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Application of AI and machine learning in modern agronomy: A comprehensive review

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Abstract

The integration of artificial intelligence (AI) and machine learning (ML) into agronomy is revolutionizing modern agriculture by enabling data-driven decision-making and automation. This in-depth study looks at how modern AI and machine learning technologies are used in farming. It covers everything from old expert systems to new deep learning models, drones and self-driving cars. We discuss about how AI has transformed farming throughout the years, including major studies and renowned people who have helped it expand. We also discuss about the primary technologies and data sources that have made smart farming possible today. The review talks about some of the most important places where applications can be used, such as precision farming, estimating crop yields, controlling pests and diseases, improving soil and water and using machines automatically. It shows each one using real-life examples and case studies of technology. We also discuss about the greatest agri-tech companies and the AI-powered goods they sell. We also talk about the economic effects, like return on investment (ROI), higher yields and savings on resources. We talk about the pros and cons of AI and how it can help people perform better and for longer. The review concludes with a discussion on practical challenges, ongoing research and the future of AI in sustainable agriculture.

Keywords: Artificial intelligence, machine learning, agronomy, precision agriculture, crop yield, decision support, sustainable farming

Introduction

The world population is expanding, resources are running out and climate change is making farming harder and harder. Agronomists are using more modern, data-driven methods to get the most out of land, water and nutrients while still meeting the world's need for food ^[1]. AI (artificial intelligence) and ML (machine learning) are great techniques to automatically look at difficult agricultural data and come to conclusions that other approaches can't. Artificial intelligence (AI) and machine learning (ML) are making agronomy, the science of cultivating crops and taking care of soil, more accurate, useful and long-lasting. AI algorithms may make planting schedules, watering, fertilizing, insect control and harvesting better by looking at satellite photos, sensor data, weather forecasts and data from past harvests ^[2]. AI systems have made a lot of progress in several domains. Studies have indicated that crop yields can go up by 20 to 30%, the use of pesticides can go down and resources can be used more efficiently. The cost ratios look excellent because of these benefits. AI-powered precision agriculture has helped major farms make more than 100–150% on their investments (ROI). This review talks a lot about how AI and ML are employed in farming these days ^[3]. It begins by going back at the past and talking about the first expert systems and the scientists who used computers to help them farm. Then it talks about the primary AI/ML methods and technologies, such as drones, sensors and robots that have revolutionized how we gather information ^[4]. The main premise of the review is how farms use things like figuring out how much crops will grow, keeping the soil healthy, robotic harvesting and controlling greenhouses. There are real-world examples of how each kind of AI model and application has worked. We also discuss about the finest platforms and firms that provide AI-based farming solutions ^[5]. People think about topics like higher yields, cheaper costs, return on investment (ROI) and environmental benefits (such as using less

water) when they think about how AI will change the economy. When it makes sense, we summarize the numbers from case studies to explain how AI could be helpful. Finally, we speak about concerns (such as worries about data quality and adoption) and the future (including AI advisers that make things happen and farms that run themselves) ^[6]. This review seeks to function as a thorough guide on the revolutionary influence of AI and ML on agriculture in the 21st century by analyzing their historical, contemporary and future advancements.

