

Surveillance agriculture and peasant autonomy

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Abstract

‘Big Data’ digital technologies are beginning to make inroads into peasant agriculture in the Global South. Of particular importance is the subset of technologies that appropriate agricultural decision-making, here theorized as surveillance agriculture. These technological regimes aspire to not only remove decision-making from the farmer, but eventually to replace the farmer with, for instance, ‘autonomous’ tractors. This paper looks ahead to ask what a technological trajectory that aspires to autonomy for the tractor may portend for autonomy for the peasant farmer. It compares surveillance agriculture to other forms of surveillance capitalism, noting that it shares a will to not only sell products and services but to manipulate behaviour but differs in that the behaviour being manipulated is professional productive behaviour. The paper surveys the vested interests of the entities behind surveillance agriculture and asks how informational relations of production may be changed between farmers and these entities. It then examines the informational relations of production among peasant farmers that may be interdicted by surveillance agriculture, especially the group-level decision-making dynamics that make ‘individual autonomy’ a misnomer. But surveillance agriculture is resolutely individualized, which raises concerns for peasant decision-making autonomy.

KEY WORDS

autonomy, deskilling, digital agriculture, peasants, surveillance

1 | INTRODUCTION

Digital agriculture is often called ‘Big Data’, and it is big indeed, having gotten so by monetizing the small. Digital technologies can monitor field conditions down to the inch and instruct the farmer on what to do and exactly when and where to do it. They run on a ravenous diet of intimate data, collected from great distance (satellites), near distance (drones), from up close (the tractor console and cell phone) and from deep within (microchips embedded in livestock). One agricultural technology company estimates that participating farms will be generating over 4 million data points per day by 2050 (Gralla, 2018), although in actuality the types of technologies that will be in place by then are unfathomable. Digital technologies are becoming established as the next major external input into agriculture and are used on over 75% of corn acres in the United States, 80% of grain farms in Australia and two-thirds of all arable land in the Netherlands (Carolan, 2017, p. 3; Michalopoulos, 2015). The digital technologies known as *precision agriculture* (PA) are the most widely used, including detailed soil mapping; ‘variable rate application’ control of seeding, fertilizing, irrigating and spraying; automatic machine guidance; and autonomous vehicles (Say et al., 2018). But digital applications are highly diverse and rapidly evolving.

Digital agriculture increasingly has the Global South in its sights (Rotz et al., 2019, p. 204), with varied projects and technologies starting up or planned in Asia, Africa and Latin America. In this push, agri-capital is joined by other players including the USDA and the CGIAR¹ network, which gives cash awards to emerging digital technologies through its ‘Inspire Challenge’ programme and which recently hosted a smallholder-focused virtual Convention on Big Data in Agriculture with over 1500 attendees and over 500 speakers. How new digital technologies may impact the small farmers that the CGIAR is supposed to serve is a good question but also a speculative one since the move is in its early stages and there has been scant empirical research on impacts. There has been little challenge to the potential untoward effect on peasants (as happened with genetically modified crops, for example; Schurman & Munro, 2010), and few critiques have ventured much farther than Wolf and co-workers’ early arguments specifically on PA in the Global North; they argued that, futuristic innovativeness notwithstanding, the real impact would be to further the ‘integration of on-farm activity into a coordinated system of industrial manufacture’ (Wolf & Wood, 1997) and the subordination of farmers’ interests to those of agribusiness (Wolf & Buttel, 1996). Similarly, Mooney (2018, p. 8) predicts a continuation and exacerbation of the past trend of vertical and horizontal consolidation in agri-food companies ‘leading to more mergers and grander monopolies’; Clapp (2021, p. 406) sees continued extension of the leading agri-food corporations’ market power; Rotz et al. (2019, p. 208) see continuation of historical trends of increasing market integration, rising farmer debt and exclusion of ‘small, peasant and agro-ecological farmers’. Even Ravis and Notkin (2020), in their notable critical intervention, essentially see PA as furthering the metabolic rift between rural and urban. ‘Less a revolution than an evolution’, writes Miles, ‘precision agriculture is conventional agriculture’ (Miles, 2019, p. 1).

In some senses, the ‘old wine in new bottles’ critique is indisputable. PA is definitely an industrializing technology that continues the processes of ‘appropriation and substitution’ in agriculture (Goodman et al., 1987; Wolf & Buttel, 1996, p. 1270), a new frontier of commodification and ‘pulling-away of the natural ground’ in agriculture to substitute capital for experiential knowledge (Marx, 1973 [1857], p. 527; Wolf & Wood, 1997, p. 184). Its rise has been propelled not simply by advances in digital technologies but because chemical-intensive agriculture needed insulation from rising environmental challenges (Wolf & Wood, 1997, p. 180). Digital agriculture’s research intensiveness also continues the capturing of value from and loyalty of publicly funded academic researchers (Kenney, 1986; Lipton, 2015).

On the other hand, lumping precision (and other digital) agricultural technologies with ‘conventional’ agriculture may obscure how new decision-appropriating technological regimes could pose novel threats to the autonomy of

¹The USDA is the United States Department of Agriculture. CGIAR is the Consultative Group on International Agricultural Research, a network of 15 non-profit agricultural research centres.

some types of farmers. In fact, a report from the US President that was repeated in a European Parliament report cited as a ‘profound challenge’ the ways in which

big data analytics may ... create such an opaque decision-making environment that individual autonomy is lost in an impenetrable set of algorithms ... Unless individuals are provided with appropriate information and control, they ‘will be subject to decisions that they do not understand and have no control over’. (Kritikos, 2017; Office of the President, 2014)

But digital technologies probably pose no novel threat to the autonomy of industrialized farmers, many of whom have been consumers of commodified decision-making for decades (Wolf, 1998a, 1998b; Wolf & Wood, 1997); my argument here is that peasant farmers may be a different story, especially after we undertake a fresh rethinking of what autonomy actually means in peasant agriculture.

Note that ‘industrialized farmers’ here refers to entirely commercial, capital-intensive operators with heavy dependence on purchased inputs. ‘Peasants’ here are rural farmers who produce some for the market in asymmetrical power relationships with buyers (Wolf, 1966), who rely primarily on labour-based intensification and maintain a partly self-controlled resource base including a farm smallholding under 5 ha (Dove, 2011; Netting, 1993; van der Ploeg, 2008). By this or similar definitions, peasants produce between 50% and 75% of the food calories consumed globally (Ricciardi et al., 2018; Samberg et al., 2016). For this vast class of farmers, production processes have vital social elements, including the supra-household organization of production and especially the key social elements in decision-making. Potentially at stake here are *informational relations of production*, defined as relationships that control the creation, interpretation, dissemination and deployment of information needed for productive processes (a concept developed below). Some digital technologies obviously can—indeed *aim to*—disrupt and reformulate such relations.

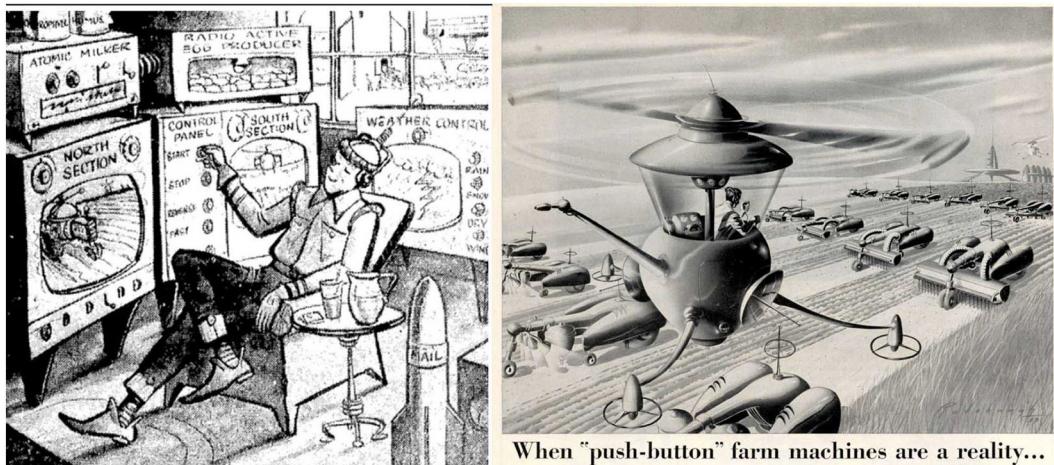
First note that even though digital agricultural technologies are often lumped as ‘decision-support tools’,² they will have markedly different impacts on informational relations of production. Most importantly, there is a continuum of appropriating rather than supporting decision-making (Lioutas et al., 2019, p. 1). Some technologies deliver generic information, such as weather reports or market pricing. These are sometimes labelled ‘dumb technologies’ (Stone, 2011, p. 11; van der Meer et al., 2003) although this is a misnomer as they can help farmers operate more smartly. Other technologies provide digital communication conduits among farmers without advising or deciding for them. Further along the continuum is what I define below as surveillance agriculture: digital technologies that appropriate decision-making based on the flow of data from individual farms and farmers. At the end of the line (?) are technologies that largely remove the farmer from decision-making, epitomized by ‘unmanned aerial vehicles’ (Radoglou-Grammatikis et al., 2020) and ‘autonomous’ tractors: the apotheosis of mid-century depictions of hyper-mechanized de-farmered agricultural futures (Figure 1).³

What does a technological trajectory that aspires to *autonomy for the tractor* portend for *autonomy for the peasant farmer*?

