

Agentic AI with Large Language Models for Precision Farming: Advancing Sustainable Resource Optimization in Smart Agritech

Gautam Kumar¹, Ishwari Singh Rajput², Gulbir Singh³,

Anuj Kumar⁴, Sonam Tyagi⁵

^{1,4}Assistant Professor School of Computing, Graphic Era Hill University, Haldwani Campus, Nainital, Uttarakhand-263139, India

^{2,3}Assistant Professor, Department of Computer Science & Engineering, Graphic Era Hill University, Haldwani Campus, Nainital, Uttarakhand-263139, India

⁵Electronics & Communication Engineering, ABES Engineering College, Ghaziabad, U.P., India

*Corresponding Author Email: Gulbir.Rkgit@Gmail.Com



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Abstract

Precision Agriculture tries to ensure maximum use of resources to get maximum production of crops with minimum use of water, fertilizers, and agrochemicals under highly dynamic climatic and soil conditions. Most existing precision farming approaches, however, depend on static rule-like logic or are single-task machine learning models, which possess limited contextual reasoning capabilities, multi-objective coordination, and adaptive decision making capabilities. In this paper, present a new Agentic Artificial Intelligence approach where a Large Language Model (LLM) acts as a high-level cognitive controller for autonomous and sustainable farm management. The proposed solution processes multimodal data such as soil and climate sensor data, weather predictions and crop growth stages information, along with historical farm operations and agronomic knowledge to recommend coordinated irrigation, fertilization and crop protection decisions. Instead of traditional advisory or threshold-based methods, the framework uses closed-loop agentic control where the candidate decisions produced by the LLM are tested for agronomic, environmental, and resource feasibility then carried out via IoT-based actuators. Adaptive refinement of policies and context-aware optimization of policies is made over time, enabled by continuous field monitoring. It focuses on explainable autonomy through a combination of natural language reasoning and machine-readable action commands, achieved by reducer farmer decision burden with transparency and safety. The results suggest the potential to substantially enhance water- and nutrient-use efficiency with less loss in crop yield using the proposed method. This study builds a foundation for the design of multi-scale, interpretable and autonomous precision agriculture systems with Agentic AI, hence it makes a stride toward realizing sustainable smart agritech.

Keywords: Precision agriculture; Agentic AI; Large Language Models; Sustainable resource optimization; IoT-based farm automation

1. Introduction

Precision agriculture has emerged as a viable tool to address the concerns of food security, resource limitations, and environmental protection, especially for developing countries like India, which have scattered landholdings, uncertain monsoons, and high agro-climatic variations. It has been found that sensor-based monitoring applications can increase productivity and reduce the use of fertilizers, pesticides, and water [1]. Meanwhile, due to the swift proliferation of cheap IoT sensors, UAVs, weather APIs, and satellite images, farms have transformed into cyber-physical systems producing voluminous and heterogeneous data streams of soil moisture, canopy indices, microclimate data, and equipment telemetry, which call for intelligent analytics [2]. With the remarkable development of machine/deep learning, AI, and ML, and the myriad of applications, ranging from detection of diseases to variable-rate fertilization, scheduling of irrigation and prediction of yield, much of these systems still behaves like isolated prediction tools, that lack a certain degree of contextual reasoning, and certainly do not integrated decisions over irrigation, nutrients and pest control. Multi-agent systems provide automation yet are still limited by static rules and lack cognition and multi-step planning. At the same time, large language models (LLMs) are promising in the generation and extraction of agronomic knowledge, advisory systems, and multimodal reasoning, but current use cases are limited to information retrieval or text-based answering [3]. This highlights a definitive gap in research. To this end, we propose an agentic AI framework in which an LLM serves as a cognitive controller that orchestrates the integration of multimodal sensor data, predictive models, and agronomic knowledge to generate coordinated, context-aware decisions for irrigation, fertilization, and pest management. Such a system is designed to promote a more sustainable, less resource-wasteful, and adaptable, explainable, and autonomous management of the farm [4].

Evolution of Precision Agriculture Intelligence Toward Agentic AI

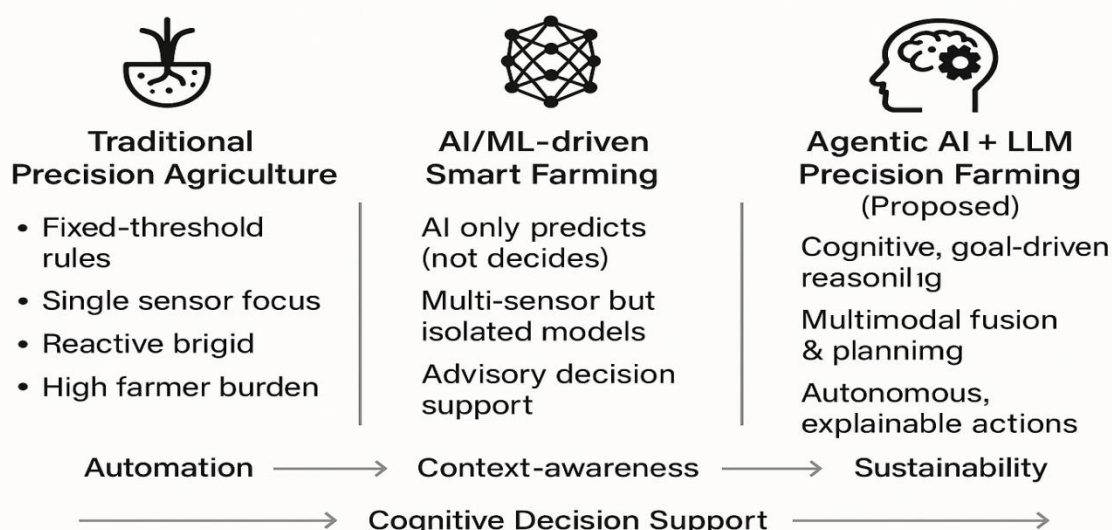


Figure 1: Evolution of Precision Agriculture Intelligence toward Agentic AI

Figure 1 shows that precision agriculture is evolving from rule-based methods to AI-dominated models to agentic AI systems that can reason, plan, and act independently. It implies a transition from rudimentary mechanization to smart, sustainable, and explicable farm assistance [5].

1.1 Motivation

Contemporary agriculture is challenged with water shortages, uncertain climate, and inefficient use due to rule-based and rigid decision-making. Current tools for precision farming are based on predetermined thresholds and they require continuous human intervention, which adds to the workload of farmers. Newly developed Large Language Models allow reasoning-aware-of-context using sensor, weather, and ag knowledge. Meta seeks to boost food security. This provides the rationale to pursue an autonomous, adaptive and sustainable decision-making system for precision agriculture.

1.2 Objectives

This work proposes an Agentic AI framework based on a Large Language model for intelligent farming decision-making. The framework is designed to control water, fertilizer, and pesticide use in a context-aware and data driven manner. In addition, it strives to minimize farmers 'workload by allowing precision agriculture systems to be autonomous, adaptive and explainable.

