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Towards a New Era of Sustainable Agriculture: AI Applications and Case Studies in Crop Management

Viswa Chaitanya Marella
College of Business Administration, Kansas State University
Manhattan, 66506, KS, USA

Sai Teja Erukude
Department of Computer Science, Kansas State University
Manhattan, 66506, KS, USA

Suhasnadh Reddy Veluru
College of Business Administration, Kansas State University
Manhattan, 66506, KS, USA

ABSTRACT

Agriculture is experiencing a digital revolution, and Artificial Intelligence (AI) is emerging as the catalyst for sustainable crop management. This paper provides a concise review of AI-enabled applications in precision agriculture, focusing on four key areas of crop management: yield prediction, precision seeding and fertilization, pest and disease control, and optimal irrigation and soil health. Several case studies and real-world implementations are highlighted to exemplify technical outcomes and practical benefits. AI is now leveraging machine learning (ML) and deep learning (DL) models to model yield prediction in real-time, utilizing multi-source data (weather, soil, remote sensing components) to predict crop yield and empower proactive decisions. In precision seeding and fertilization, AI-enabled systems, including computer vision-based planters and variable rate fertilization systems, demonstrate uniform sowing and optimal nutrient application, thereby increasing efficiency and eliminating ceremonial waste. In pest and disease control, deep learning-based image recognition achieves expert or better-than-expert performance in image recognition. Aside from thorough identification (pests or diseases), innovative sprayers and robotics enable interventions directed at the affected areas, reducing pesticide use (up to 90% in some cases). In irrigation and soil health, smart irrigation scheduling and AI-enabled soil monitoring optimize water use (30-40% water savings compared to conventional practices) and maintain soil health (e.g., salinization). This paper also discusses implementation and deployment issues, including limited data, costs, barriers to adoption by farmers, and the interpretability of various models. Taming these issues highlights the need to scale up AI-based solutions in agriculture. The case studies demonstrate ontological progress and opportunities for continued development toward more resilient, productive, and sustainable farming systems.

Keywords

Precision Agriculture, Machine Learning, Crop Yield Prediction, Sustainable Farming, Smart Irrigation

1. INTRODUCTION

Sustainable agriculture has never faced the challenges of the modern 21st century. Climate change alters precipitation patterns and extreme weather events, directly impacting crop production [3]. In parallel, population growth drives food consumption, making it necessary to produce food at high levels, while resources such as land, water, and energy are increasingly challenged. These demanding metrics will require new strategies to manage crops that allow for increased yields, effective farming inputs/resources utilization, and consideration for future environmental impacts. In the face of these challenges, precision agriculture as a new paradigm has emerged with the goal of "producing more with less" using technology to match farm management practices to local conditions. AI is expected to contribute significantly to precision agriculture by analyzing historical datasets (e.g., weather data, soil condition monitoring data, satellite images) and generating actionable insights or automated decisions.

In the past decade, machine learning (ML), deep learning, computer vision, and robotics have developed into several creative applications across agricultural contexts. Several early successes are related to yield forecasting using predictive models, intelligent control systems for farm machinery, and image-based diagnostic toolkits [6] for plant health assessments. Recent systematic reviews confirm that the convergence of AI and machine learning approaches is increasingly effective for accurate crop yield estimation, incorporating diverse data sources and robust models [8, 10]. While farmers and agricultural companies are just beginning to adopt the tools of AI, the field cropping sector is closely trailing behind modeling, as seen in the first ever tech sector report, where Cropping fieldwork accounted for 61.5% of AI use [2] in agriculture as of 2024 —demonstrating the value that has been realized in optimizing open field agriculture operations. Solutions originating from AI technology can provide answers that analyze the many factors that make agriculture complex: farm outcomes depend on numerous factors, including climate variability, soil properties (and variability), crop genotype, and management practices. AI systems learn from historical and real-time data, which aids in developing more timely, accurate, and site-specific decisions than traditional agriculture approaches. This paper will focus on four applications of

AI technology using case studies to frame a new era of sustainable crop management: (1) Yield Prediction, (2) Precision Seeding and Fertilization, (3) Pest and Disease Management, and (4) Irrigation & Soil Health Optimization. The results will discuss a few representative case studies and deployments that illustrate current agri-tech models and the subsequent improvements in agricultural practice. The listed outcomes are emphasized including real-world examples like improved accuracy of yield estimation, input efficiencies, or reduced environmental impacts, and what technology that secured these outcomes. Common barriers to AI implementation encountered when the technology is integrated into an agricultural workflow include data limitations, required infrastructure, and user acceptance challenges.

