ANNUAL REVIEWS

Annual Review of Resource Economics

Precision Farming at the Nexus of Agricultural Production and the Environment

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Annu. Rev. Resour. Econ. 2019. 11:313–35

First published as a Review in Advance on April 24, 2019

The *Annual Review of Resource Economics* is online at resource.annualreviews.org

https://doi.org/10.1146/annurev-resource-100518-093929

JEL codes: D2, O3, Q1, Q2, Q5

Keywords

precision agriculture, smart farming, digitalization, variable rate technology, big data, site-specific management, sustainable intensification, technology adoption

Abstract

Precision farming enables agricultural management decisions to be tailored spatially and temporally. Site-specific sensing, sampling, and managing allow farmers to treat a field as a heterogeneous entity. Through targeted use of inputs, precision farming reduces waste, thereby cutting both private variable costs and the environmental costs such as those of agrichemical residuals. At present, large farms in developed countries are the main adopters of precision farming. But its potential environmental benefits can justify greater public and private sector incentives to encourage adoption, including in small-scale farming systems in developing countries. Technological developments and big data advances continue to make precision farming tools more connected, accurate, efficient, and widely applicable. Improvements in the technical infrastructure and the legal framework can expand access to precision farming and thereby its overall societal benefits.

1. INTRODUCTION

With the large-scale mechanization of the agricultural sector in the twentieth century, labor was increasingly replaced by machinery, land productivity increased, and economies of scales were achieved (Martín-Retortillo & Pinilla 2015). The switch from labor- to capital-intensive farming enabled farmers to manage larger fields and farms. From the mid-twentieth century on, the Green Revolution brought productivity gains via genetically improved varieties, synthetic chemical fertilizers, and pesticides that reduced crop losses. These innovations favored the development of larger and more uniformly managed fields in many parts of the world. In contrast, before agricultural mechanization, farmers could adjust their within-field management to account for variabilities in yield potentials, topography, soil characteristics, nutrient demands and both abiotic (e.g., weather) and biotic (e.g., pests and weed infestation) stresses in mainly manual practices (Zhang et al. 2002). But in gaining the economies of scale from mechanization and moving to uniform practices, farmers sacrificed the ability to manage efficiently the spatial and temporal heterogeneity of farm fields.

The new and ongoing agricultural revolution in information technology, called precision farming (PF), began to be developed in the 1980s. PF technologies became commercially available beginning in the early 1990s. PF addresses the challenge of tailoring management to site, crop, and environmental traits (Swinton & Lowenberg-DeBoer 1998, Lowenberg-DeBoer 2015) and promotes the use of new technologies and data to address heterogeneities of a field (e.g., Zhang et al. 2002). Thus, PF comprises standardized approaches to reduce the unknowns related to the knowledge base for farm management decisions (Liaghat & Balasundram 2010) and enables temporal and site-specific farm management even for agricultural systems that became mechanized and large scale. In short, PF enables big farms to tailor management as small farms do (Swinton & Lowenberg-DeBoer 1998, Lowenberg-DeBoer 2015). It represents a paradigm shift, as the field is treated as a heterogeneous entity that allows for selective treatment and management (Aubert et al. 2012). PF is not exclusive to specific farms but could be applicable and beneficial for all farms, ranging from small to large, organic to conventional, as well as from developed to developing country farms. Besides PF, precision livestock farming is also an important and emerging field (e.g., Wathes et al. 2008, Berckmans 2014, Busse et al. 2015), but beyond the scope of this review.

Adoption of PF technologies to date varies both geographically and by type of technology. Although various components of PF became mature technologies in developed countries (e.g., georeferencing technologies and guidance systems), the overall picture is that PF has not yet been taken up widely in the agricultural sector at large (e.g., Bramley 2009, Tey & Brindal 2012, Tamirat et al. 2018). This is especially the case for more complex applications like sensor-driven variable rate application of inputs.

However, the ongoing evolution of many PF technologies is lowering costs and expanding applications in ways that bode broader adoption. Developments in information technology allow an increasingly finer degree of precision than previously possible (Aubert et al. 2012), and the costs for sensor technologies are declining rapidly. Technological developments related to the digitalization of the agricultural sector are currently complemented by advances in data processing and robotics (e.g., Walter et al. 2017, Wolfert et al. 2017, Weersink et al. 2018). These developments have led some to argue that PF will advance the sustainability of agriculture (e.g., Walter et al. 2017).

The question remains whether, where, and how technological developments can be transformed into benefits in the agricultural sector. Policy makers became increasingly interested in PF recently because of its potential to address current challenges of the agricultural sector (Kritikos 2017). These challenges comprise the need for high quantity and quality of food produced but also the reduction of negative external effects of agricultural production, such as environmental pollution, loss of biodiversity, and the substantial contribution of agriculture to greenhouse gas emissions (e.g., Tilman et al. 2002, 2011). These challenges are accelerated due to climate change, globally changing dietary patterns, and changing societal demands for ecosystem services (Schröter et al. 2005, Swinton et al. 2007, Zhang et al. 2007, Power 2010, Vermeulen et al. 2012, Wheeler & Von Braun 2013). In response, agri-environmental policies are becoming stricter, motivated by the urgent need for solutions reducing the environmental and human health implications of agricultural production. These steps, however, shall not jeopardize food production and the economic viability of the sector (Zhang & Wen 2008, Osteen & Fernandez-Cornejo 2013, Finger 2018). Sustainable development of the agricultural sector requires addressing this nexus of productivity, environmental problems and economic viability of agricultural activities.

This review argues that PF is not a panacea, but it has great potential to contribute to a more sustainable development of the agricultural sector. Because PF is fundamentally a set of information technologies used for decision support, the change it promises will vary with the pre-PF farming practices and degree of information use. The goal of this article is to investigate and assess developments of precision farming from the perspective of both farmers and policy makers. The article examines the mechanisms, use, trends, and future prospects of PF. Based on foundations from agronomic and technical perspectives, we review the economics of PF, adoption and diffusion, barriers to success, and environmental impacts. Moreover, policy aspects of PF are investigated, and the interrelation with other agricultural and environmental policies is analyzed.

2. PRECISION FARMING

PF aims to tailor management in a coherent and holistic manner (Lowenberg-DeBoer 2015), especially exploiting high spatial and temporal variability of crop and environmental traits (e.g., Zhang et al. 2002, Lowenberg-DeBoer 2015). Variabilities in yield potentials, topography, soil characteristics, nutrient demands, and abiotic (e.g., weather) and biotic stressors (e.g., pest and weed infestation) are addressed (Zhang et al. 2002). Pierce & Nowak (1999, p. 4) summarize PF as a technology that allows a farmer to "…do the right thing, in the right place, in the right time and in the right way." To this end, farmers can use different (combinations of) technologies. We especially distinguish diagnostic (collecting or generating information) and applicative (implying adjusted management actions) tools in PF technologies.[1] Collecting and structuring data are the foundation of PF, but ultimately, the high potential of PF results from the combination of different technologies applied to derive management practices from the collected data.

