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Sustainability and Environmental Footprints of AI-Integrated Agrifood Production Systems

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Abstract
Global food systems are facing challenges in meeting the rising demand for food while also reducing their environmental impact, including carbon and water footprints. Artificial intelligence (AI) offers promising solutions to improve efficiency, effectiveness, and resilience throughout the food supply chain. However, the use of AI in food production, particularly in advanced industrial settings such as Industry 4.0 and 5.0, also presents its own environmental and social challenges. This study examines the potential benefits of AI in creating a sustainable food system, including better resource use, less waste, improved water efficiency, and enhanced crop protection. It also considers the significant energy needed to train and operate AI systems. To ensure AI-based technologies truly support sustainability in food production, we need a balanced approach that includes fair access, responsible resource management, and integrating AI with other sustainable agricultural practices. Future efforts should focus on making AI tools easier to use for a wider audience, implementing strong governance rules, and aligning AI advancements with environmental, economic, and social impacts. By preventing these challenges, AI can be used to develop a more efficient, resilient, and environmentally friendly food resource system, contributing to global sustainability goals.
Keywords: Sustainability, environmental footprints, carbon and water footprints, AI-integrated food production, zero waste and water efficiency

Introduction

The integration of AI into agrifood production systems presents a dual narrative regarding sustainability and environmental footprints. While AI offers substantial promise in optimizing resource utilization, minimizing waste, and enhancing the precision of agricultural practices – thereby potentially reducing the environmental burden associated with conventional farming (Shamshiri et al., 2018; Hussain et al., 2024). The development and deployment of AI technologies themselves carry inherent environmental and social costs that necessitate careful consideration (Rolnick et al., 2019). A comprehensive understanding of the sustainability implications of AI in agrifood requires a nuanced evaluation that encompasses both the benefits derived from its application and the environmental and ethical considerations of its implementation (van Es and Woodard, 2017). AI-driven solutions in agriculture, such as precision farming techniques, have demonstrated the capacity to optimize the application of water, fertilizers, and pesticides, leading to significant reductions in resource consumption and environmental pollution (Shamshiri et al., 2018; Hussain et al., 2024). Furthermore, AI applications in monitoring crop health, predicting yields, and managing livestock can contribute to increased efficiency and reduced waste across the food production chain (Kamilaris et al., 2018; Wolfert et al., 2017). These advancements align with the goals of sustainable agriculture by enhancing productivity while minimizing negative ecological impacts. However, the sustainability benefits of AI integration must be weighed against the environmental footprint associated with AI technologies, including the energy consumption for training complex models and the resource demands for hardware production and data storage (Rolnick et al., 2019).
Addressing the sustainability and environmental footprints of AI-integrated agrifood systems requires a holistic approach that considers the entire lifecycle of both the AI technologies and the agricultural practices they enable. Future research and development should prioritize energy-efficient AI algorithms, the use of low-carbon infrastructure for AI deployment, and the establishment of ethical and environmentally responsible design principles (Rolnick et al., 2019). Furthermore, comprehensive life cycle assessments (LCAs) are needed to quantify the environmental impacts of AI in agriculture, from the manufacturing of sensors and AI hardware to the energy used in data processing and the disposal of obsolete equipment. By adopting a balanced perspective that maximizes the sustainability benefits of AI while mitigating its potential environmental and social costs, the agrifood sector can move towards a more resilient and environmentally sound future (Ahmed and Shakoor, 2025). This paper explores the potential of AI to revolutionize agrifood production for enhanced sustainability, resource optimization, waste reduction, and crop protection, while also addressing the associated environmental and social challenges and outlining future directions for accessible, governed, and impactful AI integration.

The Challenge of Global Food Systems

Global food systems today face a complex set of challenges that intersect with environmental sustainability, socio-economic equity, and political governance. As the global population continues to grow, current agricultural practices are increasingly being scrutinized for their impact on natural resources and their contribution to climate change. Feeding an estimated 9.7 billion people by 2050 requires a food systems transformation that not only ensures food security but also addresses sustainability and equity. Traditional and intensive agricultural practices have been reported to lead to biodiversity loss, soil degradation, and water resource depletion (Godfray et al., 2010; Tilman et al., 2011). These challenges call for an integrated approach that simultaneously addresses production efficiency and ecosystem protection.

