

## Integrating Artificial Intelligence and Machine Learning in Smart Agriculture: A Review

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### Abstract

Climate variability, scarcity of resources, and sustainable agricultural production under the global demand in modern agriculture, including food security. There is no denying the fact that Artificial Intelligence (AI) and Machine Learning (ML) are proving to be significant solutions to these critical issues. This paper is an extensive study on the latest research in the field of Artificial Intelligence (AI) and Machine Learning (ML) techniques or systems used for farming, exclusively emphasising their applications within agriculture context related to agriculture yield prediction, soil health assessment, and resource management and intelligent decision support systems. This study provides a comprehensive literature search that systematically collates and reviews the current knowledge and understanding of the potential for predictive analytics, Internet of Things (IoT), remote sensing, geographic information systems (GIS), and cloud-based technology to help optimize yields, crop forecasting, and sustainability. The review revealed that AI techniques are effective tools for improving yield predictions and monitoring soil health (including nutrient levels, moisture content), for identifying pest and disease issues, and for documenting good practice in the use of water, fertilizer, and pesticide. Furthermore, it addresses the significance of implementing Smart Agriculture based on smart irrigation systems, autonomous machines, and real-time farm monitoring based on using AI-powered automation. Yet on the ground, there are several important challenges to address before the technology can reach its potential, and these will be the determining factors in its future: data quality and interoperability, poor digital infrastructure, high application costs, technical skill, and data privacy and deployment issues. The paper also captures future research directions, such as multimodal data integration, climate-resilient predictive model development, and collaborative models between researchers, policymakers, technology developers, and farmers. On the whole, the paper reveals how AI and ML technologies have the ability to enable an intelligent agriculture ecosystem through which better crop production and resource management can be achieved, and environmental sustainability can also be ensured. These ongoing processes will facilitate the development of resilient, eco-friendly, as well as sustainable food production systems to live up to the future demand of global food security.

**Keywords:** Artificial Intelligence, Machine Learning, Smart Agriculture, Precision Agriculture, Yield Prediction, Temperate Climate, Soil Health, Resource Optimization.

### Introduction

Agriculture remains the most prominent sector in terms of global food security, providing livelihoods and financial well-being to the people. The sector is nevertheless challenged by fast growth in population, climate change, environmental degradation, and scarcity of resources, conditions that impose a heavy burden on food production systems (Foley et al., 2011). The total population of the world is estimated to touch an unprecedented figure of 9.7 billion by 2050, which means food production will have

to be increased by 70% to satisfy the future demand (Godfray et al., 2010). At the same time, traditional methods of farming are typically resource-intensive, inefficient, and not well suited to unpredictable climates, pests, and diseases (Tilman et al., 2011).

All these factors are responsible for unsustainable agriculture of low yield worldwide.

For such developments to happen, precision agriculture and digital farming techniques have proved revolutionary in their ability to harness the potential of data, automation, and advanced analytics to increase production in agriculture (Gebbers & Adamchuk, 2010). Precision agriculture is a concept that involves field and soil technology, such as geographic information system (GIS), remote sensing, internet of things (IoT) devices, and robots, to monitor soil variability and management input use and decision-making for monitoring (Mulla, 2013). These developments have the potential to be used for site-specific crop management and bring better production results while minimizing the consumption of water, pesticides, as well as fertilizers.

In this era of Precision Agriculture, Machine Learning (ML) and Artificial Intelligence (AI) are playing a pivotal role in shaping the future of farming. Predictions with AI and ML algorithms using enormous data collected from drones, sensors, satellites, and weather stations can be made at an unprecedented level, with insights into crop yields, diseases, soil health, and how resources can be allocated. The vision of data-driven making of decisions in Agriculture presented in this digital era is a paradigm shift in agriculture where farming decisions are made now in a proactive instead of a reactive way, using predictive models instead of traditional farming heuristic approaches (Liakos et al., 2018). Furthermore, automation technologies like autonomous tractors, robot harvesters, and intelligent irrigation systems are tackling the scarcity of workers and boosting productivity (Shamshiri et al., 2018). The blend of these technologies enables the development of "smart agriculture" ecosystems that can promote resilient and sustainable food production systems with the integration of data, real-time analytics, and intelligent automation (Wolfert et al., 2017).

