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Review Article

The Future of Technologies for Agriculture

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Abstract

This work studies the adoption of precision agriculture technologies (AP), from the economic point of view, determines if the economic results can be taken as indicators of adoption, and identifies some potentially profitable technologies. The data shows that the most widely adopted technology worldwide is the GPS navigation system (satellite flagger, autopilot, etc.), while the variable dose (DV) technology grew more slowly. This is a trend that was correctly predicted in the 1990s [1]. The most recent studies of the last decade show that the most cost-effective AP technologies are the variable dose of sensor-based N, agricultural robotics, artificial intelligence (AI) and the use of Big Data [2]. This work also analyzes the future of soft technologies for the future, including the paradigms of Climate-Smart Agriculture, Environmental Footprints and the Circular Economy.

Keywords: *Satellite Flagger; Agriculture; Footprints*

Introduction

In 2017, the World Economic Forum [3] published the list of the 10 most important emerging technologies throughout and across all the economic sectors of the world, among which Precision Agriculture appears in sixth place (AP). The WEF defines the PA as a set of tools of the Fourth Industrial Revolution, applied to the Agricultural Sector to increase the yield and quality of crops, and at the same time reduce Environmental Footprint from the use of water and chemical products. Also called Agro 4.0, this technology uses sensors, robots, GPS, mapping tools and data analysis software to optimize production and environmental, social and economic sustainability. More recently, the WEF places robots and artificial intelligence first on the list of the 10 most important technologies of 2018 and 2019 [4]. Therefore, the future of agricultural technologies will be analyzed within this prioritization of the World Economic Forum from technology management, that is, from the economic perspective.

While the PA has great potential to reduce agriculture's environmental footprints and increasingly collaborates with the social implications of the technology, the widespread adoption of PA technologies will depend on their cost effectiveness. Agriculture is a business and as such technology is adopted if it generates profits. Sometimes, these benefits are qualitative (e.g., more efficient use of time, reduced fatigue, less stress, etc.), but monetary benefits (higher and more stable margins) are generally sought. The agricultural sector is subject to "economic physics" in the sense that there must always be someone who pays the bills, just as we are all subject to the law of gravity, whether we consider it fair or not. All factors of production must be remunerated, including management, labor, capital, the opportunity cost of land and other natural resources. Consequently, the general objective of this work is to summarize the state of the art in precision agriculture economics. On the other hand, assuming that adoption is the best indicator of the profitability and benefits of technology, the specific objectives of this work are: 1) to review the adoption of PA, 2) to determine if the research correctly predicted the technologies of APs taken by producers, and 3) identify some potentially profitable AP technologies.

The first reviews on the profitability of the PA are the works of Lowenberg-DeBoer and collaborators [5,6].

After 2004, the number of studies increased exponentially and reviews of the AP economy became more difficult. There were some general studies, such as that of Tenkorang and Lowenberg-DeBoer [7], which reviewed hundreds of articles and reports on remote sensing. Only a few who reported economic benefits and an even smaller number explained how that economic benefit was estimated. Twelve studies indicated an average yield of USD 31.74 ha^{-1}.

Little by little, the countries of the European Union and the OECD were studying the economic importance of the PA, and generated some incentive policies for GPS navigation systems and controlled traffic, although they confirmed that the profitability of DV is very variable, because it depends on the crop, soil conditions and many other factors [8,9].

In Australia, Cook., *et al*. [10] noted that slow adoption of APs was mainly due to lack of profitability. Zhang., *et al*. [11] confirmed that despite a substantial investment in research in AP in the USA. In the US, Canada, Australia and the European Union, only a small part of producers use the technology. Kitchen [12] confirmed that the adoption of precision agriculture was hampered because agronomy and engineering have not come together to generate commercial solutions in a way that compensates the investment of time and money.

