Computers and Electronics in Agriculture 197 (2022) 106944

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Special report: The AgAID AI institute for transforming workforce and decision support in agriculture

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A R T I C L E I N F O

Keywords:
Agriculture
AI
Decision support

A B S T R A C T

Tackling the grand challenges of 21st century agriculture (Ag) will require a fundamental shift in the way we envision the role of artificial intelligence (AI) technologies, and in the way we build agricultural AI systems. This shift is needed especially for complex, high-value agricultural ecosystems such as those in the Western U.S., where 300+ crops are grown. Farmers and policy makers in this region face variable profitability, major crop loss and poor crop quality owing to several challenges, including increased labor costs and shortages of skilled workers, weather and management uncertainties, and water scarcity. While AI is expected to be a significant tool for addressing these challenges, AI capabilities must be expanded and will need to account for human input and human behavior – calling for a strong AI-Ag coalition that also creates new opportunities to achieve sustained innovation. Accomplishing this goal goes well beyond the scope of any specific research project or disciplinary silo and requires a more holistic transdisciplinary effort in research, development, and training. To respond to this need, we initiated the AgAID Institute, a multi-institution, transdisciplinary National AI Research Institute that will build new public-private partnerships involving a diverse range of stakeholders in both agriculture and AI. The institute focuses its efforts on providing AI solutions to specialty crop agriculture where the challenges pertaining to water availability, climate variability and extreme weather, and labor shortages, are all significantly pronounced. Our approach to all AgAID Institute activities is being guided by three cross-cutting principles: (i) adoption as a first principle in AI design; (ii) adaptability to changing environments and scales, and (iii) amplification of human skills and machine efficiency. The AgAID Institute is conducting a range of activities including: using agricultural AI applications as testbeds for developing innovative AI technologies and workflows; laying the technological foundations for climate-smart agriculture; serving as a nexus for culturally inclusive collaborative and transdisciplinary learning and knowledge co-production; preparing the next generation workforce for careers at the intersection of Ag and AI technology; and facilitating technology adoption and transfer.

1. Introduction

Agriculture (Ag) is on the cusp of a fourth revolution. Viewed as a pathway to sustainably intensifying agriculture, the Agriculture 4.0 revolution (Rose and Chilvers, 2018) is necessary to meet the caloric needs of a growing global population while addressing production and environmental challenges such as shortages in skilled labor, weather and climate variability, and scarcity of natural resources (USDA, 2020). Digital technology, artificial intelligence (AI) in particular, is expected to be a key component of this fourth revolution. From real-time spatiotemporal sensing on farms, to sophisticated weather and crop models for understanding and applying the science behind agricultural production, to mechanized robots for automating agricultural tasks and operations – AI has the potential to revolutionize workforce and decision support in agriculture. For this to happen, fundamental breakthroughs are required not only in the AI technology, but just as importantly in the way we design and improve AI-enhanced workflows to meet the needs of diverse individuals working in agriculture. Furthermore, these technologies need to be context sensitive and fieldable. Keeping in mind potential uses, the technology should be designed with equity, diversity, explainability, and fairness as fundamental design constraints rather than an afterthought. In particular, agriculture in the Western U.S.,

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https://doi.org/10.1016/j.compag.2022.106944
Received 19 February 2022; Received in revised form 2 April 2022; Accepted 4 April 2022
Available online 19 April 2022

including Washington (WA), California (CA) and Oregon (OR), is a multibillion-dollar industry, accounting for hundreds of crops including (but not limited to) specialty crops such as tree fruits, nuts, grapes, and berries (Astill et al., 2020). Production of specialty crops is highly labor-intensive, accounting for 87% of the U.S. agricultural labor workforce, with WA and CA alone accounting for over 55% of the labor-intensive crop production (Hernandez et al., 2013). Farmers in this region, however, are facing uncertain and variable profitability due to increased labor costs, fewer workers, and a shortage of skilled labor (Hernandez et al., 2013). Weather also contributes to this uncertainty. Years with major crop loss and poor crop quality due to extreme or unpredictable weather events are now increasingly likely (Smith and Katz, 2013); as is a compression of the harvest period, resulting in a scramble to harvest billions of fresh market fruits in very little time. Water scarcity is also exacerbating the situation, as watershed and irrigation district managers as well as policy makers continue to face substantial obstacles in optimally allocating limited water resources (Mekonnen and Hoekstra, 2016). Collectively, these challenges have cost the Ag industry significant production and revenue. For instance, up to 50% of the annual state ag production losses (equivalent of millions of dollars in revenue) can be sustained in a single weather event (Snyder and de Melo-Abreu, 2005). Similarly, in recent drought years, WA, OR, and CA reported hundreds of millions of dollars in losses (Sandison et al., 2017).

