The ethics of big data in big agriculture
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Abstract: This paper examines the ethics of big data in agriculture, focusing on the power asymmetry between farmers and large agribusinesses like Monsanto. Following the recent purchase of Climate Corp., Monsanto is currently the most prominent biotech agribusiness to buy into big data. With wireless sensors on tractors monitoring or dictating every decision a farmer makes, Monsanto can now aggregate large quantities of previously proprietary farming data, enabling a privileged position with unique insights on a field-by-field basis into a third or more of the US farmland. This power asymmetry may be rebalanced through open-sourced data, and publicly-funded data analytic tools which rival Climate Corp. in complexity and innovation for use in the public domain.

Keywords: Agriculture, Big data, Ethics, Data-driven farming

PREDICTING THE FUTURE OF AGRICULTURE AND FOOD

Agribusinesses, such as Monsanto or John Deere, have high stakes in big data, as it gives them the ability to construct an unprecedented predictive business model over each aspect of farming. This signals a profound change for the autonomy of farmers, public and private sector agricultural business, and society at large. Big data, aggregated from a number of sources, are collected not only to interpret past events, but to predict the future and intervene before events, processes or behaviours are set in motion. This orientation towards the future and fixation over pattern-discovery has been used to justify an unprecedented access to data, creating what Angwin (2014) calls “dragnets”, or unfiltered data collection that is “increasingly future-oriented
and concerned about the predictive power of the information it gathers” (Whitaker, 2000, p. 45). Indeed, big data is very big business. Though big data has been commercialised elsewhere, little scholarly attention has been given to the ways in which large data resources have come to bear upon industrial agriculture, often called “data-driven farming” or “smart farming”. Investor Paul Matteucci sums up the stakes for investing in agricultural data more simply: “It’s going to be big... because everybody eats” (Sommerville, 2014). Indeed, Robb Fraley, Monsanto’s chief technology officer, comments: “I could easily see us in the next five or ten years being an information technology company... where the information itself becomes the business, we see a lot of opportunity” (McDonnell, 2014). Monsanto’s recent purchase of Climate Corp., for US$930 million, brings the company into focus as the most aggressive and largest biotech agribusiness to buy into big data, in addition to its current business of producing and patenting genetically engineered seeds.

With wireless sensors mounted on modern tractors monitoring or dictating every decision the farmer makes – from when to plant the crops and irrigate them, to the quantity and timing of applying pesticides and herbicides, to the precise day to harvest – and detailing the smallest change in microclimate conditions, Monsanto can now bypass the farmer entirely and amass a previously unheard-of amount of data directly through a wifi data connection, sensors and its new data analytics app “Climate FieldViewPro”. This wireless data collection procedure is partially legally regulated via Monsanto’s “Technology Use Agreement” which the farmer has to sign. By amassing huge quantities of previously proprietary, private, or untapped farming data, companies are gaining a privileged position with unique insights into what farmers are doing around the clock, on a field-by-field, crop-by-crop basis into what is currently a third or more of the US farmland (Climate Corp., 2014a). This signals an unprecedented power shift in the industrial farming process that may be rebalanced through open-sourced farming data, and publicly-funded data analytic tools which rival Climate Corp. in complexity and innovation for use in the public domain. Though big data analytics can be a powerful tool for farming, can it be used equitably? What are the ethics, power dynamics, and possible consequences surrounding the use of big data in agriculture and food production?

In order to answer these questions, a first chapter shows which actors are involved in big data for industrial agriculture and with what power. The relationship between biotech companies and farmers will be examined through the lens of expert power, coercive power, and informational power (Foucault, 1975; French Jr. & Raven, 1959; Raven, 1965). Uneven access to big data use leads to a very selective application of big data in agriculture, as outlined in the following section. This allows big agribusinesses to increase their power over farmers, as is illustrated by Monsanto’s use of big data and embodied in its technology use agreement in the third chapter. A broader access to big data and data analytic tools for agriculture, as in existing open-access initiatives, promises to re-calibrate the power relation between large agribusinesses and farmers, as shown in chapter four. The final section concludes on the role that research and public policy should play.

