Unoccupied aerial systems adoption in agricultural research

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Keywords

drone, survey, unoccupied aerial vehicle (UAV), unmanned aerial vehicle, unoccupied aerial system (UAS) value, barriers, precision agriculture, phenomics, phenotyping

Core Ideas

1. Agriculture is transitioning from early to mainstream adoption of UAS technology.
2. UAS technology is more valued by active users.
3. The primary barrier to adoption is perceived as the cost of deploying UAS.
4. Effective methods for encouraging adoption include providing detailed protocols and in-person training.
5. Multidisciplinary teams can accelerate UAS adoption.

Abstract:

A comprehensive survey and subject-expert interviews conducted among agricultural researchers investigated perceived value and barriers to the adoption of unoccupied aerial systems (UAS) in agricultural research. The study involved 154 respondents from 21 countries representing various agricultural sectors. The survey identified three key applications considered most promising for UAS in agriculture: precision agriculture, crop phenotyping/plant breeding, and crop modeling. Over 80% of respondents rated UAS 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 UAS 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 UAS in specific applications and identifying crucial barriers to address for wider adoption in the agricultural sector.

Introduction

Unoccupied aerial systems (UAS) 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, UAS offers advantages in terms of very high-resolution spatiotemporal data collection, speed and ease of deployment, and payload flexibility (Ayankojo, Thorp and Thompson, 2023). These advantages are particularly relevant for the crop (or animal herd) scouting and agricultural research communities.

Commercial production of user-friendly hardware platforms and image processing tools have alleviated many of the technical hurdles that previously limited widespread UAS deployment yet outright adoption across agricultural research disciplines have lagged behind these technical achievements. Similarly, on U.S. farms, the use of drone, aircraft, or satellite imagery has not exceeded ten percent (McFadden, Njuki and Griffin, 2023). 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 relate to UAS and developing a roadmap to alleviate such obstacles is an important objective 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 understand their adoption of UAS. We also conducted 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 UAS in agricultural research.

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. One branch was focused on project directors or team leaders to inquire about team size and budgets. 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 current UAS users to determine pipelines in place. Common questions to all respondents assessed demographics and perceived value in using UAS 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 identified as including research using UAS in relation to agriculture, and society administrators were requested to distribute the survey via listserv. The survey was advertised during presentations as society meetings and through web-based workshops. 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, multiple options were available and the sum of percentages will exceed 100%.

In-person interviews were performed between January 2022 and January 2023. With approval of all interviewees, transcriptions of the interviews can be found at the following repository: https://ars-usda.box.com/s/fop052vcb6rnoekqo5djiy4l6pbjoozx

Statistical analyses and data visualization was completed using R (citation needed). Code is available at https://github.com/Lachowiec-Lab/agDronesSurvey.

Results

Survey respondents' demographics and perceived value of UAS in agricultural research

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

Multiple sectors involved in agricultural phenotyping were well represented. Research institutions (non-university, non-profit) 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 cereals, 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 pathogens. Interview respondents identified the applications of UAS as precision agriculture (75%), crop phenotyping / plant breeding (60%), and crop modeling (60%).

We examined the perceived value of UAS for phenotyping across both users and non-users. More than four out of five rated UAS valuable (82.1%), almost half of these (47.6%) rated UAS as very valuable. Four percent rated UAS as minimally valuable, and all respondents found some value in UAS for phenotyping. Respondents also provided information about their use of UAS, and the perceived value of UAS varied across groups (Fig. 1). More than nine out of ten respondents use (41%) or are interested in using (49%) UAS while 9% are not interested. Among those actively using UAS, 63.9 percent found UAS very valuable, nearly 25% higher than those reporting interest in using UAS in the future (39.4%).