Georeferencing technologies, such as the global positioning system (GPS) and mapping via geographical information systems (GIS), are key elements of many PF applications. These technologies allow the use of guidance systems and controlled traffic during field operations such as tillage, harvesting, and application of inputs such as nitrogen, seeds, and pesticides. Because no further skills or new machinery are needed to make use of georeferencing technologies, Weersink et al. (2018) refer to them as embodied-knowledge technologies. However, georeferencing information is especially powerful in reaching efficiency gains if used in conjunction with other sensors to provide georeferenced maps of yield, salinity, or other measurable environmental traits, but also by simply reducing overlap during field operations.

Diagnostic tools gather information using sensing or sampling techniques along various scales (e.g., Wang et al. 2006, Zhang & Kovacs 2012, Mulla 2013). The most important sensing tools use spectral indices that are taken from images and provide information on the coloration of the observed vegetation. Frequently, sensors and scanners mounted on tractors are used to provide

[1] Barnes et al. (2019) use the terms recording technologies and reacting technologies instead.

information on nutrient status (e.g., Li et al. 2010). Initial sensing approaches have established the normalized difference vegetation index (NDVI) as a measure for soil covered with functional leaf tissue. NDVI has been calculated from data in the near-infrared and in the red wavelength range since the 1970s. In the meantime, many more spectral indices have been used in PF to derive proxies for canopy cover, organic carbon content of the soil, soil moisture, leaf area index, or plant biomass (Mulla 2013). Images taken from satellites have been used since the 1970s to extract relevant agricultural information (Bauer & Cipra 1973, Mulla 2013). The first of those satellites, Landsat 1, collected information in four spectral bands (red, green, and two infrared bands) at a spatial resolution of 80 m and at a return frequency of 18 days. In the meantime, satellites such as QuickBird and RapidEye that are equipped with more sophisticated sensor technology can provide revisit times between one and three days, spatial pixel resolutions of less than 1 m, and higher numbers of spectral bands. Data from these satellites are not easy to process and are costly. Since 2017, data from Sentinel 2 are publicly available, with a spatial resolution of 10 m in 13 possibly relevant spectral bands, leading to cheaper and more precise options for the diagnosis of vegetation and nutrient status than previously possible (Lilienthal et al. 2018). Moreover, near-remote sensing is based on unmanned aerial vehicles (UAVs) such as drones. Within a small field, UAVs have increasingly been used to provide images with resolutions in the centimeter range (Candiago et al. 2015, Agili et al. 2018) and allow for the detection of a high number of relevant traits (Walter et al. 2015, Hunt & Daughtry 2018) such as crop biomass, developmental stage, photosynthetic efficiency, nitrogen nutrition status (Gnyp et al. 2016), or soil properties without the nuisance of clouds possibly covering the information, as is often the case for satellites. Moreover, scouting for weeds, for example, can be facilitated with UAVs (Lottes et al. 2017, Walter et al. 2018). To monitor crop traits and certain other environmental conditions, other sensing [e.g., thermal imaging, electrical conductivity of the soil (Corwin & Lesch 2005)] and sampling techniques (e.g., GPS-based soil sampling regarding available nutrients, pH level, soil moisture, etc.) are frequently used. Furthermore, in situ sensors capable of real-time monitoring of soil nitrogen can improve fertilizer management, seeding rates, and use of growth regulators exploiting the spatial variation of soil nitrogen (e.g., Shaw et al. 2016). Finally, also handheld devices are used to measure the nutritional status of plants.

Diagnostic tools are not only focused on measurement during the growing period, but they are also applied at harvest. Based on sensors on grain and bulk crop harvesters, yield monitors record crop yield, especially to document within-field variability. These monitors are available for most grain and bulk crop harvesters. This allows a precise and highly localized performance measurement within the field. Yield monitoring also plays an important role in different horticultural crops ranging from vegetables to fruits and from mechanically harvested to handpicked systems (see Zude-Sasse et al. 2016 for an overview). Beyond crop quantity, quality is also monitored. For cereals, quality traits such as protein and moisture content are measured in yield-monitoring combines using near-infrared spectroscopy. In addition, forage quality traits such as moisture, protein, or fiber are frequently monitored at harvest. Yield quality monitoring is of special relevance for high-value horticultural crops (e.g., Aggelopoulou et al. 2011).

Next to the use of high technology sensor solutions, low-cost, low-technology tools are also used as diagnostic tools, especially in developing countries. For example, Mondal & Basu (2009) report that portable diagnostic tools such as chlorophyll meters and leaf color charts for in situ measurement of the crop nitrogen are used in various Asian countries.

Applicative tools enable management response to spatially and temporally precise diagnostic information. This can be done using manually operated systems, e.g., for the variable rate application of fertilizer (Robertson et al. 2012). In theory, however, the full capacity of PF is utilized when applications are performed with automated treatment technology, such as shown for highly site-specific nitrogen fertilization (Fulton et al. 2005, Kim et al. 2008, Diacono et al. 2013), tree spraying (Jeon & Zhu 2012), or site-specific center pivot irrigation (Evans et al. 2013). These variable rate technologies (VRTs) also comprise precision soil preparation or variable rate seeding. For the latter, adjustments in spacing and depth according to environmental conditions such as soil moisture and soil organic matter content are made. Yet, in practice, a frequently applied concept for site-specific application of inputs is that of management zones (Khosla et al. 2002, Seelan et al. 2003, Nawar et al. 2017): Highly resolved prescription maps are translated to maps that show a small number of regions, for which differing intensities of fertilizer, irrigation, or other input are applied using available, often conventional machinery. These management zones are based on a number of monitored input parameters, and the number of zones can be chosen with respect to the given task (e.g., a high, medium, or low rate of fertilizer applied). Nawar et al. (2017) showed that an optimal number and outline of these management zones are important prerequisites for profitable application of PF. Delineation of site-specific management zones today is performed with methods of machine learning (Chlingaryan et al. 2018). Yet, machinery is also increasingly used that allows even further refined precision application of inputs, e.g., specific precision fertilization or spraying equipment.

VRTs also increasingly involve new types of equipment and machinery. For example, UAVs can be used to apply inputs such as pesticides (Xiongkui et al. 2017). The use of autonomous machinery and robots is another area of increasing development along the line of PF technologies. Here, positioning information and multiple sensors are combined with machines allowing autonomous activities such as seeding or weed control (e.g., Slaughter et al. 2008, Van Evert et al. 2011, Naik et al. 2016, Walter et al. 2018). Greenhouse-based production is also highly suitable for automation and use of robots (e.g., Roldán et al. 2018), e.g., by measuring and adjusting the use of inputs such as water and fertilizer but also heating, CO_2 injections, and ventilation (Roldán et al. 2018).

