ARTIFICIAL INTELLIGENCE FOR CLIMATE CHANGE MITIGATION ROADMAP (SECOND EDITION)

CHAPTER 4:

FOOD SYSTEMS

Kevin Karl, Lily-belle Sweet, Cameron Kruse, Matteo Turchetta, Sarah Garland, Elena Mendez Leal, Ranveer Chandra and Alex C. Ruane

November 2024

Innovation for Cool Earth Forum

CHAPTER 4:
FOOD SYSTEMS

Kevin Karl, Lily-belle Sweet, Cameron Kruse, Matteo Turchetta, Sarah Garland, Elena Mendez Leal, Ranveer Chandra and Alex C. Ruane

A. Food Systems and Climate Change Overview

Food systems—encompassing activities in agricultural production, land use change, supply chain activities and waste management—are critical to sustaining livelihoods and delivering nutrition worldwide (Figure 4-1). Food systems also contribute significantly to climate change. Recent estimates suggest that food systems produce about 30% of annual anthropogenic greenhouse gas (GHG) emissions: over 20% of carbon dioxide, 50% of methane and 75% of nitrous oxide.[1] Climate change, in turn, has a significant and growing impact on food systems. For example, climate change is poised to increase heat stress for crops and livestock, accelerate soil moisture loss and reduce the nutritional content of food.[2,3] The increasing frequency and duration of climate extremes, such as severe droughts and extreme rain events, endanger global food and nutrition security.

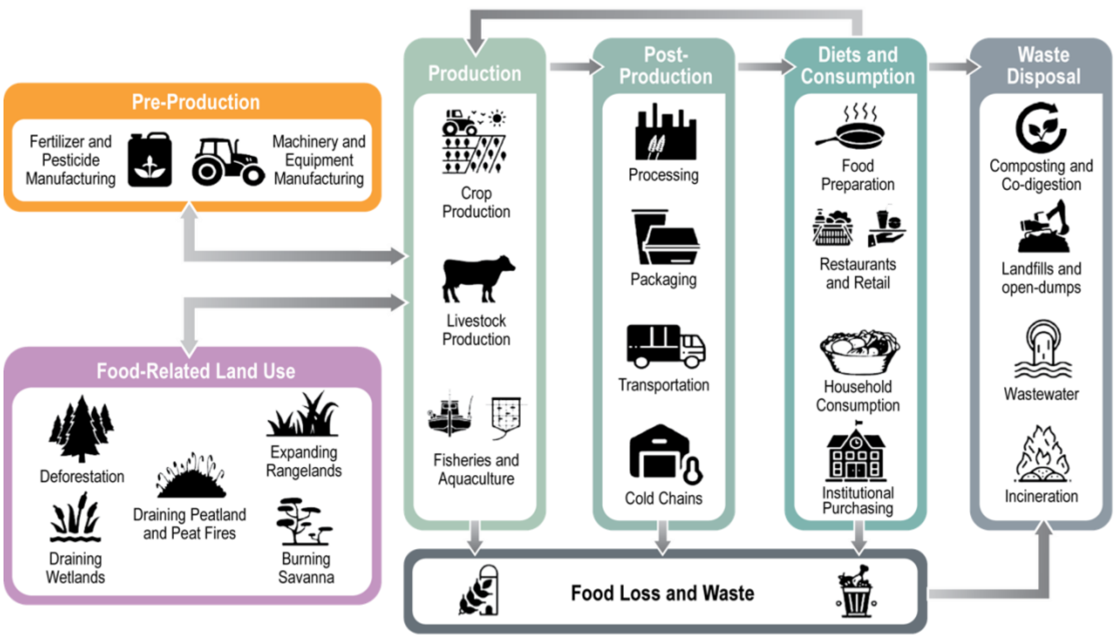

Figure 4-1. An integrated overview of food systems. Food systems comprise a wide variety of inter-related activities, from the production of agricultural inputs (pre-production), food-related land use change, agricultural production and fisheries, post-farm-gate supply chains, consumption activities, and waste disposal. Adapted from Rosenzweig et al. (2020).[4]

A grand challenge lies in transforming food systems to be more sustainable, resilient and equitable, while increasing food security for a growing population in the face of climate change. Artificial intelligence (AI) technologies and processes offer significant potential to address this challenge by enabling more efficient, data-driven decision-making across food system activities. Recent advancements in AI, such as deep learning, computer vision, and natural language processing, combined with the increasing availability of large-scale agriculture and land use data, have created a unique opportunity to harness AI for transforming food systems.[5]

However, AI applications carry significant risks if models are developed and used without considerable caution. For example, an AI model trained to achieve a specific target (such as improving near-term agricultural yields) could produce results that ignore other objectives (e.g., social, nutritional, economic, cultural, environmental or ethical goals). The result could be suboptimal or even harmful outcomes.

Close collaboration between AI researchers, food system experts, farmers, policymakers and the private sector is necessary to ensure that AI solutions are aligned with broader goals in sustainability and justice. An ideal AI information ecosystem would feature coordination across various nodes of information transfer, supported by a series of guardrails and accelerators that ensure AI models are adaptive to changing conditions, inclusive of diverse and representative perspectives, and embedded in appropriate context (Figure 4-2).

