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Chapter 2: Leveraging artificial intelligence to enhance precision farming practices

2.1 Introduction

A growing and largely urban world population, already exceeding 7 billion and predicted to reach almost 10 billion in 2050, needs more food increasingly produced in decreasing agricultural areas. The problems tied to agricultural production are related not only to its increment but also to the security and safety of this production regarding natural events and human dealings. Extreme weather events have become more frequent due to climate change. Aware of the consequences of unregulated exploitation, humans have acquired more sensitivity in safeguarding the environment and developing sustainable agriculture to maintain biodiversity and ecosystem health. Precision farming is one of the initiatives focused on achieving this agricultural sustainability (Kamilaris & Prenafeta-Boldú, 2018; Liakos et al., 2018; Jha et al., 2019).

Adopting precision farming practices brings advantages to farmers, such as a reduction in operational costs and an increase in income, to the environment in terms of less pollution and wastewater production, and to society for sustainability promotion. Precision farming consists of monitoring real-time crop status and environmental parameters to plan the distribution of agricultural inputs in variable doses and at proper times according to the needs of each specific zone of the field. In this way, both the excessive application of fertilizers, pesticides, and water, which lead to pollution and waste of resources, and the insufficient application, which hampers plant growth and productivity, are avoided. Traditional precision farming practices require complex technology to reveal crop and environmental nutrient status. Remote sensing and unmanned aerial vehicle technology have recently emerged as alternative solutions to help farmers implement precision farming but their usability is still not generalized (Mishra et al., 2020; Zhang et al., 2021).

2.1.1. Overview of Precision Farming Principles

Precision farming encompasses a set of integrated technologies intended to provide the owner or manager of an arable farm, in a timely and convenient manner, with information on the spatial variability of the crops, soils, topography, and terrain indices that influence crop production. This information then enables the adoption of decisions aimed at producing a real improvement in the profitability of production and/or a reduction in the environmental impact of the activity. The key factor of success is the early identification of the action variables and the periodic evaluation of the effectiveness of the actions taken. Precision farming suits small, medium, and big farms.

Fig 2 . 1 : Precision Farming

The particular variable of the extension of the farm is not decisive but the organization and management of the productive process, and the access to the necessary technology for creating and updating maps of the factors influencing crop production, continually in time and space. The global trend in agricultural production is to increase the demand for quality foods and minimize the environmental impact of farming practices. At the same time, the cost of agricultural production is increasing and the average size of the holding is decreasing. Precision farming intends to satisfy the demand for food safety and the reduction in the level of environmental impact through more careful management of agricultural production. The main concept of precision farming is to understand the influence of spatial variability, temporally modified, of soils and crops, on crop production, to create maps to manage the variables that determine it. Artificial intelligence models have provided adequate responses for modeling these processes but, in general, they have been implemented at a small scale, depending on the type of crop and in specific areas.

2.2. Understanding Precision Farming

Precision farming (or precision agriculture) generally denotes an approach to managing crop production that employs improved communication and information technologies to perform plant and soil analysis for optimizing yields and profits while minimizing waste, water consumption, and pest and fertilizer management. More specifically, it is a science-based management practice focused on spatial and temporal variation in the growth and development of crops and livestock, usually applied to environmentally sensitive areas and in compatible farming systems. It creates a framework for developing the whole chain of linkages between novel technology, field trials, interpretation of aerial surveillance images, remote sensing, computerized decision support systems, and farm management decisions worldwide.

The rapidly increasing acceptance of precision agriculture extends to countries such as Brazil, India, Japan, Mexico, and the United States. Both satellite-based frontal analysis for forecasting corn yield and net-area-solar-absorption tracking techniques to satellite imagery for predicting corn yield have been demonstrated. However, currently, farmers or scientific research institutions have to request analysis services. As evidenced by the many commercial soil-nutrient-testing devices and decision-support systems available in the market, the provision of precision agriculture services will no longer be restricted to satellite remote-sensing data though such data are essential for a differential yield-potential mapping or for discerning the spatial climate variability of farming regions throughout the world.