These challenges are real, but the emergence of AI alongside increased availability of data have opened a new window of opportunity to help mitigate the impacts from these critical challenges. However, delivering on the promise of an AI-enabled Agriculture 4.0 is only possible with a carefully coordinated and concerted transdisciplinary team-science effort. Furthermore, water scarcity, farm operations, and Ag workforce challenges are not unique to the Western U.S., but their combination does make the region a unique testbed for the AgAID team to design and deploy effective AI solutions for this diverse set of growing national challenges. In particular, AI-enabled agriculture will require advances in several foundational areas of AI including:

1. Modeling – Process-simulation models are common; however, interactions with unknowns often affect their accuracy. A new systematic modeling framework is required for integrating knowns (data, process models, and domain expertise) with unknowns (e.g., human behavior and influence), in a way that can make simulation and decision engines more site-specific, more consistent with theory and data, and more aware of uncertainty.
2. Decision Support – Ag decision problems span the spectrum of challenges for AI decision making. They involve high uncertainty, complex decision spaces, and multiple scales of space (state to district to farm to tree) and time (seasonal to weekly to daily to seconds). Operational scenarios also vary from long interactive sessions with decision makers to real-time support in the field. New principled frameworks are needed to cover these problem classes and to flexibly interface with orthogonal AI advances in modeling.
3. Workflow Design – Ag applications involve many types of tasks and human actors, giving rise to many possibilities for inserting AI into established workflows. Currently, however, the fundamental principles for designing inclusive human-AI workflows that maximize net benefit (and hence adoption) are in their infancy. Agricultural AI applications provide a fertile testbed for developing and testing a systematic framework and process for designing and iteratively improving human-AI workflows that amplify productivity and accelerate adoption. Each of these foundational areas require new advances involving multiple AI topics. Developing these techniques under the Ag application framework presents opportunities to innovate and solve problems at the intersection of these different topics.

The AgAID Institute vision and approach: In summary, tackling the grand challenges of 21st century agriculture will require fundamental shifts in the way we envision the role of AI technologies, and in the way we build AI systems. This shift is especially true for diverse, high-value, labor-dependent agricultural ecosystems such as those in the Western U.S. The traditional approach toward development and deployment has been to view AI and technology designers as solution providers and the domain users as consumers. This monolithic view of producers and consumers, however, becomes grossly inadequate when brought to the fore in agriculture, which is a complex, commercial, multi-crop enterprise involving multiple stakeholders including the farmers (growers), farm laborers, consultants and technology service providers, state and regional policy makers, researchers and extension scientists, and students who form the future workforce. The role of weather and climate change, decisions under incomplete knowledge, risk management, and market uncertainties add to the complexity. Therefore, for any AI-driven endeavor to succeed in this complex "Ag-sphere", there must be a strong alliance built between the AI designers and this broad range of stakeholders. This AI designer – Ag stakeholder (people) alliance also needs to be complemented by a strong AI technology – human factors (system) alliance – i.e., AI capabilities need to include an inherent ability to integrate human input and account for human behavior. Humans can provide expert (scientific or in-field) guidance or be influential actors in complex dynamic processes (e.g., water use). Clearly, forging these two dimensions of alliances, people and system, is beyond the scope of any specific research project or disciplinary silo, and warrants a transdisciplinary multi-party institute-scale effort – one that can propel AI developments throughout the Ag industry.

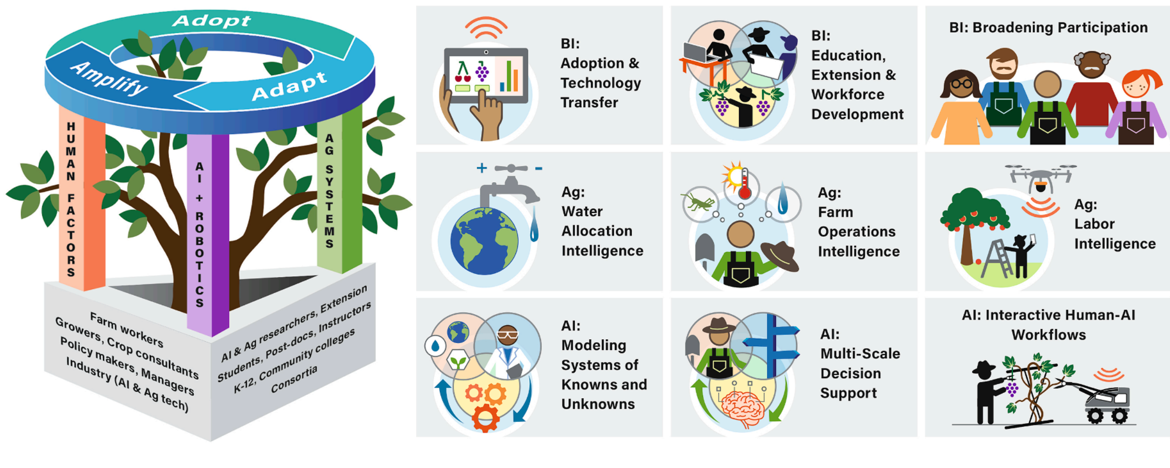
To realize this vision, the AgAID Institute is built on the foundations of our partnerships between the team and our stakeholder groups, with AI, Ag, and humans as its three major intellectual pillars, and guided by three unifying principles that can be succinctly summarized as "Adopt-Adapt-Amplify" (Fig. 1a). More specifically, we consider:

