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Responsible artificial intelligence in agriculture requires systemic understanding of risks and externalities

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Global agriculture is poised to benefit from the rapid advance and diffusion of artificial intelligence (AI) technologies. AI in agriculture could improve crop management and agricultural productivity through plant phenotyping, rapid diagnosis of plant disease, efficient application of agrochemicals and assistance for growers with location-relevant agronomic advice. However, the ramifications of machine learning (ML) models, expert systems and autonomous machines for farms, farmers and food security are poorly understood and under-appreciated. Here, we consider systemic risk factors of AI in agriculture. Namely, we review risks relating to interoperability, reliability and relevance of agricultural data, unintended socio-ecological consequences resulting from ML models optimized for yields, and safety and security concerns associated with deployment of ML platforms at scale. As a response, we suggest risk-mitigation measures, including inviting rural anthropologists and applied ecologists into the technology design process, applying frameworks for responsible and human-centred innovation, setting data cooperatives for improved data transparency and ownership rights, and initial deployment of agricultural AI in digital sandboxes.

For more than a century, technological innovation has been the main route to increasing agricultural productivity. New plant varieties and chemical formulations for nutrient management and pest control have improved farm productivity and profitability. With an estimated 2 billion people afflicted by food insecurity, including some 690 million malnourished people and 340 million children suffering micronutrient deficiencies[1], advanced technologies, such as AI and its subset, ML, promise further substantial benefits for agricultural intensification and food and nutritional security[2]. ML may support, and in several instances enable, rapid plant phenotyping, monitoring of farmlands, in situ assessment of soil composition, disease diagnosis and surveillance, facilitation of automation and bundling of agro-chemical application, weather forecasting, yield prediction, decision support systems (DSS) with real-time agronomic advice, and new methods for post-harvest handling and traceability.

However, technological modernization in agriculture has also contributed to ecological degradation, including water and land contamination, and soil erosion, which may ultimately undermine food security[3–5]. Moreover, prioritization of a small number of plant varieties has resulted in the loss of over 75% of crop genetic diversity[6].

In some instances, agricultural industrialization has increased human suffering, including via exposure to detrimental chemicals[7], and social exploitation[8]. In other instances, mechanization in farming has moved in lockstep with land consolidation[9], as owners of small and fragmented parcels often lacked the means to invest in advanced machinery and compete with large landholders who exploited economies of scale. Increase in farm sizes and mechanization carried considerable benefits for labour efficiency, agricultural output and profitability[10,11], yet has also resulted in displaced labour, wage loss, and detrimental changes to rural landscapes and communities[12,13].

These are not failures of technology as such, but rather failures to anticipate and account for the impacts of technology. Comprehensive risk assessment and technology governance frameworks may help to avoid future pitfalls, and exacerbation of current predicaments, in the widespread and rapid diffusion of agricultural AI.

To anticipate problems and advance mitigation actions, in this Perspective we first analyse systemic risks in data management, AI and ML design, and wide-scale system deployment. Within data management, we pay particular attention to issues of data findability, accessibility and interoperability. Within AI and ML design, we highlight the dynamics through which models may compromise ecosystems as well adversely affect smallholders' identity, agency and ownership rights. When considering deployment at scale, we identify risks that could leave growers and agrifood supply chains open to cascading accidents and cyberattacks. On the basis of this analysis, we outline a set of proposals to mitigate envisioned risks, building on frameworks of responsible research and innovation, data cooperatives, and hybrid cyber-physical spaces for low-risk deployment of experimental technologies. We highlight the main benefits of these approaches and techniques, and how they might be adapted to AI in agriculture.

AI risks for farms, farmers and food security

The study of AI risks is relatively new, and concerns associated with bias, inequality, privacy, safety or security play out differently in different domains. In global agriculture, a safety-critical system of high consequence for human development, we consider three types of risks: (1) risks relating to data, including acquisition, access, quality and trust; (2) risks emerging from narrow optimization of models and unequal adoption of technology during design and early deployment of ML systems; and (3) risks associated with deployment at scale of ML platforms.

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Risks relating to data acquisition, access, quality and trust. Agricultural data ranges from the molecular to the landscape scale, and spans domains from agronomy and plant breeding to remote sensing and agricultural finance. National and international agricultural research institutions collect copious amounts of data, which could in principle support ML models. However, these data are too often not discoverable, interpretable or reusable.