**The study's prime contributions are listed as follows:**

- Analyze the application of AI & ML for enhancing the prediction and management of crop yield and thereby food production efficiency and food yield variability (Jeong et al., 2016).
- Explore how AI as well as ML can benefit in improving soil health, such as nutrient prediction, moisture monitoring, and soil degradation assessment (Chlingaryan et al., 2018).
- Analysis of the role such technologies play in optimizing resources like water, fertilizers, and pesticides in sustainable and cost-effective agriculture (Gutiérrez et al., 2014).
- Identify existing innovations, implementation hurdles, and research directions for using AI and ML in the agricultural field (Rose et al., 2021).

## **Literature Review**

### • **Artificial Intelligence and Machine Learning in Agriculture**

Artificial Intelligence (AI) is a computer science's comprehensive field that involves designing and developing intelligent machines, which are able to perform functions that are generally dealt with by human intelligence, including aspects such as language understanding, reasoning, perception, decision making, etc. (Russell & Norvig, 2016). In the context of AI, Machine Learning (ML) is the computer's ability to comprehend patterns and then carry out the task of predicting or making decisions with the help of data with no explicit programming for a particular task (Jordan & Mitchell, 2015). As more data is used to train the ML, they become more accurate, which makes it ideal for dynamic and complex environments such as farming. Deep Learning (DL) is actually a Machine Learning's subset, and with the application of deep artificial neural networks to model non-linear and complex relationships in large datasets, it aids in such high-stakes domains as image recognition, disease prediction, and autonomous control (LeCun et al., 2015).

For decision-making and implementation of AI in agriculture, the adoption of IoT and data analytics plays a crucial role. Real-time data in large volumes are gathered by IoT devices like climate stations, soil moisture sensors, and remote imaging devices (Wolfert et al., 2017).

### • **Evolution of Smart Agriculture**

In the last century, from labour-intensive and traditional agriculture to mechanized agriculture, agricultural practices have grown much, and subsequently to precision and smart agriculture. Traditional

agriculture was largely based on human work and empirical practices, which led to inefficient use of resources and a vulnerability to environmental variability (Zhang et al., 2002). Mechanization in the 20th century increased productivity, but came with problems of water use, fertilizer, and chemical use, leading to degradation of the environment (Tilman et al., 2002).

Precision agriculture is a relatively new concept that was developed in the 1990s and has its basis in site-specific management and the application of technologies like Geographic Information System (GIS), remote sensing, and Global Positioning System (GPS) (Mulla, 2013). Precision agriculture allowed farmers to adapt what they applied to the variability in the field, which helped to minimise waste and boost productivity. Smart agriculture is the next step in evolution from this, which combines the use of AI, ML, IoT, and robotics to enable fully autonomous, data-driven systems of farming (Shamshiri et al., 2018).

Sensors, drones, and robotics combined with AI technologies have played a key part in this revolution. Soil moisture, nutrient status, and climatic information are constantly monitored by sensors, while drones take images with high resolution for crop health assessment and pest monitoring (Hunt et al., 2010). Other techniques, such as weeding, planting, and harvesting, using autonomous machinery or robotics, improve operational efficiency without requiring a lot of human intervention (Bac et al., 2014). These technologies, when combined, allow a transition from the old style of reactive agriculture to the new style of predictive and prescriptive agriculture (Shamshiri et al., 2018).

- **AI-Driven Agricultural Systems and Platforms**

With the proliferation of extensive data sets, cloud computing, and sophisticated algorithms, AI-powered agricultural systems and platforms have come into existence. The data on these platforms comes from certain sources, like sensors, satellites, weather stations, and drones, and they have the potential to be used to make informed decisions throughout the agricultural value chain (Kamilaris & PrenafetaBoldú, 2018). Cloud computing-based DSS use scalable computing power to handle voluminous data as well as give information to farmers via a user-friendly dashboard and mobile app (Wolfert et al., 2017). These systems can forecast the weather, provide irrigation timing advice, and even advice on fertiliser strategies for individual field conditions.

Predictive modelling is critical to AI agriculture, with algorithms of ML such as Artificial Neural Networks (ANN), Support Vector Machine (SVM), and Random Forest used to forecast crop production, disease occurrence, and pest infestations (Jeong et al., 2016; Khaki & Wang, 2019). For example, models of yield prediction use weather data along with soil characteristics and historical yields to accurately estimate yields, which is essential for farmers' production forecasting and market predictions (Liakos et al., 2018).