- **Adopt**ion as a first principle in AI design, to remove barriers to AI technology adoption in Ag applications. This is accomplished by treating practical constraints and user considerations as central to the AI design process, and creating an environment of technology and knowledge co-production, via proactive and continuous bidirectional engagement with the stakeholders.
- **Adapt**ability to changing environments and scales, an ability that our approaches inherently encode – to address the impacts of climate variability and weather fluctuations on agricultural productivity, and to provide decision support at multiple spatiotemporal scales of the Ag-sphere.
- **Amplify**ing human skills and machine efficiency by augmenting automation with human skills and creating a close human-AI partnership. This is critical to closing gaps in the workforce, while ensuring behavioral consistency and reduced uncertainty in decision support. Amplification can both enhance human skills and knowledge and improve machine efficiency, leading to a whole that is greater than the sum of its parts.

These three important cross-cutting principles of design guide our approach to the core activities of our Institute, and are being coordinated along nine interwoven dimensions (Fig. 1b).

Consequently, the **overarching goals** of the AgAID institute are (a) to bring about a fundamental transformation in Ag decision support, farm operations and workforce development, using foundational developments in AI, and (b) to build a new coalition to create inclusive AI-Ag that is prepared and ready to take on future challenges of societal importance.

The AgAID Institute Team: The AgAID Institute is a transdisciplinary coalition of Ag and AI researchers, educators, extension professionals, industry technology providers, growers, crop consultants, managers, and policy makers, creating an ecosystem for driving the Agriculture 4.0 revolution. The core members include six universities,



(a) (b)

Fig. 1. (a) The AgAID Institute and its three institutional pillars, key stakeholders (foundation) and the guiding design principles (roof). (b) The matrix of major thrusts of the AgAID Institute.

two regional colleges, and two technology companies. Fig. 2 shows the lists of all member organizations along with their respective key capabilities and programs relevant to the Institute's vision and goals.

1.1. Organization

The rest of the manuscript is organized as follows. Section 2 describes the focal points of the various research activities ongoing at the AgAID Institute as well as key elements of related extension and workforce development activities. Section 3 discusses key challenges in the implementation of the Institute and strategies to address those challenges. Section 4 summarizes the major components and expected impact and outcomes of the Institute.

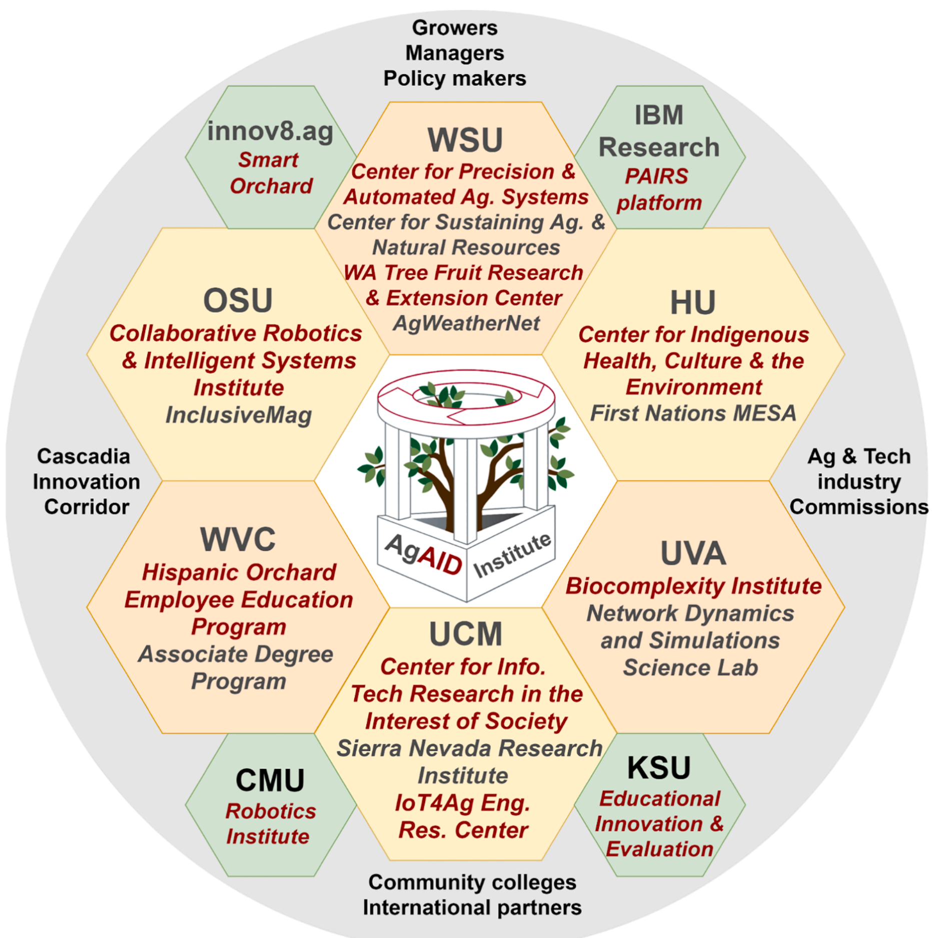


Fig. 2. The AgAID Institute team and partners.

