SPECIAL ISSUE • July/August 2024

RESOURCE

engineering and technology for a sustainable world

AI IN AGRICULTURE

AI is set to revolutionize agriculture, optimizing farming practices and addressing labor shortages. However, it is crucial to consider the limitations and challenges accompanying this transformation. AI can enhance farming efficiency and sustainability through automation, resource optimization, and data-driven insights. For example, AI-powered drones and robots can monitor crop health, detect disease or pest outbreaks, and apply targeted treatments, reducing manual labor and chemical usage. AI can also optimize planting and harvesting by analyzing factors like weather, soil conditions, and crop growth patterns, increasing yields and reducing waste.

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Bringing Value to Technologies and Solutions to Problems

The term "silo" (the organizational kind, not the silage fermentation and feed storage kind) is used to describe isolation as a barrier to collaboration. While important knowledge and technologies can be developed in such silos, greater value is realized when they are used to solve problems through *applied engineering.* Applied research and applied engineering often involve integration of diverse expertise and technologies, as well as understanding of the problem(s), tools, constraints and capabilities (systems approaches). *Applied engineering brings value to technologies and solutions to problems.*

As discussed in this issue of *Resource,* artificial intelligence (AI) promises to make our technologies smarter. There are many exciting developments in sensors and communications technologies, data processing and analytics, and smart systems that integrate data, knowledge, models, and machine learning. These smart systems can be complex, but they simplify integration of data and knowledge, often from multiple sources, processing and packaging information into understandable formats for improved decision making and automation.

These new tools can bring greater value and functionality to existing hardware, infrastructure, and equipment systems; hence they build upon and depend upon legacy systems, equipment and infrastructure. *As we need both traditional and emerging technologies, we need expertise to support and integrate them.* There is a role for each of us in solving current, emerging, and future problems in agriculture, food, and natural resources systems.

Continuing professional development, technical sessions at ASABE meetings and specialty conferences, developments in industry and academic programs, and articles in ASABE journals and *Resource* highlight the importance of high quality data from the field; need for data management, quality, processing and analytics; potential for AI and other smart tools; and the importance of professional experience, discernment, and ethics.

Agricultural equipment and associated technologies are getting both bigger and smaller; more complex, yet simpler to use; more data driven, and more integrated. Agricultural and biological engineers and agricultural systems technology professionals have important capabilities to develop the equipment and technologies; knowledge of the systems in which they are applied, and understanding of the applications and end-users.

As a long-time member and 2023-2024 ASABE President, I have enjoyed many wonderful opportunities to meet with other ASABE members and learn more about our technology developments, our research and academic programs, and issues addressed by our profession. To all ASABE members, volunteers, partners, and staff, thank you for your vision, your energy, your generosity of time and resources, and for sharing your knowledge, skills, and passion to find solutions to important problems. You are making the world a better place and inspiring the next generation of problem-solvers.

It has been a privilege to serve with you, and it will be an honor to keep working with you, as we continue disrupting for good.

Dana Porter
d-porter@tamu.edu

events calendar

ASABE CONFERENCES AND INTERNATIONAL MEETINGS

To receive more information about ASABE conferences and meetings, call ASABE at 800-371-2723 or email mtgs@asabe.org.

2024

July 28-31	**ASABE Annual International Meeting.** Anaheim, Calif., USA.

2025

Feb. 9-12	**Agricultural Equipment Technology Conference (AETC).** Louisville, Ky., USA.
July 13-16	**ASABE Annual International Meeting.** Toronto, Ont., Canada.

2026

Jan. 11-17	**ASABE Global Symposium on Sustainable Microirrigation Advances: Drop to Boom.** Aguadilla, Puerto Rico, USA.
July 12-15	**ASABE Annual International Meeting.** Indianapolis, Ind., USA.

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Magazine staff: Joseph C. Walker, Publisher, walker@asabe.org; Melissa Miller, Managing Editor, miller@asabe.org; Glenn Laing, Technical Editor; Jill Straub, Consultants Listings, GuideToConsultants@asabe.org; Darrin Drollinger, Executive Director, drollinger@asabe.org.

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ON THE COVER:
In a galaxy not so far away, AI emerges as a force for change in agriculture. This special issue takes a look at AI in ag.

The cover text was generated by ChatGPT in 2023 from a prompt asking about the role of AI in the future of agriculture.

ASABE
American Society of Agricultural
and Biological Engineers
2950 Niles Road
St. Joseph, MI 49085-9659, USA
269.429.0300, fax 269.429.3852
hq@asabe.org, www.asabe.org

RESOURCE

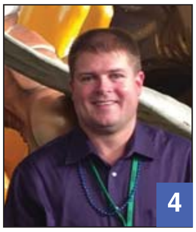
engineering and technology for a sustainable world

July/August 2024

SPECIAL ISSUE: AI IN AGRICULTURE

Guest editors: Tony Grift and Luis Rodriguez

FEATURES



DEPARTMENTS

Q&A

with the incoming ASABE President Doug Otto

Resource recently sat down with incoming **ASABE President Doug Otto** to get his take on the present state of our Society and the future of ASABE. Here's a summary of that conversation.

Let's start with your ASABE story. How long have you been a member, and how did you get involved?

I've been a member of ASABE for 24 years. I joined ASABE within the first year of my employment with New Holland (now CNH Industrial). Several of the engineers in our design group were members, and they encouraged me to join and participate with them on committees. I started by observing a few disc mower safety committees and reviewing standards proposals with my mentors, who were voting members of the committees. My initial involvement was based on mentorship from senior engineers, but it grew into an opportunity for me, an early-career engineer, to have a leadership role on our design teams.

What experiences as an ASABE member have been most meaningful to you? Are there any ASABE members whom you credit for helping create those experiences?

The most meaningful experiences for me are the relationships, and the life-long friendships, that were inspired by my participation in ASABE. My involvement in various committees and projects has given me the opportunity to build a network of colleagues, friends, and experts in academia, government, and industry. I credit my participation to Ken McLean and Phil Ehrhart, my mentors at New Holland, who encouraged me to take advantage of the opportunities to collaborate with other engineers across the ag industry.

What was the first ASABE event you attended, and how did you make the most of it?

My first ASABE event was the Agricultural Equipment Technology Conference (AETC) in February 2000. I was still in my first year of employment with New Holland, and I was just starting to make a contribution to the product development team. Several engineers on my team were planning to attend as technical session speakers and standards committee members. Our manager suggested that I attend the conference to soak up knowledge and meet other engineers. The open collaboration and knowledge-sharing across the group made a huge impression on me. I tried to attend every session and most of the standards committee meetings. By the end of the conference, I was overwhelmed with information but excited for future events.

What can we expect of you as ASABE president? How would you describe your leadership style, and what inspires you?

My leadership style is to drive a culture of transparency, trust, and accountability. My goal is to inspire our members to communicate openly across all groups within ASABE, build relationships between groups, and establish accountability. As a leader, my responsibility is to remove barriers and enable the team to execute. I'm inspired by engineers, many of whom are ASABE members, who identify an industry need and then take ownership of delivering a solution. As ASABE president, I will challenge our members to take actions that will enable the Society to better serve them and, at the same time, help to clear away obstacles that stand in the way.

The ASABE Foundation Dinner is always a great event. In 2015, the evening began at Mardi Gras World in New Orleans, Louisiana.

You're not new to Society governance, having served as president-elect over the past year and previously as a trustee. What are some of the pivotal decisions that the Board has made in recent years, and what priorities will the Board consider in the coming year?

The recent establishment of the Strategic Initiatives Council will have a big impact on our ability to organize and support projects that reach all the communities within ASABE. We currently have two initiatives, the Circular Bioeconomy Systems Institute and the Alliance for Modernizing African Agrifood Systems, that will be governed by the new council, and the structure is intended to provide a template for additional projects. These initiatives are vehicles for the growth and long-term sustainability of ASABE. Over the next year, the Board will give priority to enabling the success of these initiatives. Growing the recognition of ASABE among the general population, increasing the presence of ASABE in technical discussions, and driving the relevance of ASABE for funding sources are all critical to that success.

You have an industry background. Are we doing a good job of serving industry, and serving our members who work in industry?

ASABE serves industry well with technical standards and provides an important space for collaboration among members in areas that rely on standards development. However, we're missing opportunities to provide value for members in other areas, specifically in professional development and technical content. Historically, ASABE has relied on in-person meetings as its primary way to engage with members. We deliver a strong program for those who attend the meetings, but that exposure is limited to the attendees. Our challenge is to find more ways to provide content that our members can access from any location, to reduce their investment of time and their travel expenses. Our in-person events are still important, but we need other channels to reach our members.

The Board recently voted to recognize graduate students with full-voting privileges. How will this affect the engagement with those young members?

I'm certain that including graduate students as full-voting members will encourage them to take leadership roles in ASABE. That leadership experience will provide a safe space for professional development, as a supplement to their graduate school curriculum. Their status as full-voting members will also allow ASABE to better serve their needs, and it will ensure their connection to ASABE in their future careers.

There is much talk about collaboration with external partners. Why would other organizations want to partner with ASABE, and what value do such partnerships bring?

This is our greatest opportunity. One of the strengths of ASABE is our culture of cross-functional collaboration. Many potential partners are passionate about a project, but they don't have the technical expertise or an established process to deliver a solution. ASABE provides both of these: technical experts in the production of food, fuel, and fiber, and a collaborative process for linking our experts with others who are enthusiastic to make an impact. Partnering with outside groups will expand the visibility of ASABE beyond our traditional boundaries, and it will establish ASABE as the primary professional society for ag and bio engineering. External partnerships will also provide additional research and employment opportunities for our members.

The 2024 National Machinery Show in Louisville, Kentucky, was special. I was able to introduce ASABE President Dana Porter and Executive Director Darrin Drollinger to the brand new CASE IH AF11.

Let's talk tech. What current technology innovations do you find most exciting, and how do you see them impacting the profession?

My background is in ag machinery, so the current path toward autonomous machinery is very exciting. Innovations in control systems to facilitate reliable and safe operation will have a major impact on our ability to develop standards and design guidelines. Innovations in electric drives will replace traditional mechanical and hydraulic systems with more integrated electromechanical systems. Strong knowledge and experience in electrical systems will become a requirement for our design engineers.

And let's crystal ball a bit. What's your image of a healthy, vibrant ASABE ten years from now? What does success look like?

My vision for a healthy and vibrant ASABE is that we have delivered on our goals to position ASABE as the leading source of technical expertise in agriculture, food, and biological systems. We have expanded our engagement and influence into new areas, which drive additional opportunities and value for members and increase our funding base. Success means that we have created an environment in which our members propose initiatives that are relevant to ASABE's mission, and that we establish goals, drive actions, and execute delivery. As we successfully execute these projects, we expand our influence and our reputation.

Guest Editor
ASABE Fellow Tony Grift
Professor
Agricultural & Biological Engineering
University of Illinois
Urbana-Champaign, USA
grift@illinois.edu

Guest Editor
ASABE member Luis Rodriguez
Associate Professor
Agricultural & Biological Engineering
University of Illinois
Urbana-Champaign, USA
lfr@illinois.edu

Welcome to this Special Issue on AI in Agriculture

Tony Grift

Ostensibly, artificial intelligence will dictate the future of everything alive, but since you can't go anywhere unless you know where you are, let's have a look at the past. Some of our members may remember the January/February 2011 special issue of *Resource* on "The Farm of the Future." For the fun of it, I searched that issue for the word "artificial" and found only a single mention. In the opening sentence of his article, **ASABE Fellow John Schueller** claimed the following:

> *"The typical U.S. crop farm of 2035 is not that different from the typical farm of 2010, in the same way that the 2010 farm was not the artificially intelligent, self-sufficient, robotic paradise that many predicted way back in 1985."*

Apparently, AI was not yet on anyone's ag radar, including my own. When people mentioned neural networks in recent years, I thought that the field was near death. Therefore, when ChatGPT was announced, it hit me like a frying pan in the face. I did not see it coming. When I started digging into AI technology, I found it exciting, but also frightening because I fear that the truth will become a scarce commodity in a world of AI-generated misinformation. But let's keep it positive.

Too often, I disparagingly refer to the latest novelty as "more of the same," as if it doesn't really add anything new. AI may be a big exception to that. If you have only a laptop, then you can only do so much. But if you have millions of connected computers and armies of people labeling data, then you can achieve feats that are not just more of the same; they are radically different.

Arthur C. Clarke famously said that "any sufficiently advanced technology is indistinguishable from magic." AI sure looks like magic. AI can not only mimic reality, it can also create its own reality! Even the experts don't completely understand how AI comes up with new things, but there are some clues about the working of the beast. For example, AI-generated images of people often get the hands wrong, such as showing too many fingers or too few. Hands are relatively small, they appear in many different poses, they are often partly obscured, and—in contrast to faces—there are not as many pictures of hands available to train on.

Of course, AI dovetails nicely with big data, and I see even more local control applications using MIT's Liquid Neural Network concept, which is targeted at the opposite end of the scale. The idea is that small networks can keep learning after training, which seems logical, but what is more intriguing is that their algorithms can run on embedded controllers such as a Raspberry PI. Turns out I was wrong about the limitations of laptop computing, just as I was wrong about neural networks.

One year ago, my co-editor Luis Rodriguez and I gathered a group of people who had AI experience, mainly in teaching, to discuss the ramifications of this new technology. We reported our opinions in the July/August 2023 issue of *Resource* in an article titled "Artificial Intelligence: Super-Power or Super-Villain?"

In the current issue, we present a range of articles written by researchers who are actively using AI in agriculture. You'll read about current and potential applications of AI, including applications that combine AI with robotics, computer vision, and other technologies. These contributors candidly share what AI can do, how it can do it, what they learned, and what AI means to society.

We are grateful to all our contributors for their insights, and to ASABE's editorial staff for their pursuit of excellence. This issue also serves as a tribute to the ASABE membership. We are a large and diverse group of engineers who relentlessly develop, embrace, and employ new technology, especially when it has clear potential for improving our food system. I think we all deserve a pat on the back.

Using Robotics and Digital Twins to Advance Phenomics

Changying Li and Daeun Choi

Based on our research in agricultural automation, we believe that AI will have a significant positive impact on a variety of areas in agriculture, including plant and animal breeding, precision crop and livestock management, pest and disease surveillance, and food quality and safety monitoring. In particular, we highlight two promising AI-enabled technologies to advance plant phenomics.

Real-time phenotyping robots

Despite the proliferation of research in automated phenotyping systems over the past few years, the vast majority of plant breeders have not adopted phenotyping robots. One reason for this low adoption is that current robotic systems are typically slow and require a separate offline processing stage after the initial data collection.