Additionally, AI is being applied to autonomous machines like robotic planters, self-driving tractors, and automated harvesters. With the real-time data feed from these sensors and algorithms, these devices can navigate, identify obstacles, and perform tasks, in addition to decreasing human efforts and improving operations (Shamshiri et al., 2018). Furthermore, cloud-connected autonomous systems offer remote monitoring and control features, which can optimise the use of resources and ensure consistent performance from different agricultural uses (Kamilaris, 2018; Prenafeta Boldú, 2018).

AI platforms are also deployed in combination with blockchain and supply chain approaches to boost food safety, transparency and traceability from Farm to Fork (Tripoli & Schmidhuber, 2018). This holistic approach is very transparent with the potential of AI for re-inventing the agri-food system.

## **AI and ML for Crop Yield Prediction and Enhancement**

- **Predictive Analytics and Forecasting**

Some of the most significant applications of Artificial Intelligence and Machine Learning are Predictive Analytics and crop yield prediction, which enable farmers and agronomists to make sound decisions regarding crop production, resources, and market dynamics. Other methods of yield prediction, such as gathering data manually and using basic linear statistical models, are time-consuming, require a lot of effort, and cannot detect non-linear correlations among climate, soil, and farm management variables (Lobell et al., 2015). However, ML models can be used to process large amounts of data and detect patterns which might influence crop productivity (Jeong et al., 2016).

Popular algorithms of Machine Learning which relate to yield prediction include Artificial Neural Networks, Gradient Boosting Machines, Support Vector Machines, Deep Neural Networks, and Random

Forest. For example, RF models are well suited to deal with relationships which stand non-linear and interactions between multiple input variables; also, SVMs are suitable for classification-based yield prediction (Jeong et al., 2016). ANNs and DNNs, which originate from networks which are biological neural networks, happen to be capable of recognizing complicated patterns in large data sets, thus making them especially applicable to multifactorial yield prediction (Khaki & Wang, 2019).

Weather parameters (temperature, rainfall, etc.), soil properties (pH, nutrient concentration, etc.), and previous yield data are further utilized to improve the capability of prediction of ML models (Chlingaryan et al., 2018). For example, Khaki and Wang (2019) tailored an intensive learning model that predicted yields of corn with high accuracy across different parts of the United States, as compared to regression approaches, by incorporating weather and soil properties. Similarly, Kang et al. (2020) found that adoption of satellite-derived vegetation indices in conjunction with weather data increased wheat yield prediction accuracy by over 20% when compared with using climatic variables only (Kang et al., 2020).

Moreover, farmers can leverage predictive analytics in early warning systems against drought, pest, and disease scenarios to mitigate risks that can occur before an issue arises (Shahhosseini et al., 2021). AI-driven forecasting emerges as a vital tool for navigating the uncertainty and variability facing farmers in the era of climate change.

#### ▪ Real-Time Crop Monitoring

Although the predictive models can be used for estimating yields over a longer time frame, ongoing assessment of health, growth stage, and stress conditions of cultivated crops is critical to conduct during cultivation through crop monitoring. AI and ML are a core part of the process of transforming the types of data gathered by sensors and imagery into an operational format of information that can guide actionable response (Kussul et al., 2017).

Unmanned aerial vehicles (UAVs), satellite imagery, and drone-based platforms with Hyperspectral, multispectral, and Thermal sensors provide robust temporal and spatial resolution data for observing vegetation dynamics within fields (Zhang et al., 2019). Utilized by machine learning algorithms, particularly convolutional neural networks (CNNs), these images help identify information such as plant health, pinpoint nutrient deficiencies, and spot water stress (Han et al., 2021). This realistic assessment from data enables farmers to use it to decide judiciously about fertilisation, irrigation, and pest management.

The amazing progress in computer vision over the past few years has also led to the possibility of automatic diagnosis of plant diseases, pest infestation and weed species from leaf images (Mohanty et al., 2016). In the agricultural sector, deep learning models, specifically CNNs, which seem to have been employed to very effectively classify crops under a smartphone-captured image, for example in maize, tomato and wheat (Ferentinos, 2018). Mohanty et al. (2016), for instance, made a CNN-centred classifier that got 99.35% accuracy in the identification of 26 different diseases pertaining to plants across 14 crop species.

#### ▪ Case Studies and Applications

There are several case studies across the world that showcase the successful use of AI and ML for yield prediction and improvement of crops. In the United States, Jeong et al. (2016) tailored an RF model to forecast maize yields at the county level, and using historical weather and yield information, they reduced the mean absolute error by 30% from the linear regression models. Likewise, Khaki and Wang (2019) showed that deep learning models performed better in yield prediction of corn in various climatic zones with  $R^2$  values greater than 0.85.

