

The Future Generation of Smart Agriculture

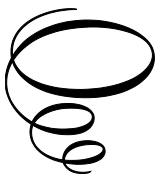
The Future Generation of Smart Agriculture:

*Bridging Plants
and Computer Science*

Edited by

Mohit Angurala,
Kulwinder Kaur,
Mandeep Kaur Sandhu
and Subham Sharma

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CHAPTER 1

INTRODUCTION TO SMART AGRICULTURE

SUBHAM SHARMA¹,
MANDEEP KAUR SANDHU²,
KULWINDER KAUR³,
MOHIT ANGURALA²

¹Department of Zoology, Guru Nanak Dev University College, Pathankot, Punjab, India.

²Department of Computer Science, Guru Nanak Dev University College, Pathankot, Punjab, India.

³Department of Botany, Guru Nanak Dev University College, Pathankot, Punjab, India.

Abstract

Smart agriculture is a revolutionary method of farming in the modern era that is driven by the integration of advanced technology such as artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), and data analytics. It utilizes precision farming technology to lower environmental footprints, optimize crop management, and enhance agricultural production. Smart farming tracks crop health, weather forecasts, and soil nutrient levels in real-time, allowing farmers to make informed decisions. Drones, robots, and other autonomous equipment, as well as sensors, take over time-consuming tasks and address challenges like labour shortages to enhance efficiency further. Smart farming reduces waste, improves yield, and enables sustainable agriculture by offering predictive analytics and intelligent monitoring. This innovative approach is vital in satisfying the continuously increasing food demand without compromising the environmental and climate-related issues of contemporary agriculture.

Keywords: Internet of Things, Smart Agriculture, Agriculture 4.0, Blockchain

1. Introduction

1.1 Evolution of Agriculture

The world's population is estimated to increase by 2 billion by 2050 from the current 7.8 billion to close to 11 billion by the end of the century [1], as put forward by UN estimates. This is the serious population growth that necessitates adopting sustainable agriculture to ensure the world feeds its growing population while keeping the environment intact. Figure 1 illustrates the evolution of farming methods and technology over time, specifically how they have adapted to meet the increasing needs of society [2]. Early on, farming relied almost exclusively on human and animal power—popularly known as Agriculture 1.0. Farming had limited land use and low productivity, where crops were grown using simple hand tools and ploughs powered by animals.

The dawn of the Industrial Revolution ushered in a new age for agriculture—Agriculture 2.0—and was characterized by unprecedented change in land use and farming. The discovery of steam power, mechanized farm equipment, and inventions like the plough, tractor, and threshing machine transformed the production of food. Thanks to these innovations, farmers could plant more land and have greater yields of crops, leading to a sharp rise in food supply [3]. This new farming system aided in sustaining the fast-growing population, which had started growing at an exponential rate. But this industrialization of farming had a chain of environmental and ecological consequences. Monoculture, or the growing of one crop across extensive lands, exhausted the nutrient content of the soil and exposed crops to more disease and pest infestation. Also, the extensive use of fossil fuel-based machinery and the intensification of agriculture played a significant role in increasing greenhouse gas emissions, inducing climate change [4]. This agriculture model, although prolific in producing vast amounts of food, has ultimately caused long-term environmental degradation. The results are soil erosion, reduced biodiversity, water shortage, and increased pollution, all of which pose a threat to future food production sustainability. With these issues as a response, there is now a growing call for the shift to more sustainable forms of agriculture.

Since the emergence of information and communication technologies (ICT), the era of agriculture 3.0 began in the 20th century, and data collection and automation started in agriculture [5]. Due to the advent of agriculture 3.0 in the last decades, a significant increase in the agricultural innovation systems is seen. The integrated technology system with TGS

(Technology Generation System), TDS (Technology Distribution System), and TPS (Technology Practicing System) facilitated the sharing of new technologies among farmers. Additionally, Participatory Technology Development (PTD) is assisting scientists worldwide in developing new, effective agricultural systems.

This is further evident through the Agricultural Knowledge and Innovation System (AKIS), which helps us to boost knowledge and innovation flow from labs to the fields. At present, AI-powered precision agriculture is needed to transform farming by optimizing resource use and improving crop management to meet global food demands sustainably [6]. The approach towards advanced technologies like machine learning, drones, and sensors for data-driven decisions, reducing waste, and environmental impact is needed. The integration of AI also introduces autonomous systems for enhancing efficiency, addressing labour shortages, and promoting smart agriculture, and agriculture 4.0 is contributing to it [7].

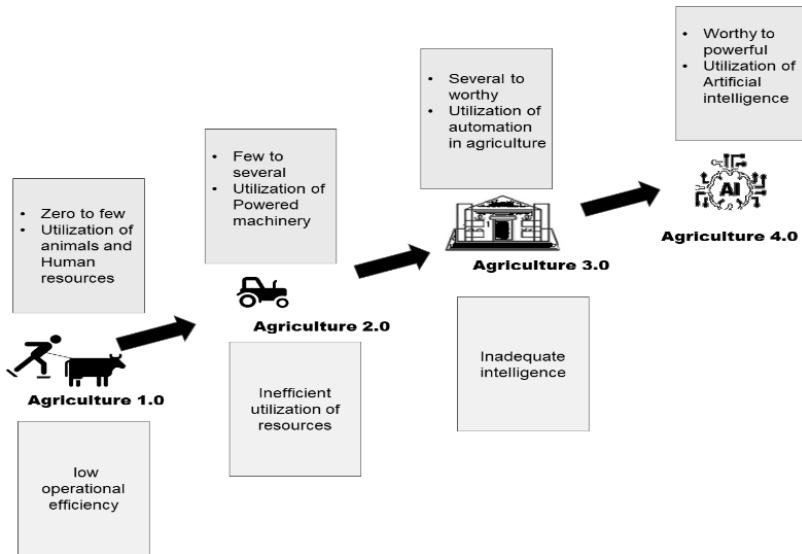


Figure 1 shows the evolution of agricultural.