The question obviously requires speculation, but it is an urgent one, and I will address it in five steps. First, I provide an overview of the digital technologies being developed and deployed in the Global South, particularly for peasant farmers. Of primary interest from the perspective of peasant autonomy are the decision-appropriating technologies noted above; these are invariably based on various forms of surveillance, and I argue that they cannot be understood apart from the new information economies termed *surveillance capitalism*. Second, I consider the nature of surveillance capitalism, particularly as theorized by Zuboff (2019a), and identify two features of it that are pivotal in what I define as *surveillance agriculture*: first that surveillance capitalism inexorably moves towards not only

²The tenet that the technologies support, rather than appropriate, decision-making is reflected in the acronym SADSS, for sustainable agricultural decision support systems (Dutta et al., 2014, p. 264).

³Farmer-replacing machines are being developed not only by major manufacturers like John Deere and Kubota but by often snarkily named start-ups such as Rowbot and Robocrop. Meanwhile, the major fertilizer company Yara is developing crewless freighters (Mooney, 2018, p. 17).



When "push-button" farm machines are a reality...



Autonomous Tractors

FIGURE 1 Above: Mid-century depictions of future hyper-mechanized almost farmerless cultivation (Novak, 2011). Below: The apotheosis of farmerless cultivation, the autonomous tractor (Louise, 2010). Autonomous tractors were introduced by two companies at the 2016 Farm Progress Show (Carolan, 2020)

predicting but manipulating behaviour and second that surveillance capitalism generates value from highly individualized interactions that may be incompatible with the social aspects of peasant agriculture. In the third section, because farmers may be manipulated to many different ends, I survey the roster of players that are developing and promoting surveillance agriculture in the Global South—‘Big Others’ in Zuboff’s terminology—and their vested interests. Fourth, I consider how the vested interests of Big Others may lead them to interact with peasant farmers. Lastly, I consider how these interactions—new informational relations of production—may affect peasant autonomy, which requires a fresh thinking of what autonomy really means given the highly social nature of peasant agriculture.

2 | DIGITAL AGRICULTURE HEADS SOUTH

Technologies for delivering generic information—the non-surveilling end of the continuum noted above—have appeared in many areas of the Global South in recent decades. In this, India has been a leader, with its advanced ICT

sector and large population of peasant farmers reliant on simple technology; there have been several Internet Kiosks (or ‘e-Choupal’) projects there, most of which provided information on weather, market prices and pest/disease outbreaks (Stone, 2011). Other technologies essentially provide digital communication conduits among farmers; examples are the farmer-made video platforms run by Digital Green (Harwin & Gandhi, 2014) and Access Agriculture (Bentley et al., 2016).

The next step along the continuum would be technologies that provide specific advice in response to farmer requests. The responses may be generated automatically; an example is the ‘PlantVillage Nuru’ programme in Tanzania and Kenya, developed by scientists at Penn State University, in which farmers use a smartphone app to send information to a computer with algorithms for diagnosing crop diseases (Mrisho et al., 2020; Neno, 2020). Responses may be semi-automated; the Ushauri project fielded by the BiodiversityInternational-CIAT Alliance, also in Tanzania and Kenya, lets farmers call in and select recordings (Alliance, 2021). Responses may also be generated by human advisors; an example is the ‘e-Sagu’ project run by the International Institute for Information Technology in India, in which ‘agricultural experts’ responded to images of cotton cultivation problems with tactical advice (Stone, 2011).

Further along the decision-appropriating end of the continuum are technologies that push information to farmers. PAD (Precision Agriculture for Development, an NGO that partners with various agencies and input companies) runs a programme in Nigeria that pushes cell phone messages to farmers with information and advice keyed to the cropping schedule. Whereas some messages simply contain information about soils and harvest practices, others recommend chemical fertilizer amounts and urge farmers to buy pesticides (Precision Agriculture for Development, 2021c).

Further along the continuum are systems that prescribe what input vendors should offer and farmers should adopt based on farm location and characteristics. The Biosense Company’s Mexico-based ‘Machine Learning for Smarter Seed Selection’ project advises on specific maize seeds, ‘optimized’ on the basis of ‘deep learning’ analysis of research plots. Key decisions about seed choice are given using criteria that are opaque to the farmer (CGIAR, 2018); it allows ‘seed companies and government programs ... to make more specialized selections that are individualized to farmers’ needs’ (AgNews, 2019) rather than having farmers save seed and make their own choices.

Further yet along the continuum are the more surveillance-intensive decision-appropriating technologies that are of special interest here. PAD’s Ama Krushi project in Odisha, India, broadcast up to 24 messages each week to 1.3 million farmers; the messages are time specific and customized to their field locations, crops grown, irrigation status, smartphone ownership, language and gender (Precision Agriculture for Development, 2021a). Another example is the 2017 CGIAR Inspire Challenge-winning ‘Seeing is Believing’ project in India that implemented picture-based advisory and picture-based insurance systems (CGIAR, 2019). Farmers ‘enrol’ individual plots in the app and then submit geotagged photographs that are analysed by software and agronomists who provide ‘provide personalized agricultural advice based on real-time observations of crop conditions, from sowing to harvest’ (Kannan et al., 2019, p. 1). The images are also used to surveil farming practices to assess farmers’ creditworthiness and improve timing of credit disbursement (Kannan et al., 2019). From India, the project has expanded into Ethiopia and Kenya.

Farther along this continuum lies PA, which metabolizes much of the decision-making process by micro-managing farm operations. PA has yet to make major inroads into peasant agriculture, but technology developers clearly relish this possibility (Lutz, 2018; Precision Agriculture for Development, 2021d; Rudolph, 2019), and there are already calls for PA as a key to food security in Africa (Ncube et al., 2018). An early example is the ‘FirstLook’ satellite-based PA system for water management has been launched for fruit growers in Western Cape, South Africa; this is state sponsored with hopes of eventually being able to charge farmers for the service (Ncube et al., 2018, pp. 169–170). Digital infrastructures capable of supporting widespread surveillance agriculture are currently rare in the Global South, but there are movements to remedy this, again with India in the lead. The non-profit corporation Digital Green is working on the development and deployment of Farmstack—a platform for sharing farmer data and monitoring farmer compliance (FarmStack, 2021)—beginning with cashew farmers in India (AgriLinks, 2021). Meanwhile, in spring 2021, the Indian Department of Agriculture, Cooperation and Farmers

Welfare unveiled *The India Digital Ecosystem of Agriculture* that includes Agristack, described as ‘a collection of technology-based interventions in agriculture’ that comprises a massive farmer surveillance system. To build Agristack, ‘required data sets’ are being provided non-consensually by farmers to private companies including Microsoft, which will develop a cloud-based Unified Farmer Service Interface for ‘smart and well-organised agriculture’ and AgriBazaar (an Indian agricultural commodity trading company) for land profiling and building a generalized advisory platform for farmers. Information on individual farmers will be attached to the national system of unique digital identification numbers (‘Aadhar’), raising concerns about ‘information asymmetry, data privacy and consent, profiling of farmers, mismanaged land records and corporatisation of agriculture’ (Kapil, 2021).

It should be clear from this brief overview that there is significant movement towards surveillance-based decision-appropriating technologies being developed and deployed for peasants in the Global South. There have yet to be published any thorough surveys of these technologies, but there is an emerging literature on the rise of surveillance capitalism that will provide an invaluable framework for understanding surveillance agriculture.