1. THE “BIG DATA DIVIDE”

Big data, as a tool for revealing hidden patterns, requires large mobilisations of technologies, infrastructure, and expertise, which are much too elaborate for an individual farmer. Big data constructs hierarchies around research because of the difficulty and expense of gaining access to the data. Large agribusinesses have no responsibility or obligation to make their data available and have control over who gets to have access (Boyd & Crawford, 2012, p. 674). In fact, John
Deere, a company which manufactures agricultural machinery, filed a copyright claim along with General Motors to prevent farmers from accessing, modifying, or repairing software on their tractors (Wiens, 2015). Similarly, Climate Corp. stipulates farmers cannot “modify, edit, adapt, disassemble, scrape... decompile, reverse engineer or create derivative works from any Climate Products” (2014b). Lev Manovich writes of three classes of people in the realm of big data: those who create data, those who have the means to collect it, and those who have amassed the expertise to analyse it (2012, p. 460). The farmers constitute the first group. For the second group, the one which holds informational power (Raven, 1965), the trade in data is so lucrative that companies such as Acxiom and Experian act as “data brokers” (Cukier & Mayer-Schoenberger, 2013) and exist only to collect and trade data. The analysts in the last group hold the expert power, and it is they who dictate the rules about how the data will be used, who gets to have access, and who gets to participate. As Mark Andrejevic puts it, there is a “big data divide” (2014, p. 1673) between people and their data: they are rarely granted access to their own data, and they lack the tools or the context to analyse it – it is corporations, not individuals, that benefit from big data collection. Many people are unaware of the extent to which their data get stored, traded and analysed for future use.

Farmers are well aware of this secrecy. Following a survey conducted by the American Farm Bureau in October 2014, “Fully 77.5 per cent of farmers surveyed said they feared regulators and other government officials might gain access to their private information without their knowledge or permission. Nearly 76 per cent of respondents said they were concerned others could use their information for commodity market speculation without their consent”. While “more than 81 per cent believe they retain ownership of their farm data”, more than 82 per cent said they had no idea what companies were going to do with the farmer’s data (American Farm Bureau, 2015). What do we know about who has access to this data?

2. THE SELECTIVE USE OF BIG DATA IN INDUSTRIAL AGRICULTURE

Big data collection and analytics on conventional industrial farms, otherwise known as “big agriculture”, focus almost exclusively on inputs and production. Remarkably, there is no big data collection on industrial agriculture externalities and vulnerabilities, hindering research on that topic. For example, the use of Bayer Cropscience neonicotinoid pesticides has proved to cause the bee Colony Collapse Disorder (Schneider, Tautz, Grünewald, & Fuchs, 2012) which in turn has had major consequences on crops depending on these pollinators. Big data could yield new insights into the effects of neonicotinoid, or other pesticides. The practice of monocropping is another example of vulnerabilities specific to industrial agriculture. Planting a single variety of crop year after year on the same field exposes farmers to major blights that wipe out entire regions when the crop variety cannot resist a disease (Fitzgerald, 2010) as in the US state of Mississippi, when a bacterial blight wiped out all the cotton fields in 2004 (Pechlaner, 2010, p. 296). As of now, there is next to no collection of data on industrial agriculture externalities and vulnerabilities by agribusinesses who promote this agricultural model, or on loss of biodiversity due to the adoption of a few high yield commercial seeds. Such a big data base however would be of the utmost ethical and practical importance for research on the best agricultural model for the future of global food production.

An industrialised farm runs like a factory, and is considered a great success in efficiency, though smaller farms using methods such as intercropping, no-till, and drip-irrigation actually produce
more agricultural output per unit area than large farms (Kimbrell, 2002, p. 19). For instance, there is an estimation “that a switch to organic production would lower the external costs of agricultural production in the United Kingdom by 75%, from £1,514 million a year to £385 million a year” (Pretty, Ball, Lang, & Morison, 2005). Such statistics are even more striking given that the use of big data is nearly absent in non-industrial farming, which still makes up most of the world’s agricultural practices (Lowder, Skoet, & Raney, 2016). Most agroecological small farmers have little use for precision farming or smart farming in their current incarnations, as these technologies are mostly tailored to monoculture industrial farms. For example, many of the micro-data feeds Climate Corp. relies on for its predictive data analytics are from sensors installed on heavy tractors. This machinery is not appropriate for smaller intercropped fields which require more manual labour and less mechanised processes. Big data could be potentially very useful for non-industrial farming practices, but at present big data and data analytic tools are designed by big agribusinesses for industrial agriculture.

