



Science
Societies

Cultivating artificial intelligence in agricultural research and production

Overview of applications and responsible use

By Varun Kumar Reddy Cheruku, Sofia Comineli, Gustavo Roa Acosta, Alexa Nolan Park, and Arpan Das

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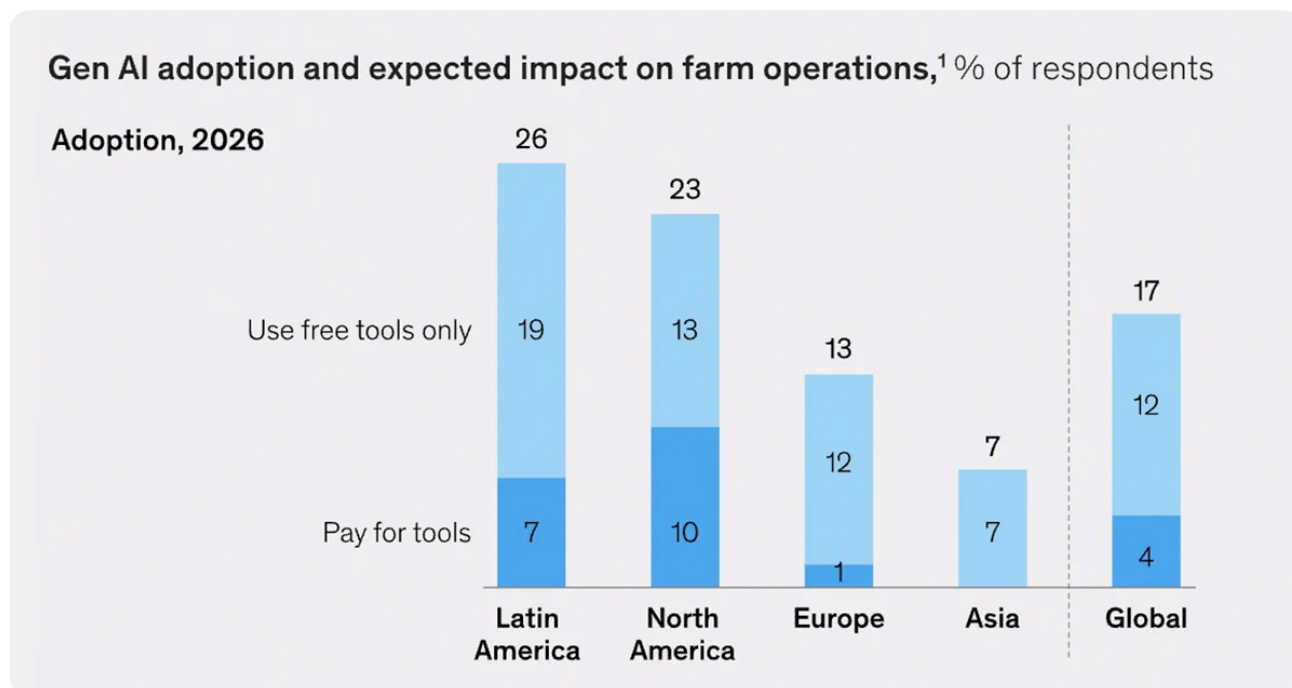
A solar-powered autonomous AI robot made by the company Aigen is used to distinguish crops from weeds in the field. Photo by Photo by JOSH EDELSON/AFP via Getty Images.

Artificial intelligence is rapidly reshaping agriculture, from precision crop management and soil mapping to plant breeding and autonomous field equipment. This article explores where AI is delivering real value today, where its limitations remain, and why responsible, transparent use is essential for researchers and producers alike.

Artificial intelligence (AI) is becoming an increasingly important part of agricultural research and production. Building on advances in mechanization, genetics, and omics, AI is changing how agricultural data are collected, analyzed, and translated into decisions. Its growing role extends beyond new software applications to automated machinery, field monitoring, and the interpretation of large, complex datasets (Figure 1).