In Europe, Kussul et al. (2017) applied satellite data and ML classifiers to estimate the yield of winter wheat in Ukraine with more than 90% accuracy and improve regional yield forecasting, which in turn facilitated policy decisions on grain export strategies. In India, Chlingaryan et al. (2018) used ANN and SVM models for yield prediction of rice using weather data and remote sensing inputs to supply timely advice to farmers and improve the process of decision-making for fertilizer application and irrigation scheduling.

IBM's Watson Decision Platform for Agriculture leverages weather forecasts, data from IoT sensors, and ML analytics to forecast crop yield and offer farm management recommendations that are specific to individual farms (IBM, 2020). Similarly, the AI Sowing App by Microsoft in Andhra Pradesh,

India, suggests the best seeds to be planted on the basis of soil moisture and weather data, thus boosting farm productivity by 10-30% for farmers with small landholdings (Bendre et al., 2015).

The case studies illustrate how AI and ML are being used beyond the lab setting to benefit agricultural practices. Combined with decision support systems, the application of predictive analytics and real-time monitoring empowers farmers to move towards intelligent data-driven farming to ensure higher yields with lower costs and better sustainability.

### **Enhancing Soil Health with AI and ML**

- **Soil Data Acquisition and Sensing Technologies**

Soil health is an important factor that affects various aspects of agriculture, like nutrient cycling, crop growth, and water retention. However, conventional soil sampling approaches, like laboratory-based sampling, are prone to being time-consuming and expensive, and are also limited to a smaller spatial scale, which is not suitable for large-scale precision farming (Vishnoi et al., 2021). In recent years, with the introduction of IoT-centred soil sensors, the collection of soil data has transformed, with the potential to gauge various soil parameters in real-time and continuously (Vishnoi et al., 2021). These sensors are positioned directly in the field and send wireless signals, which gives farmers exact and location-specific information that enables them to make management decisions.

Soil monitoring systems can be further enriched by the integration of geospatial and spectral data. Reflectance data from RS platforms like drones and satellites with hyperspectral and multispectral sensors are correlated to soil organic matter, moisture, salinity, and nutrient status (Mishra et al., 2020). ML algorithms will use these datasets to create soil health maps or maps that summarize the spatial variability within fields and help to make site-specific management decisions. For example, Mishra et al. (2020) proposed hyperspectral imaging with Random Forest algorithms for pinpointing soil organic carbon content in various agroecosystems with good accuracy. These developments allow us to move from the uniform application of resources to precision soil management, thereby minimizing losses of resources and improving sustainability.

Furthermore, these sensors together with other data, such as weather and crop growth, provide the ability to closely track soil conditions over time (Wolfert et al., 2017). The integration of this information enables the development of more advanced decision-making tools and predictive models, offering insights for decision support in proactive soil management.

- **AI in Soil Nutrient and Moisture Management**

AI and ML are also beneficial for predicting soil nutrient status and fertility, resulting in more targeted fertilizer management, reducing the risk of pollution through over-fertilising. Traditional soil testing approaches only provide snapshot interpretation, while ML algorithms can be efficient in processing sensor data in “real-time” and remote sensor imagery to generate a real-time availability prediction of nutrients (Chlingaryan et al., 2018). Commonly used models for nutrient prediction are SVR, ANN, and RF. For instance, Chlingaryan et al. (2018) tailored a model for predicting nitrogen and phosphorus content in soil using ML technology, which has helped with more accurate fertiliser recommendations and improved crop yields.

Apart from the prediction of nutrients, AI also remains instrumental in soil moisture management within crop decision-making. Irrigation needs and the health and productivity of plants and crops are directly related to soil moisture. When combined with the weather forecast and evapotranspiration rates, ML models can predict soil moisture changes, which remains vital as far as irrigation scheduling optimization is concerned (Dutta et al., 2020). Using predictive irrigation methods can minimise water losses, energy consumption, and water logging and nutrient leaching.

AI-powered DSS integrate nutrient and water level forecasts with real-time sensor data to equip farmers with tailored recommendations. These systems suggest the most efficient type, rate, and timing of fertiliser use and irrigation timing depending on the water requirement of the plant (Dutta et al., 2020). Essentially, Dutta et al. (2020) developed a DSS that enabled data integration from Internet of Things (IoT) sensors with ML models to optimise irrigation and fertiliser scheduling for rice, contributing to a reduction of 20% in water use and an increase of 15% in yield.

