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ORIGINAL ARTICLE

Adoption of unoccupied aerial systems in agricultural research

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Abstract

A comprehensive survey and subject-expert interviews conducted among agricultural researchers investigated perceived value and barriers to the adoption of unoccupied aerial systems (UASs) in agricultural research. These systems are often referred to colloquially as drones and are composed of unoccupied/uncrewed/unmanned vehicles and incorporated sensors. This study of UASs involved 154 respondents from 21 countries representing various agricultural sectors. The survey identified three key applications considered most promising for UASs in agriculture: precision agriculture, crop phenotyping/plant breeding, and crop modeling. Over 80% of respondents rated UASs for phenotyping as valuable, with 47.6% considering them very valuable. Among the participants, 41% were already using UAS technology in their research, while 49% expressed interest in future adoption. Current users highly valued UASs for phenotyping, with 63.9% considering them very valuable, compared to 39.4% of potential future users. The study also explored barriers to UAS adoption. The most commonly reported barriers were the "High cost of instruments/devices or software" (46.0%) and the "Lack of knowledge or trained personnel to analyze data" (40.9%). These barriers persisted as top concerns for both current and potential future users. Respondents expressed a desire for detailed step-by-step protocols for drone data processing pipelines (34.7%) and in-person training for personnel (16.5%) as valuable resources for UAS adoption. The research sheds light on the prevailing perceptions and challenges associated with UAS usage in agricultural research, emphasizing the potential of UASs in specific applications and identifying crucial barriers to address for wider adoption in the agricultural sector.

1 | INTRODUCTION

Unoccupied aerial systems (UASs) fill a unique niche within a rapidly expanding remote sensing arsenal for agricultural research (Khanal et al., 2020). While satellite constellations provide a vast and autonomous source of field-scale remote sensing data and sensor-equipped ground vehicles monitor features under the plant canopy, UASs offer advantages in terms of very high-resolution spatiotemporal data collection, speed and ease of deployment, and payload flexibility (Araus & Cairns, 2014; Ayankojo et al., 2023; Gebbers & Adamchuk, 2010; Herwitz et al., 2004; Shi et al., 2016). These advantages are particularly relevant for agricultural research and the crop (or animal herd) scouting communities.

Commercial production of user-friendly hardware platforms and image processing tools has alleviated many of

the technical hurdles that previously limited widespread UAS deployment; yet, outright adoption across agricultural research disciplines has lagged behind these technical achievements. Similarly, on US farms, the use of drone, aircraft, or satellite imagery has not exceeded 10%. This contrasts with other precision agriculture technologies, including yield monitoring and guidance systems, with much higher rates of uptake of over 40% (McFadden et al., 2023; Schimmelpfennig, 2016). Financial constraints, insufficient technical knowledge, regulatory hurdles, lack of perceived value, and practitioner attitude are a few factors that may impede the rate at which new technologies are applied in agriculture. Understanding how the relative influence of these factors relates to UASs and developing a roadmap to alleviate such obstacles are important objectives toward realizing the impact of this technology in agriculture.

In this study, we surveyed an international population of agricultural practitioners, researchers, and those working in adjacent roles to quantitatively understand their adoption of UASs. We also conducted qualitative detailed in-person interviews with domain experts who currently utilize UAS technology in their research program. We considered respondents' demographics and their perceived value of drones as applied within their program. We examined perceived barriers to adoption and explored potential resources that could support adoption, including determining characteristics of the pipelines in use by current UAS users. With these findings, we propose steps to broaden accessibility to adoption of UASs in agricultural research.

Core Ideas

- Agriculture is transitioning from early to mainstream adoption of unoccupied aerial system (UAS) technology.
- UAS technology is more valued by active users.
- The primary barrier to adoption is perceived as the cost of deploying UASs.
- Effective methods for encouraging adoption include providing detailed protocols and in-person training.
- Multidisciplinary teams can accelerate UAS adoption.