2.2.1. Definition and Importance

Precision farming, often synonymous with precision agriculture, describes a management concept that employs information and telecommunication technologies such as the Global Positioning System, Remote Sensing Technologies, Ground-Based Sensors, Variable Rate Technology, and Geographic Information Systems for crop production and management at spatial resolution finer than traditional, uniform field management. We refer to this approach as precision farming, since it implements not only careful resource and crop management but also information-gathering systems at a higher density than generic approaches. Precision farming aims to make the maximization of production more efficient, sustainable, environment-friendly, and safer for consumers and farm workers.

The primary philosophy of precision farming is based on variations within the field, on a high spatial resolution. These variations are driven by differentiations such as soil physical and chemical properties, competition among plants and between plants and their environment, weather effects, etc. The increasing globalization of the economy and the commercial environment enhances the urgency for farmers to produce as much as possible on less land with less input. This would increase profitability and reduce pressure on natural resources. From an economic perspective, precision farming consists of many business decisions, particularly the threshold production problem–how much to invest for increased production.

2.2.2. Historical Context

Introduction 1. Definition 2. Scope of Changes in Smart Agriculture 3. Stakeholders 4. Technology List 5. Adoption Canvas 6. Evolutionary Perspective 7. AI 8. Data 7. Other Evolving Technology 2.2. Historical Context Increased agricultural production has long been a concern of policymakers, scientists, and farmers. From the manorial times through and following the British Enclosure Acts leading up to the Green Revolution in the latter part of the 20th century, advances in technology have increased food production per unit area. Concurrently a trend to progressively more sophisticated technologies has been apparent. Initial changes included the development of crop varieties with higher yield potential, resistance to diseases, drought, and other adverse factors. Gradual mechanization and the offloading of farm tasks and specialization of tasks to contractors of various stages of the agri-food chain have followed. Another parallel trend has been the increasing complexity of production decisions—the need to match a range of inputs to a desired input-output response function and the complex relationships between operations at all stages of production and processing and also the outcome of production and processing flow. Agriculture is now moving toward what has been called “precision” “smart” “high technology” or “post-modern” agriculture; all of many terms for the same basic set of changes. What is different about these sets of changes is the following: a greater range of advanced technologies is available and applied to the farm and food value chain; the scale and impact of the new technologies are larger; and the decision-making sphere of agriculture is expanding to incorporate far more information about life cycle implication of choice, food quality and safety topics about which consumers are increasingly vocal. These new technologies span the use of Global Positioning Systems and sensors, genetic engineering, computer modeling, satellite imagery, electronic tags and tracking, biotechnology, nanotechnology, and robotics.

2.2.3. Current Trends

Here we take a brief look at some of the current trends that are driving the development of precision agriculture including advances in data access, sensor systems, analytics, new platforms for user access, and sustainability. These trends are by no means exhaustive but merit inclusion as they are bound to have a significant impact on the future of precision agriculture.

Machine learning, machine vision, sensor systems, blockchain, and artificial intelligence are just some of the technical advances that are driving the current interest in precision agriculture. Many farmers are busy implementing farm-data management systems to collect, curate, and efficiently analyze images and data from numerous sources from airborne missions with some fixed-wing UAVs to ground or low-flying multirotor UAVs, satellite systems, self-driving tractors, and hand- or tractor-drawn multi-sensor striping systems for hyperspectral, thermal infrared, multi-spectral, LiDAR, radars, and RGB cameras. Ultimately, these data and image collection efforts should be fed into public and commercially validated models that are then used by farmers and their associates to predict, in a timely way, how various management decisions will affect crop performance, such as the likelihood of a successful harvest, or loss. Lighting models can indicate how to manage supplemental lighting to boost growth and accelerate blooming and ripening, and crop growth simulation models can assess the impacts of irrigation, fertilization, and pesticide application on the likelihood of a successful harvest, or loss.