3 | SURVEILLANCE CAPITALISM AND SURVEILLANCE AGRICULTURE

It is ironic that we were proclaimed to have entered the post-industrial ‘Information Age’ in the 1960s (Matchup, 1962) because it was the 1970s that brought us remote sensing and the 1980s that brought personal computers and the 1990s that brought the Internet—all *before* the world entered the ‘digital age’ that some pinpoint to 2002 (Hilbert & López, 2011). The early 2000s also saw the beginnings of innovative systems for surveilling and recording people’s daily actions on computers and other digital interfaces, beginning with google searches and then social media posts, emails, online purchases and a rapidly expanding ‘Internet of Things’ technologies that surveil bodies, homes and vehicles. Recognizing the socio-economic impacts of this evolving nexus of technologies, norms and institutions today is no easier for us than it was for social philosophers in late 18th-century Britain to understand what would later be known as the Industrial Revolution, but there have been helpful attempts to discern the economic logic and unfolding impacts of what is being constructed as *surveillance capitalism* (Foster & McChesney, 2014).⁴

In *The Era of Surveillance Capitalism* (2019a), business philosopher Shoshana Zuboff analyses surveillance capitalism as a novel mode of accumulation based on companies finding ways to *render* and develop *prediction products* from vast swaths of everyday behaviour. *Render* has two meanings. The first is to form something out of something else, as heat renders animal fat into oil. Thus, our google searches, Facebook ‘likes’, commands to Windows’ Cortana, and sleeping habits are turned into commodified data by increasingly sophisticated forms of surveillance. The second meaning is to give up, as in *surrender* or *render unto Caesar*. Thus, detailed and even intimate information on ourselves and our behaviour is surrendered, or rendered unto Google, and it happens by default: Surveillance capitalism companies have deftly outflanked consumers and regulators in establishing privacy norms allowing them to capture and own our ‘data exhaust’. Writing at the dawn of surveillance capitalism, Roger Clarke labelled the collection of digital data to investigate or monitor individuals or groups *dataveillance* to distinguish it from physical surveillance (Clarke, 1988). Today, most dataveillance happens at the computer, but our purchases, physical movements and bodily details are also dataveiled by credit cards, mobile phones, fitbits, football players’ shoulder pads and, in a truly sobering development, Internet-enabled rectal thermometers (Zuboff, 2019b).

But what Clarke did not foresee was that dataveillance produces individualized data sets that are most valuable as grist for algorithmic analysis to not only predict, but to *manipulate* behaviour, moving ‘from knowledge to influence to control’ (Zuboff, 2019a, pp. 153–154). Consumers are not only anticipated but ‘tuned and herded and shunted and coached and modified’. The case of Cambridge Analytica using ‘micro-behavioural targeting’ to

⁴Even before the birth of what was originally dubbed the ‘microcomputer’, James Rule (1974) envisioned agencies and corporations sharing surveillance information ‘central clearing house’ for mass surveillance and control.

influence the 2016 votes for president in the United States and for Brexit in the United Kingdom was probably a harbinger of manipulation of sentiment and political allegiance; new vehicular monitoring systems can keep your car from starting if you fall behind on payments. In China, credit scores are compiled from dataveillance, and calls to a debtor trigger an alarm and recorded message saying: 'Warning, this person is on the blacklist. Be careful and urge them to repay their debts' (Campbell, 2019).⁵

In surveillance agriculture, the formidable power to manipulate is sanitized by the insistence that the technologies simply 'support' farmer decisions to improve farm profitability and 'sustainability'. New digital technologies may provide so much data that the farmer suffers from 'decision paralysis', at which point having outsiders take over decision-making may seem like a blessing (Swindoll, 2018).

The ability and inclination to manipulate behaviour is important because of the unusual nature of surveillance agriculture as compared with other forms of surveillance capitalism. What surveillance capitalism dataveils and manipulates are generally not skilled professional behaviours: Its business model is not to dictate how teachers teach, preachers preach, or painters paint, but to sell information to third-party advertisers. The targeted ads obviously may relate to one's profession—painters may see ads for brushes—but how they use the brush to paint is not directly manipulated. But in surveillance agriculture, it is *farmers' farming* that is dataveiled and potentially manipulated: Unlike typical interactions with surveillance capitalism that manipulate consumer behaviour, surveillance agriculture manipulates professional productive behaviour. Of course, agricultural practice can be manipulated in many different ways and directions, which is why it becomes important to survey the roster of players that are developing and promoting surveillance agriculture in the Global South—'Big Others', to borrow Zuboff's terminology—in the following section. The Big Others themselves are certainly not new—agri-capital, state agencies, NGOs and agricultural researchers all have deep histories on the farm scene—but they will now relate to farmers in new ways allowed by surveillance, and I will consider these new informational relations between farmers and Big Others.

Another pivotal feature of surveillance capitalism is that key interactions are individualized and temporally and situationally specific. Indeed, it is precisely this specificity that makes surveillance capitalism's prediction products so valuable: Advertisers can buy information on not just who is likely to buy, but when they are most likely to buy and what sort of come-ons, they are likely to respond to. Surveillance agriculture also hinges on specificity—the name 'precision agriculture' invokes the new levels of temporal and spatial resolution—but it also capitalizes on the power to predict and manipulate farmer behaviour that is gained from surveillance. It is becoming clear that purveyors of technology see the individualization of interactions as a means of devising more persuasive messages and enforcing obedience. Technology supporters are frank about this; writing in *Science*, Fabregas et al. (2019, p. 1) explain that

Customized information allows farmers to choose language, dialect, or literacy levels. Mobile technologies can also provide reminders and other nudges to address behavioral biases.

Note: A farmer choosing not to follow a practice or adopt an input is chalked up to 'behavioral bias' to be overcome by customized information from surveillance. Such information can also be used to calibrate the timing of messages to maximize their influence. Whereas surveillance capitalism can let vendors schedule ads based on intimate life details—like 'clicking "yes" on an offer of new running shoes as the endorphins race through your brain after your long Sunday morning run' (Zuboff, 2019a, p. 9)—PAD has developed an algorithm-driven system to push mobile phone calls to Nigerian farmers that includes 'comprehensive monitoring tools' to analyse pickup and listening rates and calibrate calling strategies to daily work routines and religious observances (Precision Agriculture for

⁵And we can assume that state security apparatuses are already liaising with dataveillance companies to exert control over some political activity (Foster & McChesney, 2014). The rapid development of affective computing, which can read people's eye movements, facial expressions and moods, portends a truly Orwellian future in which advertisements and more intrusive forms of manipulation not only target the individual, the time and the place but operate dynamically, adjusting tactics to exploit one's reactions. The ability and willingness to manipulate individuals is not widely appreciated, one reason being that the surveillance capitalism interactions are sanitized by the conceit that it is merely improving the relevance of advertisements that one will see anyway. This innocuous account is reinforced by advertisers' dialog boxes designed to create a 'sense of control' to facilitate the 'Use Targeted Advertising in a Data Paranoid World' (Hatch, 2018).

Development, 2021c). The organization also reports progress with mixed messaging methods based on surveillance: Farmers in Gujarat, India, were more likely to adopt fertilizers after receiving visual aids and weekly push calls, and farmers in Kenya were persuaded to adopt lime treatments by customized SMS messages (Precision Agriculture for Development, 2021b).

Such individuation is crucial not only because of the increase in predictive and persuasive power but because it may be incompatible with key social aspects of peasant agriculture. As argued below, many agricultural operations involve consultation and collaboration; even more important are the social aspects of agricultural learning (or skilling) that surveillance agriculture is wont to appropriate and individualize. Indeed the ‘individual autonomy’ in decision-making that concerned the Office of the President is misleading; if we think of autonomy as the ability to make and act on informed decisions, then autonomy always involves supra-individual relations. We will return to this issue in our discussion of New Informational Relations of Production.

The ends to which the developing technologies of surveillance agriculture will be put depends on the interests of the developers and promoters, to which we now turn.

4 | BIG OTHERS

Zuboff constructs the ubiquitous digital apparatus as an entity in its own right, which she names Big Other and describes as the ‘sensate, computational, connected puppet that renders, monitors, computes, and modifies human behavior’ through its ‘vast capabilities to produce instrumentarian power’ (Zuboff, 2019a, p. 376). She analyses the processes by which data are rendered and monetized, but she simplifies the nature of surveillers and surveillees on either side of these interactions: There is essentially *us* and *them*, with *us* being we consumers and googlers and talkers and drivers and joggers and house-dwellers and *them* being ‘surveillance capitalists’ who are purely out for profit. Even when they manipulate behaviour, it is to discipline consumers to ensure profits (cf. Foster & McChesney, 2014). Many other writers accept surveillance capitalism as driven by profit (Gerardi, 2021).

