowledge, requires students to integrate concepts from engineering, computer science, horticulture, chemistry, and environmental science. Many of the most meaningful learning experiences reported by students come from this full “end-to-end” workflow: being on the farm, collecting and preparing samples, and then returning to the lab to synthesize all the data into actionable information for the farmer. This end-to-end structure was

¹ NDVI: Healthy plants strongly reflect near-infrared (NIR) light $NDVI = (NIR - Red) / (NIR + Red)$

intentionally designed to align with experiential learning theory, which emphasizes iterative cycles of action, reflection, and application [1–3]. By requiring students to move from data collection to interpretation to stakeholder communication, the model extends beyond technical task completion and situates learning within authentic decision contexts.

The drones–data–AI program described in this paper emerged from an externally funded initiative designed to: (1) give students sustained, hands-on experience with unmanned aerial systems and agricultural data; (2) foster collaboration across engineering, horticulture, computer science, and environmental science; and (3) generate analyses and reports that participating farmers could use in decision-making. Grant funds were used to purchase and maintain drones and multispectral cameras, license image-processing software, and, critically, pay undergraduate students for their research contributions.

Students were recruited from multiple majors through coursework, faculty recommendations, and departmental announcements. Depending on their background, students joined the project as



Figures 4-6. Field Work Soil Samples and Lab Preparations Respectively

drone pilots, image-processing specialists, data analysts, or field/laboratory assistants. All students received introductory training on FAA regulations and safety, basic mission planning, and data-handling protocols. Engineering and computer science students typically focused on flight planning, automation, and analysis scripts; horticulture and environmental science students focused on soil and tissue sampling, crop scouting, and interpretation of biological and environmental stressors.

Faculty from the participating departments met regularly to identify partner farms and define project scopes. Each farm collaboration followed a similar workflow:

1. **Problem framing:** Farmers described specific concerns (e.g., suspected disease, variable yield, irrigation issues).
2. **Mission design and data collection:** Student teams planned and executed drone flights, collected multispectral imagery, and coordinated ground-truth sampling.
3. **Data processing and analysis:** Students processed imagery using specialized software, generated vegetation and stress indices, and combined these with soil or tissue test results.
4. **Reporting and feedback:** Teams prepared farm-specific reports, met with farmers to discuss findings, and recorded reflections on both technical and educational outcomes.

Unlike many UAV-based instructional models that focus primarily on flight proficiency or isolated image analysis tasks, this initiative embeds drone operations within a multidisciplinary agricultural decision workflow that culminates in farmer-facing reporting. The deliberate integration of aerial sensing, ground-truth sampling, laboratory analysis, and AI-supported interpretation creates a level of systems integration and stakeholder accountability not typically present in single-course project, capstone, or service-learning formats.

The program ran across multiple semesters and summers, combining formal coursework with paid research appointments. Because students were compensated, they could commit substantial time to the projects during peak growing seasons, return across multiple terms, and take on increasingly complex responsibilities. To clarify the structural features of the drones–data–AI initiative, we summarize here the core design components that distinguish this model from more traditional project-based learning implementations. While individual elements such as drone flights or soil sampling are not unique in isolation, their intentional integration within a sustained, community-facing framework defines the program’s pedagogical architecture.

1. End-to-End Agricultural Data Workflow.

Students engage in a complete workflow that begins with mission planning and drone-based multispectral data acquisition and extends through image mosaicking, NDVI and yield map analysis, targeted ground-truth sampling, laboratory testing, and farmer-facing reporting. This full-cycle structure requires students to connect sensing technologies, biological interpretation, and decision communication rather than working on isolated technical tasks.

2. Integration of Aerial, Ground, and Laboratory Data.

Rather than treating drone imagery as a standalone dataset, students are required to triangulate aerial observations with harvester yield data, soil cores, tissue samples, and farmer knowledge. This layered approach reinforces systems thinking and exposes students to the complexity of real agricultural decision-making.

3. Multidisciplinary Team Structure.

The program intentionally assembles teams from engineering, computer science, horticulture, and environmental science. Responsibilities are differentiated but interdependent, requiring students to translate across disciplinary boundaries and develop professional communication skills in authentic contexts.

4. Embedded Artificial Intelligence and Analytics.

AI and data-processing tools are incorporated not as classroom exercises but as operational tools within real farm projects. Students learn to apply image analysis and scripting methods to datasets that directly inform field interpretation and farmer reports.

5. Farmer-Facing Accountability.

Each project culminates in a deliverable presented to the partner farm. This reporting requirement introduces authentic accountability, professional standards, and iterative feedback rarely present in simulated classroom projects.