1.3 Problem Statement

Systems are either based on fixed rules or on standalone machine learning methods, which make them incompatible with dynamic weather, soil and crop conditions. As a result, farmers often over-apply water, fertilizers and chemicals which drives up costs and impacts the environment. However, there is no doubt that farmers would benefit from the availability of such a system, since it would make farming resource optimization compatible with crop yield and sustainability.

2. Review of Literature

2.1 Precision Agriculture and Sustainable Resource Use

The concept of precision agriculture (PA) has experienced a dramatic metamorphosis in the last ten years evolving out of the field mapping using GPS to a data-intensive agronomic practice. Recent reviews highlight that PA systems, which combine remote sensing, GIS, soil-plant monitoring, and variable-rate technologies, allow optimising inputs on the site and save resources significantly [3][5]. The literature has regularly indicated improvements in the efficiency of fertiliser use, lessening pesticide load, and larger water productivity in cases of a PA interventions being enforced in smallholder farming systems and commercial farming systems alike, specifically in climate-vulgar agroecosystems. The issue of water management is still an important theme of PA scholarship. [10] present evidence that precision irrigation plans that are informed by soil moisture sensors, evapotranspiration simulation, and the monitoring of microclimate can have quantifiable advantages in terms of water use efficiency and crop yield. Similar results reported [16] show that machine learning-based data-driven irrigation scheduling enhances the precision of water application and lowers the operational expenses. Meta-analyses of nutrient and chemical control also indicate that variable-rate fertilisation leads to nutrient conservation and better soil sustainability than blanket application [1][4]. Altogether, these results place PA as a viable way of sustainable input governance.

2.2 IoT and Cyber-Physical Systems in Agriculture

In line with the innovation of agronomics, cyber-physical systems have transformed the digitalized farming infrastructures. The research on smart sensors and IoT platforms records a tremendous increase in the applications of soil electrical conductivity sensors, multispectral imaging, in-field weather node, and UAV-based mapping systems [16]. These technologies have made it possible to

monitor the conditions of crops and soil continuously, which makes it possible to make adjustments to irrigation, providing nutrients and destroying pests in real time. Nevertheless, significant challenges are also mentioned in the literature: the piecemeal nature of data standards, the heterogeneity of the sensing technology, and the lack of interoperability between different platforms [17]. The combination of sensor information with powerful analytics is still a major constraint, which highlights the necessity of smart systems that would be able to process multimodal data and convert raw measurements into agronomic decisions.

2.3 AI and Machine Learning in Precision Irrigation, Fertilization, and Crop Protection

The methods of machine learning (ML) have become an inseparable part of contemporary research in the field of PA. [1] demonstrate that the ML models random forests, neural networks, and support vectors machines are effective in eternally transforming environmental and soil data into irrigation decisions, which beats the customary rule-based systems. Later developments built upon this work by the application of model predictive control and, thereby, allow more responsive irrigation recommendations during varying climatic conditions [10] The same can be seen with the ML uses in fertiliser management. Spatially explicit soil and crop data have revealed site-specific nutrient models that decrease the rate of nitrogen application but remain stable in yield [11] [12]. Convolutional neural networks have become the dominant method in crop protection with disease identification due to deep learning showing a substantial enhancement in the detection of leaf and canopy diseases at an early stage [13] [14]. Although these successes have been attained, most ML applications are modular and single-purpose-based ones, or those focused on prediction and not holistic farm-level decisions.

2.4 Multi-Agent Systems and Distributed Intelligence in Smart Farming

Multi-agent systems (MAS) have been extensively studied to resolve problems of system-level coordination in smart agriculture. MAS designs present farms as distributed systems, in which autonomous agents (sensors, actuators, or decision modules) can collaborate to complete tasks, such as irrigation scheduling, greenhouse climate regulation and coordination of machinery (Obeidat et al., 2024). Applications to platforms like JADE have been published with various advantages being reported like modularity, scalability and better fault tolerance. What has been said notwithstanding, MAS in agriculture tend to be based on fixed rule bases, fixed workflows, or specialized optimisation routines. Recent reviews note that the agents are capable of coordination but generally do not have the mental capacity to interpret and modify their strategies according to the changing environmental conditions, based on the complex agronomic goals [15]. This is a drawback that prevents MAS to enable higher-level decision-making capabilities like multi-objective optimization, contextual planning or natural language engagement with human operators.

2.5 Large Language Models and Multimodal AI in Agriculture

Recent advances in the form of large language models (LLMs) and vision-language models (LVLMs) have become promising to allow more flexible and generalizable intelligence to be applied in agriculture. There is prior research exploring the use of LLMs as knowledge synthesis engines, agronomic supporting policies, and advisory system improvements [18]. AgroLLM and AgriGPT with the help of LLM, show how retrieval-augmented reasoning, domain-grounded knowledge and tool integration can be valuable to structure agronomic evidence [21]. Further research combines the use of LLM with organized bodies of knowledge. It is demonstrated [19] that the integration of an LLM and an agricultural knowledge graph enhances the detection of plant diseases because, in this way, the model can correlate the symptoms with the contextual data related to the biological and

environmental factors. Similar progress of LVLMs indicates their capability to conduct multimodal reasoning between images, text, and sensor-generated descriptors, and is applied in tasks including disease detection, crop grading, and interpreting field conditions [20] Regardless of these advancements, the literature shows that the primary use of the LLM is advisory or analytical. They have not yet been studied as agentic controllers, who are capable of autonomous task breakdown, orchestrated use of tools, interactive planning, and performance of field missions. Table 1: Summary of Related Works Supporting

Table 1: Summary of Related Works Supporting AI-Driven Precision Farming and Smart Agritech

| Reference | Key Contribution | Relation to Title Components |
|--------------------------------|--|---|
| Liu et al., 2023,[21] | Developed a high-precision plant disease detection method using dynamic pruning for low-computing platforms. | AI-Driven, Precision Farming, Smart Agritech |
| Mana et al., 2024, [22] | Surveyed sustainable AI applications in agricultural production. | Sustainable Resource Optimization, Agentic AI, Smart Agritech |
| Khalid et al., 2023, [23] | Used CNNs for real-time plant health monitoring. | AI-Driven, Precision Farming |
| Bouguettaya et al., 2023, [24] | Surveyed deep learning for crop disease detection using UAVs. | Smart Agritech, AI-Driven |
| Santhosh et al., 2023, [25] | Introduced "Agni", a robot for plant disease detection. | Autonomous Systems, Precision Farming |

Agentic AI vs. Traditional Automation

- Traditional automation follows strict rule-based workflows and predefined sequences.
- Agentic AI can assess complex situations, adapt dynamically, and modify its approach based on real-time inputs.