CGIAR, a global consortium of agricultural research institutes, has in recent years espoused FAIR (findable, accessible, interoperable and reusable) data principles. Although there is progress in increasing findability through standardization, syntactic and semantic interoperability remains elusive due to lack of common data formats and structure protocols, as well as disordered or unused standards.

Reliability and relevance of agricultural data are additional concerns. A decades-long focus on staple crops such as wheat, rice and corn has outweighed research efforts concerning crops of crucial importance to the poorest producers and subsistence farmers, including quinoa, cassava and sorghum[14].

Similarly, the people and practices at the centre of Indigenous farming systems are often under-represented in data, despite their contribution to local food security and dietary diversification[15,16]. For instance, typical agricultural datasets have insufficiently considered polyculture techniques, such as forest farming and silvopasture. These techniques yield an array of food, fodder and fabric products while increasing soil fertility, controlling pests and maintaining agrobiodiversity[17].

Partial, biased or irrelevant data may result in poorly performing agricultural DSS, thereby eroding smallholders' and Indigenous farmers' trust in digital extension services and expert systems, eventually compromising food security.

Risks from narrow optimization and unequal adoption. While optimizing for yield, past agricultural technologies contributed to new pest complexes, loss of biodiversity and pollution[3,4]. These risks are broadly known, yet may be difficult to avoid if agriculture is further intensified through AI, and yield is prioritized over ecological integrity.

Expert systems and autonomous machines could improve the working conditions of farmers, relieving them of manual, routine tasks[18]. However, without deliberate and inclusive technology design, socioeconomic inequities that currently pervade global agriculture, including gender, class and ethnic discriminations[19,20], and child labour[21] will remain external to ML models applied in agriculture. This is no minor concern; over 98 million children work in farming, fishing, forestry and livestock, in an intensity that deprives them of their childhood and development opportunities[22]. Agronomic expert systems that remain agnostic to agricultural labour inputs, namely disadvantaged communities and children in employment, will ignore and thereby might sustain their exploitation.

Furthermore, small-scale farmers who cultivate 475 of approximately 570 million farms worldwide and feed large swaths of the so-called Global South[23] are particularly likely to be excluded from AI-related benefits. Marginalization, poor Internet penetration rates[24] and the digital divide[25] might prevent smallholders from leveraging such advanced technologies, widening the gaps between commercial farmers and subsistence farmers.

The dissemination of AI is also likely to raise concerns around the potential effects on farmers' work, identity, agency and ownership rights, including of intellectual property[26]. In such circumstances, there are clearly risks that large and small farmers will profit unequally, and smallholders get locked into proprietary systems they do not fully understand[27].

Risks from deploying AI and ML at scale. Adoption and use of earlier successive waves of technologies for agricultural intensification tended to be led by larger commercial farms with more capital to invest and ability to harvest marginal gains in productivity over larger areas[28]. This increases the likelihood that commercial farmers may be the first to harvest the benefits of AI-driven productivity, with the potential of widening the divide between large farmers and smallholders.

Concomitantly, as AI becomes indispensable for precision agriculture, we can expect an increasing reliance of commercial farmers on a small number of easily accessible ML platforms, such as TensorFlow and PyTorch. Under these conditions, farmers will bring substantial croplands, pastures and hayfields under the influence of a few common ML platforms, consequently creating centralized points of failure, where deliberate attacks could cause disproportionate harm.

In particular, these dynamics risk expanding the vulnerability of agrifood supply chains to cyberattacks, including ransomware and denial-of-service attacks, as well as interference with AI-driven machinery, such as self-driving tractors and combine harvesters, robot swarms for crop inspection, and autonomous sprayers[29]. The 2021 cyberattack on JBS[30], the world's largest meat processor, foreshadows potential risks that come from the introduction of digital technologies into agrifood supply chains. A 2021 ransomware attack on NEW Cooperative, which provides feed grains for 11 million farm animals in the United States[31], further emphasizes this emerging cyber-crime landscape.

Rapid diffusion of intelligent machines in multi-component, multi-agent systems, such as agriculture, may exacerbate nondeliberate, accidental risks as well[32]. For instance, if monocultures—where a single genotype of a plant species is cultivated on extensive lands—are irrigated, fertilized and inspected by the same suites of algorithms, a model error or poorly calibrated sensors may lead to excessive fertilization and soil microbiome degradation, at the risk of large-scale crop yield failures.