Taken together, these five components define the program's design logic. External funding enabled initial implementation and student compensation; however, the core structure rests on the integration of technology, multidisciplinary collaboration, and community partnership rather than on grant support alone. The sections that follow examine how this grant-supported, multidisciplinary structure shaped student learning and motivation, drawing primarily on qualitative accounts from students, faculty, and community partners.

While initial implementation was accelerated through external grant support, the structural elements of the program are intentionally designed to be sustainable beyond the grant period. Many project costs align with existing institutional and agricultural practices. For example, partner farms already allocate funds for soil and tissue sampling, which can be integrated into the educational workflow without additional expense. Drone platforms and multispectral cameras are reusable across multiple seasons, and image-processing software licenses are shared across courses and research projects. In addition, components of the program are being embedded into existing coursework, capstone experiences, and undergraduate research credits, reducing reliance on external stipends over time. These mechanisms position the model as scalable and transferable rather than grant-dependent.

3. Methods

3.1 Research Design

This study adopts a qualitative descriptive design aligned with the methodological pluralism² advocated in the engineering education literature [1–5]. Rather than privileging a single “best” method, we treat different forms of evidence, surveys, reflections, and stakeholder narratives, as complementary lenses on student learning and motivation. Given the small number of participants and the early stage of the program, this Work-in-Progress paper focuses on rich qualitative accounts from students who participated in the drones–data–AI initiative at York College of Pennsylvania. These narratives allow us to examine how students describe the impact of paid, multidisciplinary, community-engaged research on their learning, identities, and relationships with local farmers.

3.2 Participants and Context

The drones–data–AI program described in Section 2 engages undergraduate students from engineering, horticulture, computer science, and environmental science in collaborative projects with local farms. Students are hired as paid research assistants and typically participate for one or more growing seasons, combining drone flights, multispectral image processing, soil and tissue sampling, and report preparation for partner farms.

At the time of writing, we had collected written testimonials from three former student researchers who had completed at least one season of work on the project. These students represent different roles within the program, including drone operations and Pix4D analysis, soil

² “Following a methodological pluralist perspective, we treat surveys, student testimonials, and stakeholder narratives as complementary forms of evidence, selecting quantitative and qualitative methods based on the questions we are asking rather than assuming that any one approach is inherently more rigorous.”

and leaf sampling, and general field support. Their reflections were originally written in response to an invitation from the faculty lead to “describe what you learned from the project, how it affected you, and how you see it benefiting farmers and the college.”

To protect confidentiality in this paper, we refer to these students using pseudonyms (Student A, Student B, and Student C) and remove any identifying details about specific farms or personal circumstances. A new cohort of five students is currently supported by the same grant; we outline planned prompts for collecting comparable reflections from them in Section 5 (Future Work), and their responses will be incorporated into an expanded analysis in a subsequent manuscript.

3.3 Data Sources and Collection

At this early stage, the drones–data–AI program has engaged a small cohort of three student researchers whose experiences form the primary dataset for this Work-in-Progress paper. After completing at least one season of paid work on the farms, each student was invited to write a short testimonial describing what they learned, how they saw the project benefiting farmers, and how the experience affected them personally and professionally. The resulting narratives range from one to three sentences and were submitted by email to the faculty lead on a voluntary basis.

Across these three testimonials, students describe learning concrete technical skills, such as soil and leaf sampling, drone flight, and Pix4D image analysis, while also gaining a deeper appreciation for the complexity of real agricultural decision-making. One student emphasized the satisfaction of helping farmers and staying connected with classmates and professors after graduation; another reflected on the variety of daily challenges farmers face, from pests and invasive species to market conditions, and saw the combined use of aerial imagery and ground sampling as a powerful methodology for adapting to changing environmental conditions; a third highlighted how rewarding and engaging it was to practice drone flying while realizing how difficult it is for farmers to accurately predict yield.

Student A: *“I got to learn a lot from doing the grant work such as soil and leaf sampling. The grant is great in how it helps benefit farmers, it feels good to help them out. It is also great in how I get to see first-hand how the YCP drone capstone project works in farms. What I really enjoyed most about it was how it was an opportunity to keep in touch with classmates and professors after graduation.”*

Student B: *“During my time on the farm project it expanded my knowledge on a variety of issues that farmers face daily. From native pests to invasive species and market conditions the variety of problems that farmers face in the modern world are numerous and often overwhelming. I believe that the methodology that we implemented using drone aerial data and ground observations in tandem with sampling allows us to better help farmers and the scientific community in analyzing and adapting to environmental conditions in an ever changing and uncertain world. It has been an honor to participate in this project.”*

Student C: *“The work that I have done while researching the farms has been rewarding and engaging. It has allowed me to practice my drone flying skills while learning the PIX4D software to analyze the data we gather. Participating in this has allowed me to understand how complicated it can be for farmers to accurately predict their yield.”*

Although the broader program also generates other potential data sources, such as farm reports, email feedback from farmers, and faculty reflective notes, we limit our formal analysis here to these three student testimonials. This focus aligns with our goal of understanding how paid, multidisciplinary fieldwork is experienced by students and is appropriate for a Work-in-Progress paper with a very small initial dataset. Future work will incorporate additional perspectives from farmers, faculty mentors, and a larger cohort of student researchers to triangulate and extend these findings.