While agricultural companies, academic institutions, and governmental organizations have always been the primary suppliers of simulation models to the agricultural community, commercial entities managing farm-data enterprise systems now enhance or replace them with their own for profit, and just so everybody knows, the commercial modeling enterprises are generally a little bit behind the curve. While this initial modeling effort benefits the commercial entities and their modeling efforts, reduces the cost of hiring the agricultural company research and development, academic institution, and governmental entity modeling workforces greatly.

2.3. Role of Artificial Intelligence in Agriculture

With the exponentially rising pressure on agriculture to meet the food security or supply demands of an increasing global population, Artificial Intelligence is poised to make significant contributions. By allowing farmers and producers to monitor and manage their operations across both space and time, AI greatly enhances both the volume of produce as well as the quality. It provides real-time data collection regarding issues such as irrigation, soil and crop monitoring, soil management, climate impact assessment, etc., that might affect farming at both micro and macro levels. Agricultural processes thrive on digitalization, and the adoption of AI in agriculture is changing how produce is monitored, managed, and cultivated in value chains across the world. By analyzing complex problems curried through layers of big data, farm owners and their workers are empowered to use data-driven, precise decisions to boost yield while decreasing their reliance on costly resources in a quick, efficient manner while also using models to predict potential problems. These advantages lead to better management of equipment, supply chain resources, pest detection, and crop health monitoring. The integration of AI with sensors and robotics will assist farmers with important processes such as planting, harvesting, packing, and monitoring crops. These technologies also promise to help in the management of soil and improve irrigation, fertilizer application, and pest control. To improve the status quo of traditional agriculture that involves excessive use of human resources, and time-consuming and labor-intensive processes associated with agricultural produce, AI-based agriculture may become an indispensable aid and substitute. In addition, vast amounts of data, labeled and unlabeled, are already available in agriculture, processed or collected by different machine or manual means, that can be used to train various AI models and applications.

2.3.1. AI Technologies in Agriculture

Artificial Intelligence (AI) serves as a pivotal foundation for innovative technologies in agriculture. These innovations leverage diverse AI technologies, enabling novel ideas such as intelligent robots, unmanned aerial vehicles (UAVs), digital twins, Internet of Things (IoT), augmented reality (AR), big data analytics, cloud computing, and blockchain applications already commercially available or in the process of being commercialized. AI-based solutions are estimated to generate savings of nearly USD 50 billion annually for the global agriculture, food, and forestry industries by 2030. Coupled with a strong demand for food security and a mountain of data related to crop yields, market prices, land suitability, and changing weather patterns, the merging of AI with agriculture holds the potential to improve digital agriculture.

AI refers to machines that mimic human intelligence, automating tedious human tasks, including precision sensing, image recognition, intelligent decision-making, robotic control, and communication. AI can either augment our intelligence or operate autonomously, outside of human control. In agriculture, the basic categories of AI systems include expert systems, machine learning, and robotics.

Despite the differences in underlying technologies, AI systems share basic features based on a common objective of transforming data into information and value. To generate value, AI systems interface with the physical world through sensors, actuators, and other technologies that expand human senses and faculties. In the context of agriculture, various types of sensors acquire, analyze, and use vast amounts of data across production value chains to derive relevant insights for users. By leveraging the rapid evolution in associated sensor technology hardware, agricultural producers can now gather, store, and analyze unprecedented amounts of data about their operations. These developments are allowing farmers to integrate intelligence into their operations, thereby ushering in a new agricultural era.

2.3.2. Benefits of AI Integration

The incorporation of cutting-edge automation and AI solutions into agriculture communities can pay dividends in improved financial health and more meeting work. AI integration relieves farmers of many tedious tasks, such as manual field inspections, and gives insight into field conditions so that they can do what they value — managing the farm, increasing crop yields, and nurturing supplier relationships. Specific areas in which AI improvements are most evident include crop detection and monitoring, pest detection, soil health, weather prediction, yield prediction, and the most cost-efficient means of targeting crops that need specific nutrients, moisture, and other input supplies.

