AI and the Circular Food Economy: How Technology is Redefining Waste, Distribution, and Sustainability

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Abstract

Artificial intelligence is reshaping the circular food economy by transforming how food is produced, distributed, and recovered across global systems. This paper examines the role of AI in advancing circularity within the food sector, focusing on waste reduction, supply chain optimisation, and sustainable agricultural practices. Drawing on interdisciplinary research, the study explores how AI technologies such as predictive analytics, computer vision, smart packaging, IoT-enabled monitoring, and blockchain-integrated platforms enhance efficiency and resource regeneration throughout the value chain. Case studies, including Winnow, Too Good To Go, and Apeel Sciences, demonstrate measurable reductions in waste, emissions, and operational costs. At the same time, the paper highlights challenges associated with AI adoption, including cost barriers, data governance concerns, inequalities between developed and developing economies, and risks of technological overdependence. The analysis concludes that AI can significantly accelerate the transition to a circular food economy, provided implementation is equitable, transparent, and integrated with human expertise and regenerative practices.

Keywords: artificial intelligence, circular food economy, food waste reduction, sustainable agriculture, smart supply chains, AI in food systems, regenerative practices

1. Introduction

Over the past two centuries, the global economy has largely followed a linear “take-make-dispose” model, which relies on consuming limited natural resources and fossil fuels. As a result, it has led to negative environmental effects such as degradation, climate change, pollution, and declining biodiversity. To ensure long-term sustainability, a shift away from this model is essential. The circular economy offers a promising alternative to this traditional linear approach.

The concept of a circular economy (CE) has gained significant importance recently, drawing interest from industry, policymakers, and researchers. The circular food economy translates circular economy principles to the food sector, encompassing agricultural production, distribution networks, and consumption. Unlike the traditional "take-make-dispose" approach, it aims to keep resources in use longer and regenerate ecosystems that support food production. This involves reintegrating food scraps, by-products, and organic matter into biological cycles through methods like composting, anaerobic digestion, or converting them into animal feed and bio-based products (MacArthur, E.2019). It also emphasizes reducing waste throughout the supply chain, extending the lifespan of agricultural resources, and creating closed-loop systems that reduce environmental impact. The scale of current challenges underscores the urgency of transformation. Approximately 13.2% of all food produced worldwide is lost between the harvest and retail stages (FAO, 2023). The food system accounts for roughly one-quarter of greenhouse gas emissions

(Our World in Data, 2019). Agriculture is a leading cause of biodiversity loss (WWF, 2020), and it consumes 70% of global freshwater withdrawals (UNEP, 2021). These figures highlight the urgent need for change to protect ecosystems while ensuring food security. In this context, the circular food economy is essential as it provides a pathway toward resilient and sustainable food networks by optimizing resource use, reducing environmental harm, maintaining ecosystem stability, and ensuring long–term food security. This shift presents opportunities for organisations, whether small or large, public or private, local or global, to shape a distributed, diverse, and inclusive economy.

According to the Ellen MacArthur Foundation, the circular food economy is based on three interconnected principles, each aimed at building resilience and sustainability within the food system:

A. Reduce waste and pollution- In a CE, waste and pollution are seen as design flaws resulting from unsustainable or inefficient systems. This principle focuses on the elimination of any harmful impact on human health and the natural system, such as greenhouse gas emissions, pollution, and the use of toxic substances. By designing out waste, products can be created to serve as resources for future cycles.

B. Circulate products and materials at their highest value- This principle focuses on making sure food nutrients and resources stay in productive use and involves promoting practices that maximize product utilisation and encourage reuse, thereby preserving energy, labour, and materials invested in them. Examples include redistributing surplus food, turning fruit peels into animal feed, or processing organic waste into bio-based packaging.

C. Regenerate natural systems- Rather than simply minimizing harm, the circular model seeks to rebuild and strengthen natural ecosystems. This principle involves integrating practices that not only avoid degrading natural systems but also actively rebuild them over time. This includes composting to enrich soils, practicing regenerative agriculture, and using crop residues to boost biodiversity and soil health.

These principles guide the food sector away from a linear "take-make-dispose" model. They support the development of systems that conserve resources, lower environmental impact, and enhance food security. Implementation of circular practices has posed several challenges within the food system. Unlike linear supply chains, which move materials in a single direction, circular systems need complex reverse logistics to recover and manage materials efficiently. Traditional methods often fall short when it comes to managing these multi-directional flows, leaving room for inefficiencies. AI is increasingly used to support sustainable practices by analysing real-time data, forecasting demand, streamlining distribution, and tracking waste. By aligning with circularity's main ideas, it offers practical solutions to operational challenges while supporting more resilient and efficient food systems. Globally, countries such as Germany, Japan, the United States, China, Denmark, the United Kingdom, and the Netherlands have adopted CE initiatives, with Japan and China among the first two countries from Asia to introduce the concept of CE, particularly focusing on sustainability, on a national level and in all sectors. (Raut, S et al.2025). Roberts et al. (2024) describe the circular economy as a model that eliminates waste and keeps materials and products in continuous use, promoting sustainability.

