

The Rise of AI and Digital Technologies in Modern Agronomy: A Comprehensive Review

Deekshith HN^{1*} and Karthik R²

¹Senior Project Associate, Agrotechnology Lab, CSIR - CSIR-IHBT, Palampur, HP

²PhD Scholar, Department of Entomology, CSK HPKV, Palampur

*Corresponding Author E-mail: deekshithdiv@gmail.com

Received: 4.02.2025 | Revised: 18.03.2025 | Accepted: 10.04.2025

ABSTRACT

The convergence of artificial intelligence (AI) and digital technologies has revolutionized agronomy, addressing global challenges such as food security, climate change, and resource scarcity. This review provides an in-depth analysis of the evolution, applications, and transformative impacts of these technologies in modern agriculture. Key areas explored include precision agriculture, AI-driven decision support systems, remote sensing, automation, and big data analytics. The article evaluates their contributions to productivity, sustainability, and resilience, while critically examining challenges such as data accessibility, technological adoption barriers, and ethical concerns. Future directions and emerging trends are discussed, supported by an extensive range of scholarly references.

Keywords: Artificial Intelligence, Precision Agriculture, Machine Learning, Remote Sensing, Big Data Analytics.

INTRODUCTION

Agriculture is at a critical juncture, with a projected global population of 9.7 billion by 2050 increasing demand for food production by approximately 50% (FAO, 2017). Concurrently, climate variability, soil degradation, and water scarcity threaten agricultural systems. Traditional farming practices, reliant on manual labor and generalized approaches, are inadequate for these challenges. AI and digital technologies—including machine learning, Internet of Things (IoT), robotics, and cloud computing—offer

innovative solutions by enabling data-driven, precise, and sustainable practices. This review synthesizes the current state of these technologies in agronomy, their impacts, and future potential, drawing on a broad range of academic sources.

2. Historical Context and Evolution

The integration of technology into agriculture began with mechanization in the 19th century, followed by the Green Revolution's introduction of high-yield crops and chemical inputs.

Cite this article: Deekshith, H. N., & Karthik, R. (2025). The Rise of AI and Digital Technologies in Modern Agronomy: A Comprehensive Review, *Curr. Res. Agri. Far.* 6(2), 25-29. doi: <http://dx.doi.org/10.18782/2582-7146.272>

This article is published under the terms of the [Creative Commons Attribution License 4.0](https://creativecommons.org/licenses/by/4.0/).

The late 20th century saw the advent of digital tools, such as GPS-guided tractors and basic remote sensing (Pierce & Nowak, 1999). The 21st century marked a paradigm shift with AI and IoT, enabling real-time data collection and analysis. Machine learning algorithms, particularly deep learning, have enhanced predictive capabilities, while cloud-based platforms facilitate scalable data management. These advancements have transformed agronomy into a technology-driven discipline, aligning with the concept of Agriculture 4.0 (Rose & Chilvers, 2018).

3. Key Applications of AI and Digital Technologies

3.1 Precision Agriculture

Precision agriculture optimizes resource use through site-specific management. IoT sensors monitor soil moisture, nutrient levels, and microclimates, feeding data into AI models that recommend tailored interventions. Variable-rate technology (VRT) adjusts fertilizer and water applications based on field variability, reducing waste by up to 30% (Gebbers & Adamchuk, 2010). Platforms like Trimble Ag Software integrate these technologies, enabling farmers to maximize yields while minimizing environmental impact.

3.2 AI-Driven Decision Support Systems

AI-powered decision support systems (DSS) leverage machine learning to provide actionable insights. Convolutional neural networks (CNNs) analyze imagery to detect pests, diseases, or nutrient deficiencies with over 90% accuracy (Kamilaris & Prenafeta-Boldú, 2018). Tools like Microsoft's FarmBeats combine weather forecasts, soil data, and market trends to guide planting and harvesting decisions. These systems empower farmers to make informed choices, particularly in resource-constrained settings.

3.3 Remote Sensing and Imaging

Remote sensing technologies, including satellites and unmanned aerial vehicles (UAVs), capture high-resolution data on crop health, soil conditions, and water availability. AI enhances image processing, identifying issues such as weed infestations or drought

stress (Mulla, 2013). For instance, Sentinel-2 imagery, processed through deep learning models, supports large-scale monitoring with a resolution of 10 meters (Drusch et al., 2012). Companies like Planet Labs provide daily imaging, enabling rapid response to emerging threats.

3.4 Automation and Robotics

Robotic systems, guided by computer vision and AI, automate labor-intensive tasks. Autonomous tractors, such as those developed by John Deere, use GPS and machine learning to navigate fields with centimeter-level precision (Zhang & Pierce, 2016). Harvesting robots, like Agrobot's strawberry picker, selectively collect ripe fruit, reducing labor costs and crop damage. These technologies are particularly impactful in regions facing labor shortages.

3.5 Big Data and Analytics

Big data platforms aggregate information from sensors, satellites, and market sources, enabling comprehensive farm management. AI-driven analytics predict crop yields, optimize supply chains, and forecast market demand (Wolfert et al., 2017). For example, IBM's Watson Agriculture uses predictive models to align production with economic trends, enhancing profitability. These platforms also support traceability, ensuring compliance with food safety standards.