AI can help usher in the next and most important automation revolution. It gives farmers decision-making support but does not take the decisions away from them. For example, AI doesn't tell ag retailers which products to apply and at what levels to specific fields. But it can help them understand why a specific request is being made. It has the potential to be the channel through which ag retailers and their customers collaborate to make the best decisions possible based on data. AI can ingest media, including images, sensors, and other data to provide in-depth analysis when decisions need to be made. Creating a collaborative process where the customer can learn from AI can help advance agriculture while building trust between retailers and their customers.

2.4. Data Collection and Management

As a subfield of agriculture that aims to enhance accuracy and efficiency in farming practices, precision farming relies heavily on data. To achieve successful decision-making, it is crucial to collect, store, manage, share, process, standardize, visualize, and utilize the massive amounts of data generated continuously throughout the entire agricultural value chain. Moreover, these data need to be presented to the end-user seamlessly and intuitively. Applying AI to precision farming requires efficient methods of data collection, management, and dissemination between the data collectors and processors and the farmers. However, the volume, velocity, variety, variance, visibility, and complexity of the data make it a challenge for researchers and farmers.

To guide the farmers effectively in daily farm-related decisions, the data collected need to represent the farmers' unique internal conditions and external conditions while also containing relevant information. We explore what types of data are needed in precision farming, where the data comes from, and how to manage this data. AI uses vast amounts of data to train/make decisions and requires large amounts of data to avoid overfitting in small dataset settings. To aid farmers, data management systems can be coupled with AI models to determine which actions to perform and why. These systems can provide a level of "explainability" that is sorely needed in current machine-learning tools. Such a system can help farmers with integrated pest and pathogen management, soil/weed management, nutrient management, weather forecasting, as well as market forecasting, among numerous others. We provide examples of how emerging technologies are addressing these issues.

2.4.1. Types of Data in Precision Farming

The core of precision farming is data-based decision-making. Crop, soil, and weather data collections are essential to high-value management practice at commercial field scales to provide data inputs into models predicting economic, harvest, and environmental outcomes of management decisions. Several categories of data are used to inform decision processes in precision farming. All of these data vary in terms of importance and availability by location and season. Other factors affecting data's relative importance involve economic commodities and environmental goals. This creates an essential need to quantify the value of a particular set of measurements in terms of their effects on management decisions and the relative outcome of different management decisions.

Soil property data include fertility and physical properties, land-use history, data on edge-of-field hydrology, and critical areas such as point, cut, and wind erosion. Soil bare data types vary including nutrient mapping, soil sampling, bulk density, pH, and inundation or condition. Vegetation property data involve nutrient levels as they vary by time and location, crop type and stage, biomass density, canopy cover, pigments, and cell structure permittivity. Generally, all these data are obtained unevenly. Nutrient data are typically collected over short periods at specific geographic locations associated with laboratory analysis of plant samples. Crop stage and biomass density or canopy cover data are also typically obtained over short periods between periods of crop coverage and weather conditions favorable for remote sensing. Long-term cell structure permittivity data are not yet available.

2.4.2. Data Sources and Sensors

Various techniques, methods, and technology-assisted devices have been developed to increase the abilities of farmers. Remote sensing of field variables is one of the most innovative and powerful tools in precision farming. The extremely fast development of satellite technology and sensors, Unmanned Aerial Vehicles (UAV), and mini-sensor devices has permitted remote data collection over large target areas. Farmers require massive amounts of data regarding soil, water, and crops to improve productivity and the overall economy. This information will benefit from integrating data from multi-heterogeneous sources such as satellite data, local sensors, and UAV-based remote sensors. These data are valuable for the quantification of essential biophysical crop variables that affect agriculture production.