Overall, VRTs facilitate the application of inputs in a computer-based controlled way using prescription maps. Higher spatial and temporal precision in input application is used to meet crop quantity and quality targets. As an example of the latter, nitrogen is decisive for the quality of various crops such as cereals, oil seed crops, potatoes, or sugar beets. Precise application of nitrogen can allow a farmer to adequately balance trade-offs, e.g., between protein levels and oil concentration for oil seed crops, and to determine marketing channels (e.g., for potatoes) (see Blumenthal et al. 2008). Precise application of inputs also has the potential to reduce costs and effluents, i.e., residual inputs lost to environmental systems. It is an open question whether and to what extent these benefits are achieved in real-world agricultural systems. Land allocation decisions can also be improved using information obtained from sensors. For instance, high-productivity zones can be identified in the field based on yield monitors to prioritize land-use decisions. The identification of low-productivity zones in the field can be used to assign set-asides (Muth 2014, Brandes et al. 2016). Due to increasing computing power and better tools to process and analyze data, more data can be fed into decision support tools (e.g., on-tractor dashboards or apps) allowing for real-time adjustments in management decisions.

3. ECONOMIC FRAMEWORK

To help conceptualize the adoption of PF technologies, we build upon the model of Norton & Swinton (2001). Developed in the early days of PF, that model focused on how PF affects variable input use. We expand that model to accommodate PF technologies that (*a*) enhance the yield (y); (*b*) reduce undesirable effluents (e) from residual nutrients to water (e.g., NO_3, pesticides) or to air (e.g., N_2O); and (*c*) reduce the overuse of other environmentally relevant inputs such as fuel and irrigation water. We also allow PF to increase the quality (Q) of marketed goods. Product quality as influenced by inputs can take the form of intrinsic and/or extrinsic quality. Intrinsic quality comprises, for example, color, appearance, protein, starch, or sugar content as well as pesticide residue content. Extrinsic quality is associated with production practices, origin, or related aspects of the production process.

We distinguish between PF technologies that manage a limited set versus a wide set of inputs. From the standpoint of a farmer as decision maker, we frame the problem as a dynamic investment model. The decision maker choses a stream of capital and variable inputs—differentiated between information technologies and conventional ones—to maximize discounted net revenue over the farm's planning horizon. Annual capital investments may take the form of information technologies, k_I, or conventional technologies, k_x. Annual variable inputs may take the form of custom PF services, s_I, conventional inputs, x, or a mixture of both.

In deriving behavioral expectations from this model, we work from the assumption that the farmer had already optimized for spatially average conditions, $\bar{x}^*|s_I = 0$. So the inferences of interest involve how the presence of PF services ($s_I > 0$) causes accumulated wealth to change and which particular PF services have the greatest effect under what conditions.

$$\underset{k_I, s_I, k_x, x}{Max} \int_{t=0}^{T} \delta^t E(\pi_t)\mathrm{dt}, \qquad 1.$$

subject to

$$\pi = p(Q)Ay\left[x\left(s_I^x, k_I\right), s_I^{mc}, z\right] - (w_x x + w_I^x s_I^x + w_I^{mc} s_I^{mc}) - c_e e - k_I - k_x - FC, \qquad 2.$$

$$Q = Q\left[x\left(K_I, s_I^x\right)\right], \qquad 3.$$

$$e = x - \theta y, \qquad 4.$$

$$\begin{aligned} k_j &= k_j(K_{jt-1}, L_f, \int \delta^t \pi_t \mathrm{dt}, WK[Y^{nf}, credit(K_{jt-1}, i, A)] \qquad \forall j = I, x \\ K_{jt} &= K_{jt-1} + k_{jt} \\ K_{I0} &= 0;\ K_{x0} = K_0, \end{aligned} \qquad 5.$$

where $E(\bullet)$ is the expectations operator, δ is a discount factor, and π_t is net revenue in period t, with integration covering all periods up to the farmer's time horizon T. In the constraint set, the time subscript is suppressed for simplicity. Annual net revenue π_t depends on revenue, variable costs, and capital costs (k_j, FC). The revenue function, which is the first expression on the right-hand side of Equation 2, is the product of product price p, land operated A, and yield y. Product price is assumed to be increasing in quality (Q), which can be enhanced via information-based management of conventional inputs x, as shown in Equation 3. Note that price increases due to increases in intrinsic and especially extrinsic quality require that this quality information can be reliably transported to downstream actors. Yield depends on x (including seed, fertilizers, pesticides, hired labor), information services for inputs s_I^x (including nutrient and pest maps, variable rate applicators), information services for management control s_I^{mc} (e.g., yield maps, sensors, yield traceability, guidance systems), and conditioning factors z (such as human capital, management ability, and land quality). Variable costs, which appear in the second term on the right-hand side of Equation 2, depend on input levels and unit input prices w_x for conventional input x and w_I for information custom services, s_I.[2] The adoption of PF is capital intensive and leads to greater expenditures on machinery and equipment as well as for access to information, e.g., such as georeferencing services (Schimmelpfennig 2016). Effluent costs, $c_e e$, appear as the third term in Equation 2. Effluents are defined as the residual of inputs, x, that remain in the environment after share θy of x is removed by crop yield, per Equation 4 (Khanna et al. 2000). The remaining terms are the annual capital costs of owning information technologies (k_I) and conventional technologies (k_x), along with other fixed costs, FC. As indicated in Equation 5, annual investment costs of either technology k_j depend on prior capital stocks K_{jt-1}, the availability of family labor (L_f), expected future net revenues from changes in capital level (the second term), and the availability of working capital WK. WK, in turn, depends on nonfarm income Y^{nf} and credit, which is a function of current ownership of capital (K_{jt-1}), interest rate (i), and land (A). The final two constraint equations specify the dynamics of motion and the initial conditions.

Creating a Hamiltonian from Equations 1 and 2 and differentiating with respect to k_I or s_I leads to a reduced form of input demand functions that highlight the expected determinants of adoption for PF technologies:

$$k_I = k_I(\overset{+}{p}, \overset{-}{w}_I, \overset{+}{w}_x, \overset{-}{i}, \overset{+}{K}_0, \overset{+}{Y}^{nf}, \overset{+/-}{CS}_I, \overset{+}{A}, z), \tag{6.}$$

$$s_I = s_I(\overset{+}{p}, \overset{-}{w}_I, \overset{+}{w}_x, \overset{-}{K}_{It}, \overset{+}{CS}_I, \overset{+}{A}, z). \tag{7.}$$

Equation 6 suggests that apart from input and output prices, PF technology investment depends on the farm's access to investment capital, be it from an initial endowment, off-farm income, or land. Equation 7 shows that custom-hired PF services depend on relative prices and land area in the same fashion as do PF investments, but the effect of PF capital equipment is to reduce custom hired services, whereas the effect of local agribusiness infrastructure (CS_I) is to increase them. Jointly, Equations 6 and 7 address the use of PF technologies, whether through one's own capital (k_I) or custom-hired services (s_I).