Overview of the adoption of AP technologies in the world

Positioning systems

GPS navigation systems are rapidly being adopted in almost all mechanized farming countries. Conversely, Variable Dose (DV) technologies adapt only in conditions where soil variability and potential profitability combine to motivate adoption. The classic example of a high-value crop in the production of sugar beets in the Northern Red River Valley in the states of Minnesota and North Dakota in the United States. On the other hand, an example in which the variability within the lot justifies the DV, is in the Victoria Valley in Australia, where the adoption is 37% [13].

Like the GPS guide, the adoption of AP technologies based on GPS navigation is quite high. For example, the 2017 CropLife/Purdue survey found 73% adoption by sprayer contractors [14]. In Argentina, in 2017, there were 19,158 sprayers with satellite flag and 9035 sprayers with automatic guidance [15].

Data collection technologies

Combine performance monitors are part of the original AP technology introduced in the early 1990s. In more developed countries, performance monitors have become standard equipment on new combines, but many of these performance monitors are either not used at all or are used without GPS, so data cannot be mapped. For example, USDA survey data [16] shows that in 2010, 61% of corn growers used a combine equipped with a monitor, but only 34% made performance maps. In 2006, 45% of US soybean producers used a combine equipped with a performance monitor, but 20% made performance maps. For rice in 2006, 29% of respondents used a yield monitor, but only 10% made maps. For wheat in 2009, 36% of respondents used a performance monitor, but only 6% made maps. Producers complain that they do not know how to use the performance map data, and consequently they are not motivated to collect good quality performance data for the maps.

Remote sensing. Efforts to use satellite remote sensing data have been underway since the 1970s, and some service providers have embraced the technology, but the practical use of data by producers is not yet widespread. The 2017 CropLife/Purdue survey shows that 59% of service providers offer satellite or aerial imagery to producers. The most recent data from the USDA survey shows that in 2005 only 6% of corn producers used an aerial or satellite image, in 2002 only 1% of soybean producers, in 2003 7% of soybean producers. cotton and in 2004 3% of wheat producers. In Europe, Lawson., *et al*. [17] indicate that remote images were used in 2010 by 10% of German respondents, 1% of Danish respondents and none of the Finnish respondents.

Interest in drones and unmanned aerial vehicles (UAVs) increased considerably. AP conferences and science magazines are full of presentations and articles on drones. Some providers have started offering drone imaging services. The 2017 CropLife/Purdue survey shows that 32% of service provider companies offer imaging services through drones.

In the USA In Canada and Canada, most agricultural input providers offer some form of intensive soil sampling, usually based on grids or management zones. The 2017 CropLife/Purdue survey showed that 82% of providers offer this service. The USDA data suggests that the use by producers is substantially less than the supply of services: in corn, in 2010, 22%; soybean producers, in 2012, 19%; rice producers, in 2013, 12%; cotton producers, in 2007, 5%; peanut, in 2013, 24%; and wheat producers, in 2009, 6%. In the UK, a 2012 DEFRA survey showed that 14% of farmers use some form of precision soil map [18]. Lawson., *et al*. [17] indicate that 14% of German producers used grid sampling and 5% zone sampling, Danish respondents reported that 5% used grid sampling and 1% zone sampling. In Brazil, Molin [19] reports that 79% of Brazilian producers made PA soil maps, but the scale of the sample (more than 5 hectares) raises doubts about the precision of these soil maps.

Soil electrical conductivity (CE) measurement for nitrogen (N) management is a technique that predates the era of precision agriculture, but CE service offerings are limited and producers have generally not purchased those services. The 2017 CropLife/Purdue survey found that 34% of US service providers offered CE floor maps. The 2002 USDA surveys for soybeans, 2003 for cotton, and 2010 for corn showed that about 1% of respondents use EC-based soil maps. Both producers and agronomists complain about the difficulty of interpreting the EC of the soil [20].

Relationship between the profitability of a technology and its level of adoption

In general, the trend of adoption of AP technologies was predicted quite accurately by economic studies conducted in the 1990s and in the early years of the 21st century. The most useful studies were those that went beyond the Gross Margin and that included management costs, training costs and problems related to personnel. Since GPS navigation systems for on-farm agricultural equipment were introduced in the late 1990s, almost all economic studies have shown positive economic benefits that could be quantified and qualitative benefits that were more difficult to measure. Consequently, the rapid adoption of this and other GPS related technologies came as no surprise.