Monsanto, as mentioned in the introduction, has been the biggest bidder on big data in agriculture with its acquisition of Climate Corp., a powerful big data analytic tool. But before becoming a leader in the use of big data in agriculture, Monsanto consolidated its expert power by specialising in genetically modified foods (GMOs). Though genetically engineered crop varieties could arguably lead to innovations in agriculture, at present the GMO industry is an egregious example of the lack of longitudinal data collection. The real effects and cost of these engineered foods remain unknown. There have been no long-term studies of the potential environmental issues when genetically altered seeds interbreed with other non-genetically engineered plants in nature. Additionally, there have been no longitudinal studies or data collection of the potential effects of genetically engineered foods on human health. One result of this failure is the Starlink Corn contamination disaster in the year 2000, when as many as 1,000 people nearly died of anaphylactic shock from eating corn-based products that contained traces of Starlink, a type of corn only meant for animal feed (Bratspies, 2003, p. 295). Despite health risks, known and unknown, genetically modified foods in the USA are now found in much of the food supply.

In order to secure its expert power, Monsanto resorts to coercive measures. With the patenting of all commercially available seeds “invented” by the company, be it GMO seeds, inbred seeds or crossbred seeds, Monsanto has imposed this legal advantage over farmers in a ground-breaking way: they must buy new seed stock every year, even though farmers have been saving seeds from year to year since the dawn of agriculture. If farmers are caught saving seeds via Monsanto’s infamous monitoring “seed police,” (Weiss, 1999) they will be prosecuted. This warning is mentioned several times in the Technology Use Agreement (TUA) that farmers have to sign to grow Monsanto products. Monsanto, on their website, even has a page titled “Why Does Monsanto Sue Farmers Who Save Seeds?” with the ultimate explanation that “farmers need a level playing field” which is why they’ve “only” litigated 147 farmers (Monsanto, n.d.) with 700 other cases having been settled out of court (Silver, 2013). In addition to the ban on saving seeds, Monsanto has been known to litigate farmers whose fields have “traces” of its patented products (Sudduth, 2001), which can happen for example when transgenic corn pollen blows into non-GMO corn fields and cross-pollinates (Aylor, Schultes, & Shields, 2003). This disturbing display of coercive power, with a clear asymmetric relationship between the tech giants and the farmers, calls to mind the panoptic disciplinary mechanism (Foucault, 1975).

In sum, Monsanto is a business with a very long history of corporate leadership. The company “has prevailed in reorganising systems of power and control in conjunction with the introduction of agricultural biotechnologies in ways that provide new mechanisms for capital
accumulation” (Fisher, 2002, p. 301). To be clear, Monsanto is by no means the only agribusiness with this type of aggressive corporate strategy in the agricultural domain, but it is one of many players, including John Deere, Syngenta, and DuPont, among others. The focus here is on Monsanto because the company is the most innovative with the bioengineering expertise and with the coercive legal tactics. Also, it is clearly heading towards becoming an information broker with the acquisition of Climate Corp. In fact Monsanto’s “Technology Use Agreement” is a telling example of how farmers unwittingly became entrapped in a seemingly irreversible dependence on expert power, and of how coercive enforcement of patents are evolving towards an unprecedented collection of farming big data.

3. FARMER’S AUTONOMY AND MONSANTO’S TECHNOLOGY USE AGREEMENT (TUA)

Intellectual property rights over GMOs and other seeds, inbred and crossbred, have been the keystone development in agribusiness. They have opened the floodgates for a host of issues. Indeed, “patents on seeds, prohibitions on seed saving, grower contracts, and a rise in litigation between technology developers and agricultural producers all suggest that a social reorganization of agriculture may be occurring, whereby ownership and control over agricultural production is expropriated from farmers and diverted to corporations” (Pechlaner, 2010, p. 292). For farmers who plant Monsanto’s seeds, Monsanto’s required “Technology Use Agreement” (TUA) binds farmers to a number of contractual provisions in addition to setting the technology fee and restriction on seed saving: “farmers must agree to only sell their crops to approved processors; they consent to the inspection of their fields for a set number of years; they agree that any dispute will be settled in the jurisdiction of Monsanto’s hometown of St. Louis, Missouri; and they agree that any infraction will be penalized 120 times the actual damages” (Pechlaner, 2010, p. 293). Indeed, there is no doubt that a massive restructuring has occurred within industrial agricultural production since its mechanisation, especially with the introduction of patented seeds. This reorganisation has tended towards an increasing dispossession of farmers’ autonomy and control over their production process, rendering them as glorified sharecroppers or at best contract labourers, or as Shand puts it, “bioserfs” (2002, p. 240). Monsanto’s seed-use agreement in the United States mentions nothing surrounding the use of data, however the Canadian version has now opened the door for legal stipulations on the collection of data. The latest TUA states to farmers: “you are consenting to the collection, use and disclosure of your personal information by Monsanto... (including your contact information, information about your farming practices and information about the specific nature of corn, soybean, canola, sweet corn, and sugarbeets that you farm using Monsanto Technologies) via electronic communication or otherwise, for the purposes of enforcing the [TUA]... and to assist Monsanto in developing its business and operations” (Armstrong, 2016, p. 21). Industrial farmers thus have to create uneasy alliances with mega-agribusinesses such as Monsanto or DuPont to be able to access and process this type of high-level technology, which comes at the paradoxical cost of losing control over their data. Pechlaner explains: “As agricultural biotechnologies represent the perceived best practices of the up-to-date farmer, many felt that to refuse the technology was to risk obsolescence. One farmer says, ‘Those who didn’t go with the technology, it passed them by and they’re out. They couldn’t compete.”’ (2010, p. 297).