Historical Background and Pioneers

1. For a long time, farming has been using computers and other tools more and more. In the 1960s and 1970s, people first sought to utilize basic statistical models and rule-based systems to grow crops. H. built the COMAX expert system was a huge step forward for AI in farming. Lemmon used "if-then" algorithms and sensor data to determine out the optimal way to water and fertilize cotton crops in 1986 ^[7].
2. In field tests, COMAX proved that it might cut production costs by automatically adjusting the amount of water and pesticides used to match what an expert agronomist would suggest. A lot of people think that this system was one of the first AI technologies that could help farmers. In other words, computers can give you advice that is just as good as that of specialists. At the same time, agricultural scientists like Norman Borlaug and others (but not AI researchers) underlined the need for innovative ideas to boost yields. This made it possible for technology to be used in the future ^[8].
3. Agronomy began to use more statistical and machine learning technologies in the 1980s and 1990s. Researchers utilized regression models and decision trees to guess how much crops would yield in the early stages, learn about the types of soil they were working with and figure out how harmful something was. At Iowa State, Cornell and USDA labs, scientists including Gerald Anderson and Pete Thomison worked on algorithms for mapping soil ^[9].
4. Some people tried to use neural networks to figure out how much food will be made. In the late 1990s, GPS technology and variable rate devices made "precision agriculture" possible. This entails taking care of fields that are less than an acre in size. Jack Jones and other early adopters proved that site-specific management, which entails adjusting things like fertilizer in certain regions, may make work go more smoothly. They also got the first massive sets of yield maps, which were later used to teach machine learning algorithms ^[10].
5. In the 2000s, it was easier to collect information thanks to satellite photos, UAV (drone) images and sensors that were connected to the internet. Two agronomists, David Lobell and Senthil Asseng, employed machine learning and remote sensing to see how stressed crops were from space. In the 2000s, a lot of people tried to use decision support systems (DSS) to manage nutrients and keep pests under control ^[11].
6. Many governments and academic institutions started building automated systems that used weather forecasts and agronomic models to benefit people. Two big steps forward that made it possible to keep an eye on plant health in a fair way were the IIRRI crop models for rice and NASA's work on the NDVI (Normalised Difference Vegetation Index) ^[12].
7. AI has developed a lot in the previous ten years. High-performance computation and new methods, especially deep learning, have made it possible to see photographs and

complicated data streams in real time. Researchers in the field of ag-tech today employ deep convolution neural networks to discover diseases on leaves ^[13].

8. Generative models help farmers grow better crops, while reinforcement learning helps them develop better irrigation schedules. A group of the best AI researchers, most of whom are computer scientists, have worked with agronomists. For example, John Deere eventually bought Blue River Technology, which used computer vision technology in farming. The guys who made Blue River and other companies that used to work for Google or Facebook employed the most recent machine learning to develop robots that could weed ^[14].
9. Many professionals from various professions work in agricultural science these days. Computer scientists and agronomists from the past set the stage for all the smart tractors, drones and sensor networks we use today. It's easy to understand why scientists love H. has been connected to each other throughout history. Lemmon and many other AI and agronomy experts have worked together to make precision farming with AI possible today ^[15].

Key AI and Machine Learning Techniques in Agronomy

1. Modern farming uses a lot of AI and ML techniques. These can be anything from old-fashioned methods to the most recent deep learning architectures. Regression, support vector machines (SVM) and decision forests are all types of supervised learning that are typically used to predict things that happen over time, like yield or soil moisture, or to sort things, like the health of a plant ^[16].
2. For example, random forests and multiple linear regressions have been used for a long time to work out how much crops would yield based on things like the weather, the quality of the soil and how well they were managed in the past. Deep convolution neural networks (CNNs) are the most common way to do things with images, such as figuring out what sort of crop it is or finding weeds. CNNs can detect where things are in space just by examining at pictures taken by satellites or drones ^[17].
3. People typically utilize Long Short-Term Memory (LSTM) networks and other newer versions of Recurrent Neural Networks (RNNs) to guess how the weather will change over time or how things will grow over time. These networks could be able to find connections between events that happen at various periods ^[18].
4. In agronomy, unsupervised learning methods like clustering algorithms (like k-means) are used to group field zones with similar soil or yield characteristics. Principal component analysis (PCA) is used to reduce the number of dimensions in high-throughput sensor data. Reinforcement learning (RL) is becoming more and more common for professions that require making judgments, such as regulating irrigation and directing self-driving cars ^[19].
5. By testing things out and getting feedback, an RL agent learns the best things to do, such as how much to water. In this way, it can get the most out of the circumstance and not waste too much time. Bayesian networks and probabilistic models assist us deal with things we don't know and understand risks. For example, they can help us determine estimate how likely it is that a pest outbreak will happen based on the weather. Fuzzy logic systems have been used in farming to deal with uncertainty. For example, fuzzy controllers can figure out "moderate" irrigation settings using inaccurate information about the weather and the

amount of moisture in the soil ^[20].

6. Another useful method is transfer learning. You can use AI models that were trained on one crop or area on another crop or area with smaller datasets. This makes deployment go a lot faster. For instance, you could utilize a CNN that has previously trained a lot about plants to discover diseases
7. Decision support systems also usually combine both rule-based expert knowledge, such the "if-then" logic used in early expert systems and machine learning models to develop systems that work together ^[21].

