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## Managing the risks of artificial intelligence in agriculture

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### ABSTRACT

In this paper, we survey the ethical, social, and policy issues that are likely to arise as Artificial Intelligence (AI) begins to impact on agriculture. We highlight possible unintended consequences of the adoption of this technology, which have been neglected in most discussions of the topic to date. A range of current, as well as proposed, applications of AI in agriculture are described, alongside applications of AI in the broader society and economy that are likely to impact on agriculture. AI may bring many benefits, for agricultural producers, consumers, and the environment, but also significant risks. We draw attention to various design choices and policy tools that may help manage the risks – and promote the benefits – of AI and highlight the ethical choices involved in attempts to trade off these risks and benefits. An ongoing and inclusive conversation, about the ethical issues raised by AI and its potential applications in agriculture, should be facilitated to guide policy in this area.

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Artificial Intelligence (AI) is the project of designing machines that can perform tasks that we typically hold require intelligence to perform, as well as the products of that project. After a long “AI winter”, AI is now advancing rapidly. In particular, recent progress in machine learning, which involves creating machines that “learn” how to perform some task rather than being explicitly programmed to do so, has greatly expanded the range of tasks that AI is capable of performing. New algorithms are increasingly capable of seeing patterns in data that have eluded humans and finding new ways of achieving efficiencies in solving complex problems. Insofar as agriculture requires responding to a large and complex set of variables and relies heavily on farmers’, and other entrepreneurs’, predictions of the future, it seems ripe for the application of AI. Some farmers are already using highly automated

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equipment, informed by large datasets generated by sensors and aerial or satellite photography, and acting on the basis of advice provided by sophisticated computer programs (Vincent et al., 2019). The existing investment, both rhetorical and real, in precision agriculture more-or-less guarantees that AI will play some role in agriculture in the future (Pham and Stack 2018; Smith 2020). Moreover, key areas of research and application upon which agriculture relies heavily – most obviously climate science and weather prediction, economic modelling, and plant and animal breeding – will almost certainly be dramatically impacted by machine learning.

In this paper, we offer an initial survey, and evaluation, of the ethical, social, and policy issues that are likely to arise as AI begins to impact on agriculture. We highlight a number of possible unintended consequences of the adoption of AI, which have, for the most part, been neglected in discussions of the topic to date, as well as some of the ways in which the intended impacts of AI are likely to prove controversial. In [Section I](#), we briefly survey the range of current or proposed applications of AI in agriculture, as well as highlight some applications of AI in the broader society and economy that are likely to impact on agriculture. [Section II](#) outlines the many benefits that AI may produce, for agricultural producers, consumers, and the environment. In [Section III](#), we turn to consider various risks associated with the use of AI, in general, and in the specific context of agricultural applications. A clear account of these risks is a necessary first step towards taking action to minimise them. [Section IV](#) draws attention to various design choices and policy tools that may help manage the risks – and promote the benefits – of AI. However, choices about how – indeed whether – to apply AI in various contexts are inevitably ethical choices. In [Section V](#), we therefore highlight the ethical choices involved in attempts to trade off these risks and benefits, as well as, in some cases, conceptualising them either as risks or benefits. Finally, we advocate for an ongoing and inclusive conversation about the ethical issues raised by AI, and its potential applications in agriculture, to guide policy in this area. The more powerful we expect AI to be, in agriculture as elsewhere, the more important it is that decisions about its uses should be made democratically.

## **1. Current and future applications of AI with implications for agriculture**

The literature on AI, including on its applications in agriculture, is moving so quickly that any attempt at a comprehensive survey would quickly go out of date. For this reason, we have not attempted any such survey here. However, our account of the ethical and policy issues raised by the use of AI in agriculture is informed by consideration of the following applications identified in this literature.

- Decision support systems, in particular, yield prediction systems, for farm management (Chlingaryan et al., 2018; Navarro-Hellín et al., 2016; Pérez-Pons et al., 2021).
- Climate modelling and weather forecasting (McGovern et al., 2017)
- Environmental and ecological modelling, including, especially, of the spread of pests and diseases (Chen et al., 2008; Grieve et al., 2019; Stevens & Pfeiffer, 2011).
- Farm finance and administration (Wolfert et al., 2017).
- Economic and agricultural modelling to predict future demand for agricultural goods and services (Weersink et al., 2018; Coble et al., 2018).
- Maximising crop yields while minimizing applications of pesticides and fertilisers (Pham & Stack, 2018).
- “Intelligent” irrigation systems (Goumopoulos et al., 2014; Jimenez et al., 2020).
- Machine vision and image recognition systems to facilitate: fruit picking and weed detection by robots; handling, processing, and packaging of agricultural goods; and, perhaps, recognition of disease in plants and animals (Chen et al., 2002; Dubey & Jalal, 2015).
- Intensive animal production (Matthews et al., 2016; Morota et al., 2018).
- Product tracking and food safety (Weersink, et al., 2018).
- Supply chain management (Gesing et al., 2018; Weersink et al., 2018).
- Machine vision, localisation, and mapping to enable autonomous and semi-autonomous tractors and farm robots (Auat Cheein & Carelli, 2013).
- Plant and animal breeding, and genetic modification of both crops and animals, informed by genomics (Ferraz et al., 2014; Libbrecht & Noble, 2015; Ma et al., 2014; Weersink et al., 2018).