2.6 Identified Research Gap

Three recurring constraints can be seen in the reviewed areas:

1. Precision agriculture AI systems have not yet become multi-purpose and multi-moded, as they are still limited to single-purpose applications, with limited scope to combine the multiple data feeds they receive with decision-making that is responsive to changing agronomic conditions.
2. Multi-agent systems are cognitively shallow, offering organizational structure, and they are also strongly dependent on predetermined rules and fixed optimization.
3. The use of LLMs as high-level, agentic decision-makers with the capability to combine analytics, understand the context and autonomously plan irrigation, fertilization, and crop protection is not realized yet.

3. Problem Formulation

Modern precision farming aims to maximize production while also minimizing the depletion of critical resources, such as water, fertilizer, and agricultural chemicals. However, most current farming

decision systems are based on either fixed thresholds, temporal inputs, or farmer judgment, which limit their capacity to adapt to changes in time and geography. In this section, the autonomous resource optimization problem will be defined, and the methodological gaps that serve to motivate this approach will be discussed.

3.1 Problem Definition

Modern precision agriculture is still based on fixed rules and decisions received from a single sensor; these rules cannot react in the execution phase to changes in weather, soil, and crop conditions. This results in unwarranted over-application of water, fertilizers and chemicals. Hence, there is a demand for smart context aware system which can analyze data and suggest/determine optimum watering, fertilizing and crop protection.

Suppose there is a farm to be partitioned into Z number management zones. For each and every zone $z \in Z$ and decision epoch t :

State and action definitions

- $S_t(z)$ = state vector (soil moisture, nutrients, weather forecast, crop stage, plant-health indicators, etc.)
- $A_t(z)$ = action vector (irrigation rate, fertilization dose, pest-control actuation)
- $C(A_t(z))$ = resource consumption cost function
- $Y(S_t(z), A_t(z))$ = projected yield / plant-health outcome

Reward function

$$R_t = f(Y(S_t(z), A_t(z))) - C(A_t(z))$$

Sequential decision-making formulation

$$\pi^* = \arg \max_{\pi} E[\sum_{t=0}^{T} (\gamma^t * R_t(S_t, A_t))]$$

Constraints

1. Crop health:
 $Y(S_t, A_t) \geq Y_{\min}$
2. Water use constraint:
 $\sum_t C_{\text{water}}(A_t) \leq W_{\text{budget}}$
3. Nutrient/environment constraint:
 $C_{\text{fert}}(A_t) \leq F_{\text{env_safe}}$

Policy definition

$$\pi : S_t \rightarrow A_t$$

3.2 Optimization Goals

The proposed intelligent system must solve a multi-objective resource optimization problem:

$\min_A \{ \text{Water use; Fertilizer use; Pesticide use} \}$

while maximizing yield and sustainability indicators

Primary goals:

Table 2: Evaluating Precision Agriculture Efficiency

| Objective Class | Measurable Indicators |
|----------------------|--|
| Water-efficiency | Reduced irrigation events; ET-aware scheduling |
| Nutrient-efficiency | Contextual fertilization per growth stage |
| Sustainability | Lower runoff/leaching; preserved soil health |
| Economic benefits | Input-cost reduction; yield protection |
| Cognitive automation | Reduced farmer decision load |

The table 2, lists objectives for precision agriculture and the associated indicators to quantify the achievement of these objectives. It illustrates how water and nutrients may be used more efficiently, sustainability enhanced, and economic benefits gained, and how the farmer’s decision-making load can be alleviated by cognitive automation. Thus, the core challenge is continuous, context-aware control under uncertainty.

3.3 Limitations of Existing Approaches

Table 3: Limitations of Current Precision Agriculture Practices Across Key Categories

| Category | Current Practice | Key Limitations |
|---------------------|-------------------------------|--|
| Decision foundation | Fixed threshold rules | Ignores future weather, growth stage, visual condition |
| Data usage | Single-sensor logic | Poor fusion of multimodal data (IoT + imagery + climate + knowledge) |
| Autonomy level | Advisory tools | Human still required to finalize decisions |
| Adaptation | Non-adaptive or manual tuning | Cannot learn from outcomes or environmental shifts |
| Objective structure | Yield-only focus | Sustainability metrics rarely optimized jointly |

The table 3 identifies the discrepancies among existing precision agriculture methods. It reveals that today's systems are based on fixed rules with a limited sensor data input and are advisory level, and therefore they cannot adapt, learn or optimize in terms of sustainability and yield.

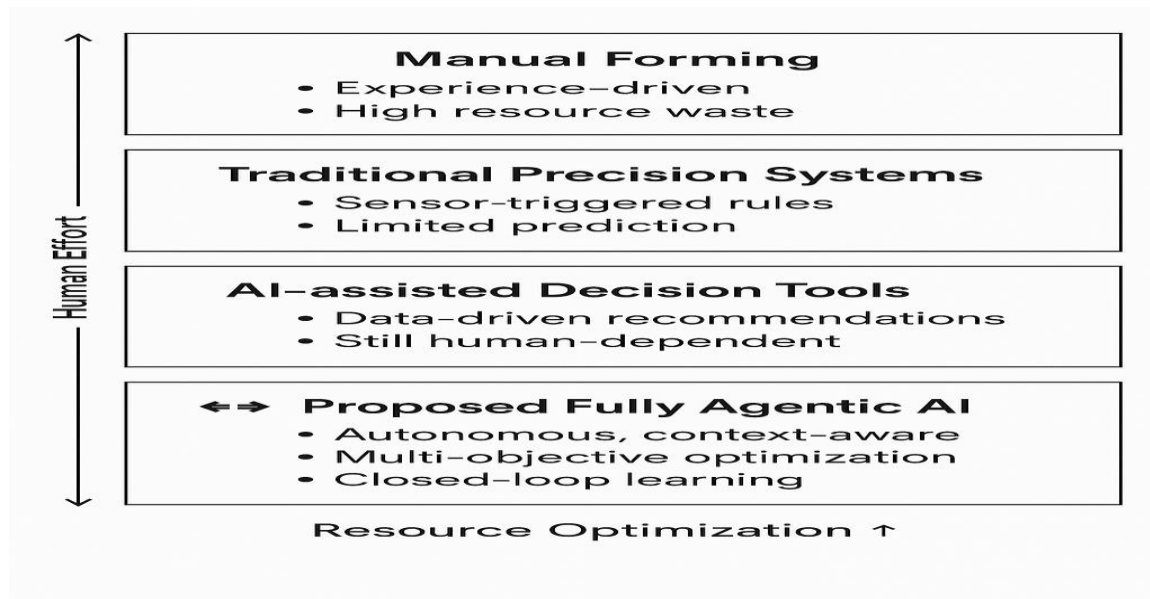


Figure 2: Maturity Gap in Autonomous Decision Systems

Figure 2 clearly illustrates the gap that exists today in fully autonomous systems, demonstrating that even the best solutions today are still heavily reliant on static rules with no advanced reasoning, ability to adapt, or holistic decision making. These three figures collectively convey why an enhanced intelligence, context-awareness, and agentic AI framework is essential for the realization of sustainable and fully optimized precision agriculture.

