**A Review on IoT, Remote Sensing, GIS and AI for Climate Smart Agriculture**

**Abstract**

To address these issues, this paper examines the integration of artificial intelligence (AI) and remote sensing (RS) into climate-smart agriculture (CSA). By utilizing AI's strengths in predictive analytics, crop modeling, and precision agriculture, as well as RS's strengths in climate projections, land management, and continuous surveillance, this review demonstrates how these advancements can improve agricultural resilience, productivity, and sustainability. One of the main strategies discussed was combining AI and RS to control risks, optimize resource use, and improve agricultural practice selections. The review also covers the issues of capacity building, policy frameworks, and accessibility that prevent these technologies from being widely used. This review describes how IoT, AI, GIS, and remote sensing can help CSA and offers details on how they might help ensure food systems' security in the face of climate change.

**Keywords**

IoT, Agriculture, Smart irrigation, Precision farming, Crop monitoring

**Introduction**

Agriculture is the main source of a nation's income and has a big impact on its GDP [1]. Leaders in the world like the US and the EU make significant investments in new farming equipment. With the majority of people likely to live in cities by 2050, food productivity is predicted to need to rise by 70% in order to fulfill demand [2]. Approximately 70% of all available water is being used for agriculture, which is a necessity for agriculture. However, food production is inadequate owing to environmental changes, and conservation of resources is necessary [3]. New farming methods are being developed in an effort to address this issue. Traditional agricultural methods, which have not integrated technological technology as well as other industries, have been superseded by modern farming techniques [4]. New precision agriculture techniques and Internet of Things technology have completely changed farming in the computer age. Advanced farm management, waste reduction, and crop production can result from the application of IoT technologies in agriculture with little negative influence on the environment [5]. Agriculture is changing due to technologies including cloud computing, machine-to-machine transmission, wireless sensor networks, radio-frequency identification, and data analytics. For instance, wireless sensor networks are capable of gathering information on meteorological parameters such as temperature, humidity, wind speed, and precipitation. They can also identify plant diseases, monitor food development, and figure out how to fertilize and water crops most effectively [6,7]. Machine-to-machine communication allows for the implementation of tasks like watering and pest management, and radio-frequency identification (RFID) made it possible to track individual plants, animals, or pieces of equipment [8]. For the storage and analysis of massive volumes of data gathered by sensors from different devices, cloud computing is important. Farmers can improve their operations and services by gaining fresh insights from further data analysis utilizing tools like machine learning [9].

 Farmers are now able to enjoy better livelihoods as a result of the shift towards farm mechanization [10]. The type of crop being grown, however, determines how much farming is mechanized [11]. For crops like rice and wheat, extensive technology is used to prepare the soils prior to harvest, but for others, such pulses, more straightforward field preparation is sufficient [12]. Mechanization has been essential in solving many of the problems that farmers encounter in quickly expanding nations like India [13]. Moreover, agricultural mechanization facilitates the production of a variety of crop kinds, saves water, lowers labor costs, and increases farm profitability [14]. Conventional irrigation techniques are weather-dependent and require a lot of work. Irrigation systems have been developed to increase food production because insufficient precipitation might hinder agricultural output [15]. However, the excessive water use of these watering systems may eventually result in a shortage of water. However, excessive water use from these irrigation methods may eventually result in water scarcity. Precision irrigation, or metered water use, has been used as a result of this worry and has revolutionized agriculture's environmental impact. It is a noteworthy invention in tackling the difficulties that farmers encounter [16]. Because precision agriculture maximizes resource utilization and reduces environmental impact, it provides substantial advantages. In addition to ground-based sensors and yield monitors, satellite and aerial photography offer vital insights on production variability at both the macro and micro scales. Large volumes of agricultural data can be processed, represented, and modeled thanks to these technologies, which makes precision agriculture techniques possible [8,9]. time-spatial models, especially capture the dynamic interaction between location and time, which is crucial for comprehending intricate agricultural systems, and hence have notable advantages over conventional spatially explicit models [10]. This ability is further enhanced by hierarchical models, which handle complicated interactions by introducing random effects and specifying parameters that vary across numerous layers [11]. This strategy enables more precise forecasts and customized management plans, which will eventually increase crop yields and resource efficiency. By combining these cutting-edge modeling methods with high-resolution data, we may more effectively tackle the problems of sustainability and agricultural variability in the face of global change. Precision agriculture uses cutting-edge technologies like IoT sensors and data analytics to help farmers make well-informed decisions regarding crop management, which results in more economical use of pesticides, fertilizers, and water.

