AG2PI SEED GRANT PROPOSAL

Title of Proposal:
Facilitating community unoccupied aerial systems (UAS, drone) knowledge, communication, and data processing

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0. Background

Unoccupied / unmanned aerial systems (UAS, also termed UAVs or drones) have unique advantages for advancing the phenome component of genome to phenome research (Shi et al. 2016, White et al. 2021, Jung et al., 2021; DeSalvio et al., 2022). UAS are becoming relatively inexpensive scientific instruments for leveraging the massive amounts of field-grown research plots (Bhandari et al. 2022, Adak et al. 2022; Rejeb et al., 2022; Jang et al., 2020; Haghighattalab et al., 2016) or animal and rangeland research (Abdulai et al. 2021, Gillian et al. 2021, Los et al. 2022). Unlike laboratory and genomics tools with expensive consumables, a field researchers' investigations can and have been leveraged into world class discovery with as little as a DJI Phantom 4 drone ($2500) and a computer ($5000); very accessible and scalable to those with limited resources. Based on successful knowledge and decision making (Guo et al. 2021), as well as anticipated future applications, UAS could become an important tool in every plant and animal field researcher's phenotyping tool-box within the next five years, but adoption will be stymied unless a community is built to share experiences and advance the technology. Many successful and potentially transformative case studies already exist. However, given accessible UAS technologies are recent, examples and analyses tools are new and largely exist in silos. For most researchers attempting to incorporate UAS into their research, education and extension, unknowns and perceived limitations exist as barriers. Other researchers use cases have overcome such challenges, but disparate publication, reporting and communities leave gaps in awareness. Even at the most basic level we experienced research published in the same species using the term 'UAV' was unaware of highly similar work published four years earlier because the term 'UAS' was used. In other cases, researchers in different regions, crops or species have developed a better or easier methods to use for the same task. Such levels of technical application and knowledge are considered scientifically unremarkable; thus details, tips and tricks that would allow a new investigator to get started are unlikely to be published in peer-reviewed publications. Other sources of this information have been developed and are available such as webinars (e.g. PhenomeForce, Plant Phenome Journal), manuals, tutorials, and software but remain incomplete, developed in silos and/or difficult to find and synthesize.

Another major concern about every new phenotyping technology is that it is data collection for data collections sake, a solution in search as a problem, or collection of data with hope that there will be a future application or algorithm with which to analyze it. UAS experts often hear from researchers who have collected 1000's of images but have them on a hard drive without making any useful discoveries or decisions from them because of limited knowledge in data extraction. The large volume of datasets collected are at the risk of becoming "dark data" (Guo et al., 2021). In contrast, other researchers have already transformed research programs and knowledge using UAS data by developing capacity for processing. The key, we believe, is making existing workflows and software well known and reviewing their specific applications and limitations. In this project we will attempt to build on the success of and integrate momentum in UAS activities across different groups (described in section 6. Engaging AG2P scientific communities & underrepresented groups). Yet even for these expert groups, community questions exist (Heidorn 2008; Guo et al., 2021). For example, broadly unknown is what the data lifespan of these products are. How long should raw images be saved to give constant extraction improvements? How long should processed products be saved given their enormous size, versioning, and potential for re-extraction? Should the industry provide image acquisition standards so different datasets can be co-analyzed? These uncertainties and UAS best practices need some consensus to advance UAS as a routine phenotyping tool.

1. Objectives/aims

The overall goal of this project is to advance phenotyping knowledge and activities (both adoption and application) through advancing UAS data collection, processing, analysis, and community discussions.

The overall hypothesis to this project is that there are many great, yet disparate UAS activities, occurring in silos and that better communication, including personnel solely dedicated towards advancing communication and analysis activities across research, education, and extension, will create transformative change for all stakeholders, regardless of species.

The overall objectives of this project are to:

1) Enhance networks and communication of best practices between groups and individuals currently successfully developing and using UAS tools, as well as those that seek to use UAS tools in the future.

