Climate Adaptive Smart Systems for Future Agricultural and Rangeland Production

A White Paper

on

Artificial Intelligence Applications in Agriculture

by

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August 2019

Executive summary

Climate Adaptive Smart Systems for Future Agricultural and Rangeland Production

Global food supply and food security are at risk due to an increasing world population, climate variability, diminishing natural resources, and limited available land. In the agricultural sector, the primary challenge has been how to be more productive with less – less arable land, less water, less labor, less certainty. In the largely rural arid and semi-arid Southwest US, including New Mexico, the challenges and opportunities are amplified as agricultural production systems struggle to cope with rapid changes in water availability, environmental stress, and labor availability. Innovative solutions can be realized through employing artificial intelligence (AI) based systems in agriculture to address these challenges. However, the speed of advancement and adoption of AI solutions has not reached all agricultural sectors equally and has been hindered by lack of practicability and the acceptance of AI as safe and secure.

New Mexico State University (NMSU) is uniquely positioned and equipped with the tools to address these challenges and opportunities. NMSU is an open laboratory for innovation in agriculture, a place where transdisciplinary and collaborative research is evident, where diffusion and adoption of technology is encouraged and achievable through its statewide network of science centers and extension agents, and where public accessibility of vetted science-based solutions is part of the philosophy of its land grant mission. In addition, the state of New Mexico is home to emerging high tech and entrepreneurial industries, major national laboratories and maintains a commitment to high level research in sustainable food, agriculture and water systems. These features lay a pathway for NMSU to excel in harnessing AI for agriculture and to become a model for the southwest US and other similar parts of the world to follow. This white paper highlights NMSU's vision of some of the critical areas (Fig. 1) where the adoption of AI is likely to increase sustainability in agriculture in general, and for the US southwest in particular, addresses the mechanisms by which this might happen, and suggests pathways forward.

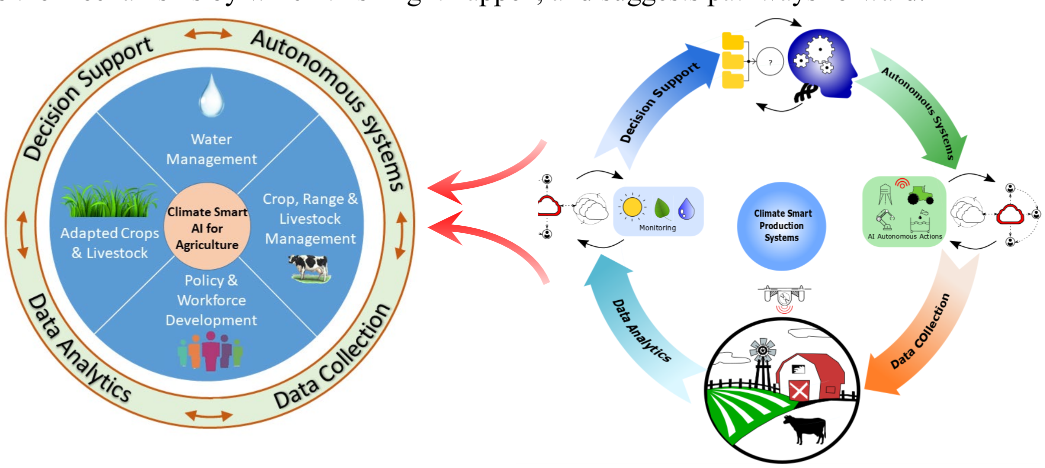

Fig. 1: Critical areas for AI research and development (left) in a Systems of Systems framework (*SoS*; right).

Harnessing AI to Solve Problems in Agriculture

Harnessing the power of AI in agriculture will require the integration of diverse AI tools across the entirety of the agricultural production system and adoption of enhanced systems-based approaches (i.e. a System of Systems based approach (*SoS*)) to ensure it is scalable, adaptive and sustainable. Crop and livestock agricultural production systems in arid and semi-arid regions face concurrent pressures of water scarcity, climate uncertainty and labor shortages. There is a need to develop crops and livestock that are better adapted to climate and environment variability. AI can accelerate the process of creating region specific crops and livestock by harnessing the tools of machine learning to mine existing and new geospatial and temporal, genotypic and phenotypic datasets to analyze relationships and predict outcomes.