Recently, our group developed a lightweight graph neural network model that can be deployed on the embedded computer of our customized phenotyping robot, called MARS-X, to perform plant organ tracking in real-time . We leveraged active learning to train a strong flower detector with minimal annotation effort. The model on the robot can process data from three cameras concurrently, and it can use the robot's pose estimate to determine the location of each flower that it detects. This approach shows promise in both its counting accuracy and inference speed (exceeding 40 frames per second) on the embedded computer.

The customized mobile robot, called MARS-X, performs real-time crop phenotyping. It carries a multi-view imaging system, and a lightweight graph neural network model runs in real-time on its embedded computer.

In the future, we believe that multi-modal foundation models (including large language and vision foundation models) designed specifically for agriculture will significantly enhance the zero-shot learning (without labeled training data) and reasoning capabilities of agricultural robots. Some of these foundation models are already feasible to run on laptops or embedded computers. Deep reinforcement learning, another AI method, is expected to enhance the capabilities of mobile robots and manipulators in active phenotyping tasks.

Digital twins and synthetic data

Another promising area of AI is digital twin technology and the use of synthetic data in agricultural robots. Digital twins create virtual replicas of crops and fields that accurately reflect their physical counterparts, enabling detailed visualization and analysis.

Because agricultural environments are diverse and constantly changing, gathering enough real-world data to adequately train AI and robotics algorithms is often impractical. For instance, collecting disease data can be time-consuming and expensive. Conventional methods, such as inoculating plants with certain diseases, require significant labor and resources. Digital twins can effectively simulate these processes visually, allowing researchers to study plant disease outbreaks without extensive field trials.

The synergy of digital twin technology and synthetic data provides comprehensive, cost-effective robot training across numerous realistic scenarios. In agriculture, the integration of AI and digital twin technology offers an innovative approach to advancing precision agriculture. By leveraging AI, digital twins can incorporate real-time data and simulate various environmental conditions.

This technology can also play a role in the testing and training of agricultural robots and sensors. By simulating a wide range of scenarios, developers can conduct rigorous testing without the need for physical prototypes, accelerating the development process and ensuring that the robotic systems and sensors will be reliable and efficient in real-world settings.

Conclusions

Although AI is not new to agriculture—researchers have applied AI to solve problems in agriculture since the 1980s, with mixed results—this time is different. The latest AI technologies are more transformative because of unprecedented access to data, powerful new algorithms, advanced computational power, and the collaborative spirit of the global community.

The scientific community has reached a consensus that AI is now poised to transform many domains, including agriculture and food systems. The resulting innovations can contribute to solving some of the world's most pressing challenges, from food security to sustainable farming practices. The work that ag and bio engineers do will advance this technology, improve lives, and create a more equitable world by fostering a better quality of life for all. We are fortunate to live in this exciting time, and we should embrace technology that makes a positive impact.

ASABE member Changying "Charlie" Li, Professor, and
ASABE member Daeun "Dana" Choi, Assistant Professor,
Department of Agricultural and Biological Engineering,
University of Florida, Gainesville, USA, cli2@ufl.edu, dana.choi@ufl.edu.

Further reading

Petti, D., & Li, C. (2024). Data-efficient real-time flower counting with a ground mobile robot. ASABE Paper No: 2400607. St. Joseph, MI: ASABE. https://doi.org/10.13031/aim.202400607

The Unlimited Possibilities for AI in Agriculture

W. Edwin Harris and Megan Lewis

Artificial intelligence in agriculture has transformative potential to improve productivity and sustainability. While the range of AI applications is vast, so is the pace of change within the field and the expectation of results. Our work in the Centre for Agriculture Data Science typically involves other academics, farmers, agriculture engineers, and agri-tech businesses. A challenge we face is communicating these with stakeholders and balancing their expectations of AI with the reality of engineering solutions. We oversee projects involving diverse technologies and aims, which exemplify how AI can improve decision-making in agriculture.

AI and fine-tuning potato agronomy

Our recent work in potato agronomy aimed to make predictions about potato growth and size distribution while avoiding destructive sampling. This is critical for farmers to meet the needs of buyers, who often have specific contractual requirements. We used a range of tools to address this challenge, including remote sensing data, computer vision for stem counting (to exploit the relationship between stems and potato size distribution), weather data, and predictive modeling with the Decision Support System for Agrotechnology Transfer (DSSAT).

We used computer vision AI to classify potato growth at large spatial scales, and we used different computer vision tools to identify and count stems at a much smaller (single plant) scale. By integrating these tools with other conventional monitoring methods, we were able to create automated and highly accurate predictions of potato yield, size, and optimal harvest date, accounting for weather and agronomic management while avoiding the need for destructive sampling.

Resolving the GEM conundrum

The complicated interplay between animal or plant genetics (G), the environment in which the farm operates (E), and on-farm management decisions (M) is what we refer to as the GEM conundrum. This is a real challenge for researchers trying to understand how farm systems work because the interplay among the GEM components makes it hard to generalize results. A related project concerned the management of carbon and greenhouse gas (GHG) liberation on farms. While carbon calculators are becoming more widely available, their usefulness for farmers is still evolving.

Our project involved a collaboration between a cooperative of 350 beef farms across Great Britain (ABP Beef) and a popular carbon calculator (Agrecalc). Using machine learning (a form of AI) on this large dataset, we ranked the top variables (more than 300) that contributed to variation in GHG liberation (by various measures, e.g., grams of CO_2 per kg of beef produced). Of course, the most important variables that impact GHGs are the ones that should affect management decisions, and within these, the easier-to-manage variables should be prioritized.

Due to privacy concerns (for farmers and agritech businesses), farm data is seldom shared. However, by working with a cooperative, we were able to overcome this limitation and create a benchmarking system that is generalizable to many farms. This project highlighted a principal challenge for AI applications in farming and for agri-tech innovation: the lack of a clear and general business case for sharing farm data.

Digital twins for farm biodiversity

Leveraging AI through digital twin technology is not a new idea, but it offers a groundbreaking approach to managing biodiversity on farms. Our recent work at the Harper Adams Future Farm aims to combine AI-enabled monitoring of farm biodiversity with a digital twin that integrates other farm data. For example, we can identify bird species from soundscape recordings in real-time, and we can identify moth species from computer vision-enabled light traps.

This work aims to simulate farm ecosystems in real-time by integrating remote sensing data, field sensor data, and ecological data. The technology allows us to model interactions between specific species and their habitats, eventually providing farmers with detailed insights into how agricultural practices impact biodiversity. For instance, digital twins can predict the effects of different farming strategies on local wildlife, helping to balance crop production with the conservation of beneficial species.

By simulating scenarios such as the impact of crop rotation or pesticide use on pollinators, digital twins enable proactive and informed decision-making to enhance both farm productivity and ecosystem health. These tools are crucial for fostering sustainable practices that support biodiversity and long-term environmental resilience. While all of these technologies already exist, the

Potato stem identification and counting using computer vision AI.

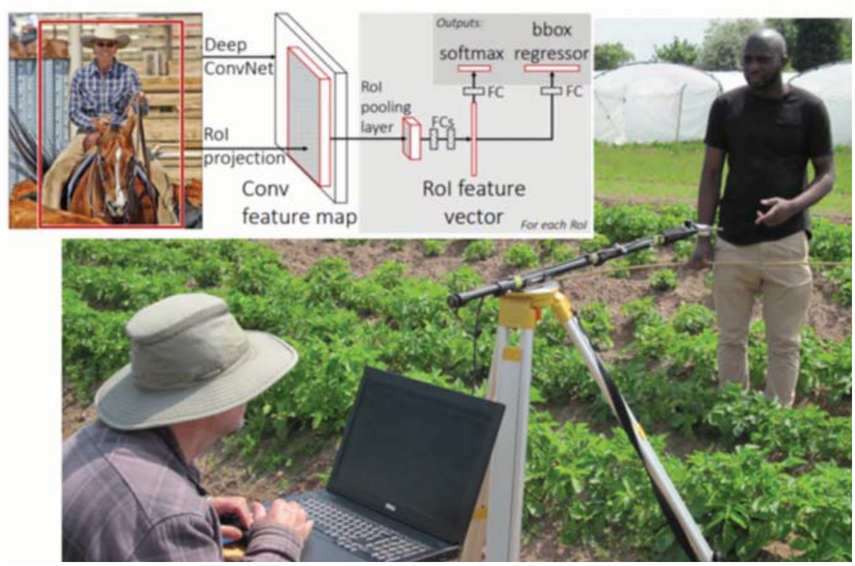
novelty here is in combining them to create information that is typically not practical or available on farms.

The current and future impacts of AI

The integration of AI into agriculture encompasses a range of technologies and models, each tailored to enhance specific aspects of farming. Computer vision, for instance, is essential in analyzing visual data from crops, which enables precise monitoring of crop health, identification of pests, and optimization of harvesting processes. In our potato agronomy research, we applied computer vision to count potato stems using drone images, providing crucial data for predicting crop size distribution and optimizing harvest schedules. This approach helps farmers reduce waste and meet market demands more effectively.

Similarly, sequential data models analyze time-series data from sources like weather sensors or audio recordings of bird vocalizations, which are essential for monitoring environmental conditions and their impact on agriculture. These models contribute significantly to sustainable farming by tracking and predicting ecosystem changes.

Predictive and machine learning models analyze historical and real-time data to forecast future trends such as weather patterns, crop yields, and market prices. These predictions enable farmers to make informed decisions about planting schedules, resource allocation, and market strategies, thus enhancing their overall productivity and profitability. Meanwhile, large language models (LLMs), like those developed by OpenAI, facilitate better communication and knowledge dissemination within the agricultural sector. They can answer farmers' questions, provide guidance on best practices, and translate scientific research into practical applications.



Creating high-quality training data is crucial for efficient AI models.

The future of agricultural innovation will likely involve combinations of multiple AI models (ensemble methods) and the integration of data from diverse sources, such as satellite imagery, field sensors, and weather data. This holistic approach will offer comprehensive solutions to complex challenges, driving more sustainable and efficient farming practices. For example, our carbon data benchmarking work involves analyzing emissions data across various farms to inform strategies that align farm operations with sustainability goals, promoting practices that contribute to net-zero emissions in agriculture.

Agriculture offers a unique opportunity to harness AI technology to solve critical challenges in food production and sustainability. Researchers will integrate existing AI tools in innovative ways to tackle issues like crop resilience and resource optimization. By leveraging edge computing and enhancing rural connectivity, systems that deliver real-time, actionable data directly to farmers are possible. High-quality, diverse datasets are the foundation of effective AI applications, and assembling and justifying disparate data sources are crucial for generating valuable insights.

Most of all, balancing technical sophistication with practical interfaces is key to ensuring that farmers and other stakeholders can readily adopt and benefit from these technologies. We must address the complexities of data ownership and intellectual property through secure frameworks like blockchain and use knowledge graphs to overcome these challenges. Ethical considerations must be included in our work to promote fairness, sustainability, and bias-free applications. Finally, we must minimize the carbon footprint of AI, aligning innovation with broader environmental goals. These efforts can lead to smart, sustainable farming practices that support both food security and planetary health.

W. Edwin Harris, Director, and **Megan Lewis,** Postdoctoral Researcher, Centre for Agriculture Data Science, Harper Adams University, Edgmond, UK, EHarris@harper-adams.ac.uk.

Further Reading

Mhango, J. K., Grove, I. G., Hartley, W., Harris, E. W., & Monaghan, J. M. (2022). Applying colour-based feature extraction and transfer learning to develop a high-throughput inference system for potato (*Solanum tuberosum* L.) stems with images from unmanned aerial vehicles after canopy consolidation. *Precision Agriculture, 23,* 643-669. https://doi.org/10.1007/s11119-021-09853-4

Rozenstein, O., Cohen, Y., Alchanatis, V., Behrendt, K., Bonfil, D.J., Eshel, G., … Lowenberg-DeBoer, J. (2024). Data-driven agriculture and sustainable farming: Friends or foes? *Precision Agriculture, 25,* 520-531.

Intelligent Vehicles for Orchard Farming

Francisco Rovira-Más

After completing my doctoral degree at the University of Illinois in Urbana-Champaign, followed by two years working for John Deere in Iowa and Illinois, I joined the Polytechnic University of Valencia in Spain, where I founded the Agricultural Robotics Laboratory.

Although I'd spent several years living in the Midwest, surrounded by soybeans and corn, several of my research projects involved working with specialty crops in Washington State, where the great potential of AI-based automation for orchard farming became apparent.

In Spain, which has a long tradition of specialty crop farming and is facing structural problems similar to those in U.S. agriculture, data-driven, AI-based systems are essential for achieving efficient and sustainable production.

Our lab is developing intelligent orchard sprayers for sustainable crop protection as well as ground robots for large-scale data collection for use with AI algorithms. We believe that AI can align with farmers' knowledge by letting computers do what they excel at while allowing farmers to do what they do best.

This work is progressing steadily, as **ASABE member John Schueller** anticipated in his 2011 *Resource* article. John said that technological changes would not be radical, but they would make production more efficient, safer, and ultimately sustainable.

To determine the impact of AI on agriculture, we should first understand what AI is, what it can and can't do, and the limitations of its solutions. Let's start with the definition of an intelligent vehicle, which is a common source of confusion. An intelligent tractor, sprayer, or harvester is an agricultural vehicle equipped with AI for the purpose of automating some of its functions. The level of automation can range from light operator assistance to complex actuation.

And what is AI? Basically, AI is a set of algorithms that can solve problems whose complexity requires some sort of reasoning. Not all algorithms are adequate for every problem, and therefore not all algorithms are appropriate for agriculture.

When many people talk about AI, they're actually referring to deep learning, which is a specific type of machine learning that requires little knowledge of the process but large amounts of data. For example, a multilayer neural network requires a training set that is several times larger than a decision tree algorithm to reach a similar percentage of correct answers.

In agriculture, researchers typically face the opposite situation: the field data are limited, but they have solid knowledge of the physical and biological processes. In our experience with autonomous off-road navigation, our knowledge of sensor performance and steering mechanics allowed us to deal with the inherent uncertainty of AI probabilistic reasoning algorithms, such as the Kalman filter or fuzzy logic.

The VineScout

VineScout and Cerberus are two EU-funded projects (the former ended in 2020, and the latter will end in December 2027) that use ground robots for data collection to facilitate the application of AI algorithms that rely on big data. Figure 1 shows a VineScout robot monitoring a Portuguese vineyard.

