Artificial Intelligence applications in agriculture need a justice lens to address risks and provide benefits to smallholder farmers

Pablo Carcamo (Virginia Polytechnic Institute and State University); Skye Brugler (South Dakota State University); Maaz Gardezi (Virginia Polytechnic Institute and State University); Shreya Mitra (Virginia Polytechnic Institute and State University); Ben Ryan (University of Vermont); Ajoy Kumar Saha (South Dakota State University); Maryam Sahraei (South Dakota State University)

Abstract

Artificial Intelligence (AI) in agriculture can promote sustainable farming practices, increase profitability, and reduce environmental impacts. However, careful assessment of this technology is needed to ensure benefits for smallholders. From a governance perspective, appropriate arrangements are needed to improve the sustainability of food and agriculture systems. A justice-based governance lens can ensure that data acquired and processed by AI models is accessible and usable by smallholder farmers without reproducing social inequalities and dependencies. Analyzing the potential of Artificial Intelligence models and the data they use through a justice-based lens could help steer technology development toward sustainability.

Smallholder farmers, Artificial Intelligence, and technological inequity

Artificial Intelligence (AI) applications in agriculture have the potential to promote sustainable farming practices using localized agroclimatic farm data at the appropriate time and location to increase farm profitability and reduce negative impacts on the environment. However, this optimistic scenario is based upon high uncertainty about technology adoption and requires adaptation to the multiplicity of local configurations that agriculture may take. These challenges are specifically severe for smallholder farmers. Five of every six farms in the world are less than two hectares (approximately 5 acres) and smallholders still account for 35 percent of the total world food production and are known to be critical for building climate change resilience in agriculture[1].

There is an urgent need to place smallholders at the front and center of innovation in AI used for agricultural purposes. A redirection in innovation is necessary from an economic standpoint and from an equity and justice perspective. Smallholders promote ecological diversity, many farmers in the Global South are women and children, and crop and livestock production on small farms sustains food security for a burgeoning population[2]. Smallholders' role and position in the food system make it necessary to steer innovation pathways of AI technologies that respect incumbent farming practices and traditional ecological knowledge[3]. Using a justice-based framework can promote technological development in agriculture that takes into account smallholder farmers' productive and ethical context[4,5].

Advancements in remote sensing applications in agriculture

Remote sensing techniques, such as satellite imagery, are increasingly used to achieve sustainable food security in Global South. This technology helps to reduce fieldwork and provides accurate data at different scales[6]. Since the launch of the first civilian earth-observing satellite Landsat 1 in 1972, the number of geo-products produced by agencies and private companies has increased. Federal agencies such as ESA, NASA, and USGS and commercial providers such as Planet, Airbus, and Maxar offer a range of satellite data products. The NASA/USGS Landsat program continues to launch satellites, and the latest, Landsat 9, produces 30-meter resolution images with a revisit time of 16 days. However, commercial satellites such as RapidEye may be more suitable for more specialized applications such as disease detection because of their higher spatial resolution and shorter revisit times[7–9].

Although most satellite imagery is free to use, processing raw data requires technical expertise for real-world applications[8]. This is where cloud-based computation platforms such as Google Earth Engine have come into play, significantly reducing the time required to process satellite data and providing open-access data with various applications[10]. Hansen et al.[11] used the Google computational infrastructure to generate a map of global forest change, using 654,178 Landsat 7 images in just 100 hours. This process would have taken over a million hours without such technology, as stated by Amani et al[12].

Satellite imaging has advanced significantly with the latest generation of satellites capable of capturing images with improved temporal and spatial resolution[13]. For example, the Jilin-1 satellite can capture images from the earth's surface six times a day at resolutions ranging from 30 cm to 1.2 m[14]. These satellites can also produce high-resolution imagery and cover a wider range of color bands, resulting in more detailed and nuanced imagery. Data captured by satellites has supplied the creation of AI models that can use them to inform agronomical decisions.