Currently, well-placed weather stations provide information on local weather conditions. A wireless data acquisition system using various sensors for monitoring many features and conditions, such as humidity, temperature, luminosity, CO2 level, and flow meter for monitoring agriculture research activities has been used. Other systems based on remote sensors for the determination of different parameters have been reported. Remote data acquisition for evaluating soil water potential using tensiometers was described. Data acquisition systems for accessing soil moisture measurements at different depth levels were developed. Different multi-layered sensor networks, such as dielectric soil moisture sensor networks for monitoring soil moisture variability over specified fields, were developed and deployed. Data from all the above systems will offer critical information for the optimization of irrigation requirements in any cultivated field or crop.

2.4.3. Data Management Tools

Producing different data types from different sources creates the need for a variety of data storage techniques. Especially in precision agriculture research, a wide variety of data is generated and used, both at the within-field level and the whole farm level. In addition to agricultural management records, a variety of sensor-generated and model-generated data sets are used in developing and refining VRT functions. Applications of spatially and temporally sensitive data in agro-environmental modeling at many different levels of aggregation, and their derived products, support the concept of precision conservation agriculture. Furthermore, to accommodate spatial and temporal sensitivity, these agro-environmental models often require considerable data management and post-processing efforts. The various data types of precision agriculture research at multiple spatial and temporal resolutions and their respective data management challenges are presented. To decrease the burden on researchers who want to apply precision agriculture concepts in their work, specific software programs that provide reliable tools to handle and manage these various data types are discussed. Sensor-generated and model-generated data sets are often used together in optimizing crop response functions. Spatially sensitive geographic information systems and spatial statistical programs are standard tools for the described data sets. However, these programs were initially designed to work with static layer files rather than dynamic raster files that change based on temporally sensitive degrees of freedom. Over time, these programs have received several upgrades, such as the dynamic and temporal capabilities, that enable building 3-D raster and temporal models.

2.5. AI Algorithms and Models

Many types of AI algorithms have been widely applied to enhance precision farming practices, of which the most commonly used algorithms are machine learning, predictive modeling, and computer vision models. Here, the three types of models are briefly explained.

1. Machine Learning Techniques

Machine learning algorithms seek a function that approximates the mapping between the inputs and the corresponding outputs, by learning from the set of samples consisting of feature vectors and their target outcomes. The performance of machine learning algorithms greatly relies on the selection of model parameters, and additionally the specific algorithm for some advanced models. The corresponding inputs are often sensor data and the outputs could be categorical, ordinal, or continuous variables.

2. Predictive Analytics

Predictive analytics creates analytic models that incorporate ground truth and explanations about prediction. These models are coded in understandable languages, taking advantage of software engines that are open-source or proprietary. Predictive analytics provides automated feature selection and hyperparameter tuning, so analysts without machine learning backgrounds but with domain knowledge can produce predictive analytics models with little effort. Using predictive analytics has several advantages: the prediction model is understandable and hence easily interpretable; predictive analytics has been extensively used for relatively simple models, including linear regression and decision trees; predictive analytics language engines also incorporate more advanced machine learning models; predictive analytics systems have easy-to-understand output. The input of predictive analytics is generally ground truth data that could come from either passively observed historical data or actively labeled data sets, and of course, it is preferable to be large and good quality data.

2.5.1. Machine Learning Techniques

Machine learning has revolutionized data analytics across various fields, by providing intelligent tools that can extract and learn from available data. ML allows self-learning from experience, using algorithms designed to improve machine performance through systems and programs, and any implemented design is itself an engine for progressive learning. In ML, statistical learning techniques build models from known data and apply these models to analyze new data and make decisions. The need for raw data to be literally transformed into knowledge, combined with humanity's latent desire for technological progress, has stimulated the development of data mining algorithms, which implement the principles of artificial neural networks, mathematical logic, and, more generally, mathematical statistics. The relationship between data mining and ML relies on the use of algorithms as instruments for the study of concrete problems.

Using learning algorithms, researchers have developed tools capable of performing simple tasks such as recognition and classification of characters, images, speech, and DNA sequences, and of more sophisticated functions such as diagnosis, prognosis, and the support of decision-making processes in various research fields. Researchers in ML have honed the techniques that often lie at the heart of data mining tools: auto-association coding, hidden Markov models, and artificial neural networks might be considered the three main building blocks of the existing data mining systems. The development of new data query and visualization tools should stimulate the creation of new ingenious learning algorithms and new intelligent methods for using the existing algorithms.