In addition, the use of soil nutrient and moisture models in combination with crop growth simulation models improves prediction accuracy and facilitates sustainable soil fertility management. Using multisource data like soil sensor readings, remote sensing imagery, and weather predictions, AI

systems can support site-oriented data-driven strategies of soil management that maximise productivity and natural resource conservation (Wolfert et al., 2017).

- **Soil Degradation and Erosion Monitoring**

Degradation of soil, such as erosion, salinisation, and nutrient loss, threatens food security across the globe as it has been estimated to cover almost 33% of the planet's arable land (FAO, 2017). The traditional assessment of soil erosion is based on field surveys and field models involving empirical equations, which are generally lacking in spatial resolution and prediction. AI and ML-based models solve these limitations by combining multiple data types like topography, land use, rainfall, soil properties, and more to provide high spatial and temporal resolution soil degradation hazard prediction (Kuhn et al., 2020).

Different predictive models like RF, GB, and ANN have been incorporated to identify the erosion areas and forecast erosion trends from the degradation area. In Mediterranean agricultural lands, for instance, the ML models used by Kuhn et al. (2020) predicted the soil erosion risk with higher accuracy than methods based on the Universal Soil Loss Equation (USLE). These models may be able to identify high-risk areas, where it may be necessary to employ such conservation practices as contour ploughing, cover cropping or buffer strip planting.

Estimation of soil degradation using remote sensing and geospatial information is also possible because they provide time series information on land cover changes and on vegetation dynamics and soil moisture patterns (Mishra et al. 2020). The data streams are used in ML algorithms to detect possible causes of degradation in the early stages, allowing for corrective measures to be taken. Moreover, the integration of climate models allows prediction of the future erosion pattern under different climate change scenarios and land use, thereby allowing for long-term land management planning (Kuhn et al., 2020).

The application of AI-based predictive modelling with remote sensing information has the ability to enhance the efficiency of measuring soil degradation levels, while also providing a way to take preventive steps to conserve soil health. By assessing vulnerable regions and forecasting the outcomes of practice, AI contributes to sustainable soil management, a key component for long-term success in agricultural and ecosystem health and vitality.

### **Resource Optimization through AI and ML Model Architecture Frequency**

Production sustainability in agriculture depends on efficient use of natural resources, chemical resources, and human resources. In most conventional agricultural production systems, excessive amounts of water, fertilizer, pesticide, and human or animal labour are used either to increase production or to meet growing demand, while also experiencing high production costs (Tilman et al., 2002). What makes AI and ML applications so effective is their ability to use analytics to improve resource management and ensure that all inputs are used to their best advantage to produce a crop of the desired quality and quantity without compromising the primary quality aim of optimized resource utilization.

- **Precision Irrigation and Water Management**

Water which is used in agriculture for irrigation amounts to almost three-fourths of global fresh water consumption, leaving it as one of the greatest challenges in agriculture today (FAO, 2017). Traditional irrigation methods were devised on a fixed-time schedule, which did not match the water needs of the crop and resulted in high losses in the water supply. Smart irrigation systems, which are AI-driven, can mitigate this problem by merging real-time sensor, weather, and soil moisture models to provide individual, precise watering solutions (Fahad et al., 2021). Through these systems, evapotranspiration, soil moisture, temperature, and humidity are monitored, and the amount and timing of watering are adjusted in accordance with ML algorithms.

For instance, historical weather data coupled with real-time data from plant sensors can be used for irrigation scheduling in ML-based decision-making systems for different types of crops and growth stages (Fahad et al., 2021). Such a practice not only increases irrigation water efficiency but also stimulates plant health and production. Furthermore, ML models like SVR, RF, and ANN have been developed for evapotranspiration (ET) prediction, which is a vital component for water demand. (Tian et al., 2021). These models incorporate climatic data and characteristics of the soil to provide a reliable prediction of ET and water needs.

Tian et al. (2021) showed that the linkage of satellite images with ANN-based ET prediction provided over 25% higher accuracy in irrigation scheduling over traditional methods. Furthermore, IoT-based smart irrigation systems with AI have proven to be potential in lowering water usage by thirty–fifty percent and hence yielding better crop output (Fahad et al., 2021). These new technologies are particularly vital in arid zones, where water-efficient irrigation systems can have a profound impact on the sustainability and climate-resilience of agriculture.

