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Harnessing artificial intelligence and remote sensing in climate-smart agriculture: the current strategies needed for enhancing global food security

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ABSTRACT
Global food security is seriously threatened by climate change, which calls for creative agricultural solutions. However, little is known about how different smart technologies are integrated to enhance food security. As a strategic reaction to these difficulties, this review investigates the incorporation of remote sensing (RS) as well as artificial intelligence (AI) into climate-smart agriculture (CSA). This review demonstrates how these advances can improve agricultural resilience, productivity, and sustainability by utilizing AI's capacity for predictive analytics, crop modelling, and precision agriculture, along with RS's strengths in climate projections, land management, and continuous surveillance. Several important tactics were covered, such as combining AI and RS to regulate risks, maximize resource utilization, and enhance agricultural practice choices. The review also discusses issues like policy frameworks, capacity building, and accessibility that prevent these technologies from being widely adopted. This review highlights how AI and RS can further CSA and offers insights into how they can help ensure food systems remain secure in changing climates.

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1. Introduction

The effects of climate change, resource scarcity, and fast-expanding populations are posing growing threats to global food security (Mirzabaev, Kerr, et al., 2023). There will be a greater demand for food when the world's population arrives at 10 billion by 2050 (Molotoks et al., 2021). Between 2010 and 2050, global overall food demand is predicted to rise by 35–56% (Van Dijk et al., 2021). To feed everyone on the planet by that year, food production must rise by 70% (FAO, 2019). The severe weather and crop disruption brought on by climate change exacerbate problems like land degradation and shortages of water (Booker & Trees, 2020; Bouteska et al., 2024; Mirzabaev, Strokov, et al., 2023). Food scarcity is made worse by economic inequality and unequal access to resources, especially in vulnerable areas (Lukwa et al., 2020). Further complicating food distribution are supply chain obstacles and political unrest (Y. Khan et al., 2024). To guarantee the consistent availability of wholesome food for all people worldwide, addressing these issues calls for creative and sustainable agricultural methods, enhanced resource management, and equitable solutions.

Climate change has an enormous effect on agriculture due to its alteration of weather trends, an increase in the frequency of catastrophic events, and reduction of crop yields (Bibi & Rahman, 2023; Habib-ur-Rahman et al., 2022). While extended droughts and erratic rainfall patterns worsen water shortages and lower yields in agriculture (Seleiman et al., 2021), elevated temperatures can cause heat stress in crops (Bucheli et al., 2022) and animals (Thornton et al., 2022). For instance, despite increasing irrigation, it has recently been demonstrated that increased heat stress lowers the yield of three important crops in Pakistan's Punjab region (Becker et al., 2023). Furthermore, climate change amplifies the occurrence of pests and diseases and degrades soil (Alfizar & Nasution, 2024). These impacts impair crop productivity and quality, which puts food supply at risk. Consequently, adaptive approaches are

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needed to improve agricultural practices' resilience and sustainability. In the face of climate change, solving these issues is essential to preserving global food supplies.

By incorporating tactics that improve crop yields, resilience, and sustainability in the midst of changing climates, climate-smart agriculture (CSA) has a critical role in tackling the shortage of food (Bazzana et al., 2022; Hellin et al., 2023). The three primary goals of CSA are to reduce greenhouse gas emissions, adapt to the effects of climate change, and increase productivity in a sustainable manner (Paul et al., 2023; Sawhney & Perkins, 2015). CSA helps maximize resource use and lessen the negative effects of the changing climate by implementing strategies like enhanced crop varieties, efficient utilization of water, and soil conservation (Abate et al., 2023; Zhao & Boll, 2022). Additionally, it encourages the implementation of cutting-edge methods and technologies that strengthen food system stability and increase resistance to severe weather (Kurgat et al., 2020; Teklu et al., 2023). By taking these steps, CSA helps to protect food supplies and guarantee that agricultural systems continue to be adaptable and productive in the face of climate change.

Agriculture is undergoing a technological revolution owing to artificial intelligence (AI) and remote sensing (RS), which increase efficiency as well as sustainability (Ahmad et al., 2024; Ennouri et al., 2021). AI integrates automation, machine learning, and data analyses to maximize farming methods (Songol et al., 2021; Talaviya et al., 2020). Through the analysis of large datasets, it facilitates precision agriculture, predictive modelling, and decision-making by predicting crop yields, identifying pests, and effectively managing resources (Al-Adhaileh & Aldhyani, 2022; Javaid et al., 2023). AI increases food security by cutting waste and improving farming methods. By assisting farmers with planting and harvesting planning, predictive analytics can maximize yields while consuming the fewest resources possible (Assimakopoulos et al., 2024; Mana et al., 2024). Drones and sensors are examples of precision agriculture tools that optimize fertilization and irrigation while monitoring crop health (Pandey & Mishra, 2024; Wongchai et al., 2022). Furthermore, supply chain optimizations and AI-powered pest detection tools guarantee effective production, lower losses, and fair food distribution (A. Khan et al., 2024; Talaviya et al., 2020). By making a variety of tasks easier, such as crop identification (Wäldchen et al., 2018) crop disease authentication (Abade et al., 2021; Shubhika et al., 2024), weed identification (Wang et al., 2019), water management (Sun & Scanlon, 2019; Virnodkar et al., 2020), animal health and husbandry (N. Li et al., 2020), ML can enhance agricultural sustainability or food security.

On the other hand, RS includes collecting information on crop health, the condition of the soil, and weather trends using drones and satellite images (Inoue, 2020; Weiss et al., 2020). This continuous information helps to improve the precision of mapping, managing, and evaluating farming operations (Radočaj et al., 2022; Sishodia et al., 2020). When combined, AI and RS help farmers respond to the threats posed by changing climates, make data-driven choices, and maximize resource use—all of which contribute to increased productivity in agriculture and food availability (Linaza et al., 2021) (Figure 1).

Traditional agricultural methods are not enough as climate change poses more and more threats to global food security (Bibi & Rahman, 2023; Bucheli et al., 2022; Habib-ur-Rahman et al., 2022; Seleiman et al., 2021). Using AI and RS in CSA can greatly help with food security issues by offering cutting edge instruments for optimizing resources, climate change mitigation, and precision farming (Jung et al., 2021; Mandal et al., 2024) (Figure 1). Yet, the successful application of these technologies necessitates a thorough comprehension of existing approaches and how they enhance crop yields and resilience. This is crucial for optimizing these technologies' advantages and removing obstacles to their widespread use. However, not much is known about how AI and RS are currently being integrated into CSA to increase food security.