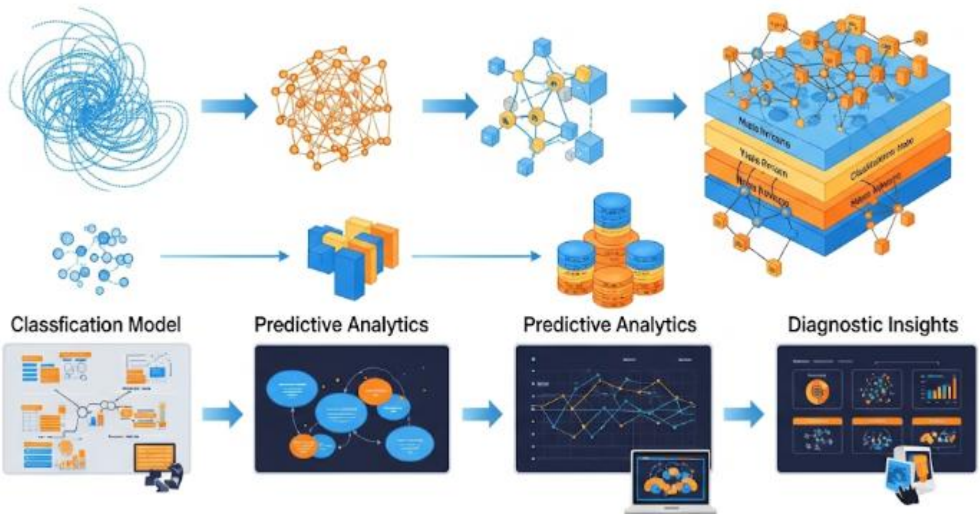

Fig 2 . 2 : CMachine Learning: Transforming Data into Insight

2.5.2. Predictive Analytics

Predictive analytics is defined as the use of predictive modeling to analyze data to derive patterns of past behaviors and recommend future behaviors, thereby optimizing an outcome. In the agriculture arena, predictive analytics proposes to integrate historical data sources covering year-on-year comparative results, continuously measure real-time data, and provide predictive data analytics available in the farmer's pocket. Functionally, predictive analytics can help farmers leverage the information and insights from these vast oceans of big data to determine when and how much to irrigate, what different types of fertilizers to use, and what to plant—such as the optimal variety of seeds that would achieve maximum yield for the local area, based on weather and climatic conditions. These capabilities can dramatically improve productivity and yield during the high-cost capex cycle. The onus for implementing precision farming today rests largely on the farmers' shoulders. They need to invest in setting up sensor-enabled technologies to gather data from the field and to ensure that the collected data is measurable and meaningful. In addition, only a select few farmers own state-of-the-art smart computing devices that use AI and machine learning to decode these data patterns and produce recommended insights or actions. Predictive analytics is at the heart of an ecosystem approach that weaves all the elements of big data—from data capture, data storage, data mining, data analytics, through to data visualization—seamlessly for farming, and presenting it in a way that farmers can understand and use effectively. To achieve this, we present the conceptual model for agri-precision analytics, below. There are several challenges in implementing agri-precision analytics. First, credible aggregate data from farmers over time is needed to derive large-scale models, covering a wide array of different crops across different regions.

2.5.3. Computer Vision Applications

Computer vision (CV) applications have become integral to progressive advancements, facilitating the development of high-performing vision-based systems that have improved specific tasks and made them technically feasible. In agriculture, robotics and unmanned aerial vehicles assist farmers in developing farms that are temporarily free of labor as they can now be handled remotely. Moreover, farmers can use these systems for monitoring purposes or to detect certain conditions in the farms that require specialized attention. Vision-based systems consist of hardware and software that use combinations of low- and high-level processes in order to accomplish a particular task. The hardware sensors are used for capturing the image and converting it into electrical signals that can be further processed. The algorithms then analyze these signals and may achieve specific tasks. Built-in applications have assisted in the processes that were once thought to be impossible to perform without a computer.