Furthermore, unanticipated, cascading system failures have been shown to arise when the interactions between intelligent agents, specifically in human–machine hybrid systems[32], happen faster than humans are able to respond[33]. As digital tools begin to permeate all aspects of agriculture, and agrifood supply chains, the risk of such 'flash crashes' of the type seen in other domains may increase.

Governance mechanisms

Data stewardship, ownership and cooperatives. We identify the need for FAIR data frameworks and improved standards for transparency, ownership rights and oversight, across all phases of the agricultural data value chain, including data generation, acquisition, storage and analysis.

Specifically, farmers sharing information on soil type, composition and nutrient availability, land surface phenology, choice of crops, amount of fertilizer used, crop rotations, historical crop yield records and actual yield should all follow open-science data-sharing requirements, specifying the repository and dataset. Addressing ownership issues by democratizing data access and use via standards-compliant repositories is likely to be a foundational aspect of this approach, enabling more open, multi-stakeholder science and technology development[34]. In this context, data-stewardship tools that facilitate agricultural data lakes are essential as global agriculture contends with a deluge of data from multiple sources of varying types. These tools must protect farmers' proprietary rights, ensure data can be trusted, determine how data can be used and enable effective data mining. The use of industry standards such as ontologies and controlled vocabularies in data lakes should support data mining across disciplines, heterogeneities and sources that differ in modality, granularity, structure and scale[35].

For example, CGIAR's Platform for Big Data in Agriculture provides tools and workflows[36] to generate FAIR data with support from several platform-mediated communities of practice and

Table 1 | List of approaches and techniques for responsible AI in agriculture

RRI dimension	Approaches, mechanisms and techniques	Prospective outcomes, and new knowledge, disseminated into routine AI research and development practice
(1) Anticipation	Foresight of unintended consequences and potential knock-on effects of agricultural AI	Foresight activities that feed into agricultural AI design, including scenario building, back-casting and horizon scanning, to pre-empt and prevent potential long-term risks, such as soil degradation as a result of a DSS optimized for crop yield productivity. Activities could be organized by CGIAR centres, IFAD, WFP Innovation Accelerator and FAO Decentralized Offices.
	AI and ML technology assessment in cyber-physical farms; that is, digital sandboxes, or open science partnerships	Using supervised spaces that simulate different agricultural environments, including crop farming, livestock ranching, aquaculture and horticulture, to comprehensively assess and prevent potential hazards of experimental autonomous agricultural machinery. This could include assessing susceptibility to cyberattacks in partnerships with white-hat hackers.
	Technology deployment scenarios with AI and ML developers and users; for example, smallholders and subsistence farmers	Exploring the social and ethical aspects of data cooperatives and AI technologies adoption, including questions of accessibility, affordability and equal use by subsistence and Indigenous farmers, informed consent of data owners, and implications for narrowing the 'digital divide'.
	Smallholder–commercial farmer integrated agricultural AI vision assessment	Producing integrated reviews on future agricultural ML applications and their associated social and ecological risks, including farm consolidation, drawing on a variety of potential technology users, with fair compensation for farmers' participation.
(2) Reflexivity	Embedded rural anthropologists and ethicists in national and regional AI and ML research laboratories and innovation hubs	Opening research laboratories and innovation hubs for multiple expert perspective, including ethics and anthropology. This should ensure various value systems inform data-gathering efforts, and novel DSS development, thereby avoiding potential algorithmic biases.
	Codes of conduct—reviewed periodically—that prioritize ecological integrity and regenerative agriculture over yield intensification and land productivity	Setting sustainability standards, such as UNCTAD's voluntary sustainability standards, to promote sustainable agricultural intensification in corporations developing and deploying agricultural sensors, expert systems and autonomous agricultural machines.
(3) Inclusion	Civil society frameworks and fora, including a wide range of partners, to premeditate matters concerning accountability, fairness and transparency in agricultural data and ML models	Planning consensus conferences where expert opinions on the envisaged benefits of agricultural AI are questioned in public and citizens' juries where a representative sample of citizens examine the implications of novel expert systems. The McGovern Foundation's Data and Society is a model initiative in this space. Together, these measures may bring vulnerable and marginalized communities with no access to digital platforms into the technology design process, with the ancillary benefit of increasing farmers' trust in ML models.
	Deliberative polling including of marginalized communities with no access to digital polling platforms	Eliciting opinions of random samples of smallholders, mainly Indigenous subsistence farmers with no Internet access, to consider technology deployment options, and proposed AI-powered agricultural extension services, through small-group conversations, with remuneration for farmers' participation.
	Lay membership of expert quasi-governmental institutions and non-governmental institutions, including CGIAR, the UN FAO, IFAD and the WFP, in parliamentary research, science and technology committees	Appointing representatives of expert institutions to parliamentary agricultural AI committees, and scientific advisory committees, to convene a range of different actors and ensure decision-making processes rely on comprehensive evidence and advice.
	Lay membership of voluntary organizations and civil rights groups in parliamentary research, science and technology committees	Appointing representatives of subsistence and Indigenous farming systems to science and technology committees, with fair compensation for participating farmers.
	Democratizing agricultural AI innovations through community-led activities that facilitate user-led, user-centred technology design	Private- and public-sector-led maker spaces and fabrication laboratories (FabLabs) for autonomous agricultural machinery; hackathons and bootcamps for ML models development; mainly, in developing regions. The FabLab in Bangladesh Agricultural University, and the AI for Agriculture Hackathon of the Government of India, are two working examples.
	Training to leverage open-source ML tools and open datasets	Sponsoring technical training and education in open-source ML platforms and packages, such as Apache Mahout and Core ML, with an emphasis on interrogating ML training datasets to prevent discriminative expert systems.