2. Research thrusts

The key research activities of the AgAID Institute are organized around three Ag-inspired research thrusts (“Ag thrusts”) that work hand-in-hand with three foundational AI research thrusts (“AI thrusts”) – see Fig. 3. Each Ag thrust represents a coherent group of use-inspired AI development activities, motivated by a central Ag theme. The activities will focus on establishing application testbeds over which to develop, apply, and demonstrate the AI utility. Each AI thrust, on the other hand, represents a set of core abstractions that encapsulate specific needs from one or more of the Ag thrusts.

2.1. Agricultural use-inspired research (Ag thrusts)

Water Allocation Intelligence. The central hypothesis driving the Water Allocation Intelligence thrust is that addressing allocation challenges will require new AI-enabled models of the coupled human and natural system, and AI-enabled decision support. The key objectives are to complement hydrologic sciences and enhance applicability by incorporating the human-water nexus; facilitate a shift from water “supply” to “availability” forecasts; and develop tools for optimal water allocation decisions. Fig. 4 illustrates the main research schema of this research thrust including its key components and target use-cases.

Farm Operations Intelligence. The central hypothesis driving the Farm Operations Intelligence thrust is that AI-enabled, real-time, site-specific decision making can optimize the management of farm resources thus increasing productivity, mitigating crop losses, and improving produce quality. The key objectives are to develop site-specific models connecting accumulated management decisions to seasonal crop yield and quality outcomes, and construct sensor-driven, adaptive, real-time farm operations decision support frameworks. Fig. 5 shows the main research schema of this research thrust. Several use-cases relating to deficit irrigation, frost management, and harvesting are part of this thrust.

Labor Intelligence. The central hypothesis driving the Labor Intelligence thrust is that the challenges posed by increasing labor costs and a shortage in skilled workforce can be effectively addressed through human-machine partnerships. The key objectives are to: improve the efficiency of existing field machines with AI; augment a less experienced workforce with intelligent machines; and amplify more-experienced workers’ productivity by training machines. Several use-cases that involve labor-intensive operations to tree fruits (e.g., pruning, thinning) and nut trees (e.g., mechanical harvesting) are part of this thrust, as shown in Fig. 6.

2.2. Fundamental AI research and development (AI thrusts)

Agricultural AI involves a spectrum of attributes: interacting biophysical processes (known and unknown), high uncertainty, multi-scale spatiotemporal data, a range of decision timescales (real-time vs. long-horizon), a diversity of users, and many possible human-AI workflows. This drives the research activities that are part of our foundational AI thrusts.

Modeling Systems of Knowns and Unknowns. Agricultural AI needs to model systems of biophysical and human processes, from watershed dynamics to orchard temperature dynamics, to tree-machine dynamics. The systems include known processes (e.g., water dynamics) with well-established simulation models, and unknown processes (e.g., human actions) for which there is only sparse data and weaker knowledge. Therefore, modeling frameworks need to use data, science, and AI to jointly infer the unknowns and improve the knowns. The resulting models will be site-specific (e.g., for particular regions, fields or trees), scientifically consistent, explainable, will explicitly account for uncertainty, and will help direct data collection for improving the model.

Multi-scale Decision Support. Agricultural AI needs multi-scale decision support for humans and robots, from water delivery scheduling by irrigation districts to real-time frost mitigation, to semi-autonomous tree-shaking robots for mechanical harvesting. The decision frameworks need to improve existing models to make them suited for site-specific decision support, ranging from real-time execution to long-term planning. The frameworks also need to support learning from human expertise, human-AI collaboration, and account for uncertainty to help ensure safe and trustworthy support.

Design of Interactive and Inclusive Human-AI Workflows. Adoption of agricultural AI entails identifying workflows with human-AI roles and interactions that amplify productivity. This may range from desktop decision support for an irrigation district, to hand-held real-time decision support for a farmer, or farm workers interacting with robots.