I suspect that the ‘profit only’ analysis is oversimplified in surveillance capitalism in general, but I know it is in surveillance agriculture, in which there are various entities with diverse (even if sometimes overlapping) vested interests: Big Others. Francisco Klauser (2018) is right that we need to understand ‘the actors, interests, and sources of authority’ that come together in digital farming, and I highlight this as a key arena for research especially by critical agrarian scholars. But considering the track record of entities involving themselves in digital agriculture, I can tentatively identify four interest bundles.

First is agri-capital, which will obviously be instrumental although it will not completely dominate surveillance agriculture as it does on industrialized farms. It will interact with farmers *qua* consumers and seek to increase the scale (and predictability) of accumulation from them, although beyond this companies’ interests differentiate in some way. A common boast is that digital technologies (such as PA) can reduce farmer expenditures on inputs like chemicals and water (e.g. Fabregas et al., 2019, p. 1), although most of the world’s biggest agrochemical sellers are deeply involved in digital agriculture, including Syngenta/ChemChina, Bayer/Monsanto, BASF, Corteva (formerly DowDuPont) and FMC (GRAIN, 2021; Rotz et al., 2019, p. 214), and other companies like John Deere, AGCO and CNH have formed alliances with seed, pesticide and fertilizer companies (Mooney, 2018, p. 12). The same technology that directs farmers to fertilize or spray less can direct them to fertilize or spray more and surely will do so given industrial agriculturalists’ view of the Global South as always needing more agrochemicals. Indeed, high-profile articles digital agriculture applaud that one such technology—text messaging systems—increased ‘adoption of recommended agrochemical inputs by 22%’ by smallholders in sub-Saharan Africa and India (Fabregas et al., 2019, Summary1).

Surveillance agriculture can also help agri-capital steer farmers to their own brand of inputs; in the Bayer-supported PAD Bangladesh project noted above, participating farmers were more likely to use and recommend to other farmers Bayer’s fertilizer or other Bayer products (Ravis & Notkin, 2020, p. 113). The same technologies can

induce farmers to buy higher margin inputs, addictive inputs and predictable inputs, most notably data services that claim to keep other input costs down. Prediction products like those used in surveillance capitalism may be innovative sales tools. Target stores detect pregnancies by women's buying habits using the information to time inducements to buy diapers and cribs (Hill, 2012); surveillance agro-capitalists can use seed planting data to calibrate recommendations for sprays, specialized harvesting services and the like. Thus, Farm Market ID sells time-sensitive predictions to input companies of when specific farmers are 'in need' of their products and services.

The companies at the forefront of developing surveillance capitalism's behavioural prediction products are now quickly joining the ranks digital agri-capital. Google's parent, Alphabet, has unveiled robotic buggies that monitor individual plants in intimate detail and determine their needs (Leprince-Ringuet, 2020), whereas in China Internet giant Alibaba has announced its 'ET Agricultural Brain initiative' that uses visual recognition and real-time environmental monitoring to track the growth conditions of crops and livestock (Liao, 2018). Microsoft is an interesting case. The company was late to the surveillance capitalism game, but leapt into it in 2014 (Zuboff, 2019a, pp. 162–163), surveilling with its browser, its Cortana assistant, and in 2015 with its notorious Windows 10 operating system that 'gives itself the right to pass loads of your data to Microsoft's servers, use your bandwidth for Microsoft's own purposes, and profile your Windows usage' (Zuboff, 2019a, p. 165). That year, Microsoft also made its play for the agriculture market, launching FarmBeats, an 'end-to-end IoT system that enables seamless data collection' from drones, sensors and the farmer's home (Vasisht et al., 2017); the surveillance agriculture platform has spread from the United States to India, Kenya and Brazil (Wiggers, 2019).

Agri-capital, then, can profit from sale of inputs through surveillance technology but also from selling surveillance technology itself (and the associated fee for services). Agri-capital profits relatively little from peasants with their penchant for labour-based intensification, and surveillance technology may have ripple effects undermining the partly-self-controlled resource base that sustains peasant economies (van der Ploeg, 2008). One such effect would be farmers using equipment that they could not maintain and repair, or even entrust to 'shade tree mechanics' (Rotz et al., 2019, p. 215). (The inability to repair their own equipment has even emerged as a major bone of contention among wealthy farmers (Waldman & Mulvany, 2020).)

Lastly, I will note that beyond its interest in promoting, disciplining and selling to farmers, agri-capital's interest in the move South is propelled by the digital regime needs for data, which is 'the new soil' (Fraser, 2019). Algorithm-driven software has to constantly expand like capitalism itself, and data streams data from new parts of the world and different types of cultivation systems are crucial to the development of digital technologies and algorithms.

But profit-driven capital will hardly be the only Big Other. States are playing a significant role in surveillance agriculture, and their interests are more complicated. Zuboff sees the state as basically serving as handmaiden to surveillance capital's profiteering, and indeed, this is already one interest it is pursuing through its development arm. USAID⁶ has a long history in opening markets for US agricultural input sellers, often billing its efforts as intended to benefit peasants; for instance, in recent years, it has worked actively to create entry points for Monsanto and other US seeds companies in Africa (Schnurr 2019, p. 140). USAID has been enthusiastically promoting a range of digital agriculture (including surveillance-based) projects, although its primary focus has been on projects connected to the ostensibly non-profit CGIAR network. It remains to be seen the extent to which this is ultimately intended to promote US agri-capital.

States have other institutional interests that are distinguishable from—even if consistent with—their interest in supporting capital accumulation: they monitor, mollify and shape farmers. The well-known text on state interests in monitoring peasant farmers is Scott's (1998) *Seeing Like A State*, which shows how projects and technologies purporting to improve agriculture are often riven by the state's intent to 'make the countryside, its products, and its inhabitants more readily identifiable and accessible to the center' (p. 184). These interventions too are framed as helping peasants, even when they lead to disasters like China's Great Leap Forward; so today, it is with China, a

⁶United States Agency for International Development.

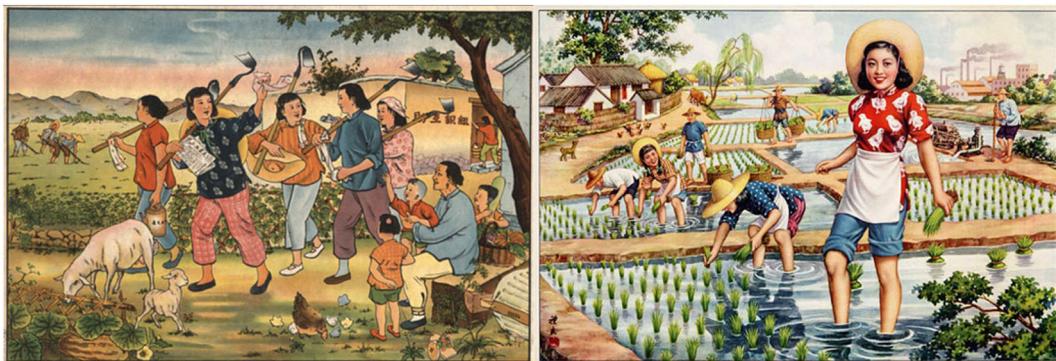


FIGURE 2 Chinese state propaganda posters from the 1950s promote labour-based intensive farming with simple sustainable technology. Compare these with Figure 1 from the United States around the same time

Source: ChinesePosters.net

global leader in developing and deploying surveillance agriculture that is presented as a vehicle for poverty eradication and rural revitalization (Hinrichs, 2018).

The ‘shaping’ of farmers refers to states taking an interest in promoting certain types of and qualities in farmers; models of the good farmer change through time, affecting what farm technologies are developed and adopted. For instance, in its early days, the United States valorized the Jeffersonian ‘yeoman’ farmer (Appleby, 1982, p. 834), but by the early 20th century, with the rise of Taylorization and the ‘industrial ideal’ in agriculture (Fitzgerald, 2003), the federal government was campaigning to replace the ‘bucolic, turkey-in-the-straw style of farmer’ with ‘a business man, a capitalist, an executive’ (Danbom, 1979, p. 136). By mid-20th century the United States had refined its national integration model of agricultural development (McMichael, 2000), and government ideals became increasingly aligned with the interests of input corporations; government and corporate marketing images alike routinely depicted the farmer deploying commercial input technologies (as in Figure 1). It is interesting to contrast this with the type of labour-based intensive farming with simple technology being valorized by the Chinese state at the same time (Figure 2). But in China today, large-scale state-owned farms are frequently portrayed as the model that other farms should emulate, and it is on these farms that surveillance agriculture technologies are being developed and promoted.

