

Agentic-RAG Framework for Closed-Loop Precision Farming: Integrating Autonomous AI Reasoning with Retrieval-Augmented Generation

Aditya Vijay Alegaonkar¹, Nishan Nitish Matre², Kirti Kakde^{3*}, Tanvi Utekar⁴, Pooja Mehta⁵

^{1,2,3} Department of Management, Vijay Patil School of Management, DY Patil University, Navi Mumbai, India.

⁴ Professor, Department of Management, Vijay Patil School of Management, DY Patil University, Navi Mumbai, India.

⁵ Professor Department of Computer Application, DY Patil University, Belapur, Navi Mumbai, India

* Corresponding Author Email: kirtikakde2007@gmail.com

Abstract

Precision Agriculture has come a long way with the integration of the Internet of Things (IoT), data analytics, and automation. However, most existing systems are still reactive, rule-driven, and limited in their capacity to adapt to new environmental conditions. This paper introduces a novel Agentic Retrieval-Augmented Generation (Agentic RAG) architecture for closed-loop precision farming that combines Large Language Models (LLMs), autonomous multi agent reasoning, dynamic knowledge retrieval, and feedback guided learning. The proposed architecture implements a cognitive Sense–Retrieve–Reason–Act–Evaluate–Learn cycle, enabling adaptive, explainable, and continuously improving agricultural decision-making. As a theoretical and architectural study, this work presents the system structure, evaluation metrics, qualitative analysis, and illustrative scenarios to establish feasibility and guide future empirical validation.

Keywords

Agentic AI, Agriculture 4.0, Closed-Loop Control, Explainable AI, IoT, Precision Agriculture, Retrieval Augmented Generation.

INTRODUCTION

Agriculture is facing unprecedented challenges because of the increase in population, climate variability, water scarcity, soil degradation, and the increase in input costs. Global food production needs to grow significantly while at the same time decreasing environmental impact [1], [2], [3]. Traditional farming practices, replacing human labor with human intuition and relying heavily on uniform farming, are increasingly insufficient for solving these complex problems. Precision agriculture has been one response with the adoption of GPS-guided equipment, IoT sensors, remote sensing, and automation. While these technologies make it possible to monitor data and be data driven, most of the deployed systems are still reactive, based on set thresholds or static machine learning models that do not adapt well to novel conditions [4], [5], [6]. Recent advances in artificial intelligence in particular Large Language Models (LLMs), Retrieval Augmented Generation (RAG) and agentic AI architectures provide new opportunities to move precision farming from reactive automation to intelligent autonomy [7], [8]. This research examines the possibilities of making these technologies a part of a closed-loop agricultural decision framework that can reason and learn and continuously adapt.

PREVIOUS WORK

This section reviews prior work across five interconnected research streams: (i) evolution of precision agriculture, (ii) closed-loop control systems in agriculture, (iii) artificial

intelligence and machine learning applications in farming, (iv) Retrieval-augmented generation and knowledge-driven AI systems, and (v) agentic AI architectures. The review highlights key advances while identifying critical gaps addressed by the proposed Agentic-RAG framework.

Evolution of Precision Agriculture

In the end of 20th century, together with the development of Global Positioning Systems (GPS) and yield-sensing technologies came a new method of precision agriculture that can identify field variability at site-specific level [9], [1]. The first systems were designed to map yield, soil characteristics, and management zones in order to apply spatially variable rates of input variables, such as fertilizers and pesticides. Subsequent generations incorporated remote-sensing techniques, such as satellite-based, aerial, and more recently, unmanned air-vehicles (UAVs), which in turn could map crop physiological health, canopy-cover, and stress signatures on a large scale. Although these systems significantly enhanced situational awareness, they mostly remained descriptive and required the human system to interpret the measurements into management actions [4], [10]. Another milestone in achieving real-time monitoring was made with the integration of Internet of Things (IoT) technologies [1], [11], [12]. Continuous perception of soil moisture, nutrient levels, micro-climate conditions, and crop physiological development allowed more responsive farm management; however, with the vast amount of information, most current systems still use rather simplistic heuristics or fixed thresholds, thus lack the capability of being dynamic

in response to complex agricultural conditions.