Given our experience with vehicle dynamics, the AI techniques used for robot navigation and safeguarding were decision trees and 3D perception algorithms. However, modeling of water stress as a quality indicator for the oenological potential of grapes (i.e., the potential to produce a great wine) was a less understood process that required large amounts of data.

Massive sampling with the robot allowed us to increase the data from fewer than 50 manual samples per hectare (20 points per acre) to more than 20,000 points per hectare (8,000 points per acre). On the other hand, this massive sampling led to a dismaying reality: data curation and processing became a problem. Every mapping session with the robot

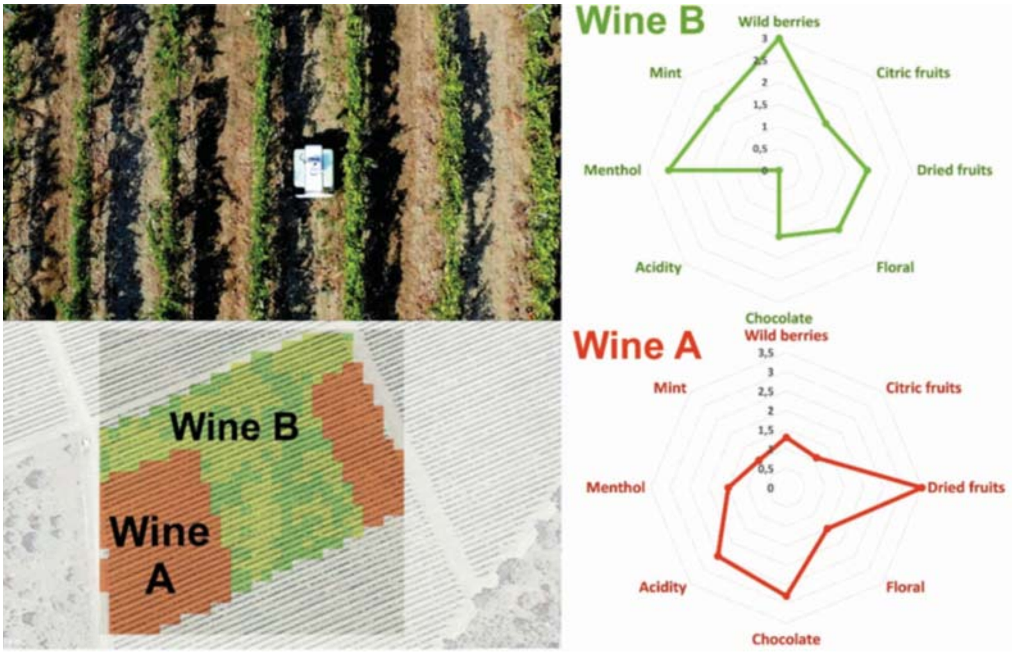


Figure 1. The VineScout robot in a vineyard and the resulting wine classification.

required between one and three hours and resulted in thousands of measuring points, each with over 20 measurements.

Of all the climatic and crop measurements, the strongest correlations with vine water stress were obtained using the difference between the air and canopy temperatures for each vine and its spectral index (NDVI).

For logistical reasons, the winery limited the wine classes to two, so the vineyard only had to be geographically sorted into two types of grape vines: low-stressed and high-stressed. Given the amount of data acquired for the vineyard, a supervised classification method was not affordable; therefore, we used k-means clustering to classify the vines.

Figure 1 shows the result of the classification and the different properties of each wine, as later evaluated by an expert panel. In reality, the viticulture manager already knew of the two distinct zones. His motivation to join the project was to assess how these zones will evolve with climate change. The challenge for the winery is determining how to keep up with consumer expectations, given the climatic uncertainties.

The challenge for the research team was dealing with all the data that we collected in the field. As it turned out, most of the data remained unprocessed, even though the European Commission abides by open data. We posted the data series on Zenodo for anyone to use.

The smart sprayer

Orchard farmers in southern Europe are having a hard time coping with the structural problems that occur in industrialized countries, including labor shortages, an aging workforce, and a need to increase productivity while reducing equipment size. AI-supported equipment can help with these challenges.

In addition to farmers' obvious motivation to produce food and make a living, another motivation for their interest in intelligent vehicles is legislation. For example, a draft of legally binding targets, that may become a regulation for all EU member states, includes the implementation of crop protection solutions that contribute to a 50% reduction in the use of chemical pesticides by 2030.

Recently, such proposed regulations have been protested by farmers in Germany, France, Italy, Portugal, and Spain.

In the 13th century, Thomas Aquinas stated that a bad law is no law (*lex malla lex nulla*), meaning that laws should be fair and reasonable for people to obey. Farmers would be willing to achieve chemical reductions of 50% as long as they can do so without jeopardizing their crops and livelihoods.

Regardless of the reduction rate, everybody, especially farmers, is interested in producing food sustainably. Our Smart Sprayer project pursues that goal. Tractor driving is relatively easy, but actively adjusting the spray rate while in motion, as a way to reduce pesticide use, is unmanageable, even for experienced farmers. A smart alternative is to hire someone to drive the tractor and then let computer algorithms determine the optimum application rate for each location.

This is precisely what our Smart Sprayer does. The left image in figure 2 shows the sprayer's path in an olive grove. A spray rate map (center) is loaded in a simplified format developed for the sprayer, and the spray actually applied (right) reveals a satisfactory application according to an optimized map, resulting in 10% to 20% savings of the applied chemical. This technology offers a way to comply with new regulations, respect the environment, and save money on crop protection products.

The two examples described here (the VineScout and Smart Sprayer) required a variety of AI algorithms to create an intelligent vehicle. If we consider the wide variety of vehicles, crops, and operations needed on farms, the potential for AI solutions in agriculture is enormous. This is great news for the next generation of agricultural engineers, because they will have powerful new tools for solving the grand challenges in agriculture.

Is there any reason to be afraid of AI? Not at all! Algorithms reside in computers, computers are machines,

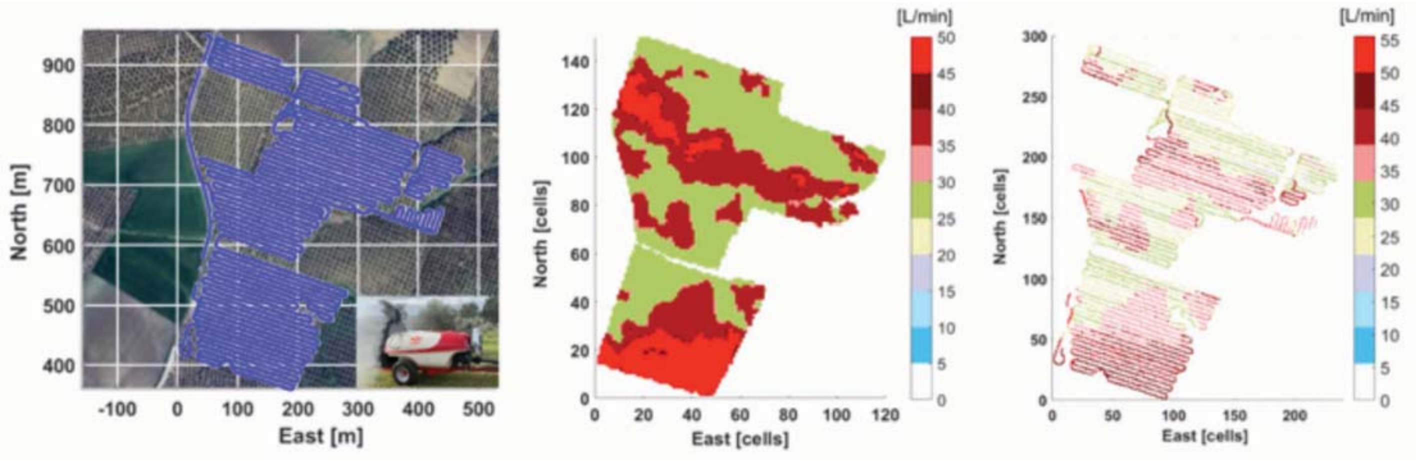


Figure 2. The Smart Sprayer in an olive grove (left to right): the sprayer's path, the prescription map, and the actual product delivery.

and machines can be turned off. Artificial intelligence, by itself, is not a threat. However, we should remain cautious of the misuse of AI by human intelligence.

ASABE member Francisco Rovira-Más, Professor, Universitat Politècnica de València, Spain, frovira@upv.edu.es.

Further Reading

Cerberus. (2024). Cerberus project website. Retrieved from https://cerberusproject.eu/

European Commission. (2024). Sustainable use of pesticides. Retrieved from https://food.ec.europa.eu/plants/pesticides/sustainable-use-pesticides_en

Rovira-Más, F., Saiz-Rubio, V., & Cuenca-Cuenca, A. (2021). Augmented perception for agricultural robots navigation. *IEEE Sensors J., 21*(10), 11712-11727. https://doi.org/10.1109/JSEN.2020.3016081

Rovira-Más, F., Saiz-Rubio, V., & Cuenca-Cuenca, A. (2021). Sensing architecture for terrestrial crop monitoring: Harvesting data as an asset. *Sensors, 21*(9), article 3114. https://doi.org/10.3390/s21093114

Rovira-Más, F., Saiz-Rubio, V., Cuenca, A., Ortiz, C., Pérez Teruel, M., & Ortí, E. (2024). Open-format prescription maps for variable-rate spraying in orchard farming. *Journal of the ASABE, 67*(2), 11-25. https://doi.org/10.13031/ja.15750

Saiz-Rubio, V., & Rovira-Más, F. (2019). VineScout_ROBOTdata_22July2019_TN102. Retrieved from https://zenodo.org/records/3451840

Schueller, J. K. (2011). A report from 25 years hence. *Resource, 18*(1), 20 (Jan/Feb). St. Joseph, MI: ASABE.

VineScout. (2024). VineScout website. Retrieved from https://vinescout.eu/web/

Advancing Agricultural Engineering through AI and Simulation

Gen Sasaki

Agricultural engineering is at the forefront of using advanced technologies like artificial intelligence (AI) to tackle the pressing issues of food security, sustainability, and environmental conservation. The shift towards integrating AI into farm machinery and systems marks a significant move beyond traditional mechanization, offering novel solutions. However, it also presents new challenges. It is imperative that AI is not considered in isolation but is seamlessly integrated while considering its effects on surrounding systems. This requires simulating AI algorithms alongside other components to verify their effectiveness and ensure compatibility. This article delves into how engineers leverage simulation and AI to address challenges related to efficiency, model reliability, and data quality, marking a new era in agriculture's evolution.

The convergence of AI and simulation in agricultural engineering manifests in three critical areas: addressing data scarcity, simplifying complex agricultural systems, and enhancing embedded systems.

Navigating the data challenge

Collecting, cleaning, and cataloging real-world data in the agricultural sector is challenging and time-consuming. In addition, AI models typically operate on static parameters but are continuously exposed to new data that might not necessarily be captured in the training set. This underscores the critical role of data preparation in the AI development process.

Projects are also more likely to fail without robust data to help train a model, making data preparation a crucial step in the AI workflow. “Bad” data can leave an engineer spending hours determining why the model is not working without promising insightful results.

Simulation offers a powerful avenue for overcoming these challenges. In recent years, data-centric AI has shifted the AI community's focus from tweaking the AI model's architecture and parameters to improving the training data, often yielding greater improvements in accuracy. The use of simulation to augment existing training data has multiple benefits:

- Computational simulation is, in general, much less costly than physical on-machine experiments.
- The engineer can simulate scenarios that are difficult or too dangerous to create in the real world, such as the development of automated tractors.
- The simulation gives access to internal states that might not be measured in an experimental setup, which can be very useful when debugging why an AI model doesn't perform well in certain situations, including testing the viability of models predicting nonlinear values like an engine's NOx emissions.

With a model's performance so dependent on the quality of the data it is being trained with, engineers can improve outcomes with an iterative process of simulating data using tools such as MATLAB® and Simulink®, updating an AI model accordingly, observing what conditions it cannot predict well, and collecting more data both real and simulated for those conditions to improve the models further.

Efficient design of complex systems

When designing algorithms that interact with agricultural systems, a simulation-based model representing the model of the system being controlled is crucial for enabling rapid design iterations. In the controls field, the system model is called the "plant model." In the wireless vehicle communications area, it's called "channel model." In the reinforcement learning field, it's called the "environment model." Whatever you call it, the idea is to create a simulation-based model that gives you the necessary accuracy to recreate the physical system your algorithms interact with.

The challenge with this approach is that traditional methods of building high-fidelity models from the first principles of physics or biological theory are difficult to build or simulate for complex systems like crop growth or water flow. This is where AI can make a significant impact. Engineers can approximate a complex system, such as soil-water-plant interactions, with an AI (reduced-order) model. Alternatively, they might train the AI model directly from experimental data, sidestepping the need to create a detailed physics or biology-based model. The advantage of using a reduced-order model is its low computational demand compared to theory-based ones, allowing the engineer to explore a broader range of design options more efficiently. Engineers can also decide which aspects of the system are most amenable to AI approximation by evaluating the trade-offs between speed and accuracy. This advantage of AI can be seen in such applications as early detection of crop diseases.

Recent advancements in AI, such as neural ODEs (ordinary differential equations) blending AI training methods with models grounded in physics-based principles like physics-informed neural networks (PINNs), are particularly promising. These models are invaluable for agricultural engineering applications where certain physical aspects of the system must be preserved while approximating others with a data-centric approach. This hybrid modeling strategy enables a more nuanced and efficient exploration of agricultural systems, enhancing the potential for innovation in sustainable farming practices and resource management.

AI-driven algorithm development and deployment

Agricultural engineers, particularly those working on precision farming and smart agriculture systems, are increasingly turning to simulations for algorithm design. These engineers often develop virtual sensors or observers that estimate values not directly measured by the available sensors in the field, such as estimating soil moisture levels from other environmental data with various methods such as linear models and Kalman filters.

However, the complexity and nonlinear behavior of agricultural environments often limit the effectiveness of these traditional methods. Consequently, engineers are exploring AI-based approaches that offer the flexibility to model the intricate interactions within agricultural systems. They utilize both measured and simulated data to train AI models capable of predicting unobserved states (e.g., crop health) from observed states (e.g., spectral images from drones or satellites).

Incorporating AI models into farm management systems also presents advantages that allow them to be run on lower-powered hardware, such as field sensors and control units, which may have limited performance and often operate with lower-level programming languages. This necessitates the selection of AI models that balance accuracy with the performance limitations of on-field devices, requiring engineers to evaluate various models to find the optimal trade-offs. At the forefront of research in this area, reinforcement learning is a potential solution to these challenges through reward-based adaptation of the control algorithm while additionally providing the benefit of adapting to changing environmental conditions.