2) As a case study and nucleating force, to process most existing Genomes to Fields (G2F) UAS datasets (2017 to 2023, and up to eight locations) into usable end products for the community to directly use, making them publicly available.

3) Develop a user-friendly webpage that acts as a centralized platform to find necessary resources and information related to UAS based HTP.

The overall activities of this project following the objectives are to:

1) Support a UAS Activities Coordinator that can connect with existing UAS in agriculture user groups (see section 6; and try to involve and organize livestock and rangeland users), listen to their needs, provide support for their communication, answer questions, summarize their knowledge and connections across discipline, institutions, and species; then ultimately distribute this wisdom through regular communication.

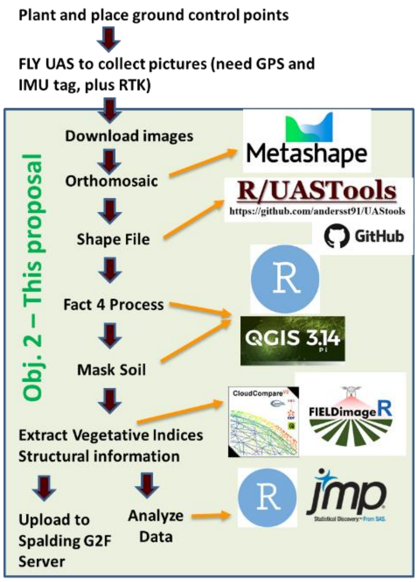
1.a) Collect and maintain opt-in contact lists of investigators with expertise in or interest in the use of UAS from existing groups. Share regular email newsletters on UAS work and knowledge with this group, especially from across the many UAS use groups that exist.

1.b) Support attendance at the S1069 multistate UAS meeting from 10 first-time diverse attendees (background, species of study, research topic - working with S1069 leadership [see letters] and others to review applications).

1.c) Organize discussions of major unsolved topics of community wide interest to develop technical best practices. Examples “UAS data organization and storage”, “UAS data lifecycle and lifespan – what data to keep”, “UAS in extension”, “UAS open-source software”, “data ownership/best approaches to make data publicly available.”

2) Support a G2F Orthomosaic Data Technician to use an existing published workflow (Adak et al. 2022; see figure below and Adak letter) to process existing UAS G2F temporal season-long image sets collected on approximately 500 plots on up to eight complete environments each over three years. However, many environments were collected using different UAS and cameras and have differing spatial parameters and temporal modes. While some workflow steps have been or could be automated, differences necessitate expert intervention. The proposed workflow (in green in the figure) can be adjusted and other software (e.g. Progeny / Plot-Phenix, ImageBreed) may be incorporated based on community input. A reference dataset(s) will be selected from among these for comparison with multiple data processing software in Objective 3.

The processed products will be placed into collaborator Spalding's public server following G2F and AG2PI data guidelines (data management section 9 and Spalding letter). If successful, this would be the largest public data set of processed UAS data and allow new insights into multi-environmental comparisons of temporal and genetically variable small-plot data. This dataset contains corresponding genotype, phenotype and environmental data and would be an extremely unique and useful resource to explore.



3) Develop a comprehensive UAS in agriculture website: An organized, easily navigable webpage will be designed and developed to host all the information needed for UAS-based phenotyping. In addition, this webpage will have the link to all the image processing pipelines and software highlighting their advantages and disadvantages obtained from activity 3a. The webpage will be built using a website builder (for example DIVI) and hosted using commercial platforms where the domain (for example GoDaddy) will also be obtained. Additional languages such as HTML (provides the structure of the pages), CSS (visual layout), Javascript (webpage interactions), and MySQL (to store and retrieve information/data) will be used as needed.

3.a) Working with the technician in objective 2 and collaborators, compare at least one G2F reference UAS dataset in terms of available software workflows and make this comparison available. Several image processing pipelines (Agisoft Metashape (www.agisoft.com), Pix4D (www.pix4d.com), Bison-Fly (Matias et al., 2022), FIELDimageR (Matias et al., 2020), ImageBreed (Morales et al, 2020), UASHUB developed by Texas A&M University-Corpus Christi and Texas A&M AgriLife Research, Plot-Phenix (www.plotphenix.com), ArcGIS (www.esri.com) are available, each with advantages and disadvantages. Pipelines will be evaluated in terms of accessibility, efficiency, processing needs, capabilities, and convenience.