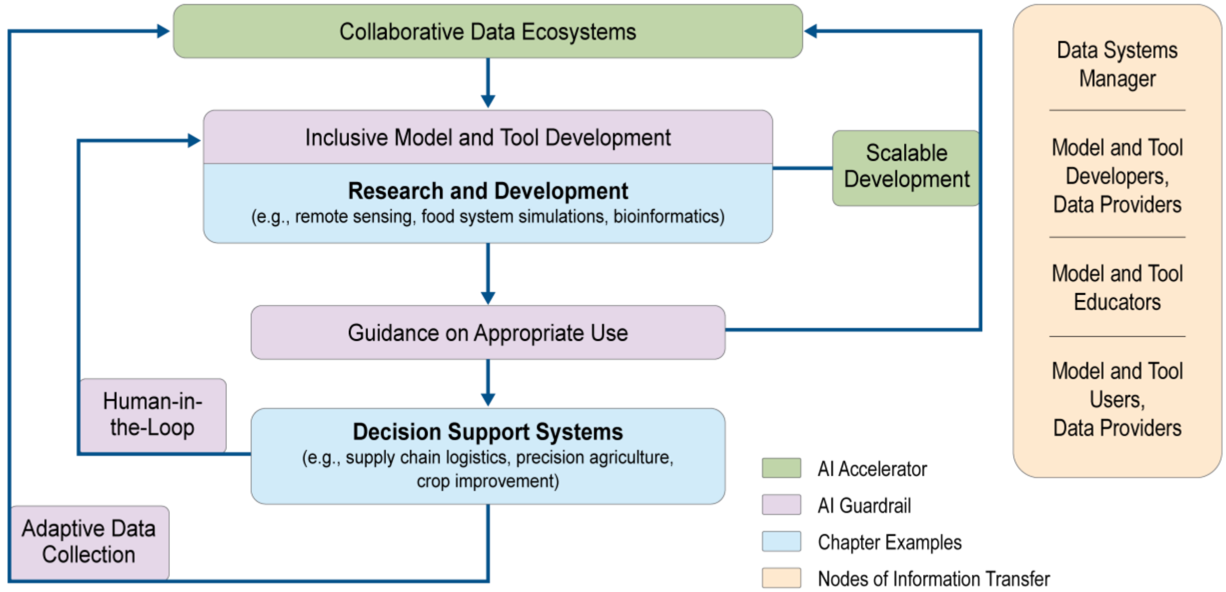

Figure 4-2. A coordinated, adaptive and inclusive AI information ecosystem for food systems. *A responsible and effective AI information chain is supported by AI acceleration processes (green) as well as process that establish AI guardrails (pink). Blue boxes represent examples of specific food systems applications or processes highlighted in this chapter. Red boxes represent where different groups of people fit into the picture as nodes of information synthesis and transfer.*

This chapter will describe example AI applications at the nexus of climate change and food systems, explore key components of an effective and responsible AI information chain, and conclude with recommendations for governments, businesses, scientists, international organizations, and civil society to ensure the appropriate use of this promising suite of technologies.

B. Examples of AI Applications in Food Systems and Climate Change

i. Overview

AI applications in food systems run the gamut from establishing early warning systems for pest and disease pressure on crops, optimizing energy use during food transportation and storage, and enhancing soil carbon sequestration efforts, among other transformational application areas.[6-8] AI tools are also used to rapidly develop novel alternative protein products with much lower carbon footprints than many animal-sourced foods, which are a key source of emissions from food systems.[9-13] AI-enhanced supply chain monitoring and solid waste management practices—such as improved resource recovery through computer vision—can greatly improve circularity in food systems and significantly reduce emissions from food waste in landfills (which contributes roughly 8% of global anthropogenic methane emissions).[14,15] Recent studies show that large language models, like GPT-4, perform well on agricultural exams and questions, sometimes outperforming humans.[16] AI models demonstrate potential in supporting agricultural education, assessment, and management decisions, offering new tools to assist farmers and agricultural professionals as they navigate novel challenges posed by climate change. There are myriad examples of promising use cases for AI to enhance food systems decision-making, reduce emissions, and enhance climate resilience. This chapter will focus on just a few.

ii. Remote sensing

Remote sensing involves synthesizing and analyzing satellite, drone and/or ground-based imagery to facilitate a wide array of food systems decisions.[17] Use cases span a variety of spatial scales—from field level monitoring of crop health, soil conditions, and land use change to regional monitoring of agricultural conditions to provide early warning for international trade markets.[18,19] There are currently roughly 50–100 remote sensing specific foundation models, each with unique architectures and strengths.[20] In Table 4-1, we break these use cases into three broad categories: object recognition, land use identification and temporal monitoring.

Table 4-1. *AI-Enhanced Remote Sensing Applications for Mitigation and Adaptation in Food Systems*

CATEGORY	USE CASE	VALUE
Object recognition	• Identifying concentrated animal feeding operations (CAFOs) and landfills • Estimating and anticipating crop yields using satellite imagery	• To better monitor and account for methane emissions from point sources (including from food waste in landfills) for improved decision-making in climate mitigation • To improve adaptation planning by accurately assessing crop production levels in historical conditions and improving satellite-based seasonal projections

CATEGORY	USE CASE	VALUE
Land use Identification	• Monitoring soil erosion and land degradation • Identifying the use of climate-smart agricultural practices	• To advance soil carbon sequestration potential and land suitability assessments (e.g., to support sustainable intensification and reduce land conversion pressure) • To monitor the prevalence of climate-smart practices, such as cover cropping, reduced tillage and no-till systems; can also be used to monitor and encourage the climate impact of agricultural land use through the albedo effect
Temporal monitoring	• Monitoring coastal erosion affecting agricultural lands • Tracking changes in water bodies affecting irrigation systems • Monitoring heat and water stress on crop and grassland productivity • Tracking the spread of plant diseases and pests over seasons	• To facilitate adaptive coastal management strategies that protect agricultural areas from the impacts of coastal erosion • To optimize irrigation management and water allocation by monitoring changes in water availability and distribution • To develop early warning systems for timely food security interventions • To facilitate early detection and control measures to mitigate the spread of diseases and pests, thus minimizing crop losses

As the success of OpenAI's ChatGPT demonstrated, applications that connect users with AI models are just as important as the models themselves. Figure 4-3 illustrates a tool called Earth Index, a product designed to connect users to geospatial AI models to increase accessibility for earth monitoring. The tool transforms satellite imagery into machine learning (ML) embeddings and makes them interactable by allowing users to select features of interest. Based on the embeddings, the model predicts where similar features would be located. After a few labeling iterations, the model can accurately predict new features that match. Earth Index has been used to identify illegal gold mining in the Amazon, find unregistered concentrated animal feeding operations (CAFOs), quantify plastic in landfills and much more.