Table 1: The following table summarizes some of the major AI and ML techniques and their typical agronomic uses ^[22,23,24]

Technique	Description	Agronomic Application Example
Linear Regression	Models linear relationship between inputs and output	Predicting crop yields from features (weather, soil)
Decision Trees / Random Forest	Tree-based classification or regression	Classifying crop types or predicting yields
Support Vector Machine (SVM)	Marginal classification (or regression) boundaries	Disease vs. healthy plant classification
Neural Network (ANN)	Multi-layer networks for general prediction tasks	General sensor data modeling, crop classification
Convolutional Neural Network (CNN)	Deep learning for image and spatial data analysis	Weed/disease detection from drone imagery
Recurrent Neural Network (RNN/LSTM)	Sequence modeling for time series	Forecasting crop growth or weather impacts
K-Means Clustering	Unsupervised grouping of similar data points	Segmenting fields into management zones
Reinforcement Learning (RL)	Learning optimal actions via trial-and-error	Optimizing irrigation or controlling machinery paths
Bayesian Networks	Probabilistic graphical models	Pest outbreak risk analysis under uncertainty
Fuzzy Logic	Rule-based handling of vague or overlapping states	Irrigation control under imprecise moisture levels
Genetic Algorithms	Search/optimization inspired by evolution	Selecting crop traits or fertilizer mixes
Support Vector Regression	SVM variant for continuous outcomes	Estimating biomass or nutrient content
Transfer Learning	Adapting pre-trained models to new tasks	Reusing vision models for new crop-disease pairs
Deep Learning (General)	Complex multi-layer models with many parameters	Multi-modal data fusion, predictive modeling
Expert Systems	Rule-based decision support systems	Fertilizer or pest management recommendations

These AI/ML techniques are complemented by domain-specific considerations in agronomy, such as working with unbalanced data (e.g. rare pest events) and integrating multi-source data (e.g. combining satellite images, soil sensors and farmer inputs). In practice, modern ag-tech solutions often employ ensembles of models and combine machine learning with agronomic knowledge to improve reliability ^[25].

Data Sources and Technological Advances

AI can only be useful in agronomy if there is a lot of data and tools for sensing. In the last few years, the agricultural industry has gotten a lot of new sources of information. Some important technologies are:

- **Remote Sensing (Satellites and Drones):** Satellites like Landsat and Sentinel have cameras that can see in many colors and take pictures of farms in large areas multiple times. You can use these pictures to figure out NDVI (vegetation index), which tells you how healthy your crops are, how much biomass there is and how many plants are sick or stressed. Drones, also called unmanned aerial vehicles (UAVs), are now being used to do field surveys ^[26]. Drones can fly under clouds to take very clear pictures (down to the centimeter level) and can carry special sensors including RGB cameras, thermal cameras, LiDAR and multispectral cameras. AI algorithms use pictures taken by drones to do a lot of tasks, such as check on the health of plants, count fruits and make maps of areas where weeds grow ^[27].
- **Ground Sensors and IoT:** Sensor networks and Internet of Things (IoT) devices collect data on the weather and soil in real time. Some examples are leaf wetness sensors, nutrition probes, sensors that detect soil moisture and weather stations. When applied in machine learning models, this sensor data helps adjust how much fertilizer and water is used ^[28]. A reinforcement learning agent can acquire data from a network of soil moisture sensors that are spread out throughout a field. This agent then turns on the irrigation systems at the proper times to save water and still get amazing results. With smart irrigation controls and soil analysis kits, farmers can get data much more often than they could with manual samples taken every so often ^[29].
- **Autonomous Machinery and Robotics:** Many new tractors, combine harvesters and sprayers come with computers and sensors like GPS, cameras and LIDAR. These cars could collect data while they were driving. For instance, plants contain sensors that measure moisture, while harvesters have monitors that measure yield ^[30]. They can also use AI to adjust how they work in real time, as with targeted spraying and auto-steering. More and more, robotics is being used in specialist crops. For example, self-driving weeding robots use machine vision to find their way between rows and pluck up weeds ^[31].
- **Farm Management Software and Databases:** Cloud-based platforms and apps connect information from the past about the farm, including planting dates, types of seeds used and past yields, with information from other sources, like soil maps and market prices ^[32]. These systems employ machine learning to discover trends and give people personalized advice. You may now train ML models using large agricultural databases, such those from the government or research groups. Data sharing projects are making agricultural data from all across the world more accessible ^[33].
- **Genomic and Phenotypic Data:** Genomic data (DNA markers, gene sequences) and high-throughput phenotyping (digital trait assessments of plants) are both growing swiftly in the field of crop breeding. AI connects genotypes to traits that are wanted, which speeds up the process of developing new types. For instance, deep learning algorithms can look at photographs of crop canopies and locate plants that are stronger or less likely to get sick ^[34].