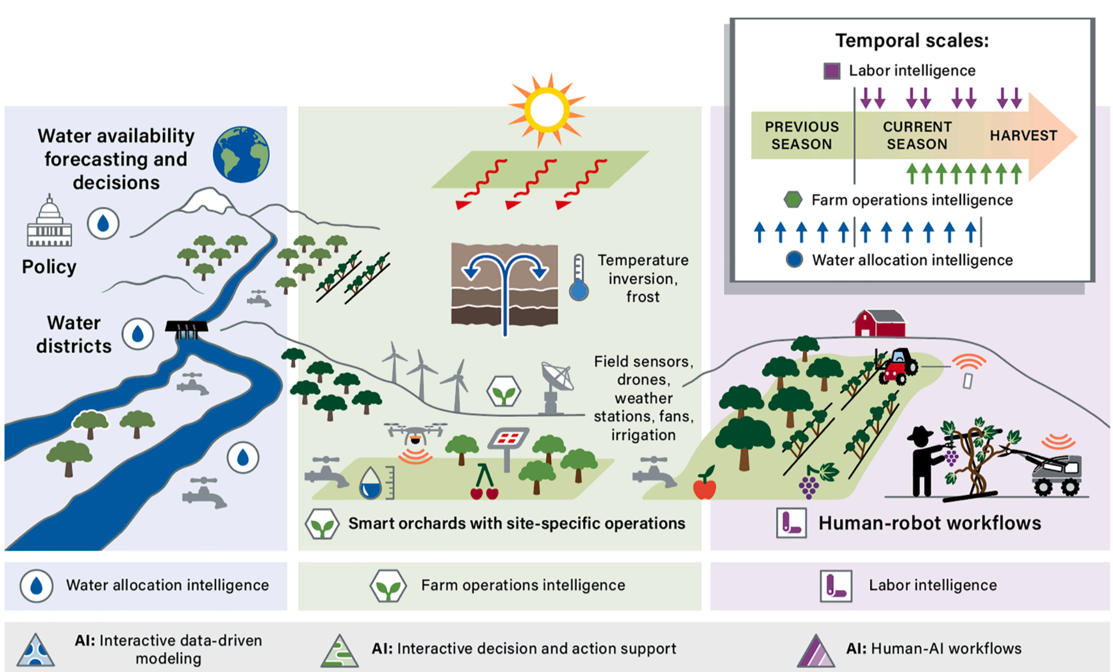


Fig. 3. A schematic illustration of the AgAID Institute research thrusts in the Ag-sphere.

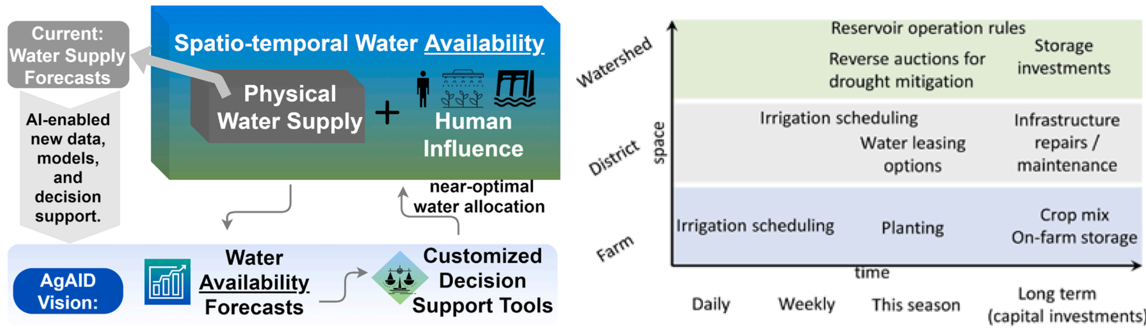


Fig. 4. Water allocation intelligence: (left) Thrust capabilities; and (right) Short and long-term decisions at different spatiotemporal scales.

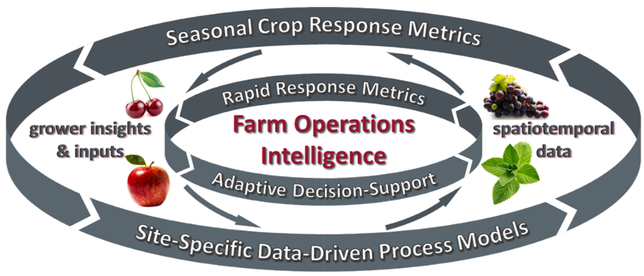


Fig. 5. Farm Operations Intelligence: Integration of near real-time decision-support with empirical seasonal models predicting economically important outcomes.

Our work is developing new frameworks and processes for designing human-AI workflows based on the military concept of after-action-review. The result will be simple iterative workflows, as shown in Fig. 7, that encapsulate AI capabilities using explainable interfaces, while prioritizing inclusiveness for equitable adoption. The resulting workflows can adapt to new information, amplify productivity, and create easier adoption pathways.

2.3. Engagement, extension, and workforce training

Agricultural extension and workforce development are an integral part of the AgAID Institute's mission. The goal is to create a bridge for continuous engagement between researchers, educators, and key Ag and technology stakeholders, and emphasizes an actionable, pragmatic approach that builds towards knowledge co-production and co-dissemination, while creating an environment for responsible AI innovation (Rose and Chilvers, 2018). The AgAID extension and workforce development activities are focused on continuous and iterative engagement with the agricultural community in order to further the adoption goals of the Institute. More specifically, the extension team is working on: (i) Facilitating needs-driven co-development of inclusive and responsible AI tools via learning circles, resulting in tools with higher adoption likelihood, and that are adaptive to changing requirements; (ii) Jumpstarting the adoption process by leveraging stakeholder relationships to recruit an early adopters' network which will provide critical feedback on prototype tools and accelerate adoption in their social networks; and (iii) Supporting adoption amplification into user communities through training programs, and engagement with intermediaries to scale tech transfer and adoption. This iterative and multi-stage process is illustrated in Fig. 8.