Nowadays, AI is also becoming part of everyday work for graduate students, researchers, and agricultural professionals in academia and industry. Tools for data analysis, coding, and modeling can automate portions of technically demanding tasks, increasing the importance of human critical thinking in evaluating outputs and interpreting results. This transition is mostly driven by accessible generative AI and the emergence of embedding AI machine learning directly into field equipment. The need for faster and precise decision making is another factor driving the adoption of AI in agriculture. [The Bloomberg report](#) on Sept. 8, 2026 states that farmers are adopting AI

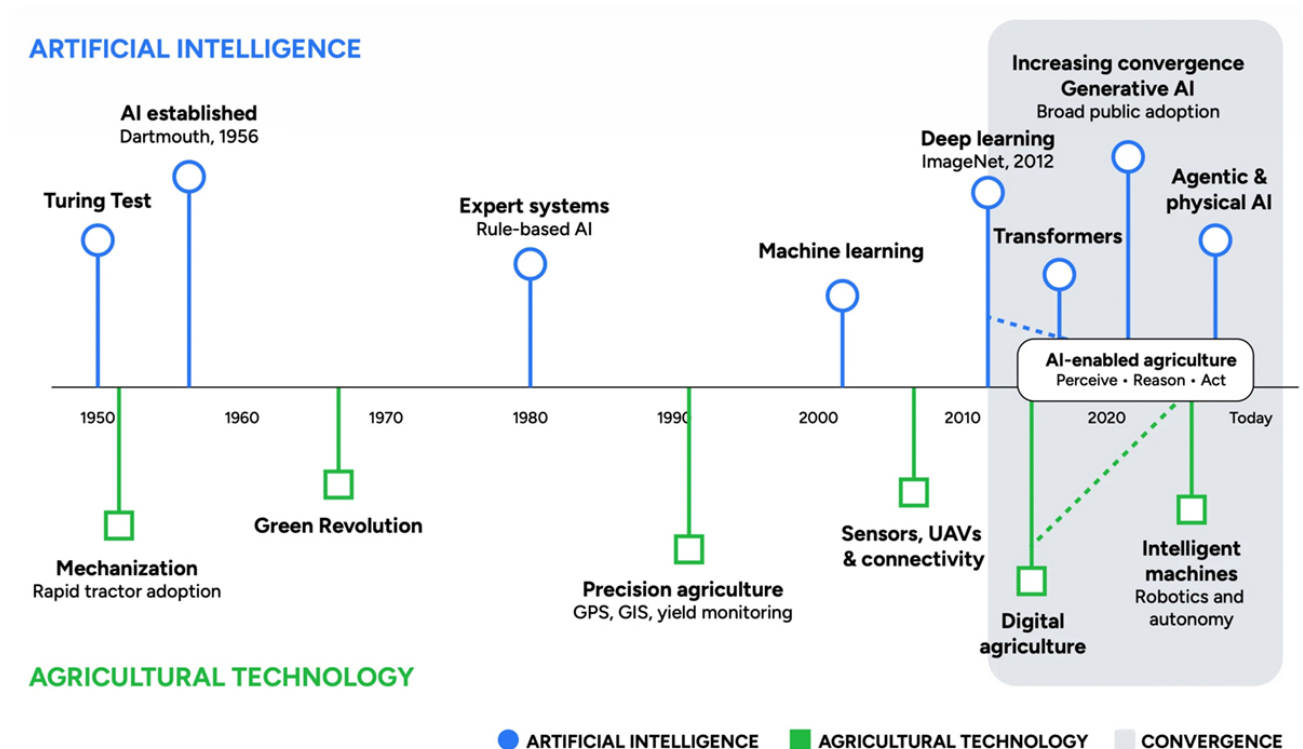
faster than any other tech as they are looking for some high-tech help in planning and on farm operations.