Agronomy has never been data-driven like this before, thanks to high-resolution sensors, robots, cloud computing and strong algorithms. Drones that don't cost much can fly over farms and capture images. These photographs are then relayed to CNNs to aid with automated watering valves or sprayers. These technologies all function together. We can do things now that we

couldn't do ten years ago because every new sensor, connection, or AI model makes the others operate better ^[35].

Key Applications in Agronomy

AI and ML work well together; therefore they can be used on a farm in a lot of different ways. We discuss about some of the most essential ways that AI is changing things below, along with some examples and what they mean.

- **Precision Crop Monitoring and Yield Prediction:** AI systems use data from the past and the present to forecast how well crops will do. For instance, an ML model might be able to predict how much a field will yield weeks or even months in advance by looking at weather data, soil conditions and multispectral photos ^[36]. Farmers can use these kinds of weather forecasts to figure out when to plant and sell their crops. You can always check on how your crops are doing at different points in time by using computer vision on photographs obtained by drones or satellites. The system shows a part of a field that isn't expanding as it should. It might not have enough nutrients or it might be sick. This kind of early warning lets you take concentrated action. Many farmers report that using AI to make better predictions about when to plant and what to use makes their crops grow 10–30% better in real life ^[37].
- **Getting rid of pests and diseases:** It's very vital to identify pests or diseases early. AI image analysis can recognise spots on leaves, blights and insect damage in photos. For example, a machine learning model that has been trained on hundreds of photographs of plant leaves can tell when a plant is sick, such when potatoes have late blight or wheat has rust. It can be just as accurate as a human specialist in a lot of circumstances ^[38]. AI with drones that can see may be able to cover a lot more ground. For example, neural networks can locate dirty places by looking at photographs of whole orchards or fields. Companies say that these technologies reduce the need for pesticides by just treating the regions that require it. This can cut the use of chemicals by 50% or more while keeping production losses to a minimal ^[39].
- **Robots in the field and weed control:** Robots driven by AI are revolutionizing how weeds are controlled. John Deere now owns Blue River Technology's "See & Spray" technology, which uses computer vision to identify the difference between crops and weeds as it moves through a field. At that time, only the weeds should be sprayed with herbicide ^[40]. Compared to spraying everything at once, this exact strategy can cut down on pesticide use by about 90%. This is better for the environment and saves a lot of money. There are also tests going on with self-driving robots that have mechanical weeders in row crops. They may go about their business every day without any aid from people thanks to machine learning ^[41].
- **Managing Soil and Nutrients:** Machine learning algorithms look at soil data (pH, organic matter, nutrient levels) and the needs of crops to propose different amounts of fertilizer to use. Instead of putting the same amount of fertilizer all over the field, AI helps produce fertility maps

that show how much to use in each location ^[42]. This "site-specific management" helps crops grow better and cuts down on waste. Some studies have shown that AI-optimized fertilizer algorithms can use nutrients more than 20% better. Models can also tell you where the dirt will wash away or get hard. This can help you fix things more precisely ^[43].