One of the key challenges is inadequate food distribution. Although global food production is sufficient to feed the entire population, more than 828 million people were reported to be undernourished in 2021 (FAO, 2022). At the same time, food waste remains a widespread problem. Approximately one-third of all food produced globally is lost or wasted each year (Gustavsson et al., 2011). In addition to these problems, market volatility, trade restrictions and economic volatility also contribute to difficulties in accessing food. Foley et al. (2011) reported that innovative policy measures and collaborative management models that promote food supply are needed. Adaptive strategies such as climate-smart agriculture, improved infrastructure and sustainable land use should be prioritized to build resilience to environmental shocks (Wheeler and von Braun, 2013). Transforming the global food system requires a holistic approach that integrates environmental sustainability, economic viability and social justice. As the EAT-Lancet Commission stated, "a global transformation of the food system is urgently needed" to protect both human and planetary health (Willett et al., 2019). To overcome the multidimensional challenges of feeding the world sustainably, international collaborative efforts based on science and equity will be crucial.

The Promise of Artificial Intelligence in Agrifood Production

AI holds transformative potential for the agrifood sector, promising increased efficiency, sustainability, and resilience in food production systems. As global agriculture faces escalating pressures due to climate change, labor shortages, and the need for more precise resource management, AI-driven technologies are emerging as critical tools to address these challenges. According to Kamilaris et al. (2018), AI applications in agriculture including machine learning, computer vision, and robotics are facilitating more accurate crop monitoring, yield prediction, pest detection, and autonomous machinery operation, thus enabling data-driven decision-making at unprecedented scales.

One of the most significant contributions of AI is its role in precision agriculture. AI-powered platforms analyze large datasets from satellites, drones, and IoT sensors to provide real-time insights on soil conditions, crop health, and weather patterns. These insights allow for targeted interventions that minimize input waste and enhance productivity. For instance, Liakos et al. (2018) highlight the use of machine learning algorithms in predicting crop yields and optimizing irrigation, which not only conserves water but also reduces the environmental footprint of agricultural activities. In livestock farming, AI systems are employed to monitor animal behavior and health, improving welfare and early disease detection (Wolfert et al., 2017). Despite these advancements, the integration of AI in agrifood systems is not without limitations. Challenges such as high initial costs, lack of digital infrastructure in rural areas, and concerns over data privacy and ownership remain significant barriers to widespread adoption. Moreover, the ethical implications of AI deployment especially in smallholder farming contexts demand careful consideration to ensure inclusivity and equity. As van Es and Woodard (2017) suggest, the development of AI solutions should be accompanied by policies that support technological access and capacity-building, particularly in developing regions.

Sustainability Benefits of AI Integration

The integration of AI across sectors has shown tremendous promise in enhancing sustainability by optimizing resource use, minimizing waste, and supporting climate adaptation strategies. AI technologies facilitate real-time monitoring, predictive analysis, and intelligent automation that collectively contribute to more sustainable systems in energy, agriculture, transportation, and urban planning. AI can be a powerful tool for mitigating climate change if developed and implemented responsibly, particularly through applications such as energy optimization, precision agriculture, and smart logistics (Rolnick et al., 2019). In the energy sector, AI enables significant efficiency gains by predicting demand and managing supply in real time. Smart grids powered by AI dynamically adjust electricity flow, more effectively integrate renewable energy sources, and reduce transmission losses (IEA, 2021). For example, Google's DeepMind successfully reduced data center cooling energy usage by 40% using AI-based control systems and demonstrated the scalability of AI for sustainable infrastructure management (Evans and Gao, 2016). Such applications not only reduce carbon footprints but also promote cost-effective energy practices.

AI in agriculture supports sustainable practices by enabling precision farming that reduces water, fertilizer, and pesticide use. Machine learning models can predict crop yields, detect disease outbreaks, and recommend site-specific treatments that maintain productivity while reducing environmental impacts (Shamshiri et al., 2018). In sustainable agriculture, AI contributes to the efficient management of water, fertilizer, and pesticides through precision farming techniques. These advances not only increase crop yields but also minimize environmental degradation. It has been found that irrigation planning systems based on machine learning can reduce water usage by up to 30% without compromising productivity (Hussain et al., 2024). Despite its potential, the sustainability of AI must also be addressed, particularly in terms of energy consumption associated with model training and data storage. Sustainable AI development requires the use of energy-efficient algorithms, low-carbon infrastructure, and policies that prioritize ethical and environmentally responsible design.