Interestingly, surveillance agricultural technologies may induce a change in some states’ approach to monitoring and controlling farmers. In Scott’s analysis, states’ reading and control of agrarian countrysides hinged on homogeneity, which was imposed: Crop arrangements, field patterns and settlements were administratively ordered, simplified and standardized. Such projects were undone by the imposed homogeneity overriding smallholders’ need to adapt to heterogeneous growing conditions, crop needs and the complex social choreography of labour (Richards, 1989; Stone et al., 1990). Surveillance agriculture may offer an inverted dynamic of control based on heterogeneity that it can monitor and claim to analyse and manage better than farmers.⁷

Beyond the inward-looking interests of monitoring and control, states have outward-looking interests. The advent of new agricultural technologies often sets off international competition⁸; today, Ireland exemplifies state-level designs to ride surveillance agriculture to international prominence in ‘export-oriented agri-digital industry’. How its analytic services will affect peasant farmers remains to be seen, but Ireland’s aspirations have already led it to lean on Irish farmers to go digital, with the national government’s research and technology body taking the

⁷I am grateful to an anonymous reviewer for discussion of this.

⁸For example, one reason American agriculture today is so fertilizer-intensive is the government’s promotion of a chemical fertilizer industry to compete with Germany after World War I (Johnson, 2016).

position that 'New technologies and farming systems will only contribute adequately to a globally sustainable Irish agri-food and bioeconomy sector if adoption rates [among Irish farmers] are improved' (Fraser, 2019, p. 902).

Another key Big Other in surveillance agriculture's move South is agricultural-development non-profits. Unique in this category because of its size and prominence is the CGIAR network, which has had a complicated and changing relationship with peasant farmers. From its beginnings in the 1960s, it has constructed itself as dedicated to the interests of peasant farmers, and it has indeed made contributions to peasant autonomy in that it has been credited with some successes in aiding peasant decision-making (Price & Palis, 2016). Yet, the Green Revolution that brought the first CGIAR centres into existence has also undermined local informational relations of production (Cullather, 2010). The extent to which the CGIAR's interests lie with peasants versus farm input industries is a contentious and evolving question. Even leaders of the Rockefeller Foundation that funded most of the 'revolution' admit the failure to benefit peasants along with the heavily capitalized farmers (Conway, 1997).

To understand the CGIAR's vested interests, we need to recognize that much of what the Green Revolution was really intended to do, beyond boosting the input intensiveness of farming in the Global South, was to create spectacle (Stone, 2018). Green Revolution hero Norman Borlaug was explicitly aiming for a technological package that would be 'spectacular', pursuant to his unwavering ignorance of any form of agricultural growth apart from external inputs and his belief that peasants had to be 'shocked' into any change (Cullather, 2010; Stone, 2018). 'The genius of the dwarf seeds', writes Cullather (2010), 'was to create a cultivar that was at once so spectacularly productive and so needy of the kind of inputs only government could provide' (p. 267).⁹ The 1968 spectacle of magic seeds and overflowing granaries in India, accompanied by a narrative of famine averted, opened floodgates of funding from both states and philanthropies, and by 1983, the CGIAR network had grown to 13 agricultural research centres. But by the 21st century, the network had fallen on hard times; inflation-adjusted budgets were flat and, after a brief surge, have been dropping sharply since 2014 (Beintema & Echeverria, 2020). The biggest problem may have been the lack of spectacle like the Green Revolution; the CGIAR has produced many crop varieties but no headlines. Digital agriculture has superb potential in this regard. The juxtaposition of digital technology and palaeotechnic peasants and the narratives of technology to the rescue are irresistible (Stone, 2011; Waldman, 2004) (Figure 3).

The one major philanthropic funder the CGIAR has been able to attract in recent decades is the Bill & Melinda Gates Foundation (BMGF), which increased its support through the 2010s and emerged as the network's top funder by 2020 (Beintema & Echeverria, 2020). The interests of corporations and their affiliated philanthropies are often deeply entangled; the Green Revolution, largely funded by philanthropic Rockefeller oil money, was in essence a programme to induce governments to subsidize petroleum-based fertilizers (Cullather, 2010). It is notable that the CGIAR launched the Big Data in Agriculture platform—a high-profile project running from 2017 through 2021—a few years after philanthropic money from Microsoft's founder arrived on the scene.

Like states, the CGIAR has promoted particular characteristics in farmers, and there are already indications that surveillance agriculture will be wielded as a tool to promote market-oriented entrepreneurialism. A current CGIAR posting explicitly aspires to develop 'cutting-edge precision solutions to support small-scale farmers to become successful, high producing agro-entrepreneurs' (Van Loon et al., 2018, p. 1). Note how this goal deviates from the well-documented (and eminently sensible) characteristic peasant strategy of prioritizing risk reduction (Edelman, 2013; Netting, 1993; Scott, 1976; van der Ploeg, 2008)—a point to which I return below.

In some cases, non-profits have been founded specifically to promote digital agriculture in the Global South. Digital Green was launched by Microsoft Research in 2006 and was later spun off as an independent non-profit funded in part by the BMGF. It has been garlanded by Microsoft, including winning the Microsoft Alumni Inspired Leader Award in 2017. Precision Agriculture for Development (later renamed PxD) was founded in 2016 with a main remit of providing 'personalized agricultural advice'; two of its four original funders were anonymous (Precision Agriculture for Development, 2017).

⁹The famous seeds weren't even any more inherently productive (Stone, 2019, p. 4), they were just part of a programme to attract state subsidy. They were also winners of a weather jackpot: The seed multiplication programme in India happened to coincide with an unusual severe 1966–1967 drought, and the first crop happened to coincide with the return of the rains.



FIGURE 3 Top: Image from a CGIAR annual report showing African women farmers marvelling at an iPad (CGIAR, 2020). Bottom: Image from Endeva showing a simple plow being pulled by satellites (Endeva, 2021)

Professional academics comprise another Big Other. At the institutional level, digital (especially surveillance-based) agricultural technology development is proving an even better avenue for aligning university values with those of capital than earlier phases of agricultural technology. A century ago, the advent of hybrid seed breeding pushed academic/public research institutions into the role of research for seed companies (Fitzgerald, 1990; Kloppenburg, 2004); now surveillance agriculture arrives at a time when academic neoliberalism is well established and normalized in many countries, and universities are establishing whole centres with strong corporate links to develop surveillance-based technologies that can be licensed for profit—even when the research has been supported by public funds. A few of many examples are the University of Florida's Precision Agriculture Laboratory (<https://abe.ufl.edu/precag/>), the University of Minnesota's Precision Agriculture Center (<http://precisionag.umn.edu/>) and the Internet of Farms 2020 consortium led by Wageningen University (Iof2020, 2021). There is also a large population of faculty in fields including data science, artificial intelligence, agronomy and agricultural economics. There are abundant avenues for conventional academic rewards through publication, including journals dedicated specifically

to digital agriculture like *Precision Agriculture*, *Computers and Electronics in Agriculture* and *Artificial Intelligence in Agriculture*, as well as dozens of related journals.¹⁰ But especially in the United States, professors patent their inventions and start for-profit corporations without compunction. Many faculty in potentially money-making fields have, as Rasmussen (2014, pp. 3–4) puts it, ‘worked to adjust the values, intellectual focus, and reward systems in [their] scientific fields’ and come to see market uptake of technology based on their research as the gauge of scientific success, ‘effectively leaving questions of scientific truth to the purported wisdom of nonscientist crowds’.