As several items on this list suggest, it is difficult to fully disentangle the contribution of AI and robotics in some of the applications of these technologies in agriculture. Nevertheless, for the most part, we have attempted to do so here, for two reasons. First, trying to discuss the ethical, social, and policy issues raised by the applications of robotics *and* AI in agriculture is simply too ambitious for an article-length treatment. Second, two of the authors have treated the ethical, social, and policy issues raised by the use of robots in agriculture elsewhere (Sparrow & Howard, 2021). While, of necessity, we acknowledge the potential impacts of advances in robotics made possible by advances in AI, especially when it comes to the implications of AI for the future of work in the agricultural sector, throughout we have tried to distinguish between the impacts of progress in AI, as the “brains” (and also the “eyes” and to some extent “hands”) of robots, and improvements in the design (the “bodies”) of robots themselves, and focus on the former.

Note that the applications on the list above are the applications of AI that are most directly related to operations on farms or livestock facilities or in food processing and handling. However, some of the largest impacts on farming and food production from AI may originate from applications of these technologies in the broader society and economy. Thus, it is also worth highlighting:

- The possible impacts of share-market trading algorithms on the prices of agricultural goods and services as well as on the economy more generally (Patterson, 2012; Rabhi et al., 2020).
- The uses of AI in logistics to reduce shipping costs and deliver goods more swiftly and/or “just in time” (Başligil et al., 2011; Gesing et al., 2018; Jouanjean, 2019).
- The uses of AI within government and organisations to improve planning and administration (Schuilenburg & Peeters, 2020).
- The uses of AI for economic modelling in general (Einav & Levin, 2014).

As may be seen from these two lists, the number of potential applications of AI that may play a role in shaping the future of agriculture is large indeed and exceeds that to which we could pay detailed attention in a single article. Moreover, AI is a technology that is both advancing rapidly and is surrounded by a significant amount of “hype”, which makes predictions about its future development and applications especially fraught (Sparrow, 2020). Consequently, our approach here has been to foreground those ethical, social, and policy issues that might arise, should AI have a significant impact on agriculture via any of a range of applications.

## 2. Benefits

Given the range of proposed applications of AI in agriculture, it is little wonder that the range of benefits that have been advertised as flowing from the use of AI is equally large (Kamilaris et al., 2018).<sup>1</sup>

AI has significant potential to help farmers achieve higher outputs with lower inputs by directing the latter more effectively (Bu & Wang, 2019). It is likely to be especially effective in contexts, such as hydroponics, greenhouses, and industrial livestock facilities, where it is possible to measure inputs and outputs relatively precisely and control a number of variables more-or-less in real-time (Matthews et al., 2016; Pala et al., 2014). AI may reduce wastage and spoilage in the food industry by allowing producers to forecast yields and demand more accurately (Weersink et al., 2018). AI may also facilitate more efficient distribution of resources within the agricultural sector by allowing more dynamic and effective planning within enterprises and new mechanisms whereby different enterprises can pool their resources or compete to bid for resources offered by third parties. New means for identifying, analysing, and communicating with finely delineated

groups of consumers on the basis of patterns of online activity (Olson & Chae, 2012; Trusov et al., 2016), as well as their purchasing and investment, facilitated by AI, may assist agricultural producers develop new markets and better satisfy the desires of consumers in existing markets. AI will also make it easier for agricultural producers to dynamically control environmental and other factors relevant to food safety (Kamilaris et al., 2017) and to reassure consumers about the safety and origins of their food by tracking individual items or batches of food across the entire chain of the production, handling, packaging, and transportation using the “Blockchain” (Coble et al., 2018; Weersink et al., 2018; Xu et al., 2020). The agricultural sector is also likely to receive significant benefits from the increase in the predictive power of various other sorts of forecasts relevant to the deliberations of the sector, including climate models and long-range weather forecasts (McGovern et al., 2017), estimates of the likelihood of outbreaks of (and predictions about the spread of) pests and diseases (Stevens & Pfeiffer, 2011), and economic modelling more generally (Heaton et al., 2017; Zhao et al., 2017). Farming “smarter”, in all these ways, will allow farmers to do more with less.

Insofar as AI is one of the key enabling technologies for robotics and especially for semi-autonomous and autonomous robotics, AI may also play a pivotal role in generating all the benefits that might flow from the increasing use of robots in agriculture. In particular, increasing the number of tasks that can be performed by robots might allow the sector to overcome the limitations imposed by labour shortages on productivity (Duckett et al., 2018). This might allow farmers to grow crops or pursue methods of farming, such as organic farming or permaculture, that are currently not economically feasible owing to the price of labour (Daum 2021). Improvements in machine vision, as a result of machine learning, may allow farmers to deploy robots to destroy weeds without recourse to the use of herbicides (Slaughter et al., 2008).

All of these outcomes might in turn make a substantial contribution to the sustainability of agricultural practices. In particular, if AI systems succeed in reducing the amounts of pesticides, fertilisers and water used to produce food, this would benefit the environment as well as farmers (Kamilaris et al., 2017).

