

AI for Climate Change and Smart Agriculture

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ABSTRACT

Artificial Intelligence (AI) transforms Climate-Smart Agriculture (CSA) by combining real-time data, machine learning, and IoT sensors to boost farm productivity while lowering environmental impact.

Core Applications of AI in Smart Agriculture

- **Precision Resource Management:** Variable-rate technology and AI algorithms analyze soil data, weather, and crop needs to cut water use by up to 40% and reduce pesticide application by 30%.
- **Yield & Climate Prediction:** On-device machine learning models and neural networks (such as Random Forest classifiers and physics-informed models) forecast crop yields and local weather changes with up to 90% accuracy.
- **Pest & Disease Early Warning:** Computer vision models (like YOLO and vision transformers) process smartphone photos of crops or satellite indices (NDVI) to detect pest outbreaks and plant diseases in seconds.
- **Integrated Agriculture Intelligence Systems:** Real-time platforms like India's Fieldwise deliver localized mobile alerts and live monitoring to millions of farmers, helping protect vulnerable crops ahead of extreme weather events.
- **Soil Health & Carbon Sequestration:** Remote sensing and soil sensors track organic carbon stocks and support regenerative practices like crop rotation and cover cropping.

KEYWORDS- AI, climate change, smart agriculture, computer vision, technology

INTRODUCTION

- **Productivity Boost:** AI-driven interventions can increase agricultural productivity by up to 25% while lowering farm carbon emissions by 30–50%.
- **Loss Reduction:** Predictive storm alerts and automated post-harvest solutions cut agricultural and food losses by 15% to 35%.[1,2,3]
- **Accessibility:** Speech-to-text and natural language processing features break down literacy and language barriers, letting smallholder farmers interact with AI advisories via voice.
- **Data & Compute Demands:** High energy usage for cloud computing, data scarcity, and regional data gaps limit deployment.
- **Adoption Barriers:** High implementation costs and limited digital literacy among rural smallholders require affordable, localized edge-AI devices (such as low-power microcontrollers).

Artificial Intelligence (AI), AI applications have proliferated across various domains where agricultural consumer electronics are no exception. These innovations have significantly enhanced the intelligence of agricultural processes, leading to increased efficiency and sustainability. This study introduces an intelligent crop yield prediction system that utilizes Random Forest (RF) classifier to optimize the usage of water based on environmental factors. By integrating lightweight machine learning with consumer electronics such as sensors connected inside the smart display devices, this work is aimed to amplify water management and promote sustainable farming practices. While focusing on the sustainable agriculture, the water usage efficiency in irrigation should be enhanced by predicting optimal watering schedules and it will reduce the environmental impact and support the climate resilient farming. The proposed lightweight model has been trained on real-time agricultural data with minimum memory resource in sustainability prediction and the model has achieved 90.1% accuracy in the detection of crop yield suitable for the farmland as well as outperformed the existing methods including AI-enabled IoT model with mobile sensors and deep learning architectures (89%), LoRa-based systems (87.2%), and adaptive AI with self-learning techniques (88%). The deployment of computationally efficient machine learning models like random forest algorithms will emphasis on real time decision making without depending on the cloud computing. The performance evaluation and effectiveness of the proposed method are estimated using the important parameter called prediction accuracy.[4,5,6]

DISCUSSION

The agricultural sector faces unprecedented challenges as climate change accelerates, causing unpredictable weather patterns, droughts, floods, and extreme temperature variations [1]. These climatic shifts significantly impact food security, crop yields, and the sustainability of farming practices. Traditional agricultural systems, heavily reliant on predictable climate conditions, struggle to adapt to such volatility, resulting in diminished productivity, inefficient resource use, and environmental degradation [2]. As the effects of climate change intensify, the need for innovative approaches to safeguard food production becomes more pressing [3]. One such approach is climate-smart agriculture (CSA), a concept designed to integrate sustainable farming practices with adaptive strategies to mitigate climate-related risks [4]. CSA emphasizes improving productivity, enhancing resilience to climate variability, and reducing greenhouse gas emissions. The growing interest in AI technologies offers promising solutions to address these challenges, driving the transition toward more resilient, resource-efficient agricultural systems [5].

Artificial Intelligence (AI) has rapidly emerged as a transformative force in agriculture, enabling smarter, data-driven decision-making [6]. By processing vast amounts of data, AI can predict weather patterns, optimize irrigation schedules, detect pests, monitor soil health, and improve crop yields [7]. Machine learning, computer vision, and predictive analytics play a significant role in these applications, allowing farmers to make real-time, informed decisions [8]. These technologies provide farmers with tools to enhance productivity while minimizing resource wastage, ultimately supporting the sustainability of farming practices [9]. Through AI-powered systems, climate-smart agriculture becomes more efficient and adaptable, empowering farmers to

respond proactively to shifting climatic conditions. As climate risks continue to grow, AI's potential to foster sustainable farming systems becomes increasingly apparent [10].