With these domains, the aim is to show how the applications of AI technology are starting to achieve sustainable agriculture goals and discuss best practices and remaining gaps. The remainder of the paper is organized as follows: The next sections (Case Studies) account for AI technologies that support yield prediction and analysis, precision seeding/fertilizer rate application, pest/disease management practices, irrigation optimization, and soil health, respectively. Finally, several shared challenges in deploying AI technologies for agriculture at scale will also be discussed.

2. CASE STUDIES IN AI-DRIVEN CROP MANAGEMENT

2.1 Yield Prediction

Reliable crop yield predictions are necessary to plan food supply and other supply requirements, market conditions and stability, farm operation, seasonality, and investments. Yield predictions were previously based on farmer knowledge or statistical methods and models with fewer variables, often failing to consider the effects and relationships of complex dynamic variables. This could also be a significant source of error [3] in yield estimates. Artificial Intelligence (AI) provides robust models and approaches as it can learn from multiple data sources and recognize and relate nonlinear relations between crop yield and driving factors. Research suggests that combining environmental big data with machine learning/deep learning (ML/DL) models can demonstrate utility for determining crop yield and enhance crop yield prediction accuracy [6].

2.1.1 Data and Variables. New crop yield prediction models utilize unique multi-dimensional data sources that capture climate data (temperature, precipitation, solar radiation), soil properties, topography, management factors, crop phenology, and crop health information. Remote sensing can provide vegetation indices (e.g., NDVI, EVI, LAI) [4] that can generally be correlated to plant biomass for crop health; a comprehensive investigation from 2024 found predictors helpful for accurate yield estimation stemmed from, temperature, precipitation, soil type, humidity, temperature, vegetation indices, and also stressed for model performance it was important to acquire “highly accurate environmental and agricultural data” to estimate yield. For instance, combining NDVI time series extracted from satellite images and weather data could increase crop yield forecasting accuracy while providing insights into the crop’s trading dynamics over the growing season.

2.1.2 AI Models. Many approaches, models, and ML/DL methods have been developed for yield prediction. Standard machine learning models such as Random Forests, Support Vector Machines, and Artificial Neural Networks are built to handle multivariate inputs and provide good predictive performance in many scenarios. For instance, in practice, compared to linear regression, RF models have to consider nonlinear interactions in yield factors, and even in yield prediction specifically, RF models generally outperform their linear regression model counterparts. Similarly, regarding deep learning models, well-established methods exists such as Convolutional Neural Networks and recurrent networks (e.g., Long Short Term Memory) models. CNNs, in particular, are an excellent choice for input data that contains spatial imagery information (e.g., soil properties maps or remote sensing imagery) as they are designed to extract spatial features above all else. Recurrent models, such as LSTM, are perfect for temporal sequence questions or time series data (e.g., time series weather data or phenology data) as they capture temporal feature connections with crop development. Recent frameworks like the agro-deep learning model proposed by Logeshwaran et al. (2024) demonstrate how integrating DL architectures with precision agriculture workflows can improve crop productivity predictions [5]. More recently, hybrid models have been introduced to consider combinations of spatial and temporal issues; researchers have started to propose groundbreaking ideas, such as the CNN-GAT-LSTM model [6] for crop yield prediction that includes geospatial and temporal features.

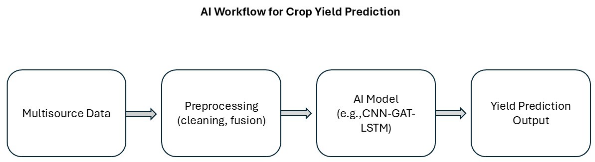

Fig. 1. AI Workflow for Crop Yield Prediction, highlighting the progression from data sources to model output.