Generative AI adoption on global farm operations. Courtesy of McKinsey & Company (Farm Policy News, University of Illinois, Urbana-Champaign).

Researchers are increasingly incorporating pre-trained models to analyze complex data and decision making instead of multi-season destructive field testing. Computer vision and deep learning models are replacing manual plant measuring and visual scoring sheets (Ibnat et al., 2026). These AI tools can process hundreds of images (drone and smart phone) almost instantly to evaluate canopy architecture, segment plant components, and quantify real-time stress responses with precision. With seamless precision and capability for data integration, pattern recognition, and predictive analytics, AI significantly enhances the efficiency of tools like CRISPR-Cas in genome editing (Saini et al., 2025). Researchers are also using AI-based open-access data intelligence hubs such as the GAP IQ platform at Virginia Tech and specialized

LLMs like CropWizard (from University of Illinois, Urbana–Champaign) to diagnose crop diseases. These tools instantly cross-reference extension documents and model complex environmental dynamics.



Convergence of artificial intelligence and agricultural technology, 1950 to today (Thomasson, 2026).

Macroscale AI applications include processing global weather grids and historic climate records to project regional yields along with predicting migration vectors of invasive pests and pathogens. At the field level, machine-learning models, computer vision, cameras equipped with AI, and advanced sensor fusion running on autonomous machinery enable real-time task execution. For example, variable-rate microspraying reduces herbicide use by a vast margin. At the microscale, AI is accelerating plant breeding through enhancing predictive algorithms, which use terabytes of genomics and phenomics data, helping to make meaningful selections rapidly. These tools also

enhance predictions of the traits in unknown environments. In plant gene editing, machine-learning tools are being developed to predict the efficiency of guide RNA, helping to cut down on errors (Mu et al., 2024).

With continued advances in AI technologies and current trends of their incorporation, the future of agricultural research and production could entirely transition to fully autonomous systems with minimal human intervention. Lab and field settings may rely on permanently embedded, continuously acting physical AI infrastructure. Cutting-edge modern AI tools like vision transformers and foundation models (systems that perceive the world much like humans do) could adapt instantly to microclimates and unknown environments. Changing global climates and labor shortages could drive the global agricultural AI market to expand significantly, making automation standard practice rather than a luxury.

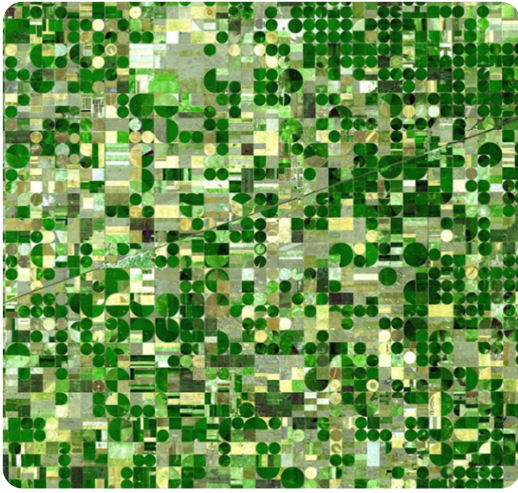
This article provides a comprehensive overview of AI applications in agronomy, crop, and soil sciences, evaluating their pros and cons in research and production. Also, it explores the critical legal boundaries of ethical use and ownership, offering readers insights into technologies that are already becoming deeply embedded in daily agricultural activities.

AI in field monitoring and management

At the field level, AI is becoming useful for converting large amounts of field information into management decisions. Yield monitors, soil tests, weather stations, satellites, drones, proximal sensors, and farm machinery can describe fields at spatial and temporal scales that are difficult to evaluate manually. Artificial intelligence can help identify patterns, forecast outcomes, and generate management options. For agronomists, however, the value of AI ultimately depends on whether those outputs improve decisions under real field conditions.