4. Proposed Agentic AI Framework

This part of the paper describes the suggested Agentic AI architecture, making use of a Large Language Model (LLM) as the main logic processing tool for sustainable precision farming. The framework follows the architecture of layers with multimodal sensing, structured state representation, reasoning with the help of the LLM, agentic decision control, and closed-loop actuation and feedback.

4.1 Layered Architecture

It is a system that will be a farm-level autonomous agent, which constantly communicates with the environment. The high-level architecture is represented in figure 4.

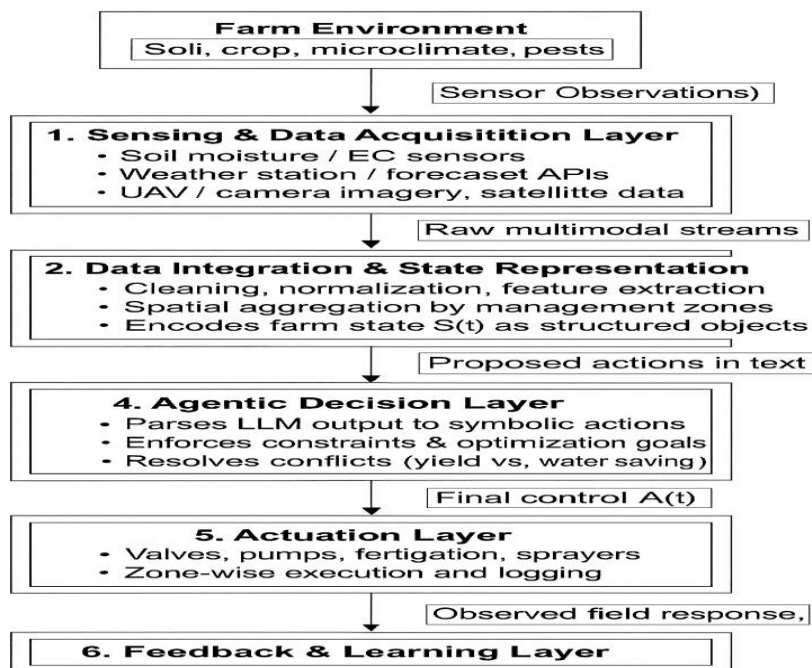


Figure 3. Layered Agentic AI Architecture for Precision Farming

Figure 3 shows an end-to-end autonomous farming management architecture from sensing and data integration through decision-making to actuation. It supports the cycle of continuous learning by connecting observations of the environment, AI-based decisions, and feedback from the field.

The framework:

- Enhances decision context with non-uniform sensor thresholds through merging non-homogeneous data and textual agronomic expertise.
- Couples what to do with how to execute, so that it is safe to post-process the results of LLM models and match them to hard resource limits.
- Allows seasonal qualitative learning by adapting promptly, learning better rules, and being constrained by updated constraints, with or without large labeled datasets.
- Gives human-understandable reasons whilst retaining the ability to operate in full autonomy as desired.

4.2 LLM Integration and Knowledge Modeling

The LLM is not applied as a black box. Rather, it is incorporated within a tool-augmented agent which communicates with structured information, encoded domain information, and optimization constraints

4.2.1 Input Representation and Prompt Design

The data integration layer creates a structured state representation, such as:

- Zone-level depth profile and soil moisture.
- Weather prediction (precipitation, ET 0, temperature)
- Type of crop, stage of growth of a crop, date of sowing.
- Past activities and new yield or biomass measures. This state $S(t)$ is flattened into a succinct JSON-like data and injected into a prompt template: System prompt: stipulates high-level

objectives, agronomic standards and hard safety regulations (e.g., do not waterlog, do not exceed nutrient limit).

- Context prompt: offers crop-specific recommendations, local laws, and sustainability goals.
- State prompt: codifies the current farm state $S(t)$ and decisions made in the past.

It is therefore dictated that the LLM should act as a virtual agronomist whose performance should specifically state the recommended actions, reasons, and awareness of the uncertainty.

4.2.2 Output Structure and Post-Processing

The LLM is limited in its reply to a hybrid form:

- A brief natural language definition of human interpretability.
- An action specification block (e.g., JSON), readable by a machine: start/stop times and per-zone rates of irrigation, type of fertilizer, application rate, and products and triggers of pest control.

This block is then distributed to the agentic decision layer, which evaluates it against:

- budgets of resources (water, fertilizer),
- agronomic limitations (max/min levels),
- optimization preferences previously (e.g., water-saving priority during drought years).

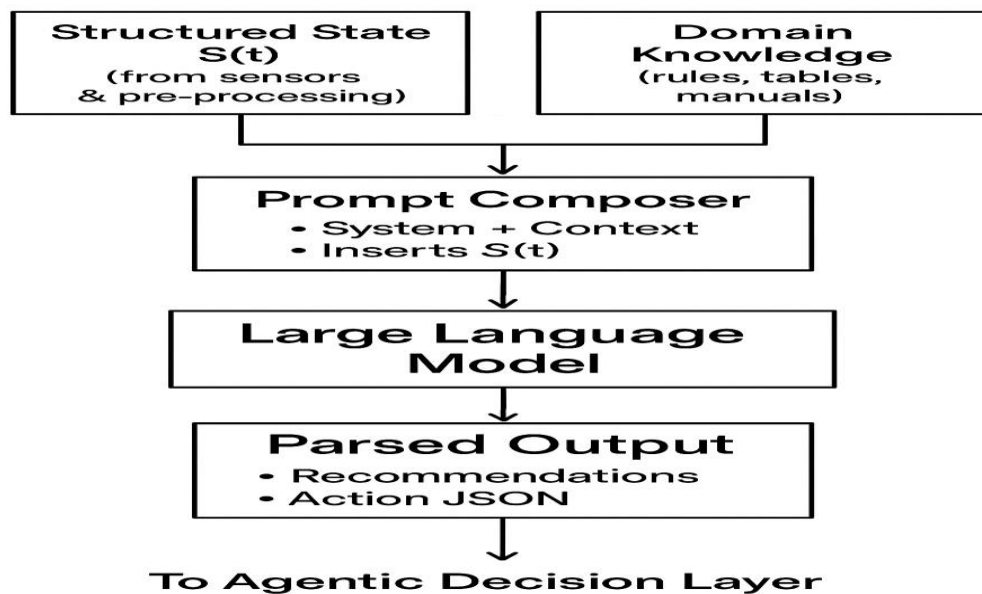


Figure 4. LLM Integration in the Agent Loop

Figure 4, The entity state derived from raw sensor data, and domain knowledge are instrumented through a prompt composer to produce context rich inputs for a LLM. The LLM generates.

4.3 Agent Workflow and Decision Cycle

The Agent Workflow and Decision Cycle explains how the decision is carried out by agents and agents as part of the workflow. The Agentic AI is a repetitive decision-making mechanism that

bridges the gap between observation, reasoning, and actuation.

