Original Research Article

Big Data & Society
January–June 2019: 1–12

DOI: 10.1177/2053951719849444
journals.sagepub.com/home/bds
SAGE

The combine will tell the truth: On precision agriculture and algorithmic rationality

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Abstract
Recent technological and methodological changes in farming have led to an emerging set of claims about the role of digital technology in food production. Known as precision agriculture, the integration of digital management and surveillance technologies in farming is normatively presented as a revolutionary transformation. Proponents contend that machine learning, Big Data, and automation will create more accurate, efficient, transparent, and environmentally friendly food production, staving off both food insecurity and ecological ruin. This article contributes a critique of these rhetorical and discursive claims to a growing body of critical literature on precision agriculture. It argues precision agriculture is less a revolution than an evolution, an effort to shore up and intensify the conventional farming system responsible for generating many of the social and environmental problems precision agriculture is presented as solving. While precision agriculture advocates portray it as a radical, even democratic epistemological break with the past, this paper locates truth claims surrounding datafication and algorithmic control in farming within deeper historical contexts of the capitalist rationalization of production and efforts to quantify and automate physical and mental labor. Abjuring the growing cultural tendency to treat algorithmic systems as revolutionary in favor of social and historical dimensions of precision agriculture, can help re-frame the discussion about its design and use around real, socially and ecologically oriented change in farming, and so ensure that the possibilities and benefits of precision agriculture are as evenly and effectively shared as possible.

Keywords
Precision agriculture, algorithm, normativity, capitalism, rationality, digitization

This article is a part of special theme on Algorithmic Normativities. To see a full list of all articles in this special theme, please click here: https://journals.sagepub.com/page/bds/collections/algorithmic_normativities.

Introduction

In *Capital*, Marx points out that before machines could become useful, legitimate, common—in a word, normal—people themselves had to first be made machine-like (1976). Much the same has been true of the land itself. Before tractors could trawl the plains, or crops stand like soldiers on a field of battle, orders of property, systems of farming, and ideas about agricultural practice had to first take something like a factory form. Today, the 500-year-old political-economic system responsible for that mechanization is confronted by the ruinous, epochal consequences of its tenure (Chakrabarty, 2009). Yet, advocates contend, the reach of digital media technologies, Big Data, and algorithmic processing appear to offer a way out. As in the 19th century, imaginaries and economies, tools and everyday tasks are being made mechanical, only now

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in the image of the information machine. And, then as now, slower and more resistant to such transformations than other types of work (Goodman et al., 1987), farming in the United States is nevertheless following suit.

The process of agricultural digitization has unfolded unevenly across different areas of farming over the past 40 years, but might be grouped into two general fields, the biological and the mechanical (ETC Group, 2016). The first and earlier was the computerization of agricultural biology: the digital apprehension of genetic matter and the development of information-based tools for biological management, experimentation, and manipulation of seeds, livestock, pesticides and hormones (Kloppenberg, 2004; Pechlaner, 2012). The second encompasses farm machinery and the insinuation of computerized information technology into farm management, from satellites and tractors to drones and machine learning algorithms, and is popularly known as precision agriculture (PA).[1] Together, these developments mean that most aspects of conventional farming, from seeds to harvesters to the "supply chain" itself, are increasingly understood through and executed with information, data, and digital media technologies. PA has been under *de facto* development since at least the mid 1980s. But as automation, the harvest of Big Data from fields and farm operations, algorithm-assisted weather prediction, and planting prescriptions have been integrated into farm equipment and management, PA has been swept up in a broader enthusiasm about Big Data and algorithmic technologies.

The most consistent discursive features of PA are a claim and a framework. The claim is that world population will rise to nearly 10 billion people by 2050, and global food production must grow from 60% to 100% while also *reducing* its net impact on the environment using roughly the same amount of land currently in cultivation, in order to keep the world fed and secure (e.g. Debats et al., 2016; Grose, 2015; Santhosh et al., 2003. This is equally *de rigeur* in reporting and scholarly texts.). Accordingly, precision farming is often framed in popular press, industry marketing, technical literature, and critical accounts, as "revolutionary" answer to this problem; a disruptive, and broadly positive force changing agriculture for the better, by degrees ranging from cautiously optimistic to epochal (Ryder, 2014; Sonka and Cheng, 2015). Some see PA as "technological alchemy" (Brummel, 2014) ushering in nothing less than a "3rd green revolution" (CEMA European Agricultural Machinery, 2015; Powell, 2017); others describe it as part of an even broader 4th industrial revolution precipitated by the rise of Big Data, machine learning, automation, and artificial intelligence (Lelea and Goswamib, 2017). Even the as yet limited critical scholarship on PA tends to frame it this way: in an earlier volume of this journal, Bronson and Kzneviac (2016: 1) open their (excellent) commentary on "Big Data in food and agriculture" with the declaration that "farming is undergoing a digital revolution." Carolan describes the datafication of farm operations in a similar idiom: "it is a bit of a surprise that social scientists are only beginning to critically analyze and understand what the Big Data and precision revolutions mean for farmers and food futures more generally" (2018: 749).