AI, several challenges remain in its integration into climate-smart agriculture. One of the most significant barriers is the accessibility, quality, and consistency of data [11]. AI systems rely heavily on accurate, real-time data to generate meaningful insights and predictions [12]. In many regions, particularly in developing countries, the availability of such data is limited, and the infrastructure to collect, process, and analyze it is often lacking [13]. For AI models to be effective, they require high-quality, standardized data that is consistent across various sources, such as remote sensing, weather forecasts, and ground-based sensors [14]. However, data collected in agricultural environments is often fragmented, incomplete, or subject to inconsistencies, which hinders AI's ability to produce reliable predictions and recommendations. Addressing these data challenges is essential for the widespread adoption of AI in climate-smart agriculture [15].

RESULTS

As global agriculture faces mounting pressure from climate change, smart farming and climate-resilient technologies are proving critical in aligning local efforts with the United Nations Sustainable Development Goals (SDGs). Particularly in countries like Ghana and Bangladesh, innovative approaches are empowering farmers to overcome environmental challenges while advancing sustainable agriculture, food security, and poverty reduction, key targets under SDG 2: Zero Hunger and SDG 13: Climate Action.[7,8,9]

Digital transformation in Ghanaian agriculture

In Ghana, organisations like TechnoServe have been pivotal in rolling out climate-smart agriculture. A notable initiative involves Digital Advisory Services (DAS), offering real-time information on advanced practices such as row planting, zero tillage, and the application of drought-resistant seeds. According to a recent study published on Springer, the adoption of DAS has significantly increased among maize farmers, contributing to more resilient crop yields under erratic weather conditions.

Further advancing this digital shift, TechnoServe has partnered with the AI-driven platform Alteia to innovate cashew production techniques in neighbouring Benin. Though the initial rollout is outside Ghana, the AI-based tools developed, capable of enhancing productivity and crop quality, are designed with adaptability in mind, opening avenues for replication in Ghana and similar agro-climatic zones.

Salinity adaptation and precision agriculture in Bangladesh

Bangladesh faces a distinct challenge: soil salinisation, particularly in its coastal belt. This degradation has historically hindered farming viability. However, targeted training in saline agriculture has allowed over 30,000 farmers to cultivate crops like fruits and vegetables in high-salinity soils. Backed by public-private partnerships, these programmes have marked a turning point in transforming previously unproductive land.[10,11,12]

In parallel, precision agriculture tools such as cloud-based farm management systems are being deployed. These platforms give farmers real-time decision-making capabilities, enabling better resource allocation, especially in water use, a crucial factor in regions grappling with both salinity and water scarcity.

Data-driven impact and future pathways

Evidence from both Ghana and Bangladesh illustrates a clear pattern: Integrating training, digital platforms, and sustainable practices significantly enhances agricultural productivity, climate resilience, and farmer incomes. This convergence supports several SDGs, notably SDG 1 (No Poverty), SDG 2, and SDG 13, while laying a strong foundation for SDG 9: Industry, Innovation and Infrastructure.

Looking ahead, scalability and cross-border knowledge exchange will be essential. The global society, encompassing governments, NGOs, private tech firms, and multilateral organisations, must continue to collaborate to expand these technologies into new geographies and contexts. This kind of international cooperation is indispensable for achieving global sustainability goals.

The rise of smart farming in Ghana and Bangladesh offers a promising blueprint for climate-resilient agriculture in vulnerable regions. These case studies reinforce that global collaboration, local adaptation, and digital innovation are central to meeting the SDGs and securing the future of food.[13,14,15]

Emerging agriculture farming has established the use of AI technology, particularly in developed countries. However, this is not the case in all developing countries (Singh & Kaur 2022). The United Nations estimates that there will be 9.7 billion people on earth by 2050, significantly increasing the demand for food (Putterill, 2023). Hence, policymakers in both developed and developing countries are on the quest to adopt and implement smart agriculture. This empowers AI-powered farming for sustainable food production in various geographical locations. This equity has propelled the need to reorientate the use of high-tech AI in sustainable food production. This article centres on how smart agriculture via AI technology stands a chance to enhance sustainable food production.