Backed up by an enormous database, agriculture 4.0 can record data, diagnose problems associated with crops and lands, and predict the best possible ways to increase crop production. IoTs and other smart devices and programs not only help in promoting smart agriculture, but they also help

to complete the goal of sustainable agriculture [8]. Higher outputs from agriculture can be achieved through a variety of intelligent systems and remote monitoring technologies, such as IoT.

1.2 Agriculture 4.0

Inspired by Industry 4.0, agriculture 4.0 aims at the development of systems in which all modules of the systems are connected constantly and fluently, as shown in Fig. 1.2. The integration of all devices together and the development of communication between them serve as an essential part of the smart agriculture. [3] The 4th revolution in industry and agriculture aims to reform current agricultural practices to more advanced ones, meeting the world's upcoming needs. [4] Agriculture 4.0 is equipped with cutting-edge technologies such as the use of IoTs, AI and machine learning, uncrewed vehicles (UAVs), remote sensing and satellite imagery, virtual and augmented reality, GIS and analytics, CPS technologies, etc. [5]. It aims to introduce and modify efficient irrigation and fertilization systems, reduce herbicide and pesticide use, implement continuous monitoring approaches for timely identification and solutions of plant diseases, and maintain extensive databases for further analysis and problem-solving.[6]

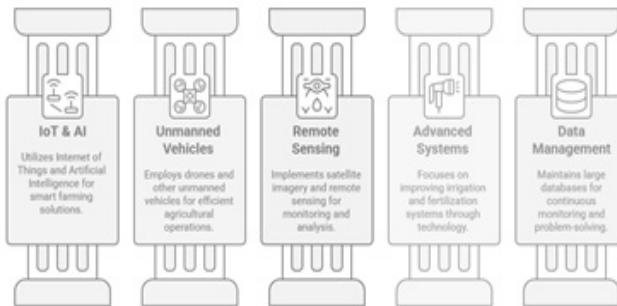


Figure 1.2: shows Transformation in agriculture via IoT and Automation

2. Technological Innovations in Smart Agriculture

2.1 Internet of Things (IoT) In Smart Agriculture

The "Internet of Things" (IoT) refers to a network of integrated machines, sensors, and gadgets that are all individually identifiable and can sense and monitor their surroundings remotely over the internet [9]. Six layers make

up the typical IoT architecture: the perception layer (hardware devices), the application layer (data integration and analytics), the middleware layer (device management and interoperability), the network layer (communication), the end-user layer (user interface), and the service layer (cloud computing). IoT sensors at the physical layer in agriculture gather data on crop and environmental parameters like pH, water levels, temperature, humidity, and leaf colour. This data is transmitted via the network layer, whose design varies according to the size, location, and farming style of the farm.

Technologies like Sigfox, LoRa, and ZigBee are commonly utilized in outdoor fields because of their great transmission range, low cost, and low energy usage. On the other hand, even though Bluetooth is secure, its small range limits it to indoor farms. Despite becoming widespread in different sectors of the economy, Wi-Fi's high cost and energy consumption make it unsuitable for agriculture. Technologies such as NFC (Near Field Communication) and RFID (Radio Frequency Identification) are becoming more popular for tracking products in agricultural systems [10]. A popular application of GPRS and mobile communication technologies (2G, 3 G, and 4G) is the periodic monitoring of soil and environmental conditions. In agricultural contexts, communication protocols including HTTP, WWW, and SMTP are frequently used.

2.1.1 Productivity and sustainability in agriculture using IoT

Employment of growth accounting methodology shows that IoTs have a positive impact on overall productivity, but the effect is still modest. IoTs offer the potential to track and predict changes in agriculture at almost every step, thereby minimizing congestion at several key points.

When it comes to sustainability, Agricultural businesses are progressively embracing digital technologies, such as the IoT, to improve results. It sets the standard for sustainable supply chain processes in the future and ensures several opportunities to obtain a competitive edge. Industry 4.0 enables a prompt response to customer demand. It increases output and helps farmers, supply chain managers, and associates make decisions more quickly in real time. It undoubtedly makes it easier to implement new business strategies and enhance the manufacturing process.

2.1.2 Challenges to Internet of Things Implementation in Smart Agriculture

Since the IoT is still in its infancy stages, the impact is still minimal. Better infrastructure and investments are required to unlock the full potential of

IoT in the agricultural sector. Challenges include a lack of awareness, complicated software, security threats in IoT applications, and a lack of technical skills, as well as the use of IoTs in agriculture by technical workers. These challenges hinder the widespread adoption of IoT technologies in the agricultural sector. To overcome these barriers, it is essential to enhance education and training programs, streamline software solutions, and implement robust security measures that protect sensitive data.

2.2 AI and ML in smart agriculture

Artificial intelligence (AI)-enabled smart agriculture is essential for advancing environmentally friendly farming methods. The success of the agricultural sector depends on the application of AI technology in critical areas like crop development, disease detection, weather forecasting, soil and irrigation management, and livestock care.

Machine learning, a pervasive and versatile technology, is increasingly integral to numerous global domains, with smart agriculture emerging as a key area of interest for researchers. In India, an analysis of crop statistics reveals challenges in qualitative field monitoring, which can be significantly improved through the adoption of machine learning-based innovative agriculture systems. This technology enhances various aspects of agricultural practice, including crop yield, soil health, plant disease detection, weed control, water management, and livestock management. Integrating machine learning with sensor data and artificial intelligence further optimizes complete farm management and supports informed decision-making. Artificial neural network (ANN)-based algorithms enhance plant management, while machine learning facilitates improved data collection for crop, soil, and weed management, leveraging adaptable agro-farm datasets.