2 | METHODS

We developed a survey in conjunction with the Montana State University Human Ecology Learning and Problem Solving (HELPS) Laboratory to examine UAS adoption in agricultural research. Institutional Review Board approval was obtained under number JL100821-EX. The survey includes branching sets of questions to target certain populations (Figure 1). One branch was focused on project directors or team leaders to inquire about team size and budgets. Another branch focused on current UAS users, and those identifying as future UAS users were surveyed for barriers to UAS adoption and desired resources. Finally, another branch focused on only current UAS users to determine pipelines in place. Common questions to all respondents assessed demographics and perceived value in using UASs for phenotyping in agricultural research. The anonymous results are available at https://github.com/Lachowiec-Lab/agDronesSurvey.

Surveys were distributed through multiple mechanisms to solicit responses. Academic and professional societies were identified as including researchers that utilize UASs in relation to agriculture (e.g., International Plant Phenotyping Network, Potato Association of America, American Society of Plant Biologists, Animal Science Society of America, CGIAR Platform for Big Data in Agriculture, Crop Society of America, Agronomy Society of America, and Soil Science Society of America), and those society administrators were requested to distribute the survey via listserv. The survey was advertised during presentations at society meetings (e.g., North American Plant Phenotyping Network Conference, Potato Association of America) and through web-based workshops (e.g., PhenomeForce). Personal networks of the authors were also used to distribute the survey.

A total of 154 surveys were completed or partially completed and analyzed. For calculating percentages, the denominator was determined based on the question's completion rate, which varied across questions. In some cases, the ability to select multiple options was available, and the sum of percentages exceeded 100%.

In-person interviews were performed between January 2022 and January 2023. With approval of all interviewees, transcriptions of the interviews are archived alongside data and code.

To compare use of UAS in commodity versus specialty crops, we searched Web of Science with the queries:

-For commodity crops: "ALL = ((UAV OR UAS OR Drone) AND (Corn OR Maize OR "Wheat*" OR "Soy* OR Soybean*" OR "Cotton*" OR "Rice*" OR "Barley*" OR "Sorghum*" OR "Canola*" OR "Oilseeds" OR "Legumes"))"

-For specialty crops: "ALL = ((UAV OR UAS OR Drone) AND ("Specialty Crops" OR "Fruit*" OR "Vegetable*" OR Viticulture OR Orchard* OR Berries OR Berry OR "Tree Nuts" OR "Greenhouse Crops" OR "Horticulture"))"

Statistical analyses and data visualization were completed using R (R Core Team, 2023). Data and code are archived (Lachowiec et al., 2024) and also available at https://github.com/Lachowiec-Lab/agDronesSurvey.