- **One of the most common uses of this technology is smart irrigation.** AI systems use weather forecasts, estimates of how much water evaporates and sensors that assess soil moisture to figure out when to water. Studies demonstrate that a lot of water can be conserved. For example, an AI-controlled irrigation system in one vineyard lowered water use by more than 30% and made the grapes better and more plentiful ^[44]. On a large scale, these kinds of gadgets can save millions of liters of water. As the weather changes, reinforcement learning and adaptive control algorithms keep improving the rules for watering plants better. AI also quickly discovers leaks or problems with too much water, which stops the water from going lost ^[45].
- **Greenhouse and Controlled Environment Agriculture:** AI watches the temperature, humidity, light and fertilizer solutions in real time for greenhouse farming. Neural networks get data from sensors and then look at all the factors to identify the fastest growth rate. Some high-tech vertical farms have AI systems that run on their own. Deep learning algorithms modify the amount of fertilizer and the LED lighting in a couple of milliseconds. Cameras and weight sensors keep an eye on how big the plants are. These farms grow a lot more crops per square meter than normal farms do and they don't consume a lot of resources ^[46].
- **After the harvest, taking care of the animals and the farm:** Agronomy is largely about crops, but AI may also be able to aid with running the overall farm. AI watches on the health and behaviour of animals on farms that raise cattle, which are sometimes part of larger farms. After the harvest, computer vision automatically grades and sorts fruit or verify the quality of grain. This means that fewer people have to do this job. AI and cameras can discover problems with almonds and apples on a production line faster than people can do it by hand ^[47].
- **Supply Chain and Market Optimization:** Some AI farming systems are all about getting things where they need to go. By predicting how much crops will be worth on the market, machine learning can assist farmers decide which crops to grow and when to sell them. Supply chain software employs optimization algorithms to find the best ways to move and store goods so that less waste is created ^[48].

The breadth of applications is vast

These applications are interrelated. For instance, AI-driven soil analysis informs irrigation control; yield prediction feeds into supply chain planning. Together, they constitute a precision agriculture ecosystem where data continuously flows and is acted upon by algorithms to optimize each step of the agronomic process.

Table 2: below summarizes key areas, AI approaches used and typical outcomes ^[49,50,51]

Application Area	AI/ML Approach	Key Benefit / Outcome
Crop Yield Prediction	Regression, RNN (LSTM)	More accurate forecast of harvest volume
Pest & Disease Detection	CNN / Computer Vision	Early identification enables targeted treatment
Weed Management	Computer Vision + Robotics	Automated weed removal; up to 90% reduction in herbicide use
Soil & Nutrient Management	IoT Sensors + ML Optimization	Optimized fertilizer use; improved nutrient efficiency
Precision Irrigation	Predictive Analytics, RL	Significant water savings (e.g. approx 30%+ reduction)
Harvest Automation	AI + Robotics (Autonomous Tractors)	Reduced labor cost; timely, efficient harvesting
Crop Breeding & Genetics	ML (genomic data analysis)	Faster development of high-yield/resilient varieties
Weather & Climate Forecasting	Machine Learning Models	Better risk management; optimized planting schedules
Field Monitoring	Drones/Satellites + AI	Real-time crop status maps; quick stress detection
Decision Support Systems	Expert Systems / ML	Data-driven farm management recommendations
Greenhouse Automation	AI Controllers (Fuzzy/RL)	Controlled environment with maximum yield
Crop Quality Assessment	Computer Vision	Automated grading; consistent quality control
Supply Chain Optimization	ML + Data Analytics	Reduced post-harvest waste; improved logistics
Market Analysis & Pricing	Time-Series Forecasting	Better selling timing; reduced price volatility impact
Sustainability Monitoring	Data Fusion + AI	Track soil health, carbon footprint and compliance

Industry and Corporate Initiatives

Agri-tech has grown so swiftly because of research done in schools, businesses and new businesses. Some of the major IT

and farming organizations have built AI-based tools and platforms that will help modern agronomy move forward ^[52].

Table 3: lists some well-known companies, their AI solutions and the fields they work in to help you understand what we're talking about ^[53,54,55]