Innovation in technology has made precision watering much more advanced by making it possible to gather, share, and use extremely precise control methods. Temperature, humidity, and soil moisture are among the important characteristics that sensors measure and communicate to the operator or an intelligent watering system, which is frequently accessed by a smart phone interface [17, 44]. The use of precision irrigation has caused a major shift in agriculture, and many farmers are now using this method. Machine-to-machine communication, cloud computing, wireless sensor networks, radio frequency identification, and data mining are just a few of the IoT technologies that precision agriculture incorporates to improve a variety of agricultural processes. This paper explores the various ways that IoT can be used in agriculture, looking at how various IoT solutions might help with the particular problems that the industry faces. The scope encompasses an examination of many Internet of Things, Remote Sensing and GIS based technologies and their pragmatic implementations in domains like supply chain management, livestock monitoring, smart greenhouses, precision farming, smart irrigation, agricultural drones, pest and disease control, and crop and soil monitoring.

**Digital agriculture (DA)**

In the last three decades, farming practices have been transformed by the widespread adoption of technologies like automation and control systems, data analysis tools, and web-based and mobile applications. Digital agriculture (DA) is based on the following five levers for action that, when mobilized together, lead to innovation: (1) abundance of data due to the development of sensors (from nano sensors to satellites) and facilitated communication and storage; (2) increase in computing power, which makes it possible to implement artificial intelligence and new modeling methods; (3) connectivity and information exchange interfaces; (4) knowledge management and engineering for agricultural decision support systems; and (5) automation, control, and robotics. Over the last thirty years, the extensive use of technologies like data analysis tools, web-based and mobile applications, and automation and control systems has transformed farming methods. Increasing agricultural lands' and resources' productivity has been the main objective of these developments. Between the early 1990s and 2010, growers used GPS, satellite maps, and local sensing tools like data recorders to keep an eye on their field and spot any problems. Precision agriculture is the term for this method (PA). With the advent of long-range wireless sensors, Unmanned Aerial Vehicles (UAVs), and Internet of Things (IoT) devices, PA and smart farming techniques have progressed toward digitization. This has given people fresh hope for improving the food supply's sustainability. PA leverages the data gathered from multiple sources, including satellite images and mobile sensing systems, to pinpoint issues and improve agricultural productivity by efficiently employing the resources at hand. In order to improve field efficiency and reduce costs, smart and digital agriculture simultaneously use robotics, wireless systems, mobile applications, and IoT-based automation to detect, evaluate, and control the state of the soil, water supplies, and weather fluctuations on croplands [11,12, 43]. Wireless sensors and IoT devices have been crucial in the automation space, helping to install smart irrigation, limit water loss, and continuously identify soil nutrient levels in remote locations [12]. DA technology adoption and use differs by region of the world, and this diversity is influenced by a number of reasons. DA technologies are being adopted and used at a comparatively high rate in Europe, especially in nations like France, Germany, and the Netherlands that have substantial levels of agricultural productivity. Additionally, the European Union has been encouraging the use of PA methods by means of its Common Agricultural Policy [13, 42]. DA technology acceptance and use are comparatively strong in North and South America, with the US, Brazil, and Canada being the top three nations in this regard. These nations invested in the study and creation of new technology and were among the first to implement PA practices. The use and adoption of DA technology is expanding quickly in Asia, with China at the forefront of this trend. Utilizing PA technology to boost crop yields and lessen their impact on the environment has been encouraged by the Chinese government [14, 41].

**Using UAVs for remote sensing**

 The use of unmanned aerial vehicles (UAVs) to gather data and photographs of the earth's surface in this case, the agricultural sector from above is known as UAV-based remote sensing [17], [40]. With the use of several sensor types, including radar, lidar, thermal, multispectral, and hyperspectral sensors, this technology makes it easier to collect high-resolution data from land, vegetation, water bodies, and both natural and man-made features. When drones are equipped with high-resolution imaging sensors, they may gather datasets that can give farmers more precise information than satellite photos. Crop stress and soil properties are the main targets of UAV-based remote sensing [19]. In order to create decision support systems for intelligent irrigation, fertilization, and pest control, this produces useful data. Fixed wing (planes), single-rotor (helicopter), hybrid system (vertical take-off and landing), and multirotor (drone) are only a few examples of varied UAVs [20, 39]. Drones (multi-rotor technology), which are powered by four (quadrotor) or six (hex-rotor) rotors, have gained popularity in the agricultural industry because they are simpler mechanically than helicopters, which use a far more complex plate control mechanism [21, 38].