A final benefit, which we will highlight because we expect it may be very significant in the longer term, will flow from humanity’s increased power to “design” plants and animals, either through selective breeding or via direct genetic modification, over the next few years and decades (Ma et al., 2014; Ferraz et al., 2014). AI plays a crucial role in modern genomics, which in turn relies heavily on big data. The increases in the yields of modern crops and livestock as a result of selective breeding have been dramatic and we should expect that, via its contribution to genomics, AI will enable further, possibly large, increases in yield by facilitating a better understanding of the metabolisms of plants and animals and allowing us to manipulate them to suit our purposes.<sup>2</sup>

Applications of AI in the broader society and economy may also generate significant benefits for the agricultural sector. A fully realised driverless vehicle technology might reduce the cost of bringing crops to market via (driverless) long-haul trucking. To the extent that one believes that contemporary stock markets represent an efficient way of allocating resources, including investment, then the increase in the speed and scope of stock markets facilitated by AI should be celebrated for its capacity to price and distribute agricultural goods more efficiently. To the extent that one believes that government planning and regulation is essential to ameliorate the potentially disastrous effects of the market on consumers – and especially the poor – when it prices goods out of their reach or distributes them to more profitable markets overseas, and/or to reduce the risks of the various destructive cycles and crashes to which agricultural markets are prone, then the development of AI tools to facilitate more effective planning and more comprehensive surveillance of production and consumption should be applauded.

For the most part, all of these benefits are, as yet, theoretical and it is unclear how many, or which, of them will be realised and to what extent. We believe that many of them, especially those deriving from increases in scientific knowledge due to AI, *will* eventually be realised, although the timeline for this to occur is likely to be longer than many pundits advertise. While we have emphasised the benefits to *producers* in the agricultural sector, many of these should also flow onto consumers in the form of lower prices and/or better products. Society will also benefit, if the result of all these various improvements is a more sustainable agriculture and secure food supply.

### 3. Risks

Inevitably, the pursuit of these benefits will also involve risks. In this section, we highlight various possible unintended consequences of the applications of AI in agriculture and the impacts for agriculture of developments in AI elsewhere. We describe these as “risks” rather than “costs” because it is not certain that each will eventuate (or to what extent they will eventuate if they do eventuate) and because some of them, especially those involving changes in power relations or transformations in social practices, are not necessarily negative for all parties concerned.<sup>3</sup> We have chosen to spend more time on the risks of AI than the benefits, not because we think that the risks are more likely than the benefits, or will outweigh the benefits, but because the incentives, particularly in the private sector, to realise the benefits are stronger, and more likely to be effective, than are the incentives to avoid the risks, which may require acting in the collective interest rather than in the pursuit of private gain. For this reason, we believe it is important to clearly identify the risks and draw them to the attention of those actors and institutions that might have the power to mitigate them. The risks should be of especial

concern to governments, which are charged with serving the public good, and to the broader community who may be affected by them. Although we do not treat it separately below – not being a risk “of” AI – it is also clear that failure to secure the potential benefits from AI should itself be counted as a risk that should be taken seriously in deliberations about these matters.

### **3.1. Technologically mediated unemployment**

Perhaps the first risk that occurs to people when they think about AI is that it will take over their jobs.<sup>4</sup> The capacity of AI to replace human beings in carrying out cognitive tasks is both what *makes* it AI and makes it attractive to industry. Once machines are better at performing the tasks that are required to produce some good and/or can produce it more cheaply, there will be little incentive to employ human workers.

Use of agricultural robots enabled by AI, for the most part, might threaten the jobs of people currently performing manual labour. However, the idea that AI might eliminate many white-collar positions is now being widely promulgated (Brynjolfsson & McAfee, 2014) suggesting that AI might threaten job losses in both blue-collar and white-collar roles in agriculture, as elsewhere in society (Frey & Osborne, 2017). While the applications of AI will undoubtedly generate *some* new jobs it seems unlikely that will create as many jobs in agriculture as it would eliminate.

However, there is significant uncertainty regarding the timescale over which job losses due to AI are likely to occur. The extent to which AI impacts on farming and rural communities will depend upon how capable AI becomes and how widely it is adopted. In particular, it depends on how long it takes for improvements in machine vision, navigation, and planning to allow robots to play a significant role in agricultural production. In the short term, we suspect that large impacts are unlikely, given the limitations of existing robots (Kamilaris et al., 2018), which struggle to integrate the various discrete technologies (machine vision, navigation and localization, battery technologies, safe operations, and dextrous grasping) required to carry out useful tasks in agricultural contexts (Duckett et al., 2018) and/or to operate effectively in the unstructured, often cluttered and highly variable environments characteristic of agricultural settings (Bechar & Vigneault, 2016), despite the current hype around them.<sup>5</sup> Over the longer term, however, we anticipate large impacts.