2.2.1 Productivity and sustainability in agriculture using AI and ML

Early identification of plant pests and diseases through AI-based image analysis enables early intervention with targeted treatments, reducing the use of broad-spectrum pesticides. Crop health can be monitored effectively by employing drones and satellite images that are equipped with artificial intelligence (AI) algorithms. These technologies can detect stressors like water stress or nutrient deficiencies and track crop health over large regions. AI assists in the analysis of sensor data to optimize water, fertilizer, and pesticide application based on the specific needs of each field zone for

resource efficiency. Yield prediction is also a purpose of artificially intelligent models, assisting with risk management and marketing planning through forecasting crop yields using past data and existing conditions. IoTs and AI together can maximize water usage by regulating irrigation systems using real-time measurements of soil moisture. Big data can be processed using AI models to identify favourable traits in crops, accelerating breeding programs for better varieties that will enable us to grow more resistant crop species—something that is desperately needed in light of the recent impact of climate change.

Deep learning, a sub-specialty of machine learning, offers tremendous advantages, including the automatic derivation and refinement of features to attain desired outcomes. Its neural network architecture is remarkably flexible, and its application is possible to virtually any type of data and problem. In addition, the adaptability of deep learning architectures makes them amenable to modification in response to upcoming challenges, which is complemented by strong generalization abilities. Although the training process of deep learning models is more time-consuming compared to traditional methods, their computational efficiency in the testing process is significantly better.

2.2.2 Challenges to Artificial Intelligence and Machine Learning Implementation in Smart Agriculture

Technology complexity, privacy and security issues, and underdeveloped infrastructure are some of the challenges in the application of smart agriculture, as shown in Fig. 2. International Regulations on the Use of Pesticides and how smart agriculture will adapt to them are also not clear to date. Incorporation of technology in agriculture comes with a cost. Integrating technology in agriculture and keeping a check on the food prices is also a challenge. Proper training centres for farmers are still not available in most countries. Farmers can be provided with sufficient training to integrate intelligent systems in farming. Still, it is challenging to train them on the possible chances of hacking attacks on innovative machinery and databases. Smart agriculture aims to increase productivity, but the method by which it will achieve this while preserving natural resources remains unclear. Security is vital as limited-capacity devices in farming generate and send large data volumes to gateways or the cloud. Data must be protected from collection to decision-making and storage using lightweight encryption, secure protocols like TLS, and strong access controls. Edge computing can minimize risks by processing data locally, despite the devices' resource constraints.

2.3 Autonomous Machinery and Robotics in Smart Agriculture

Automation and robotics are revolutionizing precision agriculture by utilizing advanced technologies to operate farms with increased precision and efficiency. As the farm workforce dwindles, there is a need to maximize the efficiency of farming activities to sustain and develop the agricultural economy. One of the most critical methods of doing this is through the development of fully autonomous farm machinery, which does not involve human input. It requires robust remote control and monitoring systems, reliable safety systems to facilitate safe autonomous operation, and reliable positioning technology that will function well in small fields or large tracts. Farm robotics is an integrated combination of disciplines incorporating automated control systems, precise mechanical engineering, and computing technology. Farm operations have always been segmented into distinct stages, all crucial to the farm operation. These include preparing the soil for sowing, transplanting, manuring, and protecting plants; reaping crops and evaluating yields; and phenotyping to maximize crop improvement and study. Robotics offers specialized machinery tailored to the unique demands of each stage, fitting the changing conditions found in different farm settings. By integrating these new technologies, farmers will be able to increase operational effectiveness and support sustainable practices and, by extension, address the problems of a fast-changing industry.

2.3.1. productivity and sustainability in agriculture using Autonomous Machinery and Robotics

Robots and autonomous machinery not only assist in field functions, such as crop cultivation, land management, and harvesting, but they also feature sensors that detect various macro- and micronutrient levels in the soil, as well as soil moisture, humidity, and other factors influencing crop growth. These autonomous uncrewed vehicles can be controlled remotely and also navigate fields using GPS navigation systems. The collected data is sent to IoT sensor systems, which investigate soil conditions and provide recommendations on crop improvements using AI.

The photographic systems integrated with these robots also help to assess the physical changes in crops, any insects or pathogens present, and the weeds growing nearby.

Agricultural electric vehicles have also been introduced recently to promote energy efficiency and reduce dependency on alternative green fuels.

Agricultural electric vehicles offer precise controls and enhanced comfort during operation.

2.3.2. Challenges to Autonomous Machinery and Robotics

Vigorous safety systems are still under development in the automated machines. Proper training of farmers, employment of safety engineers, and safety regulations by national and international organizations are required. Risk assessment and techniques to mitigate the problems regarding the use of these machines are still needed.

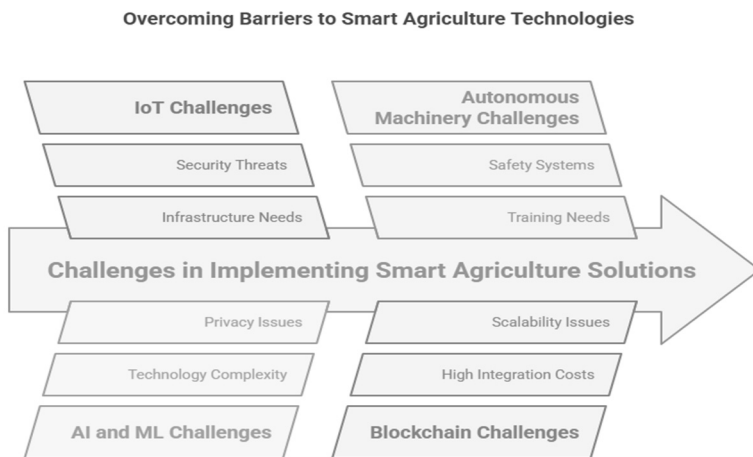


Figure 2.2: Challenges in Implementing Technology in Smart Agriculture

2.4. Blockchain technology in smart Agriculture

Blockchain technology is being developed as a disruptive solution in smart agriculture, providing transparency, security, and efficiency in supply chains and data management within agriculture. Through the use of decentralized and tamper-proof ledgers, blockchain is improving traceability, augmenting transaction security, and building trust between farmers, suppliers, and consumers. Blockchain is solving some of the most fundamental challenges within agriculture, such as fraudulent activities, inefficient record-keeping, and the inability to share real-time data.