Variable-rate management provides one example. de Lara et al. (2023) used on-farm precision experimentation and machine learning to estimate site-specific economic optimum nitrogen rates in 20 wheat and barley trials. Their models combined soil, terrain, crop, and remotely sensed variables. Yield predictions had an average error of 13.7%, but machine-learning approaches with similar yield-prediction accuracy produced substantially different estimates of economic optimum N rates. Soil-available P and organic matter were among the influential variables, although their effects varied among fields. The authors also cautioned that models trained across fields may not reliably produce site-specific recommendations when transferred to new fields. This illustrates an important distinction between predicting yield and generating a reliable management recommendation.

Weed detection provides a more direct example of AI moving from sensing to field operations. Iowa State University conducted a soybean demonstration using Sentra's Aerial WeedScout to map weeds with a drone and generate an executable herbicide prescription (Houser, 2024). The targeted treatment used 70 gallons of tank mix across 8.7 acres compared with 130.5 gallons for a 15-gal/ac broadcast treatment, resulting in nearly 50% less spray mixture and an estimated chemical-cost savings of \$13.42/ac. Of 118 initially identified weeds, 111 were dead 17 days after treatment. At harvest, soybean yield in the targeted area was within 1.5 bu/ac of the broadcast comparison with no significant difference between treatments. The potential savings depended on weed pressure, illustrating how the value of AI-enabled application can vary with field conditions.



Satellite view of agricultural fields in Kansas, illustrating the spatial variability captured by remote sensing. Image: NASA/ASTER, June 2001 courtesy of [Wikimedia Commons](#).

Yield forecasting is another application.

Desloires et al. (2024) developed a field-level corn yield forecasting approach using Sentinel-2 and Landsat satellite observations together with agroclimatic information. The model was evaluated on 1,319 corn fields in the U.S. Corn Belt from 2017 to 2022.

Including Landsat land-surface temperature improved in-season forecasting by providing information about early drought effects that were not immediately visible in optical imagery. Earlier estimates of yield potential or risk could support scouting, drought

assessment, and harvest planning.

Artificial intelligence can also be combined with crop models rather than replacing them. Shahhosseini et al. (2021) found that incorporating variables generated by the APSIM crop model into machine-learning models reduced yield-prediction RMSE by 7–20% in the U.S. Corn Belt. Soil-moisture-related variables, including simulated drought stress and water-table depth, were among the influential inputs. This approach illustrates how data-driven methods can be combined with process-based crop models to incorporate agronomic knowledge into AI systems.

Similar approaches are being explored for irrigation, where soil moisture, weather, crop development, and evapotranspiration data can be combined to support irrigation scheduling. Artificial intelligence can also be used to evaluate crop rotations and management sequences under changing environmental and economic conditions. In

both cases, the quality and representativeness of the underlying data remain important because field conditions can change substantially across locations and seasons.

The progression from digital information to physical action is also beginning to appear in autonomous agronomy. Mwitta et al. (2024) developed an autonomous cotton-field robot that combined deep-learning weed detection, GPS navigation, visual servoing, and diode-laser weed control. With weed tracking, the system achieved 72.35% weed elimination in a single pass. Although such systems remain an emerging technology, they illustrate a potential progression from detecting a field problem to automatically responding to it.

For agronomists, the most useful framework may therefore be observe, interpret, diagnose, act, and verify. Agronomic knowledge remains important for interpreting those outputs, considering economics and environmental consequences, and determining whether an AI-generated recommendation makes biological and practical sense. The future of field-level AI will depend not only on better models, but also on reliable data, field validation, and effective integration with existing agronomic decision-making.