In addition, the AgAID Institute is setting up a new smart orchard infrastructure to test and showcase new AI tools as well as to train the

Fig. 6. Labor Intelligence: Use-cases include a) nut harvesting, b) blossom thinning, and c) tree skeleton for automated pruning.

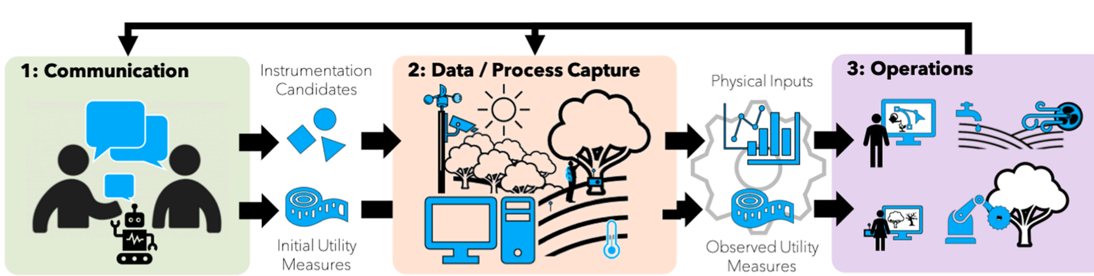


Fig. 7. AgAID Institute' human-AI workflow showing an iterative human-centered design loop.

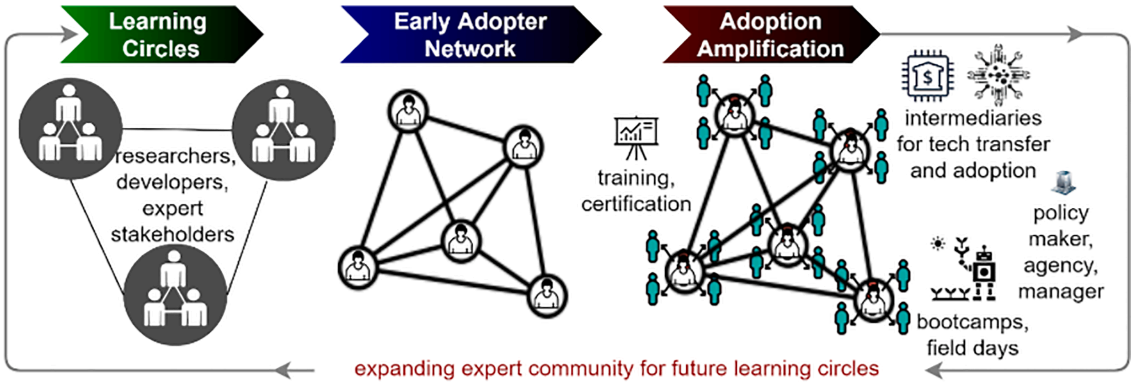


Fig. 8. AgAID's engagement and extension activities.

current and next generation workforce. More specifically, an instrumented AI-driven demonstration farm and community learning hub is being established as an Institute-level resource. This demonstration farm will provide: (1) an interactive research platform for transdisciplinary teams to work side-by-side to better understand how AI technologies should be developed for different agricultural use cases; (2) an educational hub for students to gain hands-on experience; and (3) an experiential learning site for key stakeholders including growers, field workers, educators, and technology providers.

Toward the goal of preparing the next-generation workforce, the AgAID Institute is targeting its training programs at learners from all levels with an emphasis on "transition points" when students often make career-defining choices. In particular, at the K-12 level, the focus is on middle and high school levels when students identify career preferences and often opt-out of STEM. At the undergraduate level, the focus is on community colleges and 2-year associate degree programs, which offer vital stepping stones to 4-year colleges, especially for lower income, underrepresented, and first-generation students. At the graduate level, the focus is on graduate students and postdoctoral scholars who will form the workforce in research and technology development. Finally, as part of an effort to train the current Ag workforce, the AgAID team is also developing training materials and bootcamps for use at ongoing training programs such as the Hispanic Orchard Employee Education Program at Wenatchee Valley College.

3. Challenges and alternative strategies

One of the main challenges of the AgAID Institute will be the transfer and adoption of technologies. Adoption will depend on several critical factors, including economic (return on investment, variability in returns), financial (borrowing limits, leverage), psychological (risk aversion), and social (marketing, learning) (Baerenklau, 2005; Barham et al., 2015). To effectively address this challenge, the AgAID Institute is implementing a number of proactive strategies to develop an ecosystem that accelerates innovation feedback cycles and supports the uptake of new technology.

Early adopter network: Social factors and network effects play a fundamental role in technology adoption in agriculture (Micheels and Nolan, 2016). A small number of early adopters play a critical role in demonstrating the effectiveness of new technologies and communicating success through action and adoption. The AgAID Institute is using existing grower networks to promote R&D outcomes with AI-ready and Ag-aware user groups. These networks and local advisor groups can collectively provide a specialized group of early adopter stakeholders for tech demonstration and potential adoption.