Links between AI applications and data availability and use

AI and remote sensing capabilities have increased in the last few years[15], and reductions in the cost of images, remote sensing technologies[16,17], and main electronic components[18] have made the field attractive to investment and research. Investment in technology in the agricultural sector by Venture Capital has increased constantly, except for a slight decrease in funding in 2022[19,20]. Research outputs present a similar upward tendency, constantly growing from 2014[21]. On the other hand, public investment in research and innovation in agriculture does not correspond with the value produced by agricultural production, and has shown stabilization or decline in recent years[22]. The data shows that the innovation ecosystem is maturing, a situation that will impose harder challenges to the governance arrangements in agriculture.

One application of AI in agriculture is Precision Agriculture (PA), which enables site-specific application of farm inputs (seeds, chemicals, irrigation) to improve farm profits and environmental sustainability. Although PA has the potential to increase farm yields, profits, and can reduce agriculture's ecological footprint, its adoption is currently limited, and its benefits are shared disproportionately. Many smallholder farms have little use for PA due to limited technical skills and knowledge, small acreage providing few marginal economic benefits of adoption PA and economic instability[23]. However, it is still unclear how these technologies influence smallholder farmers and their effects on the sustainability and inclusiveness related to their practices [24].

Successful AI applications in agriculture depend greatly on the availability and quality of data collected. However, there are several challenges related to access, ownership, and privacy of farm data. Access to publicly available satellite images, once privately held data, is now being opened to public and corporate entities. Farmers often lack the technical capacity to make use of these geospatial data, while it may be used by more powerful actors like corporations or governmental regulators.

Some of the greatest barriers to widespread adoption of PA[25] are economic limitations, data privacy concerns, and a lack of trust in corporations and government. Economic limitation among small farms compared to larger farms has produced a technology gap. Surveys of have demonstrated that larger farms have more capital to invest in the technology and software, are more capable of taking risks due to the ability to absorb decreases in profit, and can create specialized jobs to analyze and make decisions based on the collected data[26,27].

In terms of data, there is dissonance between AI developers and farmers (users of technology and producers of data). Adopting data governance principles, like the FAIR principles, could alleviate some of the central concerns in power between various actors regardless of scale. The FAIR principles include the requirement for data production to be Findable, Accessible, Interoperable, Reusable[28]. Similarly, the five principles of the European Union Code focus on (1) data ownership, (2) data access, control, and portability, (3) protection and transparency, (4) privacy and security, and (5) liability and intellectual property rights. These principles can provide institutions and stakeholders with a framework to regulate data production and use in agriculture[29].

Finally, a lack of trust in the recommendations provided by new technologies in agriculture usually stems from a lack of communication because companies create the technology due to technology push, and stakeholders provide limited input in its development[30]. Farmers may disagree with the recommendations from scientists because of their experiential site-specific knowledge, termed the paradox of acceptability[31].

Looking through a social justice lens at AI and remote sensing applications for smallholders

To tackle these challenges, governance issues related to the position of smallholders in the context of AI development will require support under a social justice framework that achieves global benefits while respecting and uplifting small producers. We understand social justice under four dimensions:

- *Distributive Justice*. The dimension most discussed under governance arrangements, this aspect of justice deals with the problem that the benefits of new technologies are not shared equally by members of society. Caring for the situation of smallholders will require that governance considers how benefits of new technologies reach all groups participating in agriculture.
- *Procedural Justice*. This element relates to the role of participation of users in technology development. Procedural Justice looks to open spaces for participation in the spaces of data collection and the technologies used. Since technology development in agriculture is usually a supplier-dominated endeavor[32], smallholders' role in the design decisions of new technologies needs to be fostered by ethical guidelines in a justice-led governance framework.
- *Recognition Justice*. This third dimension looks at the role of representation and participation in terms of the ethical standing of groups that might bear the negative consequences of social and technological activities. By providing public acknowledgment of differences and contexts, Recognition Justice towards smallholder production can inform policies that provide protection and foster alternative pathways depending on the multiplicity of views of stakeholders.
- *Restorative Justice*. It considers the role of balance by repairing and restoring material conditions after harm has occurred. It has recently been used to analyze the role of a justice framework in problems related to sustainability transtions[33]. When linked with Data-based AI technologies, Restorative Justice allows to frame considerations of equilibrium in power relations and avoiding damages to traditional knowledge and biodiversity.