The agri-food industry's adoption of UAV-based remote sensing is sluggish because to problems like [20]:

* Cost: For many farmers, the expense of purchasing and maintaining remote sensing equipment might be prohibitive.
* Complexity: Farmers may find it challenging to interpret and use the complex data produced by remote sensing technologies to their operations.
* Standardization: Data collection and analysis are not standardized, which can make it challenging to compare data from various sources or technologies.
* Data quality: Depending on the tools utilized and the circumstances surrounding the data collection, the quality of remote sensing data can differ. This may cause skepticism over the technology's efficacy.
* Access: Many farmers may find it difficult to obtain dependable, high-quality data and an internet connection, especially in remote or underdeveloped nations.
* Privacy and security: Data gathered via remote sensing technology raises privacy and security concerns, especially when it comes to sensitive data like crop yields and land use.

The use of remote sensing technology in agriculture has often been hampered by these problems, although initiatives are being taken to resolve them and boost its uptake.

**IoT and Big Data Integration in CSA**

 Sustainable agriculture has greatly benefited from IoT and AI technologies, which maximize resource use and enhance environmental results. By guaranteeing timely and accurate irrigation based on real-time soil moisture and weather data, IoT-enabled precision irrigation systems have been shown to boost agricultural yields and reduce water use by 30% [18]. In a similar vein, Perennial's and other AI-driven digital soil mapping algorithms have decreased the need for physical soil sample by 40%, increasing the precision of carbon sequestration estimations and allowing for focused interventions for regenerative agricultural practices [19]. According to research on smart water wells by López-Morales et al. [19], energy consumption can be decreased by up to 25% with IoT-integrated energy-efficient irrigation systems. Building on the IoT, the IoAT allows for automation and data-driven insights in agricultural processes [20]. Sensors are essential for monitoring environmental factors such as soil moisture, temperature, humidity, and air variables at the perception layer [22, 36]. Soil moisture sensors, for instance, offer real-time data that aids in irrigation plan optimization. Infrared gas analyzers for CO2 and methane detection, Normalized Difference Vegetation Index (NDVI) sensors for crop health evaluation, and weather stations for gathering microclimatic data are some of the sensors for monitoring greenhouse gas emissions that are included in this layer. Precision agriculture requires a comprehensive environmental profile, which is produced by various sensors working together. But when it comes to technology like smart irrigation systems, it's important to evaluate the term "smart" seriously [21, 37]. Although these systems are intended to initiate precise irrigation in response to sensor inputs, their actual "smartness" hinges on the precision of the underlying models and thresholds, which need to be carefully established by thorough investigation and localization. The IoAT's incorporation of sophisticated sensing features guarantees a more resilient and contextually aware agricultural system that can react quickly to data in real time.

In order to facilitate automation, agricultural equipment, including tractors, is increasingly outfitted with sensors and actuators. With the use of GPS sensors and actuators, tractors led by the Global Positioning System (GPS) can now efficiently carry out operations like fertilization and planting. By taking airborne photos and data over vast areas, drones help check crop health and broaden the application of this technology [23], [29]. Communication between these elements is crucial at the networking layer. But using the word "seamless" to describe this communication can be deceptive. For additional analysis, the data from these sensors is sent to the cloud; however, this calls for reliable infrastructure, which isn't always available in agricultural settings. IoAT provides solutions like supply chain optimization, crop monitoring, precision agriculture, and predictive maintenance at the application layer. The application of such systems varies depending on local infrastructure and economic conditions, but they have the potential to completely transform agriculture, especially in regions with abundant resources. This revolution should be viewed critically because it frequently makes assumptions about the availability of technology and overlooks the difficulties of implementing it in areas with limited resources.