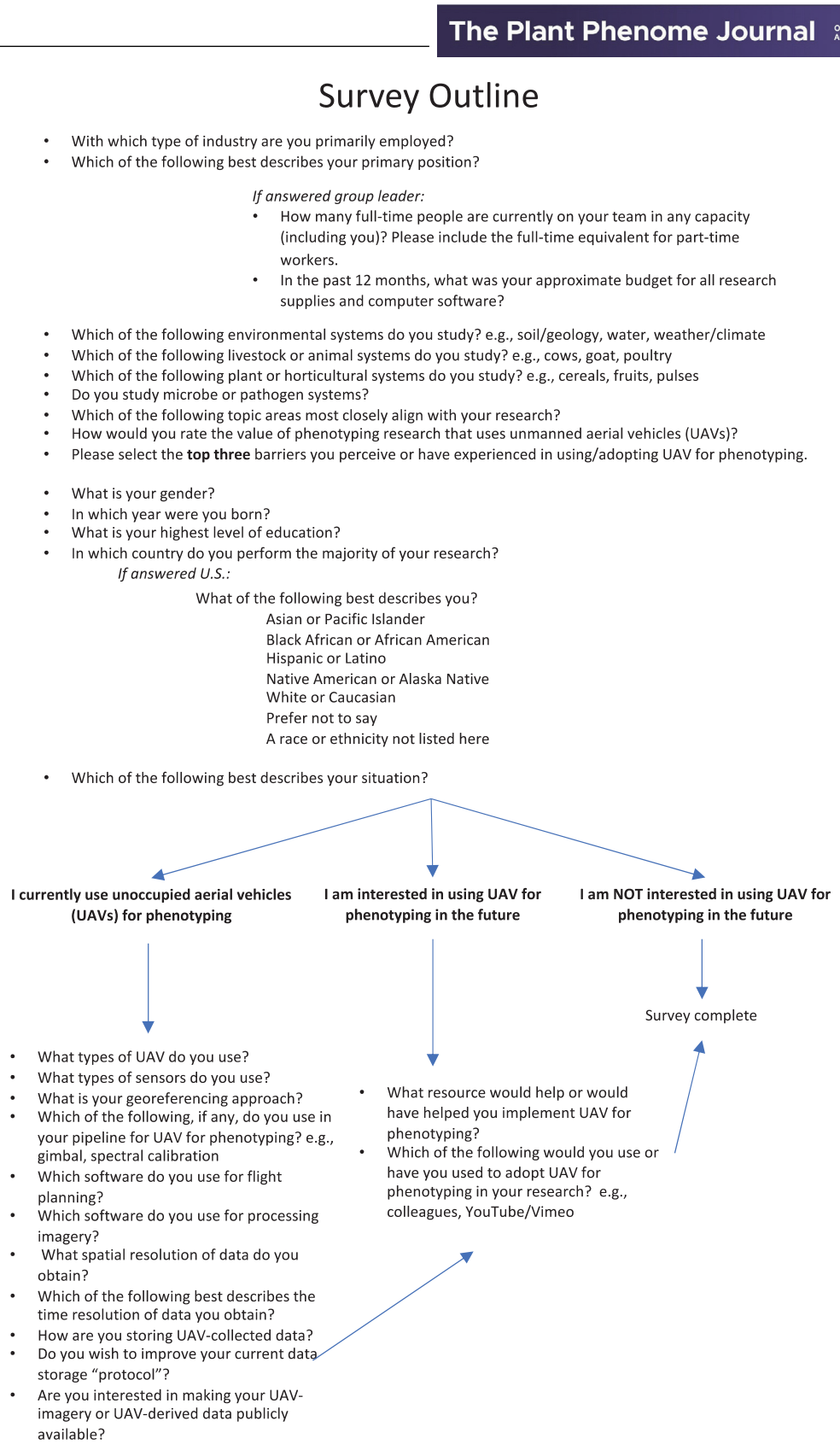

FIGURE 1 Branching structure of survey and questions asked.

3 | RESULTS

3.1 | Survey respondents' demographics and perceived value of UASs in agricultural research

Respondents perform their agricultural research across 21 countries, though most respondents were from the United States (67.4%), with Brazil and Canada tied as the second most represented countries at 5.2% each. The majority of respondents were male (69.3%), White (73.6%), and between the ages of 30 and 39 (28.9%).

Multiple sectors involved in agricultural phenotyping were well represented. Research institutions (nonuniversity, nonprofit) employed respondents at 28.8% and colleges or universities (not primarily undergraduate) at 26.7%. Private industry represented 22.6% of respondents. Other industries represented included government agencies (9.6%), primarily undergraduate academic institutions (6.2%), and self-employment (4.1%).

A large diversity of study systems and topic areas were represented; however, certain crop groups and topics predominated. Allowing for multiple species to be selected, 45.9% of respondents study cereal crops, followed by rhizomes, tubers, roots, and bulb crops at 31.5%. Livestock and animal systems were also studied, but at much lower levels (1.5% and 6.6% of respondents, respectively). Over half (51.4%) identified agronomy as their primary area of research, followed by breeding (41.1%) and statistics (17.8%). Approximately one third (33.8%) study animal or plant pathogens. Interview respondents identified the applications of UASs as precision agriculture (75%), crop phenotyping/plant breeding (60%), and crop modeling (60%).