There is also a need to develop innovative solutions for range management and livestock production that increase the sustainability of ranch operations and the natural resources on which they depend. Real time adaptive decision support systems that integrate diverse data streams to optimize actions as varied as evaluating animal health to planning future pasture usage are needed. In addition, the development of AI for large-scale applications that can provide improved short- and long-term management and planning for regional water and crop management is critical. A *SoS* that links individual end-users (farmers, ranchers) to regional water and crop management could be used to support agricultural planning and reservoir operation, irrigation management for cropping systems and regional scale crop monitoring through integration and collection of diverse data streams, data analytics, autonomous systems and ultimately decision support.

The complex interactions within and between agricultural subsystems is where both the challenge and the opportunities lie. There is a need for development of holistic models that can account for all factors that impact a process and assess their interactions (Fig. 1). Thus, the realization of AI in Agriculture as a *SoS* will require advancement in multiple technological areas, including: seamless integration and management of diverse data streams; novel methods for data fusion and extraction of knowledge; seamless automation and control; optimized and adaptive decision making; smart, connected and secure communities; data security, privacy and provenance.

Societal Impacts

AI-based systems are constantly evolving and its transformational effects have, and will continue to have, tremendous impacts on society. Thus, aside from the technical issues, it is critical to prepare for the impacts of AI in agriculture on policy, legal, and economic issues and to plan for the effects of AI on society, including technical and social issues. For example, it will be important to develop a framework to measure the economic and environmental impacts of AI more holistically, to develop regulations to safeguard security and privacy and maintain safety, and to remove impediments to the democratization of AI.

Scientific and technological advances in the use of AI in agriculture are taking place rapidly and at the interface of several disciplines. Thus there is a need to support diverse models of research, education and outreach including: development and dissemination of interdisciplinary research, education, and training programs, enhanced partnerships between academia and industry, expanded access to technology training for agricultural communities, and development of partnerships between veteran and 'NextGen' farmers, ranchers and water managers to support on-going feedback from the end-users to the developers.

Challenges for the Adoption of AI in Agriculture

AI-based technologies have their unique contexts and their adoption in agriculture faces several challenges including:

- Reliability of systems
- Security of information
- Data privacy and provenance
- Social acceptance
- Real-time delivery and accessibility of reliable information
- Cost effectiveness
- Ease of use and training

Recommendations

The adoption of AI for agriculture will require simultaneous advancement on multiple fronts in order for stakeholders to benefit from it rapidly. Thus we recommend:

- Increased support for research and development efforts in the application of AI in agriculture. Development of pilot, large-scale research and application units will allow for effective assessment of AI tools, their interaction with end-users and education efforts.
- Development of secure and adaptive systems that take a holistic systems approach (i.e. a *SoS* framework) to facilitate scalability and rapid response to changes in water, climate and labor availability.

- Concurrent development of policies and principles for safe, secure, and responsible use of AI in agriculture.
- Development of strategies to facilitate the adoption and diffusion of AI in agriculture utilizing a model of distributed science centers and extension agents who can leverage stakeholder participation effectively to get the technology out into the larger community.

The sustainable supply of food, water and energy is one of the grand challenges identified by the National Academy of Sciences. Implementing AI effectively in agriculture will move us towards meeting that challenge. NMSU has the strengths needed in the diverse disciplines that will be necessary to manage the technical, computational, environmental, economic, social and ethical dimensions of AI in agriculture.