2.1.3 Performance and Case Studies. AI-based yield models have been documented as having very predictive accuracy in experimental scenarios. An illustrative example was provided by Mohan et al. (2025) in their method using an ensemble of regression models (Decision Trees, Random Forest, and LightGBM) to predict rice yields for climate change scenarios. Their model provided an R2 value of 0.92 with mean square error values down to a value of 0.02 on the test data [6], constituting an impressive level of precision and relative accuracy by ongoing traditional forecasting standards. In both of these studies, temperature emerged as the most important feature for yield, with meaningful interactions between precipitation patterns and soil nutrient amounts. Significantly, they utilized eXplainable AI (XAI) tools (SHAP and LIME) to provide an understanding of the model’s decisions, confirming agronomic knowledge (e.g., showing how extreme temperature events depress yields) and fostering user confidence. In another example, a Frontiers 2024 study by Jagan Mohan et al. utilized an XGBoost model with historical yield, weather, and soil data across multiple states. The model could predict wheat yields with over 90% accuracy and was implemented in a pilot decision support system for farmers, illustrating how AI predictions can trigger timely actions, e.g., adjusting planting dates or changing irrigation schedules. Large-scale applications are also being developed. For example, the Agroview platform was developed at the University of Florida, where AI, drones, and satellite imagery are used to predict citrus and specialty crop yields [1]. Agroview growers receive yield estimates for their field and "stressed plant zone" visualizations several weeks before harvest. This gives farmers early insight to make interventions (e.g., additional irrigation or pest control in low-performing zones) to increase final yields. According to Ampatzidis, the researcher behind Agroview, it will save the user up to 90% of their data collection and analysis time compared to scouting. This AI-based yield mapping is especially consequential for perennial crops (fruit trees, vineyards) with substantial within-orchard variability. As shown in these case studies, there is strong evidence to suggest that AI models can predict yields with greater accuracy and detail than ever before. Successful models relied on having robust data (historical and real-time) and proper algorithms for the data type. By providing reliable early predictions, farmers and policymakers have an opportunity to be proactive, ensuring food supply chains, facilitating decisions around storage and marketing, and adjusting management practices to reduce losses. Yield prediction is, therefore, a prime example of how AI can improve productivity and sustainability. Accurate predictions lead to more targeted resource allocation (e.g., adjusting fertilizer or irrigation based on expected yield) and reduce the risk of surplus or shortfalls [3, 6, 1].

2.2 Pest and Disease Control

Crop pests (insects, weeds) and diseases are constant threats to agriculture, substantially reducing yield and quality if not well managed [9]. AI has shown potential to transform the pest and disease management field through early detection, accurate diagnosis, and precise management; can be referred to this suite of developments as "smart crop protection." Two areas in which AI is making a significant impact include visual diagnosis (using computer vision to identify pests, weeds, or disease symptomology) and optimized pest management (using AI to determine when/where to intervene and even intervene using smart machinery) [7].

2.2.1 AI-Based Disease Diagnosis. Accurate and rapid identification is integral to timely intervention for plant diseases. Farmers traditionally will either scout their crops or consult an expert to identify an issue based on visual symptoms, which can take a long time to get an accurate answer and may have some errors. Deep learning, particularly convolutional neural networks (CNNs), sometimes surpasses human experts for image-based plant disease recognition. For example, a study published in 2023 reported accuracy rates above 99% [9] using CNN models by classifying images of diseased and healthy leaves across crops such as potatoes, tomatoes, and bell peppers. Some more sophisticated configurations (e.g., InceptionV3, VGG16, and custom CNNs) achieved near-perfect (98–100%) performance on test datasets of common foliar diseases. These studies often used somewhat controlled datasets (e.g., PlantVillage image repository) to train their models. However, these results demonstrate the potential of AI to act as a virtual plant pathologist. In the meantime, researchers are also working to bridge the gap between the lab and field by training models to generalize to the field with novel lighting conditions, backgrounds of various colors/textures, and multiple disease symptoms. A 2022 article in Frontiers in Plant Science used several deep learning models to solve the challenge of real images and achieved 96-99accuracy for different crop disease pairs. This accuracy could facilitate smartphone apps for diagnosis and scout drones that detect real-time diseases in larger fields. It is evident that AI disease diagnostic tools. Smartphone apps, like Plantix and Agrio, are already using CNN backend, where a farmer can take a picture of the suspect plant and get the app (nearly instantaneously) the likely disease and recommendations to control it...and these apps are getting better, with the capacity to aggregate labeled images submitted by users, and feedback positively their improvement to the AI. Some greenhouse companies use cameras with AI, which continually monitor and record IPM elements, i.e., early powdery mildew on leaves, about vectors, so IPM management intervention can be localized immediately. The potential for AI to detect early disease is tremendous, whether in slowing the spread and crop loss or reducing the blind application of IPM.