The use of IoT into Climate-Smart Agriculture (CSA) is a significant development in farming methods. The Internet of Things (IoT) is a network of linked sensors and gadgets that make it easier to gather data in real time from a variety of agricultural components, including fields, animals, and machinery. It is crucial to understand, though, that farmers have long gathered data, albeit informally, and that IoT merely formalizes and digitizes this process. IoT's usefulness in CSA is found in its capacity to deliver more precise and detailed data, which can help with resource optimization and decision-making [24]. Improved techniques to increase productivity and sustainability are made possible by knowledge of soil health, moisture content, and meteorological conditions. The notion that IoT "revolutionizes" farming methods in every situation should be questioned, though. IoT's remote monitoring and control features enable farmers to more successfully address issues like climatic variability. IoT adoption is still restricted in many areas, though, because of financial, educational, and infrastructure constraints, and its advantages are not equally available. It is necessary to critically assess how IoT can promote sustainable and climate-resilient behaviors in this regard. The availability of reliable models, socioeconomic circumstances, and local adaption all affect how effective IoT is. Only the wealthiest farmers will be able to fully utilize these technologies, and the introduction of IoT into agriculture runs the risk of escalating already-existing disparities if these basic issues are not resolved.

 Artificial Intelligence of Things (AIoT) [25] is incorporated into CSA to improve data processing and decision-making by utilizing cutting-edge sensor technology for real-time emission monitoring, especially for gases such as CO2, CH4, and N2O. Technologies include photoacoustic gas sensors [25], electrochemical sensors, and Non-Dispersive Infrared (NDIR) sensors [26] provide accurate monitoring of emissions from livestock management and fertilizer use. This information helps reduce emissions and promotes sustainable farming methods when paired with AI-driven models. Furthermore, whereas IoT systems track climatic, micrometeorological, and soil moisture data, they do not directly assess plant factors like temperature or pH. Rather, by monitoring variables like temperature, humidity, and nutrient levels, AIoT uses environmental sensors and predictive models to infer plant health and optimize resource use for improved growth and sustainability.

**IoT-based CSA research and development can be divided into three main categories:**

1. IoT is used to collect vital agricultural data using sensors that measure crop and environmental aspects like temperature, humidity, pH, leaf colour, etc. in order to inform farming methods [27].
2. Farming methods that are automated, including the use of wireless sensor and actuator networks for cloud-based decision-making and irrigation systems that are optimized [28]. The principles of system visibility, safety, simplicity, feedback, extensibility, and cognitive load reduction serve as the foundation for this method, which uses a variety of sensors and robots or actuators to automate farming tasks. [29].
3. Using in-network control to lower overhead and power usage without sacrificing Quality of Service (QoS). In the Internet of Things network, this entails optimizing the use of resources, such as power sources and communication channels. Such innovations include AI-enabled energy-efficient networking for wireless sensor networks and resource allocation that is aware of traffic patterns [30] and [31]. But the correctness of the models behind the data processing and integration is crucial to how well these solutions work. Although they can drastically cut down on overhead and power usage, if the models are not reliable or suitable for the given situation, inaccuracies or inefficiencies could still occur.

**Cloud-based models driven by AI**

 To fully analyze the enormous volumes of data gathered from agricultural settings, cloud-based models driven by AI must be developed. These models forecast and optimize carbon footprints using cutting-edge machine learning (ML) and deep learning techniques [31]. To offer practical insights for sustainable farming operations, they examine a variety of factors, such as engine sizes, mobility patterns, and particular farm tasks.

 Accurate carbon footprint monitoring and improved sustainability are made possible by the combination of AI-powered cloud computing, collaborative learning, and sophisticated analytical models in agriculture. Utilizing federated artificial intelligence, reinforcement learning, and scalable computer platforms, these methods offer data-driven insights for maximizing resource utilization, reducing emissions, and guaranteeing sustainable agricultural practices. Federated learning, for instance, provides a decentralized machine learning method that improves data privacy in sustainable agriculture [32]. Using Apen theory, graph-based models are employed to examine intricate relationships in agricultural data in order to gain a deeper understanding [34]. Known for its capacity for adaptive decision-making, reinforcement learning is used to maximize agricultural operations [33]. These cutting-edge AI models' incorporation into cloud computing frameworks marks a major advancement in climate-smart agriculture by enabling more accurate and predictive insights into environmental impacts and empowering more intelligent, data-driven choices for sustainable agricultural methods. To process complicated agricultural data, they provide smart, dynamic, and scalable solutions. This makes it easier to make decisions in real time and makes a big difference in sustainable farming methods, which helps to match agricultural operations with more general sustainability and environmental objectives.