2.4.1. Enhancing Productivity and Sustainability with Blockchain

Blockchain enhances productivity through smart contracts, which automate and streamline processes. By leveraging smart contracts, blockchain boosts efficiency, enabling payments and contract enforcement without the need for intermediaries. Blockchain simplifies buying and selling farm produce, eliminating bottlenecks and administrative costs. Blockchain also facilitates sustainable agriculture by ensuring effective management of resources. Farmers can track inputs such as pesticides, fertilizers, and water consumption, ensuring that they comply with environmental regulations. Also, with the integration of Blockchain and IoT, soil fertility, crop development, and animal well-being can be tracked in real-time more effectively, enhancing farm efficiency as a whole.

In the food chain supply, blockchain enables traceability of food from the farm to the fork. All processes in the supply chain, from planting to harvesting, processing, packaging, and distribution, are recorded in an unmodifiable ledger. Traceability prevents food fraud, reduces food loss, and enhances customers' trust in product authenticity.

2.4.2. Challenges in Implementing Blockchain in Agriculture

A series of challenges confront the blockchain technology in agriculture. The technology's high price tag, ranging from specialized hardware to software, presents a challenge for smallholder farmers. The nature of blockchain technology is equally complex, requiring appropriate training and awareness from stakeholders.

Another significant challenge is scalability because large-scale farming data processing using a blockchain can be computationally demanding. Additionally, regulatory policies for using a blockchain in farming are still in their early stages in most parts of the world, raising concerns around compliance and governance.

3. Conclusion

Smart agriculture is a paradigm shift for agriculture, where new-generation technologies are utilized for addressing food security issues, efficient use of resources, and enhancing productivity. Shifting from conventional farming approaches to Agriculture 4.0 can revolutionize the sector, emphasizing sustainable food production. IoT and AI are the main drivers behind predictive analysis, precision farming, and real-time decision-making,

whereas autonomous machines and robots mechanize agriculture. Nevertheless, their adoption is being hindered by challenges like infrastructure shortfalls, security threats, and high cost. To realize the full potential of smart agriculture, combined efforts from scientists, policymakers, and stakeholders must be made to improve education, invest in sound technological infrastructure, and implement regulatory systems that encourage innovation. Addressing these challenges will allow farmers around the world to take advantage of the potential of smart agriculture, establishing a more productive, sustainable, and resilient agricultural sector.

References

- [1]. Bipesh Subedi, Gajendra Sharma. "Smart Agriculture: Components, Processes, Challenges, and Future Perspectives." *Journal of Data Mining and Management* 8(2), (2023), 28-40.
https://www.researchgate.net/publication/374088732_Smart_Agriculture_Components_Processes_Challenges_and_Future_Perspectives.
- [2]. Shruti Aggarwal, Amit Verma. "Transformations in The Ways of Improving from Agriculture 1.0 to 4.0." 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, (2022), 170-174.
doi:10.1109/IC3I56241.2022.10072298.
- [3]. Zambon, Ilaria, Massimo Cecchini, Gianluca Egidi, Maria Grazia Saporito, and Andrea Colantoni. "Revolution 4.0: Industry vs. Agriculture in a Future Development for SMEs." *Processes*, 7(1), 2019. <https://doi.org/10.3390/pr7010036>.
- [4]. Ye Liu, Xiaoyuan Ma, et al. "From Industry 4.0 to Agriculture 4.0: Current Status, Enabling Technologies, and Research Challenges." *IEEE Transactions on Industrial Informatics*, vol. 17(6), (2021), 4322-4334. doi: 10.1109/TII.2020.3003910.
- [5]. Mehmet Ali Dayıođlu, Ufuk Turker. "Digital Transformation for Sustainable Future - Agriculture 4.0: A review." *Journal of Agricultural Sciences*, 27(4), (2021), 373-399.
<https://doi.org/10.15832/ankutbd.986431>.
- [6]. K. A. Patil and N. R. Kale. "A model for smart agriculture using IoT." 2016 International Conference on Global Trends in Signal Processing, Information Computing and Communication (ICGTSPICC), Jalgaon, India, (2016), 543-545.
doi: 10.1109/ICGTSPICC.2016.7955360.