Continued

Table 1 | List of approaches and techniques for responsible AI in agriculture (Continued)

RRI dimension	Approaches, mechanisms and techniques	Prospective outcomes, and new knowledge, disseminated into routine AI research and development practice
(4) Responsiveness	Monitoring of ML models and ML-based machines to ensure the protection of famers' rights and safety, including training sets and learning objectives that consider the welfare of impacted marginalized communities as well as children in employment	Improving government oversight through evaluation of novel agricultural ML models and experimental machinery. These evaluations would use designated environmental impact assessments, social impact assessments and regulatory impact assessments to ensure, for instance, that AI systems are not blind to agricultural labour inputs.
	Promote—and continually refresh—integrated data, ecology and ethics standards in technology design	Engaging agricultural data owners and providers, as well as AI actors, and building awareness of the potential social and ecological risks associated with fragmented or discriminatory datasets and hasty deployment of expert systems in agriculture. This process would emphasize the need to implement FAIR data principles across the agricultural data value chain.
	Institutional mechanisms for moratoria if high-risk ML innovations are proposed	Advancing a precautionary approach through legislation and policies for instances in which experimental and potent technologies have the potential for significant negative ecological implications. These might include overharvest, excessive fertilization and soil microbiome degradation at large scales. Institutions would be supported in carrying out risk assessments for these technologies to inform moratoria decisions.
	Staged rollout of innovations from low-risk environments such as sandboxes, moving progressively towards higher-regulation locales to inform broader deployment	Where governments can act as landlords, public lands available for farming should be allocated as monitored digital sandboxes for experimentation with novel agro-technologies, specifically in countries where new technologies require regulatory approval for wide-scale use.

RRI, responsible research and innovation; IFAD, International Fund for Agricultural Development; WFP, World Food Programme; FAO, Food and Agricultural Organization of the United Nations; UNTCAD, United Nations Conference on Trade and Development.

including the development and use of ontologies to improve semantic interoperability.

Data cooperatives, or platforms owned and controlled by their members, are a recent model and potential response to the need for more transparent and democratic governance of farm and farmers' data. Several examples in the United States include the Ag Data Coalition (ADC) and the Grower Information Services Cooperative (GiSC). Some data cooperatives such as ADC offer secure data repository solutions where farmers can store their data and decide which agencies or research entities to share it with. Others, such as GiSC, offer 'data pools' with shared data resources and analytics services to provide peers with improved insight into their farming practices.

Similar approaches are being tested in emerging economies. For example, Digital Green is developing FarmStack, a data-sharing platform and peer-to-peer data-sharing standard for farmers in India, with offerings like those of ADC. Yara and IBM are collaborating to enable farmers to securely share data and determine who uses the data and how[37].

A key challenge emerges from the tension between a democratized access to data and data monetization. On one hand, if ML systems profit from data contributed by farmers, farmers should be fairly compensated for generating these data. Furthermore, monetization should incentivize growers to share more and better-structured data. On the other hand, various AI systems provide benefits without financial gains, and would be limited if the cost of access to data is prohibitive.