In the case of AI and remote sensing technologies, a justice lens can help address the challenges of smallholder producers. Figure 1 highlights different approaches to governing big data and AI through a social justice lens.

Policy recommendations

Governments or public-private partnerships need to adapt data privacy and ownership regulations to the agricultural landscape, while safeguarding the data preferences of smallholders. At the same time, voluntary or regulated standards of transparency of models used in AI need to be made publicly available and easy to understand for potential users. Even if many technology companies have preemptible developed ethical guidelines in their products, oversight will be necessary to guarantee that smallholders agree with their assumptions and objectives.

In terms of market regulation, controlling the power of oligopolies and AI developers should be paramount. Promoting competitive markets will limit the power of suppliers and technology developers. This could be achieved by an increase of investment in public funding for research and development in this industry. Funding will also allow for the creation of local capabilities to control and steer AI technologies. Such control must be integrated with local knowledge of farming to ensure that smallholders' culture, traditions, practices, and goals will be treated fairly by those who hold greater power in this arena.

Participation and engagement of users in adapting technology to their needs and goals should be a critical imperative of governance that promotes justice. As the previous section showed, almost every dimension of a justice-based approach to the governance of AI technologies requires an active involvement of users. In this area, participation can be fostered by promoting extension services to help educate small farmers about technologies that work best in their operations.

Specifically related to the usage of remote sensing in agricultural settings, facilitating access to satellite data, while paying special attention to unintended consequences, such as increased land concentration derived from the abuse of new technologies.