We suspect that the prospect of being replaced by a machine will be viewed negatively by most of those currently employed in the agricultural sector. However, this is one case where the framing of this outcome as a “risk” must be accompanied by two significant caveats. First, in at least some cases, the elimination of agricultural work should be celebrated, where the jobs that people previously needed to perform were dangerous, backbreaking, or degrading. For that matter, there is an argument to be made for celebrating



the elimination of all “work”, presuming that new social and economic relations can arrange to ensure that every person is provided with material abundance (Srnicek & Williams, 2015). Second, given that human workers will only be replaced if it is cheaper to produce agricultural products using AI and robots than human beings (Lowenberg-DeBoer et al., 2020), this eventuality will lower the price of agricultural goods and benefit consumers as well as producers. Whether this prospect should be judged a risk or a potential benefit, therefore, depends on a value judgment about the relative importance of providing people with the opportunity to work versus the economic benefits of full automation (Sparrow, 2021).

### **3.2. Transformation of the nature of agricultural work**

Those jobs in the agricultural sector that survive the widespread adoption of AI are, nevertheless, likely to be significantly transformed. By allowing fewer human beings to supervise more machines, AI systems will make farmers’ jobs more white-collar and professional (Bell et al., 2015). In the future, management of the farm may differ little from management of any other complex enterprise carried out by teams of humans and robots. Bell et al. (2015) argue that a transformation of the cultural image of the farmer from a person involved in manual labour on the land to a white-collar manager is already being promoted in the advertising of fertiliser, pesticide, seed and farm machinery manufacturers. An emphasis on “management” and attention to data as key skills in farming is in turn likely to transform farmers’ relation to the land and landscape, and to their crops and animals, and further attenuate their relationship to the history of the practices in which they are engaged.

However, alongside this transformation of the role of the farmer, AI is also likely to change the nature of those jobs that do remain for farm workers. When the only jobs available to humans are those that machines can’t do, many of the jobs that remain are actually likely to require less skill (Bell et al., 2015; Carr, 2015). The susceptibility of a job to computerisation is a function of whether it is predominantly cognitive or manual labour and if it is routine or non-routine (Autor et al., 2003; Frey & Osborne, 2017). With increased automation, the labour market has progressively polarised, with employment growth occurring in complex cognitive tasks (non-routine cognitive) and certain physical work (non-routine manual). However, while machine learning and the availability of large data sets is enabling further expansion of automation into the area of non-routine cognitive tasks, the same is not true for manual labour. Physical activities that require dexterity, physical flexibility, sightedness, and adaptability to unstructured environments and across tasks are difficult to automate, even with AI, while remaining straightforward to most workers (Frey & Osborne, 2017; Acemoglu & Autor, 2011; Autor et al., 2003; Autor & Dorn, 2013). Consequently, unskilled farm labour requires little training but, by virtue of

needing to be completed in unstructured environments, stubbornly resists automation. Thus, until we see very significant improvements in the capacities and performance of agricultural robots, increased use of AI in agriculture is likely to lead to the elimination of many jobs for skilled workers in agriculture and increase the percentage of agricultural work that consists in unskilled labour.

### **3.3. Concentration of ownership**

Another risk, which is relatively pronounced in the agricultural sector, if not unique to it, is that AI, and especially the “big data” on which it relies, will lead to increased concentration of ownership of land and capital (Fleming et al., 2018; Wolfert et al., 2017).

As with the introduction of any new technology, AI has implications for power relations between individuals and within organisations. While, in theory, AI systems might be designed to flatten hierarchies and empower individuals, in practice these systems tend to centralise political power by making it easier to surveil a wider number of locations and persons and also by establishing incentive structures that effectively require individuals and organisations to “sign on” or risk missing out on opportunities associated with participation (Campolo et al., 2017; Holt et al., 2017; Prainsack, 2019). Network effects are very powerful when it comes to AI. Larger enterprises are better placed to take advantage of AI both because they can better afford to invest in it and also because, by virtue of being larger, they generate more data upon which the AI can operate, theoretically leading to more powerful AI. Indeed, AI risks establishing and exacerbating a “big data divide” between data rich and data poor individuals, organisations, and nations (Andrejevic, 2014; Boyd & Crawford, 2012; Rotz et al., 2019). Sometimes this is a matter of there simply being less data where there are fewer sensors or means of gathering it. Sometimes it is a matter of there being different sorts of data about rich and poor (Eubanks, 2018). However, whatever its origins, differences in the data about different groups will lead to them being differently served by AI. Thus, as an early discussion of the implications of big data had it, ‘big data has power effects of its own, which privilege large government and corporate entities at the expense of ordinary individuals’ (Richards & King, 2013). That the use of big data might privilege some actors over others is a significant risk in the context of agriculture, where the agricultural sectors of some nations are much more highly industrialised than others. A related issue, which seems to have received less attention, is the possibility that the introduction of AI into farming will lead to the intrusion of more claims about intellectual property in methods of farming and food processing, which in turn might exacerbate inequalities between wealthier and poorer enterprises (Carbonell, 2016; Kamilaris et al., 2017).

Thus, while, in theory, early adoption and aggressive use of AI might allow smaller farms to develop a competitive advantage over larger concerns, which are likely to be less agile adopters, in the longer term it seems unlikely that AI will buck the larger historical trend of new agricultural technologies favouring consolidation. If it has any impact on the size of farms or production facilities, then, it seems more likely that AI will allow larger enterprises to outcompete and then absorb smaller enterprises, leading to higher levels of concentration in the sector (Fleming et al., 2018; Wolfert et al., 2017). Although such consolidation is associated with, and helps generate, various efficiencies in production, we believe that it should be counted as a risk, given the threat that industrialised agriculture poses to biodiversity (Foley et al., 2011; Raven & Wagner, 2021) and – especially in the context of climate change – food security (Food and Agriculture Organisation of the United Nations (FAO) et al., 2015).