AI Guardrail

HUMAN-IN-THE-LOOP MODEL AND TOOL IMPROVEMENT

Developing effective human-in-the-loop model-user interfaces is crucial for adopting and using AI tools in food systems applications, especially given the diverse backgrounds, expertise levels and information needs of end-users in this domain. These interfaces should be intuitive, user-friendly and adaptable, providing clear and actionable insights while allowing users to explore and interrogate the underlying data and assumptions behind AI model outputs. Moreover, these interfaces should incorporate mechanisms for user feedback and input. Such features would enable users to validate, refine and improve AI model performance over time by flagging inaccurate or irrelevant outputs, suggesting new data sources or features, and sharing their domain expertise and local knowledge. By actively engaging users in the iterative process of model improvement, human-in-the-loop interfaces can build trust, transparency and accountability in AI tools. This process would also ensure that such tools are tailored to the specific contexts and needs of end users.

Remote sensing benefits from large-scale, non-invasive monitoring of agricultural land use with high spatiotemporal and spectral resolution. Data are frequently updated, with near-global coverage, and can be integrated with physical models to enhance decision-making capabilities. However, challenges in gathering ground-truth data to validate analyses, combined with difficulties in obtaining consistent, high-quality imagery (e.g., due to cloud cover), can significantly reduce the robustness of decisions based solely on remotely sensed data.[21] The relatively short historical record also limits long-term climate change impact analysis. These factors necessitate careful consideration in implementing AI for remote sensing in food systems, such as developing human-in-the-loop processes as a guardrail.

iii. Agricultural simulations

Agricultural simulations, such as process-based climate-crop models, can project crop growth, yield, runoff and emissions under various genetic, environmental and management regimes. Process-based models form these projections by simulating biophysical processes in both current and future climate scenarios.[22] These models have been used to optimize yields, improve grain quality, reduce the environmental impacts of farming and increase profitability.[23] However, crop growth is influenced by complex interactions across myriad biophysical factors, and many of these compound effects are not yet well-understood, nor are they fully represented in process-based models.[24,25]

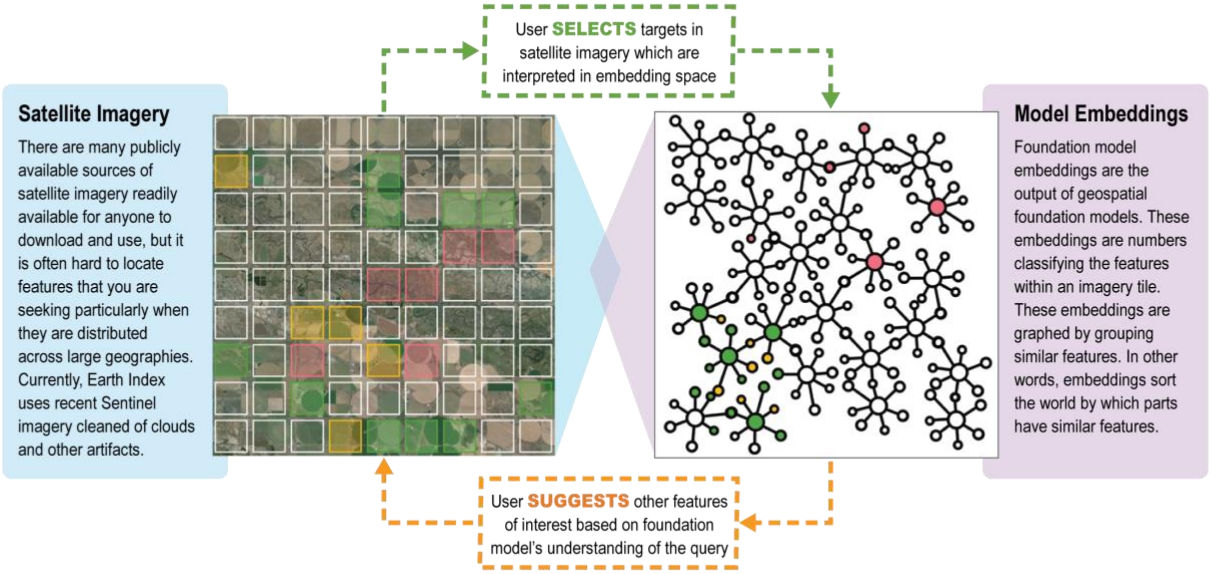

Figure 4-3. Efficient human-in-the-loop learning for AI-enhanced remote sensing analysis. *This schematic illustrates how Earth Index connects users to interactive geospatial AI models.*

ML models have emerged with new capabilities to predict global and regional crop yields based on climate conditions, satellite vegetation indices and other drivers.[26-28] These forecasts can be used to estimate regional or national crop production, assess potential supply chain disruptions, quantify high-resolution soil organic carbon changes, and guide allocation of resources to support farmers in adapting to changing climate conditions.[29] ML methods can also benefit from pre-training on available data from other crops and regimes or even on synthetic data from process-based models when dealing with data-limited crops or regions.[30-32] Recent research has experimented with novel ways to combine traditional process-based models with powerful ML models, resulting in hybrid models that are more likely than standalone ML models to produce plausible predictions when exposed to situations outside of the training set.[29,33,34] The Agricultural Model Intercomparison and Improvement Project (AgMIP) Machine Learning Activity (AgML) is coordinating efforts to build a collaborative community, including developing approaches that make the best combined use of process-based and data-driven models for agricultural impacts and adaptation analysis.

Precision Agriculture

OPTIMIZING RESOURCE USE FOR CLIMATE-SMART AGRICULTURE

Farmers can utilize the latest AI advances in remote sensing and agricultural simulations to optimize their use of inputs, such as irrigation, fertilizers and pesticides. For example, an AI-based decision support system for precision irrigation in a lettuce crop used a combination of soil moisture sensors, weather data and ML algorithms to optimize irrigation scheduling.[35] The results showed a 20% reduction in water use compared to traditional irrigation methods while maintaining crop yield and quality.

