SYSTEMIC UNDERSTANDING OF RISKS AND EXTERNALITIES OF ARTIFICIAL INTELLIGENCE IN AGRICULTURE

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Abstract- For over a century, the primary means of boosting agricultural output has been through technological innovation. Novel plant species and synthetic nutrient-management formulas intensification as well as the security of food and nourishment. Rapid plant phenotyping, farmland monitoring, in situ soil composition assessment, disease diagnosis and surveillance, automation and bundling of agrochemical application, weather forecasting, yield prediction, decision support systems (DSS) with real-time agronomic advice, and novel approaches to post-harvest handling and traceability are all potential applications of machine learning (ML) that may be supported and, in some cases, made possible. But agricultural modernity has also brought about ecological deterioration, such as soil erosion and contaminated water and land, which could eventually jeopardise food security. Furthermore, more than 75% of crop genetic variety has been lost as a result of the prioritization of a limited number of plant varieties.

1. Introduction

Agricultural modernization has occasionally resulted in more human misery, such as through social exploitation and exposure to harmful chemicals. In other cases, agricultural mechanization has followed land consolidation closely. This is because small-scale farmers frequently lacked the capital to purchase sophisticated equipment and compete with larger landowners who benefited from economies of scale. Larger farms and more mechanization have greatly benefited worker productivity, agricultural output, and profitability; nevertheless, they have also caused labour displacement, wage losses, and negative effects to rural communities and landscapes.

These are not technological failures per se, but rather an inability to foresee and take into consideration the effects of technology. Thorough risk evaluation and technological governance structures could potentially prevent. In this perspective, we first assess systemic risks in data management, AI and ML design, and large-scale system deployment in order to foresee issues and advance mitigation steps. We provide data findability, accessibility, and interoperability special consideration in data management. We draw attention to the ways that models used in AI and ML design may jeopardise ecosystems and negatively impact the identity, agency, and ownership rights of smallholders. We highlight hazards that could expose producers and agrifood supply networks to cyberattacks and cascading accidents when considering deployment at scale. Building on frameworks of responsible research and innovation, data cooperatives, and hybrid cyber-physical environments for low-risk deployment of experimental technologies, we propose a series of ideas to lessen envisioned hazards based on this analysis. We highlight the key advantages of these methods and strategies, as well as potential applications of AI in agriculture.

Farms, farmers, and food security are at risk from AI The research of AI hazards is still in its infancy, and different areas present distinct challenges when it comes to bias, inequality, privacy, safety, and security. We take into account three categories of risks in global agriculture, a safety-critical system with significant implications for human development: (1) risks linked with data, such as collection, access, quality, and trust; (2) risks resulting from limited model optimization and unequal technology adoption during the design and early deployment of machine learning systems; and (3) risks related to the large-scale implementation of machine learning platforms. In this perspective, we first assess systemic risks in data management, AI and ML design, and large-scale system deployment in order to foresee issues and advance mitigation steps. We give finding, access, and interoperability of data special consideration in data management.

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International

List of approaches and techniques for responsible AI in agriculture

Anticipation

1. Foresight of unintended consequence sequence and potential knock on effect of agricultural AI

2. Open science partnership

3. Technology Development scenario with AI.

Reflexivity

AI and ML technology assessment in cyber-physical farms; that is, digital sandboxes or open science partnership

Inclusion

Civil society framework and for a, including a wide range of partners, to premeditate matters concerning accountability, fairness & transparency in agricultural data ans ML models..

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.