AI in soil science

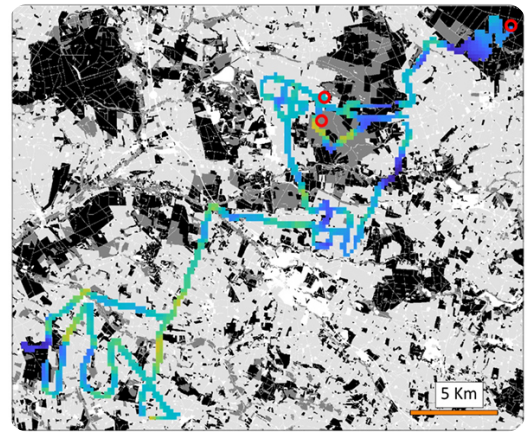
Many AI applications in soil science use machine-learning algorithms to learn relationships between soil observations and information available across a wider area (Wadoux, 2025). The idea is to connect what we can collect extensively, such as satellite imagery or sensor readings with properties that require soil sampling and laboratory analysis. Once trained and tested, a model can estimate those properties at locations that were not sampled.

Satellites record light reflectance from the land surface across visible and infrared wavelengths. When soil is exposed, its reflectance can have information about its composition, and from that, we can infer organic matter related to soil color or clay content related to a particular shortwave-infrared wavelengths. Researchers match these spectra data with laboratory measurements from georeferenced soil samples. A model can then use the relationship to predict organic matter or texture at other locations. Soil pH is different; it does not have a distinct spectral feature that a satellite can measure directly. Instead, models estimate pH from its relationships with soil observations and other information, such as parent material, climate, terrain, and land use. A random forest model, for example, might receive laboratory results alongside reflectance, elevation, slope, and climate data for each sampled location. It learns patterns across those variables and applies them where the same predictor data are available. This is the basis of digital soil mapping, including products such as SoilGrids (Poggio et al., 2021).

The limits are as important as the maps. Optical measurements of soil reflectance describe the exposed surface; vegetation, crop residue, and moisture can change or obscure the signal. A prediction for a deeper soil layer relies on relationships learned from soil samples and other environmental data, rather than on a satellite directly seeing into the profile. Predictions are also less dependable when applied to soils or conditions poorly represented in the training data (Meyer & Pebesma, 2021).

More challenging are processes that change in shorter periods, such as soil moisture, nutrient leaching, and carbon sequestration. Soil moisture rises after rain and declines with evaporation, drainage, and plant water use. Satellites observe moisture near the surface, while ground sensors provide repeated measurements at particular locations and depths. A long short-term memory network can learn patterns across successive observations. Atmospheric data, land characteristics, and model-simulated moisture can be combined to extend the satellite record of surface soil moisture (Fang et al., 2017). On the other hand, nitrate leaching is harder to observe directly. It depends on how much nitrate is present and how much water moves downward through the soil. One approach runs a process-based crop model, such as APSIM. Across many combinations of weather, soil, and management conditions, the model then trains a faster machine-learning model to reproduce its outputs (Shahhosseini et al., 2019). This makes scenario exploration more practical, but the resulting model inherits limitations in the original simulations.

Carbon sequestration poses a different difficulty; changes in soil carbon stocks are slow and can be small relative to variation across a field. The AI method, knowledge-guided machine learning, combines data with representations of processes such as plant growth, carbon inputs, and decomposition (Liu et al., 2024). Such predictions can help investigate sequestration potential, but establishing that soil carbon has actually increased requires repeated measurements of carbon stocks.