We examined the perceived value of UASs for phenotyping across both users and nonusers. More than four out of five rated UASs valuable (82.1%), and almost half of these (47.6%) rated UASs as very valuable. Four percent rated UASs as minimally valuable, and all respondents found some value in UASs for phenotyping. Respondents also provided information about their use of UASs, and the perceived value of UASs varied across groups (Figure 2). More than nine out of 10 respondents use (41%) or are interested in using (49%) UASs, while 9% are not interested. Among those actively using UASs, 63.9% found UASs very valuable, nearly 25% higher than those reporting interest in using UASs in the future (39.4%).

3.2 | Barriers to and resources for UAS adoption

The use of UASs has gained popularity in agricultural research (Aslan et al., 2022), with 41% of respondents currently employing UAS technology. However, "High cost of instruments/devices or software" (46.0%) and "Lack of knowledge or trained personnel to analyze data" (40.9%) ranked in the first and second position for reported barriers, respectively. We analyzed the data excluding responses from the United States and found similar barriers. We also found that both current and potential future users identified the same primary obstacles. Our qualitative interviews identified these same barriers to entry, with the lack of knowledge or trained personnel to collect or analyze data considered to be a larger bottleneck to adoption than equipment and software costs.

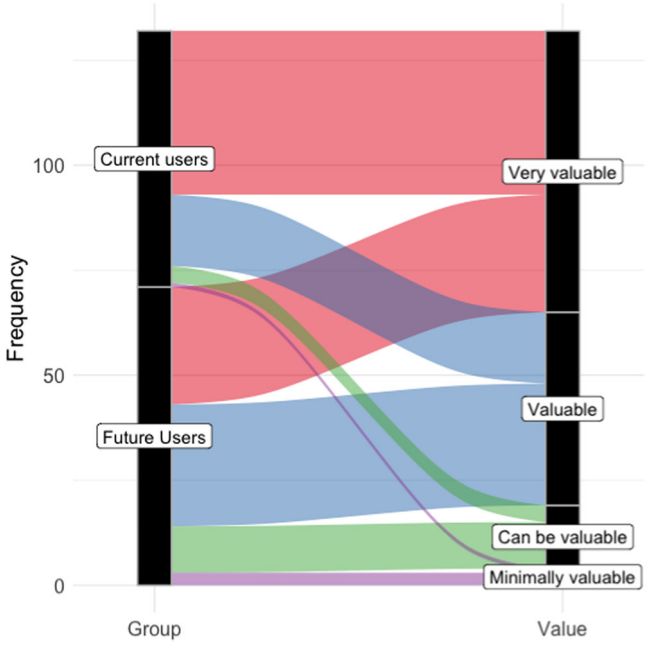

FIGURE 2 Perceived value of unoccupied aerial systems (UASs) for phenotyping in agricultural research stratified by UAS users and those identifying as future users.

Despite the consistency in the barriers reported, we found differences in the barriers that were less frequently faced by current and potential future users. The "Lack of validated and publicly available protocols" was the third-ranked barrier for current users but was only ninth of 13 ranked for potential future UAS users (Figure 3a).

The other major shift in ranked barriers was the "General lack of personnel to add more research," which shifted from fifth position for potential future UAS users to 10th position for current UAS users (Figure 2a). We did not detect a difference in team size for future UAS users compared to current users, with both groups showing a similar distribution of team size (Figure 3b, $\chi^2 = 1.8$, $p = 0.6$). Similarly, the distribution of funds was similar between future and current UAS users (Figure 3c, $\chi^2 = 5.8$, $p = 0.3$).

In addition to the barriers listed in the survey as options, barriers listed by respondents included uncertainty of applicability of data, lack of data management solutions including metadata standards, lack of progress in analyzing multivariate