By leveraging AI technology, we can streamline processes, improve decision-making, and promote the development of innovative solutions to address the urgent challenges facing the global food system. According to the Ellen MacArthur Foundation & Google 2019), AI could generate up to USD 127 billion annually by 2030 by helping reduce food waste. There are various ways in which AI is contributing to tackling food waste, supporting the circular economy, and enhancing sustainability in food production. A pilot program by Nestlé in the UK demonstrates this potential by saving up to 700 tonnes of high-quality surplus food, which is equivalent to as many as 1.5 million meals, thereby preventing up to 1,400 tonnes of CO2 emissions, which could save up to £14 million in operational costs. (Hall, R. 2025). Beyond waste reduction, digital innovations such as drones, the Internet of Things (IoT), big data, additive manufacturing (AM), modern robotics, AI, automated vehicles, and blockchain are crucial for maintaining supply chain continuity and sustainability in the growing economy. These concepts are also supported by (Akbari & Hopkins, 2022). For example, Machine Learning (ML) enhances crop yields by analyzing weather patterns and soil conditions, AI image recognition helps reduce food waste by ensuring only quality products reach consumers, IoT-enabled systems monitor nutritional value during storage, and blockchain, combined with AI, increases transparency and accountability throughout the supply chain, thus reducing losses and inefficiencies. (Onyeaka, H et al. 2023)

This report examines the relationship between AI and the circular food economy, exploring how AI applications are transforming waste management, food distribution, and sustainability throughout the value chain. It also evaluates associated risks, ethical considerations, and opportunities for responsible implementation.

2. Theoretical Background

A. Operational Strategies of Circular Food Economy

Transitioning to a circular food economy requires practical measures that achieve meaningful results. These strategies focus on reducing, reusing, recycling, and regenerating, providing a roadmap for achieving systemic change.

Reduce. The first step is to reduce food loss and waste across every stage of the supply chain. The FAO estimates that around 14% of the world's food is lost between harvest and retail, while an additional 17% is wasted at the consumer level (FAO, 2021). Enhancing storage facilities, strengthening cold-chain infrastructure, and using AI-based demand forecasting help curb these losses.

Reuse. Safe surplus food can be redirected for human consumption, donated to food banks, or repurposed as animal feed. Initiatives like Feeding America in the United States and Too Good To Go in Europe show that redirecting surplus food can reduce waste while supporting food security.

Recycle. Organic by-products unsuited for reuse can still contribute to the circular economy through composting, anaerobic digestion, or transformation into bio-based packaging and materials. In the European Union, recycling food waste into biogas can reduce methane emissions by up to 30% compared to disposal in landfills (European Commission, 2020).

Regenerate. Beyond managing waste, circularity also means regenerating natural systems. Regenerative agriculture, which focuses on restoring soil, biodiversity, and carbon storage, is key to this approach. According to the Ellen MacArthur Foundation (2019), widespread adoption of regenerative practices could reduce food-related greenhouse gas emissions by up to 49% by 2050, while improving soil health and long-term agricultural productivity.

These strategies represent the practical side of circularity, transforming a broad vision into practical actions that restore ecological balance and increase system efficiency.

B. Shift from Linear to Circular Food Systems

Traditional linear models, common in many industries and countries, have relied on product innovation and hierarchical governance. While they have been effective in certain contexts, these models are increasingly unsustainable given the limits of natural resources and the pressures of environmental degradation. By 2030, this linear model is expected to exacerbate resource scarcity, resulting in a projected gap of roughly eight billion tons between supply and demand (Scheel, C.2025). Globally, the FAO (2019) reports that 1.3 billion tonnes of food are wasted each year—about one-third of all food produced for human consumption. Food waste accounts for approximately 8–10% of global greenhouse gas emissions, uses substantial land and water resources, and threatens biodiversity. Economically, it causes losses of about USD 940 billion annually.

The linear growth model must transition into a system that actively restores and regenerates natural resources, reuses waste, and reduces harmful emissions. Following this approach, the traditional linear economy is being "circularized". A circular food system aims to eliminate waste and keep nutrients in closed loops. The Ellen MacArthur Foundation (2019) points out that incorporating circularity into food systems could create USD 2.7 trillion in annual benefits by 2050, driven by improved health outcomes, climate resilience, and resource efficiency. Successfully making this shift requires coordinated supply chain efforts, stakeholder engagement, and technologies to manage the complex feedback loop.

C. AI as a Driver of Innovation in Green Transitions

Implementing circular practices on a large scale presents significant challenges. Unlike linear models, circular systems need reverse logistics, real-time monitoring, and multi-directional flows of products and nutrients. Traditional methods struggle to manage this complexity, which is why artificial intelligence (AI) is becoming vital for green transitions. With AI, food processing and manufacturing are becoming smarter and more environmentally sustainable, giving rise to 'smart food manufacturing.

At the production level, AI-based predictive models optimize planting and harvesting, reducing overproduction and matching outputs with actual market demand.

During distribution, AI-powered logistics platforms can shorten transport distances and ensure timely delivery, lowering emissions and minimizing spoilage.

In retail and consumption, Computer vision and IoT sensors track freshness, adjust prices in real-time, and extend product shelf life. Much of the consumer-level food waste in developed countries arises from buying more than needed, discarding imperfect-looking items, or poor storage practices—issues that AI tools can help address effectively. According to the FAO, consumer-level waste accounts for over 60% of food waste in developed economies.

In waste management, AI enables the automated sorting of organic waste, detecting contamination, and integrating into recycling or bioenergy systems.

Research supports AI's potential: (Garcia, D et al.2021) emphasize AI's role in optimizing food waste management, while (Jagtap, S et al.2022) show how AI-driven platforms can cut inefficiencies throughout global supply chains. By combining real-time data analytics with sustainability goals, AI is more than a supporting tool; it plays a central role in the circular food economy by aligning ecological, economic, and social goals.