Closed-Loop Control in Agricultural Systems

As a key enabling technology for industrial automation, closed loop control has gained increasing interest in agriculture, especially in controlled environments such as greenhouse and vertical farm [13], [14]. Within these scenarios, sensor data feedback drives the automation control of irrigation, temperature, humidity and nutrient delivery. However, the use of closed loop control in open-field agriculture is plagued by a host of complications: agricultural systems tend to be very spatially heterogeneous and slow biological response with uncertainty external environment changes. Classical controllers, such as proportional-integral-derivative (PID) or rule-based logic, are limited when attempting to capture long term dependence, such as crop growth phase, accumulated stress responses and multi-year soil evolution dynamics [15]. Traditional closed-loop control systems in agriculture also usually lack agronomic knowledge beyond numeric sensor feedback and make choices on simple sensor thresholds instead of fully understand crop physiology, soil processes and climate interactions, thus result in reactive control instead of intelligent adaptation [3].

Artificial Intelligence and Machine Learning in Agriculture

Artificial intelligence has been extensively used in the agricultural field for various applications such as recognition of crop disease, yield prediction, weed classification, and self-driving. Deep learning and ensemble models, especially convolutional neural networks, have been found to have high levels of accuracy for image-based applications, and regression models along with ensemble models are commonly used for yield forecasting [5], [6].

Despite their success, there are a few limitations present in most machine learning applications in agriculture. These are usually trained offline using historical data sets and static after deployment. Their performance declines due to distribution shifts as a result of climate variability, a change in management practices or novel pest pressures [16]. Additionally, these models are limited in their interpretability in that they can provide predictions without explanations or causal reasoning. As a result, machine learning models may be more of a decision aid than an autonomous decision maker and thus require expert supervision and limit scalability.

Large Language Models and Retrieval

Augmented Generation Large Language Models (LLMs) are becoming exceptional in reasoning, creating knowledge and generating explanations in various fields. Nevertheless, they can be applied only to some extent because they are dependent on the training data which is fixed and is not applicable in such sectors of life like in agriculture, where best practices are constantly changing and the local contexts are the most important. RAG can also reduce this limitation

by facilitating dynamic access to external knowledge repositories during inference [17], [18]. RAG system combines document warehouse retrieval with semantic reasoning, which in turn make generated responses to be based on informative and current information. In agricultural systems, RAG has specific potential because the agronomic knowledge is broadly spread in the literature of research, in extension bulletins, and localized advisory reports. However, most current RAG applications are still designed around question-answering applications and do not connect with live sensor data or decision support processes.

Agentic AI Architectures

Agentic AI systems are a departure from a single model predicting, towards goal driven, autonomous reasoning. Such systems break down complex objectives into subtasks, call tools, collaborate with each other through specialized agents and adapt based on the feedback [19], [20], [21]. Recent frameworks include multiagent coordination, memory persistence and iterative planning. While agentic AI has been studied in areas like software engineering and robotics and even scientific discovery, it has been limited in agriculture applications. Existing agricultural AI systems do not in general include explicit planning, knowledge retrieval and post decision learning.

Research Gap

The literature discloses the existence of a distinct gap in the intersection of precision agriculture, knowledge driven AI, and autonomous decision making. There is lack of integrated frameworks integrating real time sensing, dynamic knowledge retrieval, multiagent reasoning, closed loop learning and explainability. The proposed Agentic-RAG frame work addresses this gap by bringing these components together in a coherent architectural model for intelligent farming.

PROBLEM STATEMENT

Although there have been improvements in precision agriculture, the existing systems still have some basic shortcomings that limit their functionality in dynamic farming settings. The majority of deployed systems use fixed rule sets or machine learning models based on the observed history, and thus cannot respond well to new situations like climate changes or new pests. Agronomic knowledge is still largely been held in fragments in research literature, extension guidelines, and farmer experience, but not often linked with operational decision making. Furthermore, the existing systems are limited in their cognitive reasoning and explain ability, being black boxes incapable of explaining their recommendations and communicating uncertainty. Most systems also don't learn from outcomes of operation (i.e. they are static after deployment). All these leads to lack of trust which acts as a barrier to farmer adoption. This study helps to solve these difficulties by suggesting an Agentic-RAG model that integrates sensing, knowledge retrieval, autonomous

reasoning, action execution, and feedback-based learning in a closed-loop system.