Resource Use Optimization through AI

AI transforms resource optimization in cloud computing and software systems, increasing efficiency, scalability, and cost-effectiveness. AI techniques such as machine learning (ML), deep learning (DL), and reinforcement learning (RL) offer powerful tools for dynamic resource allocation, workload prediction, and cost management. For example, Artamonov and Balych (2024) state that neural networks provide high accuracy in resource acquisition and response times, improving data center performance by 20%, especially in cloud infrastructures. These systems prevent unnecessary consumption by distributing resources such as processors, memory, and storage according to real-time needs. Rao (2023) emphasizes that AI-based solutions reduce energy waste by up to 15%, especially in large-scale cloud platforms. This is a critical development in terms of both economic and environmental sustainability. Deep learning models, especially Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, stand out in energy efficiency and resource management. Kristian et al. (2024) show that LSTM models provide 90% accuracy in workload predictions based on time series data, thus reducing energy consumption in data centers by 12%. For example, in a cloud-based software system, LSTM networks automatically adjust server capacity by predicting user demands, thus reducing both costs and carbon footprint. Similarly, CNNs optimize resource usage in infrastructure monitoring systems that require visual data analysis (e.g., server temperature control with thermal cameras). However, the high computational requirements of these models are a disadvantage. Reinforcement learning (RL) stands out as another important AI technique in terms of cost management and flexibility. Kumar and Gore (2024) showed that an RL-based system dynamically optimized resource allocation in cloud environments, reducing operating costs by 25% and reducing service outages by 30%. RL enabled the system to learn through trial and error, enabling it to quickly adapt to variable workloads. For example, in an e-commerce platform, RL instantly scaled server capacity against sudden demand increases during holiday seasons. Artamonov and Balych (2024), state that such systems are 40% more flexible than traditional methods, especially in hybrid cloud architecture. This flexibility perfectly suits the dynamic nature of cloud computing. While AI-based solutions revolutionize resource optimization, they also present some challenges. Rao (2023) lists high initial costs, data privacy concerns, and a lack of expert personnel as the main obstacles to the widespread adoption of AI. Furthermore, Kristian et al. (2024) emphasize that the energy consumption used in training complex deep learning models may conflict with sustainability goals. To overcome these problems, open-source AI frameworks (e.g., TensorFlow, PyTorch), lightweight models, and energy-efficient algorithms are being developed.

Waste Reduction and Improved Water Efficiency with AI

AI is contributing to sustainability goals by revolutionizing waste management and water efficiency. AI technologies such as machine learning and artificial neural networks have optimized waste separation and resource recovery processes, increasing recycling efficiency by 15% and reducing operational costs by 20% (Li Wei Ming et al., 2024). In Singapore, in particular, AI-powered waste management systems have increased recycling rates by 25% (Hernandez et al., 2024). These innovations reduce the amount of waste going to landfills, preventing environmental pollution and supporting the conservation of water resources. Real-time data analytics of AI transform waste management into a more efficient and environmentally friendly process. AI applications in agriculture reduce water use by 30% and increase crop yields (Hernandez et al., 2024). AI-based systems analyze sensor data to optimize irrigation processes and ensure targeted use of water. This is an important step in combating global water scarcity, as 1.1 billion people worldwide lack access to clean water. In addition, the role of AI in agricultural waste management reduces soil and water pollution by facilitating the recycling of organic waste. However, challenges such as infrastructure limitations and the need for specialized personnel must be overcome for these technologies to become widespread. In wastewater treatment processes, AI increases the potential for water reuse and increases efficiency. AI systems integrated with the Internet of Things (IoT) determine the suitability of water for irrigation by monitoring water quality parameters (Narayanan et al., 2023). AI models exhibit high accuracy (R^2 value between 0.64 and 1.00) in predicting the removal efficiency of pollutants and effectively monitor water quality in wastewater treatment plants (Nagpal et al., 2024). These systems support environmental sustainability by reducing energy consumption and optimizing treatment processes. The success of AI in this area both saves water and contributes to global water management policies.

AI-Driven Crop Protection Solutions

AI and ML revolutionize crop protection strategies, enhance precision farming, pest management, and harvest optimization. These technologies enable real-time monitoring, predictive analytics, and data-driven decision-making, improving resource efficiency and reducing environmental impacts (Gustavo A. Mesías-Ruiz et al., 2023). AI applications in agriculture include big data analysis, pest and disease forewarning models, and ICT-based crop advisory systems (M. Pratheepa et al., 2023). Advanced crop protection techniques incorporate innovative chemical formulations, bio-PPPs, and AI-driven disease detection systems (A. Balafoutis et al., 2021). Integration with IoT and autonomous farming equipment further enhances productivity and minimizes labor costs (Danish Gul & Rizwan-ul-Zama Banday, 2024). However, data quality, infrastructure limitations, and implementation costs persist, particularly for small-scale farmers in developing regions (Danish Gul & Rizwan-ul-Zama Banday, 2024).