3.AI in Food Waste Reduction

Food waste is a major global problem with severe economic, social, and environmental effects. Each year, over 1.3 billion tons of food intended for people is lost or wasted worldwide. This causes economic losses exceeding US$1 trillion and accounts for 8 to 10% of global greenhouse gas emissions (FAO, 2023). In Europe alone, agriculture produces over 700 million tons of waste annually, with more than half derived from the farming sector (Pawelczyk, A.2005). Wasted food not only depletes crucial resources like water, land, and energy but also worsens food insecurity, particularly in areas already facing shortages. Adopting new technologies becomes essential as the population grows and climate change impacts agriculture. Artificial intelligence (AI) offers an effective way to reduce waste across the entire food supply chain, from production and post-harvest handling to retail and consumption, by enabling data-driven and real-time decision-making (Raut, S.2025).

Predictive Analytics for Demand and Inventory Forecasting

One of the major causes of food waste in retail and restaurants is imprecise demand prediction. It often leads to overstocking, spoilage, and financial losses (Chauhan, C et al., 2021). AI-powered predictive analytics uses machine learning models like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks to process large datasets. These datasets include historical sales, market trends, weather patterns, social media sentiment, and competitor activity. This technology makes demand predictions more accurate (Zong, Y. & Guan, W. 2024). This helps businesses manage inventory just in time. It reduces overproduction upstream and ensures food reaches consumers while still fresh.

For restaurants and retailers, predictive analytics aids in dynamic pricing, planning promotions, and redirecting near-expiry products. Using AI this way can reduce overall food waste by up to 40%. Predictive inventory models can cut operational costs by about 30% (Wang, X et al.2022). These tools are becoming more accessible to smaller businesses, allowing more organizations to benefit from AI-driven waste reduction.

Computer Vision for Food Quality and Spoilage Detection

Conventional methods of checking food quality are often time-consuming, subjective, and destructive. This results in unnecessary waste (Mavani, K et al., 2021). AI-based computer vision systems, which use Convolutional Neural Networks (CNNs), provide a faster, non-destructive, and highly accurate way to assess food quality. They can analyse visual features such as colour, texture, shape, and signs of microbial activity to detect defects, ripeness, or contamination.

These systems can be used throughout the supply chain, including sorting fresh produce and detecting pathogens in perishable items. For instance, CNNs can spot defects in tomatoes and mangoes with over 94% accuracy. Additionally, hyperspectral imaging can identify microbial growth early (Romanello, R. & Veglio, V.2022); Frontiers in Sustainable Food Systems, 2025). By preventing edible food from going to waste and ensuring safety, computer vision helps reduce the environmental footprint of discarded products.

AI-Powered Smart Packaging

Smart packaging uses IoT sensors, AI, and cloud analytics to track food quality in real time, predict spoilage, and dynamically estimate shelf life (Romanello, RR.& Veglio, V,2025). Unlike traditional packaging with fixed expiration dates, smart packaging adjusts to conditions like temperature, humidity, and gas composition. This improvement helps retailers manage inventory, set dynamic pricing, and send near-expiry products to areas with high demand. It reduces waste while creating value for communities (Chauhan, C et al. 2021).

Examples show notable results. Apeel Sciences' plant-based coatings, along with AI monitoring, can double the shelf life of produce and cut spoilage by up to 50% (Apeel Sciences, 2024). Freshness indicators like Mimica and FreshTag provide clear cues for retailers and consumers. Platforms like FoodCycle AI connect packaging data to redistribution networks, directing surplus food to shelters and community programs (FoodCycle AI, 2025). When combined with predictive analytics and computer vision, smart packaging creates a strong AI-driven method to reduce food waste throughout production, distribution, and consumption stages.

Case Studies

The potential of AI to reduce food waste is best shown through the success of companies that have used these technologies in real-world settings. This section highlights three case studies.

A. Winnow: Revolutionizing Commercial Kitchen Operations

Winnow delivers an AI-driven solution for commercial kitchens, enabling chefs to minimize food waste. The company's technology is active in over 1,500 locations across 50 countries and has saved users $42 million annually. The key part of the technology is the "Winnow Vision" system, which combines AI, computer vision, smart scales, and cameras to track and analyze food waste automatically in real time. Machine learning algorithms can classify different types of discarded food, offering kitchens valuable insights into both the nature and causes of food waste.

A partnership between Winnow and IKEA serves as a strong example of the system's effectiveness. Since 2017, IKEA has implemented the Winnow system in its kitchens, serving over 560 million people each year. This partnership not only helped bring Winnow Vision to market but also delivered meaningful results. IKEA successfully cut its kitchen food waste by 50-54% within a year, achieving this goal nine years early compared to the UN Sustainable Development Goal 12.3 target date. This reduction resulted in significant cost savings of over £1.4 million in 2018 and helped avoid 36,000 tonnes of CO_2 emissions. The success of this initiative stemmed from a key principle: what gets measured gets managed. The AI system's value lay in generating actionable insights, not in automation. The data enabled kitchen staff to make informed decisions on production and menu changes, turning them into more engaged managers of food waste. This human-in-the-loop approach to waste reduction is crucial for achieving a circular economy, allowing companies like IKEA to internalize the costs of food waste and turn it into a profit opportunity.

B. Too Good To Go: A Marketplace for Surplus Food

Too Good To Go is a mobile app that uses AI to create a marketplace for surplus food that would otherwise be thrown away by restaurants, cafes, and grocery stores. The app connects customers with these businesses, allowing them to buy a "surprise bag" of food at a discounted price (one-third of the original cost), effectively saving it from landfills.

The app's AI capabilities are central to its effectiveness. It uses real-time supply data to match available food with nearby users based on location, past behavior, and preferences. This smart matching system leads to a high rate of successful transactions and efficient food redistribution. The company has also created a tool called "Magic," which provides grocery stores with AI predictions to forecast overstock and near-expiry products. This tool enables better inventory management and facilitates preparation for surplus. The app's success comes from a win-win business model that offers financial incentives (discounted food) and a social incentive (reducing waste) to shift consumer behavior.