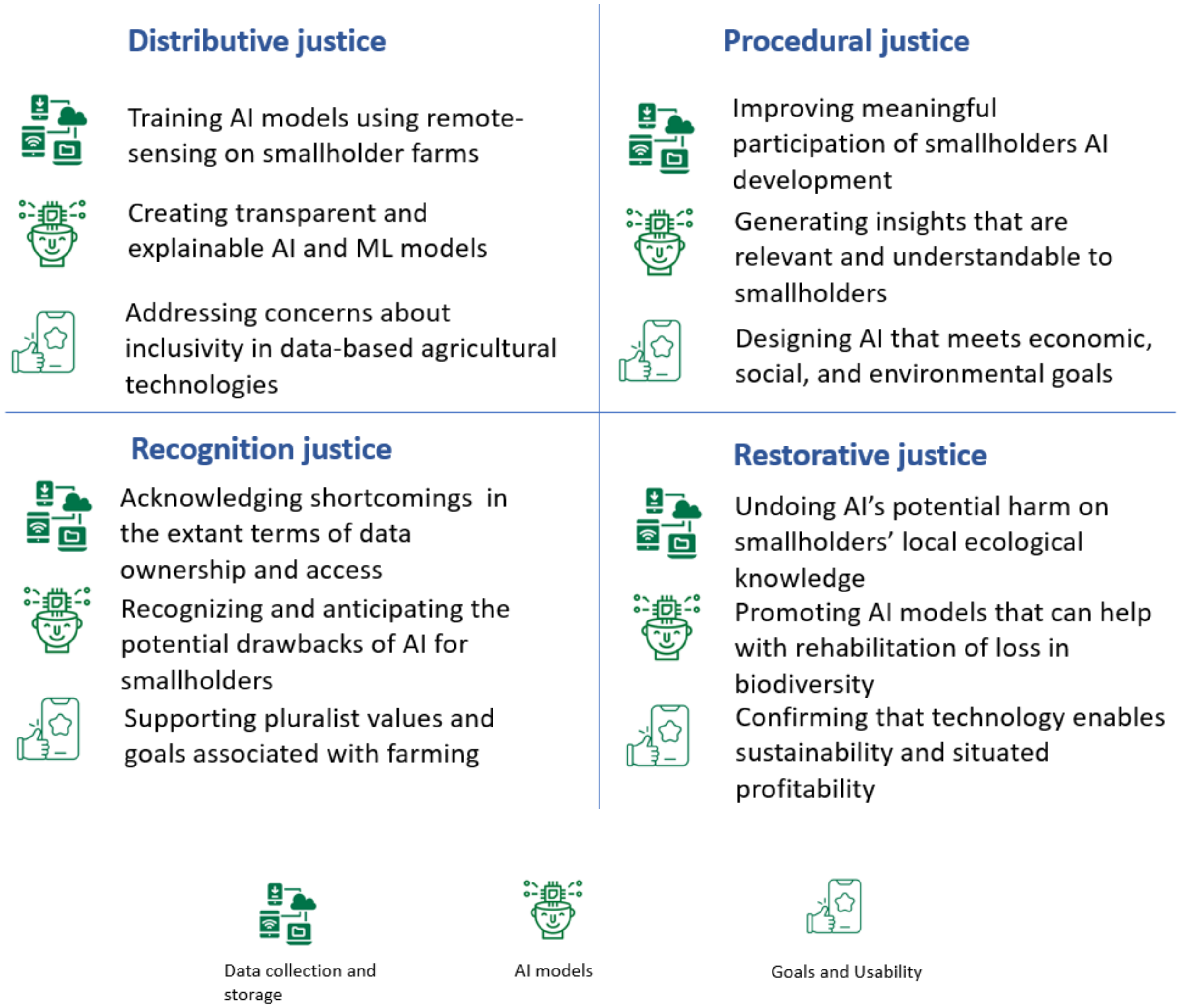

Figure 1. Governance challenges of AI technologies in agriculture from a justice lens.

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Annex

Component	Description	EU Principles	Description
Findable	Data are assigned a globally unique and persistent identifier. Data are described with rich metadata. Data clearly and explicitly include the identifier of the data it describes. Data are registered or indexed in a searchable resource	Data ownership	Rights are assigned to the entity that engages in the creation or collection of ag-data either (i.e., Data originator) This entitles the 'data originator' to exclusive control over ag-data, its subsequent use, access and/or distribution. 'Data originators' can be farmers, but also other parties in the value-chain whose data are being collected (such as, for example, input suppliers, nurseries, the slaughterhouse)
Accessible	Data are retrievable by their identifier using a communication protocol which is open, free, and universally implementable. Data are accessible, even when the data are no longer available	Data access/control /portability	The access, use, storage, and potential sharing of ag data with third parties is *only* permitted if the 'data originator' explicitly consents to this in the contract
Interoperable	Data use a formal, accessible, shared, and broadly applicable language for knowledge representation. Data use vocabularies that follow FAIR principles. Data include qualified references to other (meta)data.	Data protection and transparency	Unauthorized ag-data sharing cannot occur with third parties that are not originally referred to in the contract. Prior consent must first be received to rectify the contract should circumstances change and include the intended third parties.
Reusable	Data are richly described with a plurality of accurate and relevant attributes. Data are released with a clear and accessible data usage license. Data are associated with detailed provenance. Data meet domain-relevant community standards	Privacy and security	Personal data should not be subject to potential losses, theft, or unauthorized access General Data Protection Regulation becomes applicable in circumstances where a data originators' personal/sensitive data is exploited to the advantage of third parties and utilized to 'make decisions about the data originator as a natural person
		Liability and intellectual property rights	Liability does not ensue from the faultiness of data machinery or devices during farming operations. There must be protection of any relevant IP rights that may result from the ag-data value chain

Table 1. Mapping FAIR Principles to EU Code