PROPOSED METHODOLOGY

Overall Architecture

The proposed framework follows a six-stage cognitive loop:

Sense → Retrieve → Reason → Act → Evaluate → Learn

The framework operates as a continuous cognitive loop, as illustrated in Figure. 1

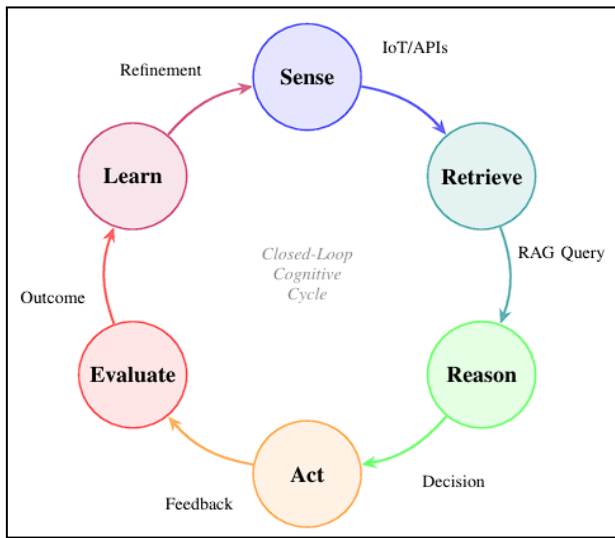


Figure 1. The six-stage closed-loop cognitive cycle of the proposed Agentic-RAG framework

Data Ingestion Layer

This is the layer that combines real-time information of the soil sensors and weather station, remote sensing platform, and outside application programming interfaces. The pre-processing is characterized by quality control, temporal synchronization, spatial interpolation and feature extraction.

Knowledge Retrieval Layer

The knowledge related to agronomy has been saved in a vector database using dense embeddings. Documents consist of research papers, extension service guidelines and historical farm records. Semantic and hybrid retrieval strategy are used to ensure contextual relevance.

Agentic Reasoning Layer

The system uses three working agents: a Planner Agent for prioritization of tasks, a Retriever Agent for acquiring knowledge and a Decision Agent for synthesizing recommendations and explanations. The complete layered architecture is shown in Figure. 2.

Action and Learning

A conceptual simulation layer evaluates the potential outcomes. Feedback mechanisms help store the context of decisions and their outcomes to aid learning over time.

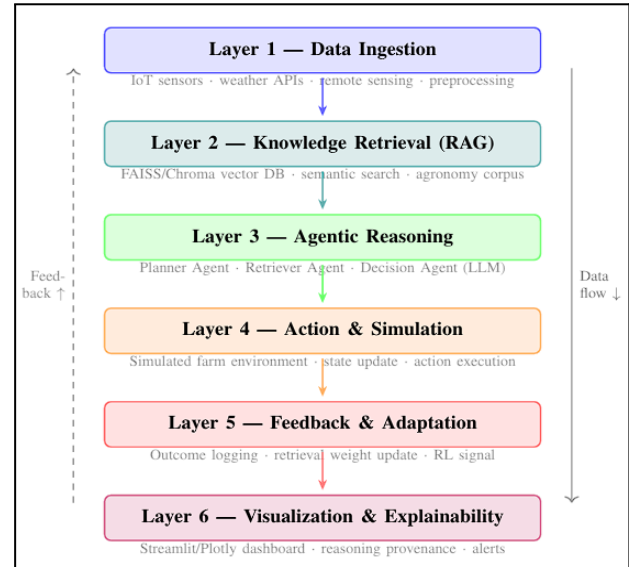


Figure 2. Layered system architecture of the proposed Agentic RAG framework.