In this study, 216 journal peer-reviewed articles, reports, and relevant documents were chosen at random from PubMed, Google Scholar, and ScienceDirect. Search terms included different combinations of the following key terms; artificial intelligence, remote sensing, climate-smart agriculture, food security, weather trends, climate change, environment, collaboration, and use as directed. The inclusion criteria were: 'papers on artificial intelligence, remote sensing, climate-smart agriculture', 'papers in the form of peer reviewed published scientific papers (journal/conference)', and 'papers published in 2011–2024'. The exclusion criteria were: 'papers not related to artificial intelligence, remote sensing and inclusion', 'Master/Ph.D. dissertations', 'Tutorial/workshop paper/ArXiv paper/magazine article/book/book chapter', 'conference version of a study with a longer journal version', 'papers that are not in English', and 'full papers which are not available online. Papers included were from 2011–2024, because there were few relevant papers available before 2011.

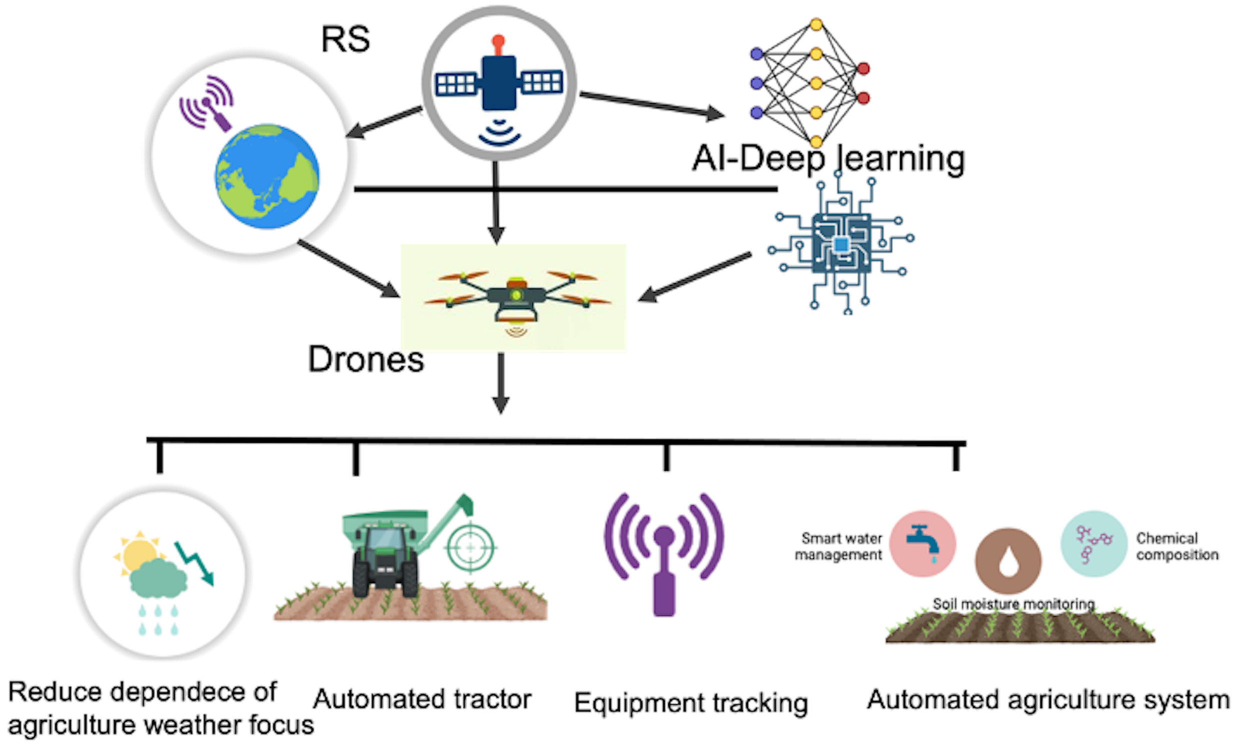

Figure 1. The interaction between remote sensing (RS) and artificial intelligence (AI) in enhancing climate-smart agriculture. The combination of AI deep learning neural networks, sophisticated crop simulation models, and remotely sensed data will advance digital agriculture. RS data, automated tractors, and equipment tracking will offer yield forecasting capabilities and prescriptive tools that will ease crop management and lessen agriculture's reliance on weather-focused practices.

This review provides insights into how AI and RS uses in CSA have the potential to revolutionize agriculture and guarantee world food supply in the face of climate change. The present approaches to incorporating AI and RS within CSA are reviewed and evaluated. The aim is to ascertain how these technologies can augment crop yields and resilience, consequently augmenting global food security.

2. Principles and ideas of CSA

CSA is a merged strategy for controlling agricultural systems that tackle the issues posed by climate change while guaranteeing food security and promoting sustainable growth (Bazzana et al., 2022; Hellin et al., 2023). Three primary goals characterize it: firstly, to enhance agricultural output and earnings in a sustainable manner, thereby contributing to food safety and economic growth; secondly, to enhance agricultural systems' capacity to withstand and rebound from shocks associated with the changing climate; and, thirdly, to minimize or completely eradicate the release of greenhouse gases, thereby lessening the negative environmental effects on farming (Paul et al., 2023; Sawhney & Perkins, 2015; Zaman et al., 2021). The goal of these interrelated goals is to build a more durable and resilient agriculture industry that can prosper in the face of ongoing environmental changes and climatic unpredictability.

The three main pillars of CSA—productivity, adaptation, and mitigation—combine to provide the framework for resilient and long-lasting agricultural systems. The goal of adaptation is to safeguard the availability of food and livelihoods by strengthening agricultural systems' ability to endure and recuperate from climate-related pressures like droughts, floods, and changing seasons of growth (Arif et al., 2020; Hellin et al., 2023). In addition, mitigation contributes to international efforts to combat climate change by lowering the release of greenhouse gases from agriculture through methods like enhanced soil management, effective utilization of water, and environmentally friendly land-use practices (Schreiner-McGraw et al., 2024; Zaman et al., 2021).

For instance, in cereal-based systems in North-West India, it has been demonstrated that CSA techniques enhance soil organic carbon pools, biological characteristics, and crop yields (Table 1) (H. S. Jat et al., 2019). Furthermore, Zizinga et al. recently found that the examined CSA practices show a higher likelihood of raising yields of maize than traditional farming practices (control) regardless of location sub-humid

Table 1. Various advantages of climate-smart agriculture techniques for enhancing agricultural productivity.