This model of wealth-maximizing decisions by a representative farmer creates a framework for developing expectations about PF technology adoption. First, because PF information technologies can enhance land productivity and because they require access to investment capital, farms with more land will be more likely to adopt PF for the revenue contribution and for access to capital embodied in land value. Hence, larger farms are expected to be early adopters of new technologies such as PF that exhibit increasing returns to scale (Bowman & Zilberman 2013). Second, in areas with higher spatial variability of field conditions, PF is more likely to be profitable and adopted because, for example, variable rate applications have higher economic benefits (e.g., Bullock et al. 2002, Isik & Khanna 2002, Liu et al. 2006). Third, farms whose product quality is responsive to PF management will be more likely to adopt PF due to the potential to gain quality premiums. This can comprise products where intrinsic quality is highly price relevant (e.g., horticultural crops) and products where prices are driven by extrinsic quality (e.g., products under specific brands or labels). Fourth, because they provide general management planning and control information, the PF diagnostic tools for management control (s_I^{mc}) are likely to be adopted earlier than the applicative PF technologies. The reason is that diagnostic tools, such as remote sensing of crop health or yield monitoring, can add value through informing management decisions on multiple inputs (e.g., nutrients, water, pesticides), while the specific applicative PF technologies tend

[2]The demand for custom services will depend on both the level of existing farm investment in information technologies, K_I, and the existing set of custom services available in the local economy, CS_I. We omit these details for parsimony.

to be limited to one or few inputs. Moreover, applicative technologies require diagnostic tools and additional investments. Fifth, embedded in the z variable are management quality elements, including human capital, suggesting that PF will be adopted more rapidly where education levels are higher. Sixth, the presence of an agribusiness infrastructure, CS_I, will be especially important for adoption of custom-hired PF services that enable adoption of PF with much reduced investment in PF hardware, software, and learning. Along these lines, the availability of information technology infrastructure—including high-speed internet access, georeferencing services, platforms for data collection and sharing, decision support tools, and advisory service—will be a precondition for the adoption and diffusion of PF technology.

Apart from expectations about farmer adoption, the annual production part of the model in Equations 2–4 suggests two additional expectations about the effect of PF adoption on farming systems. The first of these is a cautionary note: Although PF is often characterized as input saving and/or yield enhancing, neither is necessarily true. In both cases, the effect of PF depends on the prior level of management. Indeed, if (contrary to model assumptions) the farmer did not optimize input use for spatially average conditions (e.g., if the information was not available before), PF adoption may bring extra yield gains or agrichemical savings that could have been had simply by good management for average conditions. Second, PF is expected to reduce emissions by increasing the efficiency of field operations and reducing wasted agrochemical inputs that miss their targets and become effluents. Where there is a nonzero effluent cost (c_e), as in the presence of Pigouvian taxes, we would expect an even stronger effect of PF on reducing effluents.

The conceptual model presented here provides a starting point for a critical assessment of PF technology adoption. By extending the model, added adoption determinants can enter. For example, other benefits of PF beyond changes in (expected) profits, are decreasing risk exposure [e.g., reduce temporal yield variability (Lowenberg-DeBoer 1999)], reductions of labor requirements (e.g., for autonomous field operations), or improved quality of working conditions (e.g., higher work safety, reduced exposure to pesticides, reduction of physically demanding manual labor, autosteer systems) (e.g., Gebbers & Adamchuk 2010). The goal function depicted in Equation 1 reveals that investment costs for equipment (e.g., Reichardt & Jürgens 2009) and/or learning costs due to complexities of PF production systems (e.g., Kutter et al. 2011) can represent adoption hurdles. This framework can be extended to also incorporate the role of risk and risk preferences for investment decisions (see also Sunding & Zilberman 2001). For example, uncertainties regarding possible benefits of PF reduce adoption incentives (e.g., Khanna et al. 2000, Tozer 2009). Technology risks are especially crucial for the adoption of PF by farmers because innovation can take place rapidly: "In the world of precision agriculture, each new growing season seems to bring a fresh batch of brand-new technologies."[3] This is expected to delay PF investment (Watcharaanantapong et al. 2014), especially if framing investment decisions in a real option theory framework (e.g., Tozer 2009).

4. EMPIRICAL EVIDENCE

The empirical evidence on the uptake of PF and its potential for environmental benefits is consistent with the expectations from the economic model and also shows that uptake of PF is highly heterogeneous across time, space, and technology. While there exists no global database of PF adoption patterns, there are many examples of the application of PF across various cropping systems and countries (e.g., Bramley 2009, Tey & Brindal 2012, Pierpaoli et al. 2013).

[3] **https://www.country-guide.ca/2018/01/23/the-precise-in-precision-agriculture/52423/**.

4.1. Adoption of Precision Farming

Consistent with expectations from the economic model, PF diagnostic technologies are becoming more widely adopted compared to the PF applicative technologies. The number of agricultural devices for gathering data worldwide was estimated at 30 million in 2015 and is expected to rise to 75 million by 2020 (Chi et al. 2017, Weersink et al. 2018). Guidance systems, GPS, and GIS mapping are common in new machinery in many countries (e.g., Winstead et al. 2010, Mulla 2013, Suprem et al. 2013, Schimmelpfennig & Ebel 2016, Zhou et al. 2017). For example, Griffin et al. (2018) report adoption rates in Kansas to be above 80%. Yield monitoring systems are also widely used and incorporated into most new, large-scale combine harvesters in North America (Griffin et al. 2018). Suprem et al. (2013) report that 46% of corn, 36% of soybeans, and 15% of wheat in the United States are harvested by a combine that allows yield monitoring. However, the share of farms that also uses GIS mapping software to store, manage, and analyze the data from site-specific technologies was found to be lower than the share equipped with yield monitors (Winstead et al. 2010).

Remote sensing (e.g., satellite imagery) or proximate plant sensing approaches are less widely adopted than in-field diagnostic technologies. For example, Castle et al. (2015) report that 25% of Nebraska farms use satellite imagery compared to an 80% uptake of yield monitors and GPS guidance systems.