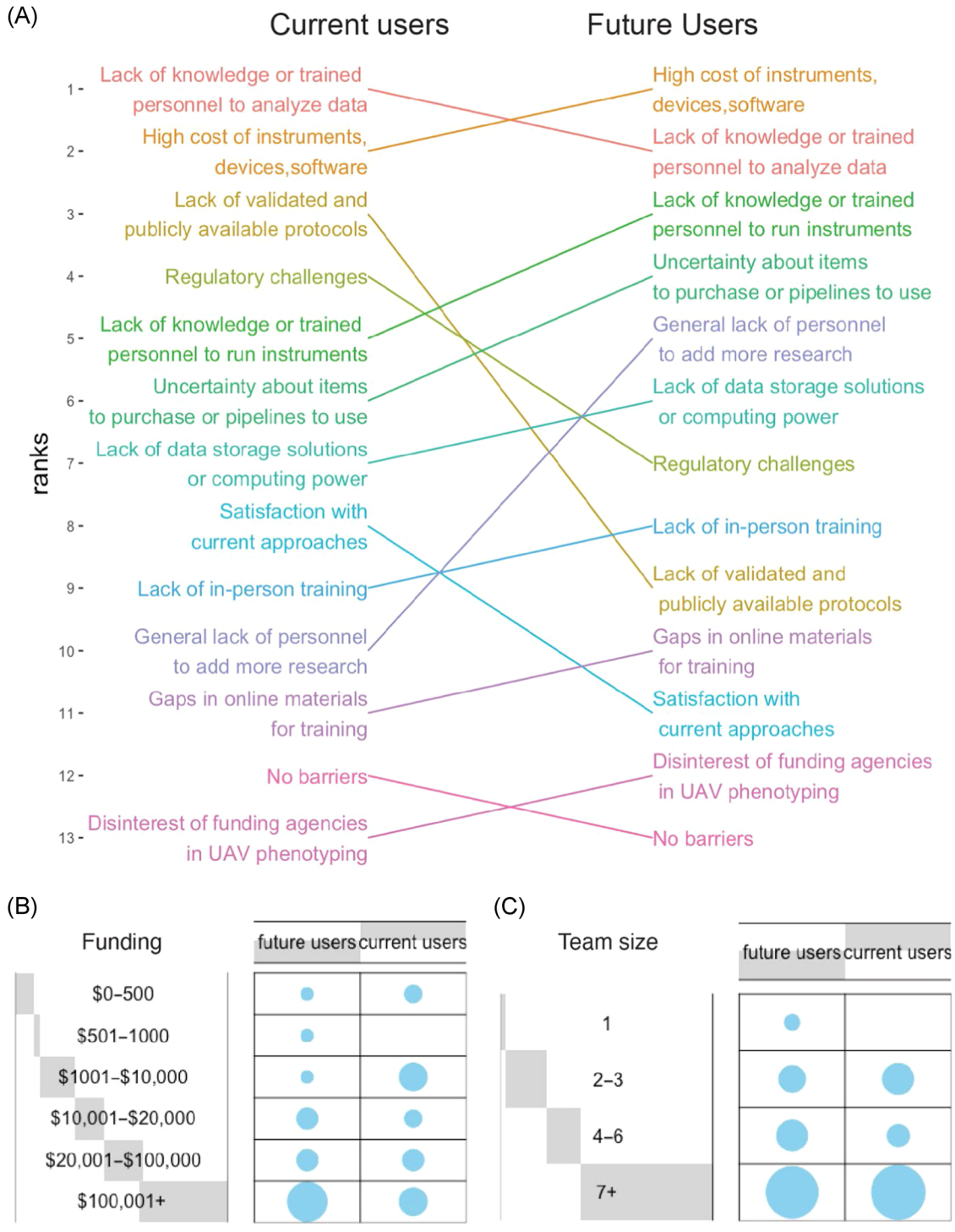

FIGURE 3 Barriers to unoccupied aerial system (UAS) adoption and group resources. (A) The rankings of barriers to adoption of UASs for phenotyping in agriculture are given for current users and future users. (B) The team size and (C) funding available for future and current users are shown.

color data, slow speeds of equipment, and competition with increasing satellite resolution.

We also surveyed the actual and expected resource needs of current and future users. The most needed resource was "Detailed step-by-step protocols for all stages of the drone processing pipeline" (34.7%), followed by "In-person training for personnel" (16.5%). Both US and non-US researchers agreed that detailed protocols are most important. Respondents identified additional needs including service providers for flights, outsourced data analysis, and database tools.