**Real-time analysis and data integration using multi-source remote sensing and GIS**

Global agricultural remote sensing research has advanced dramatically in recent decades due to the open accessibility of global remote sensing data. Agricultural remote sensing has significantly improved its real-time monitoring capabilities due to its wide spatial coverage, high timeliness, and accessibility. But even with the more frequent revisit cycles of modern satellite remote sensing systems, cloud and rain interference still makes it difficult to produce high-quality, cloud-free, daily agricultural data. We suggested a combined satellite and near-surface remote sensing approach for near real-time agricultural monitoring under ESM-GAMS in order to address this. The automatic spatial matching between satellite imagery and near-surface camera images is specifically used in this strategy [28, 39]. This method reconstructs daily time-series vegetation indices for the monitored areas by utilizing the high temporal resolution of near-surface camera views (on an hourly basis). This allows for daily agricultural monitoring in almost real-time. ESM-GAMS also facilitates the smooth integration of near-surface cameras into the monitoring system during unmanned aerial vehicle (UAV) operations or crucial satellite overpasses. During these situations, the system can immediately activate adjacent or regionally deployed near-surface cameras using 4G signals to guarantee synchronized and continuous data collection. Due to temporal constraints or unfavorable weather conditions in satellite or UAV observations, this feature successfully allows an integrated space-sky-ground agriculture monitoring system. In addition to improving spatial coverage and data consistency, this kind of collaboration also makes agricultural monitoring more dependable and timely in dynamic and uncertain field situations. A significant advancement in the creation of fully integrated, real-time agricultural monitoring systems is represented by this invention.

**Addressing research opportunities and challenges**

 Unique issues arise when integrating IoT, Big Data, Edge Computing, and ML into a specialized, end-to-end solution. It does, however, offer present a number of chances to improve the efficiency and sustainability of farming methods. These elements are explored in detail in this section, which also offers insights into the challenges encountered in practical implementations and possible directions for future development.

 One of the main obstacles is the intricate system integration needed to integrate disparate technologies, such as edge computing, big data, and the internet of things, into a coherent framework [31, 35]. Managing real-time processing, effective data flow, and smooth interoperability across multiple system levels is a major technical problem. Furthermore, handling the enormous amount and diversity of data produced by IoT devices for tracking carbon footprints is a difficult undertaking. In order to effectively store, process, and derive valuable insights from this data, sophisticated Big Data analytics and machine learning algorithms are required. Energy efficiency and sustainability present yet another significant obstacle. Devices from IoT and Edge Computing are crucial for data gathering and real-time monitoring [32], but they also raise the energy footprint of farming operations. It is essential to create sustainable system architectures and energy-efficient gadgets to make sure that these technologies help to lower the carbon footprint overall. Another problem with ML-powered predictive models is their accuracy and dependability [33], particularly in light of shifting climatic circumstances and diverse farming methods. For these models to be effective, they must be able to accurately forecast carbon emissions and other environmental effects under a variety of circumstances. Adaptability and scalability are also essential components. In order to support a variety of agricultural activities of all sizes and kinds, the system must be scalable and flexible enough to adjust to a wide range of farming methods and environmental circumstances. Because of this necessity, implementing it in various agricultural settings is difficult. However, these difficulties also present a lot of opportunity. The creation of adaptive models that can forecast carbon emissions under various circumstances is one example of how advances in AI and ML could lead to a more precise and effective study of environmental data. Innovation prospects in sensor technology are also presented by the creation of more energy-efficient sensors that can record a greater variety of environmental data, greatly improving the monitoring of carbon footprints. A further opportunity for advancement is provided by the combination of cloud and edge computing [34]. Through local data processing at the edge and more sophisticated, large-scale data analysis in the cloud, this synergy can balance computing loads, increase system efficiency, and facilitate real-time decision-making.

**Conclusion**

Growing concerns about the global food security dilemma are driving the need for modern industrial farms and improved agricultural production techniques. A plethora of innovative solutions to increase agricultural yields, decrease prices, cut waste, and preserve process inputs have been made available to the agricultural sector by the Industry Revolution 4.0 agenda, which spearheaded the spread of data-driven approaches. This assessment offers a thorough examination of the condition of digital technologies currently used in the agriculture industry. Big data and analytics, wireless sensor networks, and cyber-physical systems are still in the early stages, according to our evaluation. The majority of application cases have not yet been commercially available and are still in the development stage. The combination of technologies like IoT, AI, remote sensing, and spatiotemporal modelling has revolutionary potential for increasing output, maximizing resource utilization, pest outbreaks and change and lessening the effects of climate change.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

Option 2:

Author(s) hereby declare that generative AI technologies such as Large Language Models, etc. have been used during the writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

Details of the AI usage are given below:

1.

2.

3.

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