2.2.2 AI for Pest and Weed Management. Research and intellectual opportunity also extend beyond diagnosis. AI also helps farmers decide when or how to manage pests best. For example, ML models can tap into a dataset of weather variables, crop stage, and historical infestation patterns to predict when pest insects will likely cause outbreaks. Predictive models for pest outbreaks (i.e., locusts, fall armyworms) based on climate datasets and vegetation indices via satellite can warn farmers of threats in warm regions and prepare. The most disruptive advancement on the AI intervention front has been precision weed management using AI vision systems. Weeds are generally managed by herbicides applied across the field, while AI-powered machines can specifically target weeds and vastly reduce chemical application. A great example is the precision weed sprayer built by researchers at the University of Florida (UF/IFAS): Herbicide is applied only where a weed is present rather than uniformly. This current technology was deployed in vegetable farms, and the researchers showed farmers could "reduce pesticide use by up to 90% and still manage weeds just as effectively." This technology has reported similar results for the industry. Blue River Technology's See & Spray system (now commercialized with John Deere) utilizes a CNN vision system to distinguish between weed and crop in a cotton field and has achieved approximately 80-90% reduction in herbicide volume in production-scale trials. These reductions have significant economic and environmental consequences, saving thousands of dollars in chemical costs per farm while significantly reducing herbicide runoff and soil contamination.

Robotics makes this even more powerful. Machines that autonomously weed, like EcoRobotix (most likely store demo footage), use AI to find weeds and mechanically destroy them (either by precision spraying or even laser welding) with little input from a human. Reports indicate that some robots have reduced herbicides by ¿ 90–95% in pilot projects. AI-fueled clever traps are changing the game in insect pest management; traps that can automatically identify target insects from trap catches using image classification algorithms can provide farmers with remote alerts about pest pressures, thereby initiating action on pest management in a site-specific manner. In one example, an AI-driven pheromone trap for moths could identify species with ¿ 95% accuracy and transmit identification data to a cloud platform, effectively creating a real-time pest surveillance network for the region. This allowed extension advisors to specify which fields needed spraying and when, instead of simply recommending sprays based on a calendar schedule for everyone. Through this, farmers who participated in the program reduced their insecticide applications by 50% on average within a season while maintaining crop quality

2.2.3 Integration with Decision Systems. AI use is not restricted to direct actions via systems, but also feeds integrated pest management (IPM) decision support systems that characteristically support highly documented and supported IPM approaches. For example, model-based risk assessments of diseases, such as late blight in potatoes, then utilize weather forecasts and crop conditions to provide farmers with the most effective spray options while minimizing the total amount of fungicide used to prevent disease. The OPTIMA project, funded by the EU, developed AI based IPM decision support systems and achieved ¿20–40applications in grapes and apples, not by taking away pest threshold action but by only spraying areas of punishment once the model indicated risk levels crossed a threshold compared with systems relying on routine spraying schedules.

2.3 Real world Benefits

The recognized benefits of AI improving pest and disease management ultimately provide greater sustainability through:

(1) Early and accurate detection: causes less crop damage and promotes animal and other component-specific interventions that restrict crop yield losses and, more dramatically, eliminate the environment of potential insect outbreaks.
(2) Lowered chemical inputs: As statistically demonstrated later in this paper, both AI-driven pest and herbicide applications will often reduce the total volumes of pesticides and herbicides used by 50-90%, specifically targeted control. Lowered production costs and less excess chemical/contamination into the environment (important for protecting pollinators, soil microbes, and water-bodies from chemicals).
(3) Reduced labor: Automated scouting and weeding take some of the other laborious tasks associated with farming. For instance, a weeding robot can run continuously so the farmer can focus on other work (solving labor shortages).
(4) Better resistance management: More specific spraying also reduces the blanket spraying approach, which slows down pesticide resistance in pest populations by prohibiting excessive chemical resource use.