Both current and future users primarily learned about UASs from colleague(s) or protocols developed and shared within

teams or institutions (47.2%). However, outside the United States, the mode of information shifted to primarily protocols developed and shared within teams or institutions, followed by publicly available protocols and YouTube/Vimeo. This was also reflected in the suggestions from domain expert interviews. A majority of our expert panel recommended partnering with subject matter experts in adjacent fields to establish work teams. Multiple respondents also expressed that they developed the information and data needed themselves.

3.3 | Landscape of collecting and processing UAS imagery-based data

To understand the landscape of current UAS use, we next explored data resolution and current pipelines among current users. Users perform flights (50.0%) weekly, followed by 43.1% performing flights two to six times a year. Spatial resolution tended to be at the centimeter scale (57.7%), followed by the meter scale (51.1%). We detected no difference in the spatial resolution of data collected between respondents who selected their topics areas as breeding versus agronomy ($\chi^2 = 2.2$, $p > 0.05$).

We also found commonalities in the choice of hardware and imaging. A clear majority of drones used are multirotor (93.1%). Similar numbers of users have red–green–blue (88.5%) and multispectral sensors (80.3%), followed by thermal (45.9%). Ground control points are the most frequently used tool for georeferencing at this time (75.0%), followed by real-time kinematic (RTK) positioning (40%).

Software for flight planning and data processing have many options available. Pix4Dcapture (47.3%) and DJI Flight Planner (45.5%) were the most popular flight planning software. Pix4DMapper was the most common tool for postprocessing (60.0%), followed by Agisoft Metashape 3D (34.5%). Multiple users (9.1%) reported processing images using Plot Phenix, which was a write-in option on the survey.

We explored how users are storing data collected using UASs. Most use institutional servers (58.3%) and hard drives (45.0%) (respondents could select more than one storage type). Most (69.0%) respondents would like to improve their current data storage protocol, and most (nearly 60%) would like to publicly share UAS imagery and/or derived data.

4 | DISCUSSION

Rogers (1995) conceptualized the process of innovation adoption as a bell curve, where the *x*-axis represents time from early adoption to late adoption and the *y*-axis represents the population of technology adopters. In this context, our survey suggests that the use of UASs in agriculture is in the early majority phase—it has been widely adopted with 41% of respondents in our survey—with a large population ready to begin adoption. Although our survey was not a completely random sample of potential users, and it is difficult to reach researchers who are not interested in UASs to determine the true proportion of community adoption and value, our surveys align with a clear trend that the field phenomics research community is transitioning from the early adoption to mainstream adoption of UAS for agricultural research. Moore (2006) referred to this process as "crossing the chasm" of Roger's technology adoption curve. Similarly, Gartner, Inc. developed what is known as the Gartner hype cycle, a model describing the dynamics of the perceived value of a developing technology over time. A new technology is first overhyped, resulting in an inflated value that is diminished by disappointment when expectations are not met. Some technologies then rebound with the perceived value plateauing at a level intermediate to initial peak and trough. This framework has been used previously to understand the use of UAVs in high-throughput crop phenotyping and agronomic management (Shi et al., 2016). Seven years later, these survey results reflect the same conclusion found by Shi et al. (2016): growing adoption of and high perceived value placed in UASs for agricultural research. This suggests that the technology is stabilizing in its use and maturity, becoming commonplace. However, we suspect different research communities occupy divergent regions within the Gartner hype cycle. Commodity groups like maize, wheat, rice, cotton, and soybean that began deploying drone technology in the mid-2010s tend to have a deeper understanding of how to collect, process, and extract knowledge from the data relative to their specialty crop counterparts. As of January 2024, there are more than twice as many published uses of UASs with commodities compared to specialty crops, but no difference in the timing of uptake.

Nonetheless, results from this survey portray that the perceived value of UAS technology is greater among active users than nonusers (Figure 1). This result suggests that active users have found applications where UAS technology reliably adds value within their enterprise (Moore, 2006). Alternatively, this may also indicate that UAS adoption has value in terms of other performance benchmarks including competitive grant awards, publications, or providing trainees with a diverse, modern technical skill set. Use of UASs can be thought of as a research topic in and of itself. In-depth interviews with active UAS users identified precision agriculture, plant breeding, and crop modeling as three of the most promising applications of UAS technology. The proportion of respondents who self-identify both as an active UAS user and working within these disciplines is congruent with this conclusion.