Climate smart agriculture technique	Benefit	References
Crop diversification, residue management, zero-tillage, and crop establishment	Enhance soil organic carbon pools, biological characteristics, and crop yields	(H. S. Jat et al., 2019)
Halfmoon pits (HM), mulching (M), and permanent planting basins (PPB)	Raising yields of maize than traditional farming practices	(Zizinga et al., 2022)
Machine learning (ML) algorithms	Increase efficiency by precisely predicting the amounts of water, fertilizer, and pesticides required	(Kanuru et al., 2021; Puspaningrum et al., 2022; Tanaka et al., 2024)
Artificial Intelligence (AI)	Improves the control of pests and diseases by early identification, observation, and control	(Kariyanna & Sowjanya, 2024)
Artificial Intelligence of Things (AIoT)	Protecting crops from pest and disease dangers	(Blanco-Carmona et al., 2023; C.-J. Chen et al., 2020; Muhammed et al., 2024)
Robots and drones, ML and soil water sensing methods	Maximize the use of herbicides and pesticides, cutting down on chemical use and lowering crop harm	(Indu et al., 2022; Talaviya et al., 2020)
Remote sensing (RS) and satellite	Accurate monitoring of parameters like soil moisture, nutrient levels, and pest activity	(Babaeian et al., 2019; Kumari et al., 2023; Mu et al., 2022)

regions with unpredictable and inadequate precipitation (Table 1) (Zizinga et al., 2022). Moreover, productivity seeks to raise crop yields and efficiency in a sustainable manner so that food production can meet the increasing demand for food worldwide without depleting natural resources (Andati et al., 2023; Tanti et al., 2024). Together, these pillars can create resilient, environmentally friendly, and commercially successful agricultural systems.

CSA methods and innovations aim to improve the long-term viability and adaptability of agricultural systems. Using crop varieties tolerant to drought (Oyetunde-Usman & Shee, 2023), effectively managing water through drip irrigation (Ali et al., 2020), and conserving tillage to preserve soil health (Das et al., 2020; M. L. Jat et al., 2023) are important tactics. Additionally, there is a different approach called agroforestry, which combines trees with livestock and crops to increase carbon storage and biological diversity (Tuturop et al., 2022). Precision farming, which maximizes input utilization and boosts productivity, is fueled by methods like data analytics and the Global Positioning System (GPS) (Shofiyati et al., 2024; Tetteh Quarshie et al., 2023). Furthermore, farmers can react to variations in the climate with the use of alert systems and climate prediction systems, resulting in greater stability and sustainable production of crops (Noma & Babu, 2024; O'Grady et al., 2021).

Globally, there is plenty of variation in the implementation of CSA practices; some regions have made significant progress, while others are facing difficulties (J. Li et al., 2024; W. Ma & Rahut, 2024). Several variables have been demonstrated to have a mixed (positive or negative) effect on the widespread use of CSA practices, including age, gender, education, risk perception and choice, credit availability, farm size, farming conditions, off-farm income, and labour allocation (J. Li et al., 2024). Besides, high-income nations are progressively incorporating cutting-edge CSA technologies into conventional farming, such as precision agriculture and crops resistant to climate change (Maloku, 2020). Conversely, while CSA has gained traction in certain nations, such as Ethiopia (Abegaz et al., 2024; Teklu et al., 2023), low-income areas—especially those in Sub-Saharan Africa (SSA) and some parts of Asia—are typically slower to adopt the technology because they have less availability of resources, information, and technology (Sanogo et al., 2023; Wakweya, 2023).

The governments of most SSA countries were against the enhanced, genetically modified varieties because they believed that they could harm their health and their natural environments (Mmbando, 2023, 2024). This may account for the lower CSA adoption rate in these countries. In addition, studies has indicated that the primary barriers to implementing modern smart irrigation techniques in South Africa are inadequate communication channels, an absence of funding, unreliable land tenure systems, and inadequate training (Serote et al., 2023). Global partnerships and campaigns, on the other hand, are aggressively pushing CSA through monetary incentives, support for policy, and capacity building. This is helping farmers cope with climate variability and progressively raising adoption rates while enhancing food security (Chevallier, 2023; Davila et al., 2024).

3. The application of AI to climate-smart agriculture

AI-related innovations in agriculture involve robotics, computer vision, and machine learning, which improve the precision of agriculture (Gryshova et al., 2024; Zhang & Qiao, 2024). Large-scale data is analyzed by machine learning algorithms to forecast yields, identify diseases, and improve the management of crops (Durai & Shamili, 2022). While

AI-powered drones and robots efficiently and sustainably execute tasks like planting and spraying (H. Li et al., 2023; Talaviya et al., 2020), computer vision helps monitor crop wellness and automate harvesting (Ghazal et al., 2024).

By using sophisticated algorithms to evaluate vast amounts of climate data, such as historical records, satellite images, and real-time environmental assessments, AI dramatically improves climate forecasting and risk evaluation (Karanth et al., 2023; Konya & Nematzadeh, 2024). AI tools, like machine learning models and neural networks, can accurately predict weather trends, catastrophic incidents, and how they will affect agriculture. With the use of these tools, preventive actions can be taken in the event of potential hazards like heatwaves, floods, and droughts (Dikshit & Pradhan, 2021; Lopez-Gomez et al., 2023; Puttinaovarat & Horkaew, 2020). Farmers and policymakers can better adapt to the impacts of climate change and reduce related risks by utilizing AI in climate models, which can provide timely alerts and actionable insights.

AI revolutionizes CSA by enabling precision agriculture to maximize resource use (Shaikh et al., 2022). AI technologies use data analysis from a variety of sources, including sensors, satellites, and unmanned aerial vehicles (UAVs), also known as drones, to offer useful information on the state of the soil, crop health, and environmental variables (El Alaoui et al., 2024; Muhammed et al., 2024; Rajak et al., 2023). Machine learning algorithms decrease waste and increase efficiency by precisely predicting the amounts of water, fertilizer, and pesticides required (Table 1) (Kanuru et al., 2021; Puspaningrum et al., 2022; Tanaka et al., 2024). Additionally, continuous evaluation and decision-making are made possible by AI-driven systems, guaranteeing that resources are used as efficiently as possible (Subeesh & Mehta, 2021; Talaviya et al., 2020). Farmers can increase yields, reduce their environmental impact, and more effectively and precisely adjust to variations in climate by incorporating AI into their CSA operations (Javaid et al., 2023; M. H. U. Khan et al., 2022).

AI also improves the control of pests and diseases by offering cutting-edge instruments for early identification, observation, and control (Table 1) (Kariyanna & Sowjanya, 2024). AI systems precisely detect pests and diseases at the earliest stages by analyzing data from sensors, cameras, and drones using computer vision and machine learning (Gautam et al., 2022). For instance, it has been demonstrated that the Artificial Intelligence of Things (AIoT), a hybrid of the Internet of Things (IoT) and AI, may be a useful tool in protecting crops from pest and disease dangers (Table 1) (Blanco-Carmona et al., 2023; C.-J. Chen et al., 2020; Muhammed et al., 2024). Based on past data and environmental factors, predictive models predict outbreaks, allowing for timely interventions (Kariyanna & Sowjanya, 2024). In addition, AI-driven solutions maximize the use of herbicides and pesticides, cutting down on chemical use and lowering crop harm (Table 1) (Indu et al., 2022; Talaviya et al., 2020). AI helps CSA practices become more accurate in managing pests and diseases, which lowers losses and promotes resilient and sustainable farming systems.