Reinforcement learning (RL) methods have recently been used to inform agricultural decision-making based on complex and high-dimensional data, such as historic weather, soil information, forecast and remote sensing data. Coupled with crop simulation models, RL interfaces can combine to create virtual farms by simulating different crops, weather conditions and soil properties.[36-39] By simulating a variety of management scenarios, researchers and farmers can set customized parameters and optimization algorithms. These simulations explore various crop growth and environmental outcomes, aiming to balance economic viability, GHG emission mitigation and other elements of environmental sustainability in food production.

AI applications in precision agriculture benefit from the availability of low-cost, reliable sensors and internet-connected farm equipment, the increased availability of agricultural drones and the growing adoption of digital platforms for farm management.[40] However, barriers exist, such as high upfront costs of the new technologies, limited data availability in some regions, and the need for technical expertise among farmers. Risks include the possibility of short-term over-optimization leading to reduced farming system diversity, data privacy and security concerns, potential unintended environmental consequences, job displacement, and the loss of traditional agricultural knowledge. Additionally, the highly contextual nature of precision agriculture systems means that successful AI approaches in one field may not be easily transferable to others.

Simulation models are flexible enough to incorporate multi-modal data (e.g., from remote sensing, biophysical crop models, newspaper articles and crowd-sourced images) for more accurate and timely predictions, potentially incorporating relationships not captured by current process-based models alone. Foundation models trained on large agricultural datasets can be fine-tuned to perform well on a diverse range of downstream tasks where data are more limited. However, ML methods often perform poorly in conditions different from the training data— for example, data-driven prediction models that exploit spatiotemporal correlations often fail to perform well in future years or new locations.[41,42] No matter how good a simulation is, it will always be some distance from reality, especially in extremely complex systems. Additionally, an uneven distribution of sufficient, high-quality data for model validation and training across locations and farming systems, could potentially results in inequitable distribution of model performance across geographical regions and socioeconomic strata. Further, there is a risk that AI methods rely on spurious correlations, leading to inaccurate estimations of intervention effects or physically implausible simulated behavior.[43]

AI Guardrail

INCLUSIVE MODEL AND TOOL DEVELOPMENT

To ensure that AI tools are relevant and applicable across diverse contexts, it is crucial to prioritize inclusive and iterative AI development. This involves engaging local stakeholders—such as farmers, extension agents and community organizations—in designing, training and validating AI models. By incorporating local knowledge, preferences and priorities into the development process, AI tools can be better tailored to the specific needs and constraints of different agroecological regions, production systems and sociocultural contexts. Inclusive AI development also requires using diverse and representative training datasets that capture the variability of food systems across different locations and scales. Initiatives to support collecting and sharing localized data from food systems, such as participatory sensing networks or community-driven data platforms, can help develop more context-specific AI solutions.

iv. Crop breeding

Developing crops with increasingly higher yields and enhanced stress tolerance is crucial for feeding a growing population in the face of climate change.[44] AI can help accelerate the crop breeding process.[45-49] On the macro-scale, developments in robotics and computer vision have revolutionized the collection and synthesis of data on plant size, shape, color and other visible characteristics, allowing researchers and farmers to assess crop performance much faster than traditional methods.[50] On the micro-scale, AI can help analyze genetic sequencing information. The genomes of many crops have yet to be fully annotated, which means that their genomes have not been fully assembled and functions have not been identified for all genes.[51,52] When presented with a genetic sequence, AI can help predict gene function, speeding up the annotation process and unlocking potential crop improvement targets for diverse species.[53]

Combining macro-level phenotypic data with genetic sequencing information generates rich and extensive datasets that link the expression of specific genetic regions to traits displayed in the field across various environmental conditions.[54,55] Modern AI algorithms are capable of discovering strongly non-linear patterns in high-dimensional data. Thus, they can be trained on these datasets to predict complex traits of new cultivars in various environments based solely on genomic information.[56] These predictions are fed into optimization algorithms for autonomous decision-making (e.g., reinforcement learning algorithms) to optimize critical factors of breeding programs by making data-driven choices.[57,58] This prediction can cut down on the time and uncertainty involved with traditional plant breeding.[54]

AI Guardrail

ADAPTIVE DATA COLLECTION SYSTEMS

Developing adaptive data collection systems is essential for ensuring that AI tools in food systems are continuously updated with relevant, accurate and timely data from on-the-ground sources. This is particularly important in the context of climate change, where rapid shifts in weather patterns, crop yields and market conditions require agile and responsive data collection processes. These systems should be designed to collect data from across the supply chain on local conditions, practices and challenges. For example, farmers can share data on pest and disease outbreaks through mobile apps or online platforms, which can be used to refine AI models for precision agriculture and pest and disease modeling. Data collection systems should also leverage crowdsourcing and citizen science approaches to gather large-scale, fine-grained data on food system dynamics, such as food prices, consumption patterns and waste levels, which can be used to improve AI models for supply chain optimization and food security monitoring. Large-language-model interfaces can gather timely insights into emerging practices and challenges under evolving climate conditions.

In addition to assisting traditional breeding processes, AI can also be instrumental in supporting modern biotechnological breeding methods like gene editing.[59] Gene editing techniques make precise changes in a crop's genetic code that lead to a desired characteristic. Well-identified genomic information produced with the help of AI, as described above, is key for selecting regions for editing that will have a functional effect on the crop. Within that region, AI tools can help choose which specific sequence to target for high editing efficacy, as well as ensuring that any potential off-target effects are minimized.[60,61] AI can also help improve gene editing methods overall by designing new proteins for increased editing ability, continuing to evolve the field to be ever more efficient and precise.[62]

AI applications in crop breeding can significantly reduce costs and time for labor-intensive phenotyping. They can also enhance breeding efficiency through early identification of promising climate-resilient cultivars and precise design of genetic engineering techniques. However, barriers exist, such as limited access to high-quality genomic datasets for under-researched crops, the need for substantial computational resources, and limited transferability across different crop species or environments given that the complexity of plant-environment interactions cannot be fully captured by genetic data alone. Risks include an over-reliance on ML predictions without sufficient field validation, the possibility of further narrowing genetic diversity, and the potential misuse of ML-generated intellectual property. These risks need to be addressed in order to manage further consolidation of genetic control in the seed industry and to ensure that generated crop varieties effectively support local communities and agroecosystems.