> “Engineers are exploring AI-based approaches that offer the flexibility to model the intricate interactions within agricultural systems.

While much of the AI research revolves around the techniques used to develop models for use in controls, for practical use, there needs to be an efficient way that those models can be deployed to on-field hardware, usually a microcontroller or a field programmable gate array (FPGA). Such a deployment environment should be able to able to leverage technologies such as automatic code generation and hardware in-the-loop to speed up development.

Future directions

AI algorithms are becoming integral to embedded vision systems for such applications as crop monitoring, audio processing for livestock management, and signal processing for soil analysis, among others. Simulation will continue to play a crucial role in integration testing in all these cases, ensuring that the AI algorithms perform as expected within the larger agricultural system.

As models and applications grow in complexity to meet the evolving demands of agriculture, AI and simulation will become increasingly indispensable tools for agricultural engineers. Platforms like MATLAB and Simulink are crucial to integrating AI algorithms for a broad range of applications, including optimizing workflows, reducing development times through synthetic data generation, reduced-order modeling, and rapid deployment of algorithms on hardware devices for the field.

Gen Sasaki, Principal Customer Success Engineer, MathWorks, Natick, Mass., USA, gsasaki@mathworks.com.

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Current AI Research at Mississippi State University

Hussein Gharakhani, Vitor Martins,
Nuwan Wijewardane, Xin Zhang, and Alex Thomasson, P.E.

We are a group of faculty members in the Department of Agricultural and Biological Engineering at Mississippi State University who are engaged in applying AI, machine learning, and deep learning to several agricultural applications:

- Hussein Gharakhani focuses on robotic manipulators, end effectors, and autonomous systems for agricultural operations.
- Vitor Martins focuses on optical remote sensing and satellite data for agriculture.
- Nuwan Wijewardane focuses on spectroscopic sensing of soils and plants.
- Xin Zhang focuses on unmanned aerial vehicles (UAVs) and robotics for agriculture.
- Alex Thomasson's current focus is on autonomous systems for precision agriculture.

Each of us is motivated to apply AI in our applications because of the growing availability of large datasets in agriculture and the vast capability of AI to estimate, predict, and enable decision-making based on large and highly complex datasets, providing massive new benefits to agriculture and worldwide food security as well as the environment.

In the following sections, we discuss some specific implementations of AI for agriculture in our research. While each of us serves as a project leader, most of these implementations involve multiple members of our group, along with students and other contributors.

Hussein Gharakhani's work with AI involves the development of robotic perception and sensing technologies. His research team uses images from a stereo camera in conjunction with a YOLO algorithm to detect cotton bolls for robotic cotton harvesting. Harvesting cotton with robots could provide multiple advantages, including maximizing fiber quality by harvesting incrementally as bolls mature, minimizing storm losses, and reducing soil compaction. A prototype harvester was tested in the field to evaluate the perception performance, and the system detected 78% of cotton bolls in an actual cotton field when a dark background was employed.

Robotic harvesting of cotton bolls.

Hussein's research team also exploited the dielectric properties of grains to estimate moisture content and bulk density, with the goal of producing a mobile sensor for accurate, indirect, and nondestructive sensing. The team used AI to estimate these properties based on the collected data and achieved an R^2 value of 0.99 for moisture content estimation in wheat. The team is improving the AI model to make it universal across numerous grains, with the added goal of identifying grain type.

Vitor Martins's work with AI involves field variability analysis in crop plants and soils. With a large variety of soil properties, the spatial distribution of these properties across agricultural fields is fundamental information for precision agriculture, and soil sampling is critical to gathering the site-specific data that supports management decisions. Stratified sampling based on yield maps, management history, and soil property maps has been adopted to improve sub-field representation with a limited number of samples.

Vitor and his team use AI to extract field boundaries from 10-m satellite images. Each field in a satellite image is identified, and the Segment Anything Model, a computer vision model proposed by Meta for satellite-based agricultural monitoring that is computationally efficient and structured to be scalable, is adapted to provide insights into soil and crop conditions within management zones by combining the satellite observations with AI algorithms. This project is helping in the planning of sub-field soil sampling and economically feasible soil health assessment for large heterogeneous fields.

Nuwan Wijewardane's work with AI involves the analysis of hyperspectral reflectance data from plant leaves and soils. The leaf data are important for high-throughput phenotyping of plant traits by way of rapid, low-cost, non-destructive means. Nuwan's team contributed to the assembly of a large library of hyperspectral data ($n = 2460$) from maize and sorghum leaves, evaluated two AI approaches to estimate important leaf properties (chlorophyll content, etc.), and developed predictions for an external dataset ($n = 445$) that included soybean and camelina, with a mean R^2 value of 0.69. The model performance improved when a small portion of external samples ($n = 20$) was added to the library via extra-weighted spiking. Such libraries can greatly benefit physiological and biochemical plant phenotyping.

The soil data included over 20,000 mid-infrared (MIR) reflectance spectra from U.S. soils, and the team assessed the library's performance with AI in estimating physical and chemical soil properties, including organic carbon (OC). In addition to reflectance spectra, the team used auxiliary soil type variables and land use and cover data to improve the MIR model performance. The results showed that OC and several other variables could be estimated with R^2 values of >0.95. The AI models generally outperformed traditional statistical models, and soil type and land use and cover data generally improved model performance.

Collecting hyperspectral reflectance data for phenotyping.

Xin Zhang's work with AI involves the development of robotic perception for specialty crops. For example, blackberries are easily damaged during harvesting and do not ripen simultaneously, so harvesting must be delicate, and the estimation of berry numbers at multiple ripeness levels is important in determining crop load for growers. Along with the development of a soft robotic gripper designed for berries, Xin's team used a YOLO algorithm to detect blackberries at multiple ripeness levels in field conditions with a mean average precision of 91%, an F1 score of 0.86, and a high inference speed of 22 ms at 1024×1024 image resolution.

Xin's team has also worked on a robotic perception system for catfish processing. Various processes require blade-based cutting that, with human labor, is dangerous and can lead to contamination and waste of fish meat. In consideration of robotic catfish processing, the team used AI-based computer vision to detect and localize the head, body, fins, tail, and image background with 95% mean pixel accuracy at a high inference speed of 0.28 s at 640×640 image resolution.

In another study, Xin's team used a UAV with an RGB camera to measure bloom density, and thus crop load, in almond trees. Early yield forecasting is important due to new California legislation that requires growers to determine nitrogen fertilizer rates based on soil tests and yield forecasts. Predicting almond yield by estimating crop load from bloom density can help growers manage their orchards more precisely, reduce inputs, and comply with the nitrogen mandate. Xin's team used AI to segment and determine bloom density per tree, with a precision of 81% and recall of 65%, in images collected with a UAV.

Alex Thomasson's work with AI involves AI-based crop yield estimation and detecting objects of interest from images collected with a UAV. Early yield estimation can aid growers in making management and marketing decisions, but predicting yield early in the season is difficult. Alex's team developed a modular AI network called ANN+ to operate on cotton crop data collected at different growth stages. A UAV with a multispectral sensor was flown multiple times at various cotton growth stages to collect images within 100 days after planting. The ANN+ model used spectral, textural, and structural information extracted from the images as well as weather data to achieve an R^2 value of 0.90 and a mean absolute percentage error of 12% for early season cotton yield estimation.

Alex's team also used a UAV with an RGB camera to detect volunteer cotton plants growing in fields of rotated crops. After harvest, cotton seeds remaining in a field can germinate and grow amidst the corn or sorghum crop. These volunteer cotton plants can serve as hosts for boll weevil pests, so they need to be detected and destroyed. The team found that a trained YOLO model with AI-based computer vision onboard a spot-spray-capable UAV can be used for real-time detection and mitigation of volunteer cotton plants.

In another study, Alex's team studied the detection of plastic shopping bags, which are commonly discarded as roadside litter and carried by the wind to become entangled in plants in nearby cotton fields. If it's not removed before harvest, this plastic litter can end up in the seed cotton, causing problems during ginning and potentially becoming embedded in the ginned fiber, reducing its market value. The researchers used YOLO to detect plastic bags in cotton plants at three zones (bottom, middle, and top) with accuracies of 92% for white bags and 78% for brown bags. Bags at the top of the plants were detected with 94% accuracy, while those at the middle and bottom were detected with 50% and 5% accuracy, respectively. Autonomous detection of plastic bags with UAVs can help with removal efforts and reduce the amount of contamination in cotton gins.

Conclusion

We are convinced that AI will have a tremendous impact on farming, providing growers with software, devices, and systems that provide recommendations and even perform autonomous solutions for laborious farming tasks. Because of the amazing complexity of agriculture, the growing need for food and fiber worldwide, and the need to reduce environmental risks in agricultural production, the upcoming generation of engineers has incredible opportunities for using AI in agriculture.

ASABE member Hussein Gharakhani, Assistant Professor, Vitor Martins, Assistant Professor, **ASABE member Nuwan Wijewardane,** Assistant Professor, **ASABE member Xin Zhang,** Assistant Professor, and **ASABE Fellow Alex Thomasson, P.E.,** Professor and Head, Department of Agricultural and Biological Engineering, Mississippi State University, Mississippi State, MS, USA, athomasson@abe.msstate.edu.

AI in Agriculture from a Northern European Perspective

Matti Pastell

I'm an agricultural engineer in Finland. I started working with machine learning in 2006 for my PhD thesis on automatic lameness detection in dairy cows using a probabilistic neural network. Currently, I work for the Digital Technologies in Agriculture group, which is part of the Natural Resources Institute Finland, focusing on the use of AI in several applications. My work is motivated by a strong theoretical interest in different modeling approaches and my belief in the great practical value of AI.

Farming in Europe

European farmers are faced with increasing demands. For instance, the EU's Farm to Fork strategy expects food systems to have a neutral or positive environmental impact, help mitigate climate change, and reverse the loss of biodiversity. At the same time, changing climates and global crises are challenging farmers. Extreme weather events are becoming more common, demanding new adaptation methods that require new investments. Many farmers are suffering from poor profitability, which has led them to protest, using their tractors to block streets, in Paris, Brussels, and many other cities across Europe.

Digitalization and AI are expected to be a big part of the solution to these environmental, economic, and societal problems. So far, digitalization has massively increased farmers' ability to collect data. Finnish dairy farms are technologically advanced; over half of the milk in Finland is produced using robotic milkers, and about 70% of Finnish dairy farms with more than 50 cows have activity sensors for monitoring cow behavior. An increasing number of Finnish cereal farms are also adopting precision farming technologies.

The detailed information provided by the increasing number and variety of sensors on farms should lead to better management. Still, there is no conclusive evidence that farms that use precision technologies have improved economic or environmental outcomes. The best farmers are certainly making good use of the data; however, for the average farmer, the data can be overwhelming. We need better decision-making based on data-driven system-level optimization.

This poses both an opportunity and a challenge to AI. To make good decisions considering diverse objectives, our models need to provide reasonable predictions about the outcomes under different interventions. How can we make that a reality?

Data-hungry AI

Recent advances in deep neural networks trained on massive datasets are remarkable. Popular open-source AI foundation models released recently include the Llama2 large language model (LLM), which was trained with 2 trillion tokens, and the DINOv2 computer vision model, which was trained with 142 million images. How can we approach this scale in agriculture? For me, the two most promising approaches are simulation-assisted machine learning and masked pretraining.

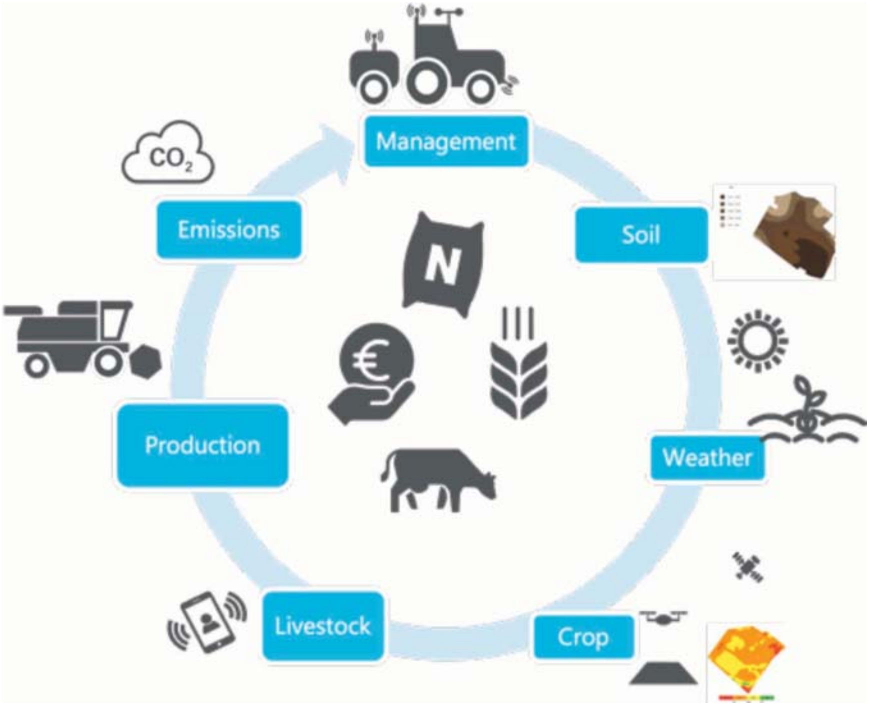
Masked pretraining is the key self-supervised method used in pretraining models when we have access to large amounts of unlabeled data. Computer vision and time series models can learn general features from data when trained to predict the contents of masked regions introduced during training. The pretrained model can then be transferred to new tasks, such as time series forecasting, with a significantly smaller dataset.

In agriculture, there are several datasets that can be used for masked pretraining. Satellite and weather data are available globally, and companies have large datasets, e.g., combine harvester yield data or milking robot data. These datasets are typically unannotated; e.g., soil or crop nutrient contents or the energy balance of animals are unobserved. Nevertheless, the datasets can hold significant value, especially when combined with other data sources or targeted data collection campaigns.

Human knowledge of agricultural systems is encoded in several different cropping systems and livestock simulation models. These models generally capture the knowledge from a series of experiments in which data were collected in much higher detail compared to what is available on a large scale. Digital twins are an approach to combining simulation models, machine learning models, and real-time sensor data for decision-making. Prescriptive digital twins that aim to provide optimal management decisions based on accurate predictive models can use many different AI approaches.

> “This poses both an opportunity and a challenge to AI. To make good decisions considering diverse objectives, our models need to provide reasonable predictions about the outcomes under different interventions.