The impact of Too Good To Go on food waste and sustainability is significant. As of 2024, the company has over 100 million registered users and has saved more than 400 million meals from going to waste. The app highlights its environmental impact by showing users the amount of carbon dioxide avoided with each meal saved. By turning a previously informal process of giving away leftovers into a scalable digital marketplace, Too Good To Go has changed waste management and redistribution systems into an economic model that benefits businesses, consumers, and the environment.

C. Apeel Sciences: Extending Shelf-Life through Edible Coatings and AI

Apeel Sciences has developed an edible, plant-based coating that serves as a natural barrier to extend the shelf life of fresh produce. This technology slows food spoilage, a major contributor to losses during transport, retail, and at the household level. However, Apeel's innovation goes beyond the coating itself; it includes AI technology that improves its effectiveness.

The "RipeTrack" digital platform uses AI and non-destructive imaging to provide real-time insights into produce ripeness throughout the supply chain. This system measures factors like firmness, dry matter, and color by shining light into the fruit and using machine learning models to analyze the reflected light spectrum. The AI interprets this data, along with the product's origin and pack date, to determine its best ripe date and remaining shelf life. This allows suppliers and retailers to make data-driven choices on sorting, shipping, and merchandising, directing produce to the optimal retailer based on its freshness. Apeel is also developing a consumer-facing ripeness scanner that uses the same technology, offering information like, "Your avocado will be ready in about 4 days," helping consumers make better purchasing decisions. The combination of this biological product with AI is a great example of how AI can enhance a non-digital product to create a closed-loop system.

Apeel has a significant, measurable impact on reducing waste and promoting sustainability. The edible coatings can extend the shelf life of avocados by up to 12% and oranges and mandarins by 7%, reducing household waste. In 2023, the company's technology helped prevent the release of over 9,000,000 kg of CO2-equivalents and saved 2.7 billion liters of water. Apeel's business model represents a systematic approach to the circular economy, creating a network of interconnected solutions that benefit all stakeholders—from farmers to consumers. The technology improves logistics, reduces in-store waste, and empowers consumers, creating a holistic system that supports a more sustainable food supply chain.

Together, these case studies show how AI can function at various stages of the food system—from production and retail to consumption—highlighting both technological innovation and changes in business models.

4. AI in Food Distribution

One of the biggest challenges in the global food system is getting food from farms to tables. Problems in this area lead to a massive amount of food waste. This waste is estimated at 931 million tons annually, resulting in $1 trillion in economic losses and contributing to 8-10% of global greenhouse gas emissions (FAO, 2023). Food waste also creates more food insecurity, affecting over 720 million people worldwide (Banerjee, P.2025). To tackle these issues, AI is becoming a powerful tool by improving supply chain efficiency, sustainability, and transparency.

AI algorithms analyze historical sales, market trends, weather patterns, and consumer behavior to forecast demand accurately. These predictions help producers, distributors, and retailers reduce overproduction, avoid stockouts, and cut down on spoilage. This ultimately improves access to food and supports environmental sustainability. For example, retailers using AI solutions from Shelf Engine and Afresh achieved a 14.8% reduction in food waste per store. IKEA reported a 30% reduction in kitchen food waste within a year by using AI-powered monitoring systems (Onyeaka, H.2025). AI systems can monitor product freshness and expiry dates, offering valuable insights to optimize inventory management.

Although AI offers significant benefits, successful implementation needs high-quality, diverse datasets, interoperability with existing systems, and teamwork throughout the supply chain. Standardized data protocols, secure storage, and effective model training are key to smooth AI integration. When executed correctly, AI not only improves operational efficiency but also helps create a resilient, sustainable, and socially responsible food system.

A. Optimizing Logistics & Supply Chains (Reducing Food Miles)

Optimized food logistics are essential for cutting food waste and lowering environmental impact. Food traveling long distances not only increases carbon emissions but also raises the risk of spoilage. AI systems look at large amounts of data on past sales, demand patterns, weather forecasts, and transportation conditions to enhance the supply chain. Predictive inventory models enable distributors to match production with real-time demand, cutting down on overstock and lowering storage costs. For example, (ee, T et al. 2021) found that predictive inventory systems helped major food distributors reduce operational costs by up to 30%. (Martinez, J et al. 2022) noted a 25% drop in fuel use in AI-optimized delivery systems, easing both economic and environmental pressures. This reduces the carbon footprint of food distribution while strengthening supply chain resilience.

AI-driven routing systems alter delivery paths based on traffic, weather, and demand fluctuations, ensuring that perishable goods arrive on time and in good condition. Seoul, South Korea, implemented an AI-based route optimization system that reduced transportation costs by 25% and cut carbon emissions by 20%(Bhat, A.2025). This is an example of how moving food can cut down the distance it travels. Additionally, AI can forecast maintenance needs for transport vehicles, helping to prevent unexpected breakdowns that could delay deliveries and cause spoilage.

Though there are costs for integration and challenges with infrastructure, AI works well with IoT sensors and edge computing to provide ongoing real-time monitoring and automated decision-making. This mix allows smaller businesses to use predictive logistics and keeps perishable goods in good condition during transit. AI cuts inefficiencies, reduces waste, and boosts the overall sustainability of food distribution networks by improving fleet management, warehouse operations, and delivery scheduling.