While these and a handful of other scholars (Carbonell, 2016; Murray, 2018; Schiller and Yeo, 2016) have articulated much about the datafication of farming, little attention has been paid to the cultural and discursive constitution of the system known as PA[2]. Bronson and Kzneviac note this explicitly in their commentary, where they call for research into the ways in which high-tech and revolutionary imagery "circulating in the promotion of Big Data tools normalize[s] hegemonic farming systems" (2016: 3).

This article seeks to answer that call with a critique of the glittering imaginary of algorithmic disruption and digital revolution in US agriculture. "Precision farming" is shorthand for efforts to reorganize conventional farming's epistemological and professional foundations around informatic, algorithmic principles. Drawing on culturally and rhetorically focused scholarship in Media Studies and STS, this article builds upon the argument Wolf and Buttel (1996) advanced over 20 years ago: that far from revolutionary, PA is better understood as a normative force—cutting-edge means for overcoming issues endemic to the industrial production of agricultural commodities and preserving capitalist modes of production. Like the "Green Revolution" before it, PA as it exists in effect offers technological solutions to social, political, and environmental problems. Such solutions appear designed to leave the conventional, market-oriented farming system responsible for many of these problems intact. In short, contrary to its dominant expression, I argue that precision agriculture *is* conventional agriculture.

What has changed since Wolf and Buttel wrote is the emergence of a language of algorithms and data-driven insights lending new persuasive epistemological force to PA. While usually presented as a break with the past, the high-tech algorithmic patina of PA obscures the reality of *evolution*; of an intensification of well-established features of conventional farming. This is not to suggest that the datafication of farming is without its own specific consequences—that digitization of farm operations does not represent any change whatsoever. The shift from a kind of disciplinary, whole-field management style towards an individualizing, informatic system of sub-field control has already raised new issues in conventional farming, from concerns about automation (Murray, 2018), to rights over data

(Carolan, 2017), to farm consolidation (MacDonald et al., 2013). But, as I will argue, these issues stem from the deeper grammar of capitalist organization of production and fundamental liberal tenets of social order via free markets and faith in rationality, rather than the technologically determinist image of data-driven "revolution."

Methods

This essay is based in part on some 40 interviews with US farmers in the Northeast and Midwest: US Extension Service and Research Station scientists, USDA employees, scholars of food and farming systems, equipment dealers, and agricultural businesspeople. It draws on observations on US farms in those regions, proceedings of industry and academic conferences, and scholarship on PA, environmental history, food and farming systems, and critical algorithm studies. This empirically grounded, discursively oriented article is intended as a contribution to the growing body of work on PA in the traditions of Media Studies and STS.

Normativity

To use a term as contested as "normative" begs clarification. I see the normal, normative, and normativity—if taken as the same concept—as belonging to two general traditions of use. One circulates largely within analytic philosophy, economics, and legal discourse: an evaluative or moral standard, prescriptively describing something as it "ought" to be, as in normative economics, or connoting the "norms" of a society (e.g. Warner, 2016).

The second sense is the normal as the hegemonic and/or legitimate—as the epistemologically, ideologically, or culturally dominant. This sense belongs to an academic lineage influenced by the work of Michel Foucault among others, which has been especially important to queer theory, Gender Studies, Cultural Studies, and related disciplines focused on power, meaning, and identity. The *normativity* of this tradition developed in opposition to the *queer* as it was established as a motive concept in the early 1990s, as scholars gathered concepts—the dominant, the legitimate, the ordinary, the typical—under a single mangle of normativity, against which the queer has been variably defined (e.g. Halperin, 1995).

When calling the use of algorithms and Big Data in farming *normative,* I invoke this latter sense of the normal as culturally hegemonic, conscious of how both senses have been historically entwined with what *normal* means today. This definition evokes what Raymond Williams meant by a dominant "structure of feeling," in his analysis of the uneven and dynamic interrelations of meaning and power at play within cultures as they change over time (1977). It recalls also the Gramscian notion of consistorial hegemony, where the legitimacy of a dominant order requires popular consent resulting from that order's ability to rearticulate challenges to its power in its own terms as common sense (Gramsci, 2011: 173). I see PA discourse as doing precisely this kind of persuasive, imaginary-shaping work.

If one wanted to synthesize these two general definitions of the norm, it would be hard to do better than "a value disguised as a fact" (Cryle and Stephens, 2017: 6). This is the sense in which I argue that PA discourse enacts a form of algorithmic normativity, and clothes a number of positioned values in the guise of simple, quantifiable, technical facts.

Precision agriculture

PA is not a single technology, but a system characterized by the "employment of computational and information technologies to improve the profitability and sustainability of agriculture" (Van Es et al., 2016: v). The following section offers a general outline of that system. It is important to note that this is an idealized description, and that actual adoption varies depending on farm size, farm type, and farmer age and education, among other variables (see Pierpaoli et al., 2013; Schimmelpfennig, 2016).