The first published study on the profitability of the satellite flagger was conducted at Purdue University with data provided by the companies that presented the first products on the market [21]. The study focuses on the benefits of GPS lightbar systems because the autopilot was not yet commercially available. It summarizes the qualitative benefits of GPS lightbar guidance and quantifies the benefits of skip reduction and overlap, less operating costs, compared to the foam and disk markers used up to that point. The results indicated a modest benefit. The situation was similar for the many growers who had already invested in GPS to monitor performance. The study predicted the growth of GPS autopilot technology in agriculture based on technologies that were already being used in construction and mining at the time.

On the other hand, the results of the studies of profitability of the fertilizer DV are uncertain and contrast with the positive results found in the studies of GPS navigation systems. Swinton and Lowenberg-DeBoer [22] conducted one of the first reviews of the profitability of fertilizer DV. They found that it was not profitable for low-margin crops, such as wheat and barley, sometimes profitable for corn, and quite profitable for higher-value crops, such as sugar beets. They concluded that the cost of soil information was a key factor in the results, and that reducing the cost and increasing data resolution with soil and optical sensors was a key requirement for widespread adoption of fertilizer DV technology. Subsequently, the Lambert and Lowenberg-DeBoer [5] reviews, and Griffin., *et al.* [6] reinforced those conclusions, reviewing 108 studies reporting that 69% of the studies reported positive benefits of fertilizer DV. 80% of the sugar beet studies reported a benefit, 72% of the corn studies and only 20% of the wheat studies. For their part, the results from Argentina indicate slightly positive profitability levels for wheat and medium to high levels for corn, depending on the complexity of the analysis [23-26].

Finally, Griffin., *et al.* [6] highlight the economic advantage of "embedded knowledge" technologies, compared to "information-intensive" technologies such as DV. Most of the successful agricultural technology of the 20th century was of the embedded knowledge type. For example, hybrid seeds, fertilizers, and most pesticides included important scientific knowledge, but did not require much experience to use. Among AP technologies, GPS navigation is a built-in knowledge technology and Fertilizer DV is a knowledge-intensive technology. Griffin., *et al.* [6] argue that DV would have to become a built-in knowledge technology to achieve widespread adoption, e.g. application of fertilizer DV using a sensor mounted on the front of the machine.

To conclude on the relationship between profitability and adoption, it can be said that economic studies successfully identified the key opportunities for technology, long-term adoption patterns, and the important limitations for widespread adoption. However, no one has been particularly successful in predicting short-term, ex ante AP adoption trends.

Implications of the most recent studies on the profitability of AP technologies

It is important to understand the causes and predict trends of adoption of AP technologies in the long term, both for producers, as well as for agribusiness and research. Producers must make long-term plans when planning production and purchasing equipment. Understanding long-term technology trends helps make decisions and avoids invest heavily in technology that is about to become obsolete. On the side of service providers, they achieve the greatest benefits when they are technologically ready to respond to the demand for a technology or innovation by producers. For their part, researchers must follow lines of research that generate funding, for which the economic studies of the last decade provide some perspectives on the future adoption of PA technologies, including.

Sensor-Based fertilizer DV

Growers are drawn to the idea of Fertilizer DV. It makes sense to manage different areas within the fields according to the productive capacity and the restrictions of that area. However, both economic analysis and attempts to commercialize fertilizer DV services and equipment show that current technology does not have a good cost/benefit ratio for most producers. The information costs necessary to develop the DV prescription maps of fertilizers are too high and the response of the crop may be limited by other factors that go beyond the chemical fertility of the soil. Real-time sensor-based systems allow fertilizer DV to more closely resemble embedded knowledge technologies, which have a proven track record of success. Real-time sensor-based systems could increase accuracy by increasing information resolution and reducing costs by turning fertilizer prescription into an algorithm.