Company (HQ)	AI/ML Solutions	Primary Applications / Impact
John Deere (USA)	Autonomous tractors, precision ag software (John Deere Operations Center)	Automated planting/harvesting; optimized operations (e.g. auto-steering)
IBM (USA)	Watson Decision for Agriculture, Environmental Intelligence Suite	Weather forecasting; crop planning; risk analysis
Microsoft (USA)	Azure Data Manager for Agriculture	Data integration from farm sensors; analytics dashboards
Bayer (Germany) / Monsanto	Climate FieldView, Xarvio Crop Manager	Field health monitoring; yield analysis; field experiment design
Trimble (USA)	GPS/GNSS guidance, field mapping tools	Precision planting; variable-rate input application
AgEagle (USA)	Agricultural drones, sensor analytics	Aerial crop scouting; plant health imaging
Blue River Technology (USA)	See & Spray AI-driven weed control	Selective herbicide application; drastic pesticide reduction
XAG (China)	Agricultural UAVs (drones), autonomous spraying	Drone-based planting, fertilizing and pesticide applications
DJI (China)	UAV drone platforms (Phantom, Agras)	High-resolution field imagery; mapping and surveying
Prospera (Israel)	Computer vision analytics platform	Indoor & outdoor crop monitoring; anomaly detection
CropX (Israel)	Soil sensor hardware + AI analytics	Smart irrigation management; soil moisture optimization
Raven Industries (USA)	Precision farming controllers, auto-steer	Autonomous farming equipment; enhanced field connectivity
Netafim (Israel)	IoT irrigation systems, field sensors	Drip irrigation optimization; water-use monitoring
Granular (USA)	Farm management software (Data-driven planning)	Operational planning; profitability analytics
Taranis (Israel)	High-res aerial imagery analytics	Early pest/disease detection; scouting alerts

- These companies exemplify how business and research may operate together. When John Deere bought Blue River Technology, a firm that makes traditional farm tools, it spent a lot of money on AI. Deere has been working on prototypes for self-driving tractors for twenty years ^[56]. They use sensors and satellite photos on board to get the most out of their crops and use less gas. AGCO and New Holland are two companies that make farm equipment. They have also integrated telematics and navigation systems that use machine learning to their products ^[57].
- Businesses that develop software and store data are also incredibly essential. Bayer and Monsanto were the first to create FieldView, a platform that uses maps and prediction algorithms to aggregate field data including yields, weather and inputs. People who utilize FieldView suggest that farmers may minimize their nitrogen use by 40% to 60% and still achieve the same or greater yields by only adding fertilizer where it is needed ^[58]. CropX and other new companies offer full solutions. Their soil moisture sensors feed information to a cloud service that utilizes AI to tell them when to water the plants. Prospera's AI technology

helps enormous tomato and lettuce farms all around the world discover problems before they get worse. People think this will keep millions of dollars from being lost ^[59].

- Companies that don't ordinarily work in farming are starting to do so. Microsoft and other big IT businesses are working with pesticide companies and farming cooperatives like Land O'Lakes to deploy cloud-AI technologies. For instance, Microsoft's FarmBeats project employs drones, sensors and Azure AI to deliver smart farming based on the Internet of Things (IoT) to places that are hard to get to ^[60]. Agrostar and CropIn both have smartphone apps that help small farmers plant by combining data from the area with satellite photos. IBM is a big corporation that has an Environmental Intelligence Suite. This suite uses AI to combine hyper-local weather data from The Meteorological firm with other data to tell farmers when to plant and warn them when the weather is bad ^[61].
- Most of the time, these company ideas contain real-life examples of people who have made them work. For example, a large grain cooperative reported that utilizing AI-guided variable-rate technology saved them more than

\$25 per acre every season by cutting the costs of seeds and fertilizers that weren't needed ^[62]. The Australian project COALA employed AI to make irrigation 20% more effective. This helped one farm save tens of thousands of dollars. Even on a small basis, individual farmers have seen big shifts. One American farmer reported that precision farming technology helped him cut his nitrogen use from 1.2 pounds per bushel of maize to 0.5 pounds, a 60% drop, while still receiving exceptional yields ^[63].

- Along with well-known enterprises, a lot of new and interesting businesses are getting their names out there. A lot more new businesses are concentrating on things like robotic fruit pickers, predictive breeding algorithms, blockchain-based supply systems and more. Table 3 only shows a few of them. The essential point is that AI and ML are being utilized more and more in farming and the results demonstrate that they work better and are better for the planet ^[64]. These changes also show that the ecology is getting bigger. For example, original equipment manufacturers (OEMs) of farm tools, software businesses, data analytics groups and research institutes are all working together on pilot projects and joint ventures. These companies compete with each other and share ideas, which helps the overall sector move forward more swiftly ^[65].