PA is often characterized as those technologies that enable a shift from "field level" to "sub-field" management within mechanized agriculture (e.g. Grisso et al., 2009: 2). Most sources point to the declassification of the Global Positioning System (GPS) for civilian use, and the development of farm-specific Geographical Information System (GIS) in the early 1990s, as first steps towards PA as such (e.g. Lowenberg-Deboer, 2015; Mulla, 2013). The earliest and most enduring GPS-linked farm technologies are lightbar and autosteer systems (Larsen et al., 1994), devices that help farmers plot more efficient routes. Autosteer, currently the most popular PA technology (Schimmelpfennig, 2016), is a kind of quasi-automation; it uses GPS and GIS to map a given field and organize routes, allowing farmers to guide their vehicles with little actual driving. Autosteer is designed to keep planting or crop row overlap to a minimum, and to offer relief to farmers planting, treating, or harvesting fields. Today, these systems are often augmented with Real Time Kinesis stations; satellite-linked relay boxes that can increase plotting control up to sub-centimeter degrees of accuracy (Grisso et al., 2009).

A second fundamental component of the PA system is field mapping, itself integral to several further types of precision technology. Proprietary mapping software offered by companies like John Deere, AGCO, or

Monsanto's Climate Corporation take satellite or drone images of a field and augment those images with data layers. These include yield or historical profitability maps, which serve in turn as a foundation for making management decisions and to identify opportunities for integrating other forms of PA technology. Variable rate technology (VRT), for instance, which allows farmers to alter seeding rate for planting crops or the amount of pesticides applied in different areas in real time, depends on these spatial computations. VRT works in concert with GIS, autosteer, and field-mapping: a farmer can take a previous year's yield map, overlay it with a soil quality map, develop planting, spraying, or watering "prescriptions" for different areas, and load the routine into the planter, which will customize the rate of application as it traverses the field.

Accordingly, surveillance and monitoring technologies constitute a third core component of contemporary PA systems. These are myriad, and include many forms of overhead sensing (multi-spectral, LIDAR, NDVI, and others) by satellite, plane, and drone; real-time soil monitors; machine-mounted sensors for tractors or irrigation systems. These also encompass Radio Frequency Identification management for livestock and equipment, behavioral surveillance, and biological monitoring of stomach content and excrement in livestock. Most of these sensing systems communicate with integrated, proprietary management platforms like John Deere's Operations Center system. Aerially sourced Normalized Vegetative Difference Index data, for instance, measure the reflectivity of chlorophyll to identify specific areas where crops are under stress, or offer prescriptions for area-specific nutrient treatments (Schmidt et al., 2009). Plugged into a PA platform, such data analytics and algorithmic treatment prescriptions can be integrated with other layers to give farmers a multi-faceted picture of a field's prospects. Combining these disparate elements into a single, quantified picture builds a faith among some farmers in these aggregated, algorithmically regulated pictures as more correct, more accurate, and more precise. As one Indiana farmer explained to me, this data-driven rigor is a big part of the appeal of PA technology: unlike subjective, fallible human observations, "the combine will tell the truth; when you go through your machine, you know it's right."

While genetic technology is not always included in discussions of precision farming, a minute engineering of biology echoes the aims and approaches of autosteer or VRT. For instance, it is increasingly common to see digital surveillance and algorithmic processing used for biometric trait assessment and behavior analytics, or for determining things like feed amounts or medication regimes for livestock to optimize things like milk productivity (Doreà et al., 2018). At an NSF conference on machine learning in agriculture, Iowa plant scientist Pat Schnable described how precision technologies build upon research on engineering certain crops to "tolerate crowding better," underway since the 1930s (2017). Using overhead time-lapse photography, researchers have observed the leaf rotations of specific hybrid lineages over the course of a day. Linked to their genetic profiles, this research maps "the genetic determinants that allow plants to rotate, or not to rotate" (2017). The goal is to engineer new discipline into the already countless, martial rows of corn, policing maize's very comportment to the degree that it ignores its most ancient urge, to follow the sun.

Algorithmically regulated automation is prominent in the socio-technical imaginary of PA. As an Extension Service farm machinery expert put it to me, in order to get the most valuable insights out of machine learning in farming, farmers will eventually need to transfer authority to machines and algorithms altogether: "the next step is to go beyond where the farmer or operator is making decisions on each field, it's going to move towards a situation where the computer is taking that data and making decisions for the farmer all the time." Perhaps unsurprisingly, opinions among farmers on this point are varied, and most owners I have spoken with prefer a vision of the future that includes *them*. Farmers have described scenarios in which they traverse their fields followed by squads of robotic tractors, human captains in command of a drone fleet. One farmer put it this way:

> A: . . . I mean a lot of these machines are being built to think for you, I mean whether it's engine performance, whether it's settings on a combine, that type of thing, it's changing those things on the go, or the capability's coming where it's going to be able to . . . take all the guesswork out. I mean in many ways that's a good thing I think, because it allows us to put an operator in the seat that's a different kind of operator. He might be an analytic guy and not a machine operator, right, as long as he can read the analytics and make sure it's functioning properly.
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> Q: So you're saying that the person sitting in a combine will be a data analyst, rather than a . . .
>
> A: A combine operator.