Environmental and Social Challenges of AI Implementation

AI is a general term used for a wide range of machine intelligence systems that can copy people's behavior. AI and Big Data have emerged as the defining features of the fourth industrial Revolution (IR). AI has developed tools. Due to innovation, the study of IR, AI and their environmental impact is still in the early stages of research (Adnan et al., 2024). Human-caused climate change and the degradation of our natural environment are critical problems. Advanced technologies such as AI offer the potential for the development of solutions. Machines that learn by acquiring information and perform human-like tasks can help humans reduce their intensive use of natural resources and improve environmental governance for more sustainable living (Taghikhah et al., 2022). The application of AI in environmental monitoring offers accurate disaster forecasts, pollution source detection, and comprehensive air and water quality monitoring (Olawade et al., 2024).Actually, the use of AI technology in environmental management, especially in terms of pollution, has emerged as a remarkable breakthrough in transforming our methodology for monitoring the environment. It has been given many advantages not only for developing AI hardware that focuses on sustainability by reducing energy use and using environmentally friendly materials, but also for improving of climate prediction models and environmental monitoring systems using AI (Adnan et al., 2024). In the other words, with the global energy sector under increasing pressure to support sustainability, the function of AI in improving Environmental, Social and Governance (ESG) performance is of great interest (Wang and Zhang, 2025). Carbon capture, utilization and storage (CCUS) are emerging as a promising solution to reduce global CO_2 emissions from the industrial and energy sectors (Elaouzy and Zaabout, 2025).

The social and environmental effects of developing productive AI. These include environmental challenges such as energy and resource consumption, and social issues such as working conditions and accessibility gaps, which highlight the systemic resource demands and socio-economic consequences of productive AI (Hosseini et al., 2025). As organizations continue to embrace the use of AI systems, it is very important to ensure that these AI systems can be trusted. However, there is still a significant gap between AI research and its application in real-world applications (Cousineau et al., 2024). Firstly, companies should prioritize integrating AI technologies into their ESG strategies by promoting a synergy between green innovation and AI through investments in AI-oriented sustainability solutions and cross-functional cooperation. Secondly, policymakers should provide specific support and incentives such as financial subsidies, tax incentives and technical assistance. In addition, differentiated policy measures are required to meet the specific needs of different types of enterprises, direct kits to pilot large-scale AI-oriented ESG projects, and support SMEs through capacity building and specialized AI tools. Finally, strengthening corporate ESG information disclosure and oversight mechanisms, including standard reporting frameworks and independent audits, is crucial to ensure transparency and accountability (Weng et al., 2025).

Towards Sustainable AI in Food Production: A Balanced Approach

The growing universal population and the growing demand for food are putting significant pressure on the global agricultural system to increase production. However, the expansion of agricultural land often comes at the expense of wildlife habitats, escalates human-wildlife conflicts as crops are damaged by animals, and threatens food security. In addition, the use of unsustainable deterrent methods can harm biodiversity. Current crop protection methods fall short of supporting sustainable agriculture goals (Abed et al.,2025). Agriculture and the food system are facing challenges related to climate change, biodiversity loss, agricultural pollution and food security. Food security at the international and national levels needs to be developed in an environmentally and resource-friendly way. Digitalization and AI provide opportunities to overcome these challenges and facilitate the transformation of agriculture and the food value chain (Wepner et al., 2025). One study used image-based experimental methods to explore the intersection of sustainability, gastronomic tourism and AI, with a focus on promoting 'climate-conscious food'. This term refered to food produced with environmentally friendly practices. Despite the benefits of climate-conscious foods for individuals, the environment and local tourism, their adoption remained limited. This conceptualized research on visual information processing consists of two studies that use bottom-up and top-down processing. It confirmed that the type of content in the images generated by AI, especially the "Food