One option to consider is a licensing structure that differentiates between commercial and non-commercial use of data. Another alternative is to share data only amongst groups who all stand to benefit from sharing, such as smallholders in polyculture systems. Data cooperatives could provide a governance structure for exploring different options and making decisions that align with farmers' best interests.

Responsible innovation. The risks delineated above emphasize the need to develop agricultural AI systems and services with sensitivity to context, giving consideration to prospective social and ecological ramifications, and placing the data owner at, or close to, the centre of design efforts. Table 1 adapts a responsible research and innovation approach[38] to agricultural AI and suggests interventions in the public and private sectors to ensure anticipatory, reflexive, inclusive and responsive development.

For instance, anticipatory design of agricultural AI would involve considering and assessing safety concerns beyond data privacy. These might include unsustainable use of chemical inputs, or overexploitation of agroecosystems. Reflexive AI development should invite deliberative collaborations of rural anthropologists, applied ecologists, ethicists and data scientists in co-creating new ML models that safeguard biodiversity and are context sensitive, ensuring AI ethical principles are translated into practice[39].

Inclusive, participatory, human-centred design should value agricultural paradigms other than industrial farming, including Indigenous knowledge systems. Civil-society frameworks and fora that give voice to vulnerable and marginalized communities, and circulate their concerns, can support these aims.

Staged, risk-aware deployment in digital sandboxes. We suggest that initial deployment of AI for agricultural purposes take place in low-risk hybrid cyber-physical spaces, which we refer to as 'digital sandboxes', where multiple stakeholders can be engaged in rapid and supervised prototyping and piloting of novel ML techniques, and associated technologies. In such cyber-physical space, models and machines could be assessed under local and closely monitored circumstances. This model is not entirely new. It has precedence, for instance, in biotechnology frameworks governing and enforcing biosafety protocols in genetic, genomic and genetically modified organism research[40].

Digital sandboxes that report on possible failures of nascent technologies would ensure that experimental practices such as autonomous pest and pathogen diagnosis and control systems are precise as well as safe and well-secured. At the same time, anonymizing data relating to failed deployment attempts and sharing it with agricultural AI communities will allow lessons to be learned and accelerate safe and secure innovations.

The Hands Free Hectare project (https://www.handsfreehectare.com/) at Harper Adams University in the UK, where autonomous precision agriculture interventions are tested and validated, is one example of such a cyber-physical space in a European context; the AI Lab at Makerere University (https://air.ug/) in Kampala, Uganda, where ML anticipates the spread of plant diseases, demonstrates how the approach works in an African context.

This approach has several ancillary benefits. For instance, digital sandboxes that operate in open-science partnerships that link public, private and non-profit institutions can create the context for prototyping AI applications safely. They can also help inform rules and regulations for rolling applications out responsibly. Whereas regulatory rigidity may prevent prototyping of novel ML techniques, government agencies could give special, interim exemption to experimentation and learning spaces such as digital sandboxes before developing targeted, customized regulatory frameworks. Moreover, multi-stakeholder approaches to experimentation and learning, such as digital sandboxes, can create opportunities to apply responsible innovation principles in technology design.

Conclusion

Widespread deployment of AI in agriculture is both valuable and expected. Nonetheless, the history of technological modernization in agriculture strongly suggests that a focus on increased productivity carries potential risks, including intensifying inequality and ecological degradation. Agricultural AI must avoid the pitfalls of previous technologies, and carefully navigate and ameliorate their predicaments by implementing comprehensive risk assessments and anticipatory governance protocols.

From data collection and curation to development and deployment, general principles of responsible and participatory AI should be tailored to the distinct challenges facing agriculture, at local and global scales. Failure to do so may ignore and thereby perpetuate drivers of nutritional insecurity, exploitation of labour and environmental resources depletion.

Previous mis-steps notwithstanding, technological modernization in farming has achieved much. Past successes, too, should inform and inspire the use of agricultural expert systems and intelligent machines. Accordingly, it is essential that a balanced approach towards innovation is practiced, and that risk assessments and responsible research and development procedures do not stifle innovation in a system so fundamental to human wellbeing.

Finally, the emerging risk landscape discussed here is also applicable to agricultural systems that provide non-food products; a similar approach should therefore be considered in the production of fibres, fuels, pulp, paper, oils, resins, cosmetics, rubber and plastics.

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