C. Barriers

i. Lack of interpretability

Many advanced AI models operate as "black boxes" to inexperienced users, making it difficult for end users to understand how the model arrives at its predictions or recommendations. This lack of interpretability can hinder the adoption of AI tools—for instance, a farmer might be reluctant to follow an AI-recommended planting schedule or fertilizer application rate without understanding the underlying reasoning. Care must be taken to generate accurate explanations of AI recommendations wherever possible, as users may be more inclined to trust a model's predictions about crop management or food distribution when given some kind of explanation, even if the prediction, or explanation, is incorrect.

AI Guardrail

GUIDANCE ON APPROPRIATE USE

Providing clear and comprehensive guidance on the appropriate use of AI tools is essential for ensuring their responsible and effective application in food systems. This is particularly important given the potential for AI tools to influence critical decisions related to agricultural production, supply chain management and policy development, which can have significant implications for food security, livelihoods and environmental sustainability. Guidance should cover key considerations, such as data privacy and security, as well as potential biases and limitations of AI tools. It should also provide practical advice on how to select, implement and evaluate AI tools based on specific use cases, user needs and contextual factors. This can involve developing best practice guides, case studies and decision support frameworks that help users navigate the complex landscape of AI tools and make informed choices about their application. Moreover, guidance should emphasize the importance of using AI tools in conjunction with other forms of knowledge and expertise, such as local and indigenous knowledge systems, to advance a truly context-sensitive decision-making approach.

ii. Limited transferability of agricultural data

Agricultural AI models are highly dependent on the specific spatiotemporal context in which they are trained. Correlative factors established in one location or time-period may not be reliably transferred to another due to differences in climate, soil, socioeconomic conditions or management practices. Even high-resourced and high-producing regions may experience challenges with model transferability due to contextual differences that are not immediately noticeable in the underlying datasets. Efforts to enhance transferability— such as the collection and publication of data from multi-environment trials, with wide spatial, temporal and production system coverage— are crucial for developing AI tools that can support decision-making across diverse contexts.

iii. Lack of available and accessible agricultural data

The development of AI applications in food systems often relies on collecting and sharing sensitive data, such as individual farm-level information on production practices, yields and financial performance. Ensuring the privacy and security of these data is crucial for protecting the interests of producers and maintaining trust in AI systems. Furthermore, some datasets may be proprietary, expensive, restricted or even classified, and some models may not have open-source code. Clear frameworks for data ownership and access rights are necessary to ensure equitable distribution of the benefits of AI applications and that producers maintain control over their data.

AI Accelerator

SCALABLE DATA-MODEL DEVELOPMENT

Integrated and scalable data-model systems are particularly critical for AI applications in food systems, given the complexity and diversity of data sources involved. Model developers would benefit tremendously from seamlessly integrated data from various stages of the food supply chain, including input distribution (e.g., fertilizers, seeds), agricultural production, food processing, distribution, consumption and waste management. For example, data from farm-management systems, precision-agriculture sensors, food-processing equipment and retail point-of-sale systems could be harmonized to enable end-to-end visibility. This integration could also allow optimization of food systems to effectively reduce food loss and waste. Additionally, managers of data systems must build platforms that are deployable at scale to handle the massive volumes of data generated by food systems, all while ensuring data quality, security and privacy.

D. Risks

i. Counterproductive results for some objectives

AI applications in food systems are often designed to help achieve specific, quantifiable targets, such as near-term crop yields. However, this singular focus can lead to damaging results unless a broader range of objectives is considered. For instance, an AI decision support system designed to maximize immediate crop output might recommend management practices that deplete soil nutrients, reduce biodiversity or increase vulnerability to pests and diseases over time. Similarly, AI-driven supply chain optimizations focusing solely on improving energy efficiency might inadvertently reduce system redundancy, leaving food distribution networks more vulnerable to disruptions from climate shocks or other unforeseen events. The challenge lies in developing AI models that optimize across multiple and sometimes competing objectives, such as productivity, environmental sustainability, economic viability, social equity and long-term resilience to climate change.

ii. Bias in agricultural data collection

The quality, availability and representativeness of the data used to train AI models can significantly impact their performance and applicability. In research and development (R&D) for food systems, data collection bias can arise from self-selection issues, in which only well-resourced producers with established best practices choose to participate in data collection efforts or publicize results. This can lead to models that are skewed toward better-performing systems and may not accurately represent the challenges and opportunities faced by a wider range of producers. Additionally, using data from already suitable agricultural areas to predict agricultural production in less suitable environments can result in overly optimistic projections and inadequate adaptation planning.

iii. Reinforcement of existing societal inequalities

Adopting AI technologies in food systems may exacerbate existing societal inequalities due to unequal access to education, digital infrastructure, data generation, data holdings and financial resources. Smallholder farmers and marginalized rural communities may face significant barriers in accessing and benefiting from AI tools, such as limited internet connectivity, low digital literacy, lack of affordable computing devices and lack of access to AI-enhanced inputs (such as improved seeds). Furthermore, many agricultural regions do not have the resources to collect, clean and digitize data. This digital divide can widen the gap between well-resourced and under-resourced communities, concentrating AI benefits among a small group of already advantaged stakeholders. Efforts to promote inclusive AI adoption, such as investments in rural digital infrastructure, digital literacy training programs and development of low-cost, user-friendly AI tools, are crucial for ensuring that the benefits of AI in food systems are distributed equitably.

AI Accelerator

COLLABORATIVE DATA ECOSYSTEMS

Establishing collaborative data ecosystems that bring together diverse stakeholders, including farmers, researchers, agribusinesses, supply chain managers and policymakers, can help to address issues of data bias, privacy and ownership in developing AI tools for food systems. These ecosystems should prioritize creation of shared, interoperable and secure data platforms that enable the pooling of diverse food system datasets while protecting the rights and interests of agricultural data providers. Collaborative data governance frameworks, such as data cooperatives or trust frameworks, can help to ensure that data is collected, shared and used in an equitable and transparent manner.

