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Review Article

Review on Applications of artificial intelligence in Indian agriculture: future and challenges

***[1]Suryakant Mane, [2]Suchita Badgire,**
[3]Pradnya Agarwal and [2]Rajendra Kadam

[1]Department of Soil Science and Agricultural Chemistry,
[2]Department of Plant Pathology, Vasantrao Naik Gramin College of Agriculture,
Nehru Nagar Tq. Kandhar Dist. Nanded, Maharashtra, India
[3]Department of Natural Resource Management, Mahatma Gandhi Chitrakoot Gramodaya Vishwavidyalaya,
Madhya Pradesh, India

Article Info:
Correspondence:
[1]Department of Soil Science and Agricultural Chemistry, Vasantrao Naik Gramin College Of Agriculture, Nehru Nagar Tq. Kandhar Dist. Nanded, Maharashtra, India
*suryamane007007@gmail.com

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Abstract:

Soil moisture measurement technologies, including capacitance and time-domain reflectometry (TDR) sensors, function by assessing the dielectric properties of soil. These sensors emit an electric field, the behavior of which—its strength and propagation—is influenced by the soil's dielectric constant. Artificial Intelligence (AI) has the capacity to process extensive meteorological datasets derived from satellites, ground-based instruments, and historical archives. In addition to forecasting, AI is utilized for agricultural field monitoring, where drones equipped with digital imaging tools identify weed growth, and decision-making systems control site-specific herbicide application using GPS guidance. Such technologies enable farmers to conduct rapid, accurate, and economically efficient field assessments, enhancing productivity by maximizing the use of existing resources.

Furthermore, technological integration allows for real-time monitoring of crop conditions—covering aspects such as soil moisture, irrigation efficiency, pest control, and nutrient management. However, in rural or low-resource environments, there may be reluctance among farmers to adopt AI-driven solutions if the rationale behind automated decisions is opaque or difficult to interpret. To facilitate adoption, it is crucial to foster trust through transparent explanations of AI outputs.

Successful implementation of AI in agriculture also depends on substantial training initiatives for farmers, extension agents, and other key stakeholders. This includes developing intuitive user interfaces, delivering practical training sessions, and creating robust support systems to improve digital competency and promote widespread technology adoption.

Keywords: AI algorithms, Soil moisture sensors, weeding, spraying, automated irrigation systems.

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Introduction

By 2050, the global population is projected to reach approximately 10 billion, thereby placing immense pressure on the agricultural sector to boost crop production and improve overall yield efficiency. In response to the anticipated food demand, two principal approaches have emerged: one focuses on expanding arable land and adopting industrial-scale farming, while the other emphasizes enhancing productivity on existing farmland through innovative techniques and the integration of modern technologies [1]. Recent scientific investigations have concentrated on the development of drone-based solutions for assessing crop health, particularly through the application of artificial intelligence (AI) tools [2].

In countries such as India, agriculture plays a vital role in the national economy, contributing nearly 18% to the Gross Domestic Product (GDP) and providing employment to nearly half of the population. Strengthening the agricultural sector is likely to accelerate rural development, which in turn could drive rural transformation and ultimately bring about broader structural changes in the economy [3].

Artificial intelligence is increasingly integrated into daily life, enhancing human capabilities and enabling a more proactive interaction with the environment [4–6]. Plessen [7], for instance, developed a harvest planning model that incorporates both crop scheduling and logistical operations such as truck routing. With such advancements, sectors that were previously limited to industrial applications are now benefiting from AI, which draws upon multiple disciplines including biology, linguistics, computer science, mathematics, psychology, and engineering. A concise overview of current automation practices in agriculture has been provided by Jha et al. [8].

Data Collection and Analysis

To map the landscape of AI applications in agriculture, a comprehensive literature review was conducted. The data collection phase began with a targeted search of journal publications, with Scopus selected due to its reliability and extensive coverage of peer-reviewed academic literature. After gathering relevant studies, articles unrelated to the core subject were excluded from the dataset. Subsequent citation analysis was used to identify relationships between authors and documents, uncovering notable citation trends. Furthermore, the review highlighted key contributors and influential publications that have made substantial impacts on the advancement of AI in agriculture.