Climate Adaptive Smart Systems for Future Agricultural and Rangeland Production

1. Introduction

Global food supply and food security are at risk due to an increasing world population, climate variability, diminishing natural resources, and limited available land. In the agricultural sector, the primary challenge has been how to be more productive with less – less arable land, less water, less labor, less certainty. In the largely rural arid and semi-arid Southwest US, including New Mexico, the challenges and opportunities are amplified as agricultural production systems struggle to cope with rapid changes in water availability, environmental stress, and labor availability. In recent years, frequent and persistent droughts, warmer day- and night-time temperatures, reduced snow packs, changes in streamflow, and increases in evaporation have been growing in occurrence. The combined effects of these changes have resulted in increased water shortages, increased depth to groundwater, increased heat stress for both vegetation and livestock, reduced crop and forage yields, reduced livestock productivity [1], increased plant disease and weeds and increased production costs, among other impacts. Projected global population growth will also exacerbate the pressure on available water resources and food production during the next 20-50 years. Thus, there is a need to adapt to these changes locally and regionally to provide management strategies to support farm and ranch level operations and regional planning. Innovative solutions can be realized through employing artificial intelligence (AI) based systems in agriculture to address these challenges. However, the speed of advancement and adoption of AI solutions has not reached all agricultural sectors equally and has been hindered by lack of practicability and the acceptance of AI as safe and secure.

So far, AI has been used in agriculture in piecemeal approaches, being treated as an umbrella of computational techniques used to improve performance in, for example, process control, resource utilization and decision-making. Some of the techniques within AI that are being used for agriculture include machine learning[1], deep learning[2], robotics[3], computer vision[4], collaborative systems[5] and the Internet of Things (IoT)[6]. However, to truly harness the power of AI in agriculture requires integration of diverse AI tools across the entirety of the production system and adoption of enhanced systems-based approaches [2]. The resultant harmonized use of AI techniques can provide improved efficiency of data collection, analysis, and task performance resulting in a more powerful knowledgebase than possible for any individual component. To effectively adapt AI for agricultural production systems, they should thus be viewed as multi-agent systems composed of heterogeneous agents whose behaviors, attitudes, and interactions determine the status of the system and whose actions are composed of a combination of these techniques. The agents in the system can be broadly categorized into three classes: human agents

[1] Machine learning is the application of learning algorithms to datasets in order to solve problems.
[2] Deep learning is learning procedures that facilitate object recognition.
[3] Robotics is the interaction of robots with the environment.
[4] Computer vision is the automatization of image and video captioning for decision making
[5] Collaborative systems are models that develop autonomous systems that work collaboratively with other systems and humans.
[6] IoT refers to a wide range of interconnected devices that collect and share information for decision-making purposes.

(HA)[1], software agents (SA)[2], and physical agents (PA)[3]. Together these agents form, for example, a water management system, a range management system, or a crop management system. Treating the application of AI in agriculture in a system of systems (SoS) framework can help in addressing critical areas and constraints that agriculture is facing in terms of scalable, adaptive, and sustainable production.

New Mexico State University (NMSU) is uniquely positioned and equipped with the tools to address these challenges and opportunities. NMSU is an open laboratory for innovation in agriculture, a place where transdisciplinary and collaborative research is evident, where diffusion and adoption of technology is encouraged and achievable through its statewide network of science centers and extension agents, and where public accessibility of vetted science-based solutions is part of the philosophy of its land grant mission. In addition, the state of New Mexico is home to emerging high tech and entrepreneurial industries, major national laboratories and maintains a commitment to high level research in sustainable food, agriculture and water systems. These features lay a pathway for NMSU to excel in harnessing AI for agriculture and to become a model for the southwest US and other similar parts of the world to follow. NMSU's vision of critical areas where the adoption of AI is likely to increase sustainability of agriculture in general and for the US southwest more specifically and the mechanisms that could be utilized (Figure 1) are addressed below.

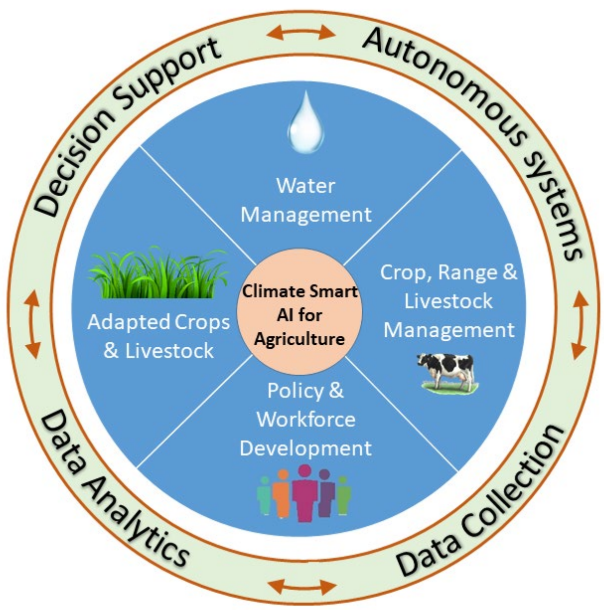

Figure 1. Critical areas for AI research and development for agriculture.