Detection of diseases in plants was one of the first problems that computer vision algorithms were designed to solve. Over the past few years, image-based detection has been used to detect numerous fungal and bacterial diseases. However, manually examining the images and checking the correctness of the algorithms requires highly qualified personnel which is often a limiting factor. Therefore, nowadays, deep learning has gained much attention and some of the best-performing non-deep-learning models are becoming obsolete. Research has also been focused on developing methods that would be based on deep learning that can be used on mobile devices. Many of these systems have poor performance; however, research is being carried out to bridge this gap, as having light algorithms that can be used on mobile devices is highly praised across the world.

2.6. Challenges and Limitations

Artificial intelligence has potential implications for the efficiency of agricultural productivity through the automation of agricultural operations. However, some challenges and limitations need to be addressed before widespread adoption, including three key aspects: data privacy considerations, technological barriers, and cost implications.

1. Data Privacy Concerns

The success of artificial intelligence is rooted in the use of data to train algorithms to recognize patterns. However, doing this in a precise farming environment requires the sharing of substantial datasets between multiple stakeholders, which raises data ownership and privacy concerns. While some have proposed the creation of third-party data custodians to oversee such sharing, it requires robust regulatory and incentive frameworks that are currently lacking. Technological companies have already superseded people in capturing and aggregating user-generated data in non-agricultural domains and are expected to control the extent and manner in which farmers can capture, curate, and monetize the data they generate in the primary sector.

2. Technological Barriers

While there currently exists software tools for a wide suite of operational and decision-making challenges in precision agriculture, the majority are provided by proprietary digital agriculture platform providers. One major impediment to farmer adoption of AI in agriculture is the confusion stemming from a chaotic domain with multiple platforms that are disconnected, some that lack adequate standards, and others that cannot operate across the many different agricultural tasks and operational functions. The barriers to entry into the digital agriculture space are also relatively low, and today's proprietary digital agriculture solutions lack the element of ethics and good corporate governance and are likely to follow exploitative business models, charging farmers exorbitant fees for using their solutions, with the justification of sharing the upswings in farm productivity.

2.6.1. Data Privacy Concerns

As agriculture becomes more technologically advanced, the ethical implications of data collection, storage, and application are also becoming more complex. Farmers, as cameras, sensors, drones, and other devices monitor their fields, have the right to know who is collecting data, how it is being used, and for how long it will be stored. Privacy concerns with precision agriculture center on sharing highly sensitive information among multiple stakeholders, which include technology providers, agribusiness partners, and possibly even competitors. With various stakeholders accessing the same data, how can farmers control the proliferation of their information? Many farmers have opted for data-sharing agreements, but unless a farmer is a trained technician, it can be hard to decipher what that means.

Some feel there should be a uniform set of regulations for precision agriculture. There is a call for creating a comprehensive, enforceable, and observable regulatory framework that lays out the rights of the public. It encourages consistent and clear terminology so that consumers understand exactly what information farmers are giving up. Farmers need to be educated on their role in data privacy, and technology providers should take it upon themselves to explain their privacy needs. In the end, data privacy is not just a technical issue, but also a philosophical one, one that needs input and discussion from all parties involved.

2.6.2. Technological Barriers

However, the integration of such advanced technology faces several challenges that hinder optimal utilization. These challenges include technological barriers such as space and size, compliance and regulatory issues, data sharing, and so on. The increase in the share of small and marginal farmers in developing countries, especially in Asia, means that technology transfer must take account of the limited resource base, lower production levels, and not generally favorable economic conditions. Precision Agriculture has inadvertently bypassed small farmers in most developing countries because the technology-intensive approach was inappropriate for small-sized farms and niche-farming operations. There would be no quick-fix solution to the Precision Agriculture dilemma in the short run. However, researchers and extension workers should explore Precision Agriculture components suitable for small farmers in the medium and long run. This is necessary to increase input-use efficiency and provide higher input support for small farmers during crop season.