3.6 Blockchain and Supply Chain Integration

Blockchain technology enhances transparency in agricultural supply chains. By recording transactions on a decentralized ledger, blockchain ensures traceability from farm to consumer (Kamilaris et al., 2019). AI complements this by analyzing supply chain data to optimize logistics and reduce waste. Platforms like AgriDigital have demonstrated success in improving trust and efficiency in grain markets.

3.7 Climate-Smart Agriculture

AI supports climate-smart agriculture by modeling climate impacts and recommending adaptive strategies. Machine learning models predict weather patterns, enabling farmers to adjust planting schedules (Crane-Droesch et

al., 2018). IoT-based irrigation systems, guided by AI, conserve water in arid regions, with studies reporting up to 40% water savings (Abioye et al., 2020).

4. Impacts on Agronomy

4.1 Productivity and Efficiency

AI and digital technologies have significantly enhanced agricultural productivity. Precision agriculture increases yields by 10-20% while reducing input costs (Schimmelpfennig, 2016). Automation streamlines operations, with robotic systems completing tasks up to 50% faster than manual labor (Lowenberg-DeBoer et al., 2020). These gains are critical for meeting global food demand.

4.2 Environmental Sustainability

By optimizing resource use, these technologies reduce environmental degradation. Precision fertilization minimizes nutrient runoff, protecting waterways (Bongiovanni & Lowenberg-DeBoer, 2004). AI-driven pest management reduces pesticide use by targeting applications, with trials showing a 20% reduction in chemical inputs (Partel et al., 2019). These practices align with sustainable development goals.

4.3 Economic Benefits

Digital tools lower operational costs and improve market access. Mobile-based AI apps, such as Digital Green's advisory platform, provide smallholder farmers with real-time guidance, increasing incomes by 15-25% in some regions (Cole & Fernando, 2021). Large-scale farmers benefit from data-driven supply chain optimization, reducing losses and enhancing profitability.

4.4 Social and Community Resilience

AI enhances resilience by predicting risks such as pest outbreaks or extreme weather. Digital platforms facilitate knowledge sharing, strengthening community networks (Sylvester, 2019). For example, Farmerline's mobile app delivers weather alerts and market prices to rural farmers in Africa, improving preparedness and decision-making.

4.5 Food Security

By increasing yields and reducing losses, these technologies bolster food security. AI-driven crop monitoring detects issues early,

preventing up to 30% of potential yield losses (Liakos et al., 2018). In developing nations, digital extension services bridge knowledge gaps, empowering farmers to adopt high-yield practices.

5. Challenges and Limitations

5.1 Data Accessibility and Quality

AI systems require large, high-quality datasets, which are often scarce in low-resource settings. Inconsistent data formats and limited internet connectivity exacerbate this issue (Basso & Antle, 2020). Public-private partnerships are needed to develop open-access data repositories.

5.2 Technological Adoption Barriers

High costs and technical complexity hinder adoption, particularly among smallholder farmers. For instance, advanced UAVs can cost over \$10,000, excluding maintenance (Sylvester, 2018). Training programs and affordable solutions, such as smartphone-based AI tools, are critical to overcoming these barriers.

5.3 Ethical and Social Considerations

The digital divide risks widening inequalities, as wealthier farmers access advanced technologies while others are left behind (Rotz et al., 2019). Data privacy concerns arise from corporate control of farm data, raising questions about ownership and consent. Algorithmic biases in AI models may also disadvantage marginalized groups, necessitating transparent and inclusive development processes.

5.4 Infrastructure and Connectivity

Rural areas often lack reliable electricity and internet, limiting the deployment of IoT and cloud-based systems (FAO, 2019). Investments in rural infrastructure, such as 5G networks, are essential to scaling digital agriculture.

5.5 Regulatory and Policy Gaps

The rapid pace of technological innovation outstrips regulatory frameworks. Policies on data governance, intellectual property, and AI ethics are underdeveloped, creating uncertainty for stakeholders (Bronson & Knezevic, 2016). Harmonized standards are needed to ensure equitable benefits.

6. Future Prospects and Emerging Trends

6.1 Edge Computing and Real-Time Processing

Edge computing enables data processing at the source, reducing reliance on cloud infrastructure. This is particularly valuable in remote areas with limited connectivity, allowing real-time decision-making (Shi et al., 2019). Future IoT devices will likely incorporate edge AI for enhanced efficiency.

6.2 Explainable AI and Trust

Explainable AI (XAI) improves transparency by clarifying how models reach decisions, fostering trust among farmers (Rudin, 2019). Research into XAI for agriculture is expanding, with potential to accelerate adoption.

6.3 Integration with Traditional Knowledge

Combining AI with indigenous and traditional farming practices can enhance sustainability and cultural relevance. Collaborative platforms, such as those piloted by the International Center for Tropical Agriculture, are exploring this synergy (CIAT, 2020).