### **3.4. Exploitation and surveillance**

There are also significant concerns about the *ownership* of the data generated, and relied upon, by AI systems and the possibility that this will be used to monitor the activity of farmers, either for the purposes of regulating compliance with policy, or in order to secure a bargaining advantage over them in the context of commercial arrangements (Wolfert et al., 2017). If data is the “new oil” then it is little surprise that those who gather and/or create it may wish to exploit it or sell it on or otherwise extract value from it (Economist, 2017). Some of these uses will inevitably be controversial. For instance, a company that leases out tractors that contain soil sensors might use the data gathered by those sensors to inform its speculations in the agricultural futures markets or sell it to other interested parties who might then use it to extract concessions from the farmers: if a company selling water has access to data about soil moisture content gathered by a farmer’s tractors or drones, they may be able to raise prices in circumstances where the farmer might otherwise have been able to bluff about their willingness to walk away from a sale. More generally, the rise of AI and big data may lead to a substantial loss of autonomy by farmers and their subjugation to a network of commercial and institutional demands that are imposed and enforced by machines (Fleming et al., 2018).<sup>6</sup> AI systems will also tend to place workers in the agriculture sector under more surveillance as the data generated by these systems will also function to track and monitor those who work with them (De Stefano, 2018).

### 3.5. Vulnerability to hacking

Adoption of AI, as with other forms of information and computing technology, renders users vulnerable to hacking and other cyber-attacks by malicious actors, which must be counted as a risk in agriculture as elsewhere. While this may seem speculative, so called “ransomware” attacks are increasingly common in industry more generally, with some attacks having caused millions of dollars of damage (Greenberg, 2018). The impacts of such cybercrime, where it does occur, are likely to increase with concentration of ownership (and thus electronic infrastructure) in the agricultural sector. If AI comes to be sufficiently widespread and play a sufficiently important role in agriculture, this may even render industrialised nations’ agricultural sectors vulnerable to cyber-attack during, or prior to, war (Clarke & Knake, 2010). For instance, a software exploit that caused autonomous tractors to plant seed too deep, or to under-water crops, or that simply “bricked” them when they were most needed, might cut a nation’s agricultural output by an appreciable amount, which in turn might have broader, even catastrophic impacts on food security and, therefore, social order.

### 3.6. Bias

Because the quality of the outputs of machine learning systems is highly dependent upon the quality of the data on which they have been trained, “bias” in the data may lead to perverse outcomes. “Bias” here may simply mean data which distorts the reality it is supposed to represent, as, for instance, when image recognition systems are trained using photos in which different classes of objects tend to be photographed in different lighting conditions, or against different backgrounds, leading the machine to classify objects on the basis of the background or lighting (McCarthy et al., 2010; Slaughter et al., 2008). However, it may also mean data which has been generated in ways that implicate it in social injustice and which might reinforce injustice when used to train machine learning algorithms (Eubanks, 2018; O’Neill, 2016).

Two sorts of bias are worthy of highlighting in the context of agriculture.

First, initially at least, the main markets for AI tools for agriculture will be the United States, Europe, and (perhaps) China. There is a danger that farmers in other regions will inherit AI systems trained on data about crop yields or soil chemistry in the US, Europe, or China, rendering them highly problematic in the local context elsewhere (Keogh & Henry, 2016); efforts to correct this by retraining the systems using data about crops grown under local conditions will still embed a preference for some crops over others.

Second, the farming practices and environments that produce this data are themselves likely to be industrial farming practices. Yet in many parts of the world there are vibrant traditions of small scale and indigenous farming, which are

unlikely to generate the sorts of data that are used to train AI systems because the technologies of digital agriculture play little role therein. If the circumstances, challenges, and experiences of small landholders and indigenous peoples are not represented in the data used to train agricultural AI then these systems will, in an important sense, be biased against such traditions. As noted above, this is likely to mean that agricultural AI will serve indigenous and small-scale farmers poorly – if they work at all in these contexts. However, the exclusion of these perspectives from a technology that is widely touted as playing a key role in the future of agriculture might also be criticised on political grounds as effectively denying the right of small-scale and indigenous farmers to contribute to shaping that future. It would also mean that society would fail to benefit from the valuable knowledge of the local climate, flora, and fauna contained in these traditions.