Besides, AI greatly improves crop modelling and forecasting yields by predicting agricultural results through the analysis of intricate datasets (Al-Adhaileh & Aldhyani, 2022; Javaid et al., 2023). AI algorithms generate precise models of growing crops and yield potential by analyzing data from weather trends, soil conditions, and crop growth phases (Agboka et al., 2022; Awais et al., 2023; Inazumi et al., 2020).

AI is essential for improving global food security because it tackles important issues in agriculture, such as post-harvest management, resource efficiency, and productivity optimization (Assimakopoulos et al., 2024; Galanakis, 2020; Mana et al., 2024). Predictive models powered by AI examine soil conditions, weather trends, and past crop data to give farmers useful information (Ghaffarian et al., 2022; Sparrow et al., 2021). For example, farmers can use IBM's Watson Decision Platform for Agriculture to help them decide when to plant, irrigate, and harvest crops (Kakani et al., 2020; R. Kumar et al., 2020). These realizations improve crop yields and cutting down on resource waste by coordinating farming methods with environmental conditions.

Also, AI-powered systems use sensors, drones, and satellite imagery to track crop health, soil quality, and moisture levels in real time (Materia et al., 2024; Olawade et al., 2024; Pandey & Mishra, 2024; Wongchai et al., 2022). As an illustration, Blue River Technology's 'See & Spray' technology applies herbicides precisely where they are needed by using AI to separate weeds from crops (Panpatte & Ganeshkumar, 2021; Yeshe et al., 2022). This improves crop quality while using fewer chemicals, saving money, and lessening the impact on the environment.

Moreover, AI uses sensor data and image recognition to enable disease early identification and pest recognition. The PlantVillage Nuru app, for instance, provides customized management recommendations to smallholder farmers by assisting them in identifying crop diseases such as cassava mosaic disease

(CMD) and cassava brown streak virus disease (CBSD) caused by viruses (Moupojou et al., 2023; Mrisho et al., 2020).

In addition, AI can forecast market trends and streamline logistics to cut down on food waste. For instance, the most widely used AI techniques for stock market prediction have been found to be support vector machines (SVM), long short-term memory (LSTM), and artificial neural networks (ANN) (Lin & Marques, 2024). Blockchain and AI work together to increase supply chain transparency, guarantee fair pricing, and cut down on inefficiencies (H.-Y. Chen et al., 2023). As a result, AI strengthens the agricultural industry, guaranteeing sustainable food production and distribution across the globe.

With the use of these predictive models, farmers are better able to plan planting times, distribute resources, and implement management techniques. CSA improves planning and control of risks, maximizes yields and resource utilization, and adjusts to changing weather patterns by integrating AI and machine learning through crop modelling (Ghaffarian et al., 2022; Sparrow et al., 2021). This leads to more resilient and effective agricultural systems that can supply the world's food needs in the future.

It has been demonstrated that AI improves precision water management. For instance, it has been demonstrated that irrigation analytics calculated using artificial neural networks (ANN) can produce maps of moisture availability that allow for variable supply and maximize daily and spatial water use (Wei et al., 2024). Furthermore, AI-based data fusion methods precisely and promptly detect and measure pest and disease outbreaks (Fahey et al., 2020) (Figure 2). AI AgriTech drones indicate their value in precision and ecological farming by gathering data from the fields and assisting human decision-makers in monitoring routine tasks (like crop surveillance and disease assessment) and AgriFood operations (like fertilization, irrigation, etc.) (Figure 2) (Spanaki et al., 2021, 2022). For example, in the Republic of Benin and the Democratic Republic of Congo, banana plants and their primary disease have been identified using machine learning models based on aerial images (Selvaraj et al., 2020). In a similar vein, Tirkey et al. offer deep learning-based methods for identifying and detecting insects in soybean crops in real time. Their research is much simpler, yields better results, and lessens the producer's workload (Tirkey et al., 2023).

With a number of benefits, such as improved accuracy, efficiency, and sustainability, AI-enabled robotic weeders in precision agriculture hold promise for adding much-needed options to the

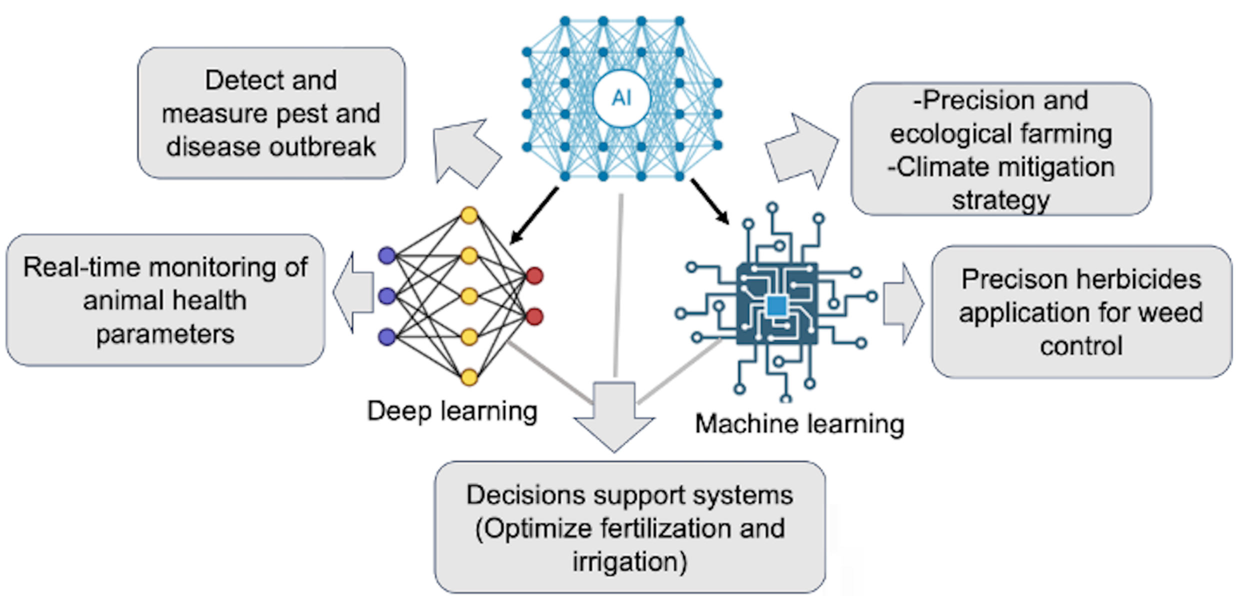

Figure 2. Various application of Artificial intelligence (AI) to enhance sustainable agriculture and adaptation to climate change. AI-based data fusion such as deep learning technique can identify and quantify disease and pest epidemics accurately and at the earliest possible stage. This AI-powered tools identify pests and diseases early, providing timely interventions and predictive models for outbreaks. AI algorithms also provide continuously monitor animal health parameters in real time, providing valuable insights for farmers and veterinarians to optimize disease prevention strategies and improve animal welfare. Decision support systems (DSS) can use AI to interpret sensor data, evaluate welfare status, predict future risks, and suggest interventions. This allows optimization of various aspects like fertilization and irrigation systems. Machine learning and cameras can enable precision herbicide application for weed control in crops like sugarcane. Therefore, DSS tailors recommendations for farmers that will enhance productivity while reducing environmental impact.