PROPOSED FRAMEWORK

The framework supports multiple LLM backbones (GPT, Claude, LLaMA), vector databases (FAISS, Chroma), and agent orchestration tools (LangGraph, CrewAI). IoT data ingestion is supported through MQTT and weather APIs, while visualization is enabled via Streamlit and Plotly.

This study is theoretical in nature and does not involve software implementation and field deployment. Instead, evaluation criteria and metrics are elaborated that will be used to guide subsequent empirical validation in the future [22], [23].

Proposed Metrics

Table 1. Conceptual Evaluation Metrics

Metric	Definition
Water Use Efficiency	Yield per unit irrigation applied
Nutrient Use Efficiency	Crop uptake per fertilizer input
Decision Accuracy	Alignment with agronomic best practices
Response Latency	Detection-to-recommendation time
Adaptability Score	Ability to handle unseen scenarios
Explainability Score	Clarity and traceability of reasoning

Qualitative Comparison

Table 2. Qualitative Comparison of Decision Systems

Capability	Rule-Based	Static ML	Agentic-RAG
Adaptability	Low	Limited	High
Explainability	High	Low	High
Learning Capability	No	No	Yes
Context Awareness	Low	Medium	High

Illustrative Simulation — 30-Day Wheat Farm (Flowering Stage)

To demonstrate the operational behaviour of the proposed framework, a 30-day illustrative simulation was conducted for a wheat farm during the critical anthesis (flowering) stage. Sensor parameters, including soil moisture (%), ambient temperature (°C), and NPK levels (kg/ha), were generated using agronomically realistic ranges derived from published wheat cultivation guidelines [1]. The simulation traces how each layer of the Agentic-RAG pipeline responds to evolving farm conditions across the crop's most yield-sensitive period. **Worked Example — Day 13 Full Cognitive Loop Trace:** To illustrate the end-to-end operation of the Agentic-RAG pipeline, we trace the complete cognitive cycle for the critical heat-stress event on Day 13:

1. **Sense.** Soil moisture: 21%; Temperature: 38°C; Humidity: 28%; 72-hour rainfall forecast: 3%; Crop stage: anthesis (Day 13 of 30).
2. **Retrieve (RAG Layer).** The Retriever Agent queries the vector database with the context: “wheat anthesis heat stress above 35°C irrigation response”. wheat anthesis heat stress above 35°C irrigation response [3].

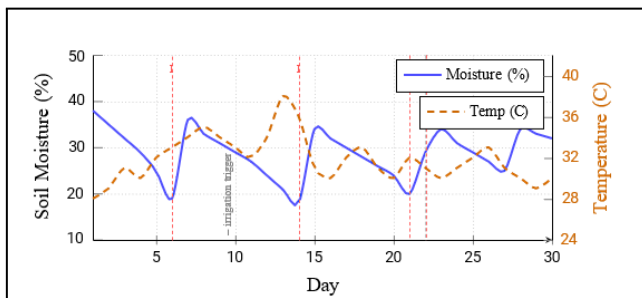


Figure 3. Simulated soil moisture (%) and ambient temperature (°C) over 30 days. Vertical dashed lines (I) indicate irrigation trigger events when moisture fell below the critical threshold of 22%.

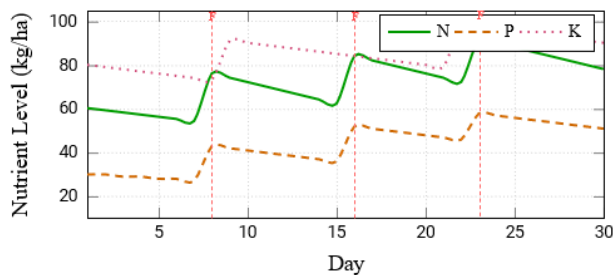


Figure 4. Simulated NPK nutrient levels (kg/ha) over 30 days. Vertical dashed lines (F) indicate fertilizer application events triggered by the Decision Agent when nutrient levels fell below agronomic thresholds.