### ***3.7. Explainability, trust, and responsibility***

Many machine learning systems are “black boxes” even to those who set them in motion (Burrell, 2016). There is a risk with some forms of AI, especially those involving machine learning systems, that no human being understands why the system does the things it does and thus what it might do in unexpected circumstances. This feature of machine learning raises urgent practical questions about when it is appropriate to trust such systems and in what roles (High-Level Expert Group on Artificial Intelligence, 2019). What should farmers do if an AI system, which is usually highly reliable, recommends a course of action that goes against the farmer's, own considered judgment? The difficulty of determining when to trust AI creates a risk of accidents as a result of over trusting – or under trusting – such systems. It also exacerbates a problem that arises for AI more generally, concerning the allocation of responsibility for outcomes generated by AI systems (Sparrow, 2007; Johnson, 2015; Matthias, 2004; Wiseman et al., 2018). Were, for instance, an “intelligent” drone crop-dusting system controlled by an AI to contaminate the fields of the neighbouring organic farm with pesticide, who should take the blame? The farmer who employed the system? Or the designers of the AI? Or the people who provided the data on which it was trained? There is a risk both that the wrong party might be held responsible and that no-one might be held responsible. Until these issues can be resolved there is a risk that the potential benefits of AI in agriculture may not be realised as a result of farmers and other producers of agricultural goods and services being reluctant to embrace AI.

### ***3.8. Transformation of rural/urban relations***

Should AI lead to significant job losses in farming and in rural communities and/or further concentrate wealth within the agricultural sector, this may lead to demographic shifts as well as shifts in the social and political relationship between rural and urban populations (Rotz et al., 2019). It may be harder to

maintain political support for farmers and for the agricultural sector, if they come to be perceived as merely part of the IT sector or if the concentration of wealth in the sector provokes populist hostility. In the long term, the emergence of new niche enterprises, in hospitality or tourism, for instance, in rural areas in response to declining job opportunities in agriculture, along with the relocation of jobs in farm management (and even farm operations, if teleoperation of agricultural robots becomes feasible) to the city may gradually blur the cultural differences between (some) urban and (some) rural areas (Gosnell & Abrams, 2011; Klerkx et al., 2019), making it more difficult to sustain a distinct “rural” political constituency.

### **3.9. Economic vulnerability**

The agricultural sector may also become vulnerable to unanticipated consequences of the adoption of AI in the broader economy and society. It is possible, for instance, that the price of agricultural goods and services might change rapidly and without regard to what might ordinarily be considered economic realities as a result of the interactions of AI share trading systems. The 2010 “flash crash” drew attention to the possibility that high-frequency trading algorithms might interact in unexpected ways to generate dangerous outcomes (Bridle, 2018). While share prices rebounded in that particular case, there is a risk that the price and short-term availability of food staples might be distorted by similar events in the future.

### **3.10. Environmental risks**

The applications of AI in agriculture mostly seem to promise environmental benefits. While there are some environmental costs of AI both in terms of the consumption and mining of rare earths to produce the hardware that sustains it, and the power to run AI systems, these are no more pronounced in agriculture than elsewhere. However, one risk is that AI contributes to the spread of monoculture, which renders agriculture more fragile by virtue of being more susceptible to crop failures owing to plant diseases and has well-known negative impacts on the environment (Tilman, 1999), via its contribution to the development of more genetically modified organisms for agriculture.<sup>7</sup>

### **3.11. Alienation from the natural world**

Another form of risk to the environment from AI is more subtle. The process of abstraction – moving away from the real world to representations of the world in databases – required to render problems amenable to solution by AI is itself ethically and philosophically significant. AI systems “flatten”, and distort our understanding of, the world by virtue of turning everything into data. Reducing

everything to data reduces the distinction between different domains: data is all. This seems especially problematic when it is the natural world that we risk losing sight of in the course of this process (Ellul, 1964; Heidegger, 1977). If widespread adoption of AI in agriculture changes the way we perceive and value the natural world and our place in it, by bringing us to understand it primarily through the lens of “data”, this might undercut political support for environmental initiatives that are not easily advocated for in terms of data trends. It might also impact negatively on animal welfare insofar as the real-world suffering of animals in some agricultural contexts might be obscured both by the data that is collected and by the fact that it is represented by data rather than witnessed at first hand (Holloway et al., 2013; 2014; Woods, 2012). The world is not data and plants and animals are not machines. Coming to treat the natural world as a data system to be analysed and manipulated may be bad for us, intellectually and spiritually, and also bad for that world.

#### **4. Discussion: Managing the risks of artificial intelligence in agriculture**

In thinking about the future of agriculture, we must be careful to avoid technological determinism. Without denying that technologies have affordances and that economic imperatives may strongly encourage particular applications of technologies, it is important to recognise the agency that citizens, communities, engineers, and governments possess when it comes to shaping technological trajectories (Jasanoff, 2016).

Some of the risks described above might be mitigated by good design and thus should be central concerns of designers and manufacturers of AI for agriculture. A number of the risks associated with use of AI in agriculture are associated with features of AI – its susceptibility to bias, “black box” nature, and vulnerability to hacking – that are equally, if not more, problematic in other contexts where AI is being adopted. To a large extent, designers and manufacturers of AI for the agricultural sector should be able to draw upon means to mitigate these risks being developed elsewhere. The dangers of bias, and methods for overcoming them, are increasingly well known and the topic of intensive discussion and research (O’Neill, 2016; Osoba & Welsler, 2017; Zarsky, 2016). Designers of AI for agriculture might make a deliberate effort to ensure that, as much as is possible (and with the appropriate consultation and consents), the experiences and perspectives of marginalised communities are reflected in the data on which AI is trained. Similarly, concerns about the transparency of AI systems have generated a flourishing research programme into “explainable AI” (Gunning, 2017; Swartout et al., 1991). It is possible that, by the time AI is starting to be adopted more widely in agriculture, this programme will have delivered sufficient results that, backed up by appropriate regulation if necessary, it will allow users to make informed decisions about the

risks and benefits of particular AI systems in particular applications and also about when to trust them. Obviously, (in)vulnerability to hacking is a key consideration in the design and manufacture of any information technology.