- [7]. E. Manavalan, K. Jayakrishna. "A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements." *Computers & Industrial Engineering*, 127, (2019), 925-953.
<https://doi.org/10.1016/j.cie.2018.11.030>.
- [8]. Muhammad Galang Satrio Wicaksono, Erma Suryani, Rully Agus Hendrawan. "Increasing productivity of rice plants based on IoT (Internet of Things) to realize Smart Agriculture using System Thinking approach." *Procedia Computer Science*, 197, (2022) 607-616. <https://doi.org/10.1016/j.procs.2021.12.179>.
- [9]. Sarfraz Fayaz Khan, Mohammed Yusoof Ismail. "An Investigation into the Challenges and Opportunities Associated with the Application of Internet of Things (IoT) in the Agricultural Sector-A Review." *J. Comput. Sci.* 14(2), (2018), 132-143.
https://www.researchgate.net/profile/Sarfraz-Khan-4/publication/319623209_An_Investigation_into_the_Challenges_and_Opportunities_Associated_with_the_Application_of_Internet_of_Things_IoT_in_the_Agricultural_Sector-A_Review/links/59b63889458515a5b493da98/An-Investigation-into-the-Challenges-and-Opportunities-Associated-with-the-Application-of-Internet-of-Things-IoT-in-the-Agricultural-Sector-A-Review.pdf
- [10]. Faisal Karim Shaikh; Mohsin Ali Memon, et al. " Artificial Intelligence Best Practices in Smart Agriculture." *IEEE Micro*, 42(1), (2022), 17-24. DOI: 10.1109/MM.2021.3121279.
- [11]. R. R. Rubia Gandhi, J Angel Ida Chellam, et al. "Machine Learning Approaches for Smart Agriculture." 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, (2022), 1054-1058.
DOI: 10.1109/ICCMC53470.2022.9753841.
- [12]. Maha Altalak, Mohammad Ammad Uddin, et al. "Smart Agriculture Applications Using Deep Learning Technologies: A Survey." *Applied Sciences*, 12, (2022), 5919.
<https://doi.org/10.3390/app12125919>
- [13]. Muhammad Hafëez Ullah Khan, Shoudong Wang, et al. " Applications of Artificial Intelligence in Climate-Resilient Smart-Crop Breeding." *International journal of molecular sciences*, 23(19), (2022), 11156. <https://doi.org/10.3390/ijms231911156>.
- [14]. <https://www.hcltech.com/knowledge-library/what-are-advantages-of-artificial-intelligence>.
- [15]. Dr Gourav Shrivastava. " Role of Artificial Intelligence in Agriculture." School of Advanced Computing, SAGE University, Bhopal.

- <https://sageuniversity.edu.in/blogs/role-of-artificial-intelligence-in-agriculture#:~:text=AI%2Denabled%20systems%20make%20weather,taken%20by%20satellites%20and%20drones>.
- [16]. Nishant K Sinha, Jitendra Kumar, Dhiraj Kumar, et al. "Application of Artificial Intelligence (AI) in Agriculture: An Indian Perspective." *Harit Dhara*, 5(2), (2022), 1-3.
- [17]. Hasyiyya Karimah Adli, Muhammad Akmal Remli, et al. "Recent Advancements and Challenges of AIoT Application in Smart Agriculture: A Review." *Sensors*, 23(7), (2023), 3752. <https://doi.org/10.3390/s23073752>
- [18]. Sameer Qazi, Bilal A. Khawaja, et al. "IoT-Equipped and AI-Enabled Next Generation Smart Agriculture: A Critical Review, Current Challenges and Future Trends." *IEEE Access*, 10, (2022), 21219-21235. DOI: 10.1109/ACCESS.2022.3152544
- [19]. Angelita Rettore de Araujo Zanella, Eduardo da Silva, Luiz Carlos Pessoa Albini. "Security challenges to smart agriculture: Current state, key issues, and future directions." *Array*, 8, (2020). <https://doi.org/10.1016/j.array.2020.100048>.
- [20]. Mohd Saiful Azimi Mahmud, et al. "Robotics and Automation in Agriculture: Present and Future Applications." *Applications of Modelling and Simulation*, 4, (2020), 130–140. http://arqiipubl.com/ojs/index.php/AMS_Journal/article/view/130
- [21]. Reza Rahmadian, Mahendra Widyartono. "Autonomous Robotics in Agriculture: A Review." 2020 Third International Conference on Vocational Education and Electrical Engineering (ICVEE), Surabaya, Indonesia, (2020), 1-6, DOI: 10.1109/ICVEE50212.2020.9243253.
- [22]. Jin Yuan, Wei Ji, Qingchun Feng. "Robots and Autonomous Machines for Sustainable Agriculture Production." *Agriculture*, 13(7), (2023), 1340. <https://doi.org/10.3390/agriculture13071340>
- [23]. Amin Ghobadpour, Loïc Boulon, et al. "State of the art of autonomous agricultural off-road vehicles driven by renewable energy systems." *Energy Procedia*, 162, (2019), 4-13. <https://doi.org/10.1016/j.egypro.2019.04.002>.
- [24]. Guy R. Aby, Salah F. Issa. "Safety of Automated Agricultural Machineries: A Systematic Literature Review." *Safety*. 9(1), (2023). <https://doi.org/10.3390/safety9010013>

CHAPTER 2

GIS-DRIVEN TECHNIQUES FOR CLIMATE-SMART AGRICULTURE

MANMEET KAUR ARUNDHATI

Assistant Professor, Civil Engineering Department, Chandigarh
University, Mohali, India

Abstract

The chapter aims to assess the role of GIS-based interventions in Climate Smart Agriculture (CSA), a form of sustainable agricultural practice to combat the challenges posed by climate change. Focusing on relative productivity increases, resilient benefits, and decreases in greenhouse gas emissions, CSA relies on GIS-based approaches as a critical, data-driven, precision intervention. By processing and visualizing the important elements like Climate, soils, and water, GIS supports proper crop choice and management, appropriate land use, alongside successful risk mitigation. GIS-based CSA applications include Climate and soil suitability analyses, cropping zoning, precision Agriculture, climate susceptibility, and water assessments. In addition, GIS integrates with other technological phenomena like remote sensing, big data, and Internet of Things (IoT) intervention to create specialized solutions for region-wise populations that prevent resource misallocation, improve crop adaptability, and reduce negative human impacts on the natural environment. As climate change increasingly takes hold with more volatile impacts on contemporary society, GIS serves as a crucial technology in realigning agricultural systems with ever-changing ecological circumstances while simultaneously supporting global food security efforts. While advocating for the use of GIS approaches, the research also finds flaws relative to GIS-based interventions, including access barriers such as limited data and information accessibility or an expensive need for use, and offers improvements for increased integration opportunities, especially for smallholder farmers.