Finally, datafication of farm management establishes a quantified stratum that allows for direct links between economic analyses and farm operations. Farmers in New York, Ohio, Indiana, and Illinois have expressed to me how critical market data are in deciding what crops or hybrids they choose to plant, as well as how, when, and why they offer futures contracts on their harvest. Harvesting itself can be dictated by markets, at both the macro- and micro-level. If a grain farmer using Cargill's Grainbridge software is told that Asian markets will close on a higher price for soybeans than is likely tomorrow, that farmer may choose to spend their night transporting their grain to an elevator for sale before the cutoff. This is another way in which sensors are useful—if your combine is equipped to measure the moisture content of your grain, you will know how much drying it needs before being sold to the elevator, which directly affects the price.

PA data is thus increasingly poised to provide ''traceability'' or ''transparency'' in the processing of food, an industry largely beholden to corporations like Nestle or Kraft, and grocery store chains like Kroger or Walmart. In an era of green or local marketing, Ag data is indispensible for a phenomenon Loconto and Busch have called ''standards governance'' (2010). Walmart, for instance, holds sway over 76 million acres of farmland, in that they can exercise serious leverage over the production choices of farmers under contract to sell in their stores (2019). Consequently, technology that provides such information is becoming compulsory for farmers who want to sell their products through such lucrative, private markets. As one executive told a ''Digital Ag'' food industry meeting this November, moving forward, if ''you wanna do business with Walmart, you gotta have the traceability.''

Digital technologies are not only involved in solving particular problems for farmers. In creating the very grounds for assessing the value of a certain strain or the parameters for when to plant, they generate problems, questions, and possibilities themselves. And as historians of computing and digital technology have repeatedly demonstrated against claims of machinic objectivity, biases and normativities inhere in computational technologies (Friedman and Nissembaum, 1996). In the same spirit, I will now turn to the ways in which PA discourse embodies and circulates algorithmic normativities.

Algorithmic rationality

Algorithms have authorized PA in two ways. The first follows from a sense in which modernity itself may be understood as algorithmic. This is algorithmic rationality: the reorganization of industry and reasoning upon rule-based grounds, fueled by the emergence of capitalism and the liberal nation-state. The second owes to emergent shifts in the connotations of *algorithm* over the past decade, discourses of Big Data, artificial intelligence, and computation as effective and democratic (Striphas, 2016). This is algorithmic epistemology: a fetishization of information that ascribes super-natural divination to digital technology (cf. Chun, 2011). Unpacking what I mean by *algorithmic* in these two ways will illustrate how, far from representing a revolutionary break, PA is better understood as part of a general intensification or evolution of long-established production systems characterized by rationalization and control.

Erickson et al. (2013) trace this process across an epistemological shift from dominant intellectual discourses of Enlightenment *reason*, to a rule-based algorithmic rationality: ''a finite, well-defined set of rules to be applied unambiguously in specified settings'' (26). While Enlightenment-era reason and modern rationality have much in common, e.g. an emphasis on risk, utility, and formal procedure, they rest on fairly distinct epistemological foundations. Reasoning is an act of judgment, and so implies wisdom, deliberation, and positioned subjectivity; it carries the potential for disagreement and uncertainty. Rules and rationalization are by contrast clearly defined, quantitative, and designed to be universal and conclusive. Where reason implies embodied history, rationality aspires to abstract, functional, rule-bound parameters (2013).

Totaro and Ninno's (2014) analysis frames the transition to modern rationality from medieval theory in terms of a move from *substance* to *function*. They argue that rationality is algorithmic, that algorithms are recursive functions, and that although rationality broke from the sphere of mathematics and ''invaded'' the fabric of everyday life over the 19th and 20th centuries, rationality *qua* algorithms remains beholden to a numerical logic incommensurate with the everyday world. Unlike a medieval Aristotelian essence, a mathematical function is a value inherently defined ''in relation to a variable or variables upon which its value depends'' (''function''.n.). For Totaro and Ninno, both physical machines and abstract algorithms involve a general form of calculability through recursive functions—sets of operations that repetitively operate on themselves, i.e. the circular action of a gear. The kinship between the mechanical and the algorithmic lies in the fact that ''all machines run an algorithm,'' and that ''one can say [machines] are the materialization of an algorithm, which in itself is a logical object'' (32). As the world became more mechanical, it necessarily grew more algorithmic.

But what precipitated this invasion? The birth of an algorithmic modernity did not simply follow from the mechanization of industry. Rather, as Marx made clear, mechanization followed more primary transformations in economic activity, and formalized procedures for manufacturing goods or managing bureaucracies that transformed human thought and activities (Marx, 1976: 455–470).

By the time Adam Smith published *The Wealth of Nations* in 1776, a capitalist world-economic system had been growing for roughly 200 years (Smith, 1981; Wood, 2017). Its spread was instrumental to the transition from a medieval ontology attuned to substances and essence (e.g. coins as intrinsically valuable owing to the metal of their mint), to inherently relational systems of commodities, valuation, capital, and money (e.g. coins, paper money, credit as symbolically valuable). This functionalist, rule-based system of production gradually reorganized economic and political systems around its logic, and lent growing material force to 18th century liberal critiques of divine political authority and economic paternalism.