Finally, I will note an interest that is vested in all of the Big Others. Developing, deploying and promoting agricultural technologies has long been an effective route to garnering humanitarian plaudits. In industrialized countries, digital agriculture companies predictably gain traction with claims that their technologies can—indeed are needed to—‘feed the world’ (The Atlantic, 2018). Some farmers are even persuaded to adopt it on this basis (Carolan, 2017). The Chinese state and the CGIAR system alike assert that the digital technologies they promote will reduce poverty. Plaudits are often available even with little evidence of contribution to human welfare. An ‘e-agriculture’ project in India (Stone, 2011) provides examples of some of the other payoffs in such endeavours. The project, a brainchild of an academic database specialist, transmitted digital images and reports from smallholder cotton fields to urban ‘agricultural experts’ who diagnosed problems and recommended management practices.¹¹ Claiming to be saving participating farmers money, the project garnered several civic awards and press attention; the university put out videos claiming to ‘benefit the common man’ through the project’s ‘amazing impact’; a local NGO that ran a study showing project benefits also shared in plaudits. The evidence for economic benefit actually turned out to be dubious, and farmers refused to pay for the service when it tried to move to a fee basis.

Here then is a tentative survey of Big Others and their interests as surveillance agriculture moves into the peasant South. The players will obviously vary with the technology and type of project, but this roster will hopefully help to frame research moving forward. But although these Big Others clearly have divergent (if overlapping) interests in their interaction with farmers, what they share is that they will be instrumental in bringing about new informational relations of production.

5 | NEW INFORMATIONAL RELATIONS OF PRODUCTION: PEASANTS AND BIG OTHERS

Even if surveillance agriculture in some ways simply continues the processes of agricultural industrialization, putting highly detailed information on farms, farmers and farm operations in the hands of external entities with such a range of vested interests will inevitably lead to novel informational relations of production. Although we might speculate on many aspects of these new relations and their impact on peasants, I contend that one certain change that will shape most other aspects of informational relations of production will be the typologies through which farmers are understood and interacted with.

Our Big Others all go to pains to categorize farmers using typologies based on various criteria to understand and guide interaction with farmers. The biases in development critiqued by Robert Chambers are, in part, simple typologies designed to make projects appear effective by categorizing farmers on their proximity to roads and towns (Chambers, 2006). More analytic typologies are often created based on farmer surveys. For instance, CGIAR projects construct typologies based on sample farmer surveys on variables selected to reflect variation relevant to the project (Alvarez et al., 2014). But most farmer typologies have hinged on technology adoption. Such typologizing has a deep history, beginning with Ryan and Gross's (1943) study of hybrid maize adoption, the seminal work in the field of innovation diffusion (Rogers, 2003). These sociologists documented salient characteristics of early and late adopters and analysed basic differences in their decision-making. Over the next few years, other scholars conjured with

¹⁰Examples are *Surveillance and Society*, *Remote Sensing*, *Agricultural Systems*, *Wageningen Journal of Life Sciences*, *Journal of the Science of Food and Agriculture* and *International Journal of Agric. Biol. Engineering*.

¹¹See Ravis and Notkin's (2020) important unpacking of the urban bias in agricultural extension.

farmer type concepts such as 'innovators', 'local adoption leaders', 'progressists', 'informal leaders', 'traditionalists', 'diehards', 'later adopters' and most notoriously, 'laggards'. Rogers (1958) devised a more formal model of farmer types distinguished on several axes of variation (Rogers, 2003, chapter 7). For instance, *innovators* were venturesome and cosmopolite, with capital on hand and ability to handle uncertainty; *early adopters* were less cosmopolitan but well-respected local leaders; the *laggards* came last, with their 'localite' focus and suspicion of change. But the characterizations were all tied to the farmer's willingness to adopt new technology. Ryan and Gross (1943, p. 18) themselves had expressed some discomfort at the pro-adoption bias inherent in such typologizing, and years later, Rogers himself would more squarely confront this bias in the typologizing he had helped to launch. He recognized that the basis for ranking farmers is shot through with implied blame and the reflexive assumption that any agricultural 'innovation' benefits farmers and that non-adoption could make perfect agroecological and economic sense (Rogers, 2003, p. 114). (Rogers (2003) cites the Iowa farmer he classified as a laggard in 1954 for rejecting 2,4-D herbicide and swine antibiotics, who 'by present day standards ... was a super-innovator of organic farming' (p. 194).)¹²

Farmer typologies have real-world effects beyond academic debate. Extension services often follow bureaucratic interests by prioritizing farmers based on their landholdings and perceived wealth (Chambers, 2008); input companies and NGOs head for localities and farmers categorized as likely to adopt. Most typologies have been based on data that are relatively superficial and cumbersome to collect, and the analyses on which typologies are based, even including those involving multivariate statistics (Alvarez et al., 2014) are primitive compared with what will be possible with surveillance agriculture. We do not yet know much about what peasant farmer data will be collected or what algorithms will be devised to analyse them, but some clues can already be seen in industrialized countries. Typologies will become highly dynamic, sensitive to minute changes in factors of production. Conventional farmer typologies were largely static: A farmer might be classified as a progressive or a laggard with little attention to why they might adopt one technology as opposed to another or why progressives might become laggards or vice versa. Compare this with the time-sensitive information the digital-agriculture firm Farm Market ID sells to input companies to identify when farmers are 'in need'—for instance 'when they have bought or sold farmland ... to help the agribusiness know when to contact, when to help' (Figure 4). In a twist on Taylorism's focus on increasing the time efficiency of workers, the value offered here is time efficiency of input providers: 'the farmer doesn't need agribusiness at their doorstep every day, but sometimes they need them and they need them now, and we want to bring the importance of time into this process' (Rao, 2019).

But the sale of classifications of farmers by their likeliness to adopt at any given time barely scratches the surface of how farmers may be analysed by algorithm to guide various external parties' interactions with farmers. The explosions in dataveillance and in data science has already ushered in a new era of individualized analysis in surveillance capitalism. Rather than a simple set of measures on wealth, landholdings and interactions with extension agents, surveillance agriculture may be able to combine intimate knowledge of agricultural operations and travel with expenditures, family situation, health and previous responses to directives and advertisements. Information inputs will be tailored to individual farmers, but surveillance agriculture will obviously need higher level analyses of farmer types to design the tailoring programmes. How will farmers be typologized, and to what effect? To what extent will critical agrarian (or critical data science) analysts even be able to see the typologies?

6 | NEW INFORMATIONAL RELATIONS OF PRODUCTION: PEASANT FARMER AUTONOMY

Finally, we address how surveillance agriculture could alter informational relations of production among peasant farmers, which will require a careful consideration of the 'autonomy' that has been cited as being threatened by the new technological regime. Farmers and farm observers often valorize farming based on the individual agency or

¹²The biases were the result of funding, he decided; he wondered how the diffusion research approach might have been different if the Ryan and Gross's research had been sponsored by a farmers' organization rather than by the Iowa Agricultural Experiment Station.

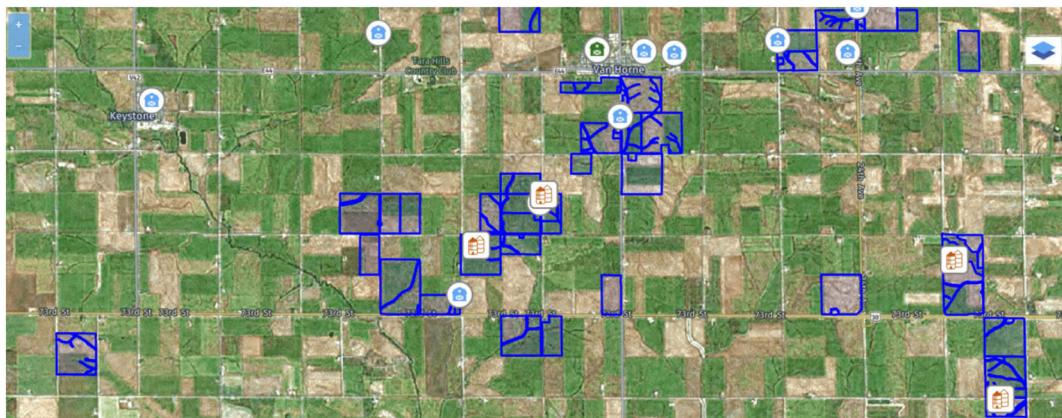


FIGURE 4 The Farm Market ID Corporation uses its database of 95 septillion data points to furnish input companies with information on farmers. The classifications in this company image are vastly simpler than their actual classifications, which are also time sensitive (<https://www.farmmarketid.com/data/>)

freedom it allows—of ‘being one’s own boss’ (Stock & Forney, 2014, p.160) or ‘rowing one’s own boat’ (Emery, 2015, p. 57). This freedom always involves decision-making. As one farmer/writer puts it, farmers

trade the benefits of agrarian collectivism—living wages, retirement, a sane workload, profitability, survivability, and the capacity to make a game-changing impact in the marketplace ... for rugged independence: complete autonomy in decision-making, the ability to grow what/where/how we want, set our prices as we please, sell wherever we choose. (Newman, 2019)

The autonomous decision-making reality never quite matches the ideal, and farmers reliably grumble about all the external constraints on what they can do (Salatin, 2007; Stock & Forney, 2014, p. 167). But as they grumble, most farmers nurture the vision of rowing their own boat, its route determined by what their hands do with the oars. However, this version of autonomy obscures the social nature of decision-making: even the least constrained farmers may make their own decisions, ‘but not as they please’. First consider that etymologically *autonomy* means making laws, hardly an individual activity. Indeed, throughout Classical times, the adjective *autonomous*¹³ explicitly applied to cities (e.g. Athens) or groups (e.g. the Athenians). Individual-level autonomy was deeply suspect and even a crime: In Sophocles’ *Antigone*, the Chorus accuses Antigone herself of being ‘autonomous’ for defying the ruler of Thebes, which was grounds for a death sentence.