Unfortunately, the economic analysis of the sensor systems currently available on the market suggests that improvement is still needed. For example, Biermacher., *et al.* [27] conducted experiments on wheat in Oklahoma during the period 1998-2006. They tested an optical sensor and nitrogen fertilizer optimization algorithm developed at the University of Oklahoma. The study found that sensor-based nitrogen DV has significant economic potential, but that the current system works by taking averages based on conventional nitrogen prescription criteria. Likewise, Scharf., *et al*. [28] reported that in 55 field trials in Missouri, sensor N DV produced higher corn yields and lower nitrogen use than conventional practices; and that, on average, the sensor DV-N resulted in an increase of USD 42 ha^{-1} in the Gross Margin, but the amortization of the equipment and the extra cost due to the complexity of the handling of the machinery were not taken into account.

One of the weak points of sensor systems for DV-N is that they do not take into account the productive capacity of the soil, for example, the color of the crop may indicate a lack of nitrogen, but in reality the problem is the depth of the floor or other restriction. Diacono., *et al.* [29] reviewed 17 PA studies for nitrogen management in wheat and recommend combining sensor data with soil maps, remote sensor images, yield maps, and other data to tailor nitrogen application to specific constraints. of the site. Also, they report that DV-N with sensors has a profitability of USD 5 to USD 60 per hectare with respect to uniform application. Therefore, some nitrogen sensor companies are beginning to introduce systems that combine sensor data with other field information.

Agricultural robotics

Economic logic indicates that robotics should be adopted quickly when the technology is suitable for repetitive agricultural tasks such as planting, controlling weeds, pests, diseases, and harvesting. In all parts of the world (even in developing countries) rural labor is becoming more expensive and difficult to find. Many developed countries (e.g., USA, Europe) have been dependent on immigrant labor for many years, but governments face increasing political pressure to reduce both legal and undocumented immigration. It is unlikely that in developed countries wages can be increased enough to attract local workers. Therefore, robots are the most likely alternative.

A key difference between automation in agricultural mechanization with GPS navigation systems and agricultural robotics is that agricultural robotics is likely to use many relatively small machines rather than a few large ones [30]. Once the operation of autonomous farm machinery is achieved and dependency on humans is reduced, the economic motivation for large farm machinery almost disappears. Carrying out swarms of small robots will surely change agronomic practices and the geography of agriculture. For example, with the application of robotic pesticides it might be possible to spray each pest individually instead of broad application. This could reduce the application of agrochemicals by more than 90% and reduce the negative effects on beneficial species. With relatively small robots, the comparative economic advantage of large large-area batches diminishes. Small robots are less likely to unleash the safety and accountability concerns that require humans in larger teams to "push the red button in the event of a problem".

Except for robotic milking, there is little data on robots in agricultural production. Milking robots have been on the market for more than 20 years. Numerous reports and studies have shown that they are practical and profitable for some farms, depending on the cost and availability of labor [31]. For robots in crop production, most economic studies have been based on economic engineering budgets, developed from technical parameters, not from field experience. For example, Pedersen., *et al*. [32] estimated the benefits of weed control on sugar beets, monitoring of cereal crops and cutting grass on golf courses. They demonstrated that robotic options were potentially cost-effective, although the main limitations were the cost of GPS RTK and the limited capacity of small robots.

Artificial intelligence (AI), Internet of Things (IoT) and "Big Data" in agriculture

AI and Big Data are hot topics in agricultural research and conferences in recent years. There are many academic works on the subject. Wolfert., *et al.* [33] reviewed 114 works. Also, an internet search shows many articles on the subject. In the US, agricultural service providers see data management as a growing area. In the 2017 CropLife survey, 58% of agricultural service providers archived soil and other data for producers, 41% worked with producers to analyze data from their own fields, 17% grouped the data between customers and 10% participated in the analysis of batch data. Only 31% of respondents said that analysis of the performance monitor data was cost-effective and only 20% indicated that the benefit/cost ratio was favorable. While it is logically attractive to use AI to extract information from the masses of data collected by sensors and other sources in agriculture, it is more difficult to assess the cost-effectiveness and other economic benefits of this approach. Problems in this economic evaluation include:

- **Define exactly what constitutes AI, IoT and Big Data**: Computer algorithms have been used for many years in agriculture. For example, since the 1960s, producers have been using linear programming to plan crop rotations and dimension the machinery park. Most of the animal feed in the developed world is formulated by computer algorithms. In most definitions, the common characteristic of Big Data is that the data allows the best decisions to be made, the most accurate and with the least risk. It is the management and analysis of huge volumes of data that cannot be processed in a conventional way, as they exceed the limits and capacities of the commonly used software tools. It can also be seen as a new generation of technologies and architectures designed to extract economic value, by allowing high-speed capture, discovery and/or analysis of the vast amount of sensor data being generated in the field, as well as performance monitoring data and satellite images stored for years.

- As with remote sensing, drones, performance monitoring and other information gathering technologies in agriculture, AI profitability and Big Data analysis depend on the decisions made and the actions taken to generate an economic value. In other words, Big Data is not only to "take the picture", but must be associated with strategies focused on the administration and creation of knowledge about the environment, to optimize the decision-making process in agribusiness.

- Most available AI and Big Data economic analyzes are based on simulation and economic engineering, rather than field data. For example, Li and Yost [34] simulated the use of artificial intelligence to optimize nitrogen management and irrigation and showed a significant economic gain. As in the case of agricultural robotics, the fact that much of the economic analysis relies on simulation rather than on field data is not sufficient reason to dismiss the idea, but it is a reason to push to obtain more data in the field.

Internet of Things (IoT) refers to the digital interconnection of everyday objects with the internet. It describes the point in time when more "things or objects" connect to the internet than people, implying that 50 to 100 trillion objects must be encoded and tracked. It is estimated that in 2020 there will be 30 billion devices with an IoT adaptation system. With the IPv6 internet protocol, all objects could be identified, including their location. The challenge of the IoT is to develop applications to control autonomous devices. One approach to achieve this is "Predictable Interaction", where decisions are made in the cloud and ask for user action to generate a reaction.

Technology is fundamental in the technological path of IoT, from the most deterministic like RFID tags, which appeared at the end of the 20th century as a demand from the logistics sector, to reduce costs and increase security; Even the most complex technology, applied to chaotic systems, that allows the monitoring and control of objects, both in the external world and on the web, through sensors and software [35].

In this sense, Purdue University, in Indiana, USA, is a pioneer in IoT applied to the agricultural sector. The Department of Agricultural Engineering has a group of researchers who work in the management of large databases and their online availability, IoT, and who specialize in the development of computer programs and applications for cell phones, to be used in agriculture. The systems are open and automatic, and among others is the autogenics system (automatically generated data for logistics). The group is called Oats and its web address is https://engineering.purdue.edu/oatsgroup. In this same Department, a software (http://www.sensorhound.com/) for IoT was developed that reduces the operating cost and increases the security of the sensors used in agriculture to upload data to the cloud.

In the private sector, there are many companies, such as SST (http://www.sstsoftware.com/), founded in 1994 by a group of professors from the University of Oklahoma, USA, a visionary in data management geo-referenced automatic machines that are converted into real-time information. It currently manages a data pool of 50 million hectares in 23 countries, which are analyzed with complex algorithms, to deliver information for management in a decentralized manner. In Europe, the case of F4F/SAP (https://www.f4f.com/), which integrates the producer-centered cloud supply chain, can be cited as an example. For its part, Big Data refers to long or complex data sets, which cannot be analyzed with traditional methods. It includes the processes of capturing, cleaning, searching, sharing, storing, transferring, viewing, consulting, updating and ensuring the privacy of the information. That is, Big Data can refer to the use of predictive analytics, user behavior, or other analytical methods to add value to data. There are aspects to consider that have not yet been resolved, such as cleaning irrelevant data and issues related to property and privacy.