- **Fertilizer and Pesticide Optimization**

The long-term effects of a high density of pesticides and fertilizers on soil health, water quality, and ecosystem equilibrium are negative (Tilman et al., 2002). AI and ML technologies empower site-specific nutrient and pest control that minimizes waste of inputs and environmental effects while guaranteeing maximum crop productivity. Based on the soil data collected using soil sensors, remote sensing imagery, and records documenting crop growth, ML can be used to create precision nutrient management strategies that are tailored to the specific soil conditions that exist within a field (Gutiérrez et al., 2014).

For instance, Gradient Boosting and RF can be used to assess soil nutrient information and the growth patterns of plants to guide optimal fertilizer use for different parts of a field (Gutiérrez et al., 2014). These are the most effective recommendations to eliminate nutrient loss through leaching and to enhance the efficiency of nutrient use. The authors of Gutiérrez et al. (2014) estimated a reduction of 25 % in fertilizer use associated with a 10% yield increase for field irrigated systems that adopted site-specific fertilization based on AI.

- **Energy and Labor Optimization**

Increased energy costs and labour shortages are becoming a problem in modern agriculture increasingly. AI and automation offer solutions to these issues, making operations more efficient and energy-optimized, and decreasing reliance on human labor. Such technology in the form of robots and drones can be used by farmers in agriculture for planting, weeding, spraying, and harvesting crops, requiring little involvement from humans (Bac et al., 2014). They are autonomous systems, having advanced sensors, GPS navigation, and artificial intelligence for navigation, enabling precise and flexible operation.

Examples include ripe product recognition and the non-damaging harvesting of produce such as fruit and vegetables from deep learning and computer vision applications (Bac et al., 2014). Autonomous weeding robots can also save on herbicides with improved target detection using image recognition technology. Drones, on the other hand, can be incorporated to give aerial images for the monitoring of crops, pesticide applications and field mapping, and are able to cover large areas rapidly and economically (Hunt et al., 2010).

Apart from field operations, AI plays a major role in scheduling and optimising logistics. The ML algorithms include analysis of the data on weather conditions, crop maturity, labor availability, and equipment performance to generate optimal schedules between the planting, irrigation, harvesting, and transportation phases (González Andújar & Fernández Quintanilla, 2019). This reduces downtime, energy usage, and optimizes operational coordination. For instance, González Andújar and Fernández Quintanilla (2019) created a scheduling model for mechanised operations which led to reduced fuel consumption by 15% and operational costs by 12%.

In controlled environment agriculture (CEA), like greenhouses and vertical farming systems, AI-powered energy optimization proves especially advantageous. In this instance, energy use is optimized and optimal conditions for growth are maintained by AI models controlling nutrient delivery systems and lighting. (Benke & Tomkins, 2017). This type of system could also decrease energy use by up to 30–40%, making the farming of produce in these greenhouses more sustainable and economically viable.

### **Research Gap**

While the research on the effect of environmental variability on yield and soil health parameters has flourished and received significant attention, a great proportion of the research has been limited to physiological responses, irrigation schedules, and genotypic screening under varying environmental conditions in more general agroecological regions or areas. There has been relatively little study in temperate agroclimatic zones where variable temperatures, short growing seasons, and unstable rainfall patterns combine to affect soil physiological stages and soil health in a unique way. Besides, the recent progress in deep learning has achieved impressive results in predicting the yield of major crops from

complex environments, such as rice, wheat, maize, and soybean, but few models are available or tested in the temperate region of the Kashmir Valley. Generally, current DL based models rely on large-scale remote sensing data and require considering crops across multiple environments but fail to consider main crop-specific traits of moisture stress and local soil water dynamics and spatiotemporal stress responses. Besides, the information on how the model's predictions can be understood is still rather restricted, making it difficult to determine what stresses and physiological characteristics are most influential on the resistant crop production. Thus, there is a need for a sensible, easy-to-understand, and well-experimented deep-learning model that is able to accurately predict the yield of all crops grown under varying environmental conditions, and which can be used to implement input and stress-adaptive management in temperate ecosystems.