agricultural landscape (Edan et al., 2023; Reddy et al., 2023). Furthermore, DarkNet53's superior performance offers a promising path forward with an efficient decision system in the machine vision components of an accurate herbicide applicator for weed control in sugarcane fields using a cheap camera connected to a single-board computer (Modi et al., 2023). Furthermore, it has been demonstrated that the You Only Look Once (YOLO)v4 model, a trained Convolutional Neural Network-based object detection system, can accurately predict 98.88% of weeds with a typical loss of 1.8 and a mean average precision score of 73.1% (Saqib et al., 2023) (Figure 2).

Real-time, continuous monitoring of animal health parameters by AI algorithms gives farmers and veterinarians important information to enhance disease prevention tactics and enhance animal welfare (S. Ma et al., 2021) (Figure 2). Through the continuous updating of productivity data, health records, and individual cow profiles made possible by this AI integration, farmers are able to make well-informed decisions regarding each animal (Mahato & Neethirajan, 2024). AI can be used by to analyze sensor data, assess welfare, forecast risks, and recommend interventions (Gutiérrez et al., 2019). AI sensors, for instance, can give quick, real-time feedback on the surroundings; these sensors can assist in preserving the best possible living conditions for the animals and can detect any unfavorable changes (Lovarelli et al., 2020). This can help farmers make well-informed, prompt, and efficient decisions that will improve animal welfare and productivity (Figure 2).

Additionally, by facilitating resource optimization and data-driven decision-making, it revolutionizes climate adaptation for sustainable agriculture. AI predicts weather patterns, evaluates risks, and guides preventative actions against climate stress through predictive analytics and climate modeling (Figure 2). It incorporates remote sensing to minimize resource waste by monitoring crop health, identifying stress, and optimizing fertilization and irrigation (Materia et al., 2024; Olawade et al., 2024). Early detection of diseases and pests by AI-powered technologies allows for prompt interventions and outbreak prediction models. By customizing suggestions for farmers, Decision Support Systems (DSS) increase output while lessening their negative effects on the environment (Ara et al., 2021; Iakovidis et al., 2024). AI has, for instance, been used to analyze data from climate models, satellite imagery, and weather patterns in order to create plans for safeguarding communities and infrastructure against the effects of climate change (Jain et al., 2023) (Figure 2). AI supports the post-COVID-19 recovery process and climate resilience (Leal Filho et al., 2022).

4. Climate-smart agriculture using remote sensing

A key component of CSA, RS technologies provides vital instruments for tracking and controlling agricultural systems in the face of changing climates (Torresan et al., 2022; Yu et al., 2024). RS collects high-resolution images and data on a range of environmental variables, including crop health, shifts in land use, and soil moisture, through the use of satellites, cameras, and UAVs (Inoue, 2020; Yu et al., 2024). Farmers can now make data-driven decisions about resource management, crop planning, and mitigation plans owing to this technology, which offers insightful information about the effects of climate change (Ayalew et al., 2021; S. Kumar et al., 2022; Raji et al., 2024; San Bautista et al., 2022). Thus, by increasing farming practices' accuracy, boosting productivity, and encouraging environmentally friendly land use, RS helps CSA and eventually builds more resilient and fruitful farming systems.

Moreover, UAV- and satellite-based RS are essential for raising crop yields and resilience (Nhamo et al., 2020; Rejeb et al., 2022). To track the effects of climate change and inform extensive agricultural plans, satellites offer long-term, comprehensive coverage as well as data on crop health, land utilization, and weather trends (Karmakar et al., 2023; Omia et al., 2023). In addition, UAVs provide high-resolution, localized observations that allow for a thorough examination of particular fields, soil characteristics, and the health of plants (Istiak et al., 2023).

Besides, satellite observations provide broad views of atmospheric parameters that are essential for forecasting adverse weather conditions and evaluating the effects of climate change, such as temperature, humidity, and rainfall patterns (Gummadi et al., 2022; Weiland et al., 2023). Numerous investigations have exhibited the great potential of satellites for agricultural water application (Cunha & Guimarães, 2023; Zhu et al., 2023). Farmers may foresee and reduce risks by using this data to predict severe weather and future climate changes. Also, farmers may make well-informed decisions regarding planting timelines, distribution of resources, and handling risk by incorporating RS data into CSA plans. This will ultimately increase productivity in agriculture and sustainability amid climate change.

In addition, by offering accurate and current data on land and soil conditions, RS is essential for efficient crop tracking, inspection of land use, and management of soil in CSA (Inoue, 2020; Yu et al., 2024).