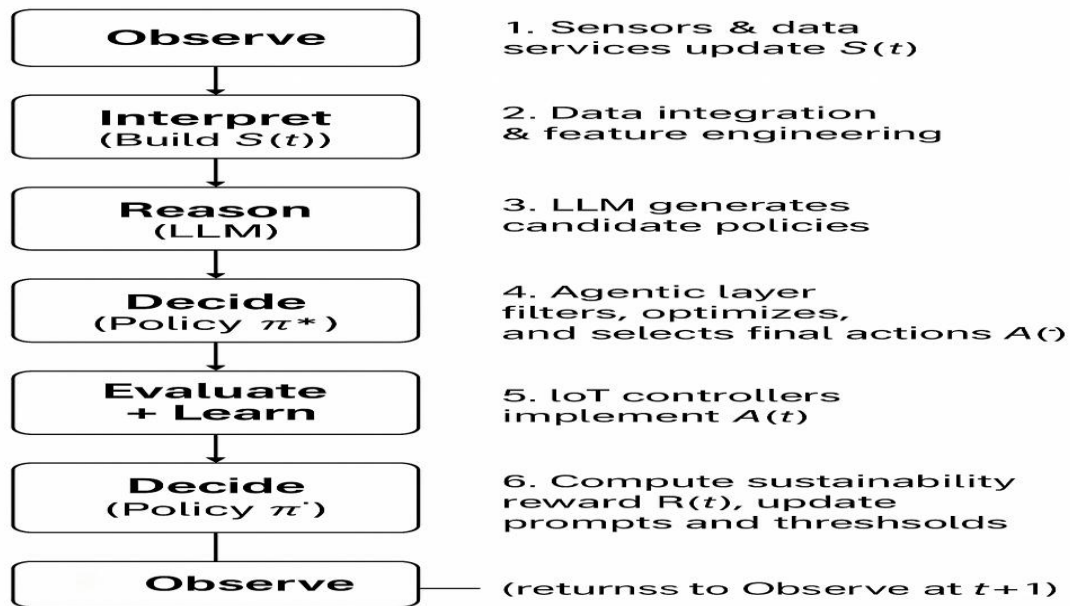


Figure 5. Agentic Decision Cycle

Figure 5, presents a closed-loop autonomous farming cycle where the system observes, interprets, reasons with an LLM, decides optimal actions, and then evaluates outcomes. Feedback from execution updates policies and thresholds, enabling continuous learning across time steps.

4.4 System Components and Roles

Table 1 summarizes the core components, their responsibilities, and interactions.

Table 4. Core Components of the Agentic AI Framework

| Component | Role in the Framework | Inputs | Outputs |
|----------------------------------|---|---|--------------------------------------|
| Sensing & Data Acquisition | Continuous monitoring of field and climate | Physical environment | Raw sensor streams |
| Data Integration & State Builder | Cleans, aggregates, and encodes farm state StS_tSt | Raw streams, historical logs | Structured state representation |
| Knowledge Base / Policy Library | Stores agronomic rules, local regulations, and crop models | Expert input, literature | Constraints and priors for LLM/agent |
| LLM Reasoning Engine | Generates context-aware recommendations and candidate actions | Prompt ($S_t +$ knowledge + goals) | Explanations, candidate action sets |
| Agentic Decision Controller | Validates, optimizes, and converts LLM suggestions into actionable commands | Candidate actions, constraints, budgets | Final actions AtA_tAt per zone |

| | | | |
|-------------------------------|---|-----------------------------|--------------------------------------|
| Actuation & Logging Subsystem | Executes control signals on physical devices and records them | Action commands AtA_tAt | Executed action logs |
| Feedback & Learning Module | Compares outcomes vs. targets, adjusts prompts, thresholds, and possibly agent policies over time | Sensor feedback, logs, KPIs | Updated parameters, reward estimates |

The table 4, illustrates the interactions among components in an agentic AI-supported precision farming system. It illustrates the processes of sensing the environment, data integration, knowledge and LLM reasoning to produce recommendations and finally to taking real actions. In the end, the system is capable of learning from feedback, enabling the model to enhance decisions as time progresses.

4.5 End-to-End Process Flow

The elements above can be summarized in a compact end-to-end flow, suitable as a master figure for the methodology section.

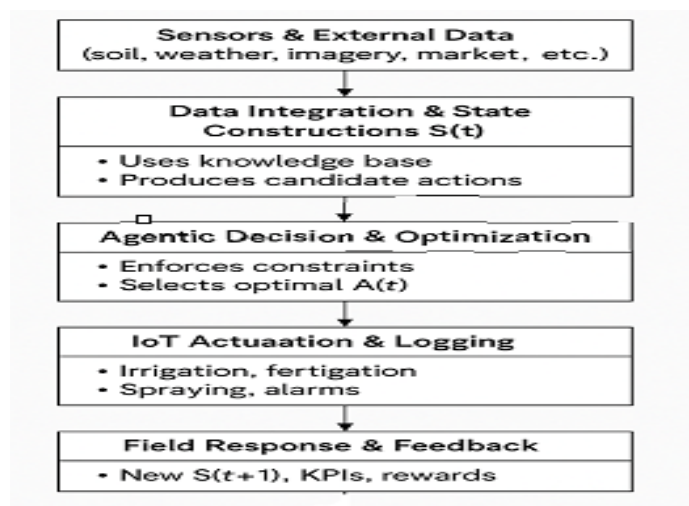


Figure 6. End-to-End Agentic AI Pipeline for Precision Farming

Figure 6, describes an end-to-end working of an Autonomous Farm, from multi-source sensor data, state construction, to optimization, IoT actuation, and real-time field feedback. This is a feedback loop in which each iteration’s updated farm state supports better decisions.

4.7 Prototype Implementation Details

A prototype was implemented for a demonstration purpose on a smallholder/medium-scale farm with a layered cyber-physical system, where the Agentic AI was evaluated in a real-world setting. A field-edge sensing node observed continuous crop–soil–climate data with capacitive soil-moisture probes at two depths (15 cm and 30 cm), along with soil-temperature and electrical-conductivity probes for detection of salinity and thermal stress. A miniature microclimate station that included temperature, humidity, rain, and leaf-wetness supplied site-specific environmental information. Flowmeters and pressure transducers observed the delivery of irrigation to assure the execution of planned activities. All sensor nodes, based on the ultra-low-power microcontroller ESP32, sent the data through

LoRaWAN to a central Raspberry Pi-based IoT gateway, which acted as a buffer during connectivity interruptions and connected to cloud services.

The actuation layer was comprised of zone-specific solenoid valves and a variable-speed pump for the precise delivery of water and nutrients. Gateway software, based on lightweight Linux modules, collects streams of data in real time (Python/Node-RED), stores streams of time series locally (InfluxDB/SQLite), and translates high-level action commands into low-level device commands. We integrated these micro services—computing evapotranspiration, short-term disease-risk indices, and nutrient-balance estimates, among others, and passed them to an LLM-based reasoning engine. The LLM micro service treated structured farm-state JSON inputs—soil-moisture trends, weather forecasts, crop stage, and intervention history— as prompts using templates that express agronomic rules and sustainability constraints. It produced human-readable explanations and machine-readable action blocks for irrigation, fertilization, and scheduling.