Impact of AI in agriculture

The rapid advancement of technology has significantly transformed various global industries [9]. Interestingly, despite being traditionally considered one of the least digitized sectors, agriculture has recently experienced substantial progress in the development and commercialization of technological innovations. Artificial intelligence (AI) has played a pivotal role in modernizing agricultural systems, leading to increased crop productivity and enhanced capabilities in real-time monitoring, harvesting, post-harvest processing, and market logistics [10]. Contemporary automated solutions—such as agricultural robotics and drone-based systems—have made noteworthy contributions to the agricultural economy.

A diverse range of advanced computational methods has been developed to monitor critical agricultural parameters, including weed identification, yield estimation, and assessment of crop quality, among others [11]. While the sector continues to face several persistent challenges—such as fragmented landholdings, labor shortages, climate change, environmental degradation, and diminishing soil fertility—it is evolving through the integration of novel technological solutions. The evolution of agriculture from manual tools and animal-driven machinery to highly mechanized systems highlights the sector's ongoing transformation. Each growing season introduces new innovations designed to improve productivity and profitability.

Nonetheless, both smallholder farmers and large agribusinesses often underestimate the value that AI can contribute to agricultural efficiency and decision-making. AI technologies offer substantial benefits across various domains of agricultural production, including yield forecasting, irrigation optimization, soil nutrient analysis, crop health monitoring, weed and pest control, and effective crop establishment strategies [12].

Given the unpredictable nature of farming—marked by seasonal weather variability, fluctuating input costs, soil degradation, crop losses, weed infestations, pest outbreaks, and climate-related risks—farmers must continuously adapt to complex and changing conditions. Therefore, a systematic review of AI applications in agriculture is essential. Such an evaluation is crucial for improving the management of soil health, crop growth, pest control, and disease prevention, ultimately contributing to more sustainable and resilient farming practices.

Soil Management

Efficient soil management is fundamental to achieving sustainable agricultural outcomes. A thorough understanding of soil types and their respective conditions is vital for enhancing productivity while ensuring the conservation of soil resources. Enhanced soil performance results from a range of management operations, techniques, and inputs designed to maintain and improve soil fertility, structure, moisture retention capacity, and overall health. Key practices include tillage, crop rotation, cover cropping, the application of organic materials such as compost and manure, and the judicious use of chemical fertilizers.

Additionally, implementing soil conservation strategies—such as contour farming, terracing, and erosion control measures—is critical to safeguarding soil integrity over extended periods. A comprehensive grasp of soil characteristics, combined with the adoption of appropriate management strategies, plays a crucial role in promoting long-term agricultural sustainability. This integrative approach not only boosts crop productivity but also enhances