PF diagnostic tools are adopted outside of the United States at lower rates, but they follow similar uptake patterns in regions such as Australia (e.g., Bramley 2009) and Europe (e.g., Reichardt & Jürgens 2009, Tamirat et al. 2018). For example, the general uptake of PF technologies in German agriculture is estimated to be between 10% and 30% (Reichardt & Jürgens 2009, Kutter et al. 2011, Paustian & Theuvsen 2017). While the overall PF adoption in developing countries is low, selected uptake has been reported in Argentina, Brazil, Chile, China, India, and Malaysia (Mondal & Basu 2009). The uptake of diagnostic tools, including remote sensing, was found to be highest among large-scale farming operations (e.g., Silva et al. 2011 for sugarcane in Brazil). More generally, adoption is increasing with farm size, consistent with the capital requirements and economies of scale for such tools highlighted in the previous section (e.g., Norton & Swinton 2001, Schimmelpfennig 2016).

Applicative technologies such as VRT have been adopted to a much smaller extent than diagnostic tools. Griffin et al. (2018) report that the share of Kansas farms using VRT fertilizer application is above 25% and VRT seeding at approximately 20%. More generally, Schimmelpfennig & Ebel (2016) report that VRT in US crop production is used on about 19% of farms (see also Winstead et al. 2010, Zhou et al. 2017). Along these lines, Reichardt & Jürgens (2009) show for German farms during 2001–2006 that approximately one out of five PF adopters used VRT. Barnes et al. (2019) surveyed farmers on adoption of PF in Belgium, Germany, Greece, the Netherlands, and the United Kingdom. In summary, their findings reveal that PF technologies also play a vital role in European agriculture, but a large share of adoption is due to the use of machine guidance, whereas VRTs play a minor role. Among Brazilian sugarcane producers in São Paulo state, fewer used VRT (29%) than used diagnostic technologies (e.g., 39% used GPS, 76% satellite images) (Silva et al. 2011). Yet, information on within-field variability does not necessarily need to be addressed using sophisticated VRTs. For example, Robertson et al. (2012) show that farmers in Australia use a pragmatic approach, applying fertilizer, lime, gypsum, and seed by management zones based on soil testing and yield maps, but without necessarily using prescription maps and variable rate controllers.

The uptake of VRT is high for horticultural crops, due to both high input costs and consumer appreciation of extrinsic quality traits (Zude-Sasse et al. 2016). For example, targeted spraying in orchards aims pesticides at individual trees (Zude-Sasse et al. 2016). Given the large number of pesticide applications to many horticultural crops, the cost savings due to PF here can be large and can create intrinsic quality attributes. Targeted pesticide applications can also augment extrinsic quality by reducing environmental effluents.

There is an increasing use of UAVs for precision pest control on horticultural crops but also on arable crops. Xiongkui et al. (2017) show high uptake rates of UAV pest control in South Korea and Japan, especially for arable crops. UAV-based application of pesticides is in an early market phase in other parts of the world. For example, in Switzerland, three companies now offer UAV application of pesticides in vineyards where in a first step, helicopter application of pesticides should be replaced. In comparison to these helicopter applications, UAVs are less noisy, more accurate, less polluting (due to greater accuracy), and cheaper (Anken et al. 2018). Technical, economic, and regulatory hurdles remain for UAV use, but it has potential as a cost-effective applicative technology in a wide range of crops and cropping systems. Giles (2016) provides an overview on the use of remotely piloted aircraft for pesticide applications. The use of autonomous robots for weed control, seeding, and other field operations is in the initial phase of market entry.

For grasslands, PF has seen less uptake than in arable crops (e.g., Schellberg et al. 2008). In part, this is due to lower values of produced output but is also because the mixed species of grasslands complicate management recommendations (Schellberg et al. 2008). However, new PF technologies are also being introduced on grasslands. Besides yield monitoring, precision fertilization, and weed detection, site-specific overseeding is a new application of PF for grasslands. In this application, seeding is focused on parts of the field with low plant density as identified with cameras. However, machines for grassland restoration, including site-specific overseeding of degraded grasslands, currently available on the market are not suitable for all types of soil and grassland conditions (Golka et al. 2016), requiring further developments (e.g., Loghin et al. 2011).

4.2. Environmental Effects of Precision Farming

PF has been widely expected to show environmental benefits. More targeted application of inputs with fewer losses of fertilizer and pesticides to the environment, reduced water consumption, and reduced greenhouse gas emissions provide a wide spectrum of environmental benefits (e.g., Zhang et al. 2002, Balafoutis et al. 2017). However, the magnitude of these effects is often not well known or is highly variable (e.g., Balafoutis et al. 2017). Moreover, most studies do not report observed impacts, but rather possible impacts based on experimental data or model predictions. Only a few studies show causal inference on environmental performance of PF in real-world agricultural applications. With these caveats, we synthesize some key areas of environmental benefits arising from PF based on the available studies.

Overall, PF reduces greenhouse gas emissions. First, machine guidance and controlled traffic farming reduce fuel consumption due to less overlap in farm operations. Guidance systems have been found to cause a 6% reduction of fuel use (Shockley et al. 2011), and Jensen et al. (2012) report a 25% reduction of fuel expenditures. These reductions are larger for large-scale fields, and they come with several cobenefits, including reductions in soil compaction, runoff, and erosion (Balafoutis et al. 2017). Second, the reduction of effluents implies, for example, reduced nitrogen losses as ammonia and nitrogen oxides (e.g., Balafoutis et al. 2017). In a case study on maize production in Germany, VRT nitrogen application resulted in nitrous oxide (N_2O) emission reductions of 34% (Sehy et al. 2003). For locations in Southern India, the Philippines, and southern Vietnam, Pampolino et al. (2007) showed the potential of site-specific nutrient management to obtain higher yields with increased nitrogen fertilizer use while maintaining low N_2O emissions. Third, the indirect energy consumption footprint from inputs such as fertilizer, seeds, and pesticides (e.g., Böcker et al. 2019) can be reduced if inputs are applied more efficiently.

By increasing application efficiency, losses of critical inputs to the environment are generally reduced. For example, for Texas citrus production, Du et al. (2008) compare airborne multispectral analysis with human inspection to identify tree health problems and to guide pesticide application. The airborne multispectral technique combined with VRT led to reductions in the use of pesticides by more than 90%. Along these lines, Balafoutis et al. (2017) show that across several studies, herbicide use could be reduced between 11% and 90% by precision application in different arable crops. At an experimental site in Germany, Dammer & Adamek (2012) show that sensor-based precision control of aphids, compared to uniform spraying, could reduce insecticide use in wheat production by more than 13%. Kempenaar et al. (2018) show possible savings on pesticide (and nitrogen) based on VRT of on average about 25%. Variable rate irrigation was found to increase water use efficiency and potentially imply water savings of up to 20–25% (e.g., Sadler et al. 2005, Evans et al. 2013). However, the findings on the use of PF in irrigation vary widely (e.g., depending on the reference technology and soil and weather conditions) (e.g., Balafoutis et al. 2017).