3.4 Analytic Approach

Student testimonials were analyzed using a basic thematic analysis approach appropriate for small-scale qualitative datasets. Initial open coding was conducted to identify recurring concepts related to technical skill development, systems understanding, professional identity, community impact, and relational engagement. These codes were then grouped into broader thematic categories aligned with the stated objectives of the program, including multidisciplinary problem solving, stakeholder accountability, and sustained engagement through compensated research participation.

Given the small sample size ($n = 3$), the analysis is interpretive rather than statistically generalizable. The goal of this Work-in-Progress study is not to claim broad causal impact, but to identify emerging patterns in how students describe their learning and engagement within this multidisciplinary, community-based context. These themes provide preliminary evidence supporting the program's design logic and inform planned expansion of the assessment framework in future work.

3.5 Ethical Considerations

This work was conducted as scholarship of teaching and learning within the context of an existing grant-funded program. Students were invited, but not required, to submit testimonials, and were informed that anonymized excerpts might be used in publications or presentations about the program. No grades were attached to participation. Identifying information has been removed from all quotations, and farm partners are referenced in general terms (e.g., "a local orchard," "a grain farm") to protect confidentiality. The project follows institutional guidelines for educational research; any future expansion to include systematic surveys or interviews will be submitted for formal review as needed.

3.6 Expanded Assessment Framework (Future Implementation)

While this Work-in-Progress study relies primarily on qualitative student testimonials, a more structured assessment framework is being developed to strengthen future evaluation of program outcomes. Planned assessment measures include both performance-based and perception-based instruments aligned with the program's learning objectives.

Technical skill development will be evaluated through structured rubrics assessing flight planning, data processing accuracy, integration of aerial and ground-truth data, and quality of

farmer-facing reports. FAA certification progress and demonstrated operational proficiency will serve as objective indicators of technical competency.

To measure multidisciplinary integration and systems thinking, students will complete guided reflective prompts mapped to program objectives, and faculty will evaluate the degree to which teams successfully synthesize drone imagery, laboratory data, and farmer input into coherent recommendations. These rubrics are being developed in alignment with established engineering education assessment practices.

Finally, student professional identity and community engagement will be assessed using pre/post survey instruments adapted from existing engineering identity and experiential learning measures [1–3]. Partner farms will also be invited to provide structured feedback on report clarity, perceived value, and usability for decision-making.

Together, these measures will allow future iterations of the program to combine qualitative narrative data with structured, performance-based, and survey-based assessment tools, strengthening the evidentiary base for evaluating impact.

4. Preliminary Findings and Implementation Insights

As a Work-in-Progress initiative with a small initial cohort ($n = 3$), the findings presented here are exploratory rather than generalizable. Nevertheless, several consistent themes and implementation insights have emerged that may inform replication efforts at other institutions. Since the initial data collection, program participation has expanded to more than six students actively engaged in the initiative.

Based on initial implementation and student reflections, several key multidisciplinary learning outcomes are emerging from the program. These include:

1. **Integrated Systems Thinking**, the ability to synthesize aerial imagery, ground-truth sampling, laboratory data, and stakeholder input into coherent agricultural interpretations.
2. **Technical Competency in Emerging Technologies**, proficiency in drone flight operations, multispectral image processing, and AI-supported data analysis.
3. **Multidisciplinary Communication and Collaboration**, effective teamwork across engineering, horticulture, computer science, and environmental science.
4. **Stakeholder Accountability and Professional Identity Development**, recognition of the real-world impact of technical work and development of professional responsibility toward community partners.

These outcomes serve as the analytic lens for interpreting the student testimonials presented below.

4.1 Emergent Student Learning Themes

Across the three student testimonials, several recurring patterns are evident. First, students consistently report the development of concrete technical skills, including drone operation under

FAA guidelines, multispectral image processing, and soil and tissue sampling procedures. Second, students describe a deeper understanding of the complexity of agricultural decision-making, particularly the uncertainty involved in yield prediction and environmental stress analysis. Third, students highlight the value of contributing meaningful work to partner farms, suggesting that authentic stakeholder accountability enhances motivation and professional identity formation. Finally, relational benefits, including sustained engagement with faculty and peers beyond graduation, emerged as an unexpected but meaningful outcome.