E. Recommendations

Food systems are highly decentralized, with an estimated 570 million farms worldwide, each operating in specific agroecological and socioeconomic contexts, challenging the notion of one-size-fits-all AI solutions. To address the myriad unique issues associated with AI applications in food systems and to ensure their responsible and effective deployment across contexts, we recommend the following priorities targeted at a range of institutional structures (Table 4-3):

1. *National governments should expand public R&D funding to develop and study AI applications in remote sensing, agricultural systems modeling, crop breeding and other high impact application areas.*
2. *Researchers, industry associations and standards development organizations should collaborate to develop and share benchmark datasets, sample algorithms and standard performance metrics for AI applications.*
3. *National governments and businesses should invest in developing adaptive data collection technology, such as Internet of Things sensors and mobile apps, to enable continuous updating of AI models with relevant, accurate and timely data.*
4. *Academic institutions and research organizations should prioritize inclusive and participatory approaches to developing AI models and tools, such as engaging farmers, extension agents and community organizations, to ensure that AI solutions are context-specific, user-centered and aligned with local needs and priorities.*
5. *Professional societies, academic institutions and international organizations should develop and promote guidelines, best practices and training programs on the appropriate use of AI in food systems, covering issues such as data privacy, model transparency, potential biases, risks and limitations.*
6. *National governments, private companies and civil society organizations should establish collaborative data ecosystems for food systems that have clear frameworks for data sharing, ownership and access rights.*
7. *Research funding agencies and philanthropy should support interdisciplinary research on ethical, legal and social implications of AI in food systems, as well as development of responsible AI governance frameworks and accountability mechanisms.*
8. *Private companies and model developers should prioritize development of human-in-the-loop model improvement approaches, incorporating user feedback and local knowledge to iteratively refine AI solutions and ensure their adaptability to evolving climate challenges and food system dynamics.*

9. *International organizations and multi-stakeholder platforms should facilitate knowledge exchange, capacity building and coordination of AI R&D with a focus on promoting inclusive innovation and equitable access to AI technologies.*

A responsible AI information ecosystem is based on the principles of true multi-stakeholder collaboration, the incorporation of local knowledge and priorities, the prioritization of transparency and accountability, and an emphasis on continuous, adaptive improvement. A coordinated approach can support the critical transition to more sustainable, resilient and equitable food systems that are bolstered against the impending challenges of climate change.

Table 4-3. *Recommendations*

GOVERNMENTS	CIVIL SOCIETY	INTERNATIONAL ORGANIZATIONS	BUSINESS	SCIENCE
Convene consortia exchanging food system data Ensure equitable access to AI tools in food systems Establish oversight and accountability mechanisms Create forums for stakeholder feedback on AI policies Support participatory collection initiatives for agricultural data Invest in rural connectivity infrastructure	Monitor data use and privacy issues Advocate for inclusive and transparent data governance Provide training in digital literacy to marginalized groups Create resources on ethics in AI for food systems Monitor AI adoption and impacts	Coordinate global data-sharing efforts in food systems Develop privacy and security frameworks for data in food systems Promote inclusive AI development Facilitate technology transfer and capacity building Identify and fill data gaps Share pre-competitive research and data	Participate in industry data consortia and standards bodies Ensure diversity in AI teams and training data Invest in Internet of Things and mobile data collection Develop scalable, accessible data architecture Co-develop tools that help identify barriers and limits to adaptation Develop open-source libraries, platforms, models and tools	Study the ethical, legal and social elements of AI in food systems Advance explainable, interpretable AI techniques Establish model evaluation protocols using open benchmark datasets Standardize data formats for ease of interoperability Identify and fill data gaps

F. References

1 Francesco N. Tubiello *et al.* Greenhouse gas emissions from food systems: building the evidence base. *Environmental Research Letters* 16, 065007 (2021). https://doi.org/10.1088/1748-9326/ac018e.

2 Matias Heino *et al.* Increased probability of hot and dry weather extremes during the growing season threatens global crop yields. *Scientific Reports* 13, 3583 (2023). 10.1038/s41598-023-29378-2.

3 Richard D. Semba *et al.* The Potential Impact of Climate Change on the Micronutrient-Rich Food Supply. *Advances in Nutrition* 13, 80-100 (2022). https://doi.org/10.1093/advances/nmab104.

4 Cynthia Rosenzweig *et al.* Finding and fixing food system emissions: the double helix of science and policy. *Environmental Research Letters* 16, 061002 (2021). 10.1088/1748-9326/ac0134.

5 Stéphanie Camaréna. Artificial intelligence in the design of the transitions to sustainable food systems. *Journal of Cleaner Production* 271, 122574 (2020). https://doi.org/10.1016/j.jclepro.2020.122574.

6 Tiago Domingues, Tomás Brandão & João C. Ferreira. Machine Learning for Detection and Prediction of Crop Diseases and Pests: A Comprehensive Survey. *Agriculture* 12, 1350 (2022). https://doi.org/10.3390/agriculture12091350

7 Jonas L. Vilas-Boas, Joel J. P. C. Rodrigues & Antonio M. Alberti. Convergence of Distributed Ledger Technologies with Digital Twins, IoT, and AI for fresh food logistics: Challenges and opportunities. *Journal of Industrial Information Integration* 31, 100393 (2023). https://doi.org/10.1016/j.jii.2022.100393.

8 Luca G. Bernardini *et al.* Learning vs. understanding: When does artificial intelligence outperform process-based modeling in soil organic carbon prediction? *New Biotechnology* 81, 20-31 (2024). https://doi.org/10.1016/j.nbt.2024.03.001.

9 Zane Swanson, Caitlin Welsh & Joseph Majkut. Mitigating Risk and Capturing Opportunity: The Future of Alternative Proteins. (Center for Strategic and International Studies (CSIS), 2023; https://www.csis.org/analysis/mitigating-risk-and-capturing-opportunity-future-alternative-proteins).

10 Rebecca Carroll. *NASA Helps Serve Yellowstone Fungi for Breakfast;* NASA's Spinoff Publication, https://www.nasa.gov/technology/tech-transfer-spinoffs/nasa-helps-serve-yellowstone-fungi-for-breakfast/ (2022).