B. AI-Driven Cold Chain Monitoring for Perishables

Cold chain management is essential for distributing perishable food items, including fruits, vegetables, dairy, and meat. AI-driven cold chain systems use IoT sensors, predictive analytics, machine learning, and automation to monitor and maintain important storage parameters such as temperature, humidity, and gas levels. Using both historical trends and live sensors, AI can detect when food is at risk of spoiling and make sure it’s stored and transported safely.

For instance, AI can spot possible refrigeration problems before they happen, preventing food spoilage and expensive losses. AI-driven image recognition systems can also check the freshness of meat, dairy, and other perishables in real time, enabling warehouse and transport managers to respond quickly to maintain food quality. Research shows that AI cold chain monitoring systems can reduce spoilage related to transportation by about 14%. They also support “just-in-time” delivery strategies that minimize inventory waste. (Kim & Park,2023)

Additionally, AI's integration with blockchain technology ensures traceability and transparency, giving retailers and consumers confidence in food safety. This is especially important for industries like dairy and seafood, where food can spoil very quickly. Although setting it up and standardizing data can be tricky, predictive models that connect environmental conditions with microbial activity can help prevent contamination, reduce waste, and make supply chains more eco-friendly.

By keeping perishable goods safe and fresh, AI not only improves food security but also helps the environment by reducing greenhouse gas emissions from wasted food.

C. Redistribution Platforms: OLIO and Apps Linking Surplus Food to NGOs

AI is changing how surplus food is redistributed. It connects excess supplies from retailers, restaurants, and households to vulnerable groups like food banks, shelters, and low-income communities. Platforms like OLIO use Natural Language Processing (NLP), Machine Learning (ML), and Geographic Information Systems (GIS) to classify donations, predict supply and demand, and optimize delivery routes. This system ensures extra food reaches those who need it most, reduces waste, and boosts its positive impact on society.

AI-powered redistribution platforms have already redirected over 1 million tons of surplus food each year, preventing major environmental and economic losses (Singh, P. & Arora, R.2023). AI has helped with dynamic pricing and inventory management, which encourages the sale of near-expiry items and further reduces waste. These platforms don't just make operations more efficient- they also make food easier to access for vulnerable groups, promote social equity, and help communities become more resilient to food insecurity.

Additionally, AI has helped in educating consumers by providing tips on meal planning, portion control, and proper storage. Predictive analytics, logistical optimization, and real-time monitoring work together to ensure surplus food is used effectively while also cutting down greenhouse gas emissions related to food waste. AI has supported a sustainable, socially responsible, and scalable food distribution network by bringing together retailers, logistics providers, and charitable organizations.

5. AI and Sustainability in Agriculture & Production

The integration of artificial intelligence (AI) into agriculture is transforming farming into a precise, data-driven, and sustainable system—an essential step to feed a global population expected to reach 10 billion by 2050. Conventional methods can no longer satisfy food needs without harming natural resources, especially since agriculture already uses nearly 69% of the world's freshwater. By utilizing data from satellites, drones, and IoT sensors, AI improves planting schedules, irrigation, fertilization, and pest control. Predictive algorithms modify irrigation based on soil moisture and weather forecasts, reducing water use by up to 30% without lowering yields, while machine learning models support real-time decision-making and diminish resource waste (Prabhat, P.K. et al, 2021).

AI's predictive power has proven transformative in boosting both productivity and sustainability. Machine learning models analyze historical yield data, soil health, and weather patterns to forecast nutrient deficiencies, pest outbreaks, or crop stress. AI-driven precision agriculture can increase crop yields by up to 20% while reducing resource use by 15%(Banerjee, P. 2025). In India, AI-based crop disease detection systems have achieved an impressive 95% accuracy rate, enabling timely interventions that prevent significant yield losses. These advancements show how AI can help lower risks, save resources, and improve food security in vulnerable areas. (Gupta, P.2023)

Beyond field-level efficiencies, AI fosters a holistic approach by linking farm operations with supply chain and sustainability goals. IoT-enabled smart farms monitor soil nutrients, temperature, and emissions, feeding data into AI systems that inform climate-smart interventions and regenerative practices such as cover cropping and soil restoration. As a result, AI enhances resilience to extreme weather, supports circular agricultural practices, and advances long-term productivity.

A. Precision Farming with AI & IoT

Precision farming, using Artificial Intelligence (AI) and the Internet of Things (IoT), is transforming agriculture by making decision-making more accurate and data-driven. By integrating IoT devices, drones, GPS sensors, and satellite imagery, farmers gain real-time insights into soil health, crop growth, nutrient distribution, and environmental conditions. AI algorithms process these inputs to recommend targeted irrigation, fertilization, and pest control strategies, ensuring resources are applied precisely where and when needed. For instance, vineyards in California using AI-guided irrigation systems have increased production by 25% while reducing water usage by 20% (Aijaz, N.2025). Similarly, farms in Punjab, India, reported 18% higher yields and 30% less water usage by deploying drones and AI for agrochemical spraying. (Liu, S et al.2024).

AI-driven precision farming also enables predictive problem-solving by continuously monitoring soil moisture, nutrient levels, and crop health. IoT-enabled sensors transmit data to machine learning models that anticipate potential crop stress, pest infestations, or nutrient deficiencies, recommending precise interventions. Satellites track how crops are developing and forecast the ideal planting and harvesting schedules according to climate patterns. Recent field trials in India and other regions show that drone-based spraying reduced water use by nearly 70% and pesticide consumption by up to 40%, while also cutting spray drift by over 50%. These efficiency gains not only lower input costs and environmental impact but also improve overall farm profitability and resilience against climate risks and crop failure (Raut & D'Mello, 2025; Liu et al., 2024).