2. Furthering the aims of the AG2PI

This proposal ***addresses three of six priority topics identified in the AG2PI community survey***: "Collecting, developing, and/or integrating phenotyping data, tools and technologies to advance AG2PI research", "Developing strategies for handling and integrating disparate data types (multi-scale, multimodal, etc.) to address research challenges across scientific communities" and "Making tools and technology more accessible and/or scalable, particularly to those with limited resources."

For the survey question "Finish this statement: I'd be more likely to collaborate if..." 33.6% said "It were easier to find collaborators outside of my discipline", 22.0% said "I had more time", and 10.0% said "There were places to publish the resulting research". ***These problems are a few that this project seeks to solve***.

For the survey question of "Which…PHENOMICS resources do you wish you had better access to…" the top answer was "Image analysis methods and applications" (which could be greenhouse or field) the 2nd answer was "Field remote sensing platforms: UAVs", 3rd was "Automated crop measurement systems" Importantly, these three top answers remained the same with positive respondents with these resources and whom are willing to share. We can conclude from this that ***there is a substantial opportunity to connect UAS collection, analysis through measurement in the phenotyping community between experienced and future users.***

Finally for the question "What types of training for your students or staff do you wish you had better access to" the top answer (30.5%) was "Quantitative sciences" – ***which is the majority of analysis workflows and software for UAS we seek to communicate in this project***.

3. Expected outcomes & deliverables

Objective 1 deliverables: *Contact information of researchers specifically interested in UAS activities. *Collections of specialized knowledge and ideas *Routine communication of UAS activities and resources geared towards their interest. *Working group meetings to discuss specific topics of interest (e.g. UAS data standards) synthesized into best practices and shared.

Objective 2 deliverables: *Processed FAIR data products including: shapefiles, orthomosaics, 3D point clouds, and plot level data extraction from G2F and other large UAS data collection campaigns that can be used by anyone interested (see data management). *A first-of its kind, multi-environmental dataset.

Objective 3 deliverables: *Compiling and compared software/pipelines, *Linking all discovered available software, protocols, and procedures needed to develop a UAS-based HTP system. *Based on outcomes of meetings, resources will be organized according to protocols for developing successful UAS-based HTP system. Specifically, specifications of sensors/platforms, geo-referencing needs/requirements, mission planning, imaging standards, processing of raw data, processing of orthomosaics and geospatial data products to derive canopy features, plot boundary creation, and feature extraction.

The ***primary outcomes*** will be 1) greater use and accessibility of meaningful UAS data by agricultural researchers and 2) enhanced communication and collaboration between different groups and domains, and 3) more rapid development of tools and applications.

In keeping with the spirit and requirements of AG2PI projects, additional deliverables and outcomes from this project will include: 1) A brief final written report of the project activities and deliverables within 60 days of the completion of the project. 2) Increased activities and outcomes visible through the AG2PI communication channels. 3) Additional survey questions for AG2PI and NAPPN surveys. 4) Presentation at NAPPN and the AG2PI organized event, as well as other meetings.

This project ***will catalyze AG2PI Priority Areas*** in the following ways. *Data Storage/ Sharing* – recommendations will be made for how to organize UAS data, how to make UAS data FAIR, where to store data, and data lifecycle analysis for users, funding agencies, institutions and policy makers – this will be exemplified using G2F data as a case study. *Cross-fertilization of ideas* – enhanced communication between different UAS use groups, a centralized web home for UAS information, broader attendance at the S1069, NAPPN and related meetings. *Education/Training* – highlighting various workshops and webinars to a broader audience, making software, code and workflows better known and findable in a centralized home. *Mitigate environmental impact* – researchers working to measure and monitor environmental impacts will find UAS tools more accessible and available. *Other* - phenotyping data, tools and technologies will be integrated to advance AG2P research. Strategies will be developed for handling and integrating disparate data types (multi-scale, multimodal, etc.) to address research challenges across scientific communities; and tools and technology will be made more accessible and/or scalable, particularly to those with limited resources.