[1] HA is a person (e.g., a farmer or rancher) who controls some components of the agriculture production system.
[2] SA is a software deployed on a particular device for a special purpose (e.g., controlling a sensor).
[3] PA is a device coupled with a controller that allows the device to operate almost autonomously depending on inputs of human or software agents.

2. Critical areas for agriculture in the next decades

2.1. Climate adapted crops and animals

Climate, environment and the genetics of the organism directly impact traits for agriculture and rangeland plants and animals. The genetic variation within any given species allows for differential responses and adaptation to environmental and climate impacts. Traditional selective plant and animal breeding takes advantage of these different adaptations to provide more productive traits for specific locations. However, as the rate of change in climate and environmental conditions accelerates, the ability of traditional breeding techniques to keep pace with those changes has diminished. Thus, there is a need to develop crops and livestock that are better adapted to climate and environment variability. AI can accelerate the process of creating better-adapted crops by harnessing the tools of machine learning to mine existing and new data sets to analyze and predict outcomes.

- Phenotypic traits of crop plants, range plants, and animals have been studied for hundreds if not thousands of years as crop and animal domestication occurred. These phenotypic traits such as plant and animal growth, taste, texture, color, quality, and production are a function of the interaction of the environment with the genetics of the organism. Phenotypic traits data for plants and animals have been collected by various means including remote and proximity sensing as well as ground truth. The genetic variation that exists in crop plants, range plants, and animals have and are currently being analyzed with genetic tools. Data mining techniques can be used to combine, analyze, and identify relationships among large genotypic and phenotypic, geospatial and temporal, and climate datasets that are relevant to specific regions.
- With these types of large datasets, AI can be utilized to <u>determine what genetics will be needed in specific regions</u> based on climate model projections and water availability. In addition, AI could also help determine regimes in which the available data are insufficient and thus more data are required for better, more accurate models. By using these large datasets and building models with machine learning it will be possible to determine what species, cultivar, or variety will have the greatest success for sustainable production in any given area in future agriculture and range lands.

2.2. AI assisted and climate adaptive range management

Labor shortages and climate uncertainty drive losses of production efficiency and increase unexpected costs in range management, putting pressure on already narrow profit margins and increasing production uncertainty. Although AI is beginning to be used in range management, it lags behind precision farming. Adapting advances in AI and developing innovative solutions for range management and livestock production will be critical for the continued success and sustainability of both ranch operations and the natural resources on which they depend. Five interconnected areas where AI can make an important contribution are:

- <u>Optimizing the use of pastures while minimizing impacts on the environment</u> is a constant concern. Knowing when and where to move animals, anticipating future moves to other pastures and tracking forage quality (and thus possible needs for supplementation) are critical. Sensor networks for climate and range condition, decision support for where and when to move animals, autonomous systems to sample forage quality and provide supplements, and data analytics to connect in situ measurements to the landscape scale are promising areas for innovation.

- Timely information on the health and welfare of individual animals is essential, but also time consuming. Individual diagnostic sensors that collect health and location data could be used with a decision support system to alert ranchers in real time to developing problems with individual animals.
- Maintaining a consistent drinking water supply for cattle is also a time-consuming task for ranch managers. Water tank and delivery systems dispersed over vast areas need to be monitored regularly for water availability and leaks, typically requiring time consuming visits to check. Sensor networks and machine learning could be used to limit repeat visits through smart monitoring. For example, by learning patterns of water draw down under different conditions, detecting anomalies and alerting managers of a need for physical intervention.
- Managing for future conditions is hindered by uncertainty surrounding climate and markets. Data mining of past, current and future climatic conditions, production data, markets, and new data streams could contextualize current conditions and suggest future management adaptations.
- Deep analysis of diverse data streams could be used to increase product value. Assessing outcomes in the quality of offspring or the quality of meat produced and relating it to the conditions the animals were raised under could provide information to producers on the most effective strategies for management as well as a traceable history for consumers.