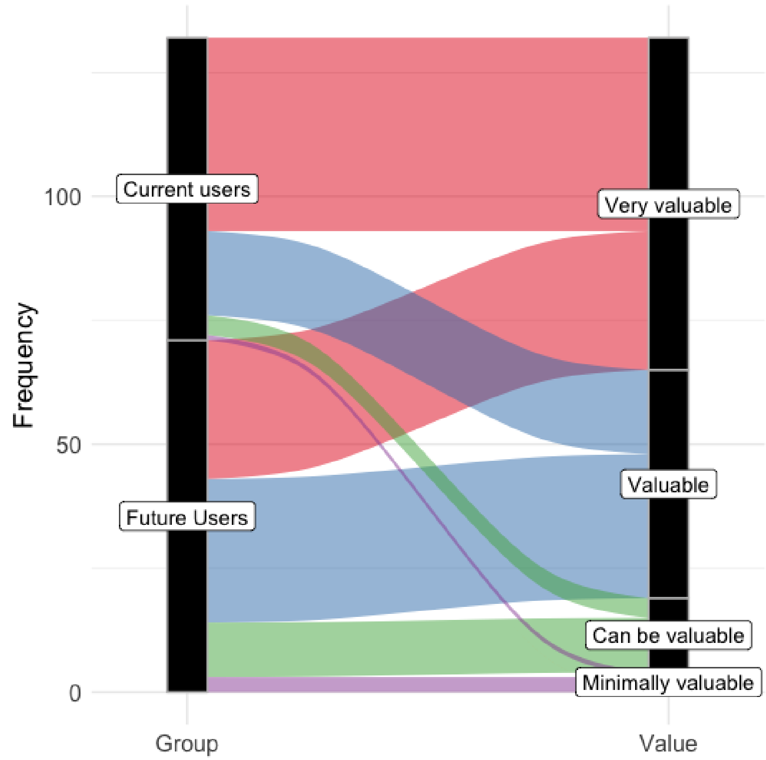

Fig. 1. Perceived value of UAS for phenotyping in agricultural research stratified by UAS users and those identifying as future users.

Barriers to and resources for UAS adoption

The use of UAS 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. 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.

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 thirteen ranked for potential future UAS users (Fig. 2a).

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 tenth position for current UAS users (Fig. 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 (Fig. 2b, $X^2 = 1.8279$ $p = 0.609$). Similarly, the distribution of funds was similar between future and current UAS users (Fig. 2c, $X^2 = 5.7734$, $p = 0.3289$).