4. Qualifications of the project team

PI Murray's use of UAS began when he and collab. Thomasson (now Mississippi State) developed the ***Texas A&M AgriLife Unmanned Aerial Systems Project of Precision Agriculture and High Throughput Field Phenotyping*** which grew to over 40 faculty across five colleges, transforming researchers' capacity and interest from geography and statistics to weed science and plant breeding. **The key to this projects success was communication - regular meetings and a professional coordinator**. Along with Thomasson, Murray was an initial writer of the ***S1069 USDA multi-state project***, and one of five writers of the S1069 renewal and the application for the multi-state project award. PI Murray founded in 2016 the ***Plant Phenome Journal*** (ASA-CSSA) because of difficulties in publishing UAS for agricultural applications in remote sensing journals; he served as editor for five years and led a monthly research webinar. Murray was elected to the inaugural ***North American Plant Phenotyping Network (NAPPN) board*** 2018-2019 and served as a co-chair of the ***Phenome meeting*** in 2020 further learning of the diversity and needs of this energetic community. Murray was ***first to make a UAS small plot data set publicly Findable, Accessible, Interoperable and Reusable (FAIR)***, hosted on CyVerse (Murray et al. 2019). He co-authored multiple documents supporting the need of a federal repository for agricultural remote sensing data (Brouder et al. 2018, Henkhaus et al. 2020). Murray participates in the ***Genomes to Fields (G2F- GxE)*** project since 2014 and collected and analyzed UAS data in G2F in thanks to three funded USDA-NIFA-AFRI grants specifically on UAS (2 PI, 1 co-I) focused on data collection and analysis only in Texas to date.

Co-PI Bhandari did his PhD dissertation research on HTP in wheat using UAS. Currently, he is building a Digital Agriculture program. The program is focused on developing UAS-based tools for HTP and precision agriculture. He is managing a UAS image processing and data management pipeline and supports several faculties across TAMU on processing and standardizing UAS data collected over cotton, wheat, peanut, and sorghum research/breeding trials. Significant involvement is on the USDA funded WheatCAP project in which the program supports the handling, processing, and management of UAS data collected from several wheat breeding programs across the country.

5. Proposal timeline

Because this project is one year – March 2023 to Feb 2024 all activities will occur simultaneously. Two of the positions already have candidates identified and can be placed nearly immediately. Multiple meetings targeting different audiences will occur each month. Each G2F environment season can typically be fully processed in 2 to 3 weeks. The draft website is expected within 6 months, to be finalized by the end of the project.

6. Engaging AG2P scientific communities & underrepresented groups

We do not seek to create a new scientific community (except for the possibility of integrating animal scientists) but to link and integrate those that exist. Major groups include: ***S1069 "Research and Extension for Unmanned Aircraft Systems (UAS) Applications in U.S. Agriculture and Natural Resources",*** – A multi-state USDA project on using UAS in agriculture that includes extension, education, research, crops, and animals. ***North American Plant Phenotyping Network (NAPPN)*** - a non-profit scientific organization leading many types of phenotyping research. ***Phenome-Force*** – an innovative phenotyping tutorial organizer with a large following and YouTube presence. ***Genomes to Fields (G2F)*** – a large community of maize researchers, many of whom have collected drone data in a semi-coordinated manner. ***Drone 2 Phenome (D2P) group*** focused on development of open software, data, and methods to support the use of UASs in plot-based research and ***Open Drone Data Processing Interest Group (ODD-PIG)***. ***Airborne and Satellite Remote Sensing Community and Precision Agriculture Community, Agronomy Society of America*** a user community; ***ASABE - Plant, Animal, & Facility Systems (PAFS)*** as a potential for animals and standards***;*** ***SPIE Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping***; and others.

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