Overall, effluents from agricultural systems to water bodies are reduced under adoption of VRT (e.g., Tey & Brindal 2012, Balafoutis et al. 2017). However, at present, the magnitudes of these effects are largely uncertain and case dependent. For example, Harmel et al. (2004) show in an experiment on corn in Texas that, compared to uniform application, VRT nitrogen application decreased total nitrogen applied by 4–7%, but the runoff water quality was similar for VRT and uniform nitrogen application regimes. For case studies of potato production in the Netherlands and olive production in Greece, Van Evert et al. (2017) show even larger reductions of fertilizer application due to VRT adoption. VRT is not the only way to reduce unnecessary input use. Using a modeling approach for corn–soybean rotations in Illinois, Rejesus & Hornbaker (1999) show that nitrate pollution can be reduced not only by VRT, but also by improved timing of fertilizer application. In summary, the literature suggests that PF has positive environmental effects, but there is some uncertainty with respect to the magnitude of these effects. Additional research into the environmental effects of PF is thus required to further justify private and public support.

5. POLICY ISSUES

Agricultural policies can play a vital role in determining whether and how PF enters agriculture. In this section, we address these policy aspects from three different perspectives: (*a*) promotion of PF adoption, (*b*) provision of infrastructure and legal frameworks, and (*c*) the possible use of information generated in PF for agricultural policies.

5.1. Promotion of Precision Farming Adoption

There is a rationale for support or intervention because PF provides means to ensure a sustainable intensification of the agricultural sector by reducing environmental footprints of agricultural production (e.g., Garnett et al. 2013). PF technologies have the potential to reduce environmental footprints of agricultural production without jeopardizing food production and the economic viability of the sector. Along these lines, policy incentives to reduce agricultural effluents are likely to encourage the use of PF technologies. For example, taxes on inputs such as fertilizer, pesticides, and gasoline can internalize external costs of these inputs and provide incentives for farmers to adopt PF for both input targeting and efficient equipment guidance. Taxes on pesticides and fertilizer are used in some European countries (Nam et al. 2007, Böcker & Finger 2016). Subsidies for adoption of environmental stewardship technologies are another price-related incentive. For example, Switzerland offers resource efficiency payments to support adoption of conservation technologies (Mann & Lanz 2013). The combination of taxation and subsidization can be especially powerful if tax revenues are used to finance better technologies (e.g., Finger et al. 2017). However, note that resolving the uncertainty regarding the magnitude of case-specific environmental effects of PF as outlined in the previous section is critical to rationalize and quantify governmental support. Input quantity quotas could also be a highly suited policy instrument, especially in an environment with significant technological change (e.g., Schieffer & Dillon 2015).

Agricultural conservation set-aside programs could be adapted to use PF information. For example, the US Conservation Reserve Program (CRP) pays farmers to set aside environmentally sensitive land. Brandes et al. (2016) show how yield mapping can be used to identify less profitable zones within fields as candidates for CRP set-aside. One can imagine extending the CRP to support precision conservation if mapping were extended beyond profitability to environmental benefits (e.g., habitat configurations to optimize biodiversity) (Landis et al. 2000, Muth 2014).

Other pathways can also be used to promote the adoption of PF. New research shows that the environmental outcomes of farming practices can be improved by behavioral nudges (e.g., Peth et al. 2018). One approach is to make available site-specific environmental models that enable farmers to run scenarios to see the environmental effects of alternative farming practices. Now available on mobile devices, simplified, field-specific programs like the Soil and Water Assessment Tool have been used in Michigan to inform farmers about the water quality consequences of phosphorus fertilizer rates and related cropping practices (Fales et al. 2016). PF offers to provide not only these feedbacks but also specific options for implementation (e.g., input application). That knowledge has the potential to nudge decisions, though more evidence is needed. Along these lines, environmental and economic benchmarking can be powerful, especially if combined with PF technologies to reduce learning costs (e.g., Foster & Rosenzweig 2010). Benchmarking is defined as the comparison of one's own farm performance, e.g. focusing on quantitative economic and environmental indicators; with the performance of others engaged in a similar activity. This enables learning from others and identifying actions that can improve performance (Eur. Comm. 2017). PF has the potential to transfer insights from other fields and farms at high quality and low costs and thus can facilitate such benchmarking. This could lead to increased productivity and reduced negative externalities from agricultural production. To enable such benchmarking, appropriate and affordable tools and platforms must be available for farmers, and farmers must be willing to share their data. Here, policy can support these developments.

5.2. Provision of Infrastructure and Legal Frameworks for Precision Farming

Along these lines, realizing the potential social benefits from wider PF adoption calls for public and private investments in data, models, tools, and hardware infrastructure. Data platforms aggregating data, enabling data exchange between systems, and providing decision support tools provide a backbone for the adoption of PF and use of decision support systems (Weersink et al. 2018). In many countries, initiatives are ongoing to create agricultural data platforms that collect and aggregate the data needed for PF decision support tools. These platforms are often created by private companies or public-private partnerships. Among the former, Monsanto took over the hardware and software company Precision Planting in 2012 and the weather data and modeling technology company The Climate Corporation in 2013 (Carolan 2017). The Climate Corporation established the Climate FieldView platform to aggregate data of different sources in one place and provide diagnostic and applicative tools to farmers. DuPont, John Deere, and DTN provide wireless data transfer systems and market and weather information, and John Deere took over Precision Planting from Monsanto and bought Blue River Technology later on (Lev-Ram 2017). Several nations are building public-private partnerships to advance the use of sophisticated data in agriculture. One example is the Dutch web-based platform Akkerweb (**https://www.akkerweb.eu**) that aggregates data on weather, parcel boundaries, and satellite and farm management into a Farm Management Information System to provide farmers decision support and recommendations via prescription maps that can be downloaded to tractor terminals (Van Evert et al. 2018). Another example is the platform Barto (**https://www.barto.ch**) in Switzerland. As a stock company, Barto brings together public and private actors to build up a smart-farming platform that also aims to reduce the administrative burden of farmers by automatizing reporting tasks.

Sufficient infrastructure is central for companies and governmental agencies to develop web- and data-based decision support tools and to allow farmers to take full advantage of PF technologies available on the market. Public policy can be decisive in realizing this infrastructure. First and most fundamentally, high-speed internet access must be available to farmers. Yet in many regions—including remote regions of wealthy nations—the required telecommunications infrastructure is not yet in place. Second, data facilitating PF use can be provided to farmers. For example, several German states provide free access to satellite data useful for high-precision GIS-based applications.[4] Third, connectivity to devices and regulatory regimes for ensuring effective data ownership are needed. For instance, to manage and control the payments to farmers fulfilling the production requirements of the European Common Agricultural Policy, the Integrated Administration and Control System (IACS) was introduced across all EU member states. This system includes the Land Parcel Identification System recording all agricultural parcels that are considered eligible for annual payments of the subsidies (Kritikos 2017). Fourth, public investments in information, training, education, and extension can support PF adoption. Several studies on the determinants of adoption of PF reveal that lack of education and knowledge gaps are determinants for nonadoption of PF (e.g., Tey & Brindal 2012, Pierpaoli et al. 2013). Along these lines, investments in knowledge and tools can be made. For example, public investment in the next generation of crop and livestock management simulation models could facilitate providing predictions on environmental outcomes from integrated systems to farmers (Antle et al. 2017, Jones et al. 2017).