- ✓ 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.
- ✓ 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

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- ✓ voluntary sustainability standards, to promote sustainable agricultural intensification in corporations developing and deploying agricultural sensors, expert systems and autonomous agricultural machines.
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- ✓ 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 examines 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

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- ✓ Improving government oversight through evaluation of novel agricultural ML models and experimental machinery.These evaluations would use designated environmental impact assessments, social impact assessment and regulatory impact assessments to ensure, for instance, that AI systemsare not blind to agricultural labour inputs

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2. Farms, farmers, and food security are at risk from AI

The research of AI hazards is still in its infancy, and different areas present distinct challenges when it comes to bias, inequality, privacy, safety, and security. We take into account three categories of risks in global agriculture, a safety-critical system with significant implications for human development: (1) risks linked with data, such as collection, access, quality, and trust; (2) risks resulting from limited model optimisation and unequal technology adoption during the design and early deployment of machine learning systems; and (3) risks related to the large-scale implementation of machine learning platforms. Hazards connected to the collection, use, authenticity, and integrity of data. Agronomy, plant breeding, remote sensing, agricultural finance, and other fields are among the disciplines that contain agricultural data, which spans from the molecular to the landscape scale. Large volumes of data are gathered by domestic and international agricultural research organisations, which may one day enable ML models. All too often, though, these data cannot be found, understood, or used again. exposure to harmful chemicals and being exploited socially. In other cases, agricultural mechanization has followed land consolidation closely. This is because small-scale farmers frequently lacked the capital to purchase sophisticated equipment and compete with larger landowners who benefited from economies of scale. Larger farms and more mechanization have greatly benefited worker productivity, agricultural output, and profitability; nevertheless, they have also caused labor displacement, wage losses, and negative effects to rural communities and landscapes.

3. The risks relating to trust and quality

The global collaboration of agricultural research institutes, CGIAR, has made FAIR (findable, accessible, interoperable, and reusable) data principles its guiding principles in recent years. Syntactic and semantic interoperability is still unattainable despite efforts in improving findability through standardization because of disorganized or underutilized standards, inconsistent data formats, and structural protocols. Other issues with agricultural data are its relevancy and dependability. Research on crops like quinoa, cassava, and sorghum—which are vital to the world's poorest producers and subsistence farmers—has lagged behind years of emphasis on staples like wheat, rice, and maize. Similar to this, despite their significance to regional food security and dietary diversity, the individuals and methods at the core of Indigenous farming systems are frequently underrepresented in data. For example, polyculture practices like salvo pasture and forest farming have not been fully taken into account in standard agricultural databases. These methods improve soil fertility, manage pests, and preserve agrobiodiversity while producing a wide range of food, fodder, and textile products. The use of incomplete, biassed, or irrelevant data can lead to agricultural DSS that performs badly, which in turn undermines the trust that smallholders and Indigenous farmers have in digital extension services and expert systems, thus jeopardising food security. Hazards resulting from uneven adoption and limited optimisation. Previous agricultural systems that optimised for production also caused pollution, biodiversity loss, and the emergence of new insect complexes. These concerns are well understood, but they might be hard to prevent if artificial intelligence is used to further intensify agriculture and put productivity ahead of ecological integrity. Farmers could have better working conditions if autonomous equipment and expert systems took over manual, repetitive activities from them18. However, socioeconomic injustices that now permeate global agriculture, such as child labour and discrimination based on gender, class, and ethnicity, will remain external to ML models used in agriculture unless intentional and inclusive technology design is used. This is a serious issue since more than 98 million children work in agriculture, forestry, fishing, and cattle at a level that robs them of their youth and

Concerns about the possible consequences of AI on farmers' labour: The identities, autonomy, and ownership rights—including intellectual property—are also likely to surface as the technology becomes more widely used. Under such circumstances, there is an obvious risk that smallholders become bound into proprietary systems they do not fully comprehend, and large and small farmers would profit unequally.

4. Dangers of large-scale AI and ML deployment.

Larger commercial farms with more financial resources and the capacity to realise marginal productivity improvements over wider areas have historically been at the forefront of the adoption and use of earlier succeeding waves of technologies for agricultural intensification28. This could lead to a greater gap between large and smallholder farmers as commercial farmers are more likely to be the first to gain from AI-driven productivity. Simultaneously, we should anticipate a growing dependence of commercial farmers on a limited number of easily accessible machine learning platforms, such Tensor Flow and PyTorch, as AI becomes essential for precision agriculture. Farmers will bring significant croplands, pastures, and hayfields under the influence of a few common ML under these circumstances.