The corporate histories of major agribusinesses, including the American companies Monsanto, DuPont and Dow, the German Bayer and BASF, the Swiss Syngenta and more recently the Chinese ChemChina, are complex but all follow an arc from being a chemical company evolving
towards the production of agrochemical and agricultural inputs. Through a series of acquisitions, mergers, sales and spinoffs, they emerge today as major multinational companies competing for global food production. Of all, due to buying Climate Corp., Monsanto stands out as the most committed agribusiness to pursue the use of big data in agriculture. Founded in 1901 by a pharmacist to produce an artificial sweetener called saccharine (Gilliam, 2009), over the next few decades the company evolved into producing a spate of industrial chemicals: polychlorinated biphenyls (PCBs), the insecticide DDT, Agent Orange, Roundup herbicide (Eeckhout, 2015). In 1996, they introduced their first biotech crop, and Roundup Ready soybeans. In 1997, swimming in controversy over its damaging chemical past, Monsanto neatly tucked its chemical arm into a new company called Solutia Inc., and became solely an agricultural biotech company. Fast forward to 2013: Monsanto decides to buy the weather-data and insurance start-up Climate Corp. for $930 million (McDonnell, 2014). This marked a turning point towards big data analytics. As hinted at in the introduction, Robb Fraley, Monsanto’s chief technology officer, even said that he could easily forecast the transformation of Monsanto into an information technology company (McDonnell, 2014).

Climate Corp. maps out multiple layers of data on a field, pulled from government satellites and weather stations, producing what it calls “Field-Level Weather”: real-time temperature, weather, and soil moisture at the field level, predicting when it is the best day to plant or harvest, and presenting trends based on weather data from the past 30 years. So far, this is included in the free version of the app; the next two tiers of services offered necessitate yearly paid subscriptions - which can sometimes run in the thousands of dollars pending on the size of the farm - and provide recommendations for how much water, pesticides or fertiliser different parts of the field may need, how much a farmer may receive in yield, along with a range of other tailored “insights” in important agronomic decisions made from a combination of all these sources of data. Combining these databases is a powerful example of the use of big data for gaining privileged information previously inaccessible. In this case, it gained Monsanto direct entry into what is now a third of US farmland, farmed under its guidance and supervision (McDonnell, 2014). Monsanto now has a direct feed via wifi-enabled sensors on tractors, mobile devices, and other technology on a field-by-field basis. The company can monitor and track what is in the soil, what the weather is, what kind of products the farmer is using, how much she’s producing, how much profit she’s making; in short, laying bare all the intricacies of a farmer’s business. Not only can Monsanto retrieve all this data, but much of it is “high resolution remote sensing in real time, allowing for maximum ability to impact farmer actions in season” (Friedberg, 2014, p. 10). Details on soil fertility and crop yield have historically been considered akin to a trade secret for farmers, and suddenly this information is being gathered under the guise of technology and miracle yield improvements.