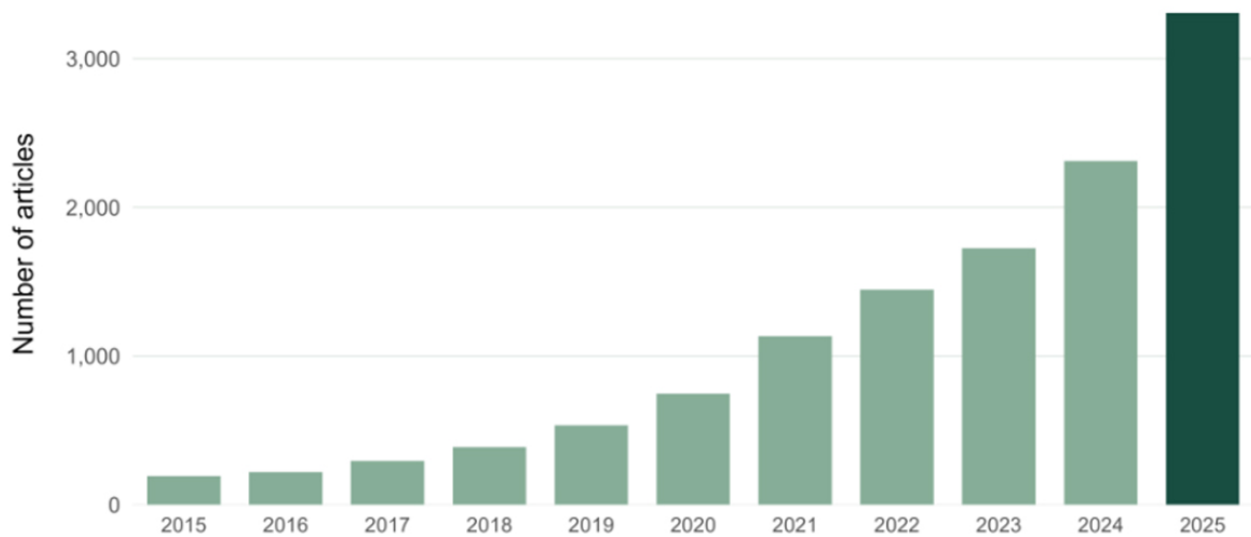
Spatial soil-moisture data can be used to train and validate AI models that predict conditions beyond directly monitored locations. Image courtesy of Mie Andreasen.

To assess soil health, there is not just a single property that we have to consider; instead it includes a set of chemicals, physical, and biological indicators. Each of these indicators usually requires its own laboratory test, which makes a full assessment of soil health slow and expensive. Proximal sensors change this. Nowadays, it is becoming more common to use a single infrared scan that takes seconds and captures information about organic matter, clay, and minerals at once. Artificial intelligence turns that scan into numbers: trained on samples with both a spectrum and laboratory results, it learns to predict several indicators from one measurement (Sanderman et al., 2020). Notice that not all indicators are predicted equally well. Those tied to organic matter and texture are the most reliable, while biological indicators, such as respiration, are predicted mainly through their correlation with organic matter rather than measured directly. No single sensor measures everything, so combining information often improves prediction accuracy. Some sensors can be mounted on field equipment to map soils in near real time, although field moisture and calibrations that do not transfer between regions still limit this approach.

To illustrate how quickly AI has entered soil research, we conducted a brief bibliometric analysis of the Web of Science Core Collection for soil science articles that mention AI methods. The number of articles grew from 220 in 2016 to more than 3,307 in 2025, about a 15-fold increase in less than a decade (Figure 4).

AI and soil science: publications by year

Articles indexed in Web of Science Core Collection, 2015–2025



Source: Web of Science Core Collection

Bibliometric analysis including research articles from the Web of Science Core Collection. Search conducted on Sept. 28, 2026 .

AI in plant breeding and phenotyping

Traditional plant breeding has involved evaluating thousands of plants, selecting a smaller number from them, and gradually making the number smaller till it becomes a desirable variety. However, the main challenge is not the number of plants evaluated. Several important traits like drought, heat, salinity, nutrient use efficiency, root architecture, disease or pathogen resistance, and ultimately yield stability are very complex and difficult to measure as they are mostly governed by multiple genes (Chivatá-Peña et al., 2023). That's where AI started to change the entire breeding process, speed, and accuracy.