While preliminary, these themes align with the program's design objectives of promoting multidisciplinary problem solving, systems thinking, and community engagement.

4.2 Resource Requirements and Operational Considerations

Institutions considering replication may benefit from understanding the practical resources required to initiate and sustain such a program. Core infrastructure includes at least one FAA-compliant drone platform equipped with a multispectral sensor, access to image-processing software (e.g., Pix4D or similar), and laboratory capacity for soil and tissue analysis. While initial equipment costs can be significant, hardware is reusable across multiple seasons and projects.

Faculty time investment is nontrivial, particularly during early implementation phases involving farmer outreach, mission planning oversight, and interdisciplinary coordination. However, embedding portions of the workflow into existing coursework, capstone experiences, or undergraduate research credits can distribute workload and reduce long-term reliance on dedicated grant funding. Partner farms often already budget for soil and tissue testing, allowing student participation to integrate into existing agricultural expenditures rather than requiring entirely new financial structures.

4.3 Scalability Across Institutional Contexts

The model is adaptable to both smaller and larger institutions. Smaller institutions may implement the program with a single drone platform and a limited number of partner farms, emphasizing depth of engagement over scale. Larger universities may scale participation by organizing multiple multidisciplinary teams operating under shared equipment and coordinated faculty mentorship.

Scalability is influenced less by institutional size than by intentional coordination across departments and alignment with local agricultural needs. The program's modular structure, mission planning, data acquisition, analysis, reporting, allows components to be implemented independently or integrated into existing courses before expanding to full end-to-end workflows.

4.4 Lessons Learned and Recommended Improvements

Several early lessons have emerged from initial implementation:

- Clear role definition within multidisciplinary teams reduces confusion and enhances accountability.
- Early communication with partner farms is critical to align expectations regarding data interpretation and report timelines.
- Synchronizing academic calendars with agricultural growing seasons requires careful planning.
- Students benefit from structured reflection prompts to help articulate connections between technical tasks and broader systems understanding.

Future iterations of the program will expand structured assessment tools, incorporate farmer feedback instruments, and formalize integration into capstone and course-based structures to further strengthen both educational and research outcomes.

Although preliminary, these findings suggest that integrating drone-based sensing, laboratory sampling, and stakeholder-facing reporting within a compensated, multidisciplinary framework holds promise as a replicable model for experiential engineering education in agricultural contexts.

5.0 Conclusion

The drones–data–AI program at York College of Pennsylvania illustrates how grant-supported, multidisciplinary experiential learning can connect undergraduate students with pressing, real-world challenges in agriculture. By combining drone operations, multispectral image processing, harvester data, and soil and tissue sampling, students engage in an end-to-end workflow that requires them to integrate concepts from engineering, computer science, horticulture, chemistry, and environmental science. The three student testimonials analyzed in this Work-in-Progress study suggest that the experience builds concrete technical skills, deepens students’ understanding of farmers’ day-to-day challenges, and fosters a sense of contributing meaningful help to local farms, while also sustaining relationships with peers and faculty after graduation.

At the same time, the study is intentionally modest in scope: our current dataset is small and primarily qualitative, and we have focused on how a first cohort of paid student researchers narrate their own learning and impact. Future work will expand the evidence base by incorporating reflections from a larger cohort of students, systematic feedback from farmers and faculty mentors, and additional assessment tools that capture changes in skills, confidence, and disciplinary identity over time. As the program matures, we also plan to document more fully the AI and analytics components of the workflow and to explore how these tools can scale analysis across seasons and fields. Even at this early stage, however, the program offers a promising model of how external funding, authentic community partnerships, and methodological pluralism can be leveraged to create meaningful, multidisciplinary learning opportunities that benefit students, faculty, and the agricultural communities they serve.

Although the program was initially accelerated through external grant support, its long-term viability does not depend solely on continued external funding. Many core activities align with existing institutional and agricultural practices. Partner farms routinely budget for soil and tissue sampling, which can be integrated into student-led workflows without additional expense. Drone

platforms and multispectral sensors are reusable across seasons, and image-processing tools are shared across courses and research projects. Elements of the initiative are also being embedded into existing coursework, capstone design experiences, and undergraduate research credit structures, allowing student participation to continue even as funding models evolve. These structural features position the program as a scalable and transferable educational model rather than a temporary grant-supported initiative.

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