The data asymmetry arises here again – farmers increasingly have to reveal their most personal farm details to gain access to the benefits of technology, while those who turn the data into useful information, such as Monsanto, reveal little to nothing about the back-end processes or how or where the information will be kept or used. Douglas Hackney, president of a business management group, puts it another way, “For a big data company, what is a farmer? It’s an account number… for a farmer, if their data falls into the wrong hands, it’s an existential threat” (Gilpin, para. 1). Big data can be immensely valuable for market speculation, and as Lina Khan elaborates, “Real-time data is highly valuable to investors and financial traders, who bet billions of dollars in wheat, soybean and corn futures. In a market where the slightest informational edge makes the difference between huge profits and even bigger losses, corporations that gather big data will have a ready customer base if they choose to sell their knowledge, or use it to speculate themselves” (2013). These concerns prompted the American Farm Bureau to act, and
in November 2014, they brought together an alliance of farm organisations and “agriculture technology providers”, including Climate Corp., to agree on a set of recommendations for governing security, data ownership, data protection, and data use (2014). In response, weeks after Climate Corp. signed the above agreement, they updated the language on their “End User License Agreement”, affirming that “We presume you own the information and data that you provide to us... including, for example, the data generated from the farming equipment you own or lease... we do not claim any ownership interest in Your Information [and it] remains yours even after you provide it to us” (2014b). Yet, paradoxically, further down in the agreement it says “we are the sole owner of the Climate Products and Generated Data and all associated technology and intellectual property rights, and we reserve all rights in and to the Climate Products and Generated Data” (2014b). So essentially, Climate Corp. is recognising farmers’ data ownership, but is also declaring farmers do not have a right to the data that Climate Corp. analytics generate, even when these data rely on farmers’ data. As for the TUAs, as cited above, though the Canadian version mentions a few lines, the US version of the 2016 TUA does not stipulate anything with regard to data collection, data ownership, or privacy rights, despite having signed (via Climate Corp.) the “privacy and security principles for farm data” agreement (2016).

4. OPEN-SOURCE DATA ANALYTICS

Despite alarming trends in, and potential issues with data-driven farming, it is not inherently negative and could be put to ground-breaking use by farmers. For example, rice cultivation in Taiwan has been at the mercy of an extremely invasive pest called the Golden Apple Snail (*Pomacea canaliculata*), introduced in the 1980s to begin an escargot industry (Carlsson, Brönmark, and Hansson, 2004). It quickly escaped the kitchens into the fields, and today it can nearly eat an entire rice field overnight if left alone. The Golden Apple Snail is also causing the same problems all over Asia (such as Japan, Korea, Philippines, Vietnam) and parts of the US (Hawaii, Florida, Texas, California) (Naylor, 1996). Although farmers have observed that the water level as well as temperature greatly affect its movements and reproduction (Y. Tsai, personal communication, 16 March 2016), much of the snail’s behaviour has not been studied in any systematic or broad way and could probably benefit from a massive big data application to understand the complexity of an ecosystem, and to come up with innovative ways of treating this problem besides laborious hand-picking, or poisonous chemicals which negatively affect the rice, the land, other native species such as birds and worms, and the health of the farmers.

There are some promising examples that promote the use of technology combined with the ability for farmers to openly access the analytic tools themselves while keeping control over their data, such as “ISOBlue” (Krogmeier, Buckmaster, and Ault, n.d.), an open-source project based at Purdue University, aimed at teaching farmers to capture and independently store their data. Another example is “FarmLogs” (Vollmar & Koch, n.d.), a company which sells data analytics software that allows farmers to fully control their own data collection. The “Open Ag Data Alliance” on its part has a mission statement to “help farmers access and control their data.”

Open data is also advocated by a small group formed in 2015 called the Global Open Data for Agriculture and Nutrition initiative (GODAN), whose mission is to support open data in agriculture and nutrition for research, innovation and presumably consumers’ choice (Szpotowicz, 2015). These open source technologies are encouraging as they may help farmers to reclaim their data ownership and regain some autonomy. Additionally, these tools are available to small non-industrial farmers, and, with the help of crowd- or publicly funded research and/or
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user-friendly software, could pave the road for innovative uses of big data by small farms using different agricultural models. Perhaps one of these tools could allow all the rice farmers affected by the Golden Apple snail in Southeast Asia to aggregate their data to find ground-breaking solutions to the Golden Apple snail pest.