Economic and Environmental Impact

There are many economic benefits of using AI in farming. Many studies and case studies show that the benefits of technology usually outweigh the drawbacks. The return on investment (ROI) for AI investments varies by circumstance; however, for large corporations, it typically ranges from 120% to 150%. A study found that large commercial farms that used AI-powered systems had an average return on investment (ROI) of about 150%. But smaller farms still made roughly 120% on what they put in. These data indicate how AI might help with things like getting more crops; spending less on inputs and helping things run more smoothly ^[66].

People in the field discuss about some significant ways to quantify impact

- **More Yields:** AI management usually leads to more crop

yields. Many reports claim that average yields for all crops have gone up by roughly 25% because of better inputs and faster reactions. Some farmers report that employing adaptive fertilization and careful monitoring has helped them by more than 30% ^[67].

- **Getting rid of pests and diseases:** AI may assist discover diseases early, which can cut losses from them by almost half. AI-powered scouting and targeted treatment can cut pest damage by more than half ^[68].
- **Input Usage Efficiency:** AI makes it easier to use chemicals, water and fertilizer the right way. Tests have shown that smart irrigation systems can save up to 30% of water. People say that the precision of using fertilizer has gone up by 80–85%. This means that plants get the nutrients they need right where they need them, which cuts down on waste. AI-optimized scheduling made one situation 80% better at using water ^[69].
- **Lower Costs:** By modifying how they do things in each zone, farmers can save money on inputs. A well-known study found that AI-guided precision farming saved an average of \$25 per acre every season by lowering the expenses of seeds, herbicides and fertilizers. Spraying with caution is another example. If you only spray weeds, you can cut down on the amount of pesticides you use by up to 90%, which saves you money straight away ^[70].
- **Work and operations that are more efficient:** Automation means that fewer people need to work. People who have worked in these fields claim that for things like gardening and keeping an eye on things, they might only have to do half as much work. The exact amounts could be different. Drones and self-driving harvesters also help you get things done on time, like picking at the appropriate moment, which makes the fruit better and worth more on the market ^[71].
- **Effects on the Environment:** AI is excellent for the environment since it uses less energy and makes less pollution. Some people think that AI-powered precision farming might cut down on greenhouse gas emissions from farming by a lot by using less fertilizer and making machines operate better. One study found that applying AI to manage crops might lower their carbon footprint by 10% to 20% for each unit ^[72].

Table 4: below synthesizes some of these impacts and cost metrics from various projects and studies ^[73, 74, 75, 76]

Impact Metric or Case	Value / Result
ROI for large-scale farms	approx 150% return on investment
ROI for small farms	approx 120%
Crop yield increase (average)	+25%
Reduction in pest/disease losses	-50%
Water usage efficiency improvement	+80%
Irrigation efficiency gain (COALA project)	+20%
Fertilizer application accuracy	+85%
Nitrogen fertilizer use reduction (Blue River case)	-58% (from 1.2 to 0.5 lbs/bu)
Herbicide use reduction (targeted spraying)	-90%
Water consumption reduction (smart irrigation)	-30%
Per-acre cost savings (Field trials)	approx \$25 per acre
Land use reduction (vertical farming vs open field)	approx 99% (same yield on 1% area)
Input cost reduction (overall, estimate)	-20%
Farmer adoption awareness	80% of agribusinesses see potential
Farm-management software adoption (US)	approx 21% (as of survey)

Challenges and Future Directions

AI in farming has a lot of nice points, but it also has some bad ones. A lot of the time, people comment about how hard it is to get good data. You need big datasets with labels to train strong

ML models. But the land, weather and ways of doing things on farms are all extremely different. You might not be able to move models from one place to another without calibrating them in each one. It can be hard to find sensor data or it can be noisy,

such when weather stations don't cover a lot of ground. It's still a work in progress to make sure that data can work together and that there are standard formats ^[77]. To employ AI technology, you also need the correct tech tools. In some isolated areas, you can't always count on having consistent power and internet. Edge computing and devices that can run without an internet connection can help, but they might also cost more. The digital divide is a different challenge. Big farms can buy and deploy costly AI systems, while small farmers in developing nations might not be able to. Some projects are trying to fix this by linking AI consultancy services with mobile networks. Some people are working on making AI tools that are inexpensive and easy for everyone to get. It's also very crucial to have trust and training ^[78]. Farmers need to be able to believe what AI says them and understand it. Putting people first is really important and agronomists can help you develop interfaces that are simple to use. Money is also a problem. It costs a lot of money to make robots and sensors that are better. It could take small farmers a long time to get their money back. Some tools that are incredibly accurate cost a lot of money and take a long time to make back what you spent on them. But as more success stories come in and business models evolve (for example, businesses might lease equipment instead of buying it outright or sign service contracts), the economics get better. Governments, NGOs and corporations can also help farmers use new technologies more safely by giving them loans or sharing resources ^[79].