2.3. Artificially intelligent large-scale automated crop and water management systems

AI has been successfully applied in many agricultural food production activities such as precision agriculture and automated crop harvesting [3]. Yet challenges remain in its application over larger scales for significantly enhanced production and economics. Hence, there is a need to develop AI and supported tools for large-scale applications that can provide improved short- and long-term management and planning. In this context, AI can be used to address and advance our knowledge in four critical areas including:

- Integrating diverse data sources to better understand the impacts of weather, climate and water use on streamflow forecasts to support agricultural season planning and reservoir operation. AI and data mining of weather data, reservoir operations, and farms and farmers practices and behavior (e.g. choice of crops, irrigation methods, energy use, and technological applications) can be used to provide adaptive crop planning, optimize water allocation and management, production costs, and labor needs.
- AI and big data can be used to effectively manage cropping systems including irrigation scheduling, prediction of crop water demand, automated irrigation systems, and enhance farm-level management practices. Deployment and combining data from proximity and remote sensors can provide spatially representative information that can be used to evaluate soil water content and properties, surface and groundwater quality (i.e. salinity), depth to groundwater, and evapotranspiration.
- High temporal and spatial resolution remote sensing data combined with AI can support precision agriculture applications for crop monitoring including detection of stress due to

lack of nutrients or water shortage and decision support for optimal and automated application of fertilizer, herbicides, pesticides, and weed control.

- Crop harvesting is a major labor-intensive operation. Using proximity sensing and image processing combined with AI can support autonomous crop harvesting tools to minimize labor.

3. Harnessing AI in agriculture

The complex interactions across subsystems is where the challenge and opportunities lie. For instance, an investigation aimed to increase pecan production in the southwestern US has to account for the impact of weather, farming practices, disease vectors, genetics and phylogeny, and market practices. Each of these are in themselves areas where researchers are utilizing big data and AI. However, there is a need to utilize a holistic modeling approach that can account for all factors that impact a process and how to assess their interplay. Specifically, a combination of the knowledge learned in each of the subsystems (HAs, PAs, and SAs) and its application at a higher-level, where the diverse threads of knowledge can be interwoven for a holistic answer is needed – an *AI System of Systems (SoS)* (Figure 2).

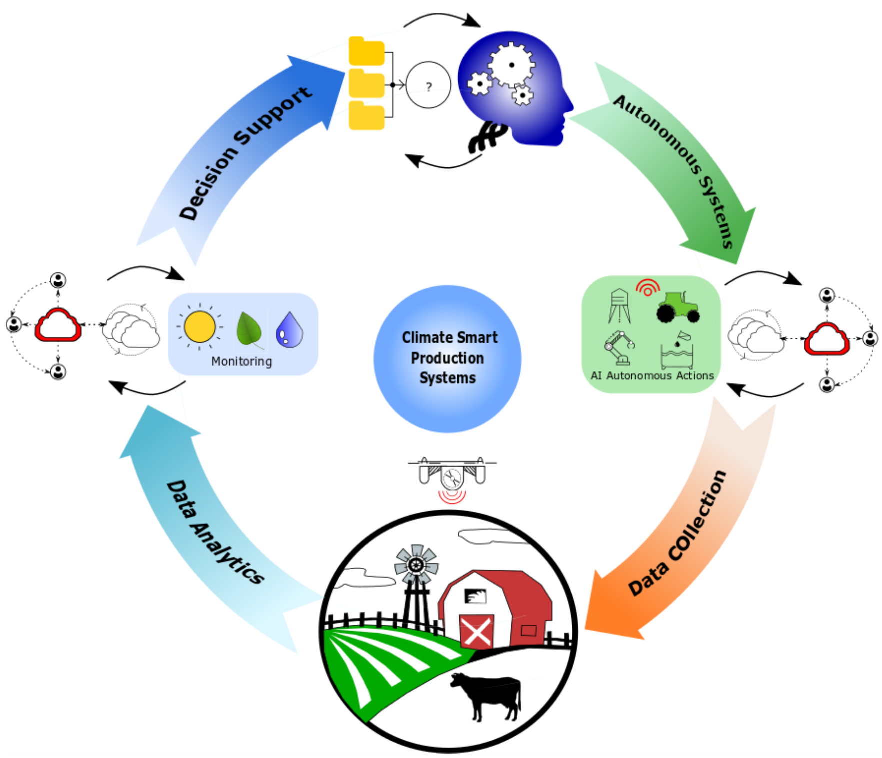

Figure 2. Components of an *AI System of Systems (SoS)* for agriculture.