These dynamics, in particular, run the risk of making agrifood supply chains more susceptible to cyberattacks, such as denial-of-service and ransomware attacks, and of interfering with AI-driven equipment, like autonomous sprayers, robot swarms for inspecting crops, and self-driving tractors and combine harvesters. The largest meat processor in the world, JBS, was the target of a cyberattack in 2021, which hinted to the dangers associated with integrating digital technologies into agrifood supply chains. This evolving panorama of cybercrime is further shown by a ransomware attack on NEW Cooperative in 2021, which supplies feed grains for 11 million farm animals in the United States. In multi-component, multi-agent systems like agriculture, the rapid dissemination of intelligent devices may also increase noncelibate, inadvertent dangers. For example, if monocultures—where a plant species' single genotype is Moreover, it has been demonstrated that unexpected, cascade system failures occur when intelligent agents interact with one another more quickly than humans can react, particularly in human-machine hybrid systems. With the increasing integration of digital tools into agriculture and agrifood supply chains, there is a possibility of experiencing "flash crashes" similar to those observed in other fields. Mechanisms of governance Cooperatives, ownership, and data stewardship. We pinpoint the requirements for more open, equitable, and supervised standards and FAIR data frameworks at all stages of the agricultural data value chain, including data generation, acquisition, storage, and analysis.

In particular, farmers exchanging data on crop choice, quantity of fertilizer applied, crop composition and availability, land surface phenology, and soil type Actual yield, historical crop yield records, and rotations should all adhere to the repository and dataset specifications set forth by open-science data-sharing guidelines. A key component of this strategy will probably involve addressing ownership issues by democratizing data access and use through standards-compliant repositories, which will facilitate more transparent, multi-stakeholder development of research and technology34. In this context, as global agriculture struggles with an abundance of data from various sources of different kinds, data-stewardship solutions that support agricultural data lakes are crucial. These technologies need to safeguard farmers' proprietary rights, guarantee the reliability of the data, specify its intended use, and facilitate efficient data mining. Data lakes should facilitate data mining across disciplines, heterogeneities, and sources with varying characteristics by utilising industry standards like ontologies and controlled vocabularies.

The CGIAR's Platform for Big Data in Agriculture, for instance, offers tools and workflows36 that facilitate the generation of FAIR data with input from many platform-mediated communities of practice. These workflows also include the creation and application of ontologies to enhance semantic interoperability. A newer approach and possible solution to the demand for more open and democratic administration of farms and farmers' data are data cooperatives, or platforms owned and operated by their members. In the US, the Ag Data Coalition (ADC) and the Grower Information Services Cooperative (GiSC) are two instances. Farmers can save their data in safe data repositories provided by some data cooperatives, like ADC, and choose which research organisations or agencies to share it with. Some, like GiSC, provide "data pools" with shared Emerging economies are testing similar strategies. For instance, using ADC-like services, Digital Green is creating Farm Stack, a peer-to-peer data-sharing standard and platform for Indian farmers. Together, Yara and IBM are collaborating to allow farmers to safely exchange data and control who can access it and how. The conflict between data monetization and demo cratised access to data is a significant challenge. On the one hand, farmers should receive just compensation for producing data if ML systems benefit from the data they supply. Moreover, producers should be encouraged to provide more and better-structured data through monetization. However, a number of AI systems offer advantages without generating profits, and their use would be constrained if the price of access to A licencing system that distinguishes between the commercial and non-commercial usage of data.