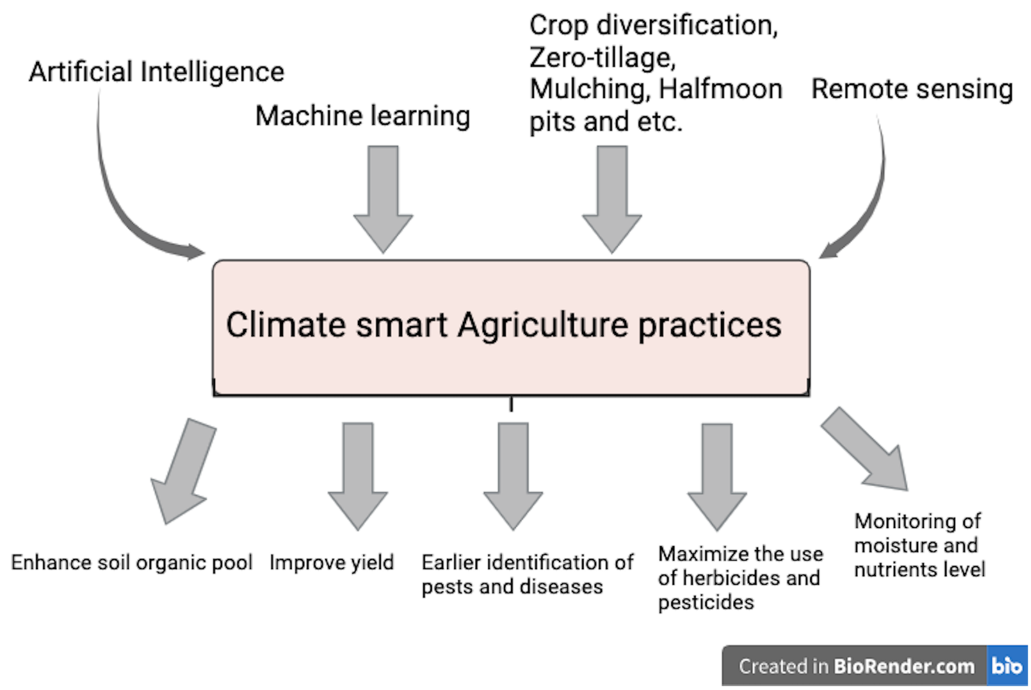

Figure 3. Improving crop resilience and yield through climate smart agriculture with the integration of artificial intelligence and remote sensing. Utilizing artificial intelligence (AI) and remote sensing (RS) in conjunction with other strategies like crop diversification, mulching, and machine learning will boost the soil organic pool, maximize the use of pesticides and herbicides, detect disease and pathogens early on, and monitor the moisture and nutrients in leaves—all of which will ultimately boost crop resilience and yield.

RS offers comprehensive, up-to-date information on crop conditions, such as patterns of growth, physical conditions, and stress signs, through the use of satellite and UAV technology. With the use of sophisticated visualization and data analysis, this technology permits accurate monitoring of parameters like soil moisture, nutrient levels, and pest activity (Babaeian et al., 2019; Kumari et al., 2023; Mu et al., 2022). Timely and focused interventions are made possible by the early detection of problems such as disease, drought, and lack of nutrients. In addition, methods such as multispectral imaging and soil property mapping facilitate the evaluation of soil characteristics, nutrient concentrations, and degradation (Orlando et al., 2022; Pande et al., 2022). Farmers may maximize soil conservation efforts, carry out focused interventions, and raise land productivity by incorporating this data into CSA techniques. This will also increase crop yields, promote environmentally friendly farming, and increase resilience to impacts of climate change.

5. AI and RS synergies to strengthen CSA

Precision agriculture combines sophisticated data analysis with thorough environmental monitoring to improve farming practices through the integration of AI and RS (Jung et al., 2021) (Figure 1). RS technologies, like UAVs and satellites, offer current information on crop health, soil state, and environmental factors along with high-resolution imagery (Yu et al., 2024). This data is analyzed by AI algorithms that forecast crop performance, maximize resource utilization, and provide actionable insights (Figure 3) (Mana et al., 2024; Talaviya et al., 2020). This combination makes it possible to accurately control inputs, such as pesticides, fertilizers, and water, according to particular field circumstances (Ennouri et al., 2021; Jung et al., 2021).

In addition, AI-driven RS data analysis is essential for crop and climate modelling because it uses machine learning techniques to handle and understand large, complicated datasets (Pokhariyal et al., 2023). AI combines these models with historical and current data through machine learning algorithms to simulate different scenarios, allowing accurate prediction and choice-making (Figure 2) (Kariyanna & Sowjanya, 2024; Padhiary et al., 2024; Yousaf et al., 2023).

Agricultural management is transformed when decision-support tools are improved with AI and RS because they offer data-driven, current information (Yousaf et al., 2023). AI algorithms examine the comprehensive imagery and environmental data collected by RS technologies to find trends, forecast results, and provide useful suggestions (Gummadi et al., 2022; Weiland et al., 2023; Yu et al., 2024). Consequently, decision-support tools become more precise and responsive when AI's analytical capacity is combined with RS's extensive data, empowering farmers to make wise decisions, optimize practices, and raise agricultural productivity as well as sustainability (Figure 3).

The combination of RS and AI is revolutionizing agriculture by improving resilience to climate shocks, decreasing resource waste, and stabilizing crop yields (Figure 1). Platforms such as CropX, for instance, use AI to evaluate RS data from satellites and drones, detecting pest infestation or nutrient deficiencies early (Vashishth et al., 2024). By enabling focused interventions, these insights reduce yield losses and stabilize productivity. Furthermore, AI-powered RS-based crop growth models, like the Sentinel-1 and Landsat satellite program, forecast crop performance in a variety of scenarios, assisting farmers in modifying their methods for the best results (M.Sekhar et al., n.d.; Sishodia et al., 2020).

The AI-RS synergy is extremely beneficial to precision agriculture, which greatly reduces water, fertilizer, and pesticide waste. RS data is analyzed by AI-driven tools such as Blue River Technology's 'See & Spray' to differentiate crops from weeds (Panpatte & Ganeshkumar, 2021; Yeshe et al., 2022). As a result, up to 90% less chemical is used because herbicides are only used where they are absolutely required.

Through risk prediction and mitigation, AI and RS improve agriculture's resilience to climate variability. For example, RS data is integrated into IBM's Watson Decision Platform for Agriculture to predict extreme weather events, such as floods or droughts (Gordon et al., 2020; Sodhi & Saxena, 2020; Thatipelli & Sujatha, 2021). Farmers can take adaptive actions, like choosing crop varieties resistant to drought or modifying planting dates, thanks to these forecasts. Similarly, RS-based AI models help track long-term climate impacts and direct sustainable farming methods to reduce risks and increase resilience (L. Chen et al., 2023).

Moreover, AI ensures a consistent flow of raw materials for the production of functional foods by forecasting demand and reducing interruptions, which improves supply chain efficiency (Attah et al., 2024; Joel et al., 2024). By combining AI and RS, agri-food systems can become more resilient, sustainable, and innovative while satisfying changing consumer demands for sustainable, health-conscious food options. For instance, during the COVID-19 pandemic, particularly when several essential services were shut down, it was crucial to use social media to learn about the attitudes, perceptions, and obstacles that affect consumer behavior and the agri-food sector's use of Internet and communication technologies like RS and AI (Galanakis, 2020; Galanakis et al., 2021).

Furthermore, the adoption of AI and RS technologies in developing nations is frequently hampered by cultural and social barriers, including low digital literacy, resistance to change, and a lack of trust in technology (Mhlanga & Ndhlovu, 2023; Smidt & Jokonya, 2022; Songol et al., 2021). Strategies for overcoming these include implementing community engagement programs to establish credibility and show advantages, providing customized training to enhance digital literacy, and enlisting local leaders to promote adoption (Serote et al., 2023). Furthermore, creating user-friendly, culturally appropriate solutions and fusing traditional knowledge with contemporary technology can facilitate the shift, encouraging acceptance and long-term use.