11 Sezin Kircali Ata *et al.* Predicting the Textural Properties of Plant-Based Meat Analogs with Machine Learning. *Foods* 12, 344 (2023). https://doi.org/10.3390/foods12020344

12 Firmenich. *The World's First AI-Created Flavor;* https://www.firmenich.com/taste-and-beyond/blog-article/worlds-first-ai-created-flavor (Accessed July 2024).

13 Richard Twine. Emissions from Animal Agriculture—16.5% Is the New Minimum Figure. *Sustainability* 13, 6276 (2021). https://doi.org/10.3390/su13116276.

14 Helen Onyeaka *et al.* Using Artificial Intelligence to Tackle Food Waste and Enhance the Circular Economy: Maximising Resource Efficiency and Minimising Environmental Impact: A Review. *Sustainability* 15, 10482 (2023). https://doi.org/10.3390/su151310482.

15 F. N. Tubiello *et al.* Pre- and post-production processes increasingly dominate greenhouse gas emissions from agri-food systems. *Earth Syst. Sci. Data* 14, 1795-1809 (2022). 10.5194/essd-14-1795-2022.

16 Bruno Silva *et al.* GPT-4 as an Agronomist Assistant? Answering Agriculture Exams Using Large Language Models. arXiv:2310.06225 (2023). https://doi.org/10.48550/arXiv.2310.06225.

17 M. Weiss, F. Jacob & G. Duveiller. Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment* 236, 111402 (2020). https://doi.org/10.1016/j.rse.2019.111402.

18 Tetsuji Tanaka *et al.* Satellite forecasting of crop harvest can trigger a cross-hemispheric production response and improve global food security. *Communications Earth & Environment* 4, 334 (2023). https://doi.org/10.1038/s43247-023-00992-2.

19 Inbal Becker-Reshef *et al.* The GEOGLAM crop monitor for AMIS: Assessing crop conditions in the context of global markets. *Global Food Security* 23, 173-181 (2019). https://doi.org/10.1016/j.gfs.2019.04.010.

20 Jack-bo1220. *Awesome Remote Sensing Foundation Models [Computer software];* https://github.com/Jack-bo1220/Awesome-Remote-Sensing-Foundation-Models (2024; Original work published 2023).

21 Catherine Nakalembe & Hannah Kerner. Considerations for AI-EO for agriculture in Sub-Saharan Africa. *Environmental Research Letters* 18, 041002 (2023). https://doi.org/10.1088/1748-9326/acc476.

22 Jonas Jägermeyr *et al.* Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. *Nature Food* 2, 873-885 (2021). https://doi.org/10.1038/s43016-021-00400-y.

23 Karine Chenu *et al.* Contribution of Crop Models to Adaptation in Wheat. *Trends in Plant Science* 22, 472-490 (2017). https://doi.org/10.1016/j.tplants.2017.02.003.

24 Heidi Webber *et al.* Framework to guide modeling single and multiple abiotic stresses in arable crops. *Agriculture, Ecosystems & Environment* 340, 108179 (2022). https://doi.org/10.1016/j.agee.2022.108179.

25 Corey Lesk *et al.* Compound heat and moisture extreme impacts on global crop yields under climate change. *Nature Reviews Earth & Environment* 3, 872-889 (2022). https://doi.org/10.1038/s43017-022-00368-8.

26 F. Lin *et al.* "MMST-ViT: Climate Change-aware Crop Yield Prediction via Multi-Modal Spatial-Temporal Vision Transformer" in *2023 IEEE/CVF International Conference on Computer Vision (ICCV)*, 5751-5761, https://doi.org/10.1109/ICCV51070.2023.00531,(2023).

27 Dilli Paudel *et al.* Machine learning for large-scale crop yield forecasting. *Agricultural Systems* 187, 103016 (2021). https://doi.org/10.1016/j.agsy.2020.103016.

28 Sem Vijverberg, Raed Hamed & Dim Coumou. Skillful U.S. Soy Yield Forecasts at Presowing Lead Times. *Artificial Intelligence for the Earth Systems* 2, e210009 (2023). https://doi.org/10.1175/AIES-D-21-0009.1.

29 Licheng Liu *et al.* Knowledge-guided machine learning can improve carbon cycle quantification in agroecosystems. *Nature Communications* 15, 357 (2024). https://doi.org/10.1038/s41467-023-43860-5.

30 Christos Pylianidis, Michiel G. J. Kallenberg & Ioannis N. Athanasiadis. Domain adaptation with transfer learning for pasture digital twins. *Environmental Data Science* 3, e8 (2024). https://doi.org/10.1017/eds.2024.6.

31 Ruben Cartuyvels *et al.* Spatiotemporal self-supervised pre-training on satellite imagery improves food insecurity prediction. *Environmental Data Science* 2, e48 (2023). https://doi.org/10.1017/eds.2023.42.

32 Yuchi Ma *et al.* Improving the Transferability of Deep Learning Models for Crop Yield Prediction: A Partial Domain Adaptation Approach. *Remote Sensing* 15, 4562 (2023). https://doi.org/10.3390/rs15184562.

33 Taewon Moon *et al.* Process-Based Crop Modeling for High Applicability with Attention Mechanism and Multitask Decoders. *Plant Phenomics* 5, 0035 (2023). https://doi.org/10.34133/plantphenomics.0035.

34 Ioannis Droutsas *et al.* Integration of machine learning into process-based modelling to improve simulation of complex crop responses. *in silico Plants* 4 (2022). https://doi.org/10.1093/insilicoplants/diac017.

35 H. Navarro-Hellín *et al.* A decision support system for managing irrigation in agriculture. *Computers and Electronics in Agriculture* 124, 121-131 (2016). https://doi.org/10.1016/j.compag.2016.04.003.

36 Michiel G. J. Kallenberg *et al.* Nitrogen management with reinforcement learning and crop growth models. *Environmental Data Science* 2, e34 (2023). https://doi.org/10.1017/eds.2023.28.

37 Romain Gautron *et al.* Reinforcement learning for crop management support: Review, prospects and challenges. *Computers and Electronics in Agriculture* 200, 107182 (2022). https://doi.org/10.1016/j.compag.2022.107182.