An other option would be to restrict data sharing to those groups—like smallholders in polyculture systems—that will collectively profit from it. Data cooperatives might offer a governance framework for examining alternatives and choosing actions that are in the best interests of farmers. Conscientious innovation. The hazards outlined above highlight the necessity of developing AI systems and services for agriculture that are sensitive to context, take into account potential social and ecological repercussions, and put the data owner at, or near, the centre of design efforts. Table 1 proposes interventions in the public and commercial sectors to promote anticipatory, reflexive, inclusive, and responsive development, and it adapts the responsible research and innovation strategy to agricultural AI. For example, anticipatory design in agricultural AI would take into account and evaluate safety issues that go beyond data privacy. These could include over-exploitation of agroecosystems or the unsustainable use of chemical inputs. When developing reflexive AI, data scientists, applied ecologists, ethicists, and rural anthropologists should collaborate thoughtfully to create new machine learning models that protect biodiversity and Indigenous knowledge systems and other agricultural paradigms other than industrial farming should be valued in inclusive, participatory, human-centered design. These goals can be supported by civil society institutions and forums that communicate the concerns of vulnerable and marginalised communities and give them a voice. phased, risk-conscious implementation in virtual sandboxes. We propose that the first applications of AI in agriculture should be implemented in low-risk hybrid cyber-physical environments, or "digital sandboxes," where a variety of stakeholders can collaborate to quickly prototype and test new machine learning techniques and related technologies. Models and machines could be evaluated in such a cyber-physical space under closely watched, local conditions. This is not a whole novel model. For example, it has precedent in biotechnology frameworks that control and enforce biosafety procedures in genetic, genomic Digital sandboxes that provide information on potential shortcomings of emerging technologies would guarantee the accuracy, safety, and security of experimental procedures like autonomous pest and disease detection and control systems. At the same time, lessons may be learnt and safe and secure innovations can be accelerated by anonymizing data related to unsuccessful deployment attempts and sharing it with agricultural AI communities. Please consult Table No. 1.2: Comparison of Term Crops.

The AI Lab at Makerere University (https://air.ug/) in Kampala, Uganda, where ML predicts the spread of plant diseases, demonstrates how the approach works in an African context. 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. This strategy offers numerous additional advantages. For example, the environment for safely developing AI applications can be established via digital sandboxes operating inside open-science collaborations that connect governmental, corporate, and non-profit institutions.

They can also contribute to the development of guidelines and policies for the responsible rollout of apps. While government agencies could grant specific temporary exemptions to testing and learning places like digital sandboxes before creating focused, customised regulatory frameworks, regulatory rigidity may hinder the development of breakthrough machine learning approaches. Furthermore, the implementation of responsible innovation principles in technology design can be facilitated by multi-stakeholder approaches to experimentation and learning, such digital sandboxes. In summary AI's widespread application in agriculture is both anticipated and beneficial. However, the history of agricultural technical development clearly implies that concentrating on boosting productivity involves some hazards, such as escalating inequality and degrading the environment. Agricultural AI needs to steer clear of the mistakes made by earlier technologies, and by doing so, carefully manage and improve their situations through the use of thorough risk assessments and proactive governance procedures.

5. conclusion

The broad principles of responsible and participatory AI should be adjusted to the unique issues that agriculture faces, both locally and globally, from data collection and curation to development and deployment. Failing to do so could lead to the perpetuation of factors that contribute to the depletion of environmental resources, labour exploitation, and nutritional insecurity. Despite past errors, technological modernization in agriculture has produced significant results. The application of agricultural expert systems and intelligent machinery should draw inspiration and guidance from previous achievements. Therefore, in a system so vital to human well-being, it is imperative that innovation be approached with balance and that risk assessments and appropriate research and development procedures do not hinder innovation. Lastly, as the developing risk landscape covered here is also relevant to agricultural systems producing non-food items, producing fibres, fuels, pulp, paper, oils, resins, cosmetics, rubber, and plastics should take a similar approach.

Table No:1.2 Comparision of Term Crops

S.No	Long Term Crops	Long Term Crop Problems	Short Term Crop Ideas	Short Term Crop Profits
1	Paddy	Water, Weather	Customized land Creation	Short time Healed
2	Vegetables & Green Leaves	Huge amount of Crops	Vegetables	Fresh & Liquid Cash
			Green leaves	Fresh & short time sales

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