Beyond resource optimization, precision farming fosters innovation through smart seeds, autonomous machinery, and AI-powered farm management platforms. Smart seeds adapt to their environment, making better use of nutrients and growing more efficiently. Autonomous tractors and harvesters equipped with AI, GPS, and IoT sensors deliver energy-efficient, cost-effective field operations, reducing reliance on labour and fuel. Meanwhile, integrated farm management platforms combine climate, soil, and crop data to provide actionable insights across multiple farms, enabling strategic planning and benchmarking. With global adoption of precision farming technologies expected to grow at a CAGR of 24.5%, this convergence of AI and IoT establishes a model of sustainable, efficient, and technologically advanced agriculture capable of meeting future food demands responsibly. (Market.us, 2024)

B. Crop Monitoring, Yield Prediction, and Soil Optimization

AI-powered crop monitoring has redefined how farmers detect diseases, pests, and environmental stressors in real time. Deep learning models, such as Convolutional Neural Networks (CNNs), analyse high-resolution aerial imagery from drones, satellites, and even smartphones to identify early signs of disease with over 93% accuracy. This method cuts down on chemical use, helping farmers save money while limiting damage to nature. Platforms like Plantix and Aerobotics are making such innovations widely accessible, enabling farmers to adopt precise interventions for irrigation, nutrient management, and pest control (Tiwari, S et al.2024). AI minimizes yield losses, enhances quality, and supports environmentally sustainable farming practices by detecting crop issues at an early stage.

AI is equally transformative in yield prediction, providing a significant advantage over traditional methods. Machine learning models, including Long Short-Term Memory (LSTM) networks, integrate historical yield data, soil health indicators, and climate patterns to deliver highly accurate production forecasts. Studies reveal that AI-driven prediction systems can improve crop outputs by up to 20%, while predictive insights allow farmers to optimize planting schedules, resource allocation, and supply chain planning. In Ethiopia, smallholder farmers utilizing the Virtual Agronomist AI tool experienced a 1.4 to 1.9-fold increase in crop yields compared to traditional farming practices. (Munyao, P.2025)

Soil optimization, another cornerstone of AI in agriculture, ensures long-term sustainability and resilience. Digital soil mapping powered by AI reduces the need for manual sampling by up to 40%, while providing tailored recommendations for nutrient application and soil amendments (Mehta, A.2024). Continuous monitoring of soil pH, organic matter, nutrient content, and moisture helps maintain fertility, improve water retention, and boost carbon sequestration. By integrating soil optimization with precision crop monitoring and yield prediction, AI enables a regenerative farming system that maximizes productivity while conserving natural resources. Reflecting this growing adoption, the global AI in agriculture market is projected to reach USD 5.27 billion by 2032, expanding at a CAGR of 17.5% from 2022 to 2032. (Spherical Insights & Consulting, 2023).

C. AI Decreasing Resource Use (Water, Fertilizer, Energy)

AI-driven technologies are transforming resource management in agriculture, tackling long-standing challenges of water overuse, excessive chemical application, and inefficient energy consumption. By leveraging real-time data from soil sensors, weather forecasts, and IoT-enabled devices, AI optimizes the timing and quantity of resource application. Precision irrigation systems powered by AI have reduced water use by up to 30% in arid regions while simultaneously boosting yields by 20–25% (Mohapatra, P.2025). Such systems prevent groundwater depletion, conserve freshwater resources, and enhance crop resilience. These outcomes demonstrate how AI can simultaneously achieve productivity and sustainability goals while addressing global water scarcity challenges.

The benefits also extend to fertilizer and pesticide optimization. Early disease and pest detection through AI enables targeted interventions, reducing the need for broad-spectrum chemical spraying. Studies indicate that AI-guided precision practices can cut fertilizer and pesticide usage by nearly 15%, lowering risks of soil contamination and water pollution. Blue River Technology exemplifies this innovation by using computer vision to identify and selectively spray weeds, thereby minimizing chemical use while improving efficiency. Similarly, in greenhouse vegetable cultivation, AI-assisted nutrient management strategies, such as adjusting fertilizer application based on soil nutrient levels, have been shown to reduce chemical fertilizer use while maintaining crop yields, highlighting AI's role in optimizing nutrient efficiency and mitigating environmental impacts (Zhou et al.2023).

AI also helps save energy, which is another big advantage of using it. Autonomous machinery equipped with GPS and IoT sensors can optimize field operations, reduce fuel consumption, and minimize labor requirements. AI systems further improve efficiency by optimizing machinery routes, scheduling maintenance, and monitoring energy use, collectively decreasing operational energy consumption by up to 15%. Besides helping the environment, farmers are making more money with AI because it increases yields and lowers costs, proving its worth in agriculture. As noted by the Government Accountability Office, this integration aligns farming operations with global sustainability targets, supporting resilient, eco-efficient, and profitable agricultural systems.

Examples: John Deere AI Tools, CropIn, IBM Watson Agriculture

Several companies are at the forefront of integrating AI into agriculture, demonstrating measurable impacts on productivity, resource efficiency, and sustainability. John Deere has pioneered autonomous tractors and combines harvesters equipped with AI algorithms, GPS, and IoT sensors. Smart machines study soil and crop conditions in real time and guide farmers on exactly how much water, fertilizer, or pest control is needed. By optimizing inputs and improving yields, John Deere showcases how AI-driven mechanization can advance both economic and environmental outcomes in farming.

In India, CropIn has emerged as a leading agritech company delivering AI-powered platforms that enable precision agriculture. By combining AI insights with digital farm records, these solutions help farmers track crop health, forecast yields, and use inputs more efficiently. By offering actionable insights, CropIn empowers farmers to adopt data-driven decision-making, enhancing profitability while minimizing resource waste. The way it's being used across India shows how AI can help small farmers move towards sustainable practices.