Different agricultural systems are affected differently by AI-RS integration, which allows for customized insights and optimizations. AI-RS improves climate adaptability in rainfed systems by tracking soil moisture and forecasting rainfall patterns (Agboka et al., 2022; Awais et al., 2023; Inazumi et al., 2020; Pierre et al., 2023). It minimizes waste in irrigated systems by optimizing water usage (Olawade et al., 2024; Serote et al., 2023). Comparative studies point out inefficiencies, like resource dependence in intensive farming, which direct system-specific innovations for increased productivity and sustainability.

Adopting AI-RS presents difficulties for small-scale farms, such as high expenses and a lack of technical know-how (Songol et al., 2021). Subsidies, reasonably priced equipment, and regional training are some solutions. On the other hand, managing large, varied data sets is a challenge for large-scale farms (Atapattu et al., 2024). Operations are streamlined by sophisticated RS systems and scalable AI platforms. Customized strategies guarantee that AI-RS improves productivity and sustainability on all scales, benefiting both large and small farms.

In Sub-Saharan Africa, AI and RS technologies are revolutionizing agriculture by tackling issues like low productivity, resource scarcity, and climate variability. AI is used, for instance, by Hello Tractor and other platforms to maximize mechanization on smallholder farms. Through a mobile app, farmers can access tractor services, increasing planting and land preparation efficiency (Daum et al., 2021). Large-scale agricultural regions are monitored by RS technologies, including drones and Sentinel-2 satellite imagery (Koeva et al., 2020). For instance, the NASA-supported project Crop Monitor forecasts crop yield and evaluates crop health using satellite data to help Kenya plan for food security (Wahome et al., 2023).

In Zambia, AgriPredict has been demonstrated to assist smallholder farmers in overcoming agricultural obstacles like pests, diseases, and droughts (Munalula & Qutieshat, 2024). Furthermore, in Tanzania, deep learning objective tools have proven to be a useful tool for diagnosing cassava diseases in the field. They also hold promise as a rapid and economical way for researchers to share their findings with farmers and agricultural extension agents (Mrisho et al., 2020). In addition, Mayo et al. demonstrate that early maize disease identification in Tanzania was made possible by the use of deep learning models, specifically convolutional neural networks (CNNs) and vision transformers (ViTs), with an emphasis on the Maize Streak Virus (MSV) and Maize Lethal Necrosis (MLN) (Mayo et al., 2024; Mduma & Laizer, 2023).

Through the integration of AI with solar-powered irrigation systems, SunCulture minimizes waste by directly delivering water to crops based on their current needs (Fairley, 2021). Africa's weather and soil data are analyzed by IBM's Watson Decision Platform for Agriculture to forecast drought risks and direct adaptive measures (McLymont, 2013). These systems enable farmers to maximize water use, boost drought resistance, and guarantee sustainable productivity—all of which are essential for ensuring food security in the arid conditions of the region of Africa.

6. Strategies for scaling up AI and remote sensing in CSA

Through their ability to foster technological adoption, policy and institutional frameworks are essential to the scaling up of AI and RS in CSA. Good policies should support funding for research and development, motivate investment in AI and RS infrastructure, and foster cooperation among stakeholders, such as the public and private sectors, research institutions, and governments (Carcamo et al., 2023; Dara et al., 2022; Rodríguez-Barillas et al., 2024; Sarvia et al., 2020; Talaviya et al., 2020). Actionable suggestions like offline AI applications or subsidized internet expansion could also be implemented by the government, enabling CSA to be widely adopted by smallholder farmers in the area. Clear rules, data-sharing guidelines, and capacity-building initiatives must be established by institutional frameworks to support technology integration (Gwagwa et al., 2021; Owusu et al., 2024; Šestak & Copot, 2023; Spanaki et al., 2021). The widespread use of AI and RS can be expedited, expanding agricultural endurance and productivity, strengthening CSA practices, and creating a favourable setting through focused policies and strong institutional support.

Table 2. Challenge hindering adoption of climate-smart agriculture techniques and possible recommended solutions.

Challenge	Recommended action
Lack of good policies favoring artificial intelligence (AI) and remote sensing (RS)	Establishment good policies frameworks supporting AI and RS infrastructure, tax reduction, foster cooperation among stakeholders
Lack of knowledge to smallholders farmers regarding the use of AI and RS.	Effective programs should be established focused on teaching stakeholders and farmers about the uses and advantages of these innovations
Technology-phobia concerns	Workshops and capacity building that are customized for each specific group of farmers
Low adoption rate of AI and RS due high cost of the tools and software	Establish public-private collaboration and investment. Governments, businesses, and academic institutions should hasten the adoption of new technologies
Ethical and data privacy issues on the use of RS and AI	Clear regulations must be put in place to safeguard farmers' confidentiality and guarantee data security as these innovations gather enormous volumes of data

An essential component of scaling AI and RS in the CSA is training and capacity building. Effective programs should concentrate on teaching stakeholders and farmers about the uses and advantages of these innovations (Musungwini et al., 2023) (Table 2). Technology-phobia concerns should be eliminated through training programs that address data analysis with AI tools, crop and soil tracking with RS technologies, and decision-making with interpreted results. For instance, technophobia issues among farmers and extension agents can be resolved through workshops and capacity building that are customized for each specific group (Boniface et al., 2019) (Table 2). Moreover, practical experience can be obtained through workshops and field experiments (Barrientos et al., 2011; Jindo et al., 2021; Piikki et al., 2022). Assuring that stakeholders can successfully incorporate AI and RS into their operations will increase CSA adoption, boost crop yields, and promote sustainable farming methods. This can be achieved by developing local expertise and offering continuing support.

Moreover, CSA must be scaled up through public-private collaboration and investment. Governments, businesses, and academic institutions working together can spur innovation and hasten the adoption of new technologies (Ferroni & Castle, 2011; Mangeni, 2019; Smyth et al., 2021). Research, facilities and policy formulation can be funded by public sector investment, while private sector participation can contribute to modern technology, knowledge, and efficiency (Akullo et al., 2018; Casey et al., 2021) (Table 2). Through easing the broad implementation of AI and RS technologies, collaborative efforts and funding programs can aid in the advancement of sustainable agriculture (Agarwal et al., 2023; Smyth et al., 2021). These collaborations can strengthen agricultural resilience, advance CSA practices, and promote sustainable growth by combining resources and expertise from the public and private sectors.

Furthermore, expanding CSA requires tackling ethical and data privacy issues. Clear regulations must be put in place to safeguard farmers' confidentiality and guarantee data security as these innovations gather enormous volumes of data (Kaur et al., 2022; Ongadi, 2024; Uddin et al., 2024; Van der Burg et al., 2019) (Table 2). For instance, research has indicated that African farmers are not well-versed in data protection difficulties nor are they able to manage who is granted access to their data (Chichaibelu et al., 2023).