### **Discussion**

The outcomes of this study clearly highlight the extreme negative impact of resource constraints on crop productivity in temperate ecosystems where erratic climatic conditions trigger changes in irrigation, input utilization, and other management practices of the resources, making plants subject to varying resource supplies. This results in a dramatic decrease in the physiological and yield parameters of the crop, especially during the stages of germination and reproductive growth. Based upon their findings, the slowdown of physiological and yield factors of the crop is believed to be significant due to fluctuations in climatic conditions.

The possibilities for AI in agriculture extend beyond just predicting successful outcomes; they involve the development of intelligent and transparent decision-making support platforms that are ultimately sustainable. While the deep learning models perform well, they can be hard to interpret and explain; thus, problems exist in their interpretability and communication for users to understand and acquire trust in the model results. Future research should include further work on incorporating other datasets compiled, including genomics, climate, soil, and remote sensing, which will help capture more complex interactions related to crop growth and stress responses. The development of enabling conditions, deployment of digital infrastructure, and the organization of farmer trainings drive widespread use of AI technologies, particularly by smallholder farmers. Incorporating technological innovation, sustainable farming, and climate-smart strategies, AI can make a meaningful contribution to improving agricultural production, using resources effectively, climate adaptation, and sustainable food security.

### **Future Scope**

Artificial Intelligence (AI) and Machine Learning (ML) have emerged with technological advancements and still have a lot of potential to realize in the sector of agriculture. Projects for the future must cover transparency, integration, scalability, and sustainability in response to climate change and resource limitations from population growth in the global food system. This section summarizes the future strategic directions for extension and research to enable innovative strategies to rapidly grow in smart agriculture.

### **Conclusion**

As opposed to the conventional way of growing crops that was mainly based on instinct, it has opened up a whole new approach of farming through the use of data science, machine learning, and artificial intelligence to predict and adapt to changing conditions. The study indicates that AI and ML solutions have the power to address some of the world's most critical challenges in the field of agriculture, like food security and climate change, and can revolutionise the sector in numerous ways, including crop production forecasting, soil health monitoring, resource optimisation and real-time decision making (Liakos et al., 2018).

AI-driven predictive analytics can aid in more precise predictions of yield, prompt earlier identification of pests and diseases, and prompt more precise and targeted interventions, leading to significant yield loss reduction (Jeong et al., 2016; Khaki & Wang, 2019). A real-time monitoring system using satellite imaging, drones, and IoT devices provides enhanced situational awareness on the farm, and AI-based nutrient and moisture management optimizes input use on the farm, leading to improvement in soil fertility and farm water efficiency (Chlingaryan et al., 2018; Dutta et al., 2020). Moreover, smart irrigation systems, site-specific fertilization, and autonomous equipment minimize water use, chemicals, energy, and labor, which is expected to result in sustainable intensification of agricultural systems (Fahad et al., 2021; Bac et al., 2014).

AI integration with IoT and big data, cloud computing, will enable intelligent, connected ecosystems that continually collect, analyze, and carry out decision-making based on data (Wolfert et al., 2017; Kamilaris & Prenafeta Boldú, 2018). However, there are many challenges and barriers in the adoption of these technologies, including data quality and standardization issues, high costs, infrastructural setup requirements, lack of competencies, and considerations of ethics and legal matters (Walter et al., 2017; Bronson & Knezevic, 2016). Addressing these challenges is crucial to unlock the potential of AI in enhancing equitable access and benefiting agriculture.

In the future, the development of smart agri-agrofood systems depends on interdisciplinary and collaborative developments between researchers, policy makers, technologists and, at later stages, farmers (Rose et al., 2021). More explainable and transparent AI models will facilitate the development of trust and increase the uptake of AI, while more biomic algorithms and emerging multi-omics and climate data can facilitate the development of more adaptive and resilient farming systems (Gunning & Aha, 2019; Van Emon, 2016). Likewise, policy and institutional frameworks that offer inclusive access, protect farmer data rights, and ensure the ethical application of AI technology are needed (Rose et al., 2021).

To conclude, the applications of AI and ML in agriculture present a promising opportunity to transform food production and consumption patterns, enhancing the productivity, resilience, and sustainability of the system while promoting its efficiency and sustainability in the face of rising population, demographic shifts, and climate change. This vision can only be achieved with farmer-centered solutions, participatory practices, and inclusive policies that will ensure technology innovations can be most effectively applied for all involved, from smallholder farmers to agribusinesses all over the world. Such cooperative effort can bring AI-empowered smart agriculture into playing a significant role in the future of food security, which is climate-smart and sustainable (Liakos et al., 2018; Godfray et al., 2010).

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