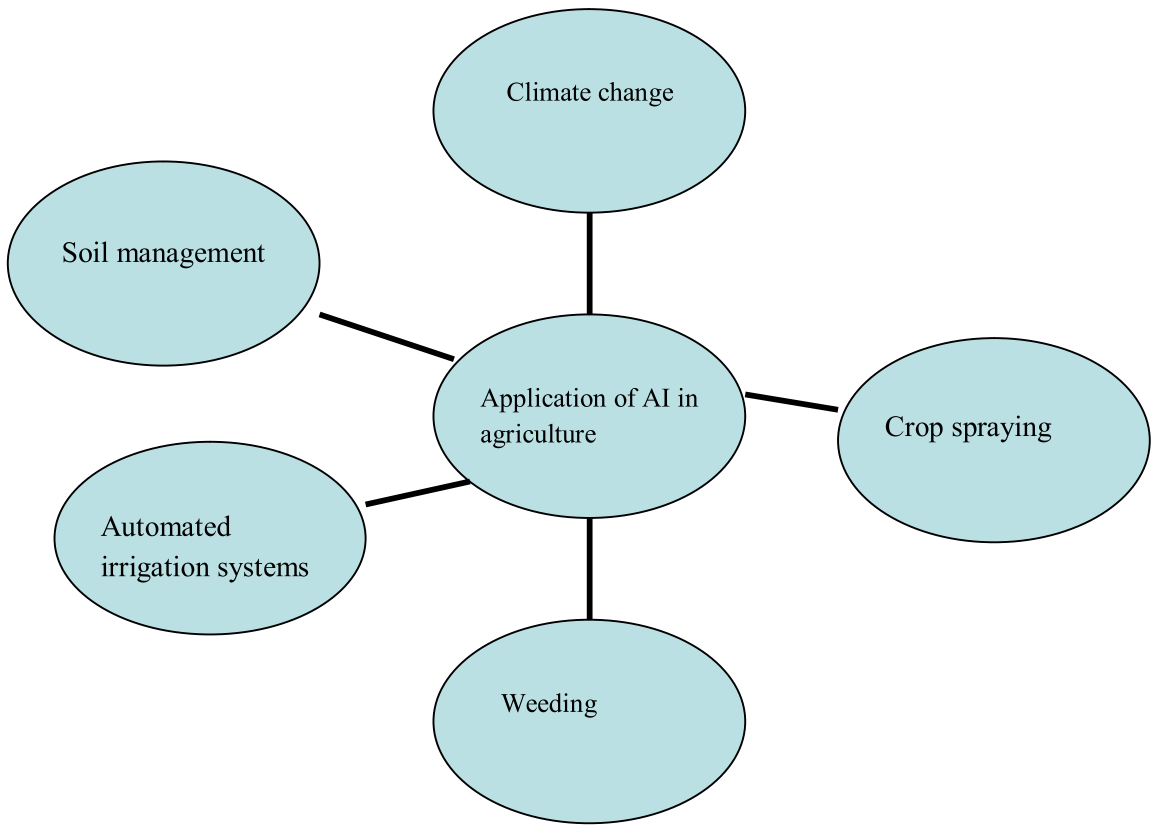

Fig1: Applications of AI in agriculture.

soil health and supports the enduring preservation of this essential natural asset.

Precision Mapping and Soil Sampling
The use of GPS-enabled technologies allows for the creation of detailed, high-resolution field maps that identify spatial variability in soil properties with great accuracy. These digital tools enable targeted soil sampling by revealing differences in soil parameters such as nutrient content, pH levels, and organic matter distribution. This site-specific data facilitates a more informed and efficient approach to soil analysis, guiding precision agriculture interventions that can significantly improve soil and crop management practices.

Variable-Rate Application and GPS Integration
Modern precision agriculture utilizes GPS-guided equipment to enable variable-rate input applications across agricultural fields. These technologies, such as automated fertilizer spreaders and sprayers, allow for site-specific administration of inputs like fertilizers and soil amendments. Rather than applying uniform rates across an entire field, inputs can be customized based on the distinct needs of various field zones, enhancing input efficiency and reducing waste.
Precision Tillage and Seed Planting Utilizing GPS-enabled tractors and planters ensures high-accuracy seed placement in terms of both depth and location. It also aids in the optimal scheduling of tillage operations, leading to the establishment of uniform seedbeds and improved crop emergence under favorable soil conditions.
Targeted Soil Conservation GPS technology also supports precision conservation strategies tailored to the specific challenges of each field. Techniques such as buffer strip planting, terracing, and contour farming can be precisely implemented to address localized issues related to soil erosion and water runoff.
Data-Driven Soil Management High-resolution spatial data collected via precision agriculture tools can be integrated with external datasets—such as weather trends and historical yield records—to gain a comprehensive understanding of field variability. This facilitates informed decision-making regarding resource allocation and soil treatment, ultimately optimizing crop outcomes and enhancing system sustainability.

Soil Moisture Monitoring through Dielectric Sensing Technologies
Accurate assessment of soil moisture is critical for effective irrigation management. Modern soil moisture sensors, including capacitance and time-domain reflectometry (TDR) devices, operate by measuring the dielectric constant (or permittivity) of the soil. When an electric field is applied, the soil's dielectric properties influence how the field propagates. These changes are interpreted to estimate soil moisture content.
Gebregiorgis and Savage [13] highlighted the utility of the dielectric constant for calculating irrigation requirements. Similarly, Kuyper and Balendonck [14] advocated for automated irrigation systems driven by dielectric sensor feedback. Zhen et al. [16] identified this method as one of the most promising for precision irrigation, although Hanson et al. [15] noted that sensor accuracy can be influenced by soil type. Despite such limitations, dielectric-based sensing remains one of the most reliable and widely adopted techniques for monitoring soil moisture in precision farming.

AI-Powered Weed Management
Weeds pose significant threats to crop production as they compete for critical resources like water, nutrients, sunlight, and space, thereby impeding the growth of intended crops and reducing overall yields [17]. To address this, it is vital to accurately distinguish between crop seedlings and weeds prior to developing any automated weed management system [18].
Unmanned Aerial Vehicles (UAVs), or drones, play a pivotal role in AI-driven weed detection.

Equipped with NDVI sensors, drones can capture imagery and generate detailed weed distribution maps through post-flight processing. These maps enable farmers to identify weed-infested zones and facilitate targeted intervention.