Commercialization: The level of success in adoption and technology transfer can be measured not only by the number of participating growers, but also by the number and size of allied technology companies that seek to integrate R&D into scalable commercial products. This level of integration will require engaging the entire ecosystem of hardware, software, and data-centric providers from the start of the innovation cycle and throughout the R&D process. While this "adoption flywheel" will be facilitated by feedback from AgAID Institute learning circles, the potential barriers to AI-centric adoption and technology transfer are well recognized. The Institute is also engaging growers and industry in adopting and building trust in data and technology frameworks by encouraging data transparency, embracing data standards, using open APIs, and exploring data sharing options to protect proprietary and/or confidential data. This will foster innovation and entrepreneurship and ultimately develop a vertical presence in commercialization from idea-tion to exit.

Third party adoption: It is well recognized that agricultural technology adoption is often paradoxical. As individual farms acquire new technology (e.g., drip irrigation) more capital and might need to be invested to operate and maintain the technology, thereby potentially reducing economic benefit. As technologies progress in sophistication, and hence cost, it becomes prohibitive for most farms to make capital investments on their own. It is often more efficient for a third-party entity to operate, maintain, and deliver technology as a service. Beyond this, it is conceivable that AI-centric adoption and technology transfer may require a shift in lending models, pooled hardware/software rental, and/or rebates on crop insurance for data sharing – though contemporary agricultural contracts have strong institutional inertia when considering what is feasible (Allen and Lueck, 2008). Business level financial analysis combined with a regional economic model will support the comparison of scenarios where AI technologies are directly adopted farm-by-farm versus those in which a specialist operation contracts separately with farms to deploy the technology, or other alternatives.

Financial intermediation: The extent to which AI technology is adopted in agriculture may be limited to some segments of the farming industry. In particular, one of the limiting factors is expected to be the financial constraints borne by smaller scale growers, or by young and beginning farmers (compared to farms that are already highly leveraged). New entrants into farming are critical for dynamism and innovation in the industry (Aghion et al., 2009), but since most farms are sole proprietorships that lack limited liability (Briggeman et al., 2009), and tech investments are capital substitutes for variable inputs such as water and labor, overcoming financial risk is a recognized barrier to adoption efforts. Thus, the Institute will build on existing relationships with public and private farm lenders to understand how lending standards may limit tech adoption, and whether special financing programs or more creative finance mechanisms are needed.

Ethics and responsible innovation: Another grand challenge for any large-scale technology- and innovation-driven initiative – to which the AgAID Institute is no exception – is to do with creating an environment for fostering ethical and responsible innovation. The AgAID approach and frameworks will draw from established principles in responsible innovation (e.g., Stilgoe et al., 2013) to create best practices that foster a long-term culture of responsible innovation. This includes providing a platform to facilitate lines of questioning around product, process, and purpose of innovation – a representation of societal concern and interest in research and innovation.

AI Fairness is a rapidly expanding field in its own right. Some issues are particular to the domain of agriculture, such as AI's recommendations that might save costs but harm the environment, reduce the very aspects of the work that are rewarding to farmers, or negatively affect the welfare of the humans and animals (e.g., (Ryan and Stahl, 2020)). To make the researchers and students aware and alert to these issues, continuous discussion of these aspects in workshops and other community engagement-centric events is needed. Furthermore, given the large diversity of agricultural and technological stakeholders – spanning multiple races/ethnicities, genders, education levels, and roles – focus must be on not only equitable treatment under the hood in algorithms and data, but also "over the hood"–i.e., in the workflows our human stakeholders must carry out.

4. Discussion

The AgAID Institute is building an innovation ecosystem for agricultural AI technology and knowledge co-production, and workforce development, and is using Ag-inspired use cases to push the frontiers in foundational AI research in three major directions: 1) modeling knowns and unknowns with data and scientific knowledge while accounting for uncertainty; 2) designing multi-scale competency-aware decision support for real-time and long-horizon decision making; and 3) designing interactive and inclusive human-AI workflows and explainable interfaces that can amplify learning and productivity in human-machine environments.

By embracing an adopt-adapt-amplify principle, the Institute's activities are expected to translate these foundational AI developments into solutions for three major Ag areas: a) water allocation intelligence, moving the forecast needle from water supply (weaker) to water availability (stronger) while accounting for hidden human and other influences, b) farm operations intelligence, providing efficient site-specific real-time decision support at multiple scales, and c) labor intelligence, creating new opportunities for farm workers and machines to collaboratively amplify productivity. Ultimately, the Institute signifies a convergence of multiple disciplines and stakeholder groups, bringing about advances that go well beyond disciplinary boundaries in order to ensure a sustained partnership between the AI and the Ag communities. Our intended outcomes range from short to long-term, and across multiple levels, from skill building and job quality improvement, to new career opportunities, enhanced regional and national food security, and improved AI adoptability (as shown in the logic model view in Fig. 9). As use-inspired factors drive development, the foundational AI elements will have the capacity to be extended to other global agricultural systems. Meanwhile, these foundational AI advances can also be adapted to other domains characterized by similar challenges and opportunities such as, manufacturing and healthcare, both of which have a strong human-AI component, albeit with a different host of stakeholders and associated challenges in operations and human workforce.