Simulation models can be used to generate data for used as a part of the training pipeline for machine learning models, i.e., the use of synthetic data. Machine learning can be combined with mechanistic models, leading to hybrid models in which model predictions can be constrained to biological limits, or reinforcement learning can be used to train decision-making agents. An important target in our work is to model relevant processes simultaneously to enable the balancing of decisions between multiple targets.



AI can benefit all aspects of agricultural production.

Online learning

There are many decision-making problems in agriculture for which we don't have existing data or strong simulation models. What alternatives do we have beyond collecting massive datasets? Recently, we developed a method to predict animal welfare scores based on a combination of activity sensors and milk yield data. The key finding was that a single model doesn't work for all farms; however, farm-specific models perform quite well.

Going forward, the solution for these types of problems can be the use of online learning or incremental learning, in which AI models are updated for a specific farm or group of farms when more training data are obtained by a human observer. This approach allows us to augment human capabilities with AI models. The need for farm-specific models is often mentioned; however, the exact method has probably not received enough attention in research. What exactly should we adapt, and how much weight should be given to general and farm-specific data?

Animal welfare is an example of a multifaceted issue in which detailed scoring by an expert of each animal's condition is required to obtain the ground truth. The target can also evolve as the definition of animal welfare changes as we gain new scientific knowledge or as society's expectations change. Additionally, new sensors may need to be added to the system. In these settings, an online learning strategy can provide significant value without a massive upfront investment in training data collection.

Conclusions

The operating environment for farmers is changing quickly, and farmers will need to adapt to new challenges. AI models have huge potential to support farmers in making better decisions. Many European farmers are very motivated to work with us to collect data, provide ideas, and put the results into practice. Data sharing and data governance models have an important role in making this a reality. In Europe, agricultural data spaces are emerging to enable fair data sharing and a new data-based economy.

AI will thrive if we combine our efforts, and open science is the key ingredient that can make us succeed. Benchmark datasets and open-source models have driven success in other areas. It's time to bring that practice to our profession as well.

Limited access to on-farm data limits our ability to develop better AI models. We still need a lot more data to autonomously manage farming systems, so we still need to work on improving sensing systems to monitor animals, crops, and soils. We also need efficient mechanisms to make existing and new data available to AI models as sensing systems are being installed on farms. I'm confident that, through collaboration among researchers, farmers, and technology companies, we can put together the right datasets and find the right methods to make significant progress.

Matti Pastell, Research Professor in agricultural engineering, Natural Resources Institute Finland (Luke), Helsinki, Finland, matti.pastell@luke.fi.

Further reading

Bloch, V., Palosuo, T., Huitu, H., Ronkainen, A., Backman, J., Pussi, K., Suokannas, A., & Pastell, M. (2023). Towards a digital twin for optimal field management. In *Precision Agriculture '23* (pp. 377-383). Wageningen Academic. https://doi.org/10.3920/978-90-8686-947-3_46

Kallenberg, M. G. J., Overweg, H., Bree, R. van, & Athanasiadis, I. N. (2023). Nitrogen management with reinforcement learning and crop growth models. *Environmental Data Science, 2*, e34. https://doi.org/10.1017/eds.2023.28

Stygar, A. H., Frondelius, L., Berteselli, G. V., Gómez, Y., Canali, E., Niemi, J. K., Llonch, P., & Pastell, M. (2023). Measuring dairy cow welfare with real-time sensor-based data and farm records: a concept study. *Animal, 17,* 101023. https://doi.org/10.1016/j.animal.2023.101023

Automation in European Sugar Beet Harvesting

Jan Schattenberg and Felix Bischoff

Sugar beets are the primary source for European sugar production, making the EU the world's largest beet sugar producer. The harvesting of European sugar beets predominantly relies on self-propelled harvesters, which perform the topping, scalping, lifting, cleaning, and loading operations in a single pass. However, the concentration of these tasks and the high work intensity, exacerbated by the narrow harvest window, impose significant demands on operators.

In addition, conventional harvesting has limitations in handling the complex influences and conditions inherent in sugar beet production. Therefore, sugar beet harvesting provides a great opportunity for intelligent automation.

Our institute has been researching AI-based automation systems for sugar beet harvesting for nearly a decade. In this article, we present a few of the challenges that have arisen in our research.

Mapping expert knowledge in algorithms

To reduce the high demands on the operator of a sugar beet harvester, we developed a system for continuous optimization of the machine settings in cooperation with a harvester manufacturer and an image processing specialist. The key to this approach was to integrate expert knowledge into the system. This expert knowledge provided a reference for the AI and thus, in terms of machine learning, the ground truth.

As with any application of AI, it was crucial that the database used for training the algorithms was as representative as possible. This is a major challenge in sugar beet harvesting due to the wide range of environmental conditions and soil types.

The development of the expert system began with expert interviews and field experiments. These experiments were designed so that a representative database could be established for the various relevant qualities. The machine settings were varied during the experiments according to the experts' opinions, and the environmental conditions were varied by using different test locations throughout Europe.

The data were then clustered according to location and machine setting, and a model was derived from the clustered data, which served as the basis for the expert system. The data were also annotated by experts for various quality parameters, including root fracture, surface damage, soil, and leaf residue. Both absolute and relative evaluation approaches were examined and implemented. In addition, both classic and AI-based image processing algorithms were developed, investigated, and mapped to the annotated data.

Expert system and AI image analysis

Based on the expert system, a method for computer-aided process optimization for a self-propelled sugar beet harvester was developed. This method adjusts the machine settings based on the driver's specifications for quality, performance, and efficiency. A prototype was implemented to reduce the driver's workload during the harvesting season and improve the overall performance.

Advances in deep learning and computer vision enabled the development of a cost-effective, image-based quality sensor. Initial results indicated that the integration of deep learning with computer vision could effectively optimize the harvesting process. The application of machine learning-based optimization also revealed the non-linear nature of the system

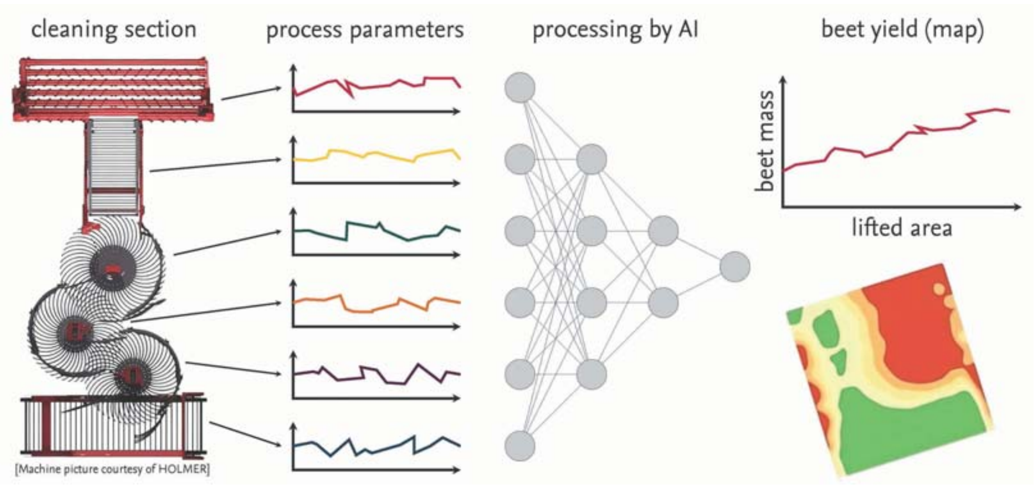
A self-propelled sugar beet harvester at work in a European field.

and highlighted the need for continuous learning to adapt to changing conditions.

Although a complex process was modeled, our approach was simple. While the potential of the model is promising, the accuracy needs to be further improved, especially in the detection of root and surface fractures.

Yield mapping for precision agriculture

The growing conditions within a field can vary considerably. Therefore, targeted application of fertilizers and pesticides is required to efficiently meet the needs of the crop.



Determining sugar beet yield from the harvester's process parameters.

A yield map provides the basis for dividing a field into smaller areas based on the different yield potentials within the field. Yield maps also give producers a tool for validating their practices in the current season and for planning the next growing season based on the differences in yield.

The harvesters available for most common crops already meet the requirements for yield mapping by providing precise yield measurements. However, in sugar beet harvesters, further development is needed to improve the accuracy and reliability of the yield measurement system. The current state-of-the-art system is only suitable for determining the bunker fill level, and it can't be used for yield measurement.

Yield measurement in sugar beet harvesters would be useful for several reasons. As a demanding crop, sugar beets accurately reflect the heterogeneity of the soil's yield potential. In addition, transport logistics from the field to the sugar factory could be better planned based on the measured yield. Furthermore, yield mapping would close the mapping gap due to crop rotations in the field.

Measuring sugar beet yields with AI

Our research is based on the theory that the process parameters of a sugar beet harvester are directly related to the harvested beet mass. Thus, the rotational speed of the cleaning elements should be proportional to the volume of beets conveyed. The pressure of the hydraulic drives should also be proportional to the conveyed beet mass.

The influence of numerous process parameters leads to high complexity for the system, making it impossible to describe with simple mathematical models. Our solution is an AI system that assigns a beet weight to the process variables that are provided on the CAN bus.

Generating training data for AI

To enable the AI system to accurately determine the beet weight from the harvester's process parameters, it is necessary to train it for this application using realistic data. The quality of the training data is crucial for the accuracy of the AI system. Therefore, for the AI system to learn the relationships between the process parameters and the beet weight during the training process, it is essential to make this assignment manually in the training data.

This manual assignment was the greatest challenge in this research project. For this purpose, a beet harvester was equipped with a chute, which picked up the flow of beets from the elevator, led it directly out of the harvester, and deposited it as a swath in the field. This beet swath was then divided into meter-sized sections and weighed manually. Due to the spatial offset between the beet swath and the crop edge, the process parameters and the weights of the beets could be synchronized and assigned in post-processing.

To enhance the dataset quality and map a broader yield spectrum, specific zones were planted. These zones intentionally reduced the beet yield due to soil heterogeneity, variations in sowing density, and targeted fertilizer application.

As shown by the preceding examples, AI can provide reliable solutions for complex problems, and it's relatively easy to use. However, it's essential to use an excellent database for training the AI system. The quality of the training data is the biggest challenge for using AI in agriculture.

Jan Schattenberg, Deputy Director of the Institute and Head of the Working Group for Automation and Robot Systems, and **Felix Bischoff,** Research Associate in the Working Group for Automation and Robot Systems, Institute of Mobile Machines and Commercial Vehicles, Technical University of Braunschweig, Lower Saxony, Germany, j.schattenberg@tu-braunschweig.de.

The Essential Role of AI in Agriculture

Abhishek Panchadi, Prakash Kumar Jha, and Sushant Mehan

Agriculture, the backbone of civilization, has continually adapted to meet the evolving needs of society. From ancient farming practices to the modern mechanized era, technological innovations have shaped how we cultivate food and manage our natural resources.

Now we stand on the cusp of a high-tech revolution in agriculture. Imagine fields not just bursting with crops but buzzing with data. This is the promise of agricultural technology, and at its heart lies a powerful tool: artificial intelligence (AI). AI is not just a smart assistant for farmers; it's a transformative force that analyzes vast amounts of data to improve everything from planting to harvest. Let's embark on a journey into the exciting world of AI and witness how it's reshaping agriculture.

In the 1950s, a pivotal time in the history of technology, a group of computer scientists laid the groundwork for machine intelligence by developing rudimentary neural networks. With the enormous increase in computing power that has occurred since then, those early systems have evolved into AI, which promises to disrupt every field of human activity, including agriculture.

According to Statista Market Insights, the market size of AI in agriculture is expected to grow at an annual rate of 28.46% from 2024 to 2030, reaching a value of $826.70 billion by 2030, with industry giants like Microsoft, IBM, and others leading the way. This rapid growth represents the immense potential of AI in agriculture, creating many opportunities for young professionals with expertise in AI, agriculture, or both.

Examples of AI in agriculture

In the AI revolution, farmers are key players in adopting this new technology by integrating AI throughout the cropping cycle. With assistance from AI, farmers will gain valuable insights, optimize their resource use, and make data-driven decisions for a more sustainable and productive agricultural future. Below are a few examples of AI in agriculture.

From sowing to harvest, AI algorithms will play a vital role in every cropping stage. These algorithms can analyze climate data to recommend the most suitable crops for the predicted weather conditions, while AI-powered sensors monitor soil moisture levels, enabling precise irrigation and minimizing water waste.

Similarly, AI can optimize fertilizer application based on soil data and crop health, minimizing waste and environmental impact. AI algorithms can also predict crop yields accurately by analyzing past data and weather patterns, allowing farmers to plan effectively and minimize losses.

Advanced robots, both autonomous and semi-autonomous, equipped with sensors and computer vision can navigate fields, identifying and treating weeds and pests, and thus reduce manual labor as well as herbicide and pesticide use.

Drones with AI-powered image recognition can scan fields for signs of disease, enabling early intervention and minimizing crop damage. Through interpretation of remote sensing data, AI can contribute to informed decision-making throughout the cropping cycle.

At harvest, advanced robots equipped with sensors and computer vision can assist in picking delicate fruits and vegetables, improving efficiency and reducing reliance on manual labor, especially during peak harvest times.

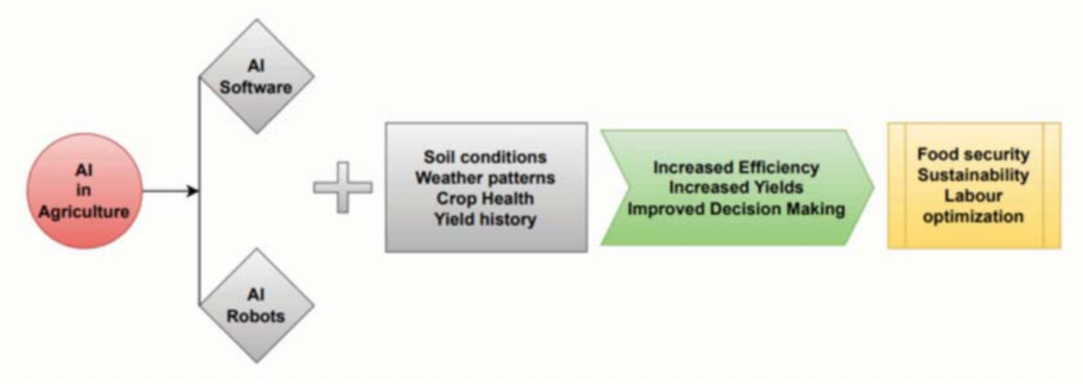
This is the power of AI in the hands of farmers, shaping the future of agriculture and highlighting the crucial role of farmers in this technological transformation.