Technological innovations such as weed-detecting robots represent major progress in the field of precision agriculture. For example, site-specific weed control in crops like maize, sugar beet, winter wheat, and winter barley can be achieved using drone-based image capture, AI-supported classification models, and GPS-controlled patch spraying [19]. Notably, classification models based on Support Vector Machines (SVM) have achieved an accuracy of up to 95% in identifying weed species.

In another notable development, researchers at the University of Illinois, led by Adam Davis, designed autonomous "killer robots" for weed eradication [20]. Sandeep et al. [21] further advanced this field by applying Convolutional Neural Networks (CNNs) and image segmentation techniques to distinguish weeds in carrot fields. Their system utilized RGB image datasets and Python-based programming for implementation.

Table1: Use of AI/Robot/drones in Agriculture

Application	Method	Strength	Weakness
Crop Management [24]	Robotics-Demeter	Can harvest up to 40 hectares of crop	Expensive:
Desease and Nutrition Management [25]	ANN	Detecting crop nutrition disorder.	A little number of symptoms were considered.
Weed Management[26]	UAV	Weed detection accuracy in short period.	expensive
Soil Management [27]	ANN	Can predict soil enzyme activity with soil structure.	Only measures a few soil enzymes.

Climate Change Adaptation Using AI

Artificial intelligence also provides robust tools for adapting to climate variability, which has become increasingly unpredictable and severe. Variables such as drought timing, frequency, and intensity are essential in selecting appropriate cropping strategies [23]. Enhanced weather forecasting and predictive models driven by AI can offer critical insights, empowering farmers to make well-informed decisions that lead to improved productivity and resilience [22].

Artificial intelligence algorithms have transformed the accuracy and reliability of weather forecasting by processing vast datasets derived from satellite imagery, ground-based meteorological sensors, and historical climate records. These systems utilize complex pattern recognition techniques to detect intricate relationships among multiple weather variables. As a result, AI-driven models often outperform traditional forecasting systems in both precision and relevance.

By accessing hyper-local and real-time forecasts generated through AI, farmers are equipped to make data-informed decisions about the timing of essential activities such as sowing, irrigation, fertilization, and harvesting. This leads to optimized resource use, reduced weather-related crop loss, and enhanced yield outcomes. Notably, AI models can be tailored to the unique geographic and climatic profiles of individual farms, making the forecasts highly localized and actionable.

Furthermore, AI-based weather forecasting systems can incorporate projections linked to long-term climate change trends. This enables farmers to proactively adapt their agricultural strategies, including crop selection and planting schedules, in response to shifting climate conditions. When integrated with other precision agriculture tools—such as soil moisture sensors, automated irrigation systems, and farm management platforms—AI-based weather systems provide a comprehensive solution for maximizing productivity and resilience in climate-sensitive regions like India.

Optimizing Automated Irrigation Systems

The advent of automated irrigation technologies has replaced conventional manual methods that relied heavily on intermittent soil moisture assessment. Modern systems incorporate microcontrollers, such as Arduino, connected to remote sensors that monitor environmental parameters in real time. Savitha and Uma Maheshwari [28] demonstrated that sensor-based automated irrigation can enhance crop production by up to 40%.

One of the most efficient methods introduced in precision irrigation is **Subsurface Drip Irrigation (SDI)**. This technique delivers water directly to the plant root zone, drastically reducing evaporation and surface runoff. It promotes water conservation while simultaneously improving yield potential. The inclusion of **wireless broadband networks** allows real-time data transmission from sensor nodes to centralized systems, empowering farmers to monitor and control irrigation remotely.

Additionally, the use of **solar-powered sensors** ensures uninterrupted operation in rural or off-grid areas. Solar energy not only supports system autonomy but also contributes to sustainable and cost-effective farming practices. This convergence of automated scheduling, sensor technology, and renewable energy sources has revolutionized irrigation management.

AI and Drone-Based Crop Spraying

Modern agricultural challenges—such as uneven pesticide application, overuse of chemicals, and labor shortages—have prompted the integration of advanced technologies in crop spraying operations. Technologies including **Wireless Sensor Networks (WSNs)**, the **Internet of Things (IoT)**, and various AI techniques such as **machine learning** and **deep learning** have found significant utility in this domain [29–36]. Unmanned Aerial Vehicles (UAVs), commonly known as drones, are increasingly employed for precise crop spraying. These UAVs offer considerable advantages over traditional spraying methods, including access to difficult terrains, reduced labor requirements, and uniform pesticide distribution. The review by Zhang and Kovacs [40] underscores the pivotal role of drones in precision agriculture, noting the need for advancements in platform engineering, image standardization, georeferencing accuracy, and data processing workflows. These enhancements are essential for delivering reliable, actionable information to farmers through UAV-based spraying solutions.