The realization of *AI in Agriculture as a SoS* will require advancement on multiple fronts:

- Data Integration: The creation of an overarching *SoS* will require seamless integration and data management from diverse sources including weather, water, soil, climate, vegetation, animal health, phylogenetics, satellite images, economic, demographic and labor just to name a few. To do so, new integration mechanisms need to be developed that utilize advanced ontologies and database storage, distribution, and accessibility tools.

The integration process should also be cognizant of data standards within diverse research communities, and the privacy and security requirements of the participating agents.

- Knowledge Extraction: Novel methods will need to be developed for enhanced data fusion and extraction of knowledge from heterogeneous sources. Such methods will allow for anomaly and regular pattern detection and prediction of future states of the system. For example, combining livestock location, health diagnostics, weather data and water level sensing to examine patterns of water usage. These methods will need to be robust, efficient and adaptive to account for a growing amount of data and to provide reliable real-time predictions.
- Seamless Automation and Control: Autonomous drones, robots, and other sensing tools can acquire real-time information that can be used, for example, to monitor crop growth, detect disease and pests, evaluate water status, and assess animal welfare. In the event that an action is required, robots specialized for specific tasks can effectively respond. Effectively coupling automation with AI involves identifying the variables to be monitored, determining the type of sensor(s) to be used (e.g. digital images taken by robots, IR sensors mounted on autonomous drone), identifying actions that can adaptively be addressed (e.g. apply treatment, additional watering, harvest crop, supply feed) and developing robotic systems capable of automatically performing the actions identified (i.e. autonomous systems and robotics).
- Optimized and Adaptive Decisions: New approaches will be needed to identify current system state and behavior to develop and apply alternative management plans. As an example, new approaches that can determine the state of an agricultural field, identify options for use (leave alone, harvest) and/or improvement (nutrients, water needed), carry out the optimal action, analyze the impact of that action (performance of crop) and refine future decisions.
- Smart, connected, and secure communities: It will be important to utilize available wireless technologies, smart devices, and applications to create a framework that connects HAs (i.e. farmers, ranchers, water managers) in a *SoS* securely and provide for a multidirectional flow of information between HAs, SAs and PAs. Stakeholders need to be connected securely to account for the desired levels of privacy..
- Security, data privacy, and provenance: In all of the above fronts, there has to be a sustained focus on security, privacy, reliability and resilience of the systems and the *AI SoS*. Novel technologies in security, such as blockchain [4, 5], zero-knowledge proofs, configurable security, searchable encryptions, distributed trust management, resilient distributed storage can be used to not only improve security and privacy but also improve trust in the data and its availability.

4. Impacts of AI in agriculture: policy, legal, and economic issues

AI-based systems are constantly evolving and its transformational effects have, and will continue to have, a tremendous impact on society. Thus, aside from the technical issues, it is critical to prepare for AI in agriculture in terms of its impact on policy, legal, and economic areas. While an argument can be made regarding the feasibility of AI-related policies due to the emerging nature of the field, it is important to plan for the effects of AI on society as summarized here:

- Multi-stakeholder impact measurement: Developing a holistic framework to assess the impact of AI-based solutions on agriculture is of high importance. Focusing on traditional financial metrics such as Return on Investment (ROI) to evaluate the AI-based investments is still relevant. However, complementing these conventional economic performance indicators with operational ones such as tracking the efficiency, productivity and quality-related measures of the agricultural economic units (e.g., farmers, ranchers) pre and post-AI-adoption will be important. The measurement framework should also move beyond the individual agricultural economic units and evaluate the impact on the whole supply chain system.
- Exploitation and collaboration: How can institutions (Government, state, academic, industry) collaborate and leverage expertise to take advantage of the inherent competitive advantages of each stakeholder? Developing strategic partnerships to reduce the reliance on the self-interest of private entities will be necessary. Additionally, it will be important to determine revenue sources to support not only basic AI research to advance the field, but also to support the social scientific research into AI's impacts on society.
- Employment and education: AI will likely have an impact on job displacement, including low, medium, and potentially high skill jobs. Therefore, it is important to identify ways to minimize such disruptions. This is particularly important in the agriculture industry, where a challenge exists to attract younger workers. Agriculture is an important economic engine and efforts in addressing these disruptions through the development of policy and educational programs is essential. For example, how to deal with AI systems that might provide sensitive services that, when performed by people, may require training and certification.
- Regulation: As AI-systems are developed, regulation changes must be implemented to minimize potential negative impacts. For example, what security, privacy, and safety issues need to be integrated into the design of AI-systems, how to deal with AI systems that are able to derive private information from available public data, how to achieve a balance between technical, legal, social, and other areas that safeguard privacy as AI-systems are developed. Another important area that needs to be addressed is how to deal with proprietary technology, which might impede the democratization of AI.

5. Education and training

It is clear that the scientific and technological advances in the use of AI in agriculture are taking place rapidly and at the interface of several disciplines, whether in the realm of basic or applied research. Overcoming interdisciplinary barriers to progress will be important (i.e. disciplinary language, focus and approach). More and more industrial or corporate employers now seek employees from a talent pool that is well versed in diverse disciplines with a record of being engaged in such activities. In addition, end-users will need to be well versed in diverse applications of AI tools. In order to keep pace with these advances and the growing industry, research and application communities there is a need to:

- Develop and disseminate interdisciplinary research, education, and training programs. These programs should involve environmental scientists, data analysts, engineers, policy

makers, extension specialists and end-users to make sure they are effectively oriented towards the needs of the community they are intended to serve.
- Enhance partnerships between academia and industry to ensure that graduates from these programs are well trained on needed technological tools.
- Expand access to technology training programs to reach agricultural communities.
- Develop and/or enhance partnerships between veteran and 'NextGen' farmers, ranchers and water managers. Adoption of AI in agriculture will not be seamless and will require training, support and, just as importantly, on-going feedback from the end-users to the developers.

6. Challenges of AI adoption and diffusion

The adoption and diffusion of new technological innovations are not new phenomena within the agriculture domain. For example, the adoption of hybrid seed corn in the 1930s and diffusion of weed spray in the 1950s have been widely studied in the innovation diffusion literature. However AI-based technologies have their unique contexts and their adoption in agriculture faces several challenges including:

- Reliability of systems,
- Security of information,
- Data privacy and provenance,
- Social acceptance,
- Real-time delivery and accessibility of reliable information over vast, largely rural areas,
- Cost effectiveness, and
- Ease of use and training.

There are several theoretical frameworks, such as Everett Roger's Model for Rate of Adoption of Innovations [6] and Unified Theory of Acceptance and Use of Technology [7] as well as a growing literature on AI technology implementations within the context of organizations [8-11] to address these challenges. This literature can be used to build an AI-specific model to predict the adoption and diffusion of these innovations by agricultural economic units.

7. Recommendations

The adoption of AI for agriculture will require simultaneous advancement on multiple fronts in order for stakeholders to benefit from it rapidly. Thus, we recommend:

- Increased support for research and development efforts in the application of AI in agriculture. Development of pilot, large-scale research and application units will allow for effective assessment of AI tools, their interaction with end-users and education efforts.
- Development of secure and adaptive systems that take a holistic systems approach (i.e. a *SoS* framework) to facilitate scalability and rapid response to changes in water, climate and labor availability.
- Concurrent development of policies and principles for safe, secure, and responsible use of AI in agriculture.

- Development of strategies to facilitate the adoption and diffusion of AI in agriculture utilizing a model of distributed science centers and extension agents who can leverage stakeholder participation effectively to get the technology out into the larger community.

The sustainable supply of food, water and energy is one of the grand challenges identified by the National Academy of Sciences. Implementing AI effectively in agriculture will move us towards meeting that challenge. NMSU has the strengths needed in the diverse disciplines that will be necessary to manage the technical, computational, environmental, economic, social and ethical dimensions of AI in agriculture.

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