Concerns and assurances about AI

Data is a valuable resource for farmers because it empowers them to make informed decisions. While AI is transforming agriculture, data privacy remains a concern. A 2022 study found that some farmers are hesitant to adopt AI due to concerns about the ownership of the data from their farms.

In response to this concern, researchers are exploring secure data marketplaces where farmers can control access to their valuable data. In particular, there's a need for greater awareness of data license agreements. A 2019 study found that 74% of farmers are unaware of these agreements, while a 2017 article in *Resource* reported that 55% of farmers sign data contracts with agricultural technology providers without seeking clarification on the data protection and usage terms.

Agreements are now being drafted to resolve this issue, based on codes



The implications for AI in agriculture.

of conduct such as the Australian Farm Data Code, Ag Data's Core Principles, and the EU Code of Conduct. Platforms such as Azure data manager for agriculture, Trimble Ag, Granular, and Farmlogs are continuously refined to provide better data management.

Cost and technological access are also hurdles to adopting AI, especially for small and remote farms. Thankfully, efforts are underway to develop more affordable AI solutions and expand internet access in rural areas. Initiatives such as government subsidies and community-based internet projects hold promise in this area.

> **AI is poised to revolutionize agriculture and achieve data-driven decision-making, optimize resource use, and increase sustainability. From AI-powered robots for weed control to algorithms for predicting crop yields, AI offers a wide range of tools to assist farmers.**

Operating AI tools can be another challenge. Training programs and user-friendly interfaces are being developed to bridge the digital literacy gap and empower farmers.

Finally, ensuring that AI recommendations are fair and unbiased is crucial. Advances in explainable AI are making AI models more transparent, and efforts are being made to use diverse datasets to train the models.

All of these efforts are a testament to the commitment to the responsible use of AI in agriculture, instilling confidence in its future.

Conclusion

AI is poised to revolutionize agriculture and achieve data-driven decision-making, optimize resource use, and increase sustainability. From AI-powered robots for weed control to algorithms for predicting crop yields, AI offers a wide range of tools to assist farmers.

The potential of AI in agriculture is vast and exciting, promising a future where technology and farming are seamlessly merged. However, challenges such as data privacy concerns, affordability, and accessibility for small farms must be addressed. In addition, transparency in data practices and educational initiatives to bridge the knowledge gap are crucial for broader adoption of AI.

As AI in agriculture matures, collaboration between researchers, developers, policymakers, and farmers is essential to ensure inclusive and sustainable growth. By using AI responsibly, we can expect a future where agriculture will flourish, feeding a growing population while preserving our precious resources. The future of agriculture is here, and it's powered by AI!

Abhishek Panchadi, Ph.D. Student, and **ASABE member and YPC Representative to the Publications Council Prakash Kumar Jha,** Assistant Professor, Department of Plant and Soil Sciences, Mississippi State University, Mississippi State, USA; **ASABE member and YPC Chair Sushant Mehan,** Assistant Professor of Water Resources Engineering, Department of Agricultural and Biosystems Engineering, South Dakota State University, Brookings, USA, Sushant.Mehan@sdstate.edu.

Further reading

Anyoha, R. (2017). The history of artificial intelligence. Retrieved from https://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence/ (last accessed 30 June 2024)

TIBM. (2024). What is artificial intelligence (AI)? *IBM Think.* Retrieved from https://www.ibm.com/topics/artificial-intelligence

Javaid, M., Haleem, A., Khan, I. H., & Suman, R. (2023). Understanding the potential applications of artificial intelligence in agriculture sector. *Advanced Agrochem, 2*(1), 15-30. https://doi.org/10.1016/j.aac.2022.10.001

Kaur, J., Hazrati Fard, S. M., Amiri-Zarandi, M., & Dara, R. (2022). Protecting farmers' data privacy and confidentiality: Recommendations and considerations. *Frontiers in Sustainable Food Systems, 6,* 903230. https://doi.org/10.3389/fsufs.2022.903230

Ryan, M. (2023). The social and ethical impacts of artificial intelligence in agriculture: Mapping the agricultural AI literature. *AI & Society, 38*(6), 2473-2485. https://doi.org/10.1007/s00146-021-01377-9

Schuster, J. (2017). Big data ethics and the digital age of agriculture. *Resource, 24*(1), 20-21.

Tzachor, A., Devare, M., King, B., Avin, S., & Ó hÉigeartaigh, S. (2022). Responsible artificial intelligence in agriculture requires systemic understanding of risks and externalities. *Nature Machine Intelligence, 4*(2), 104-109. https://doi.org/10.1038/s42256-022-00440-4

Wiseman, L., Sanderson, J., Zhang, A., & Jakku, E. (2019). Farmers and their data: An examination of farmers' reluctance to share their data through the lens of the laws impacting smart farming. *NJAS-Wageningen Journal of Life Sciences, 90,* 100301. https://doi.org/10.1016/j.njas.2019.04.007

Some Thoughts on Agricultural Robotics

Eldert van Henten

About 20 years ago, a team from Wageningen University co-authored a contribution to *Resource* highlighting a development in autonomous harvesting. It was not the first time autonomous harvesting had been demonstrated, but our cucumber harvester pushed the technology forward by demonstrating the machine in a real greenhouse. The harvest success rate was 70% to 75%. Totally excited by those results, we were convinced that our work would immediately change the future of agriculture.

Well, that turned out differently. Robotic technology was not robust enough for challenging operations like harvesting, and that was repeatedly confirmed in the years that followed.

Since then, the technology has improved dramatically, farming is experiencing a labor shortage, especially for high-value crops, and feeding the world has become a global challenge, revitalizing agricultural engineering and attracting new players to the effort. Robotics, AI, and big data have become part of the technology strategies of governments, and governments recognize that agriculture is an important application for this technology.


The EU-SWEEPER selective harvester for sweet peppers (*photo courtesy Wageningen University and Research*).

Despite all the technological progress, not many autonomous robots have made it to production. Milking robots and other machines in and around the barn are successes, and autonomous machines are gradually making their way into arable farming. However, in protected cultivation and orchard production, fully autonomous systems for selective harvesting are still in research. Only recently was a harvesting robot for vine tomatoes introduced to the market, the Ridder Grow robot.

The Moravec paradox

Why is it so difficult to deploy autonomous robots in agriculture? The Moravec paradox provides an answer. Roughly, it goes like this: what's easy for a human, such as picking an apple, is often hard to engineer, that is, it's difficult to build a machine that performs the task as effectively as a human. The other side of the Moravec paradox is that what's often difficult for a human, such as playing Go, is easy to engineer, that is, it's easy to build a machine for that purpose.

An explanation for this paradox is that human survival demanded fast perception, cognition, and eye-hand coordination. Early humans did not need to solve mathematical puzzles. The Moravec paradox explains why AI has been very successful in pattern recognition and puzzle solving. It also explains why self-driving cars are not very reliable.

The closed world paradigm

The closed world paradigm is also relevant to AI. The closed world paradigm states that what is not known to be true is considered false. An engineering translation of this paradigm is that everything that a machine should do and all the objects that it should operate on can be perfectly known in a closed system.

Most existing agricultural technology, such as seeding machines, planting machines, and machines for sorting and packing, represents the closed world paradigm. These systems are effective because there is no uncertainty in the location, shape, or size of the target objects. These machines rely largely on single-hypothesis testing: an object either is or is not.

Selective harvesting is different. The location, shape, size, color, and other attributes of the target objects can vary widely within the environment and between environments. Existing automation cannot generalize across this variation. This situation represents the open world paradigm.

The open world paradigm

The open world paradigm states that everything that is not true is not known and thus is open to speculation. The environment in which the technology needs to operate may not be perfectly structured, it may even be cluttered or chaotic, and the visibility and accessibility of the target objects may be compromised.

Humans excel in an open world due to their superior perception, cognition, and eye-hand coordination. In orchard work, humans can use their experience and their active perception, both visual and tactile, to find and grasp fruits, even when the fruits are only partially visible. This is a domain where single-hypothesis reasoning does not work. A robot needs to reason out the location of each fruit and then determine the appropriate action.

The sense-plan-act paradigm

The sense-plan-act paradigm represents how humans work. We perceive the environment actively to find hidden objects. We plan deliberately, and then we act intentionally

to grasp the target object. A lot of feedback is involved in this behavior, and we learn from our failures and remember information about the operation and its environment.

As shown in the illustration below, the sense-plan-act paradigm includes a world model. The world model is a representation of the environment. It does not have to be a geometric map. It can be a relational mapping between objects in the environment, or a collection of skills for particular conditions.

Current research on robotic harvesting strongly focuses on perception, planning, and grasping, which are usually addressed in isolation. To extend the capabilities of robotic systems, these individual skills must be further developed in the context of a complete system. For example, the gripping method largely determines the information that the perception needs to provide. So far, there is not much research on including a world model in robotic systems.

Sensing and Perception

Because robots work in a three-dimensional world, robotic perception needs to shift from 2D to 3D. Semantic segmentation will remain a cornerstone of perception, but more research needs to focus on clutter and occlusion through multi-view or active perception strategies as well as shape completion. So far, agricultural robotics has relied heavily on RGB, NIR, and RGB-D camera vision and associated imaging technologies like LIDAR.

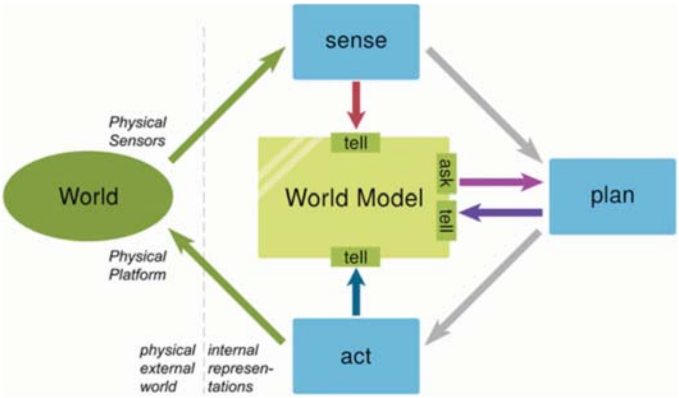
In 3D perception, sensing mostly produces point clouds. To translate point clouds into a semantic model of the perceived objects, modeling approaches like TreeQSM are used in forestry and phenotyping and could be applicable to agricultural robotics. This approach might also connect to research based on functional structural plant models (FSPM) and digital twins of crops.

Multi-modal perception, including tactile sensing, could provide further progress in sensing, especially in close contact with the target objects. Multi-view perception requires matching and tracking objects that occur in different images. Multi-object tracking is currently being developed.

Planning and acting

Robotics does not end with perception. The translation of perception into action is challenging. Eye-hand coordination for robots is a topic of ongoing research. Learning from demonstrations is an effective alternative to path-planning algorithms that need to recalculate actions again and again. Demonstrations can be provided by experienced workers and modeled using Gaussian mixture models, as an example, and rapidly replaced when needed.

Reinforcement learning is an alternative to planning and servo control that might be effective in complex environments, although this approach requires serious amounts of data for training. Recently, progress was reported on the use of basic world models for guiding the selective harvesting of fruits. In one case, multi-hypothesis testing was used to locate tomato trusses in a cluttered environment using active perception.



The sense-plan-act paradigm and the pivotal role of a world model (from Sakagami et al., 2023).

Along with developments in large language models and foundational learning, projects such as Google Deepmind have demonstrated the translation of video into robotic actions using a visual language action model that learns from the web and from robotic data and translates this knowledge into instructions for robotic control. The early results indicate that this approach generalizes across variations better than previous approaches.

Conclusion

It's not yet clear where agricultural robotics is headed. Should we rely on black-box, data-driven approaches, or is there a way to include human knowledge and experience? The debate over fully data-driven models versus mechanistic white-box models seems to have ended in favor of the data-driven approach, but this feels like a waste of valuable expert knowledge. Most likely, a mixture of approaches will push this technology forward for success in the real world.

Eldert J. van Henten, Professor, Agricultural Biosystems Engineering Group, Wageningen University and Research, Wageningen, The Netherlands, eldert.vanhenten@wur.nl.

Further reading

Henten, E. J. van, Tuijl, B. A. J. van, Hemming, J., Kornet, J., & Bontsema, J., (2005). Robot picks cucumbers in greenhouse. *Resource 12*(7), 5. https://www.asabe.org/Portals/0/aPubs/Resource/PDF/Resource12-07Sep2005.pdf

Sakagami, R., Lay, F. S., Dömel, A., Schuster, M. J., Albu-Schäffer, A., & Stulp, F. (2023). Robotic world models: Conceptualization, review, and engineering best practices. *Frontiers in Robotics and AI, 10.* https://doi.org/10.3389/frobt.2023.1253049

How to Turn Field Data into Site-Specific Decisions

André Freitas Colaço, Roberto Fray da Silva, and José Paulo Molin

Precision agriculture is considered a precursor to digital technologies applied in agriculture. Starting in the late 1980s, developments in sensor technology enabled collection of detailed spatial data to map soil and plant attributes at within-field scale. With these monitoring technologies, along with the development of machine automation tools, a new farm management strategy emerged, offering farmers the ability to treat parts of a field differently according to the spatial variability within the field.

However, a critical question that has always puzzled farmers, agronomic consultants, and agricultural scientists has been what to do with all the data collected from the fields. In other words, how do we use this data for effective site-specific decisions? Dealing with this question was never easy, especially for complex decisions such as the choice of genetic material, sowing date, plant density, and fertilizer rate, in which the interactions between environmental factors and genotype can cause variation in the system's response to a management change.

> “A critical question that has always puzzled farmers, agronomic consultants, and agricultural scientists has been what to do with all the data collected from the fields.

Limits of precision agriculture

In fact, we could argue that, in trying to implement such decisions site-specifically, precision agriculture has made farming more complex, not less. As a result, despite the use of spatial data, precision agriculture systems continue to rely on generic or simplified decision rules, resulting in inadequate decisions for the specific conditions of each location and season.

Let's take site-specific nutrient management as an example. A common strategy for deriving variable-rate fertilizer recommendations in precision agriculture has been to input information from soil fertility maps into current recommendation charts based on generalized response functions. Despite its easy implementation, this strategy does not consider local crop responsiveness to the applied nutrients, a key element of site-specific management.

In other cases, variable-rate recommendations follow agronomic frameworks based on nutrient demand and supply in the system. However, only a few factors of this framework tend to be monitored or accounted for in a site-specific manner.