Smith's intervention in debates between Physiocratic beliefs in natural order and Cameralist ''political œconomy'' over the 17th century helped popularize a new economic model in closer accord with the emerging rationality of bourgeois capitalist production (Harcourt, 2012). His (in)famous fable of the pin-factory is notable both for capturing a historical transition in action, and for providing a pithy, persuasive account of that emergent rationality: take the work of a skilled craftsman, break it into discrete steps, assign those to ''unskilled'' individual workers, and so increase the efficiency of producing both commodities and surplus value. Smith pithily captured the condition of possibility for mechanization as such—the mechanization of labor (which is to say, *laborers*)—i.e. the rationalization of production into recursive algorithmic processes necessary before actual machines became sensible for the factory floor.

Like most crafts, farming adopted industrialization unevenly. One important step towards greater rationalization and commodification in the United States was the introduction of common standards for grain, futures markets for their harvest, and the regulation of these through the Chicago Board of Trade in the mid 1800s (Cronon, 1991). These regimes not only encouraged mass production of interchangeable wheat, they helped make farmers fungible commodities themselves, in that standardized grades allowed produce to be assessed independently of the farm it came from. Where previously an important organizing logic was reputation ('farmer Tom grows excellent corn, and it fetches a higher price'); standardization rendered products quantifiably equivalent commodities within a grade ('Class 1 drinkable milk fetches a higher price than Class 3 cheese milk'; cf. Harcourt, 2012).

Similarly, a series of government acts over the 19th century were critical for developing more uniform, rationalized approaches to farming. The 1862 Morrill Land-Grant Act established agricultural research colleges across the US, the 1887 Hatch Act funded new experiment stations at those colleges, and the 1914 Smith-Lever Act created the US Extension Service for the public distribution of agricultural research. Together, these acts laid down the basic techno-scientific infrastructure needed to make ''every farm a factory'' (Fitzgerald, 2003). During the 1910s and 1920s, agricultural engineers helped spread an industrial ideal among farmers, while promoting tractors, electrification, pesticides, chemical fertilizers, and hybrid seeds in the efforts to make farms as rational and factory-like as possible (2003). Where once most American farmers had been effectively self-sufficient and raised a diversity of flora and fauna, they were increasingly encouraged through policy, education, and economic changes to reorganize their farms around mechanical logic more suited to high-intensity commodity production, which required inputs manufactured elsewhere. This in turn fueled commercial efforts to commodify farming, creating new dependencies on tractor manufacturers, chemical producers, and, later, seed supply companies. Hybrid technology created in the 1930s permitted the capture, control, and industrialization of seed production, transforming seeds from a renewable asset into a commodified input, a model extended by the legal license to patent living things through genetic ''authorship'' 60 years later.

PA represents to the present what farm management, mechanization, hybridization and artificial inputs represented to the past: a movement to further transform objects (and now activities) into discrete commodities, to extend the reach of capital, and to accumulate entire new geographies of possibility to the market's logic. The common thread connecting these two moments—the development of mechanically and chemically facilitated field-level management, and digitally facilitated sub-field management—is that of rationalization: first of physical, and later mental activities.

Algorithmic epistemology

An early step in this process occurred in 1791, when French revolutionary and mathematician Gaspard de Prony embarked on a project to translate logarithmic tables for shipping into the new decimal system. De Prony's approach was directly inspired by Smith's arguments for the rationalization of labor. Seizing on the essentially algorithmic logic of Smith's rationalized manufactory, de Prony reckoned he could ''manufacture logarithms as one manufactures pins'' (Campbell-Kelly et al., 2013: 5). Accordingly, he broke the complex mathematical work of the project into a series of simplified tasks, such that the bulk of the labor needed only basic arithmetic that could be performed by out of work manual laborers de Prony hired as human computers.

By applying the philosophy of *economic* rationalization to *intellectual* labor, de Prony took an important step towards transforming mathematical reasoning into algorithmic manufacturing (Erickson et al., 2013). De Prony's work on that score in turn influenced Charles Babbage, who saw that such a rule-based system could be *literally* mechanized; the difference and analytical engines he conceived with Ada Lovelace took the next logical step. Babbage had essentially designed a factory for numbers, and so even more intimately insinuated algorithmic rationality with economic rationalization (2013).

From this perspective, later development of the digital computer, the algorithms it embodies, and their subsequent "invasion" of everyday life were all part of a centuries-long transformation of algorithms from tools of reason to machines of rationality. The rise of algorithmic rationality in economics was substantially assisted by the engine of capital and the patriarchal, oiko-nomic epistemology that developed to harness it (cf. Dubber, 2005). If modernity entails an imperative towards rationalization, and the algorithm can operate across all walks of life as a metaphor for rule-based orders of politics, economics, and epistemology, it is reasonable in turn to describe the globally normative liberal-capitalist order as deeply algorithmic (cf. Totaro and Ninno, 2014). And if calculation could be transformed from evidence of genius to the gears of a calculator, and later to a Turing machine, why couldn't other supposedly exclusive human functions, in a world now so thoroughly rationalized, be subject to the same process?