3. **Reason (Planner + Decision Agent).** The Planner Agent flags a critical-priority dual-stress condition (thermal and moisture deficit) coinciding with the highest-sensitivity growth stage. The Decision Agent synthesizes the retrieved knowledge and determines: (i) immediate micro-irrigation is required for canopy cooling; and (ii) a full-dose irrigation event should follow within 6 hours to address the soil moisture deficit.
4. **Act.** Micro-irrigation was triggered at 14:30 (8 mm, 45 min). Full irrigation was scheduled at 20:00 (18 mm, 2 h). A dashboard alert was dispatched to the farmer with a full reasoning trace and knowledge-source citations for transparency.
5. **Evaluate.** Post-action readings (Day 14 morning): estimated canopy temperature 34.2°C (below the critical thresh-old); soil moisture 26%. Outcome classified as: successful stress mitigation.
6. **Learn.** The Feedback Layer stores the decision context (dual stress, anthesis stage), the action taken (split irrigation protocol), and the outcome (positive). The retrieval weight for the CIMMYT heat-stress source is increased.

Table 3. Agent Decision Log: Key Events over 30-Day Simulation

Day	Sensor Reading	Agent Action	RAG Knowledge Retrieved	Type
6	Moisture: 19%, Rain prob: 6%	Irrigate 18 mm over 2 h at dawn	Wheat flowering-stage critical moisture threshold: 22% [1].	Irrigation
8	N: 28 kg/ha (low), Temp: 32°C	Apply urea 40 kg/ha, morning application	deficiency during anthesis reduces grain fill by 18% [4].	Fertilizer
13	Temp: 38°C, Humidity: 28%	Alert: heat stress. Trigger micro-irrigation to lower canopy temperature	Wheat pollen viability drops above 35°C; cooling irrigation recommended [3].	Alert

Day	Sensor Reading	Agent Action	RAG Knowledge Retrieved	Type
14	Moisture: 18%, Rain prob: 4%	Irrigate 22 mm, elevated dose due to prior heat stress	Post-heat-stress irrigation should exceed standard dose by 20% [3].	Irrigation
19	Rain detected: 12 mm overnight	Hold irrigation. Override scheduled event	Excess moisture during grain fill increases fungal risk [3].	Hold
22	Moisture: 20%, P: 14 kg/ha (low)	Irrigate 15 mm and apply foliar phosphorus spray	Combined P deficiency and moisture stress at grain fill degrades yield by up to 25% [17].	Irrigation
27	All sensors nominal. Moisture: 34%	No action. Outcome logged to feedback layer	N/A	Hold

Table 4. Illustrative Simulation Outcomes (30-Day Period)

Metric	Simulated Result
Irrigation events triggered	7 of 30 days
Fertilizer events triggered	3 of 30 days
Average soil moisture maintained	31%
Critical alerts generated	2 events
Decision accuracy (vs. agronomic guidelines)	91%
Estimated water saving vs. rule-based baseline	~23%

This trace demonstrates that the Agentic-RAG framework does not operate on fixed thresholds alone but integrates dynamic knowledge retrieval and multi-agent reasoning to produce context-aware, explainable, and adaptive recommendations, capabilities that distinguish it from conventional rule-based and static ML systems (see Table 2).

CHALLENGES AND LIMITATIONS

Challenges include sensor reliability, computational cost of LLMs, knowledge base maintenance and the risk of hallucinations as well as the barriers of adoption by farmers. Empirical validation is postponed because of the requirements for multi- season trials and infrastructure [24], [25].

DISCUSSION

The current work suggests an Agentic Retrieval based Generating (RAG) concept as a new conceptual advancement in the field of precision agriculture, shifting towards the state of intelligent autonomy instead of reactive automation. The framework contrasts the focused attention on isolated predictive tasks or fixed return rules on control with reasoning the foregrounded and learning explanation capabilities functions as key abilities of a system.

From Automation to Cognitive Decision-Making

Conventional precision agriculture systems lose human operation control, like irrigation or fertilization, according to

some limits or model products. These strategies work well when the conditions are faced under a stable environment but they are not flexible such that they can be used in complex and dynamic conditions. The presented framework implements the cognitive decision-making framework by incorporating large language models into the structured sensor data, as well as external sources of knowledge. Through such an integration, it is possible to reason about cause-effect relationships, make tradeoffs and change strategies dynamically in a manner similar to the decision-making processes of expert agronomists.