More information about the Institute, its members, and thrust level organization details can be found on the Institute's webpage: https://agaid.org/

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

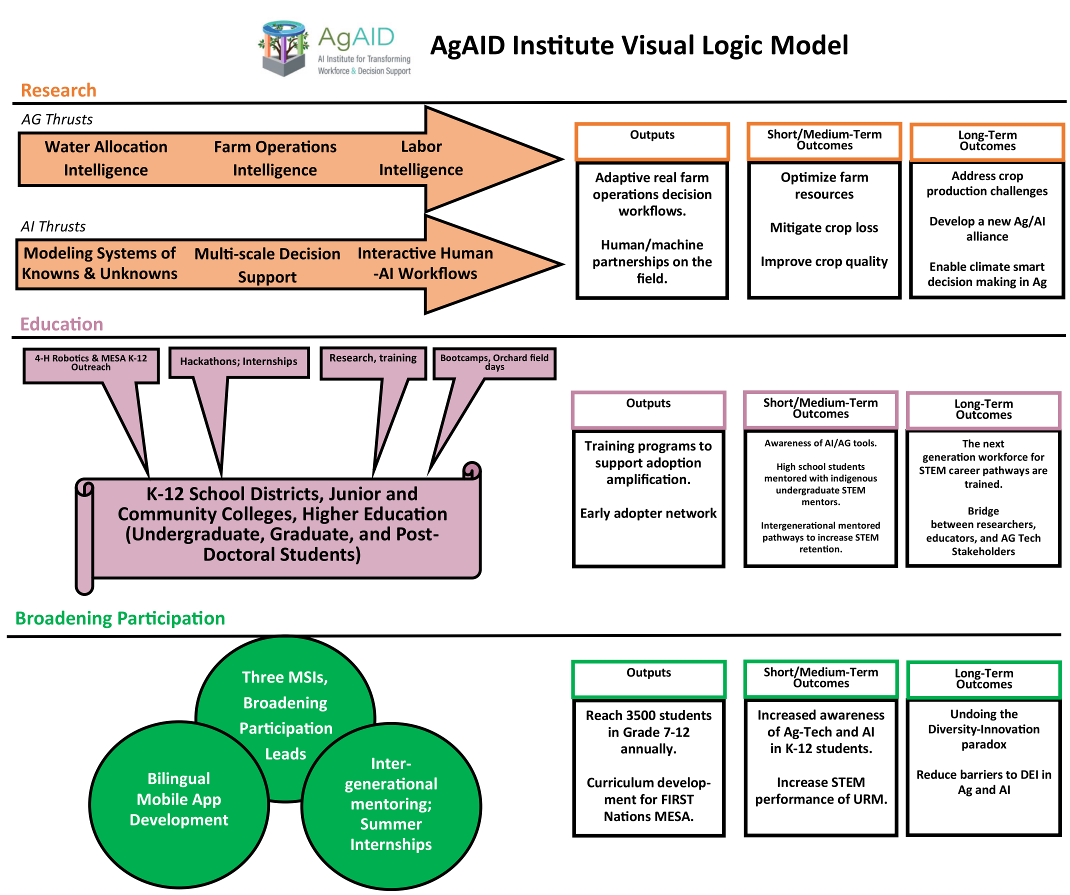


Fig. 9. A logic model showing a list of anticipated AgAID Institute outcomes and outputs.

the work reported in this paper.

Acknowledgments

Other AgAID Institute members and key contributors to this work include John Abatzoglou, Jennifer Adam, Abhijin Adiga, Leigh Bernacchi, Jessica Black, LeAnn Brosius, Jenny Bolivar-Medina, Michael Brady, David Brown, Ian Cummings, Joseph Davidson, Nancy Deringer, Amit Dhingra, Jana Doppa, Cindi Dunn, Reza Ehsani, Xiaoli Fern, Joshua Goldstein, Cindy Grimm, Sonia Hall, Rebecca Hutchinson, Jordan Jobe, Minsuk Kahng, Lee Kalcsits, Manoj Karkee, Markus Keller, Heather Knight, Chad Kruger, Stefan Lee, Mingliang Liu, Steve Mantle, Madhav Marathe, Josue Medellin-Azuara, Paola Pesantez-Cabrera, Troy Peters, Raviv Raich, Kirti Rajagopalan, Sai Ramaswamy, S. S. Ravi, Bernardita Sallato-Carmona, Sindhuja Sankaran, Claudio Stockle, Samarth Swarup, Jian-Qiao Sun, Prasad Tadepalli, Sinisa Torodovic, Anil Vullikanti, Matthew Whiting, Weng-Keen Wong, Yan Yan, Jonathan Yoder, Georgine Yorgey, Jia Yu, Wenzhen Yuan, and Qin Zhang. The AgAID AI Institute for Transforming Workforce & Decision Support is supported by the United States Department of Agriculture - National Institute of Food and Agriculture (NIFA) award #2021-67021-35344. The AgAID Institute is one of the AI Institutes supported jointly by the U. S. National Science Foundation and U.S. Department of Agriculture, as part of the National AI Research Institutes program.

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