Keywords: Climate-Smart Agriculture (CSA), Geographic Information System (GIS), Internet of Things (IoT), Precision Agriculture, Remote Sensing

1. Introduction

Inadequate adaptations for enhancing agricultural productivity in response to climate change cause more crop production instability, thereby affecting the global food supply and generating food and nutritional insecurity. In particular, where climate change reduces food production because of water shortages or pest outbreaks, or soil degradation, such yield loss will be costly for global food security (Mirón et al., 2023), (Zizinga et al., 2022). The UN projections, which have received publicity as a driver of world food demand, suggest that the global population will rise from around 7.9 billion in 2021 to about 9.7 billion by mid-century (World Population Prospects - Population Division - United Nations, n.d.). It is projected that climate change will decrease the yield of major crops by 25% globally by the year 2050. Furthermore, climate change will show more severe impacts on areas closer to the equator. But with declining global population growth, growth in per capita food consumption, which in turn comes from the subcontinent's monthly increase, is a determining consideration for per capita profits, and is also acquiring greater traction as a driver of food consumption (Godfray, 2011a). Engel's law indicates a declining share of food in total expenditures as incomes increase, whereas Bennett's law expresses the tendency for growing outlays on foods such as fruits and vegetables and animal-based products with increasing incomes in developing countries (Islam & Karim, 2019). Climate change has posed considerable negative impacts on agricultural productivity, sustainability as well and resilience. This, in turn, presents more challenges, which are intensified because of the climate patterns becoming more unpredictable. The increasing temperature results in the development of heat stress, disturbing crop cycles, declining productivity, and affecting livestock (Das et al., 2016). Changing precipitation patterns also result in extreme weather events like flooding and droughts, which lead to water scarcity and soil erosion (Furtak & Wolińska, 2023). Heatwaves and storms deteriorate agricultural infrastructure, causing a threat to food security and environmental sustainability (Mirzabaev et al., 2023; Derpsch et al., 2024). Agricultural ecosystems have been reported to be the second-largest producers of global anthropogenic greenhouse gas (GHG) emissions, accounting for approximately 56% of the total non-CO₂ emissions (Chataut et al., 2023). These emissions have created an imbalance

in the ecosystem. Some of the impacts of climate change on agriculture have been illustrated in Figure 1.1.

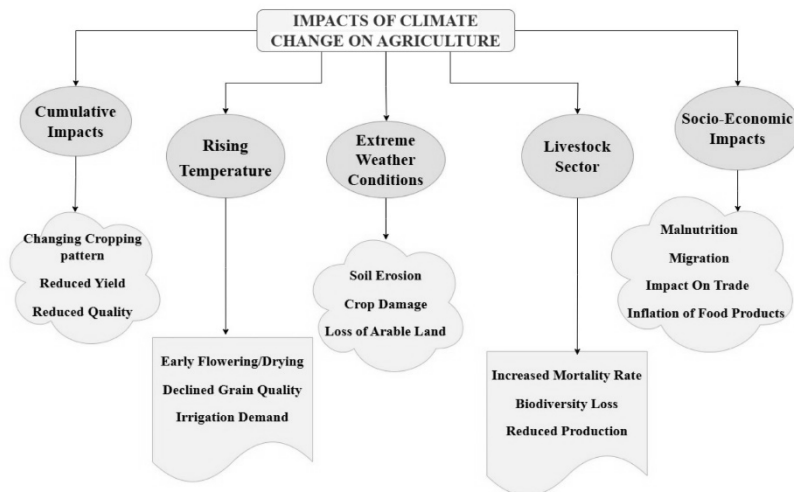


Figure 1.1: Impacts of Climate Change on Agriculture

These influences of climate change on agriculture make it necessary to implement climate-smart agricultural (CSA) approaches to help farming systems tolerate and withstand the changing environmental conditions. CSA is one of the transformative approaches that has been designed for addressing the negative impacts being imposed by increasing climate change on agricultural activities, sustainable development, and resilience (Matteoli et al., 2021). It represents the combination of different technologies that are indispensable in improving productivity and income while ensuring that the adaptability to climate change increases. It is also useful in minimizing the emission of GHGs (Hussain et al., 2022). Moreover, increasing demand for agricultural products across the world has attracted numerous stakeholders and nations to adopt Climate Smart Agriculture (CSA). CSA has three primary objectives, which are to intensify the sustainability of agricultural production, adapt and build climate change resilience, and reduce GHGs. This aims at enhancing productivity, improving resource usage efficiency, and reducing overall losses related to post-harvesting. This, in turn, results in increasing food production without imposing any negative impacts on the environment while ensuring food security. Figure 1.2 highlights the different guiding principles of CSA (Safdar et al., 2024).