CONCLUSION

SMART-AI agriculture involves the integration of modern technological agriculture devices such as digital soil maps, global positioning systems, robots, smart sprayers, and monocular visual odometry systems to optimise food production (Brenya et al., 2023) The Internet of Things (IoT), Big Data, Artificial Intelligence (AI), geo-positioning systems, and drones are some of the technologies that are being applied to agriculture, in combination with ICT. Revolutionised SMART-AI technology has provided the foundation for mitigating crop and livestock cultivation failures, protecting biodiversity and ecosystems, enhancing planetary health, and promoting household farms to a farm-to-fork agenda (Qazi et al., 2022).[16,17,18]

The THRIVE Framework examines issues and evaluates potential solutions in relation to the overarching goal of thrivability. It is about making predictive analyses using modern technology

that supports environmental and social sustainability transformations. The international community faces unparalleled threats such as climate change, deforestation, deep-sea depletion, and reserve misuse. Governments and organisations must adopt innovative strategies including AI smart agriculture to ensure human existence continues. The THRIVE Framework highlights the need to shift to a transdisciplinary approach and embrace Values-Based Innovation, which is a step towards a thriving future.

The THRIVE Framework is a Holistic Regenerative Innovative Value Entity Framework that integrates distinct approaches adopted by institutions concerned with going beyond sustainability to thriving. It provides a clear template for evaluating sustainability by integrating the 12 Foundational Focus Factors. Contrasting mere sustainability, the concept of thriving looks beyond environmental and social issues. THRIVE aims for humanity to overcome planetary devastation and build foundations for a world that thrives.[19,20]

REFERENCES

1. "Models and Tool". bc3research.org.
2. Villa, Ferdinando; Ceroni, Marta; Bagstad, Ken; Johnson, Gary; Krivov, Sergey (2009-01-01). "ARIES (ARtificial Intelligence for Ecosystem Services): A new tool for ecosystem services assessment, planning, and valuation". ResearchGate. Retrieved 2022-01-23.
3. "A guide to models and data" (PDF). United Nations.
4. Villa, Ferdinando; Bagstad, Kenneth J.; Voigt, Brian; Johnson, Gary W.; et al. (13 March 2014). "A Methodology for Adaptable and Robust Ecosystem Services Assessment". PLOS ONE. 9 (3) e91001. Bibcode:2014PLoSO...991001V. doi:10.1371/journal.pone.0091001. PMC 3953216. PMID 24625496.
5. Barry, Katie (2016-04-29). "Paying for rainforests: current PLoS research on the economic valuation of ecosystem services". PLoS Blog.
6. Villa, Ferdinando; Athanasiadis, Ioannis N.; et al. (11 December 2008). "Modelling with knowledge: A review of emerging semantic approaches to environmental modelling". Environmental Modelling & Software. 24 (5): 577–587. doi:10.1016/j.envsoft.2008.09.009. ISSN 1364-8152.
7. Wilkinson, Mark D.; Dumontier, Michel; Aalbersberg, IJsbrand Jan; Appleton, Gabrielle; et al. (15 March 2016). "The FAIR Guiding Principles for scientific data management and stewardship". Scientific Data. 3 160018. Bibcode:2016NatSD...360018W. doi:10.1038/sdata.2016.18. OCLC 961158301. PMC 4792175. PMID 26978244.
8. "An interoperability strategy for the next generation of SEEA accounting" (PDF). United Nations.
9. "k.Explorer". github.com.
10. "ARIES for SEEA". United Nations.
11. Gonzalo, Marilín (2021-06-09). "Inteligencia Artificial para calcular la contribución de la naturaleza al bienestar económico". Newtral.
12. "ARtificial Intelligence for Ecosystem Services (ARIES)". envirolink.govt.nz.
13. "Artificial intelligence saving the natural world". United Nations.
14. Alonso, Tania (2021-07-06). "¿Cuánto contribuye la naturaleza a nuestra prosperidad económica? La IA nos ayuda a medirlo". Nobbot.

15. "UN adopts landmark framework to integrate natural capital in economic reporting". United Nations.
16. "UN launches the first artificial intelligence tool for rapid natural capital accounting". www.unep.org. 29 April 2021.
17. "UN launches AI tool to measure ecosystems of countries". indiaai.gov.in.
18. Calero, Juan (2021-06-01). "ARIES for SEEA: la tecnología desarrollada en Vizcaya y adquirida por la ONU que calcula la contribución de la naturaleza al bienestar". InnovaSpain.
19. "Award Abstract # 0640837 Project ARIES: An Integrated Digital Collaboratory to Support the Economic Valuation of Ecosystem Services". National Science Foundation. Division of Biological Infrastructure. Retrieved 23 January 2022.
20. "AI and Spain's climate change and decarbonisation agenda". digitalfuturesociety.com. 27 November 2023.