Conclusion

In regions where agricultural productivity is constrained by environmental, economic, and labor-related factors—such as in many developing countries—AI-driven solutions provide a transformative path forward. Farmers can now leverage AI for rapid, precise, and cost-efficient assessments of soil conditions, crop health, water availability, and system performance. Technologies such as automated irrigation, drone-based weeding and spraying, and real-time climate forecasting empower them to make smarter decisions, reduce resource wastage, and achieve higher agricultural outputs. In an era of mounting climate uncertainty and resource scarcity, integrating AI into farming practices is not just innovative—it is imperative for sustainable agricultural development.

Challenges and Future Prospects of AI in Agriculture

Artificial Intelligence (AI) systems provide tailored, location-specific, and integrated guidance, making them highly relevant for contemporary agricultural management. Despite their potential, these technologies are still in the early stages of adoption and have seen limited commercial use within the agricultural sector [37]. A key expectation from intelligent systems is their ability to perform complex tasks swiftly and accurately. However, many existing AI-based solutions fall short in either response time or precision. Delays in system responsiveness can significantly influence user decisions, particularly in time-sensitive scenarios. Decision-making strategies in such contexts can be optimized using a cost-function model that evaluates two major parameters: (1) the user effort required to align with system responsiveness and (2) the degree of accuracy offered. Based on these variables, users may opt for one of three operational strategies—automated execution, performance pacing, or proactive monitoring [38].

Key Challenges

1. Data Availability and Quality
   The effectiveness of AI in agriculture hinges on access to large, high-quality datasets for model training and predictive analytics. In many developing regions, however, data collection is fragmented and lacks standardization, limiting the ability of AI models to deliver accurate and reliable results.
2. System Interoperability and Integration
   For AI to be widely adopted, it must integrate seamlessly with existing agricultural machinery, software, and decision-making workflows. Variability in hardware configurations, software platforms, and data formats poses a significant barrier to system interoperability.
3. Trust and Transparency
   Farmer skepticism towards AI-based recommendations is often rooted in a lack of transparency and interpretability. In traditional or resource-limited farming communities, it is crucial that AI models provide not only outputs but also understandable justifications for their recommendations, thereby fostering user confidence.
4. Accessibility and Affordability
   The adoption of AI technologies—such as drones, remote sensors, and analytics platforms—is often hindered by their high cost, particularly among smallholder farmers. Making these tools financially viable and accessible to broader agricultural populations remains a major concern.
5. Capacity Building and Digital Literacy
   The deployment of AI in agriculture is contingent upon sufficient training for end-users, including farmers, agronomists, and extension workers. Building digital literacy through intuitive user interfaces, practical training programs, and ongoing support structures is essential for meaningful adoption.
6. Ethical and Social Considerations
   The increasing reliance on AI raises important ethical issues, including data privacy, algorithmic bias, and labor displacement. The development of regulatory frameworks and ethical guidelines is imperative to ensure that AI applications are used equitably and responsibly in agriculture.
7. Infrastructure and Connectivity Constraints
   A major limitation in deploying AI systems across rural and remote agricultural areas is the inadequate infrastructure. Many regions lack consistent access to electricity and reliable internet connectivity, both of which are foundational for the functioning of AI-powered solutions.

Future Scope and Strategic Directions

Tackling these challenges requires coordinated action from stakeholders across agriculture, technology, and policy-making domains. Collaborative efforts—through public-private partnerships, strategic investment, and institutional capacity-building—can significantly lower the barriers to AI adoption in agriculture. Developing robust data ecosystems, enhancing rural connectivity, subsidizing technology costs for smallholders,

and promoting ethical AI practices are essential steps toward widespread and responsible AI integration.
Furthermore, as global demand shifts toward sustainably produced, high-quality food, advanced technologies such as robotics and autonomous systems (RAS) are expected to play a transformative role. These innovations can substantially improve productivity in traditionally low-output sectors like agriculture and food production, signaling a paradigm shift in how agriculture is managed and executed [39].

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