However, good design alone is unlikely to *entirely* mitigate, let alone eliminate, these risks. Good policy will also be required. In so far as many agricultural enterprises are likely to rely on imported AI systems trained on agricultural datasets derived from agriculture in a few key locations internationally, it may behove governments to encourage, or even facilitate, the collection of relevant data locally to ensure that systems are well-suited to local conditions. Similarly, nations with significant traditions of indigenous agricultural practices and knowledge should consider – with the permission of, and in association with, indigenous peoples themselves – documenting them and integrating them into the databases that are used to train AI. Responsibility for the “actions” of AI may be settled as a matter of law – if not as a matter of ethics – either by the operations of the common law or by regulation to encourage beneficial, and discourage harmful, uses of this technology (Gasser & Almeida, 2017). Even if AI systems are manufactured to be relatively secure against hacking, it may be some time before agricultural users of these systems become accustomed to securing them from intrusion as a matter of course, and it might be wise for governments to consider public campaigns intended to educate farmers about the risks of hacking.

The issues around privacy, surveillance, ownership of data and the uses to which data may be put, as well as the appropriate role of intellectual property in farming methods, will need to be discussed at length between relevant stakeholders. There are different interests at stake here and a risk to those who generate data may be a benefit to others who come to own and profit from it and *vice versa*. The design challenges associated with these issues will only become clear in the light of such discussions. Addressing these issues is essential to facilitating the uptake of AI and should be a matter of priority for governments and manufacturers.

Again, however, insofar as the design of technologies does not entirely determine their use and because there are likely to be powerful incentives to design technologies that serve the ends of powerful social actors at the expense of other interests, policy making by governments will have a key role to play. While much can undoubtedly be done with existing law and regulation, it does seem likely that the introduction of AI into agriculture might generate outcomes that require new regulations, either “soft”, in the form of standards and incentives, or “hard”, in the form of legislation, up to that which imposes criminal penalties. Policymakers will need to set clear rules about what kinds of data about individuals may be used to inform the deliberations of AI and to keep a close eye on the possibility that injustices might be exacerbated by the operations of AI. One suggestion that has already been advanced by a number of authors is that there needs to be more of an emphasis on open-source software solutions and open



data in order to prevent the benefits of AI being concentrated in the hands of the few (Keogh & Henry, 2016; Carbonell, 2016; Jakku et al., 2019). Similarly, regulation may be necessary to protect users from exploitation and to ensure that existing imbalances of wealth and power are not wrongfully exacerbated by the introduction of the systems (Carbonell, 2016; Klerkx et al., 2019). Ultimately, we believe, the goal should be to develop democratic, and genuinely representative, forms of oversight and governance for the use of data in agriculture, as elsewhere.

Some of the risks we have identified relate to relatively large-scale social impacts of the use of AI in agriculture, which will need to be addressed primarily at the level of policy rather than design. The question of the implications of AI for the future of work are currently the topic of significant controversy and intense discussion both nationally and internationally. We suspect governments have more time to prepare for changes in the structure of the labour force as a result of AI than some pundits suggest. Moreover, given that we should probably celebrate the elimination of many jobs in the agricultural sector, which are often backbreaking and/or dangerous, the relevant question is what governments can do to ensure that those people who no longer work in this sector can support themselves and find meaning elsewhere (Howard, 2017; Srnicek & Williams, 2015). Nor is it necessarily the case that the change in the character of those jobs that survive the arrival of AI should be thought of as bad. Jobs managing AI, or managing farms that use AI, are likely to be more intellectually demanding, which, for some people, may make them more rewarding. If the unskilled labouring jobs that survive the advent of AI and robotics risk being more unpleasant and less rewarding than the work performed by seasonal agricultural labourers today, regulations to improve working conditions and policy incentives to raise wages may serve to make them no less attractive to workers.

The implications of the adoption of AI for rural/urban relations are along the same lines as those of technological progress and demographic changes more generally: fewer people live and work in the country every decade and an increasing number of those who do live in the country earn their livings from activities that either used to be located in the cities or which rely on the movement of people from cities into the countryside. These dynamics look set to continue (Johnson & Lichter, 2019) albeit exacerbated by the advent of AI. Political parties, especially those that traditionally represent rural interests, may need to adjust their policies and “pitches” in order to appeal to voters in changed political circumstances. Governments, and local authorities will need to – indeed, in many places already are – plan for these changes, which will require changes to the delivery of services, land use policy, and perhaps taxation and other financial incentives. It is not obvious, though, that special attention will need to be paid to the implications of AI as opposed to the impacts of technological progress in agriculture more generally.