While these approaches are justified, given the need for simple and feasible tools for field application, their simplifications can contribute to precision agriculture being not very precise after all. Overall, the lack of adequate decision tools that can use all the digital data provided by the new technologies has been a critical barrier to advancing site-specific management and digital agriculture.

Challenges of data-driven decision-making

Against this background, AI is considered a key tool for making effective site-specific decisions in agriculture and for tackling the pressing question of what to do with all the data. AI can be the basis for systems that convert raw data into knowledge to improve decision-making, automate processes, and ultimately increase productivity, profitability, and sustainability.

In recent years, significant developments have been made in time series forecasting, spatial analyses, image analysis, computer vision, automation, and robotics for various applications on the farm and along the value chain. For example, state-of-the-art models are being applied to estimate important crop and soil attributes based on sensor data, estimate potential commodity prices, and evaluate the potential impacts of extreme weather events.

In particular, great effort has been put into developing yield prediction models using various data sources and AI methods. Moreover, robots, including drones, that use AI are making remarkable progress in field data collection and even conducting field tasks, such as harvesting.

However, two critical challenges must be overcome before data-driven decision-making can thrive in agriculture. The first challenge is the lack of data availability and cloud accessibility, or in other words, the incipience of agronomic IoT systems. Farming is a complex system, encompassing different crop varieties, soil types, weather, and production processes. To develop useful AI models, a considerable amount of data over time is needed so that trends in the data can be captured.

Moreover, most farms lack the computing power needed to process all the data collected by automated systems. At the same time, lack of internet connectivity limits access to cloud services. Finally, even when effective IoT systems are in place, these technologies are used for applications other than agronomic management, such as fleet management. Therefore, a shift in focus toward using IoT for agronomic purposes is required.

The second challenge relates to the lack of effective frameworks for agronomic decisions that can be combined with AI approaches. In the case of fertilizer recommendations, recent studies have shown that, despite significantly improved yield

predictions by AI, its use in simplified nutrient balance calculations did not result in more accurate recommendations due to assumptions regarding other key inputs.

In general, the effort to improve agronomic predictions with AI has been undertaken without consideration of the limited ability of current agronomic decision tools to make appropriate use of such information.

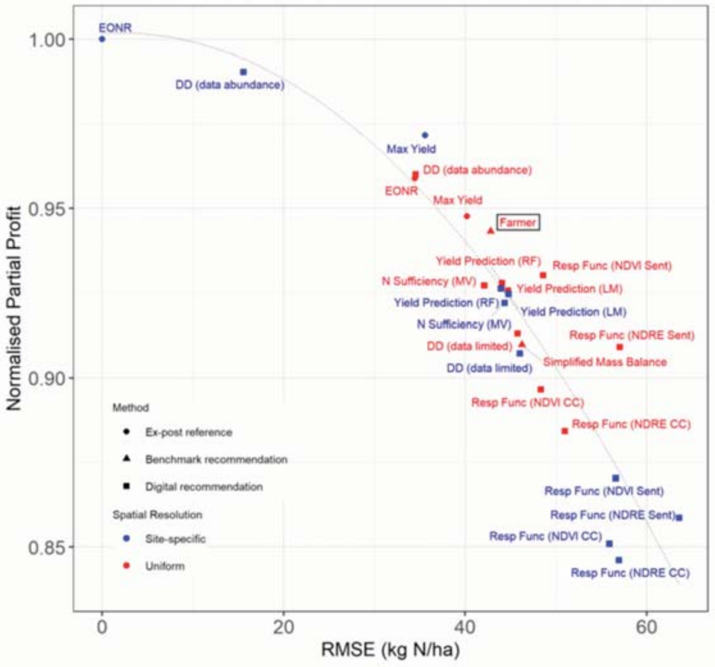
A different approach

In light of this issue, a different approach for effective data-driven, site-specific decisions has been proposed. Rather than using AI to predict the parameters needed for current decision frameworks, AI can be used in combination with on-farm experimentation (OFE) so that field data relating to various crop, soil, and climate features can be modeled directly against an optimal decision (for example, optimal fertilizer rates).

Although OFE emerged in the late 1990s, along with precision agriculture, this approach has recently received significant attention due to its knowledge-building capacity and its potential for integration with AI systems. Unlike classical agronomic experimentation, OFE is large-scale (covering all or most of the field area), is spatially distributed (making use of existing spatial variability in the field), and is implemented with a high degree of automation and use of digital technologies.

In summary, these systems allow effortless evaluation of different management practices across different environments, providing empirical observations of optimal management against which AI models can be trained. This data-driven, OFE-based approach was the only method with potential to reduce recommendation errors and increase profitability in a study that tested a range of digital and non-digital methods for nitrogen fertilizer recommendation (labeled DD, for data-driven, in the accompanying graph).

In conclusion, while AI has promise for transforming data into more effective site-specific decisions, it is unlikely to solve that challenge on its own. We must also focus on improving the availability of field data and developing new methods for making optimal decisions. For the future, it is imperative to invest efforts in agronomic IoT systems and integrate our approaches with OFE.



A plot of error versus profit showing the average results of various N recommendation methods across 21 large-scale on-farm trials. "Ex-post reference" is the observed optimum N rate after harvest for maximizing either the partial profit (the economically optimal N rate, EONR) or the grain yield (the Max Yield method). Benchmark recommendations are the methods traditionally used by farmers and consultants, and digital recommendations are the N rates based on field data (from Colaço et al., 2024).

André Freitas Colaço, Professor, **Roberto Fray da Silva,** Professor, and **José Paulo Molin,** Professor, Department of Biosystems Engineering, Luiz de Queiroz College of Agriculture, University of São Paulo, Piracicaba, Brazil, andre.colaco@usp.br.

Further reading

Bazame, H. C., Molin, J. P., Althoff, D., Martello, M., & Corrêdo, L. P. (2022). Mapping coffee yield with computer vision. *Precision Agriculture, 23,* 2372-2387. https://doi.org/10.1007/s11119-022-09924-0

Canata, T. F., Wei, M. C. F., Maldaner, L. F., & Molin, J. P. (2021). Sugarcane yield mapping using high-resolution imagery data and machine learning technique. *Remote Sensing, 13*(2), 232. https://doi.org/10.3390/rs13020232

Colaço, A. F., Richetti, J., Bramley, R. G. V., & Lawes, R. A. (2021). How will the next-generation of sensor-based decision systems look in the context of intelligent agriculture? A case-study. *Field Crops Research, 270,* article 108205. https://doi.org/10.1016/j.fcr.2021.108205

Colaço, A. F., Whelan, B., Bramley, R. G. V., Richetti, J., Fajardo, M., McCarthy, A., … Lawes, R. (2024). Digital strategies for nitrogen management in grain production systems: Lessons from multi-method assessment using on-farm experimentation. *Precision Agriculture, 25,* 983-1013. https://doi.org/10.1007/s11119-023-10102-z

Da Silva, R. F., Gesualdo G. C., Benso, M. R., Fava, M. C., Mendiondo, E. M., Saraiva, A. M., & Delbem A. C. B. (2021). A data-driven framework for identifying productivity zones and the impact of agricultural droughts in sugarcane using SPI and unsupervised learning. *Proc. IEEE Intl. Workshop on Metrology for Agriculture and Forestry (MetroAgriFor)* (pp. 226-231). https://doi.org/10.1109/MetroAgriFor52389.2021.9628570

Some Food for Thought on Horticultural Robotics

Shen Hin Lim, Mike Duke, Ben McGuinness, and Chikit Au

The deep learning revolution has exponentially increased the use of digital technology in agriculture for applications such as weather forecasting, crop monitoring, disease detection, and yield estimation. This development, coupled with the decreasing availability of human labor, has heightened the need for agricultural robotics. There are some successful solutions, such as autonomous tractors, robotic weeders, and intelligent sprayers, but more is needed to reduce the reliance on manual labor, especially in horticulture.

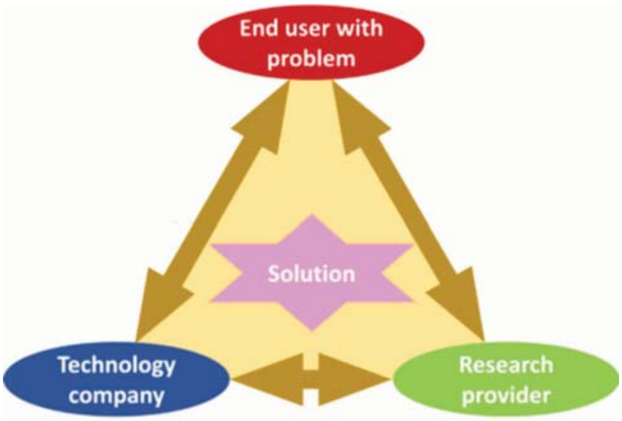
Over the years, our research group has developed a variety of smart horticulture solutions, including a selective asparagus harvesting robot. We are also part of MaaraTech, a research group that integrates AI into grapevine pruning, apple fruitlet thinning, and selective blueberry harvesting.

The golden triangle

We've found an approach, which we call the golden triangle, that helps us address the needs of growers. The golden triangle represents the synergy between three parties: the end user (grower) with a problem, the research provider (such as our group) that develops a solution, and the technology company that brings the solution to maturity.

At the start of this process, we host co-design workshops to capture the grower's specific needs, such as any pinch-point tasks that must be prioritized. These workshops are also used to learn the grower's experience and better understand the crop cycle, particularly the grower's decision-making process and work tasks. It's also important to capture the differences involved in producing different crops.

In addition, we visit the grower's operation and record how the work tasks are actually performed using videos, still images, and conversations with the workers and managers. This first-hand information allows us to develop the specifications for our proposed solution.



The "golden triangle" connects the three parties involved in finding a technology solution: the end user (grower) with a problem, the research provider that develops a solution, and the technology company that commercializes the solution. All three parties maintain constant communication.

During the research process, we have constant conversations with the grower to share our progress and gather feedback. In parallel, we engage with a technology company that supports our research and that can commercialize the solution for other growers to use.

For example, for our asparagus harvesting robot, our discussion with the technology company narrowed the proposed list of object detection methods, such as Faster R-CNN and YOLO. Due to its compatibility with the vision system, we found that Faster R-CNN was the most suitable method for detecting individual asparagus shoots. The developed solution extracted information on individual shoots, such as height and location, and then harvested the shoots based on a height threshold.

So far, we have conducted successful field trials with the asparagus harvesting robot in California and New Zealand. Field trials are vital for evaluating a solution's workability, demonstrating the solution to growers, and receiving their feedback for further improvements.

The seasonal nature of agriculture limits the time available for field trials, so we also rely on lab trials. The lab trials are typically performed before the field trials to solve basic integration issues, such as inconsistent command execution, so that the field trials can address problems due to environmental conditions.

The lab trials are also used to find criteria for the field trials. The main concern with the lab trials is how closely the trial conditions resemble the actual working conditions while allowing repetition of the work tasks. If a real crop can't be used, we use a replicated product that retains key features of the crop, such as weight, texture, color, and firmness.

When the field trials show that our solution meets the required specifications, we consider it a commercially viable solution, and we perform technology transfer to the technology company for further development. During the commercialization process, we maintain constant communication between the technology company and the growers to ensure that the commercialized solution meets their needs.

What we've learned

Working on these automation projects has re-affirmed our belief that agriculture is complicated, and it makes us appreciate human adaptability, dexterity, and hand-eye coordination in completing agricultural tasks.

However, the human ability in completing these tasks varies in quality due to multiple reasons, such as differences in skill or experience. AI can reduce this variability by capturing the ideal task performance of experienced workers and then categorizing the essential steps, such as

detection, identification, decision-making, and action.

Replication of human dexterity and hand-eye coordination is difficult. However, AI can identify the key motions and suggest end-effector or gripper innovations that can either mimic natural movement or provide alternative ways to perform the task.

Each grower also has different work criteria, and using AI to encapsulate a grower's knowledge of these criteria can streamline the decision-making process and provide a deeper understanding of both crops and humans.

Research on detecting the quality and condition of crops has benefited from AI and will remain a key area for AI adoption in horticulture. Data capture with multiple types of sensors and in various environmental conditions would enhance the accuracy of this detection capability. Identification of crops under occlusion is also a bonus.

As recognized by multiple experts, AI and robotics are essential for efficient, sustainable agriculture. To make this happen, some additional factors to be considered, such as safety, power management, and cooperative control of multiple robots.

To deliver functional robotic solutions, we need the growers on board, and the growers need us to see their point of view. Ultimately, AI will help horticultural robots perform as well as humans, or even better, and help the agricultural community provide food for the world.

Shen Hin Lim, Senior Lecturer, **Mike Duke,** Professor, **Ben McGuinness,** Lecturer, and **Chikit Au,** Senior Lecturer, Waikato Robotics, Automation and Sensing (WaiRAS) group, School of Engineering, The University of Waikato, New Zealand, hin.lim@waikato.ac.nz.

Uses of AI in Precision Agriculture

John Reid

The convergence of AI and agricultural mechanization is ushering in a new era of farming in which smart machines optimize production tasks, reduce human labor, and support sustainable practices. In 2000, the National Academy of Engineering recognized agricultural mechanization as one of the top engineering achievements of the 20th century. At about the same time, agricultural machinery, equipped with electronic control, began an era of agricultural mechatronics.

An early innovation was the commercialization of automatic guidance systems. Soon other technologies, including telematics, were commercialized to provide connectivity between machines and allow access to off-machine services. Additionally, machine systems became more controllable through innovations in electronics, electro-hydraulics, and electrification. Today, agricultural machines are software-defined, cyber-physical systems that are poised for further enhancement with AI.

Agricultural machine systems

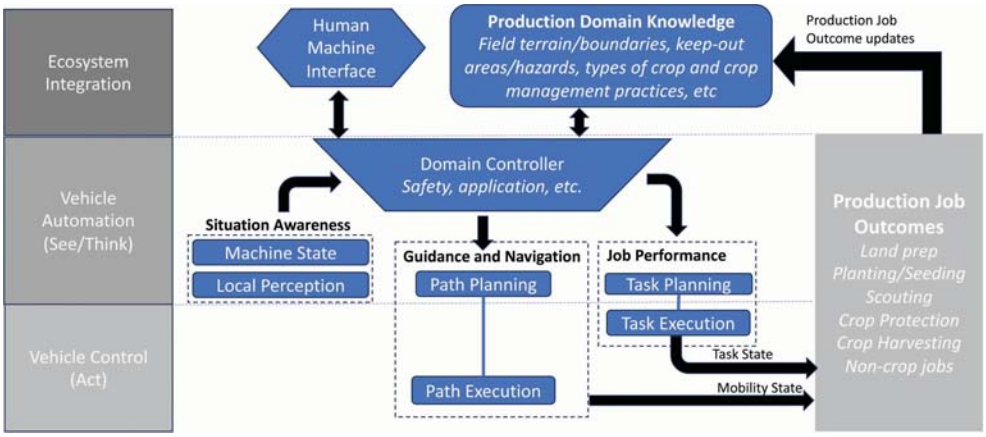
Precision agriculture has increased productivity through automation, data management, and smart-connected machines that can plan operations in process or ahead of time. These innovations are currently deployed in operator-driven machines, and they pave the way for use in agricultural robots.