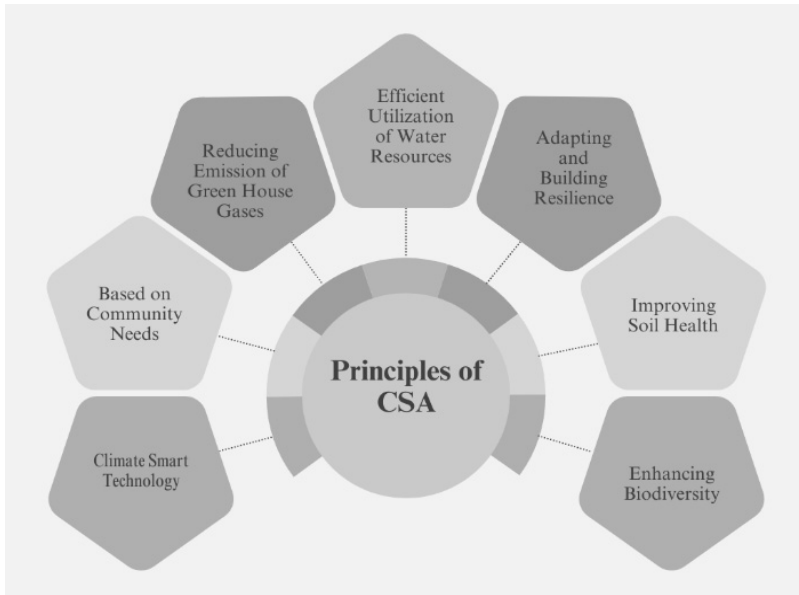


Figure 1.2: Principles of CSA (Safdar et al., 2024)

CSA, in collaboration with GIS, has emerged as one of the most influential tools used to optimize resources and develop a strategic plan. It is useful in collecting, analyzing, and visualizing spatial data. This, in turn, is beneficial for decision-makers and agriculturists to take relevant decisions for attaining economic and environmental objectives (Raihan, 2024). Moreover, it highlights the details of soil condition, suitability of crop, climatic conditions, water resources, and weather patterns. The integration of CSA and GIS has offered an appropriate sustainable farming practice in accordance with the needs of the region and Climate (Aghaloo & Sharifi, 2023). As a result, the overall ability of farmers to anticipate risks and optimize resources has been found to increase. It is because of adopting climate-adaptive strategies for crop management and land use. The ensuing segments of the book chapter aim at exploring GIS-driven techniques that aim at the core concept of CSA, such as soil suitability, crop zoning, land use mapping, precision agriculture, climate risk assessment and vulnerability mapping, water resource management, and IoT for agriculture management.

2.0 GIS-Driven Techniques in Climate-Smart Agriculture

2.1 Climate and Soil Suitability Mapping

Soil suitability is broadly categorized into four main categories based on depth, water storage capacity, slope, and salinity, namely S1, S2, S3, and NS. S1 denotes the soil that has high optimal depth, high water retention, low slope, and minimum salinity. At the same time, S3 and NS have been found to have numerous limitations, such as reduced depth, steeper slopes, lower water-holding capacity, and higher salinity levels (Rukhsana & Molla, 2023). Hence, GIS techniques along with CSA are beneficial to analyze the spatial data for generating soil suitability maps, guiding crop selection, and optimizing land use (Radočaj & Jurišić, 2022). Table 2.1 highlights the characteristics of different soil suitability classes. For identifying optimal crop zones, the primary role is played by some of the climatic factors like temperature, precipitation, topographic conditions, and soil quality. GIS enables the development of suitability maps that provide insight into soil pH, its texture, nutritional values, and climatic data (Agnolucci et al., 2020). The maps provide an analysis of regions that can be used for cultivating suitable, sustainable crops and reducing resource inputs. It further provides an opportunity to farmers for evaluating soil water-holding capacity while predicting the need for fertilizers. It also takes into consideration seasonal as well as regional climatic variations that enable the effective selection of crops having high adaptability towards local conditions. Furthermore, the identification of appropriate regions across a specific area is useful in promoting crop diversity. This is possible only with the GIS-driven techniques. The diverse cropping pattern has also been found to have increased resistance to pests associated with crop failure (Malczewski, 2004).

Table 2.1: Soil Suitability Classes

Classes of Soil Suitability	Depth in cm	Slope %	Capacity of stored water in mm	Salinity (mhos/cm)
S1	≥100	<4	≥150	<2
S2	100–60	4–8	110–150	2–4
S3	60–30	8–12	75–110	4–8
NS	>30	>12	<75	>8

2.1.2 Land Use Mapping

In general, agricultural zones are defined by nutrient-rich soil, level or slightly sloping terrain, and easy access to dependable water supplies like rivers or irrigation systems. Staple crops, including maize, rice, and wheat, can be grown under these conditions. For example, rice needs warm, humid conditions, maize does best in moderate temperatures with regular rainfall, and wheat grows best in cooler areas with fertile soil (Begizew, 2021). Table 2 provides an insight into the key characteristics of land use type. By determining the most optimal locations for particular crop types, land use maps are essential for maximizing agricultural land area. This strategy reduces environmental effects while increasing efficiency. Finding the best locations for a range of agricultural pursuits, such as crop production, grazing, and forestry, is made possible by GIS-based crop zoning. (Malczewski, 2004). Furthermore, by identifying areas within a single landscape that are appropriate for various crops, GIS-driven zoning techniques help to promote crop diversity. This diversification increases resistance to pest- or weather-related crop failures (Malczewski, 2004).

Table 2: Key Characteristics of Land Use Type

Land Use Type	Key Characteristics	Zoning Factors	References
Agricultural	<ul style="list-style-type: none"> • Fertile soil • Adequate water resources 	Soil type, water availability	(Molden et al., 2011)
Forest	<ul style="list-style-type: none"> • Dense vegetation • Conservation Areas 	Biodiversity, slope, and rainfall	(Ao et al., 2024)
Urban/Residential	<ul style="list-style-type: none"> • Built-up areas 	Population density, proximity	<i>((PDF) The Spatial Organization of Cities: Deliberate Outcome or Unforeseen Consequence?, n.d.)</i>
Water Bodies	<ul style="list-style-type: none"> • Rivers • Lakes • Reservoirs 	Climate, watershed requirements	("Lakes and Reservoirs as Water Resources," 2005)

By integrating remote sensing data with GIS systems, which offer continuous monitoring capabilities, administrators can make dynamic zoning decisions based on the state of the land (Chatrabhuj et al., 2024). GIS categorizes the land use by integrating the geographical data, including soil type, topography, and land cover (Malczewski, 2004).