These questions are the origins of a more recent form of algorithmic rationalization, part of the "era of Big Data" (Boyd and Crawford, 2012: 663) to which PA belongs. Growing faith in the application of so called "data-driven" models, analytics, and solutions to complex social and cultural issues, something Boyd and Crawford have described as the "mythology" of Big Data (663), has led to calls for the algorithmic rationalization of once ostensibly exclusively human practices, including government (Medina, 2015), policing (Ferguson, 2017), taste curation (Hallinan and Striphas, 2014), and much more. Pushes for more algorithm-driven management of economics, culture, politics, or everyday life involve some by now well-established discursive tropes: computing is objective, humans are fallible, data is the harvestable raw matter of truth (Gitelsen, 2013). They also often invoke the rhetorical trappings of egalitarianism and democracy: on the one hand, because data and computers are treated as unbiased, and on the other, through appeals to the crowd and its wisdom; the idea that "crowdsourcing" of data is a more egalitarian path to truths and best practices than are ostensible experts.

This discourse is very much at play in PA. Among the most prominent startups in PA, for instance, Farmer's Business Network (FBN) explicitly presents itself in this idiom. FBN markets itself as an "independent and unbiased farmer-to-farmer" network, that "democratizes farm information by making the power of anonymous aggregated analytics available to all FBN members... [FBN] helps level the playing field for independent farmers" (FBN, 2019). The "network" in FBN is that of their farmer members, who pool their agronomic data—varieties planted, yields, machine data, marketing and finance data, etc.—into FBN's online platform, which its co-founder characterized as "a technology-aided version of the small talk farmers would make at a coffee shop or supply store" (Konrad, 2017). In short, FBN seeks to "disrupt"—that is, supplant—the informal, embodied, local social institutions of US farming where farmers meet and talk shop, with a crowd-sourced data platform that offers "the combined intelligence of millions of acres" and "radical price transparency" (FBN, 2019).

This move to equate data with a kind of straightforward, democratic functionality is a salient facet of emergent algorithmic rhetoric, embodied in the marketing claims throughout the agricultural supply chain and in established elites of digital commerce like Amazon and Google alike. Yet I agree with Striphas (2016) when he argues that what is at stake in this phenomenon is the "privatization of process" (406). Contrary to the revolutionary, democratic language that shrouds them, what elite companies like FBN, Deere, and Cargill, let alone Amazon, are in fact engaged in is an effort to commodify and privatize public spaces, social activities, and cultural phenomena like coffee shop talk by apprehending them within the quantifiable logics of digital capitalism at the core of algorithmic rhetoric, all the while claiming the opposite. Furthermore, if as a farmer both the software running your seeder and the very seeds you plant are subject to IP protections, you no longer even meaningfully "own" the equipment you buy. Instead, you essentially license critical parts, which you thus cannot repair yourself (Sykuta, 2016). Yet in order to actually receive the advantages and value promised by precision equipment, you must simultaneously share exquisitely specific data about your farm operations—data your labor generated—for free. In such a situation it is difficult to take the rhetoric of crowd wisdom and algorithmic democracy seriously. As one otherwise enthusiastic adopter of PA technology in the North Country of New York State asked me, "why doesn't data have value? Why should we be giving away this data to companies? We're spending millions of dollars, and they're seeing everything we're doing and learning from it in real time."

In PA, acting, thinking, and doing are themselves subject to commodification via datafication. These phenomena can be translated from the indiscrete realities into quantifiable, tradable functions. They become inputs to be bought, and increasingly, to be licensed—rented rather than owned. This is not so much a revolution of ideals or ontic kind, but an expansion of market development and industrialization, ideologies of growth and structural transformation that demand life and food be industrialized in order to be incorporated. Digitization provides the opportunity to capture, access, manage, and exchange what was inaccessible before; not unlike the ways climate modeling software now permits futures trading on environmental catastrophes (Johnson, 2012).

How does viewing PA this way change or challenge its popular, revolutionary ideation? Consider the combine. These machines, which developed in form and function beginning in the 1830s, were so named for integrating several different harvesting activities (reaping, threshing, and winnowing) into a single machine. Transforming those ancient and variable practices into a series of mechanical steps is exactly akin to the algorithmic process of rationalizing and mechanizing textile production. If the farm could not at first be brought to the factory, the factory would be brought to the farm: the combine is itself a kind of roving, metal algorithm. If older combines were simple, mobile factories, today's precision-equipped combines extend the domain of algorithmic processes to a number of additional tasks, including the quantification of traits (starch, protein, moisture contents of seeds, etc.) and telemetric data (fuel efficiency, route efficiency, time driven, etc.). Modern combines are factories producing both data *and* crops in increasingly exquisite detail. This detail, and those data, is/are useful first and foremost for the production of commodities as such, and so to the production of capital.