In some important areas, the future of AI in farming will be different

- **Generative AI and Virtual Agronomists:** New generative models like ChatGPT make it look like virtual agronomists AI bots that can fully analyze agricultural data and talk to farmers in simple terms might be possible. Using more than one model, these kinds of systems would be able to answer queries such, "What should I do to change my watering next week based on the weather report?" ^[80].
- **Combining genomics and phenotyping:** AI will connect plant DNA to how well plants develop in the field more and more. For example, neural networks may find the best conditions for a new crop variety to grow or run millions of tests to evaluate what might happen if two plants were cross-bred. Robotics will speed up phenotyping (measuring traits), which will offer these models additional data to work with ^[81].
- **Edge AI with 5G:** Decisions may be made in real time with less lag time thanks to better edge computing (running AI on devices in the field) and 5G connectivity. More and more tractors and drones will have AI processors built into them. This will let people look at pictures straight away without needing to connect to the internet. When you mix blockchain with the Internet of Things (IoT), it's even more important to keep data safe and easy to find. Some agri-tech projects use both IoT sensors and blockchain to maintain track of farming activities and conditions that can't be modified. AI can then check these records to make sure they are correct and meet quality standards, such making sure that organic standards were met ^[82].
- **Autonomous Farms:** The idea is to develop farms that don't need people to work on them in the long run. Most of the work is done by AI and robots. There are already test farms with greenhouses that don't need any aid, driverless tractors and robotic pickers. This vision will move forward faster when general AI and robotics get better, such as by having higher perception and dexterity ^[83].

- **Farming that is good for the environment and can be used again:** AI will help us attain our goals for sustainability. Machine learning may help you figure out the best cover crops, crop rotations and techniques to use less tillage, all of which can improve soil health and store carbon. AI tools can also help farmers switch to regenerative agriculture without losing too much productivity by showing how different parts of the ecosystem work together ^[84].
- **Ethical and Policy Dimensions:** As AI gets smarter, there will be more issues about what is right and wrong. Policies may be needed to protect data ownership (farmers' data should help them) and to deal with problems like algorithmic bias (making sure that AI doesn't unfairly favour certain places or crops). International partnerships to make food safer may set rules for how AI can be used in farming ^[85].

Conclusion

Machine learning and artificial intelligence are changing the way we do agronomy right now. This research has looked at how rule-based systems have grown over time to become the powerful deep learning and robotic solutions we have now. H. Lemmon started it all with the first expert systems. Since then, each new generation of researchers has improved on that base by using better models and data sources. AI is used in all parts of farming today, from checking the soil and watching the crops to using machines that function on their own and predicting market trends. AI has a big effect on farming in the real world. Farmers and businesses say they get greater yields (typically 25% or more), use a lot less input (for example, 50–90% less insecticide) and save a lot of money. Most of the time, using new technology is worth it. For example, AI-driven management usually pays for itself in just a few seasons, which makes the benefit/cost ratios very appealing. The environmental benefits, such less fertilizer and water runoff and less greenhouse gas emissions, show that the goals for the economy and the environment are often the same. But we need to fix problems with data, infrastructure and getting people to use them if we want to get these benefits. It's important to spend money on things like connecting rural areas, making data more consistent and teaching farmers. To make AI technology available to all kinds of farms, we need legislation that supports them and cooperation between the public and private sectors. In short, AI and ML give agronomists tools that could change the way things are done. They take intricate data from the field and turn it into useful information that helps farmers make better decisions, lower their risks and use resources in a way that doesn't harm the environment. As technology gets better, AI will play a bigger role in farming, making food systems smarter and better prepared to deal with challenges. If people and machines work together, we could have a future where farms work as well as labs, feeding the world and taking care of the planet at the same time.

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