2.1.3 Precision Farming

To enhance crop productivity, precision farming leverages Geographic Information Systems and minimizes the input use by providing site-specific insights (Refer to Table 2.2). GIS enables the analysis of soil variability and crop health by integrating the GPS technology, remote sensing, and field data across different zones within the field (Majumder et al., 2022). GIS helps in preparing the precision maps, which help farmers to focus only on areas that require intervention, like how much water is to be utilized, fertilizers, and pesticides, with a certain accuracy. Such kind of approaches minimize the environmental impacts and resource utilization. For example, GIS can assess nutrient availability, soil moisture levels, and crop conditions, facilitating precise irrigation scheduling, nutrient application, and pest control. This kind of precision reduces the water usage and greenhouse gas emissions from fertilizers, mentioning precision farming as a vital component of CSA (Sarfranz et al., 2023). By addressing such micro-level field variations, GIS supports higher yields while conserving resources, promoting climate-resilient and sustainable agricultural practices (Sarfranz et al., 2023).

Table 2.2: Details of Resources Required for Traditional and Precision Farming

Resource	Traditional Farming (per acre)	Precision Farming (per acre)	Reduction (%)	Reference
Water (litres)	2000	1200	40%	(Mondal & Basu, 2009)
Fertilizer (kg)	100	60	40%	(Cheng et al., 2023)
Pesticide (litres)	15	7	53%	(Zanin et al., 2022)

For water, precision farming uses 40% less (1,200 litres per acre compared to 2,000 litres in traditional Farming), promoting water conservation. Fertilizer usage is also reduced by 40% (60 kg per acre vs. 100 kg),

minimizing nutrient runoff and environmental pollution. Pesticide use sees a notable 53% decrease (7 liters per acre compared to 15 liters), which reduces the chemical load on the environment and helps in pest management. These reductions result in more sustainable farming practices, boosting resource use and decreasing environmental impact.

2.1.4 Climate Risk Assessment and Vulnerability Mapping

GIS plays a critical role in assessing the risks associated with climate and vulnerability mapping, with the integration of data on topography, climate projections, land cover, and socio-economic factors. It facilitates the assessment of agricultural areas' susceptibility to climate-related hazards. With the implementation of spatial data in GIS, the farmers, along with stakeholders, can actually develop targeted interventions as it highlights the vulnerable areas in the context of extreme weather conditions, for instance floods, droughts, heatwaves, and others. Vulnerable maps thus obtained provide an insight into high-risk zones, allowing the authorities to implement strategies accordingly. Some of the most commonly adopted strategies are the adoption of resilient crop varieties, water conservation approaches, and the establishment of early warning systems. To cite an example, GIS can suggest appropriate agricultural approaches in flood-prone areas. It is useful in mitigating crop loss and attaining sustainability. Moreover, GIS tools facilitate real-time monitoring of climate risks, enabling adaptive responses to safeguard agricultural productivity and livelihoods amidst changing climate conditions.

2.1.5 Water Resource Management

One of the major threats to crop production is decreasing water levels, especially for crops like rice. Rice is a highly water-intensive crop that is dependent on the extraction of freshwater resources in Asian countries like India, China, and Pakistan. According to the climate-related reports, it has been stated that approximately 20 million hectares of agricultural land in Asian countries will encounter issues related to water shortage in the near future because of water-intensive agricultural activities. To deal with such issues, CSA is a promising solution that aims to conserve freshwater resources. CSA enables the merging of traditional and innovative agricultural techniques and technologies in relevance to a particular region for adapting to climate change and variability. These combined technologies have the capability to deal with the impact of changing climatic conditions on crop production through planning and implementation plans. As per one of the meta-analyses for crop simulation under several climate scenarios, it

has been found that farm adaptations have been able to increase crop production by approximately 14% while saving about 25 to 50 % of water in comparison to the approaches without adaptation (Ma & Rahut, 2024).

2.1.6 Internet of Things (IoT) for Irrigation Systems

IoT-based irrigation systems are being used to enhance agricultural yield and efficiency. The system uses real-time soil data for measuring soil moisture content. The pumping motor is controlled by an operational amplifier, which automatically turns it on or off in response to changes in soil moisture levels. The advent of IoT systems enables farmers and stakeholders to monitor soil moisture levels through an app to further initiate the sprinkling process. The approach is useful in reducing manual labor in irrigation. It also improves productivity and efficiency, especially in areas or regions that have low or limited rainfall. IoT-based systems also have an option to deliver a required amount of water to the crop, which illustrates the capability of these systems to automate irrigation systems, leading towards sustainability.

3.0 GIS-Based Map Preparation Techniques

3.1 Water Availability

GIS-based water availability can be assessed by delineating Ground Water Potential Zones (GWPZ). For the map preparation, toposheets may be acquired from different authentic authorities. The sheets thus collected are geo-referenced in a desired projection system like UTM WGS84. Later, the collected satellite images or geological maps are then geo-referenced with the help of ERDAS Imagine 9.3. Based on the toposheets drainage layer can be generated, and that can be enhanced by using Landsat satellite images. Further, a Digital elevation model can be used for calculating sloped by applying gradient filters in horizontal and vertical directions (Rajat et. al, 2016). The slopes can be calculated using equation 1.

$$Slope = 100 X \frac{\sqrt{DX^2+DY^2}}{Pixel\ Size} \dots\dots\dots eq\ 1$$

Where DX and DY represent filtered Digital Elevation Model (DEM) values with the horizontal & vertical gradient filters

Pixel Size represents the height value of the DEM.