This is how a combine "tell[s] the truth." It tells the truth in reliably generating quanta relevant to the functional relations of commodities and capital that organize the entire system of industrial, "conventional" agriculture. It would be absurd to say that, in expressing the starch or moisture content of a kernel of maize, the combine is telling the truth of that maize. It tells the truth insofar as it supposedly is not engaged in deliberative, contextual, positioned judgments. It tells the truth insofar as it accurately generates information relevant to the conversion of corn into a commodity-logic of function, of relational values: that is, into a thing legible to capital.

In a system economically organized by capitalist rationality, the truths that digital sensors and algorithmic processing speak are the expression of a normative function: the rational logic of capitalist production. This logic has taken on a newly mystical dimension with the introduction of machine learning, Big Data, and algorithmic epistemology, which have in turn led to a contemporary use of *algorithm* as a cipher for the occult-yet-objective, truth-generating powers of what are more accurately understood as John Deere, Nestle, or DuPont's efforts to preserve their industry by monetizing behavior.

Consequences of precision convention

PA is an intensification of conventional agriculture presented as a radical break. The realities of its use in many instances contradict this efficiency-generating, environment-sparing public image. An "unrelenting abundance" (CoBank Knowledge Exchange, 2017) of agricultural *overproduction,* crashing prices and driving farm consolidation, contradicts the major rhetorical framework of PA, as answering the call for "100% more" food by 2050 (Grose, 2015). To be meaningful, such calls must be placed within the broader context of current production and distribution systems, which waste up to 40% of the food produced in the United States (De Schutter, 2015). Issues of hunger, nutrition, and culture normally corralled under the mantle of "food security" are not issues of simple scarcity; they are in large part socially, politically, and culturally shaped issues of distribution—both of food itself, and of power more generally (Graddy-Lovelace, 2017; Gunders, 2012). Questions about production and waste are also questions of cultural norms, particularly those which tether authenticity, masculinity, vitality, and wealth to the slaughter and consumption of other species. Most cultivated land in the US is dedicated to the manufacture of singular commodity crops, the vast majority of which are not grown for direct human consumption. Monocrop agriculture is in fact tied to the production of livestock, primarily cattle; millions more acres are invested in the production of biofuels (Merrill and Leatherby, 2018). As agro-ecology and food-sovereignty movements have highlighted, conventional capitalist agriculture has at best a tenuous relationship to the dynamic needs and desires of people and other biotic communities around the world (Frison, 2016).

PA's environmental benefits are also presented in terms of greater monocropping intensity—more food can be harvested from the same land while sparing inputs. Yet more granular analysis of these issues suggests no easy answers. There is no final verdict, for instance, on whether "land sharing"—attempts to make farmland more hospitable to local fauna by adapting it more holistically to the surrounding environment, and so reducing the harm of further expansion—or "land sparing"—attempts to maintain or reduce cultivated areas overall by pursuing yield intensification—is clearly superior (Balmford et al., 2012: 2716–2717; Ericksen et al., 2009). A recent and deeply worrying review of over 70 conservation studies has shown that 40% of insect species on Earth are experiencing "dramatic rates of decline" (Sánchez-

Bayoa and Wyckhuys, 2019: 9). The authors explicitly identify conventional agriculture, and the shift from low-input to "intensive, industrial scale production brought about by the Green Revolution" as a core driver of these trends, where planting fencerow-to-fencerow with genetically uniform monocultures, using synthetic chemical inputs, eliminates not only forests but individual trees and hedgerows, effectively creating engineered deserts, hostile to anything but single, commodified species (19). Birds, fish, mammals, and reptiles have fared equally poorly, with 60% of their total populations having declined since 1970, industrialized farming again a major driver (World Wildlife Federation, 2018).

Consider the following: in July 2018, I was, invited to interview a Western New York farmer on his use of PA as he harvested a neighbor's wheat. While we drove, his combine would pass over dells and furrows of deep green. As I watched these occasional congresses of weeds appear on the combine's digital display, recent environmentally oriented arguments presented at an international PA conference were brought to mind: that datafication could identify unprofitable areas to take out of rotation, helping reduce harmful agricultural effects. I asked my companion what he thought about these patches:

> Q: When . . . you've got more topographical issues like that, would you consider rearranging your field so you leave some areas fallow?
>
> A: Oh, absolutely. If there's no way to make it economically viable, you're better off to not work that. Absolutely. And that's where the precision [technologies]—they'll just put a dollar amount to that spot . . . Now the farmer in me might have to, I see that spot right there, and what can I do to make that grow? And I'm going to figure it out. <laughs>. Usually there's an issue that can be fixed. And so I'll just use that as an example. There's a drainage issue right there. I know there's a drainage issue right there. And how can I fix that? Well, we put drainage tile in, and we can fix that spot . . . I could make that spot more consistent with the rest of the field.
>
> Q: So . . . the equipment helps you to identify those areas to say 'okay, well, it might make more sense for us to spend the money to put the tile in to make that more viable for us?'
>
> A: Yes, versus leaving it fallow.

This exchange exactly reproduced the arc of conversations at the conference panels. While everyone initially agreed precision environmentalism was a nice thought, and that NDVI images or yield and profitability maps helped identify 'problem' areas, many were quick to ask why a farmer wouldn't rather simply treat those areas, making them profitable rather than removing them from rotation. One would lose money not harvesting such areas—something the New York farmer was quick to point out as well.