CONCLUSION AND RECOMMENDATIONS

As mentioned above, Monsanto reveals little to nothing about how or where the big data it collects will be kept or used. This is consistent with the secretive aspect with which Monsanto hoards its information. Understandably, most farmers fear that their information will be secretly used for commodity market speculation (American Farm Bureau, 2015). For that reason not only should Monsanto’s TUA provide for a better protection of farmer’s data and interests but also, and crucially, legislation is needed to remedy potential misuse of data. Another way of rendering the use of big data in agriculture more equitable would be the collection of big data on industrial agriculture externalities as explained above. Moreover those (anonymised) data must be open to the public in order to respect the people’s right to informational power (Raven, 1965). Likewise, the labelling of GMO food in the USA is needed in order not only to respect people’s informational rights but also to collect data regarding the presence or absence of injurious effects on people’s health, and GMOs’ connection to other environmental disturbances.

There have been several major power shifts from farmers to corporations happening in industrial agriculture due to machinery, chemical fertiliser, herbicide and pesticide, patented seeds, genetically modified foods, and now big data. One could say that big data analytics seems to solve and thereby sanction the problems of big agriculture: if the modern large-scale farms and businesses are not sustainable given their externalities, big data analytics, as Climate Corp. claims, will come to the rescue and allow them to lower the environmental cost of farm inputs. But big data will not solve the inherent, intrinsic problems of the environmental externalities of industrial agriculture (Kimbrell, 2002), a longer discussion of which is beyond the scope of this paper. Moreover, agricultural big data analytics should have a wider focus beyond being a panacea for the ills of industrial farming. Big data analytics, of the flavour used by Climate Corp., are powerful tools that should be in the hands of many, bringing the information revolution to agriculture and allowing for experimentation, innovation, and local leadership in various agricultural models. To be concentrated in the hands of big agribusinesses limits the potential of this technology, and only reinforces the aims of a few corporations and their investments.

So how could the use of big data be more equitable? First, the collection of multiple large databases to form big datasets should be open-sourced and in the public domain, as advocated by the GODAN initiative mentioned above, under the condition of anonymising contributions from specific individuals. Open source data should always be anonymised as it is the only way to prevent the deleterious exploitation of data. Secondly, big data analytic tools are expensive, complex, and require large teams to assemble and develop. For these tools to enter the public domain, work for the common good and not just for corporate interests, they need to be funded and developed by public organisations. This was the case of ISOBlue, mentioned above, which was funded by Purdue University. In the US context the funding entities, beyond universities, could be the Department of Agriculture (USDA) or the National Science Foundation (NSF); in Europe it could be the European Commission’s programme for Research and Innovation, Horizon 2020. Big data applications in agriculture could be put to ground-breaking use around
the world, provided public structures – government agencies, universities, NGOs, international entities like the United Nations – support parallel research and development in innovative solutions benefiting a variety of farmers and diverse agricultural models around the world.
REFERENCES


OSGATA v. Monsanto, No. 13–303 (Supreme Court 13 January 2013).


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FOOTNOTES

1. To very briefly explain these power concepts, originated in a study by social psychologists John R. P. French and Bertram Raven: coercive power uses the threat of force to gain compliance from another; expert power is based on the ability, or the perception of that ability, to administer information, knowledge, or expertise; informational power comes as a result of possessing knowledge – potentially concentrated and controlled in the hands of a few – which others need or want. Specifically, Michel Foucault’s work on coercive power makes a departure from French and Raven, where power, instead of being concentrated and forcible, is diffuse, embodied, and pervasive.

2. The TUAs prescribes: “If Grower is found by any court to have... infringed one or more of the U.S. patents, Grower agrees that, among other things, Monsanto and Dow AgroSciences, as appropriate, shall be entitled to preliminary and permanent injunctions enjoining Grower... any such finding of infringement by Grower shall entitle Monsanto... to patent infringement damages to the full extent authorized” (Monsanto 2016).

3. Litigation against something a farmer cannot control is potentially perilous for a farmer’s livelihood, so much so that this issue was eventually brought before the US supreme court: if Monsanto is going to patent seeds, the company should also be responsible if traces of its products end up in non-GMO planted fields, rather than farmers being responsible for unintentional contamination (OSGATA et al. v. Monsanto, 2013). However, the supreme court refused to hear the case, because “Monsanto has made binding assurances that it will not ‘take legal action against growers whose crops might inadvertently contain traces of Monsanto biotech genes’”(Public Patent Foundation, 2013). This ruling hardly relieves the farmers from the burden of proof of “inadvertency” in situation of traces of Monsanto biotech genes.

4. This power concept originated in a study in 1965 by social psychologist Bertram Raven: informational power comes as a result of possessing knowledge – potentially concentrated and controlled in the hands of a few – which others need or want.