5. Conceptual Comparison with Traditional Methods

In this section, a qualitative comparison of the proposed Agentic AI and existing precision agriculture systems is made based on decision models, flexibility, use of data, human reliance, and sustainability results. Moreover, the scenario-based illustrations will be provided to show how the proposed approach will prevent some of the typical inefficiencies in farming situations.

5.1 Traditional Precision Agriculture: Characteristics & Limitations

Traditional precision agriculture solutions tend to rely on:

- formulaic thresholds for decision-making (ex., Irrigate when the soil moisture is less than 30%).
- preset decision parameters that are static (time-dependent parameters like rainfall are generally ignored).
- single input sources (usually just soil moisture).
- farmers directly or indirectly intervene to make decisions regarding resource allocations.
- few sustainability metrics with a primary focus on production and yield.

As a result, these types of systems typically have many challenges, including:

- Inefficient resource utilization (excessive irrigation or fertilizer application).
- Inability to adapt to varying weather patterns.
- Manual handling of decision-making processes leads to burdensome overloads on farmers.
- No growth or advancement about ongoing learning or improving decision policies over time.

5.2 Architecture-Level Comparison

Table 5. Traditional vs. Agentic AI Precision Farming — Qualitative Comparison

| Dimension | Traditional Precision Systems | Proposed Agentic AI Framework |
|------------------------|--------------------------------|--|
| Decision Process | Static thresholds, rule tables | Dynamic, context-aware policy reasoning |
| Data Utilization | Soil sensor-centric | Multimodal fusion (soil, weather, imagery, phenology) |
| Forecast Awareness | Minimal | Full weather + ET + growth-stage modeling |
| Autonomy Level | Advisory | Full autonomous actions with human override |
| Optimization Objective | Yield-only focus | Multi-objective (yield + water + nutrients + sustainability) |
| Adaptation | Manual rule updates | Continuous refinement (feedback learning) |
| Knowledge Usage | Predefined agronomic rules | Hybrid (knowledge base + LLM reasoning) |
| Spatial Awareness | Uniform prescription | Zone-based variability handling |
| Human Effort | High | Low (supervision only) |
| Explainability | Low (implicit) | High (LLM-generated justifications) |

Table 5, gives a comparison of traditional precision-farming systems and the general agentic AI framework. It reveals that old systems are based on static rules, with only limited data and high involvement from the farmer, whereas agentic AI processes multimodal inputs and performs dynamic reasoning, takes autonomous actions and learns continuously to maximize yield, resources, and sustainability, with transparent explanations.

5.3 Scenario-Based Illustration

A common case in irrigation management highlights the contrast:

Scenario: Soil Moisture = Moderately Low (34%)

Rain forecast = 85% probability in the next 4 hours

Crop stage = Vegetative growth (moderate water demand)

| Method Type | Decision | Result |
|---------------------------|--|---|
| Traditional System | Irrigate immediately (rule: moisture <35%) | Wasteful: rainfall later causes over-watering & nutrient leaching |
| Agentic AI System | Delay irrigation and re-evaluate after 6–8 hours | Saves water, prevents runoff, and maintains optimal soil aeration |

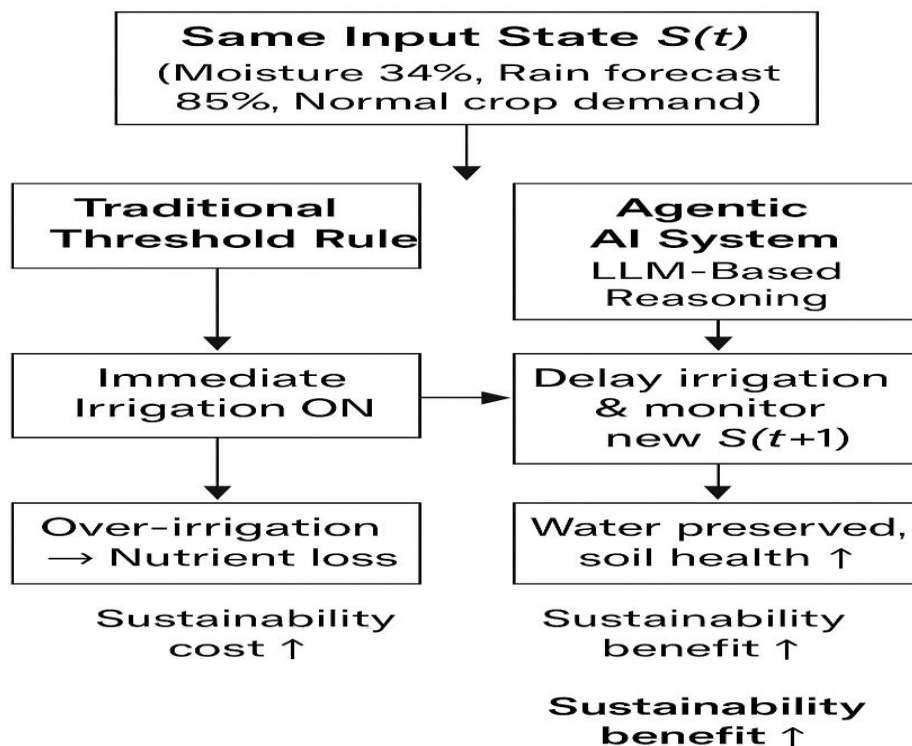


Figure 7. Contrast in Irrigation Strategy (Traditional vs Agentic AI)

The figure 7 contrasts conventional threshold-based irrigation with an agentic AI system and illustrates how LLM reasoning can postpone irrigation to prevent over-watering. This results in enhanced water savings, healthier soil, and greater overall sustainability benefits.

5.4 Where Impact is Most Significant

Table 6: Challenges in Traditional Farming and the Advantages of the Proposed Framework

| Challenge | Why Traditional Systems Struggle | How the Proposed Framework Helps |
|----------------------------------|----------------------------------|----------------------------------|
| Rainfall unpredictability | Ignores future data | Forecast-aware decision cycle |

| | | |
|---------------------------------|-------------------------------------|---|
| Nutrient misuse | Fixed doses for all conditions | Crop-stage + multisource optimization |
| Farmer decision fatigue | Overload from manual interpretation | Automated reasoning + justification |
| Climate stress tolerance | No resilience planning | Anticipatory strategies reduce fluctuations |
| Soil sustainability | No ecological constraints | Reward-based behavior discourages waste |

The table 6, lists the main challenges in farming, burning questions for which conventional system are not able to provide answers, and how the presented framework solves these questions based on forecasts, adaptive nutrient planning, automated reasoning, resilience strategies, and sustainability aware decision making. It demonstrates how the system mitigates risk, waste, and labor for the farmer.