6.4 Synthetic Biology and AI

AI is increasingly integrated with synthetic biology to develop climate-resilient crops. Machine learning models predict gene-editing outcomes, accelerating the development of drought-tolerant varieties (Jaganathan et al., 2020). This interdisciplinary approach holds transformative potential.

6.5 Policy and Global Collaboration

International cooperation is critical to addressing the digital divide and standardizing data protocols. Initiatives like the FAO's Digital Agriculture Strategy aim to promote inclusive technology adoption (FAO, 2021). Policy frameworks must prioritize smallholder farmers and ethical AI development.

CONCLUSION

AI and digital technologies have fundamentally reshaped agronomy, driving unprecedented gains in productivity, sustainability, and resilience. From precision agriculture to blockchain-enabled supply chains, these tools address pressing global challenges. However, barriers such as data

access, cost, and ethical concerns must be addressed to ensure equitable benefits. Continued innovation, coupled with inclusive policies and global collaboration, will unlock the full potential of these technologies, securing a sustainable and food-secure future.

Acknowledgement:

I would like to sincerely thank my co-author for their support and kind gesture to complete this manuscript in time.

Funding: NIL.

Conflict of Interest:

There is no such evidence of conflict of interest.

Author Contribution:

All authors have participated in critically revising of the entire manuscript and approval of the final manuscript.

REFERENCES

- Abioye, E. A. (2020). Precision irrigation management using IoT and machine learning. *Computers and Electronics in Agriculture*, 172, 105328.
- Basso, B., & Antle, J. (2020). Digital agriculture to support sustainable intensification. *Nature Sustainability*, 3(4), 254-256.
- Bongiovanni, R., & Lowenberg-DeBoer, J. (2004). Precision agriculture and sustainability. *Precision Agriculture*, 5(4), 359-387.
- Bronson, K., & Knezevic, I. (2016). Big data in food and agriculture. *Big Data & Society*, 3(1), 2053951716648174.
- CIAT. (2020). Integrating traditional knowledge with digital agriculture. *International Center for Tropical Agriculture Report*.
- Cole, S. A., & Fernando, A. N. (2021). Mobile technology and agricultural productivity in India. *Journal of Development Economics*, 149, 102586.
- Crane-Droesch, A. (2018). Climate-smart agriculture and machine learning. *Environmental Research Letters*, 13(7), 074013.

- Drusch, M. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES. *Remote Sensing of Environment*, 120, 25-36.
- FAO. (2017). *The future of food and agriculture: Trends and challenges*. Food and Agriculture Organization of the United Nations.
- FAO. (2019). *Digital technologies in agriculture and rural areas*. Food and Agriculture Organization of the United Nations.
- FAO. (2021). *FAO strategy on digital agriculture*. Food and Agriculture Organization of the United Nations.
- Gebbers, R., & Adamchuk, V. I. (2010). Precision agriculture and food security. *Science*, 327(5967), 828-831.
- Jaganathan, D. (2020). Machine learning in synthetic biology for crop improvement. *Trends in Biotechnology*, 38(10), 1083-1095.
- Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70-90.
- Kamilaris, A. (2019). Agri-food supply chain with blockchain: A review. *Trends in Food Science & Technology*, 88, 101-115.
- Liakos, K. G. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674.
- Lowenberg-DeBoer, J. (2020). Economics of agricultural robotics. *Precision Agriculture*, 21(3), 665-681.
- Mulla, D. J. (2013). Twenty-five years of remote sensing in precision agriculture. *Biosystems Engineering*, 114(4), 358-371.
- Partel, V. (2019). AI-based weed detection in precision agriculture. *Computers and Electronics in Agriculture*, 166, 105008.
- Pierce, F. J., & Nowak, P. (1999). Aspects of precision agriculture. *Advances in Agronomy*, 67, 1-85.
- Rose, D. C., & Chilvers, J. (2018). Agriculture 4.0: Broadening responsible innovation in agriculture. *Frontiers in Sustainable Food Systems*, 2, 87.
- Rotz, S. (2019). The politics of digital agricultural technologies. *Sociologia Ruralis*, 59(2), 203-229.
- Rudin, C. (2019). Stop explaining black box machine learning models for high-stakes decisions. *Nature Machine Intelligence*, 1(5), 206-215.
- Schimmelpfennig, D. (2016). Farm profits and adoption of precision agriculture. *USDA Economic Research Service Report*.
- Shi, W., et al. (2019). Edge computing for IoT in agriculture. *IEEE Internet of Things Journal*, 6(3), 4230-4247.
- Sylvester, G. (2018). *E-agriculture in action: Drones for agriculture*. Food and Agriculture Organization of the United Nations.
- Sylvester, G. (2019). *E-agriculture in action: Big data for agriculture*. Food and Agriculture Organization of the United Nations.
- Wolfert, S. (2017). Big data in smart farming: A review. *Agricultural Systems*, 153, 69-80.
- Zhang, C., & Pierce, F. J. (2016). Autonomous agricultural vehicles: Concepts and applications. *Journal of Field Robotics*, 33(8), 1141-1157.