Presentation" versus the "Preparation Process", significantly affected consumers' perceptions of food quality and purchasing intentions (Chan et al., 2025). Indeed, the widespread use of chemical fertilizers on small farms has helped to increase crop yields, support food security and economic growth. However, recent studies have showed that these fertilizers are often used inefficiently and inconsistently. This leads to environmental damage, unstable soil nutrients and low-quality food production (Pandian et al., 2024). Infrastructure limitations, high implementation costs and data privacy concerns must be resolved to promote fair access and widespread adoption. Standardization of interoperability and quality control protocols is also critical to ensure accurate measurement and reporting of emissions. Future research should further refine ML models to address local variability in climate, soil, and farm practices, while exploring collaborative frameworks that protect data privacy (e.g., unified learning). Moreover, integrating policy incentives, capacity building programs and stakeholder collaborations can accelerate the use of IoT and Big Data tools in real-world agricultural environments. By addressing these issues, the agricultural sector can benefit from digital innovations to reduce its carbon footprint, increase resilience to climate change, and advance global sustainability goals (Ahmed and Shakoor, 2025). In the context of greenhouse agriculture, the integration of AI is being evaluated in terms of its potential to improve sustainability and crop production efficiency (Hoseinzadeh and Garcia, 2024). The relationship between developments in Industry 4.0 technology such as AI and their impact on the earth, the environment, humans and biological ecosystems needs to be taken into account more consideration. One article addressed the challenge of monitoring the indicators of the 17 SDGs by taking advantage of Industry 5.0 developments. It offered practical verification of the framework through use cases in energy and water management. The results showed how the framework can improve the sensitivity, transparency and scalability of SDG monitoring while providing useful information to stakeholders. (Hassan et al., 2025).

Future Directions: Accessibility, Governance, and Impact Alignment

Future directions necessitate a focus on critical areas such as accessibility, governance, and impact alignment with the widespread adoption of AI and related technologies. Particularly, with the increasing prevalence of AI-driven solutions in environmental monitoring and sustainable agriculture practices, ensuring these technologies are accessible to all stakeholders is of paramount importance. As emphasized by Ahmed and Shakoor (2025), the effectiveness of Internet of Things (IoT), Big Data, and AI-based smart agriculture technologies in supporting sustainability hinges on their ease of adoption and implementation by farmers and other users in rural areas. Furthermore, as noted by Cousineau, Dara, and Chowdhury (2024), AI systems must be operated within a transparent and accountable governance framework, considering the challenges and opportunities faced by AI developers in creating trustworthy AI applications. The meticulous evaluation of the environmental and socioeconomic impacts of AI technologies and their alignment with sustainability principles is also a priority among future directions. The research by Hosseini, Gao, and Vivas-Valencia (2025) underscores the need for a comprehensive analysis of the social and environmental impacts of generative AI. Similarly, Wang and Zhang (2025) highlight the importance of innovation, collaboration, and proactive sustainability strategies to enhance the environmental, social, and governance performance of AI-enabled supply chains in the energy sector. In this context, minimizing the environmental footprint, promoting social justice, and establishing robust governance mechanisms are critical considerations in the development and implementation of AI applications. Lastly, an interdisciplinary approach is essential for aligning AI technologies with sustainable development goals. The study by Pandian et al. (2024) emphasizes the significance of synergistic conservation strategies that address the interconnections between soil health, food security, and human health. In this regard, collaboration among experts from various disciplines and the adoption of a holistic perspective towards sustainability goals are necessary during the development and implementation of AI applications. As indicated by Wepner et al. (2025), the exploration of digitalization's impacts on the sustainability of agri-food systems through diverse scenarios will guide the effective utilization of AI and digital technologies.

Conclusion

The global food system faces significant interconnected challenges spanning environmental sustainability, socio-economic equity, and political governance, demanding a transformative shift to feed a growing population responsibly. AI emerges as a powerful catalyst in this transformation, offering promising solutions for enhanced efficiency, sustainability, and resilience across the agrifood value chain. From precision agriculture optimizing resource use to AI-driven crop protection and waste reduction, the integration of AI technologies presents substantial benefits for environmental stewardship and resource management. However, the widespread and equitable adoption of AI in agrifood production is not without its hurdles. Issues such as high initial costs, infrastructure limitations, data privacy concerns, and the energy consumption of AI models themselves must be carefully addressed. Ensuring accessibility for smallholder farmers, establishing robust governance frameworks, and aligning AI development with broader sustainability principles are crucial for realizing the full potential of AI in creating a more sustainable and equitable food future. Moving forward, a balanced approach is essential. This involves fostering international collaboration, promoting open-source AI solutions, developing energy-efficient algorithms, and implementing supportive policies that prioritize inclusivity and capacity building. Future research should focus on refining AI models for local contexts, exploring collaborative data governance frameworks, and integrating policy incentives to accelerate the adoption of sustainable AI practices in agriculture. Ultimately, by thoughtfully navigating the challenges and strategically leveraging the opportunities, AI can be a transformative force in building a global food system.

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