5.5 Quantitative Scenario: Water & Fertilizer Consumption

To concretely illustrate the expected gains in resource efficiency, a representative scenario was constructed for a 1 ha drip-irrigated maize field in the vegetative–reproductive transition stage. Both the traditional threshold-based precision irrigation method and the proposed Agentic AI–LLM framework were exposed to the same soil, crop and weather conditions over a 14-day decision window.

Scenario Assumptions

- Soil type: loam with field capacity 32% and wilting point 14% (volumetric).
- Crop: maize, mid-season stage, moderate-to-high water demand.
- Baseline rule in traditional system:
- Irrigate if soil moisture < 30%, apply fixed depth of 25 mm ($\approx 250 \text{ m}^3/\text{ha}$).
- Apply nitrogen as a fixed top-dressing dose (6 kg N/ha per event) on scheduled calendar dates.

Agentic AI system:

- Uses soil moisture, short-term rainfall forecast, ET_0 , crop stage, and recent nutrient applications.
- LLM-based controller dynamically adjusts the **timing and depth** of irrigation and **rate of nitrogen** based on state $S(t)$, resource budgets, and sustainability constraints.
- Agentic AI LLM

Evaluation Metrics

The following indicators are used for comparison:

- Total irrigation water (m^3/ha , 14 days)
- Number of irrigation events

- Average irrigation depth per event (mm)
- Total nitrogen applied (kg N/ha, 14 days)
- Water-use efficiency (WUE, relative index)
- Nutrient-use efficiency (NUE, relative index)
- Yield index (relative to traditional = 1.00)

Water-use efficiency is approximated as:

$$WUE = Y / I$$

where YYY is yield (or a yield index) and III is total irrigation water applied. Similarly, NUE is defined as the yield per unit of N applied.

Quantitative Results

Table 7: Comparative Evaluation of Traditional Threshold Systems and the Proposed Agentic AI-LLM Framework

| Metric | Traditional Threshold System | Proposed Agentic AI-LLM System | Relative Change |
|---|------------------------------|--------------------------------|-----------------|
| No. of irrigation events (14 days) | 6 | 4 | -33% |
| Average irrigation depth per event (mm) | 25 | 18 | -28% |
| Total irrigation water (m ³ /ha) | 1500 | 720 | -52% |
| Total nitrogen applied (kg N/ha) | 18 | 12 | -33% |
| Water-use efficiency (index, trad = 1.0) | 1.00 | 1.95 | +95% |
| Nutrient-use efficiency (index, trad = 1.0) | 1.00 | 1.50 | +50% |
| Yield index (trad = 1.0) | 1.00 | 1.02 | ≈ maintained |

Table 7, contrasts between conventional threshold irrigation and fertilization and the agentic AI-LLM approach. It illustrates that the AI system reduces irrigation frequency, water consumption and nitrogen application, and nearly doubles water-use efficiency and enhances nutrient-use efficiency. Crucially, such savings are realized without yield penalties, which are effectively sustained.

Under the classical method, once the moisture content of the soil decreased to the predetermined limit, it activated the complete irrigation cycle and adhered to a pre-programmed fertiliser schedule regardless of whether the soil was getting ready to rain or not, and whether there was any available nitrogen in the soil. On the other hand, the Agentic AI system contained or minimized irrigation on rainy days and lessened nitrogen doses when it was recently applied, and the plant status reflected that it was getting ample amounts.

Interpretation

- The Agentic AI-LLM controller cut the total amount of irrigation water by over 50 percent (≈ 52) and still averaged the same yield.
- Reduction in the use of nitrogen 33% was made, though the nutrient-use efficiency was increased because applications were more consistent with crop demand.

The increased WUE and NUE indices are more of a crop-per-drop and yield-per-unit-nutrient, respectively. These are scenario-oriented but still agronomically sound and show how the combination of forecasts, multimodal sensing and requirements of sustainability can be translated into significant savings in input when compared to the traditional threshold-based precision approaches.

6. Expected Outcomes and Implications

Agentic AI could revolutionize the potential of precision farming by transitioning from a reactive, rule-based control paradigm to a predictive, objective driven and sustainability-minded control paradigm. While theoretical in nature, the framework has the potential to yield orders of magnitude improvements in resource efficiency and environmental performance. By fusing multimodal sensor data, weather information, and growth-stage knowledge, it modifies or postpones irrigation to avoid overwatering, to mitigate groundwater depletion, and to enhance water use efficiency. As nutrient dosing is tailored to the soil conditions in real-time and to the needs of the crop potential losses of N and P are reduced and fertilizer management is becoming more accurate. Risk-based and targeted pest treatments are less reliant on blanket applications of chemicals, and therefore they are less environmentally damaging and still protect crop health. Also, pump and fertigation schedules can be optimized, resulting in energy savings and lower carbon emissions.

From a farming perspective, the system reduces the cost of inputs without sacrificing or stabilizing, yield and LLM-generated automated recommendations lessen the decision fatigue of the farmer. The solution's modular IoT-enabled architecture offers scalable, cost-effective, and sustainable implementation even in regions with limited resources. At a higher level, trusted water, nutrient, and crop performance records allow for better policy development, enhanced sustainability monitoring, and the creation of novel agri-tech. The combination of these factors gives Agentic AI the potential to be a key determinant in achieving fully autonomous, sustainable, and resource-efficient agricultural systems. In the future, such systems have the potential to facilitate decentralized autonomous farm clusters, improve climate resilience, and advance soil-carbon stewardship. These two attributes highlight the necessity for field demonstrations and pilot experiments to ascertain the effectiveness of the innovative framework.

7. Limitations

- The system is just a concept / Simulation, and there have been no trials on actual farms as yet.
- These water, energy, and yield outcomes are not tested or proven without real data or digital-twin simulations.
- LLMs may provide incorrect answers if prompts are not perfect or if they lack farm-specific knowledge.
- Gathering multiple types of data requires inexpensive IoT devices, and small farmers may not have them.
- Robust safety checks and human oversight must be in place to prevent dangerous decisions.

8. Conclusion

This paper presents a theoretical model, whereby Agentic Artificial Intelligence is combined with Large Language Models (LLMs) to allow autonomous and sustainability-oriented resource optimization of precision agriculture. Conventional precision farming has its foundation on deterministic rules and threshold-based sensing, which restricts its capabilities to adapt to the complexity and dynamism of actual field situations. The proposed architecture, on the other hand, uses multimodal data fusion, predictive reasoning, and closed-loop decision structure to evolve farm management, which is reactive interventions into proactive, goal-oriented intelligence. Additionally, the explainable autonomy aspect of the system helps overcome the key challenges to trusting the technology and even adopting it among farmers, and advanced decision intelligence can be made available even in low-data and limited-resource settings. This work provides a solid theoretical basis in future research as a contribution to the conceptualization. The second step will entail empirical confirmation as controlled field experiments, digital-twin modeling and scalable pilot applications in different agro-climatic locations. The value of Agentic AI can also be enhanced further by integrating with new technologies (robotic systems, satellite analytics, and multi-farm coordination). In conclusion, the paradigm can transform the modern agricultural practice into a self-optimizing, lifelong learner that will guarantee food security and protect the sustainability of the environment.