Fortifying PF data and decision support platforms requires not only technical infrastructure but also legal rules related to the question on confidentiality of data and data ownership. Confidentiality of data is a huge concern of farmers, and legal frameworks must apply to both the unauthorized use of data and the disclosure of information delivered by farmers. Thus, for all applications, platforms and decision support tools based on farm-level and personal data, confidentiality requirements must be met. Legal rules for use and disclosure must be found not only at the country level but also at the international level, as service providers of such tools and platforms are predominantly internationally operating private companies.

Along these lines, public-private partnerships and related data standards are needed that enable public sector research on privacy-protected detailed data (Antle et al. 2017). Data security will be crucial when establishing reliable interfaces to databases used or generated by public authorities (e.g., Wirtz & Weyerer 2017). Up to now, no specific regulatory regimes for PF technologies exist (Basu et al. 2018), so new regulations and standards will be needed to fully take advantage of PF technologies. To avoid heavy-handed regulations and establish a common understanding between the different agrifood chain actors, several initiatives have started in countries all over the globe. For instance, the US and New Zealand agricultural sectors have introduced voluntary industry standards to clarify data use and ownership issues (Keogh & Henry 2016). Another example is the INSPIRE directive, a pan-European initiative aiming for standardization and harmonization of georeferenced field-level data needed for the management and control of the Common

[4]The satellite-based position service is provided by the German states (e.g., Riecken & Kurtenbach 2017; **https://www.sapos.de**).

Agricultural Policy (Kritikos 2017). Finally, also removing existing regulatory hurdles and legal gaps for the implementation of PF technologies will facilitate the adoption of PF. For example, this comprises the lack of legal rules with regard to issues of technological control, human safety, civil liability and privacy (Kritikos 2017, Basu et al. 2018).

5.3. Possible Use of Information Generated in Precision Farming for Agricultural Policies

PF data management creates new opportunities for data to inform agricultural policy. More effective and more efficient agricultural policy schemes could be developed if recording input applications and other field operations reduces information asymmetries between farmers and policy makers. This especially applies to agricultural policies that are characterized by (*a*) direct payments linked to cross-compliance criteria that farmers must fulfill and (*b*) action-based criteria for agri-environmental programs. Using data as recorded from PF technologies for administrative purposes would increase the effectiveness and efficiency of monitoring of farming practices such as input use. Under such a scenario, farmers could be required to provide PF data (e.g., on input and land use) to receive certain environmental payments or as part of cross-compliance obligations in the future (e.g., Möckel 2015). Yet, a high accuracy of such information is required for this step. Moreover, such data requirements would be feasible probably only in nations that have a history of very active government involvement in agricultural management, e.g., in Europe.

6. DISCUSSION AND OUTLOOK

The current uptake of PF is moderate and mostly taking place at larger, highly capitalized farms in developed countries. Adoption and diffusion rates predicted in earlier literature have not been met at the expected pace (e.g., Griffin et al. 2018), especially for applicative tools like variable rate input application. Thus, the full potential of PF in terms of economic and environmental benefits is far from being exploited.

A higher relevance of PF in the future will depend on the coevolution of technological, economic, and policy-related aspects: Farmers need to be provided with affordable tools allowing them to meet clear management decisions to tap potentially large economic and environmental benefits. New PF-based systems might lead to further paradigm shifts in farming systems. In the future, farmers may not need to care about the precision of their activities any longer, since precision will be handled automatically. Instead, they can focus more on strategic decisions that allow them to minimize their entrepreneurial risk in a landscape of clear policies but uncertain progression of climate and markets.

Ongoing technological developments and big data advances (e.g., Walter et al. 2017, Wolfert et al. 2017) continue to make PF technologies (*a*) more accurate, (*b*) more widely applicable, and (*c*) more efficient. Weersink et al. (2018, p. 21) go so far as to say that, "Ultimately, these technologies may even allow farmers to manage the needs of individual animals or plants in real time." This vision is supported by recent developments in such areas as multispectral sensing of plant and soil traits from UAVs (Aasen et al. 2018), remote characterization of plant diseases (Bouroubi et al. 2018, Mahlein et al. 2018), and weed detection via machine learning algorithms (Lottes et al. 2017, Bouroubi et al. 2018, Walter et al. 2018). In research projects, site-specific weed treatment has been partly realized using autonomous, robotic ground vehicles (Roldán et al. 2018, Walter et al. 2018). Given the costs of precision weed management, future prospects for adoption depend on continued technologically driven cost reductions, paired with finding ways to either attract environmental stewardship payments (Swinton 2005) or adapt precision herbicide management to address the rapidly expanding problem of herbicide-resistant weeds (Swinton & Van Deynze 2017). The potential to save herbicides or even avoid them completely (e.g., via mechanical treatment) is enormous. Yet, whether these are widely used will depend on the costs and benefits from these technologies (Böcker et al. 2019).

A crucial aspect needed for the increasing uptake of PF is the improvement of decision support systems and of software solutions that assist farmers in most efficiently administrating their purchases, planning requirements, and cost calculations. The overall vision is to come from precision to decision farming. The advent of machine learning and deep learning possibilities has begun increasing the power and reliability of such decision support systems in fields such as side-dressing of nitrogen or in timed and targeted spraying of pesticides. The future of such integrated PF decision support systems will depend heavily on market and policy incentives, the evolving legal framework, and the reliability of decision support systems. In the near future, augmented reality tools that merge graphical depictions of decision support with real status of crop fields might play an important role to elaborate whether or not decision support measures seem appropriate for farmers.

However, further sophisticated technologies will likely increase the capital intensity of PF. This in turn could mean that only few farms can afford such technologies (see Walter et al. 2017, Weersink et al. 2018). As a result, this may favor a concentration and increasing inequality in the agricultural sector. To avoid such outcomes, diverse technologies need to be available for a diverse set of agricultural systems, ranging from small- to large-scale farms as well as from crop, horticulture, and livestock production (Walter et al. 2017). Moreover, different forms of cooperation and PF technology sharing can enable many farms to benefit from new technologies. Especially in developing countries, improvements in education, and information distribution seem to be the most crucial fields to expand the potential power of PF. This could also imply that smallholder farming practices in many tropical countries or semiarid regions of the world could profit from PF technologies and considerations. This might comprise spatial and temporal aspects of input application in small-scale, labor-intensive, diverse cropping systems but can also include the support for long-term production decisions (Aune et al. 2017).