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

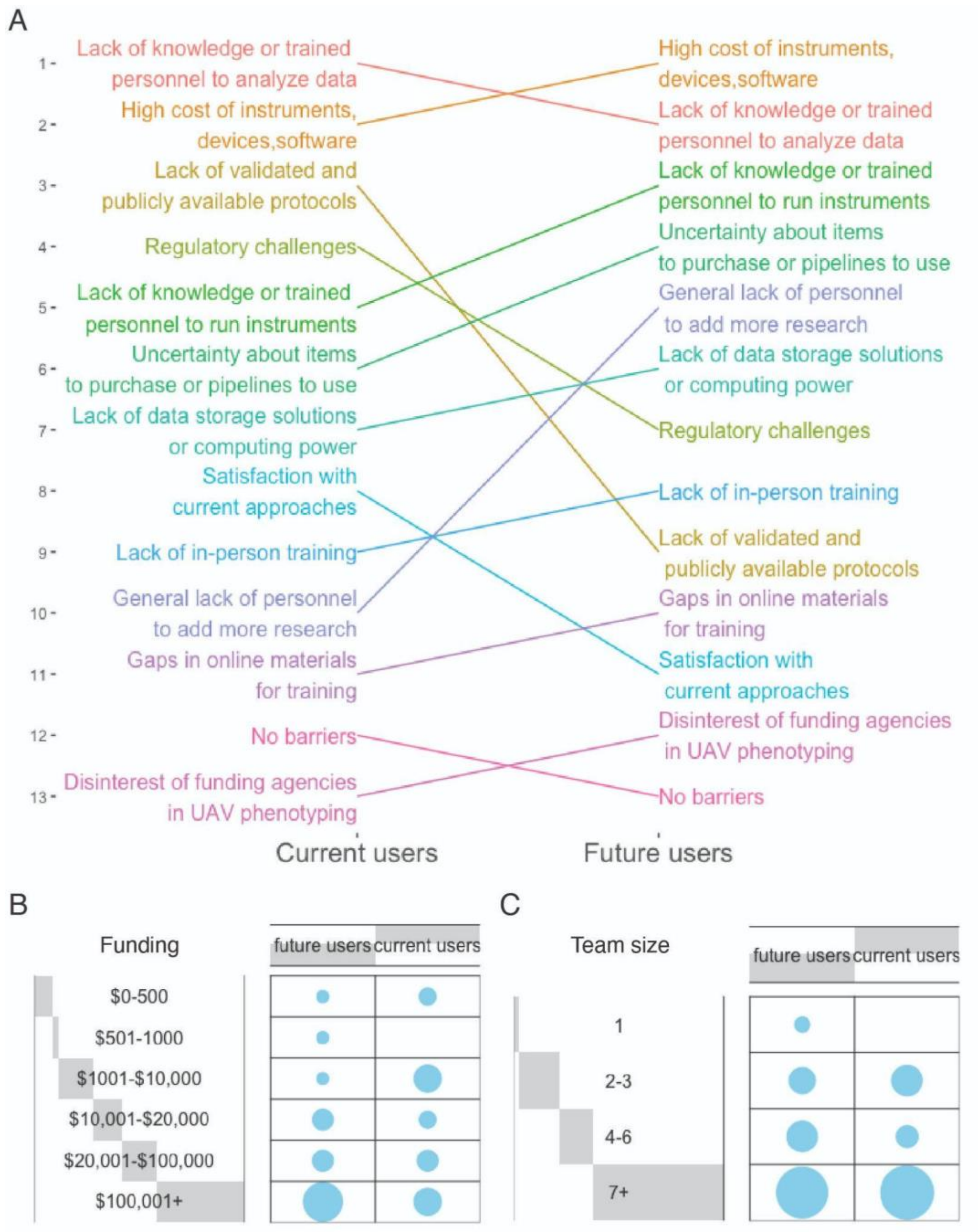

Fig. 2. Barriers to UAS adoption and group resources. a) The rankings of barriers to adoption of UAS for phenotyping in agriculture are given for current users and future users. b) The team size and c) funding available for future and current users is shown.

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 UAS 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.

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 2-6 times a year. Spatial resolution tended to be at the centimeter scale (57.7%), followed by the meter scale (51.1%).

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%).

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 post processing (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 UAS. 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 sixty percent) would like to publicly share UAS imagery and / or derived data.

Discussion

Rogers (E.M. 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 represents the population of technology adopters. In this context, our survey suggests that the use of UAS 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, 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, what Moore (Moore, 2006) referred to as "crossing the chasm" of Roger's technology adoption curve.

Results from this survey portray the perceived value of UAS technology is greater among active users than non-users (Fig. 1). This result suggests that active users have found applications where UAS technology reliably adds value within their enterprise (Moore, 2006). 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 which self-identify both as an active UAS user and working within these disciplines is congruent with this conclusion.

The cost of deploying UAS 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 UAS and those that had not. Equipment and software costs was the most commonly perceived bottleneck to adoption among non-users, 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. A breakdown estimate of hardware and software costs (Table 1) suggests that deploying 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. 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. We approximate that at minimum, 0.5 full time equivalent effort of a graduate student, post-doctoral scientist, or computationally inclined research associate will be required to set up the computational workflow to extract numerical data from drone images.

Table 1. Approximate costs of initial 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)	$150	$150
Drone (light-to-medium duty)		
Open market	$500	$6,000
U.S. government compliant	$3,000	$15,000
Drone (medium-to-heavy duty)		
Open market	Optional	$15,000
U.S. government compliant	Optional	$35,000
Extra batteries (per battery)	Optional	$700
Landing Pad	Optional	$50
Sensor		
RGB	Often integrated with drone	$7,000

Multispectral	Optional	$8,000
Multispectral and thermal	Optional	$16,000
Real-Time Kinematic correction		
Survey kit	$3,000	$10,000
On-board integration	Optional	$1,000
Ground Control Point Panels (5)	$75	$4,000
Remote ID module	Integrated with some drones	$350
External hard drive (5 TB)	$150	$150
Computer	Public computing resources	$5,000
Imagery processing software (yearly subscription)	$0 (Open-source options)	$3,500
ABC Fire extinguisher	$100	$100

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 (Kefauver, Araus and Buchaillot, 2019; Matias *et al.*, 2022; Bhandari *et al.*, 2023).

Regulatory burden is another factor which is perceived to restrict drone utilization. In the United States, practitioners using a UAS that weigh between 255 grams and 25 kilograms 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 under U.S. Executive Order 13981 and as part of Section 848 of the FY20 National Defense Authorization Act 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. In the short term, this restriction increases acquisition cost (Table 1) and greatly reduces the number options available. Additional regulations mandated under the U.S. Geospatial Data Act of 2018 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.

Based upon this survey and input from the domain experts interviewed we propose that UAS adoption can be accelerated through the formation of multi-disciplinary 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; Thorp *et al.*, 2018, 2022; Sinha *et al.*, 2022), plant breeding (Crain *et al.*, 2018; Sun *et al.*, 2019; Rodene *et al.*, 2022; Adak *et al.*, 2023; Herr *et al.*, 2023), and crop modeling (Zhou *et al.*, 2016; Chu *et al.*, 2017; Pugh *et al.*, 2018; Anderson *et al.*, 2019; Chandel *et al.*, 2022), 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.

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