Chapter 7:
FOOD SYSTEMS

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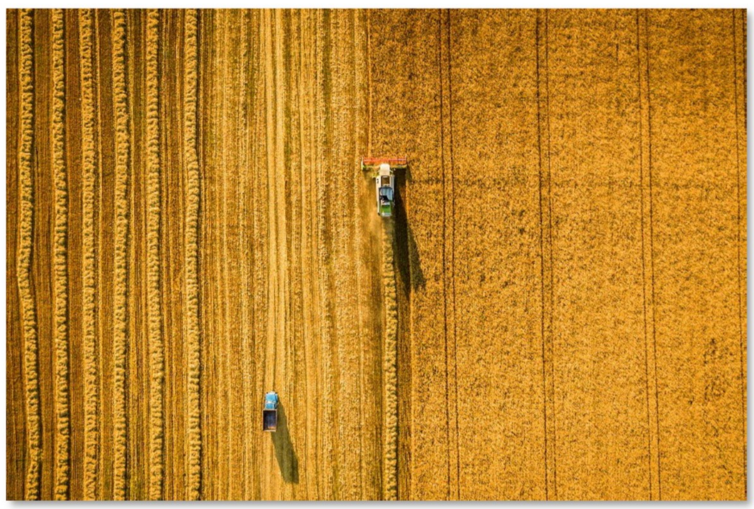

Food systems—including food production, distribution, consumption, and waste disposal—are critical to sustaining livelihoods and delivering nutrition worldwide. However, food systems contribute significantly to the climate crisis, accounting for over 30 percent of human-caused global greenhouse gas emissions[1] (e.g., methane, carbon dioxide, and nitrous oxide). Climate change, in turn, has a significant and growing impact[2] on food systems. Climate change increases heat stress and can lead to deteriorating soil health, for example, slowing agricultural productivity and reducing the nutritional content of crops and livestock. The cascading impacts of climate extremes on agricultural production are likely to destabilize global food security, endangering the livelihoods of billions of people and threatening public health.

A. Food system greenhouse gas emissions

All parts of the food system – from land use change to waste disposal – result in greenhouse gas emissions.

(i) Land-use change *The conversion[3] of natural ecosystems such as forests, marshes and grasslands into land for agriculture* . Eighty percent of deforestation and land degradation is due to land-use change intended for agricultural production. This is a significant contributor[4] to carbon dioxide and nitrous oxide emissions. Sustainable intensification can spare land from conversion and take land out of agricultural production. Well-designed land-use management strategies[5]—such as agroforestry, cover cropping and reductions in tillage—can preserve soil health and enhance carbon sequestration in working lands.

(ii) Production *The inputs and operations needed to produce food with agriculture.* For example, existing agricultural practices[6] contribute to copious[7] methane production (e.g., through flooded rice fields and enteric fermentation in livestock) and nitrous oxide production (e.g., over-application of synthetic fertilizers). Improving livestock management, including rotational grazing and optimized feed, and implementing precision agriculture techniques to reduce fertilizer and pesticide use can help lower total emissions.

(iii) Supply chains *The processing, distribution, storage, trade, marketing and handling of food following production and before consumption.* Food-system supply chains have considerable potential to employ more sustainable strategies, from increasing penetration of renewable energy into food cold chains[8] and decreasing energy expenditures across all steps of the food supply chain via improved logistics and reductions in post-harvest food loss.

(iv) Consumption and Waste *Processes related to consumer food preparation and to the disposal of food waste.* Substantial carbon dioxide emissions occur[9] in the production and combustion of biomass and fossil fuels for cooking. The disposal of food waste in landfills emits significant amounts of methane[10] globally. Food waste and consequent emissions also occur during food production, storage, and transportation.

There is substantial opportunity to mitigate the climate impact of food systems while improving the resilience of food systems to climate shocks. Mitigating greenhouse gas emissions from food systems will require, among other efforts, the adoption and improvement of sustainable practices[6] in land use, agriculture, supply chains and consumption processes. Integrating renewable energy sources and energy-efficient technologies will also be essential to reducing greenhouse gas emissions. All these efforts could benefit from leveraging technological innovation to optimize the dual needs of improving food security and reducing food system greenhouse gas emissions. With sufficient, relevant and accessible data, the emergence of artificial intelligence (AI) carries unique potential to complement existing strategies to improve food-system mitigation efforts.

B. Using AI to mitigate food system emissions

AI tools represent a sea change in terms of how data are identified, defined, interpreted and optimized. By leveraging AI technologies, real-time and historical data can be efficiently harnessed to model and anticipate outcomes and drive significant improvements in each stage of the food system in order to minimize environmental impacts.