Here, cheap(er) PF technologies can play a vital role in promoting the widespread benefits of PF. There are currently multiple services that provide site-specific advice on crop management and livestock treatment via mobile phones to farmers. For example, the Kenyan company UjuziKilimo (**https://www.ujuzikilimo.com**) promotes the use of simple ground sensory technology as combined with a database that provides recommendations on input use to farmers via text messaging. Likewise, the Virtual Irrigation Academy (**https://via.farm**) promotes tools to measure soil water and improve irrigation decisions for farmers in Africa. An example of technology sharing is the Nigerian technology platform Hello Tractor (**https://www.hellotractor.com**) that connects farmers with tractor services via apps and text messaging, enabling mechanization and technology diffusion. With these examples in mind, we believe that PF technologies have a place in small-scale developing country agriculture.

PF is paving the way for big data in agriculture (Griffin et al. 2018), and new applications based on big data might in turn make PF technologies more attractive. Beyond the field level, PF technologies have the potential to decrease transaction costs for reporting of land and input use. Such information may meet governmental requirements associated with cross-compliance obligations or certification of specific environmental stewardship practices. Similarly, such information may enable private sector certification of environmental performance to satisfy value-added labels. One private-sector example is the 4R Nutrient Stewardship program (**https://www.nutrientstewardship.com/4rs/**) that certifies agribusinesses as following the principles of applying inputs from the right source, at the right rate, at the right time, in the right place (Vollmer-Sanders et al. 2016). The 4R program creates an incentive for agricultural input suppliers to shift their revenue model from one based on agrichemical product sales to one based on precision management services. Similar programs exist in other countries, for example, in Switzerland (e.g., IP Suisse) and France (e.g., Zéro résidu de pesticides). Clear documentation of such practices based on PF technologies, possibly as combined with other technologies such as blockchain will reinforce the role of these certifications. This can play a major role in conventional but also organic farming. Furthermore, insurance products could become more efficient if information asymmetries can be reduced when providing information on yields, input use, and environmental conditions to insurance companies (e.g., Lowenberg-DeBoer 1999; Woodard 2016a,b; Weersink et al. 2018).

Another new opportunity providing additional incentives for adoption is that PF can be instrumental in developing fully transparent agri-food systems, thereby ensuring traceability from consumables to produced raw materials (e.g., Gebbers & Adamchuk 2010, Ruiz-Garcia et al. 2010). One currently discussed possibility for full food traceability is the blockchain technology that allows tracking and sharing all transactions or digital events among participating parties that can be verified at any time in the future (Galvez et al. 2018). Blockchain technology has the potential to ensure food traceability along the agri-food supply chain. In one high-payoff domain—*E. coli* outbreaks caused by contaminated salad greens that forced destruction of supermarket inventories—Walmart and Microsoft announced a partnership in September 2018 to introduce blockchain traceability in the United States in 2019 (Corkery & Popper 2018). In that way, intrinsic and extrinsic quality characteristics could be efficiently and reliably transported along the value chain. One example for a blockchain technology application in the agri-food domain is the US start-up ripe.io that tracks tomato ripeness, color, and flavor (Massa 2017). Yet, blockchain applications for the agri-food sector are currently mainly focused on pilots (Tian 2016, Ge et al. 2017, Lin et al. 2017, Casado-Vara et al. 2018). Along these lines, Poppe et al. (2013) show that information and communication technology has the potential to innovate data exchange and increase transparency between actors in agri-food chains and thus alleviate many of the current sustainability and food safety issues.

The increased interlinkage of agricultural production with up- and downstream industries based on PF technologies might also create incentives for stronger vertical integration in the agri-food sector. For example, the required integrated data systems might be realized more efficiently by highly integrated firms (e.g., Weersink et al. 2018). Moreover, the increasing transparency of farming practices and increasing need to both disclose these practices and also adjust them to consumer needs might lead to stronger incentives for backward vertical integration.

7. CONCLUSION

PF has high potential to increase farmers' income, increase extrinsic and intrinsic quality of agricultural production, and decrease negative environmental effects of agricultural production, all at the same time. PF will not be a panacea, but it has the potential to contribute to more sustainable agriculture. Currently, potential benefits are utilized only to a small extent. PF adoption is currently mostly limited to large farms in developed countries. Variable rate applicative technologies have been adopted mostly in higher-value crops. However, PF technologies need to be widely adopted to utilize their full potential. For PF to spread to small-scale and diversified farming systems (including those in the developing world) and for VRTs to expand into lower-value crops, a broad range of technologies and business models will be needed, going beyond the currently dominant focus on input cost savings.

The potential for environmental benefits from PF (e.g., fewer losses of inputs such as pesticides and fertilizer to the environment and the reduction of greenhouse gas emissions) constitutes an important rationale for new incentives to adopt, for both private and public institutions. For example, investments in technical infrastructure (e.g., access to high-speed internet, satellite images) and data platforms can be essential first steps. Establishing a legal framework prescribing terms for data ownership and sharing is a second key step. Governments can also tailor agri-environmental policy instruments so that taxes, quotas, and subsidies target defined levels of agrichemical inputs or polluting residuals. Such policies would indirectly strengthen incentives for increased adoption of PF. Private firms in the agri-food system that seek reduced environmental footprints for their products can require farm suppliers to certify responsible agrichemical input levels, facilitated by PF. Moreover, PF also allows the creation of intrinsic and extrinsic quality traits and the transfer of this information along the agri-food value chain.

Although PF has great potential for economic welfare and environmental good, its distributional effects should be observed and analyzed carefully. Many PF technologies appear to exhibit economies of scale and scope. Thus, PF technologies may lead to further concentrations in the agri-food sector, and benefits of PF technologies may be unequally distributed. These private sector distributional effects demand greater study, not only at the farm level, but also along the agri-food value chain.

Our analysis reveals that technological developments and big data advances continue to make PF tools more connected, accurate, efficient, and widely applicable. Improvements in the technical infrastructure and the legal framework can expand access to PF technologies and thereby expand their overall societal benefits.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

R.F. and A.W. thank the Swiss National Science Foundation for support of the InnoFarm project within the framework of the National Research Programme 73 ("Sustainable Economy"). S.M.S. thanks Michigan State University AgBioResearch and the US National Institute of Food and Agriculture, as well as the National Science Foundation's Long-Term Ecological Research Program (DEB 1027253) at the Kellogg Biological Station. N.E.B. thanks the Swiss Federal Office for Agriculture for supporting the project "Adoption and Diffusion of New Technologies in Agriculture." We thank the editorial board member Matin Qaim as well as Melf-Hinrich Ehlers for helpful feedback on earlier versions of this paper and thank Reto Sager and Vivienne Oggier for support.

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Annual Review of
Resource Economics

Volume 11, 2019

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Errata

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