From an economic point of view, the first effect of this increasing amount of data is that it means a lower cost of goods and services that depend on prediction [36].

As it can be deduced, it is necessary that the AP has the appropriate technology to process an increasing amount of data in real time. According to a consultancy, agriculture currently generates approximately 100,000 information points per day in the world, while it is estimated that exponential growth will occur by 2035, with 4 million daily data generated in the agricultural sector [37].

Big Data's economic potential coincides with that of the AP, which is to reduce costs in grain production, increase productivity and make more efficient use of production factors. The improvement in potential profitability can come from the increase in the value of production (quantity and/or quality of grains), from the reduction in the quantity of inputs (seeds, fertilizers, agrochemicals, etc.) or both simultaneously.

Climate smart agriculture

The evolution of precision agriculture towards environmental footprints, under the gaze of sustainability and the Circular Economy.

Climate Smart Agriculture is an approach that helps guide the actions needed to transform and reorient agricultural systems to effectively support development and ensure food security in the context of a changing climate. Climate-smart agriculture has three main objectives: A) the sustainable increase in agricultural productivity and income, B) adaptation and building resilience to climate change and C) the reduction and/or absorption of greenhouse gases [38]. Smart agriculture uses knowledge as the main input on which sustainable production rests in its three aspects: social, environmental and economic. However, knowledge is difficult to achieve, because in the best case, only data is available, which needs to be processed and analyzed with scientific criteria to make more efficient use of available resources, under the gaze of sustainability. In this sense, in recent years, methods have emerged to quantify Environmental Footprints, which allow determining critical points and proposing technological alternatives to improve efficiency and that prepares us to respond to the global challenge of increasing food production that allows sustaining the increase in world population and energy demand. In this context, precision agriculture requires a technological evolution towards data analysis and environmental footprints.

Environmental Footprints, in general, are a set of indicators of the impact generated by human demand on the resources of the planet's ecosystems concerning the Earth's ability to regenerate its resources. There are many footprints, among which the best known is the Carbon Footprint, which is defined as "the sum of greenhouse gases (GHG) emitted by direct or indirect effect of an individual, organization, event or product". This environmental impact is measured through an inventory of GHG emissions or a Life Cycle Analysis (LCA), following standards such as ISO 14064, PAS 2050, etc. The carbon footprint is measured in the amount of CO2 equivalent. One time Once the size and footprint are known, an emission mitigation and/or compensation strategy can be established.

LCA is a tool to estimate and evaluate the environmental impacts attributable to the complete or partial life cycle (only the phases determined for the case study) of a product, such as climate change, eutrophication, acidification, erosion of the ozone layer, toxicological stress on human health and ecosystems. Thus, it allows planning and generating strategies to achieve commercial benefits with an environmental criterion, that is, to achieve cleaner productions. Furthermore, among other benefits, LCA can: a) be combined with other data, such as cost and efficiency, to select products or processes that have the least impact on the environment; b) identify the transfer of environmental impacts between phases of a cycle; c) develop a systematic assessment of the environmental consequences associated with a given product/crop; d) identify technological "bottlenecks" that would allow them to be modified, providing greater energy efficiency, less environmental impact, and –at the same time– reducing costs and optimizing production.

In the agri-food sector, its application is relatively new, and most of the unresolved methodological problems in the agri-food chain come from the primary production stage. This is not surprising since LCA was developed for the evaluation of industrial systems and not agricultural/agri-food systems. INTA has just approved a Platform on Environmental Footprints, to analyze the environmental impact of the main production chains in Argentina, which will be launched in mid-2019.

It is increasingly understood that environmental improvements require the cooperation of many actors in the product chain: primary producers, manufacturers and service providers, commerce, distributors, buyer organizations, and the final consumer. That is why environmental information can be incorporated into the flow of daily information among economic actors; who also have to agree and agree on concepts and strategies for environmental improvement.