AI can make food systems more efficient. For instance, AI can optimize agricultural practices by integrating data from various sources like soil sensors and satellite imagery to create precise nutrient and fertilizer management plans. Machine learning (ML) simulations[11] can further analyze these data to recommend fertilizer application schedules that minimize nitrous oxide emissions while maximizing crop yields. ML simulations can also analyze optimal fertilizer applications across a range of projected climate conditions. AI can aid in monitoring and predicting soil health, moisture levels and disease risks, enabling proactive crop management and minimizing the demand for agricultural inputs. Similarly,

AI applications can explore optimal feedstock for Biomass with Carbon Removal and Storage (BiCRS)[12] by analyzing data on biomass characteristics, growth rates and carbon sequestration potential. AI can identify the most suitable biomass species or crop varieties for efficient carbon removal and storage by considering factors such as regional climate. Such analyses can accelerate the development climate-smart systems in ways that are both traditional and completely novel—for example, AI models can test combinations of farm management, equipment, breeding, financing, and policy instruments that do not yet exist.

Another example of precision agriculture is CYCLESGYM, an innovative tool that employs simulations[13] (i.e., reinforcement learning) to improve crop management strategies. CYCLESGYM can create virtual farms simulating different crops, weather conditions and soil properties. With adjustments to different agriculture management strategies, researchers and farmers can set custom observational spaces and reward mechanisms that explore various crop growth and environmental outcomes over short-term intervals that provide a balance between economic viability, greenhouse gas emission mitigation and general environmental sustainability in food production. For example, the CYCLESGYM environment can fine-tune the use of nitrogen-based fertilizers and water supply, strategize how to minimize nitrogen loss and environmental impact, maintain crop yield objectives and reduce crop wastage.

Other applications of AI in food systems include augmenting renewable energy generation by optimizing land use for multiple purposes, forecasting pest and disease pressure for proactive controls, identifying opportunities for multi-cropping or intercropping, improving logistics and energy consumption during food transportation and storage and enhancing soil carbon sequestration efforts. AI tools are also used to rapidly develop alternative protein products[14] with a much lower carbon footprint than most animal-sourced foods. AI is being used to scale food loss and waste reduction, such as intelligent harvest timing to prevent food spoilage. As an overarching technology for data identification and integration, AI can also help compile information[15] on successful greenhouse gas mitigation strategies in food systems to evaluate best practices across a variety of contexts (see Table 1 below).

Title	Description
Land-use change	**Map renewable energy solutions and classify land.** Through AI methods, such as deep learning, AI is improving land classifications[16], which can improve efforts to integrate biomass production (as a renewable energy source) into agricultural landscapes. Other models using simulations can indicate[17] land use as the climate changes as well as analyze[18] and optimize future land uses to assist in emission-reduction efforts
	Balance solar resources for food and energy production. AI models can predict how to use land for both sustainable food and energy production. When solar panels are located over crop fields, for example, AI can predict optimal tilt and shading[19] to maximize power production while protecting crop growth
	Observe and predict deforestation events. Deforestation is a significant contributor to greenhouse gas emissions. Monitoring and predicting deforestation and related events[20] for agricultural expansion could help minimize the carbon footprint of food production
	Soil carbon sequestration to reduce emissions and mitigate climate change. Satellite data fed into an image-based simulation model[21] can accurately predict the storage potential and management of carbon dioxide in soils and inform policy and agricultural practices around land-use change and regenerative agriculture activities (e.g., agroforestry and tillage)
Food Production	**Enhance productivity.** Precision agriculture employing AI can increase efficiency and conservation gains without sacrificing yield outcomes. Examples include watering and feed management, controlled crop management[22, 23], automation[24], and advanced livestock and crop health monitoring, including identifying field stresses and impacts from pests and pathogens[25] through image processing and neural networks. In addition, AI can help decrease food loss during harvest[26] and maximize the potential of using bioenergy and biomass[27] for greener farming inputs, such as fertilizer
	Derive new or enhanced models of farming systems[28]. This can include exploration of alternative solutions, filling observational gaps to better calibrate existing models, creating low-cost model emulators to scale analyses, and develop data-driven hybrid models that enhance predictive power
	Forecast crop yield and loss. With remote sensing and AI, farmers can better prepare for crop and yield loss to weather[29] events or other impacts of climate change (e.g., reducing on-farm and post-harvest loss).
	Develop alternative proteins. AI methods can be leveraged to improve innovation[30] around plant-based and cultivated meat, which can lead to the consumption[31] of food with smaller environmental footprints[32]. Nonetheless, at scale, the production of alternative proteins also carries an emission risk and currently depends on limited crops that could be at risk in future climate scenarios
Supply Chains	**Optimize food supply chains**. AI can increase the efficiency[33] of food supply chains using current and historical data. Through simulations, AI can predict and reduce actual energy usage in procedures needed for transportation[34], such as in cold chains[35]. This application can include providing optimal routes while weighing other relevant considerations, such as transportation resources and route maintenance
	Improve food packaging. Through simulations and predictive analytics, AI can assist in improving the design, materials and energy usage for packaging[36] food items
Consumption and Waste	**Forecast consumption patterns.** AI simulations can help predict and emulate food demand, nutritional needs, product shelf life and actual restocking[37] requirements to limit food disposal[38] and reduce overallocation of products[38]. Accurately meeting real needs for consumption can improve unnecessary[39] emission-contributing activities
	Streamline disposal processes and sort waste. AI can assist in improving[40] management of disposal processes, including forecasting waste amounts, sorting recyclables and compostable waste, and decreasing methane gas emissions[41] from landfills

Table 1: Selected examples of current AI applications for food-system emission reduction.