38 Matteo Turchetta *et al.* Learning long-term crop management strategies with cyclesgym. *Advances in neural information processing systems* 35, 11396-11409 (2022). https://proceedings.neurips.cc/paper_files/paper/2022/hash/4a22ceafe2dd6e0d32df1f7c0a69ab68-Abstract-Datasets_and_Benchmarks.html.

39 Malvern Madondo *et al.* A SWAT-based Reinforcement Learning Framework for Crop Management. arXiv:2302.04988 (2023). https://ui.adsabs.harvard.edu/abs/2023arXiv230204988M.

40 Mohd Javaid *et al.* Understanding the potential applications of Artificial Intelligence in Agriculture Sector. *Advanced Agrochem* 2, 15-30 (2023). https://doi.org/10.1016/j.aac.2022.10.001.

41 Holger R. Maier *et al.* On how data are partitioned in model development and evaluation: Confronting the elephant in the room to enhance model generalization. *Environmental Modelling & Software* 167, 105779 (2023). https://doi.org/10.1016/j.envsoft.2023.105779.

42 Lily-belle Sweet *et al.* Cross-Validation Strategy Impacts the Performance and Interpretation of Machine Learning Models. *Artificial Intelligence for the Earth Systems* 2, e230026 (2023). https://doi.org/10.1175/AIES-D-23-0026.1.

43 Davide Cammarano *et al.* Models can enhance science–policy–society alignments for climate change mitigation. *Nature Food* 4, 632-635 (2023). https://doi.org/10.1038/s43016-023-00807-9.

44 Mario Herrero *et al.* Innovation can accelerate the transition towards a sustainable food system. *Nature Food* 1, 266-272 (2020). https://doi.org/10.1038/s43016-020-0074-1.

45 Mohsen Niazian & Gniewko Niedbała. Machine Learning for Plant Breeding and Biotechnology. *Agriculture* 10, 436 (2020). https://doi.org/10.3390/agriculture10100436

46 Mohsen Yoosefzadeh Najafabadi, Mohsen Hesami & Milad Eskandari. Machine Learning-Assisted Approaches in Modernized Plant Breeding Programs. *Genes* 14, 777 (2023). https://doi.org/10.3390/genes14040777

47 Kyung Do Kim, Yuna Kang & Changsoo Kim. Application of Genomic Big Data in Plant Breeding: Past, Present, and Future. *Plants* 9, 1454 (2020). https://doi.org/10.3390/plants9111454.

48 Hai Wang *et al.* Deep learning for plant genomics and crop improvement. *Current Opinion in Plant Biology* 54, 34-41 (2020). https://doi.org/10.1016/j.pbi.2019.12.010.

49 Saritha V. Kuriakose, Ravindra Pushker & Ebenezer M. Hyde. Data-Driven Decisions for Accelerated Plant Breeding in *Accelerated Plant Breeding, Volume 1: Cereal Crops* (eds Satbir Singh Gosal & Shabir Hussain Wani) 89-119 (Springer International Publishing, Cham, 2020; https://doi.org/10.1007/978-3-030-41866-3_4, https://doi.org/10.1007/978-3-030-41866-3_4).

50 Abbas Atefi *et al.* Robotic Technologies for High-Throughput Plant Phenotyping: Contemporary Reviews and Future Perspectives. *Frontiers in Plant Science* 12 (2021). https://doi.org/10.3389/fpls.2021.611940

51 Lorena Y. Ramírez Gonzales *et al.* The role of omics in improving the orphan crop tef. *Trends in Genetics* 40, 449-461 (2024). https://doi.org/10.1016/j.tig.2024.03.003.

52 Nicholas Furnham, Tjaart A. P. de Beer & Janet M. Thornton. Current challenges in genome annotation through structural biology and bioinformatics. *Current Opinion in Structural Biology* 22, 594-601 (2012). https://doi.org/10.1016/j.sbi.2012.07.005.

53 Zhaojia Chen *et al.* From tradition to innovation: conventional and deep learning frameworks in genome annotation. *Briefings in Bioinformatics* 25 (2024). https://doi.org/10.1093/bib/bbae138.

54 Kelin Wang *et al.* DNNGP, a deep neural network-based method for genomic prediction using multi-omics data in plants. *Molecular Plant* 16, 279-293 (2023). https://doi.org/10.1016/j.molp.2022.11.004.

55 Aalt Dirk Jan van Dijk *et al.* Machine learning in plant science and plant breeding. *iScience* 24 (2021). https://doi.org/10.1016/j.isci.2020.101890.

56 Osval Antonio Montesinos-López *et al.* A review of deep learning applications for genomic selection. *BMC Genomics* 22, 19 (2021). https://doi.org/10.1186/s12864-020-07319-x.

57 Omar G. Younis *et al.* Breeding Programs Optimization with Reinforcement Learning. arXiv:2406.03932 (2024). https://doi.org/10.48550/arXiv.2406.03932.

58 Saba Moeinizade, Guiping Hu & Lizhi Wang. A reinforcement Learning approach to resource allocation in genomic selection. *Intelligent Systems with Applications* 14, 200076 (2022). https://doi.org/10.1016/j.iswa.2022.200076.

59 Emily Waltz. With CRISPR and machine learning, startups fast-track crops to consume less, produce more. *Nature Biotechnology*, 1251-1253 (2019). https://doi.org/10.1038/d41587-019-00027-2.

60 Xi Xiang *et al.* Enhancing CRISPR-Cas9 gRNA efficiency prediction by data integration and deep learning. *Nature Communications* 12, 3238 (2021). https://doi.org/10.1038/s41467-021-23576-0.

61 Jutan Das *et al.* Machine learning in the estimation of CRISPR-Cas9 cleavage sites for plant system. *Frontiers in Genetics* 13 (2023). https://doi.org/10.3389/fgene.2022.1085332.

62 Ewen Callaway. 'ChatGPT for CRISPR'creates new gene-editing tools. *Nature* 629, 272-272 (2024). https://doi.org/10.1038/d41586-024-01243-w.