The cost of deploying UASs within a research program is perceived to be the greatest barrier to entry. Surprisingly, there were no major financial or personnel resource differences between groups that had adopted UASs and those that had

TABLE 1 Approximate costs of initial unoccupied aerial system (UAS) deployment in the United States in 2023 (excluding personnel).

Component	Minimum entry cost	Premium options
FAA Part 107 exam training course (per pilot)	Optional	$300
FAA Part 107 Unmanned Aircraft General—Small (UAG) Exam (per pilot)	$175	$175
Drone (light-to-medium duty)		
Open market	$500	$6000
US government compliant	$3000	$15,000
Drone (medium-to-heavy duty)		
Open market	Optional	$15,000+
US government compliant	Optional	$35,000+
Extra batteries (per battery)	Optional	$700
Landing pad	Optional	$50
Sensor		
RGB	Often integrated with drone	$7000
Multispectral	Optional	$8000
Multispectral and thermal	Optional	$16,000
Real-time kinematic correction		
Survey kit	$3000	$10,000
On-board integration	Optional	$1000
Ground control point panels (5)	$75	$4000
Remote ID module	Integrated with some drones	$350
External hard drive (5 TB)	$150	$150
Computer	Public computing resources	$5000
Imagery processing software (yearly subscription)	$0 (open-source options)	$3500
ABC fire extinguisher	$100	$100

not. Equipment and software costs were the most commonly perceived bottleneck to adoption among nonusers, whereas current users reported lack of personnel to analyze data as the most frequently encountered bottleneck. The largest difference between these groups was the lack of personnel to collect data, suggesting that current adopters have been able to hire or train certified UAS pilots. Based on our experiences, we developed a breakdown estimate of hardware and software costs (Table 1), which suggests that deploying a UAS program may fit within the budget constraints of greater than 50% of the respondents, particularly if the hardware resources can serve more than a single research group simultaneously. Respondents stated that data collection is cost and time effective, with minimal training required; in contrast, downstream analysis requires substantial time of individuals with training in computer programming, data science, and statistics. Based on our experiences, we approximate that, at minimum, 0.5 full-time equivalent effort of a graduate student, pos-doctoral scientist, or computationally inclined research associate will be required to set up the computational workflow to extract numerical data from drone images.

Although there are some commonalities between the adoption of genomics technology and UASs, there are some fundamental differences that make the path to UAS adoption unique. Adoption of genomics technology has largely been driven by rapid decrease in sequencing costs, increase in the volume of data that can be generated, and diversity of applications where sequencing data can provide actionable information in the form of variant identification, haplotype assembly, or sample composition (Shendure et al., 2017). Decreases in cost and increased accessibility to genomics technology have stemmed from investment in dedicated genomics cores and fee-for-service sequencing labs that procure, maintain, and employ the technical staff needed to operate the requisite sequencing instruments. These cores can service large numbers of customers from a single, centralized location.

In some ways, the opposite is true for UAS adoption. Similar to the genomics revolution, the cost of acquiring the equipment and learning curve required to collect data has decreased dramatically through time. However, unlike genomics, our ability to scale data collection is dependent upon establishing a data collection network across locations where field trials are performed. For most agricultural research enterprises, it is impractical if not impossible to serve all customers from a single centralized location.

These differences aside, many of the lessons learned during the genomics revolution are applicable to current challenges

in drone adoption. The development of open-source software tools, computational genomics training workshops, and investment by funding entities have built a workforce that is familiar enough with how to use these resources to make a profound impact. We argue that a similar, train-the-trainer-type extension model focused on data collection and analysis is needed to establish comparable levels of adoption and utility of UASs in agriculture (Tuggle et al., 2024). This type of training needs to be augmented with increased proficiency in basic computer programming and statistics (especially spatial and temporal).