AI is best conceived as a set of complementary tools, rather than a solution in itself. To ensure sustainable and equitable outcomes, proper implementation of AI technologies should be grounded in scientific knowledge, physical constraints, well-defined public policy objectives, ethical considerations and a nuanced understanding of the complex operations of food system actors and changing baselines. AI models are susceptible to misuse and misinterpretation if not applied correctly or if used in an incorrect context, leading to unsuccessful interventions or maladaptation. For example, an AI model that seeks to maximize crop yields in the short-term with limited information on sustainable agriculture practices, local knowledge, or climate and weather variations could over-emphasize the promotion of monoculture crop production and harmful fertilizer use. As such, AI models must be trained with diverse datasets, consider optimization across multiple objectives and implement policy interventions that promote sustainable and responsible AI use in food systems. Nonetheless, the possibilities for integration and application are limitless—by strategically harnessing the potential of AI within a comprehensive framework, we can accelerate progress in mitigating food-system emissions and foster a resilient and sustainable global food system.

C. Barriers and risks to AI applications in food systems

Using AI simulations and models for food-system emission mitigation is associated with barriers and risks that require careful attention. First, a lack of capital may constrain widespread adoption of AI technology since the cost of AI tools (e.g., remote sensing monitors, computational power), data availability, maintenance needs and other access limitations are likely to prevent resource-constrained farmers from employing them. Moreover, concerns surrounding data privacy, security and market competitiveness may limit the willingness of food-system actors across the supply chain to employ AI-driven solutions and participate in data-sharing.

Importantly, the efficacy of AI models heavily relies on the quality and availability of input and output datasets. Insufficient or incomplete data on food-system processes can lead to inaccurate or misleading forecasts, especially under novel climate scenarios, potentially undermining the efficacy of emission-reduction strategies. Data access and intellectual property barriers from agribusinesses can impede the use of AI in designing comprehensive and inclusive mitigation strategies. In some cases, just because AI models could be applied does not mean they should be applied, or that they are an improvement on existing empirical models and analyses. Establishing proficient technical expertise and knowledge-sharing across food-system actors is important to ensure appropriate and effective application of AI technologies.

Finally, striking a balance between food-emission reduction objectives and other food-security imperatives is both a key design constraint and a significant obstacle. Finding a way to limit our footprint while increasing food security globally is not straightforward, especially with many regions relying on imports for general access and nutrition security.

D. Key considerations in using AI to mitigate food-system emissions

(i) Develop protocols for stakeholder-driven AI applications and tools across food systems. AI solutions should employ human-centered design principles focusing on the end user, such as farmers, factory managers and retailers. In addition, applications should be developed with input from relevant experts, scientists, engineers and policymakers to increase opportunities for seamless and effective AI use in food systems.

(ii) Increase transparency, accountability and standardization in AI decision-making and data collection in food systems. Encouraging larger and more shareable data collection alongside standardized AI approaches to food-system problems can increase understanding of factors influencing emission-reduction strategies and knowledge sharing around practical AI applications and methods. Such practices lead to more informed and targeted interventions across the food supply chain.

(iii) Expand and scale existing technologies to effectively mitigate food-system emissions. Capitalizing on existing AI technologies and initiatives that have demonstrated promise in curtailing emissions and improving food-system processes is crucial. Scaling AI-driven interventions in areas such as precision agriculture and energy-efficient supply chains can lead to more sustainable and efficient resource management and global food provision.

(iv) Invest in AI research and innovation explicitly tailored to food systems. By dedicating resources to developing cutting-edge AI technologies and models for food production, distribution, consumption and waste disposal networks, novel and more effective approaches for mitigating food-system emissions can be identified and implemented.

(v) Promote collaboration and public-private partnerships to facilitate scalable emission-reduction strategies across land use, production, distribution, consumption and waste. Collaboration between government, researchers, private companies, farmers and other relevant stakeholders allows for more seamless integration of AI technologies and practices across various stages of the food supply chain, such as optimizing transportation logistics, accurately predicting demand and reducing food waste.

(vi) Ensure inclusivity and accessibility so relevant stakeholders within the food system have the opportunity to benefit from AI-driven strategies and contribute to a lower-emission future. Efforts should consider improving access, knowledge sharing and technical assistance for small-scale farmers and marginalized communities. Initiatives to reduce food-system emissions using AI technologies should also align and consider other objectives of food security, health and safety.

By optimizing agriculture practices through AI, embracing data-driven decision making, investing in AI research for food systems, fostering collaborative partnerships and prioritizing technology access for all stakeholders, AI can play a transformative role in mitigating food-system emissions, enabling a more sustainable and resilient global food and climate future.

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