IBM Watson Agriculture extends the benefits of AI globally by providing predictive insights for crop management, irrigation, and pest control. By integrating historical and real-time data, Watson enables farmers to anticipate challenges, optimize resource allocation, and strengthen resilience against environmental risks. Collectively, John Deere, CropIn, and IBM Watson Agriculture illustrate how technology leaders are transforming agriculture into a data-driven, efficient, and sustainable system capable of meeting the food demands of a growing global population.

6. Challenges & Limitations

The integration of artificial intelligence (AI) into the circular food economy offers significant potential to improve resource efficiency, reduce food waste, and establish sustainable supply chains. However, achieving this potential is not simple. A closer examination reveals that several connected challenges hinder the fair and effective use of AI in food systems. These challenges include economic, technological, social, regulatory, and ethical barriers. Each of these factors can slow down adoption or make existing inequalities worse if not addressed. For example, while AI can help with resource allocation, track food products in real time, and support waste reduction strategies, global food waste remains alarming. About 931 million tonnes of food are wasted every year, with households responsible for 569 million tonnes, averaging 74 kg of waste per person. Supermarkets and businesses also add hundreds of millions of tonnes to this total. If we do not pay attention to these adoption challenges, AI could end up widening existing gaps instead of supporting the circular economy's goals of efficiency, reuse, and sustainability.

A. High cost of AI adoption for small-scale farmers and businesses

One of the biggest obstacles to integrating AI in agriculture and food systems is the high financial burden, especially for smallholder farmers and small to medium-sized enterprises (SMEs). AI systems require expensive technologies, such as sensors, robotics, and advanced data processing platforms. Besides the initial investment, ongoing expenses for maintenance, system upgrades, and training skilled personnel add up, often making AI solutions unaffordable for most farmers, particularly in developing countries. Additionally, many rural areas lack reliable internet or cloud services, which are necessary for real-time data analysis. In emerging economies, farmers may face long waiting periods to see a return on investment, leading to reluctance in adopting these technologies. This financial hurdle affects goals for a circular economy because small-scale stakeholders, who would benefit the most from AI-driven waste reduction and resource optimization, are often unable to fully participate. The concentration of AI development in high-income countries further skews adoption rates. While developed countries are expected to capture 20 to 25% more economic benefits, many developing countries may only see 5-15%, showing a clear need for subsidies, tax incentives, and more affordable AI solutions (McKinsey & Company, 2018).

B. Data privacy & ownership issues in food supply chains

The circular food economy relies on data-driven insights, such as predicting spoilage and improving resource flows. However, collecting extensive data raises significant privacy and ownership concerns. If personal or sensitive information is mishandled, it can lead to “data-driven surveillance,” where harmless datasets unintentionally expose private habits or health indicators. Additionally, companies participating in industrial symbiosis may be reluctant to share proprietary data due to misuse or lack of reciprocity. This reluctance affects the quality and integrity of AI training datasets.

Federated learning and privacy-enhancing technologies, like data anonymization, provide some solutions, yet their adoption is still limited. In developing regions, poor infrastructure and regulatory frameworks worsen these issues, undermining trust among small-scale stakeholders. It is essential to address these challenges to enable AI to effectively support circular economy principles. Secure, transparent, and interoperable data systems can optimize waste management, improve predictive analytics, and foster collaborative supply-chain innovation while maintaining ethical and legal standards.

C. Inequalities between developed and developing countries

The adoption of AI in agriculture and food systems is highly uneven, creating existing global inequalities. Developed countries benefit from superior infrastructure, fewer post-harvest losses, and easier access to AI tools. In contrast, developing countries face higher food waste and struggle to adopt AI. High-income nations lose an average of 79 kg of food per person each year. Households in poorer countries account for around 40% of all global food loss and waste. This gap is amplified by the concentration of AI knowledge in regions like the U.S., Europe, and China, which capture a larger share of the economic benefits, leaving the Global South with comparatively fewer gains. Furthermore, automation and AI-driven machines put informal jobs at risk in developing areas, affecting workers such as waste pickers and scrap collectors, raising concerns about global justice. Closing this gap is crucial for reaching circular economy goals. It is essential to ensure that AI tools not only reduce waste and emissions but also support fair involvement in sustainable resource management.

D. Risk of over-reliance on technology vs traditional practices

Although AI offers efficiency and accuracy, over-reliance on technology may weaken traditional knowledge and local practices that have supported farming for generations. AI models depend on their data and goals and can repeat biases found in training datasets, resulting in unfair outcomes. Algorithmic black boxes also decrease transparency and accountability, which can harm public trust. A slow approach is necessary: AI should enhance, not replace, local knowledge and community-based practices. Balancing new technology with user-friendly, inclusive solutions helps meet circular economy goals, such as reducing waste, optimizing resources, and maintaining livelihoods, while respecting traditional practices.

7. Future Prospects

The adoption of AI and new technologies in agriculture presents an opportunity to develop a strong, efficient, and sustainable food system. By 2050, global food demand is expected to grow by 60% (Alexandratos, N, & Bruinsma, J, .2012). Therefore, improving productivity while reducing environmental impact is crucial. AI-based solutions, combined with blockchain, IoT, and robotics, have the potential to optimize resource utilization, reduce waste, and improve decision-making throughout the supply chain. For example, AI-guided irrigation systems in India have raised average yields by 18% and lowered water use by 30% (Prabhat, P.K.,.2021). This shows the potential of data-driven approaches. By incorporating these solutions within circular economy practices, like waste recycling and resource maximization, agriculture can shift from linear to regenerative methods. Future initiatives emphasize both technological advancement and equitable governance. This approach ensures equitable access to these solutions for smallholder farmers and resource-limited regions.