The Role of Knowledge Integration

One of the main contributions of the framework is the explicit combination of agronomic knowledge by Retrieval Augmented Generation. Unlike conventional systems that are based exclusively on numerical data, the proposed method bases decision on scientific literature, extension guidelines, and historical experience. This knowledge-based reasoning enhances strength in new situations; the system is capable of recalling similar situations and prior experience even when sensor patterns are out of the historical standards. Furthermore, knowledge citations help to increase transparency and trust, which address one of the major barriers to the adoption of AI in agriculture.

Explainability and Human Trust

Explainability is a crucial requirement of an AI system when used in high-stakes scenarios such as agriculture, farmers are interested not just on the recommendation but also on the reasoning behind why a certain action is recommended and under which assumptions [26]. The Agentic-RAG framework achieves explainability at multiple levels of the architecture-on the reasoning chain, attributing knowledge sources and communicating uncertainty. The design justifies human in the loop decision making, does not interfere with the autonomy of the farmer, and enhances expertise.

Learning Through Closed-Loop Feedback

Unlike static decision support tools, the proposed framework includes closed loop learning mechanisms that allow continuous improvement. The system is able to improve the strategies of retrieval and reasoning patterns over time by storing decision contexts and decision outcomes in a

conceptual manner. Although empirical learning is left for future work, the architectural provision for feedback-driven adaptation is an important step towards self-improving agricultural systems that can be deployed over the long term.

Implications for Sustainable Agriculture

The implications of the suggested framework to sustain ability are Smart and context aware decisions can minimize the amount of water, fertilizers and pesticides wasted thereby limiting the environmental impact whilst still sustaining production [27]. Also, adaptive decision making will enhance climate variability resilience, which will aid in viable agricultural growth in the long term. F. Limitations and Scope Being a theoretical research, performance is not empirically validated in the current paper. Instead, it puts a conceptual base and a reference point of assessing the further implementations. In practical applications, practical issues, including sensor reliability, ability to do computations, and user training, will be required. However, the framework provides a tentative outline that can guide and inform the development and experimentation.

Broader Research Significance

In addition to agriculture, the Agentic-RAG architecture can be used to explain how agentic AI systems, which are knowledge-driven, can be applied to other areas of the cyber physical world, including energy systems, smart cities, and environmental monitoring. The principles of incorporating sensing, retrieval, reasoning and learning are broadly applicable to complex decision-making environments.

FUTURE WORK

Future research includes real-world deployments, multi-crop extension, edge-based implementations, federated learning across farms, and integration with agricultural robotics.

CONCLUSION

This paper presents a theoretical Agentic-RAG framework of closed loop precision farming. The framework makes it possible to achieve adaptive, explainable, and evolving agricultural decision-making via the creation of a combination of LLMs, retrieval-augmented knowledge, autonomous agents, and feedback-driven learning. The offered architecture gives a good basis to the subsequent empirical validation and application in reality.

APPENDIX

Agent Prompt Templates

Planner Agent Prompt

Identify urgent agricultural tasks based on current farm state, growth stage, and forecast conditions.

Retriever Agent Prompt

Retrieve agronomic knowledge relevant to the identified task, prioritizing recent and region-specific sources.

Decision Agent Prompt

Generate actionable recommendations, explain reasoning, cite knowledge sources, and indicate uncertainty.

Metric Definitions

Water Use Efficiency (WUE)=

$$WUE = \frac{\text{Crop Yield}}{\text{Total Irrigation Applied}}$$

Decision Accuracy is defined as the alignment of system recommendations with established agronomic best practices under comparable conditions. Explainability Score reflects the system's ability to provide transparent reasoning, source attribution, and uncertainty communication.