And one of the most promising applications of AI is rapid and non-destructive phenotyping. Modern breeding programs consist of technologies such as RGB cameras, thermal cameras, multispectral and hyperspectral sensors, LiDAR, drones, magnetic resonance imaging (MRI), and other imaging technologies to assess plant traits more easily and effectively in a large scale compared with the traditional methods (Nahakpam & Kesari, 2026). Artificial intelligence and machine-learning algorithms can then convert these images and sensor measurements into information such as plant height, canopy size, leaf area, architecture, canopy temperature, and even disease symptoms and water or nutrient stress indicators. Similar approaches are now also being used to explore belowground traits like root architecture, angles, and distribution without destroying the plant, allowing researchers to track these characteristics throughout the plant's life cycle.

For example, RootNav 2.0 utilizes a multi-task convolutional neural network (CNN) to locate seeds and root tips and reconstruct the complete root system architecture from images of different species (Yasrab et al., 2019). ChronoRoot is another tool that uses inexpensive hardware with deep segmentation network and tracks *Arabidopsis* root growth over time (Gaggion et al., 2021).

The real challenge with these modern phenotyping technologies is not image acquisition; it is turning these images into meaningful data (Watt et al., 2020). Artificial intelligence can help in this matter by identifying the patterns in large datasets and



Left panel: Intermediate wheatgrass roots imaged with a minirhizotron (left) and traced with a machine-learning program (right) to study root structure. Image by Alexandra Griffin. Right panel: A researcher images intermediate wheatgrass roots using a minirhizotron. Photo by Emma Link.

prioritizing individuals with the desired combinations of traits. This can be useful in both cases when the traits are difficult to measure directly or when their expression is polygenic, meaning it depends on multiple interacting factors (Júnior et al., 2023).

Artificial intelligence is also helping in genomic selection and other data-driven breeding approaches. A breeding program might have data in genomic, phenotypic, environmental, field history, and pedigree information simultaneously. Machine-learning models can integrate these sources to predict breeding values or performance and aid in early selection of desirable plants. In a study, Kaushal et al. (2024) used UAV multispectral imagery with deep neural networks to predict winter wheat grain yield, test weight, and grain protein content. Forward prediction of yield in early-generation lines was improved by almost 32% when models were trained on multi-location data from advanced lines compared with a single location. Even for the complex traits, these models may identify non-linear relationships or interaction, which are difficult to capture using simpler approaches. Combining high-throughput phenotyping with genomic information is important for the breeder to see a more comprehensive view of why a genotype performs well and under which environment (Srivastava et al., 2024).

However, using AI also has some limitations. If an AI model is trained using data from one specific environment, season, growth stage or sensor configuration, it may not perform equally well under different growing conditions. For example, Mohanty et al. (2016) found that their CNN trained on laboratory images of diseased leaves achieved very high accuracy on held-out images from the same dataset, but its accuracy dropped sharply on images captured under different conditions. Environmental variation, inconsistent imaging protocols, missing datapoints, and unexpected changes in the field experiments can all affect the model's performance. Interpretability of

these data is also an important consideration. A breeder needs to understand what a model can predict, how it predicts that, and why it makes that prediction. A highly accurate model can identify promising genotypes but often might miss important biological insights that may be useful for selection, which sometimes can be difficult to validate and trust. This situation occurs particularly when AI is used for traits influenced by complex genotype $\times$ environmental interactions.



*Photo by Stephen R Ausmus
USDA-ARS.*

There are also practical and ethical considerations as well. Advanced sensors, computational infrastructure, and experts in these sectors can be expensive. Artificial intelligence models can inherit biases from the dataset used to train them (Howard & Lipka, 2025). The breeder still needs to define the biological questions, choose meaningful

traits, or evaluate the prediction. Ultimately, it's the breeder who should make the decision to validate promising selections under real-life conditions.

The use of AI in plant breeding will be most effective by connecting technologies and easing the breeder's effort rather than solely depending on it. The future plant breeding pipelines could include automated phenotyping and breeders' expertise in a continuous decision-making system. The goal should not be focused on collecting more data or building more complex models. It is to use more accurate information to make the breeder's decision faster and more efficient.