Who can blame him? In a monocropping system, it makes far more economic sense to keep an entire field uniform than to drive a huge combine harvester around several four-foot-square patches. The problem is not so much that an individual farmer fails to be environmentalist enough; the problem is with a conventional system whose underlying logic inevitably makes a market-based choice more viable than an ecological one.

There are of course many other problems raised by the prospect of maintaining the conventional, capitalist food system, from digitization as a driver of consolidation and the stresses this process places on rural communities, to its contribution to waxing power of grocery store chains and food manufacturers over the labor and environmental conditions farmers and farm workers work within. Yet it would be folly to suggest that this system, on its own terms, has not been successful in a very strict sense. The increase in yields, and so overall availability of food represented by the hybridization of corn and later "Green Revolution" technologies cannot be denied. But these increases are predicated on a process of externalization that can no longer be supported; the historically limited "cheapness" of labor, environment, etc. have been all but burned through (Moore, 2017). As the UN itself has recently recognized, capitalism as such simply cannot continue (Järvensivu et al., 2018). Neither, therefore, can conventional agriculture, precise or not. The question is, what will replace it?

While it is decidedly outside the scope of this paper to answer that question in full, within the more limited scope of agriculture, I see promise for rethinking the use of PA technology along the lines of what Kate Crawford has called a design ideal of "agonistic pluralism" (2016). Unlike the functionalist rationality of algorithmic systems which enact universalist, black-boxed logics of productivity towards control over the production of surplus value, agonistic perspectives are premised upon an "ongoing struggle between different groups and structures—recognizing that complex, shifting negotiations are occurring between people, algorithms, and institutions, always acting in relation to each other" (2016: 82–83). PA shifts the scale of attention and intervention from field-level to sub-field control, but it does not question the monocrop, factory-field itself, the literal and figurative ground it is built upon. Yet there is no *inherent* reason that sensor and processing technologies, which permit more finely grained interventions in food production, could not be designed to facilitate greater ecological complexity without compromising productivity. If, at present, machine learning is designed around a commodity logic towards more efficient maintenance of the conditions of production, i.e. through neural networks designed to automatically recognize and eliminate "weeds" and other pests, agonism in this context could mean finding ways to allow for *greater* floral and faunal complexity around fields, using robotics, automation, and algorithmic machine learning to negotiate the conflicts in a multi-species ecological milieu (cf. Tsing, 2015). The tools of military-industrial "precision," that is, can and should be rethought to encourage, not eliminate, the thronging complexity of being, and so help shape our *techne* in better accord to both the real needs of people, and other forms of life.

Conclusion

This article has outlined an epistemological relationship between industrialization and information in terms of algorithmic rationality, which it has argued expresses the normative grammar of modern capitalist production, in order to advance a critique of PA discourse. This discourse, which frames PA as revolutionary, belies the more mundane reality of PA as heir to a now centuries-old historical process. PA is better understood as an intensification and evolution of dominant, normative modes of relation structured by capitalist organization of production and liberal political-economic philosophy. This is not to suggest that the move to sub-field scales of management, the reorganization of the industry and practice of conventional farming along more overtly informatic lines, or the large-scale spread of information technologies into previously unknown regions or environments do not represent real changes with their own ramifications. It is rather to contend that invocations of PA and its dazzling algorithmic patina as revolutionary have the rhetorical effect of normalizing the intensive, destructive industrial production of agricultural commodities that is in large part responsible for the very social and environmental problems it is proposed to solve in the first place.

If information is to be the new substrate of farming, then it seems we are faced with a choice. On one hand, to use algorithmic control to preserve an imperious, masculine order of factory farming with a new intensity of control that the mergers that opened this essay represent, where behemoth corporations fight over growing shares in worldwide control of land, labor, and food and governments exert digitally facilitated social control in the name of sustainability and ecosystemic sovereignty. On the other, to take the fineness, the kind of granularity of control and adaptability PA technologies might offer as a chance to do something genuinely revolutionary: to try and build new relationships to food, land, other species, and one another. As long as the conversation about PA speaks of a revolution that belies the convention at play, it will continue to offer little more than change for the same.

Acknowledgements

The author would like to thank the editors of this special edition, the anonymous reviewers, the editors of Big Data & Society, as well as Dr Daniel T Walker, Martin Law, and the members of the Medina Group for their constructive feedback and invaluable assistance.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This material is based upon work supported by the National Science Foundation under Grant No. 1755078.

Notes

1. Precision agriculture also known as "smart farming" or "digital agriculture." I use *precision agriculture* or *precision farming* throughout this article because they are more inclusive, specific terms for this phenomenon. "Smart" is ill defined and semiotically gravid; "digital" tends to signify electronic, computational technologies. Precision agriculture is the more common term among farmers and those in the Ag industry.
2. One exception is Nick Murray's outstanding article in Viewpoint Magazine on the relationship between country music, farmer identity, corporate control of agriculture, and the rise of precision farming (Murray, 2018).

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