AI-supported pest control is still in the early stages of adoption, but is in a burgeoning state of development. For example, and as an offshoot to this paper, large farming operations and agriservice providers are seeking investment into drones fitted with multi-spectral cameras and AI that can detect crop stress due to pests/diseases across hundreds of acres of farmland within minutes. Governments and NGOs, especially in developing countries, are actively trialing AI-powered advisory systems that support smallholder farmers' greater success in managing pests with limited resources. While AI models are successfully applied to local areas, the challenge of generalization is still at the core of this work. The models often cannot generalize to whether the field context is too different (different crop morphological classes [info], varieties, backgrounds, etc., and potentially different pest morphologies). Researchers are actively designing models that employ data augmentation, domain adaptation, and continual learning (to improve a system over multiple seasons of new model experience/data sources. Nevertheless, the upward trends are clear: AI will continue to improve pest and disease management, transition from reactive to proactive, and from global responses to accuracy and precision, ultimately acting toward more sustainable crop production practices [9].

3. IMPLEMENTATION AND DEPLOYMENT CHALLENGES

While the case studies above demonstrate that AI can benefit crop management, problems with the wide-scale deployment of these technologies will also arise. Many AI solutions will have practical limitations when implementing these technologies into everyday farming. This section explores important considerations and implementation challenges:

3.1 Data availability and quality

Data availability and quality are important to high-performing AI models, whether large amounts of images of diseased plants to train a classifier or years of yield statistics and weather data to train a predictor. In agriculture, data is often thin or siloed (contained within systems). Farms do not often have much historical data; the available data, such as soil tests and yield maps, may not be interoperable (usable) across different systems. This leads to data interoperability issues; agriculture lacks the standardized data formats seen in other industries, leading to fragmented data sources. For example, machines from different manufacturers may use proprietary formats for logging data, making it hard to combine. Further, collecting data for supervised learning, such as some images labeled for crop disease present, can be labor-intensive and require agricultural knowledge to apply the labels. Some areas of the world are beginning to build open data sets due to public initiatives or academic research projects (e.g., satellite data from government-produced sources or locations along the research station have associated trials), which will help. However, the biggest challenge for many farmers is: Do I have enough data to run an AI model with enough confidence to use it for my farm? This has sparked interest in many approaches, including transfer learning (using models that have been trained on big data sets and then transferring the information to a small data set based on a farm) and federated learning (like transfer learning, federated learning uses each farm as a collaborator to develop a model, but does not involve the transfer of data between the farms).

3.2 Infrastructure and connectivity

To use AI, many components need considerable levels of digital infrastructure to be in place, such as sensors, connectivity (internet, telemetry), and computing capability (on farm or cloud). There are many rural areas without adequate broadband internet. Although 85% of farms in the U.S. have internet connectivity, it is important to recognize that approximately half of the farms have constant broadband connectivity [2]. This can be even more pronounced in developing economies, especially if data-rich applications are used or want to administer real-time video analytics or cloud-based model computations. Suppose you are running your AI system without a network connection. In that case, you cannot feed the AI system timely data, e.g., you have a moisture sensor network that is not uploading any data, or models that are not supplying timely recommendations. Some solutions may be cosmopolitan through edge computing (using local devices) that can lessen the reliance on constantly connecting to the internet. However, remote support and updates can still be problematic, even in these instances. The infrastructure also speaks to the power supply. IoT sensors and drones rely on continuous power (or solar charging, etc.), and this can make life difficult in field conditions and even in farm buildings and/or homes. Therefore, deploying AI at scale will need a level of cultural investment in rural ICT infrastructures that provides sufficient attribution that indicates that the technology can withstand rugged and autonomous (i.e., may operate offline, if required).