Ethical use of AI, academic integrity, and ownership of AI-generated materials

As demonstrated above, the use of LLMs and AI-assisted tools can be a valuable addition to many researcher's tool kits. However, it is impossible to ignore that AI has

become a pervasive and divisive topic that extends well beyond academic and scientific uses. Therefore, the choice to use AI and to what extent is often a personal decision for each researcher and can spark difficult discussions regarding ethical use of these resources.

For us as scientists, ethical decisions regarding AI usage occur within a culture where your productive output can decide the course of your career. Publications, grant applications, and data analysis are all essential, yet time consuming, components of productive output. Artificial intelligence tools can be used to reduce some of that burden by helping researchers organize ideas, perform literature searches, proofread writing, develop code for data visualization, or even generating scientific figures (Khalifa & Albadawy, 2024). These applications can help improve efficiency and accessibility, particularly to researchers who are writing in a non-native language, but the pressure to “publish or perish” can make it tempting to move beyond using LLM output as a tool and instead begin outsourcing parts of the intellectual process itself. This not only can be detrimental to a researcher’s career and reputation, but also introduce complications regarding ownership and data disclosure.

Legally, U.S. copyright law serves to protect human authorship. The U.S. Copyright Office [issued a report](#) that states material generated by AI is not copyrightable simply because a person supplied the prompts. However, the use of AI as an assistive tool does not eliminate copyright protection for works authored by humans, making the question of ownership of AI-generated materials (including text and figures) depend on how much human authorship is present. Beyond the question of output ownership, it is the responsibility of the researcher to consider the inputs that they are providing to an AI system. Providing potentially sensitive information such as confidential data or manuscripts without understanding the terms of service of the AI system can breach

institutional or contractual obligations or even lead to expensive and complex disputes of ownership such as [in a recent case](#) involving a famous math equation and OpenAI.

Publishers are also more frequently issuing policies regarding the use of AI in manuscripts submitted to their journals. In fact, [the AI use policy of ASA, CSSA, and SSSA](#) states that these technologies should only be used as a tool to “improve readability” and be only employed under strict supervision of a real human, not as a replacement for intellectual contributions of the author. Almost all journals emphasize the responsibility of the author to ensure the output reflects their own expertise and state that authors must disclose their AI use if used in cases beyond basic spelling and general editing. The same responsibility applies when AI is used for literature searches. While LLMs can rapidly summarize topics or papers, they can also misstate findings or hallucinate citations that do not exist. It is therefore the responsibility of the researcher to be able to recognize these flaws and use LLM literature search output appropriately.

Additionally, more publisher policies are beginning to add portions specifically for AI-generated figures and diagrams. While most publishers allow AI to assist with conceptual diagrams, it is the responsibility of the researcher to ensure that they are factually accurate.

So, what is the “right” way to use AI, if any? Policies and laws will continue to evolve as AI tools do, and the landscape is constantly shifting, making that question difficult to answer. However, the core principle that the responsibility to ethically use AI remains with the user is unlikely to change. Researchers should be prepared to disclose their use of AI and verify every contribution an LLM or AI tool makes to their work.

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Conclusion

The use of AI in areas such as machine learning, image processing, robotics, deep learning, and neural networks is increasing at an exponential pace. Artificial intelligence serves as multi-scale computational approach, seamlessly bridging environmental and biological data. While the potential of AI to optimize workflows and increase precision is clear, it is important to recognize that the accuracy and reliability of AI-generated outputs can vary. Models may misinterpret, overlook certain complexities, and produce errors, especially when there is insufficient training data or working with unfamiliar environments. Therefore, users must remain vigilant and note that AI is not replacement of humans but a powerful companion to enhance critical thinking and accelerate discovery. Adoption of AI also raises important questions about integrity, ethical use, and ownership. Ultimately, the responsibility of appropriate and transparent use is with users as the regulations and publisher guidelines evolve.

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