The accompanying diagram shows the key elements of automated agricultural machine systems. At the base level are vehicle control capabilities that enable the actions necessary for production job outcomes. At the middle level are automation capabilities, such as guidance and navigation, that augment or replace the tasks performed by a human operator. At the top level is the human-machine interface and linkages to off-machine resources that provide production domain knowledge.

Agricultural machine systems are evolving to closely resemble robotic systems, with a key distinction being the presence of a human operator or reliance on a human-machine interface for remote management. Whether automated or autonomous, these systems create value by delivering specific production job outcomes, such as land preparation, seeding, crop protection, harvesting, and material transport. The performance of agricultural machine systems is evaluated based on their productivity and convenience for the operator, as well as their efficiency in accomplishing production jobs.

AI-based path planning

Precision agriculture employs sensors for guidance and navigation. Automatic guidance, powered by precision GNSS, has revolutionized field operations by



Key elements of automated agricultural machine systems.

enabling agricultural machines to follow planned paths with high accuracy. However, effective path planning requires more than providing the machine's route in the field. It requires an understanding of the field layout, the crop requirements, and the capabilities of the machine.

Executing a path plan also requires robust motion control systems. These systems must consider the machine dynamics, steering geometry, and terrain conditions to maintain the path's stability and accuracy. Non-holonomic constraints and motion primitives are critical factors that influence a machine's ability to follow a planned path.

AI-based path planning is crucial for precision agriculture due to the challenges posed by varying field geometries, crop types, and terrain conditions. AI-based path planning can determine the machine movements required to achieve the goal while avoiding obstacles and adhering to machine constraints. This process can include determining the optimal sequence of passes needed to cover the field while minimizing the total distance traveled. It can also minimize overlaps and misses, thereby optimizing the use of inputs, which in turn reduces costs and environmental impact.

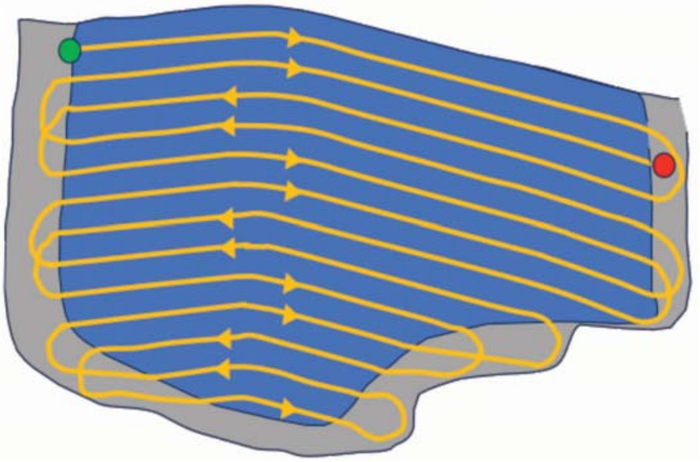
There are several computational approaches to path planning. Heuristic-based algorithms can determine the shortest or most efficient path in a complex environment. These algorithms are particularly useful in agriculture, where quick decisions must be made based on the current state of the field and machinery.

Situational awareness and machine vision

A new aspect of precision agriculture is the integration of sensors that monitor the environment around the machine. This situational awareness optimizes the performance of operator-driven machines and is an essential safety requirement for autonomous systems. The sensors that provide situational awareness can also detect the health of the crop and provide other information to the operator. The most effective systems require multiple types of sensors, including imaging and range sensors.

Vision-based guidance uses cameras to sense the crop rows to steer the machine between the rows or to follow the harvested swath edge, thus maximizing the cut width. Stereo vision uses 3D information and AI to reduce task complexity for operators during coordinated machine operations, such as when filling grain carts during harvesting.

AI methods based on computer vision and machine learning (CVML) have been developed for site-specific precision applications like spraying and cultivation. These AI methods enhance productivity beyond that of operator-driven machines while retaining similar responsibilities for the operator.



Example of a path plan for an agricultural field, including the starting point (green dot) and end point (red dot). Note that the path includes turns that the machine can actually perform and therefore does not follow adjacent passes.

Future trends

Future trends will include more sophisticated AI algorithms for real-time decision-making and the integration of IoT devices for continuous monitoring and data collection. We are already seeing rapid evolution of large-language models trained on application-specific data, providing a means to bring more context to decision-making. These AI technologies will reduce the need for human intervention, increase safety, and give producers new tools for strategic decision-making.

Altogether, AI enables many scenarios for production agriculture, ranging from operator-managed systems that use AI to increase productivity and reduce the skill level required for operation, to remotely managed or fully autonomous systems that require little or no human input. Between these extremes are the more likely scenarios that involve a combination of automated and autonomous systems. In all cases, we need to look beyond the technology and consider how the technology provides value for producers.

In the coming years, AI will dramatically improve our farming practices to increase productivity, address labor shortages, and improve resource use efficiency. I encourage you to explore the potential of AI in agriculture by seeking out opportunities to build your digital skills. Your innovations will play a crucial role in shaping the future of farming, addressing the global food challenge, and promoting sustainable agriculture.

ASABE Fellow John Reid, Executive Director, Center for Digital Agriculture, and Research Professor, Computer Science, Ag and Bio Engineering, Electrical and Computer Engineering, University of Illinois, Urbana-Champaign, USA, j-reid1@illinois.edu.

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Alliance for Modernizing African Agrifood Systems
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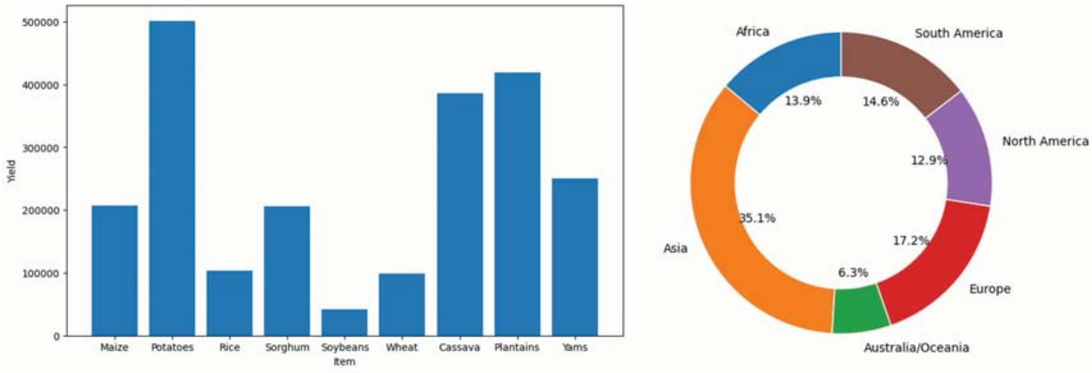
A Recap of the 2023 Smart Agriculture Workshop

Daniel Uyeh

The 2023 AMAA Conference, Summit, and Technology Show, titled "Imagining African Agrifood Systems: Looking Forward," was hosted by ASABE's Alliance for Modernizing African Agrifood Systems (AMAA) and was held last November in Dakar, Senegal. This was the first AMAA event to be hosted in Africa.



Crop yield distribution and regional contribution to agricultural production.

The Smart Agriculture Workshop was a full-day event at the 2023 AMAA Conference. With 161 participants representing eighteen African countries and the U.S., the Smart Agriculture Workshop was designed to equip students, researchers, and practitioners with practical skills in the latest agricultural technologies.

By focusing on advances such as precision farming, monitoring systems, and sustainable practices, the workshop aimed to enhance efficiency and productivity. New technologies, including the Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), and big data analytics, can help farmers make data-driven decisions, optimize resource use, enhance productivity, and improve management.

The workshop leaders demonstrated how these technologies can address the pressing challenges in African agriculture, such as climate change adaptation, efficient water management, effective pest control, and sustainable farming practices. The participants learned to implement IoT sensors for real-time monitoring, use AI and ML for predictive analytics, and leverage big data for informed decision-making. This knowledge can be applied to improve crop yields, reduce waste, and promote sustainable practices, contributing to a more efficient and resilient agricultural sector.

The workshop sessions featured expert talks, interactive discussions, and hands-on demonstrations, providing the participants with theoretical knowledge and practical experience. **ASABE member Daniel Uyeh** from Michigan State University led the organization of the workshop. With support from teaching assistant Patience Mba, the participants were guided through the hands-on activities.

Dr. Mahamed Guindo from Dakar American University of Science and Technology delivered an insightful presentation on remote sensing, crop monitoring, and variable-rate technologies. **ASABE Fellow Kumar Mallikarjunan** from Minnesota State University discussed integrating big data analytics into agricultural practices, highlighting the transformative impact of data-driven decision-making on crop yields and resource management. His presentation emphasized the importance of precision agriculture in addressing water scarcity and pest management.

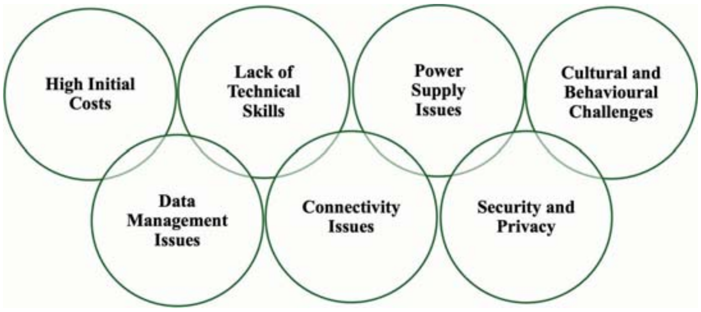
The interactive discussions allowed the participants to engage with these experts, ask questions, and explore real-world applications of the technologies, and the hands-on demonstrations ensured that the participants gained practical experience. These comprehensive sessions ensured that the participants left with a deep understanding of smart agriculture and were ready to implement these innovations in their own practices.

Internet of Things and robotics and automation in agriculture

Agriculture in Africa faces significant challenges, including climate change, resource scarcity, and the need for sustainable practices. IoT offers a promising solution by providing precise data to optimize resource use, monitor crop health, and predict yields. Dr. Uyeh, assisted by Patience Mba, guided the participants through practical activities such as environment setup, data cleaning, exploratory data analysis to identify patterns, and selecting appropriate machine learning models based on data structure and type.

The participants learned to handle missing values, remove duplicates, standardize inconsistent entries, identify outliers, and correct data and syntax errors. The hands-on experience concluded with training and evaluating models to optimize crop yields, highlighting the transformative potential of machine learning in achieving sustainable farming practices.

Dr. Uyeh also led a comprehensive session on robotics and automation in agriculture, emphasizing how automation can address labor shortages, increase efficiency, and enhance productivity. Robotics and automation can modernize agricultural practices by reducing reliance on manual labor, lowering production costs, and improving consistency and quality. These technologies perform tasks such as planting, monitoring, and harvesting, and they support maintenance, reduce waste, and enhance farm management.



Challenges for the Implementation of IoT in Africa.

Site-specific and variable-rate technologies and GIS

Dr. Guindo discussed site-specific and variable-rate technologies (VRT) in precision agriculture. These technologies optimize the application of fertilizers, pesticides, and irrigation water based on the specific needs of different field areas. VRT improves resource use efficiency, leading to better crop health and higher yields while reducing environmental impact by minimizing runoff and leaching. This approach offers economic benefits through cost savings from reduced input use and increased productivity.

Dr. Guindo provided a detailed example of VRT in fertilizer application. The process begins with collecting soil maps, historical nutrient data, and other relevant field information. To determine nutrient levels, soil analysis is conducted using GIS and soil sampling. Sensors are strategically placed to collect accurate data and detect nutrients such as nitrogen, phosphorus, and potassium. The data are analyzed to create a comprehensive soil nutrient profile, identifying the variability in nutrient levels across different field zones. Based on this analysis, prescription maps indicate the precise amount of fertilizer required for each zone.

Data analytics and artificial intelligence

Dr. Mallikarjunan presented a comprehensive overview of data analytics and AI in agriculture, emphasizing their crucial role in smart agriculture. He explained how these technologies can analyze vast amounts of data from sensors, satellites, drones, and climate models. The participants learned about the diverse characteristics of agricultural data, including structured and unstructured formats, and how AI and data analytics automate post-harvest operations and enhance food manufacturing processes.

Dr. Mallikarjunan also covered advanced topics including pattern recognition and anomaly detection using examples such as Fourier transformation and principal component analysis, and he highlighted predictive analytics for proactive decision-making. The participants gained a deeper understanding of AI's transformative impact on farming operations, enabling them to improve crop quality and yield efficiently.

Challenges and solutions in implementing smart agriculture

While the potential benefits of smart agriculture are significant, the workshop also highlighted several challenges that need to be addressed to ensure successful implementation. High initial costs can be prohibitive for smallholder farmers, and the participants discussed solutions that included developing affordable and scalable technologies and providing financial support through subsidies and grants.

Capacity building is essential to ensure that farmers and agricultural workers have the necessary skills to use and maintain smart agriculture technologies. The workshop emphasized the importance of developing training programs and education initiatives. Policy support is also crucial for adopting smart agriculture. Governments can create an enabling environment by developing supportive policies, regulatory frameworks, and standards and by facilitating access to funding, training, and infrastructure for implementing these advanced technologies.

ASABE's Alliance for Modernizing the African Agri-Food System is well-positioned to lead these efforts and collaborate with other stakeholders to drive progress in this area.

Geographic Information Systems (GIS): Used for mapping and analyzing spatial data related to field conditions.

Global Positioning Systems (GPS): Provides accurate location data for precise input application.

Remote Sensing: Involves using drones and satellites to collect data on crop health and field conditions.

Soil Sampling and Analysis: Helps in understanding soil nutrient levels and variability across the field.

Variable Rate Equipment: Machinery equipped with technology to apply inputs at varying rates based on data inputs.

Tools used in variable-rate technologies (VRT).

ASABE member Daniel Uyeh, Assistant Professor, Department of Biosystems and Agricultural Engineering, Michigan State University, East Lansing, USA; uyehdani@msu.edu

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