Others of the risks associated with AI in agriculture that we have identified here are less obviously amenable to design or policy solutions: the risk that it will lead to a smaller number of larger landowners<sup>8</sup>; the risk that AI will encourage monoculture via its contribution to our understanding of plant and animal genomics; the impact on the sector of the adoption of AI in the broader society, and especially in share trading; and, the broader philosophical and social implications of coming to see the world through the lens of big data. Confronting these issues will require a more direct engagement with the question of the balance of the benefits and costs of AI.

Moreover, even where, as above, policy options are available, there are genuine differences of interest at stake. Responding to the prospect of technologically mediated unemployment as a result of AI will pit the interests of the newly – and perhaps permanently – unemployed against those of business-owners, who may need to be taxed to provide the former with a decent minimum standard of living. There are deeper questions here too, about the role played by the opportunity to make a meaningful contribution to one's community in establishing the conditions for a flourishing human life. As we have already observed, questions about the ownership, and legitimate uses, of data pit the interests of those who generate data and those who collect it against each other. Definitions of bias – as with claims about its absence – are inherently political. Decisions about which features of the world should be represented in data, and how, inevitably involve questions of value. Even decisions about cyber-security often involve trade-offs between the openness and user-friendliness of systems and their vulnerability to malicious actors.

Borrowing a leaf from a recent report by the Nuffield Foundation (Whittlestone et al., 2019), we suggest that it is especially important that we develop a better understanding of how different communities understand both AI *and* ethics, work to identify different values and interests at stake in the debate about AI and also mechanisms to facilitate and justify trade-offs between them, and strive to develop a better evidence base about the capacities of AI in agricultural settings as well as its impacts on different interest groups and the environment.

## 5. Conclusion

In order to minimise the risks and maximise the benefits of AI in agriculture, it is necessary to have an ongoing and inclusive conversation about the ethical issues raised by AI and its potential applications in agriculture (Whittlestone, et al., 2019). It is not our place to try to prejudice the outcome of this discussion, even if the space allowed. In particular, it would be wrong to foreclose the question of whether or not AI should be used in various roles at all. Nevertheless, key questions that we believe should be considered in such deliberations include: how to ensure AI is used to expand sustainable agriculture rather than simply to intensify existing, unsustainable, agricultural

practices; how to respond to the prospect of widespread job losses in the agricultural sector in the longer term; the risk that AI will exacerbate rather than reduce inequality; who should own data generated by AI and what they should be allowed to do with it; how to ensure that relations between farmers, seed and chemical companies, and suppliers of AI systems are productive and not exploitative; and, the philosophical and cultural implications of coming to see the world solely through the lens of “data”. Several of the ethical issues raised by AI in agriculture intersect with ongoing controversies about agricultural policy more generally, including: whether governments should try to protect “small farms” from being out-competed and bought up by larger concerns; the appropriate role of the market vis-à-vis food security; the ethics of intensive animal production; the relative merits of large-scale versus small-scale farming; and, the wisdom of genetic modification of crops and animals.

We believe that it is vitally important that the broadest possible community be included in this process, both in order to benefit from the insights of a diverse range of perspectives and because what happens in the agricultural sector ultimately affects all of society. Those who are concerned about the risks of the applications of AI in agriculture should welcome the opportunity to draw them to the attention of a broader public. Those who are confident that AI overwhelmingly holds out the prospects of benefits should have no fear of such debate.

## Notes

- [1] The potential costs, which we here conceptualise as risks, are discussed in the next section.
- [2] It is worth observing that both the ethics of this project and its long-term implications for sustainability are contested (Macnaghten, 2004; Rollin, 1995; Bruce & Bruce, 2014).
- [3] We discuss these cases in the course of our treatment of the ethical and policy questions they raise.
- [4] The other, of course, is that it will take over the world (Bostrom, 2014). However, this risk is clearly independent of the applications of AI in agriculture, so we will not discuss it here.
- [5] These difficulties are more pronounced in some (especially “field”) settings than others and thus the prospects for labour savings (and job displacement) due to robots differ across different settings. For further discussion, see Sparrow and Howard (2021).
- [6] For example, the increasing need for farmers to access high-tech equipment means they are already being coerced into agreements with equipment and service providers that limit their capacity to determine how these services are used (Sparrow & Howard, 2021; Shah, 2018). The recent trend towards manufacturers providing products designed to stop consumers performing even basic repairs, thus forcing the owner to utilise the manufacturers’ “authorised” repair networks, or to upgrade or replace the product (Grinvald & Tir-Sinai, 2019) has generated a vigorous “right to repair” movement focused on reinstating consumer repair rights.

- [7] Insofar as the environmental risks associated with GMOs themselves are contested (Hillbeck et al., 2015), some may conclude that the potential of AI to contribute to the development of new GMOs itself should count as a risk to the environment.
- [8] Engineers involved in the development of AI for applications in robotics may have *some* role to play here, insofar as whether robots will only be suitable for use in large scale industrial agriculture or may be amenable to applications on smaller, biodiverse, farms, will depend, in part, on the ultimate form, and capacities, of agricultural robots (See Daum, 2021). However, as, for the most part, the relevant questions concern the “bodies” of robots rather than their “brains”, it remains true that the design of AI is unlikely to play a significant role in addressing this issue.

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