Besides, ethical principles that prioritize consent, openness, and fair access to benefits ought to regulate the use of data (Ayris & Rose, 2023; Dara et al., 2022; Mark, 2019; Uddin et al., 2024; Van der Burg et al., 2019). Preventing data misuse is crucial to avoid biased results or disadvantages for small-scale farmers (Kaur et al., 2022; Okengwu et al., 2023). This may be aided by the creation of laws like the General Data Protection Regulation (GDPR) (Kaur et al., 2022; Schuster, 2017), which was established by the European Union (EU) to protect personal data regardless of the application domain. Therefore, for AI and RS to be adopted responsibly and to support equitable and long-term CSA practices, strong frameworks for managing data must be established, and trust must be built among stakeholders.

Furthermore, implementing supportive policy frameworks for AI-powered precision agriculture and RS adoption involves tailored strategies to address financial and technical barriers (FAO, 2019; Galanakis, 2023; Talaviya et al., 2020). Governments can provide subsidies or low-interest loans to offset the high costs of AI and RS technologies, making them accessible to smallholder farmers (Galanakis, 2023; Omotilewa et al., 2019; Osorio et al., 2024) (Table 2). Omotilewa et al. (2019), for instance, found that subsidies increase farmers' interest in learning new technologies, which in turn increases the rate at which agricultural green technology is adopted (Omotilewa et al., 2019). Incentives like tax breaks for companies developing localized solutions can stimulate innovation and deployment. Establishing public-private partnerships can facilitate resource-sharing and technology transfer. The adoption of AI-RS will also rise if its knowledge is combined with interdisciplinary research opportunities, such as agricultural sciences for crop yield modeling customized to soil conditions.

7. Challenges and future perspectives

While integrating AI and RS into CSA has the potential to be revolutionary, several obstacles and constraints need to be overcome to improve global food security (W. Ma & Rahut, 2024). The affordability and availability of these innovations is one of the main issues, especially for small-scale farmers in nations that are developing. There is a digital gap that restricts the beneficial effects of these advances to more wealthy regions due to the substantial expenses related with the greater complexity and computational cost of AI tools, RS devices, and data acquisition (Abdelmajeed & Juszczak, 2024; Abiri et al., 2023; Gardezi et al., 2024; Jung et al., 2021; N. Kumar, 2023). Further exacerbating this problem and impeding the widespread implementation of AI and RS innovations is the absence of dependable internet access in rural regions, such as those found in Africa (Mhlanga & Ndhlovu, 2023; Ozor, 2023).

An additional noteworthy constraint is the intricacy of AI and RS systems. Many farmers and other agricultural stakeholders might not have the specialized information and technical skills that these technologies frequently need to function properly (Fassnacht et al., 2024). In addition, it is challenging for users to completely utilize RS's potential for resource management and decision-making due to underutilized regions and restrictions in hyperspectral data applications (Abdelmajeed & Juszczak, 2024). Moreover, the quality and accessibility of data have a significant impact on the efficacy of AI-driven solutions (Javaid et al., 2023; N. Kumar, 2023; Talaviya et al., 2020). Many areas, particularly those most susceptible to climate change, may have outdated, inconsistent, or insufficient information, which can cause errors in analyses and forecasts.

Additional significant obstacles come from worries about data privacy and ethics. Concerns concerning data ownership, access, and security are brought up by the enormous volumes of data that AI and RS are collecting (Amiri-Zarandi et al., 2022; Gardezi et al., 2024; Kaur et al., 2022; Spanaki et al., 2021). It is possible that improper use of this data could have unforeseen repercussions, like exacerbating already-existing disparities or taking advantage of weaker demographics (Dara et al., 2022). For instance, many farmers mistakenly apply more nitrogen (N) fertilizer—instead of less—in the mistaken belief that doing so will increase yields (Lajoie-O'Malley et al., 2020). To reduce these risks, it is essential to make sure that data management systems are strong and open. AI and RS can be more successfully incorporated into CSA by addressing these issues and putting these solutions into practice. This will increase agricultural resilience and make a substantial contribution to the world's food supply in the face of changing climates.

The application of AI and RS in CSA has the potential to greatly improve agricultural practices worldwide. Farmers will be able to maximize resource use and increase productivity as a result of these technologies' evolving ability to provide more accurate and timely insights into the health of crops, soil state, and environmental factors (El Alaoui et al., 2024; Muhammed et al., 2024; Rajak et al., 2023). As RS becomes more widely available, even small-scale farmers will be able to take advantage of imagery from satellites and high-resolution data (Inoue, 2020; Weiss et al., 2020). Through the advancement of predictive analytics, AI will improve resilience and lower losses by enabling early warnings for climate risks like droughts, floods, and pest outbreaks (Kanuru et al., 2021; Puspaningrum et al., 2022; Tanaka et al., 2024). More targeted and productive methods of farming will be possible with the combination of AI with IoT devices and big data analytics (Blanco-Carmona et al., 2023; C.-J. Chen et al., 2020; Muhammed et al., 2024). These technologies will be essential for effectively increasing production while reducing the effects of climate change, guaranteeing a more sustainable and safe food supply in the future as the world's food demand rises.

8. Conclusion

Using AI and RS in CSA offers a revolutionary way to tackle the pressing issue of ensuring sufficient food for all people in the world in the face of climate change. This review has shown how the proper application of AI and RS technologies can greatly improve agricultural adaptability, productivity, and sustainability. These technologies enable farmers and decision-makers to enhance farming procedures, reduce risks, and cope with climate change through precise management of resources, forecasting, and continuous surveillance.

In addition to enhancing crop quality and yield, the complementary application of AI and RS in CSA promotes sustainable land and water management, which advances the more general objectives of environmental preservation and climate adaptation. To fully utilize these innovations, though, significant obstacles must be overcome. These obstacles include the requirement for strong regulatory frameworks, more funding for technology infrastructure, and the development of farmer and stakeholder capacity. Furthermore, achieving global food security depends on providing equitable access to AI and RS technologies, especially in low-income areas (Table 2).

Future research and development endeavours should concentrate on enhancing AI and RS tools to more effectively cater to the unique requirements of heterogeneous agricultural systems. Also, new approaches to incorporating data and decision support must be investigated. The development of international collaboration and partnerships between both the public and private sectors will be crucial to accelerating the adoption of these technologies and creating a global farming landscape that can nourish a growing world population while also adapting to climate change. Building a green and food-secure world requires the thoughtful and inclusive integration of AI and RS.

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Authors contributions

G.S.M. planned and designed the study, G.S.M. performed literature search, and G.S.M. analyzed data and wrote the manuscript. G.S.M. conceived the study.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

All data produced during this study are incorporated in the manuscript.

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