Analyses of farmer autonomy often lump the individual and larger social groupings. Van der Ploeg (2008), for instance, makes no distinction in defining re-peasantization as a 'struggle for autonomy that takes place in a context characterized by dependency relations, marginalization and deprivation ... It aims at and materializes as the creation and development of a self-controlled and self-managed resource base' (p. 23). Similarly, the 'autonomy from the state' that Scott sees peasants as seeking does not distinguish between individuals and the group (Scott, 1976; Scott, 2009). Vergara-Camus and Jansen recognize both in stating that 'autonomy ... is often used to express the ability of individuals or collective subjects to escape ...'. But they also recognize the history of conflict in those locating autonomy at the group versus individual level; early Marxists sought autonomy for the proletariat with workers being able to militate for their class interests, whereas Anarchists 'understood autonomy in the libertarian sense through which the individual as a revolutionary subject rejected hierarchy and authority exercised either through the

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market or the state' (Vergara-Camus & Jansen, 2019). Others locate peasant autonomy at intermediate levels such as the household or workers councils (Modonesi, 2014; Vergara-Camus & Jansen, 2019) or the production unit (van der Ploeg, 2008). Because my concern here is how surveillance agriculture interdicts the details of agricultural practice, the level of social interaction is not formally bounded; it rather is simply the local population within which the farmer interacts in (a) accomplishing the work of farming and in (b) deciding how to farm, both of which require some explanation.¹⁴

It is well documented that most aspects of peasant agriculture have key social components. I have defined peasants in part on their reliance on labour-based agriculture, and their farm labour is always managed in part by non-monetized social arrangements. Being able to make such arrangements is crucial to autonomy; indeed, Slicher Van Bath defined peasant 'farming freedom' not in terms of individual action but the ability to choose forms of agricultural labour organization (van der Ploeg, 1990, pp. 265–266), and managing the social factors of production is an essential agricultural skill (Richards, 1989, 1993).¹⁵ A study of peasant farmers in Nigeria showed how labour institutions including household labour, reciprocal work groups and festive labour parties were organized in an intricately scheduled choreography adjusting quantities and qualities of labour with demands of crop ecology (Stone et al., 1990).

Socially managed labour relations are also informational relations of production. For instance, Wilk's study of Belizean Kekchi farmers showed how household heads would congregate to cut, burn, seed and later harvest swidden *milpa* plots in succession; the meetings provided a crucial forum for each to decide where and when to plant and to select maize varieties that would ripen at the appropriate time in the overall sequence (Wilk, 1981). Many Andean farmers used a 'sectoral fallowing' crop rotation strategy based on communal decisions about which plots should be cultivated each year to ensure sufficient time for soil fertility to recover (Hastorf, 1993); as with the Bali rice case (below), this was also part of a supra-household system for managing insect pests. Application of chemical inputs may affect other farms and therefore require social coordination; Filipino rice farmers coordinate insecticide spraying to prevent insects from transferring between fields (Palis, 2017, p. 65).

The social processes involved in deciding how to farm are even more crucial to our consideration of potential effects of surveillance agriculture. Decision-making in the digital future will be 'a complex mix of human and computer factors', write Wolfert et al. (2017, p. 73), but peasant agricultural decision-making is already a complex—and quite social—mix, as we can see through a synopsis of recent agricultural learning theory (Stone, 2016). Behavioural ecologists use the concepts of *environmental learning* and *social learning* (Boyd & Richerson, 1985; Richerson & Boyd, 2005). *Environmental learning* is observing and basing decisions on empirical payoff information, gleaned from one's own or other local farms.¹⁶ This is the more individualistic of the two processes, but it still has social aspects. The agricultural operations that are the grist for environmental learning are partly dependent on what neighbors are doing. Farming communities also share agroecological concepts that are as essential to making sense of their farms.¹⁷ *Social learning* refers to emulating models based on social criteria rather than empirical payoff information. Farmers choose behavioural models according to a set of biases, notably prestige bias (choosing models on the basis of their prestige) and conformist bias (adopting practices because of how many others have done so) (Henrich, 2001). Social learning always plays a key role in decision-making, beginning with farm children modelling their decisions on their parents; no one would ever try to figure out how to farm a field by starting from scratch. Social learning obviously

¹⁴This important but informal social nexus is what others have called an agricultural knowledge and information system (AKIS), defined as 'the set of individuals, groups, organizations, and institutions that generates, exchanges, and uses knowledge and information to solve specific problems' (Engel, 1997; Ortiz, 2006, p. 489).

¹⁵Salomon (1992) writes of the iconic image of a lone tractor on the American prairie, with its connotations of 'the farmer as an individual working the land, self-reliant and independent', noting that even scholars often assume that farm decisions are individual. But 'Nothing could be further from the truth: that farmer works that acreage by virtue of a family effort. Farming is rarely a solo occupation' (p. 1).

¹⁶Operational farms specifically, meaning that the decisions running the observed farms were oriented towards local concepts of agricultural success (as opposed to, say, a demonstration farm).

¹⁷Some Andean farmers use concepts of *dura/suavecita* to characterize how much soil has been tilled and *fria/caliente* to categorize soil fertility (van der Ploeg, 1993); some Honduran farmers use an intricate typology to understand stages of crop growth (Bentley, 1989:26); some Filipino farmers use human growth metaphors to understand and teach others about plant growth (Palis, 2017, p. 65).

can tap into vital congealed wisdom built on environmental learning, although it can also lead to maladaptive behavioural cascades when environmental learning is seriously impeded (the process known as agricultural deskilling; see Stone, 2007). But note that both environmental and social learning are rooted in phenomena local to the farming community; this is not to suggest that all farmers in an area have shared interests, but the processes are both local.

But though various forms of this bipartite learning model are widely used,¹⁸ it whiskers from view the role of off-farm entities that intervene in farmer learning/deciding processes with advice, information and exhortation. Such entities include marketers, extension agents, colonial officers, agricultural consultants, farmer field schools, environmental activists, measurement-minded bureaucrats, regulatory authorities, NGOs and organic schemes, among others. Although the methods and agendas of off-farm entities vary, their effects comprise a conceptually coherent category of *didactic learning*, distinct from environmental learning and social learning because it is driven by off-farm interests—interests that are usually obscured with claims to be out to help the farmer (Stone, 2016). Whether to sell products, sway what farmers produce, make farming practices legible, achieve public recognition or please funders, didacts' interests are never fully aligned with the farmers'; indeed, they never could align with all farmers because farmers' interests diverge in many ways. Didactic learning occurs through many channels including advertising posters and workshops, consultations with shopkeepers, visits from extension agents, village internet kiosks, field days (Stone, 2018) and field schools (Mancini et al., 2007); for a fuller discussion, see Stone (2016).¹⁹

Therefore, we can define farmer autonomy in terms of decision-making, but the measure of autonomy cannot be that individual farmers make decisions 'as they please', as agricultural decisions are always partly based on decisions made by others. Even the apparently individualistic process of a farmer experimenting with a seed is shaped by local seed repertoires, planting norms and conceptual frameworks. But more commonly, farmers are planting what others around them are planting and following similar production tactics (although they may stress the subtle differences in those tactics). But as long as decisions are based on the interlinked processes of environmental and social learning, they are 'autonomous' given that peasant agricultural autonomy operates at the communal level.