Environmental information often falls into the category of too complex and is generally ignored in favor of much simpler indicators, such as economic. For LCA to provide real benefits to the decision-making process, it needs to provide comprehensive information (including labeling), in a user-friendly format and on a wide range of relevant environmental factors. In this way, it will help to incorporate the environmental aspect at all decision-making levels in the agro-industrial sector, thus becoming another factor to consider, in addition to the economic one, for decision-making.

LCA can be combined with other data, such as geolocation, cost, and efficiency, to select products or processes that have the least impact on the environment. LCA identifies the transfer of environmental impacts from one medium to another (e.g., the elimination of gas emissions through the creation of a liquid waste) and/or the passage from one life cycle to another. It allows to develop a systematic evaluation of the environmental consequences associated with a certain product/crop. It identifies “bottlenecks” or technological “hot spots” that would allow them to be modified, providing greater energy efficiency, less environmental impact, and - at the same time - reducing costs and optimizing production.

In parallel to the development of LCA methodologies, in recent years various indicators have been developed to illustrate the level of sustainability of the activities of production or consumption of goods and services of societies, such as those related to the Circular Economy, a new economic model that seeks to modify production and consumption systems in pursuit of sustainability. It proposes to reuse the assets that are currently considered waste to achieve a more efficient use of resources. Thus, the waste is converted into raw materials that re-enter the production system and then generate a new good [39].

The circular economy is presented in opposition to the linear economy, that is, the one in which goods are generated from raw materials, and after consumption they are transformed into waste. The purpose of the circular economy is to “close the life cycle” of goods, lengthening the useful life of resources and reducing waste through its recovery and regeneration. A circular economy addresses the growing challenges related to resources and could generate growth, create jobs and reduce environmental effects, including carbon emissions. The Ellen MacArthur Foundation is a pioneer in promoting the circular economy, based on three principles:

- Promote the reuse of resources and the substitution of raw materials, creating conditions for regeneration.
- Optimize the performance of resources through rotation, both in technical and biological cycles.
- Eliminate the negative externalities of human activity in terms of pollution.

An example of Circular Economy in the agricultural sector of Argentina is the plastic waste recovery plant of the Association of Argentine Cooperatives (ACA) located in Cañada de Gómez, Santa Fe. Of the 70,000 tons of plastic waste generated in the country, ACA reprocesses 10% (6,000 tons of bag silo and 1,000 tons of drums), through reverse logistics. Once the plastic is used, the associated cooperatives have to return them so that they arrive at the plant and process them, seeking a neutral balance of Carbon Footprint.

The circular economy is proposed as a way to create sustainable production and consumption processes for the world economy. However, achieving that goal will be a challenge that the public sector, the private sector and civil society must jointly face. At the aggregate level, the circular economy has the potential to generate a sustainable economy using resources more efficiently. For private companies, it can not only represent savings at an economic level, but it can also be used to generate differentiation for their brands [40-43].

Conclusions

This work is based on the observation that the widespread adoption of technology is a good indicator of its profitability and/or other economic benefits. With this in mind, we reviewed the publicly available data on the use of precision agriculture, identified the extent to which economic research correctly predicted PA technologies that would eventually be adopted by farmers, and highlighted some PA technologies that the Economic research has recently been identified as potentially profitable and subject to adoption.

The massive adoption of smart agriculture in general, and precision agriculture in particular, is going to be given as packaged knowledge, probably with sensors that send the data to a node, and that return as information to act in real-time. Agricultural robots are going to rethink all mechanization, when the human being can no longer handle increasingly larger teams. In this context, Big Data and the Internet of Things will be the foundations for data analysis and automated decision making.

Environmentally intelligent agriculture must include the study of environmental footprints, the results of which can be used so that the companies themselves work on the continuous improvement of internal environmental management; to compare the internal performance of a chain or in comparison with other countries; as a marketing, competition, and differentiation tool; to provide information to consumers, to national/international markets; or as a tool to manage policies to support the sector and/or the region for the use of more efficient technologies.

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