A. AI + Blockchain for supply chain transparency

The combination of AI and blockchain offers a strong way to tackle ongoing issues in food supply chains, such as traceability, inefficiencies, and spoilage. Blockchain provides secure records of a product’s journey from farm to consumer. AI can analyze real-time data from IoT sensors to predict spoilage and improve storage and logistics. Retailers that have adopted AI have reduced food waste by 14.8% per store, which equals a decrease of 26,705 tons of CO_2 emissions each year (Onyeaka, H et al.2025). This shows the environmental and economic benefits. Furthermore, blockchain-enabled carbon credit trading enables farms to generate revenue from verified emission reductions, promoting sustainable practices. The integration of these technologies promotes decentralized collaboration and facilitates coordinated decision-making among different regions and stakeholders. By combining these innovations with circular economy goals, like preventing waste, improving material flows, and increasing transparency, supply chains can become more efficient and regenerative. This, in turn, supports sustainable production and consumption patterns globally.

B. Climate-smart agriculture powered by AI

AI plays a key role in advancing Climate-Smart Agriculture (CSA), an approach aimed at enhancing productivity, reducing greenhouse gas emissions, and strengthening climate resilience (Matteoli, F et al.2020). AI-powered precision agriculture has demonstrated yield increases of 20 to 25% in experimental vineyards while reducing water usage by 20% (Aijaz, N et al.2025). IoT-enabled, energy-efficient irrigation systems can cut energy use by up to 25%, as shown in (Lopez Morales, J.A. et al.2021) on smart water wells. Additionally, the use of Big data analytics in agriculture has improved crop yield predictions by up to 25% and helped optimize nitrogen fertilizer use, reducing costs by around 15% (Weraikat, D et al.2024). Genetic analysis through AI helps in the development of drought-resistant crops, optimizing resource utilization. Furthermore, AI-driven crop recommendation systems enhance planting decisions based on soil and climate conditions. This contributes to circular practices by reducing waste and energy use. Looking ahead, the integration of robotics, drones, and edge computing promises the development of smart farming systems that are capable of monitoring, harvesting, and performing precise tasks, thereby reducing labour needs and carbon emissions. Together, these innovations support a more resilient, climate-sensitive, and circular food system.

C. Global policy adoption and scaling opportunities

Unlocking the full potential of AI in agriculture requires coordinated policies, inclusive innovation, and scalable implementation frameworks. Strategic approaches such as Circular Value Extended Systems (CVES) and Zero-Residues Industrial Ecology Synergies (ZRIES) demonstrate how linear value chains can be transformed into connected, resource-efficient networks (Scheel, C, & Aruinaga, E., 2025). Case studies such as Heineken's brewery in Mexico, which recovers methane for energy, exemplify these principles in practice. Policy frameworks should prioritize cross-border collaboration, equitable access for smallholder farmers, and promotion of open-source AI technologies. This can help bridge economic gaps between developed and developing regions. Standardizing data protocols, enhancing capacity-building initiatives, and promoting sustainable practices can accelerate AI adoption while safeguarding environmental and social goals. By adopting these strategies, the future of agriculture can foster a regenerative, robust, and inclusive circular economy, ensuring sustainable growth, reducing waste, and achieving global food security.

8. Conclusion

The journey towards a sustainable and fair food system requires a drastic shift from the linear "take-make-dispose" model to a circular, restorative framework. Artificial intelligence plays a vital role in this shift. It offers practical ways to make food production, distribution, and consumption more efficient, while also reducing waste and emissions. AI's applications in precision agriculture, supply chain management, and food safety demonstrate its ability to enhance resource efficiency, boost yields, and reduce environmental impact. These technologies contribute to measurable reductions in water consumption, decrease reliance on fertilizers, and lower carbon emissions. For these benefits to be effective, we must deploy these technologies responsibly, design them with people in mind, and integrate traditional ecological knowledge. Collaborative approaches, co-designed solutions, and human oversight help ensure that the benefits of AI extend to small-scale farmers and developing regions, thereby promoting equity as well as efficiency.

The contribution of AI to circular food systems lies not only in technical innovation but also in strengthening the resilience of socio-ecological frameworks. By supporting data-driven decisions, predictive analytics, and clear carbon management, AI plays a key role in enhancing climate stability, safeguarding food security. It encourages scalable and sustainable practices. New frameworks like the Circular Value Extended System illustrate how we can grow economically without increasing resource use while turning waste into value for both society and the environment. Furthermore, leveraging IoT, Big Data, and Machine Learning facilitates emission tracking and reduction, while AIoT and explainable AI emphasize user accessibility, transparency, and trust in technology.

Despite its potential to transform, AI adoption encounters challenges such as high implementation costs, data privacy issues, limited infrastructure, and the need for standardized measures for interoperability and quality assurance. To tackle these challenges, we need coordinated governance, supportive policies, open-source innovation, and training programs that make sure AI deployment is ethical and inclusive. Future research should focus on refining models to manage local differences, integrating AI with indigenous knowledge, and incorporating sustainability metrics like water neutrality and biodiversity conservation.

Overall, AI has the potential to advance circular, resilient, and inclusive food systems, provided that technological advancements are aligned with ethical standards, user-centred design, and coordinated action across sectors. By following these guidelines, we can adapt the global food economy to move towards a regenerative future, improving resource efficiency, minimizing waste, strengthening climate adaptability, and promoting fair access to sustainable resources globally.

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