Surveillance agriculture intervenes directly in these social dynamics of decision-making. Of course, the impetus to supplant social decision-making dynamics with external 'scientific' guidance is not new. Notably, Green Revolution seeds and practices promoted by modernizers in the 1960s aimed to override Asian agricultural 'tradition' (Cullather, 2010, pp. 160–161)—that is, local way of deciding how to farm. In a famous example, Bali rice farmers were persuaded to ignore local arrangements for setting planting schedules in favour of advice from Green Revolution 'experts', which led to an explosion of crop pests that had been formerly controlled by synchronizing fallows (Lansing et al., 2017; Lansing & Kremer, 1993). But interdicting local decision-making dynamics was a side project of the Green Revolution and on many—probably most—peasant farms it did not happen. But with surveillance agriculture, it is not a side project; appropriating and individuating decision processes at the expense of group dynamics is precisely what the technological regime does. Accordingly, purveyors of digital technologies are quick to demean and misconstrue local decision processes. The leaders of Digital Green explain that didactic learning through Microsoft digital extension is needed because

One of the major problems lies in poor knowledge about farming itself. Farmers tend to find refuge in their own intuition and the hearsay of fellow villagers, which sometimes results in a downward spiral of poor decision-making [3]. (Gandhi et al., 2007, p. 1)

¹⁸See, for instance, Bass (1969); Boyd and Richerson (1985); Henrich (2001); Henrich (2002); Henrich and Boyd (1998); Henrich and Gil-White (2001); McElreath (2004); Richerson and Boyd (2005).

¹⁹Didacts often complicate matters by appropriating the social and environmental learning processes that are driven by local interests. An apparently honest farmer experiment may actually be designed as a spectacle, or the emulated high prestige farmer may be basing decisions on covert remuneration. Strategies of wooing, lobbying and bribing 'early adopters' or 'progressive farmers' are common among farm inputs marketers. But there are other ways to co-opt learning processes; for instance, Aga (2019) shows that young men from the farming communities become agents of corporate capital, operating simultaneously as farmers and agrichemical marketers (p. 1471). Such agents complicate the typology of learning modes: They still may be agents of environmental learning as other farmers will see if the spray kills the insects or not, but they are definitely agents of didactic learning as they are rewarded for getting farmers to adopt the sprays whether they are in the farmers' interests or not.

They support this dubious generalization by citing my own study of what can happen when normal environmental and social learning processes are devastated by technological change (Stone, 2007), a case in which didactic learning was an exacerbating factor!

When Marx wrote of capital ‘pulling-away of the natural ground’ in agriculture, he cited machinery, fertilizer and seeds (Marx, 1973 [1857], p. 527), but these endogenous processes by which farmers learn and choose how to farm are just as much a part of the natural ground of peasant agriculture. Whereas some digital technologies cited above are unlikely to impede (and may even enhance) these processes, decision-appropriating surveillance-based technologies explicitly aim to ‘pull them away’. Having specific farm operations dictated by opaque algorithms could impede farmer experimentation, an essential element in environmental learning that is difficult even under normal circumstances (Stone, 2016, pp. 6–7). Effects on social learning could include removing the most successful farmers—who would likely be recruited first—from local processes of emulation; after all if the technology’s dictates are highly individualized, the only way to emulate them would then be to hire surveillance agricultural services too.²⁰ The spectre of farmers’ increasing ‘need’ for such direction would be hailed as evidence that farmers recognize benefit in such services; I suggest it is better seen as agricultural deskilling. Agricultural deskilling differs from industrial deskilling, in which production systems are redesigned for unskilled workers (Braverman, 1974); that process results in jobs filled by lower paid, disempowered workers who have no need for skill. But farmers always need some knowledge of what results they are likely to get from any given practice or technology. The deskilling that some have recognized in industrialized US farmers (Fitzgerald, 1993; Vandeman, 1995; Ziegenhorn, 2000) is a less treacherous problem because of the economic safety nets those farmers enjoy; peasants always give greater weight to risk minimization, and as noted above, there are no indications that surveillance agriculture algorithms will be devised to share this priority or to take into account farmers own knowledge of past hazards (Rotz et al., 2019, p. 213). One element of deskilling then would be the potential erosion of farmers’ ongoing ability to collectively learn risk reduction strategies.

Note that previous rounds of ‘pulling-away’ have led to rising dependence on external inputs like fertilizer, seeds and motive power, again hailed as benefiting the farmers who are, after all, voluntarily buying these items. Yet, the autonomy in these adoption decisions is illusory, due to group-level dynamics such as treadmill effects. Although it is routinely ignored in the beaming literature on technology benefits, the agrotechnology treadmill was elucidated long ago by agricultural economist Willard Cochrane. New technologies, Cochrane shows, allow early (generally wealthy) adopters to produce more, accumulate higher profits and create downward pressure on prices, putting pressure on ‘laggards’ to adopt the technology to produce more to stay afloat. The process tends to push the agricultural system towards continual production growth, ever-declining crop prices, ever-increasing input costs and larger farms (Cochrane, 1958; Levins & Cochrane, 1996). It tends to be brutal to farmers whose operations were relatively small or who wished to remain less beholden to input corporations. Treadmills lead the wealthier innovating farmers to cannibalize their ‘laggard’ neighbors, as input sellers ‘continue to successfully siphon surplus from the farmers that remain’ (Ramey, 2010, p. 382). As serious a problem as this has been for industrialized farmers, it is a truly alarming spectre for peasants.

7 | CONCLUSIONS

New types of digital agriculture are finding their way into the Global South and onto peasant farms. Some argue the coming changes to be revolutionary and others see a continuation of past trends of commodification and capital penetration; but impacts will surely be highly diverse, not only because of the variation among peasant farmers and among digital technologies but because of the varied interests among the entities developing and deploying the technologies. It is hard imagine any valid conclusions ever being drawn about the effects of ‘digital’ or ‘Big Data’ agriculture in general; the analytic art will require considering functional distinctions and thinking through—or

²⁰And as Rotz et al. (2019, p. 209) point out, poorer and less educated farmers may have difficulty remaining informed about data frameworks and agreements that are stated in ‘legalistic and technical jargon’.

anticipating—potential effects on peasant farms, lives and understandings. I have done this by distinguishing digital technologies on the basis of the extent to which they use information from individualized surveillance—or dataveillance—to appropriate farmer decision-making processes. I have theorized this class of technologies as surveillance agriculture, drawing on recent analyses of how behaviour is manipulated in surveillance capitalism, although agriculture is distinct in that it is professional productive behaviour rather than consumer habits that is potentially being manipulated.

Highly data-intensive surveillance agriculture technologies such as PA are not now established on peasant farms, and even India, on the forefront of digitizing agriculture in the Global South, probably lacks the Internet infrastructure to support the PA technologies now in use in many advanced industrial economies. But there is keen interest on the part of agri-capital, major philanthropies, academic researchers and many nation-states to develop and deploy surveillance agricultural technologies in the Global South, and even claims that such technologies can be a key to food security. Zuboff shows convincingly how as surveillance capitalism developed, leading companies outflanked consumers and law- and policymakers in normalizing the rendering of intimate personal information; the ultimate point of the current paper is to begin a critical—although necessarily speculative—analysis of potential effects of surveillance agriculture on peasant farms and lives before such technologies become normalized.

External technologies developers and deployers reliably claim to benefit the farmer, citing benefits to early adopters as proof. But technocratic blinders can obviously hide many hazards to farmers. Well-known problems include initial agronomic and economic gains giving way to technological failure and new dependencies (Kranthi & Stone, 2020), potentially promoting treadmill effects that are particularly damaging to poorer smallholders (Levins & Cochrane, 1996). Less widely appreciated, but relevant as digital technologies begin their ‘move South’, are the social aspects of peasant agricultural decision-making. Whereas some digital technologies will not threaten, and may even augment, local environmental and social learning, surveillance-based decision-appropriating technologies have intrinsic incompatibilities with these local processes. There are varying conceptions of peasant autonomy (as reflected by the papers in this issue), but I have argued autonomy to be the ability for peasants to decide how to farm through processes with vital social components, and my argument is that the individuation that is inherent to—indeed is the boast of—surveillance-based decision-making poses an existential threat to peasant autonomy.

We all may have been outflanked by surveillance capitalists naturalizing our norms, expectations and understandings of surveillance encounters; I hope that this critical consideration of surveillance agriculture and peasant autonomy will help frame what we make of these technologies as they move South.

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Data sharing is not applicable to this article as no new data were created or analysed in this study.

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