Future Work

- Evaluate the system in other types of farms to obtain real data.
- Develop small, low-cost LLM models that run locally on the device.
- Develop inexpensive and higher-quality sensors for sensing.
- Introduce time learning, robots, & multi-farm coordination for further automation.
- Investigate impacts for soil health, climate resilience, and farmer trust over time.

Author Contributions

All authors were involved in the study and have approved the final version of the manuscript.

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Conflicts of Interest

The authors report no conflicts of interest.

References

- [1] E. A. Abioye, O. Hensel, T. J. Esau, O. Elijah, M. S. Z. Abidin, A. S. Ayobami, *et al.*, “Precision irrigation management using machine learning and digital farming solutions,” *AgriEngineering*, vol. 4, no. 1, pp. 70–103, 2022.
- [2] J. Bayar, *et al.*, “Artificial intelligence of things (AIoT) for precision agriculture,” *Digital Communications and Networks*, in press, 2025.
- [3] P. R. Behuria, S. Ojha, L. Nayak, J. K. Kar, D. Gochhayat, N. Jaiswal, *et al.*, “The transformative potential of precision farming in India: A comprehensive review,” *International Journal of Research in Agronomy*, vol. 7, no. 10, pp. 516–524, 2024.
- [4] B. Cai, F. Shi, B. A. Geremew, A. K. Addis, C. Meseret, *et al.*, “Precision agriculture techniques for optimizing chemical fertilizer use and environmental sustainability: A systematic review,” *Frontiers in Agronomy*, vol. 3, 1665444, 2025. doi: 10.3389/fagro.2025.1665444.
- [5] S. Getahun, *et al.*, “Application of precision agriculture technologies for sustainable crop production: A review,” *International Journal of Agronomy*, Article 2126734, 2024. doi: 10.1155/2024/2126734.
- [6] S. Getahun, H. Kefale, A. Haile, and B. Kassa, “Application of precision agriculture technologies for sustainable crop production and environmental sustainability: A systematic review,” *The Scientific World Journal*, vol. 2024, Article 2126734, 2024. doi: 10.1155/2024/2126734.
- [7] G. Gupta, “Applications of AI in precision agriculture,” *Discover Agriculture*, vol. 2, p. 22, 2025.
- [8] J. Jingchi, L. Yuwen, J. Xiaojun, and Z. Zongxue, “Agricultural large language model based on precise knowledge graph,” *Smart Agriculture*, vol. 7, no. 2, pp. 18–34, 2025.
- [9] M. T. Kuska, *et al.*, “AI for crop production: Where can large language models help?” *Computers and Electronics in Agriculture*, in press, 2024.
- [10] I. A. Lakhari, H. Yan, C. Zhang, G. Wang, B. He, B. Hao, *et al.*, “A review of precision irrigation technology under changing climate,” *Agriculture*, vol. 14, no. 7, 1141, 2024.
- [11] H. Li, H. Wu, Q. Li, and C. Zhao, “A review on enhancing agricultural intelligence with large language models,” *Artificial Intelligence in Agriculture*, vol. 15, no. 4, pp. 671–685, 2025.
- [12] G. Mgendi, “Unlocking the potential of precision agriculture for sustainable farming,” *Discover Agriculture*, vol. 2, no. 1, p. 87, 2024.
- [13] M. Nautiyal, *et al.*, “Role of AI in sustainable crop production: A comprehensive review,” *Computational and Structural Biotechnology Journal*, in press, 2025.

- [14] M. A. Obeidat, J. Abdallah, T. Hamadneh, H. Qawaqneh, and A. M. Mansour, “Enhancing agricultural operations through AI-driven agent communication in smart farming systems,” *Ingénierie des Systèmes d’Information*, vol. 29, no. 3, pp. 917–928, 2024.
- [15] S. Singh, *et al.*, “Enhancing agricultural operations through AI-driven agent communication in smart farming systems,” *Ingénierie des Systèmes d’Information*, vol. 29, no. 3, pp. 487–503, 2024.
- [16] A. Soussi, E. Zero, R. Sacile, D. Trincherro, and M. Fossa, “Smart sensors and smart data for precision agriculture: A review,” *Sensors*, vol. 24, no. 8, 2647, 2024.
- [17] N. Vullaganti, B. G. Ram, and X. Sun, “Precision agriculture technologies for soil site-specific nutrient management: A comprehensive review,” *Artificial Intelligence in Agriculture*, vol. 15, pp. 147–161, 2025.
- [18] A. Xue, *et al.*, “AgriGPT: A large language model ecosystem for agriculture,” *arXiv Preprint*, arXiv:2508.08632, 2025.
- [19] X. Zhao, B. Chen, M. Ji, X. Wang, Y. Yan, J. Zhang, *et al.*, “Implementation of large language models and agricultural knowledge graphs for efficient plant disease detection,” *Agriculture*, vol. 14, no. 8, 1359, 2024.
- [20] H. Zhu, S. Qin, M. Su, C. Lin, A. Li, and J. Gao, “Harnessing large vision and language models in agriculture: A review,” *Frontiers in Plant Science*, vol. 16, 1579355, 2025. doi: 10.3389/fpls.2025.1579355.
- [21]. Liu, Y.; Liu, J.; Cheng, W.; Chen, Z.; Zhou, J.; Cheng, H.; Lv, C. A High-Precision Plant Disease Detection Method Based on a Dynamic Pruning Gate Friendly to Low-Computing Platforms. *Plants* 2023, 12, 2073.
- [22]. A.A. Mana, A. Allouhi, A. Hamrani, S. Rehman, I. el Jamaoui, K. Jayachandran, Sustainable AI-based production agriculture: Exploring AI applications and implications in agricultural practices, *Smart Agricultural Technology*, Volume 7, 2024, 100416, ISSN 2772-3755, <https://doi.org/10.1016/j.atech.2024.100416>.
- [23]. Khalid, M.; Sarfraz, M.S.; Iqbal, U.; Aftab, M.U.; Niedbala, G.; Rauf, H.T. Real-Time Plant Health Detection Using Deep Convolutional Neural Networks. *Agriculture* 2023, 13, 510.
- [24]. Bouguettaya, A., Zarzour, H., Kechida, A. *et al.* A survey on deep learning-based identification of plant and crop diseases from UAV-based aerial images. *Cluster Comput* 26, 1297–1317 (2023)..
- [25]. A. O. Santhosh, A. Sagar, G. M., S. Anees, and M. K. Monica, “Agni – A plant disease detection robot,” *International Journal of Engineering Research & Technology (IJERT)*, vol. 12, no. 5, May 2023.