3.3 Cost and Return on Investment (ROI)

Also, at the end of the day, the capital investment required to deploy all of the advanced AI systems, autonomous robots, individual sensors, enterprise software, etc., can be a barrier, particularly for smallholder farmers and/or medium-scale farmers. Surveys suggest that high cost is the most significant barrier to technology adoption in farming; in a recent survey of North American farmers, 52% said that cost was a significant concern, and 40% said unclear ROI was also a concern [2]. Even if a technology promises savings or yield gains, farmers are risk-averse without some assurance that it will pay off. For example, suppose a precision sprayer costs significantly more than a traditional sprayer. In that case, farmers will only feel the price difference is justified if, over time, they see it always reduce herbicide use (and costs) by a given margin. To counter this, some firms provide services (e.g., contracting AI services by the acre) rather than requiring farmers to buy expensive equipment outright. To demonstrate ROI, companies often need to utilize field trials on farms and extension education on the efficiency benefits they will see based on their specific conditions. Over time, as AI components become more commonplace, costs may go down. For instance, cameras and computing units have become less expensive, and AI solutions have become cheaper. The potential for economic risk remains an important barrier to deployment, especially in an industry with tight margins.

3.4 Integration with Existing Practice

Farmers cannot change all practices overnight; new AI systems can not forget or throw away what equipment and workflows they have. Compatibility is an issue, for example, decision support apps that need different variable rate prescriptions, but all of which a tractor controller can understand. Not all platforms use universal standards (like ISOXML for farm data). More compatible alternatives need to be developed to build on farmers' existing systems. For example, an AI tool producing yield predictions should work best if the algorithm could inform the farm's marketing plan or insurance program, or if an AI weed identification device could be fitted to the farmer's current sprayer instead of requiring a dedicated new sprayer fit-out. More and more companies and researchers recognize the importance of interoperability, modularity, and open API, allowing their systems to connect. Even so, the lack of perfect integration can slow down the deployment of systems as farmers wait for a solution that fits their farm system.

3.5 Scalability and Generalization

AI models can perform exceptionally well in the scope of a pilot project or research plot. However, when it comes to scaling up to widespread, real-life scenarios, this can be complicated and cumbersome. Agriculture is unique due to its heterogeneity: different crops, varieties, climates, and management styles mean that a model built in one condition may struggle in another. While the risk of model overfitting can exist anywhere, local conditions may interest farmers most. For example, a disease detector built almost exclusively from images of a tomato variety may fail when diagnosing issues in another variety of tomatoes. For AI to be used across regions, models need to be robust enough or retrained considering local conditions. This usually means greater training data must be collected to capture the diversity of a crop, variety, climate, and management to train the model and offset the management and consequences of possibly several more region-specific models (increasing complexity and costs). Some commercial solutions are actively trying to create solutions that continuously relearn with user training data (with approval and consent) to ensure each model is adjusted as it comes into contact with new scenarios. Extending AI algorithms to new crops or tasks also takes considerable R&D; an AI working for corn may need significant adjustments to be ready for orchard management. As such, achieving the breadth of functionality required to cover all farming systems globally is an ongoing pursuit.

4. CONCLUSION

AI technologies are ushering in a new era of sustainable agriculture by enabling farmers to manage crops with greater precision, efficiency, and insight than ever before. In this paper, key application areas are reviewed where AI-driven tools and techniques are making an impact, from predicting yields and optimizing planting to protecting crops from pests and judiciously managing water and soil resources. The case studies discussed provide concrete evidence of technical success and practical benefits: data informed yield forecasts with over 90% accuracy [6], intelligent planters and sprayers that achieve higher productivity with lower inputs, diagnostic models that catch diseases early, and autonomous systems that save significant amounts of water and preserve soil health. Collectively, these advancements contribute to the overarching goals of sustainable agriculture: producing adequate food while minimizing environmental footprint and ensuring farm economic viability. Despite these advances, unlocking the full potential of AI in agriculture requires overcoming persistent implementation challenges. Data, infrastructure, cost, and user adoption need continued attention. It is evident that technology alone is not a silver bullet; support systems – training, advisory services, business models that lower adoption risk, and policies fostering digital inclusion are integral to success. Ongoing research is also needed to improve AI models' robustness and interpretability, ensuring recommendations are trusted and valid across diverse agricultural contexts. Interdisciplinary collaboration will be important: agronomists, computer scientists, engineers, and farmers working together to fine-tune AI tools that are agronomically sound and user-friendly on the farm. Looking forward, the trajectory of AI in crop management appears promising. In the next few years, it is expected to see:

(1) More integrated farm AI systems: where a single platform might handle multiple tasks (yield prediction, pest alerts, irrigation control) in a coordinated way, providing a holistic decision support to farmers.
(2) Advances in sensors and robotics: that will generate richer data (e.g., cheap soil nutrient sensors, better remote imaging) and physically execute AI decisions (e.g., fleets of small robots handling weeding or harvesting), further closing the loop between prediction and action on the field.
(3) Data ecosystems and transparency: as the community develops open benchmarks and shares successful models (akin to open source), which will accelerate innovation and trust. Efforts like Agricultural Data Coalitions and open AI model repositories for agriculture can play a role.
(4) Policy frameworks: that encourage sustainable practices using AI (for example, subsidy programs that support precision farming equipment, or carbon credit systems that reward reduced input use documented by AI systems) [2].

In conclusion, AI is rapidly becoming a catalyst for sustainable crop management, transforming how decisions are made on the farm. By gleaning patterns from complex data and enabling targeted actions, AI helps farmers "do the right thing at the right place and time", the essence of precision agriculture. This paper's case studies and examples illustrate early achievements towards that ideal. Continued progress will depend on addressing current challenges and scaling the solutions responsibly. If achieved, the outcome will be a more productive agriculture that meets global food needs while conserving the natural resource base, truly a new era of farming where science and technology empower stewardship of the land. The convergence of AI with traditional agricultural wisdom holds great promise for feeding the world sustainably in the decades ahead.

5. REFERENCES

[1] Yiannis Ampatzidis, Victor Partel, and Lucas Costa. Agroview: Cloud-based application to process, analyze and visualize uav-collected data for precision agriculture applications utilizing artificial intelligence. *Computers and Electronics in Agriculture*, 174:105457, 2020.

[2] POPA Cosmin. Adoption of artificial intelligence in agriculture. *Bulletin of University of Agricultural Sciences and Veterinary Medicine Cluj-Napoca. Agriculture*, 68(1), 2011.

[3] Md Abu Jabed and Masrah Azrifah Azmi Murad. Crop yield prediction in agriculture: A comprehensive review of machine learning and deep learning approaches, with insights for future research and sustainability. *Heliyon*, 2024.

[4] Bing Li and Jiyun Li. Optimized deep neural network and its application in fine sowing of crops. *Computational Intelligence and Neuroscience*, 2022(1):3650702, 2022.

[5] J Logeshwaran, Durgesh Srivastava, K Sree Kumar, M Jenolin Rex, Amal Al-Rasheed, Masresha Getahun, and Ben Othman Soufiene. Improving crop production using an agro-deep learning framework in precision agriculture. *BMC bioinformatics*, 25(1):341, 2024.

[6] RNV Jagan Mohan, Pravallika Sree Rayanoothala, and R Praneetha Sree. Next-gen agriculture: integrating ai and xai for precision crop yield predictions. *Frontiers in Plant Science*, 15:1451607, 2025.

[7] Pavan Kumar Pativada. *Real-time detection and classification of plant seeds using YOLOv8 object detection model*. PhD thesis, Kansas State University, 2024.

[8] Sarowar Morshed Shawon, Falguny Barua Ema, Asura Khanom Mahi, Fahima Lokman Niha, and HT Zubair. Crop yield prediction using machine learning: An extensive and systematic literature review. *Smart Agricultural Technology*, page 100718, 2024.

[9] Muhammad Shoaib, Babar Shah, Shaker Ei-Sappagh, Akhtar Ali, Asad Ullah, Fayadh Alenezi, Tsanko Gechev, Tariq Hussain, and Farman Ali. An advanced deep learning models-based plant disease detection: A review of recent research. *Frontiers in Plant Science*, 14:1158933, 2023.

[10] Mohamed Farag Taha, Hanping Mao, Zhao Zhang, Gamal Elmasry, Mohamed A Awad, Alwaseela Abdalla, Samar Mousa, Abdallah Elshawadfy Elwakeel, and Osama Elsherbiny. Emerging technologies for precision crop management towards agriculture 5.0: A comprehensive overview. *Agriculture*, 15(6):582, 2025.