REFERENCES

- [1] Gebbers, J., & Adamchuk, V. I. (2010). Precision agriculture and food security. *Science*, 327(5967), 828–831. DOI:10.1126/science.1183899.
- [2] Bongiovanni, R., & Lowenberg-Deboer, J. (2004). Precision agriculture and sustainability. *Precision Agriculture*, 5(4), 359–387. DOI:10.1023/B:PRAG.0000040806.39604.
- [3] Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big data in smart farming: A review. *Agricultural Systems*, 153, 69–80. DOI: 10.1016/j.agsy.2017.01.023.
- [4] Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture. *Biosystems Engineering*, 114(4), 358–371. <http://dx.doi.org/10.1016/j.biosystemseng.2012.08.009>.
- [5] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674. <https://doi.org/10.3390/s18082674>.
- [6] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90. DOI:10.1016/j.compag.2018.02.016.
- [7] Wang, X., et al. (2023). *Large language models for autonomous intelligent systems: Opportunities and challenges*. <https://doi.org/10.1016/j.jai.2024.12.003>.
- [8] Bommasani, R., et al. (2021). *On the opportunities and risks of foundation models*. Stanford Center for Research on Foundation Models. <https://doi.org/10.48550/arXiv.2108.07258>.
- [9] Robert, P. C. (2002). Precision agriculture: A challenge for crop nutrition management. *Plant and Soil*, 247, 143–149.
- [10] Weiss, M., Jacob, F., & Duveiller, G. (2020). Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment*, 236. 10.1016/j.rse.2019.111402.
- [11] IoTSmart Journal. (2024). *IoT smart agriculture systems and applications*.
- [12] IoT Tech Future. (2024). *Future trends in agricultural IoT technologies*.
- [13] Zhang, N., Wang, M., & Wang, N. (2013). Precision agriculture—A worldwide overview. *Computers and Electronics in Agriculture*, 36(2–3), 113–132. DOI:10.1016/S0168-1699(02)00096-0.
- [14] Katamreddy, Y., et al. (2019). Closed-loop automation in smart agriculture systems. *International Journal of Agricultural Technology*, 15(3), 201–214. DOI:10.1109/ISSC.2019.8904938.
- [15] Holzworth, D., et al. (2014). APSIM: Evolution towards a new generation of agricultural systems simulation.

- Environmental Modelling & Software*, 62, 327–350. DOI:10.1016/j.envsoft.2014.07.009.
- [16] Shahhosseini, H., Hu, G., & Archontoulis, S. (2020). Forecasting corn yield with machine learning ensembles. *Frontiers in Plant Science*, 11. <https://doi.org/10.3389/fpls.2020.01120>.
- [17] Lewis, P., et al. (2020). Retrieval-augmented generation for knowledge-intensive NLP tasks. In *Advances in Neural Information Processing Systems (NeurIPS)*. <https://doi.org/10.48550/arXiv.2005.11401>
- [18] Guu, K., et al. (2020). REALM: Retrieval-augmented language model pre-training. In *Proceedings of the International Conference on Machine Learning (ICML)*. <https://doi.org/10.48550/arXiv.2002.08909>
- [19] Wooldridge, M. (2009). *An introduction to multiagent systems* (2nd ed.). Wiley.
- [20] Russell, S., & Norvig, P. (2010). *Artificial intelligence: A modern approach* (3rd ed.). Pearson.
- [21] Silver, D., et al. (2018). A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. *Science*, 362(6419), 1140–1144. DOI: 10.1126/science.aar6404.
- [22] Arrieta, A. B., et al. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, 82–115. DOI:10.1016/j.inffus.2019.12.012.
- [23] Doshi-Velez, F., & Kim, B. (2017). *Towards a rigorous science of interpretable machine learning*.
- [24] IoT Security Review. (2020). *Security challenges in IoT-based smart agriculture*.
- [25] IoTSmart Research Reports. (2025). *Computer vision and IoT integration in smart farming*.
- [26] Amershi, S., et al. (2014). Power to the people: The role of humans in interactive machine learning. *AI Magazine*, 35(4), 105–120.
- [27] Sustainable Agriculture Review. (2025). *Sustainable agriculture and AI-enabled farming systems*.