Accordingly, survey respondents indicated that informational resources, particularly detailed step-by-step protocols and in-person training, were the most effective methods to encourage adoption. Generally, most respondents preferred to learn new techniques directly from their colleagues and from protocols developed and shared within their research group or institution. Indeed, this approach is gaining traction as evidenced by several recently published protocols (Bhandari et al., 2023; Kefauver et al., 2019; Matias et al., 2022).

Regulatory burden is another factor that is perceived to restrict drone utilization. In the United States, practitioners using a UAS that weighs between 255 g and 25 kg for business purposes must obtain a Federal Aviation Administration Part 107 license by taking a certification test. This was identified as a bottleneck in both our survey and interviews with domain experts but can be alleviated through enrolling pilots in workshop-style training courses designed to provide the knowledge required to pass the licensing exam. Hardware restrictions implemented by the US federal government (National Defense Authorization Act for Fiscal Year 2020 [Public Law 116–92 § 848]; U.S. Executive Office of the President, 2021) are somewhat controversial in the agricultural research community. Federal researchers in the United States are unable to purchase UAS instruments on the open market using federal funds and instead must purchase drones approved by the Department of Defense/Defense Innovation Unit's Blue UAS certification program ("US government compliant" in Table 1). In the short term, this restriction can more than double the total equipment cost (Table 1), greatly reduce the number of options available, and, due to reduced usability, increase costs of operation, maintenance, and training. Additional regulations mandated under the U.S. Geospatial Data Act of 2018 (FAA Reauthorization Act of 2018 [Public Law 115-254 § 751]) promise to enhance the availability and quality of data collected using federal resources, but compliance will require the development and implementation of data quality standards, standardized metadata annotation, and computing platforms to realize the goals of this legislation.

This survey and interviews were an effective starting point to understand the use of UASs in agricultural research, particularly in crops. This project was developed with the viewpoint that increasing use of UASs would be beneficial to the agricultural research enterprise by increasing efficiencies and improving precision, at the very least. Future surveys and interviews should incorporate measuring the realized impacts of incorporating UASs into research programs. Periodic redeployment of this survey, supported by the HELPS lab, would be a time- and cost-efficient way to capture how the value in UASs changes over time and better reveal the adoption of UASs by researchers. Furthermore, survey outreach should include more of the agricultural engineering and animal and range science communities. We suggest that people developing similar surveys consider the trade-offs between a brief survey versus a comprehensive survey (Galesic & Bosnjak, 2009); we found a middle ground, given that this report had a median response time of 7 min that still allowed for detailed insights into UAS use.

Based upon this survey and input from the domain experts interviewed, we propose that UAS adoption can be accelerated through the formation of multidisciplinary work teams that leverage the individual strengths of agronomists, geneticists, remote-sensing engineers, and statisticians. This approach will certainly help address knowledge gaps encountered between groups and enable dissemination of protocols, skills, and metadata through channels desired by our survey respondents. Cooperative projects that support field data collection, computing, and storage/data management resources may help further reduce the costs of deployment. Although UAS technology has been demonstrated to make useful contributions in precision agriculture (Shi et al., 2016; Sinha et al., 2022; Thorp et al., 2018, 2022), plant breeding (Adak et al., 2023; Crain et al., 2018; Herr et al., 2023; Rodene et al., 2022; Sun et al., 2019), and crop modeling (Anderson et al., 2019; Chandel et al., 2022; Chu et al., 2017; Pugh et al., 2018; Zhou et al., 2016), additional reports outlining utility will certainly enhance the value of UAS data to broader audiences and shape the attitude of agricultural practitioners. Afterall, perhaps the most exciting and valuable applications will be the ones we have not yet discovered.

AUTHOR CONTRIBUTIONS

Jennifer A Lachowiec: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; visualization; writing—original draft; writing—review and editing. **Max Feldman**: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; writing—original draft; writing—review and editing. **Filipe Matias**: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; writing—original draft; writing—review and editing. **David Shaner LeBauer**: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; writing—original

draft; writing—review and editing. **Alexander Gregory**: Investigation; methodology; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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