Nonetheless, recent developments in sensor technology, data fusion, communication technology, and robotics, coupled with favorable economic returns, are bringing about changes in Precision Agriculture philosophy, concepts, and technology transfer at a more rapid pace than technological change in conventional agriculture. In addition, the trend toward improved connectivity may offer an exciting opportunity for cognitive-based decision support for site-specific management. Therefore, there could be increasing scope for the development of Precision Agriculture-relevant approaches suitable for smallholder farmers in the near future with squeezed profit margins. Indeed, most developing countries are located in the tropical and subtropical regions that would benefit from weather forecasts based on improving predictive capability and estimating the impact of climate variability. The future development must include smallholder farmers and their interests at the center of attention.

2.6.3. Cost Implications

With the advent of Artificial Intelligence and rapidly developing machine learning algorithms, Artificial Intelligence in agriculture is steadily gaining interest. A plethora of research has been published, further driving the understanding and exploration of the influences of AI and big data on the modern evolution of agriculture, both in economic and commercial aspects. The investment cost of integrating AI into precision agriculture has been a major limitation in its widespread application. Initial investment costs of adopting AI technology in crop management can often be unfavorable, especially for smaller businesses. Adopting automation in any form comes with a cost. Farmers must consider the financial implications of such investments before they incorporate any new technology, especially for routine farming tasks that may increase their total operational expenses. To employ these technologies, initial investments in infrastructure, layout manipulation, and machinery with high precision, as well as drones or other platforms for data acquisition, are all obligatory. Investment in AI systems for monitoring pests, weeds, diseases, and soil and nutrient management are also key and important components of the adoption process.

Over time, these high costs may be mitigated, but in the interim have not only large economic implications for farming businesses considering these technologies but could also serve as a barrier to entry for commercializing these systems. Protection and insurance issues also remain largely unresolved, especially for machine manufacturers who face hurdles in their contract terms and conditions, warranty payments, or self-insurance or performance guarantee requirements for the adoption of AI technologies by farmers. The developments that have been made in these systems thus far have been made through public funding to enable them to reach a commercial stage, on a cost-neutral basis with low or no market prices. Despite their potential for high productivity and reducing the use of already strained natural resources, the commercial stage of these technologies draws criticism, due to their resource demand and multiple-scale complexity.

2.7. Future Directions in AI and Precision Farming

While AI and machine learning have already made positive impacts in precision farming, enhancing future agricultural production is always necessary given the countless challenges that agriculture has to face in modern days. In the coming years, there are ample opportunities and room for more advanced AI technologies to be implemented in the agriculture industry, especially in crop monitoring, crop management, livestock and soil monitoring, in-field robots, and drones. Specifically, emerging technologies such as the Internet of Things, computer vision, swarms, blockchain, and digital twins can be used for precision farming efficiently. However, it is important to make sure that those technologies do not only emphasize the potential of profit-making but also aim to achieve sustainability and at least no detrimental social effects, considering that social effects include the effect of agriculture on public health and the effect of agriculture on community values. Without careful legislation and regulations, the unexplored risks of misusing new technologies when implementing them can produce undesired effects on social values.

Technology development aside, future precision farming systems should aim for complete sustainability throughout the entire development process, regarding both the environment and the business chain. From the view of the ecosystems, precision farming is an important and promising step to reduce agriculture placing an additional burden on the public treasury. This reduction can be achieved with a decrease in carbon footprint, nitrogen surplus, phosphate surplus, etc., and an increase in the circularity of farm systems. But it is also important to keep in mind that there are not only natural ecosystems but also human-made ones, where future precision farming systems interact with local consumers. For the human-made ecosystem, farm viability and the business model are key factors determining its sustainability.

2.7.1. Emerging Technologies

Over the past years, we witnessed a huge rise in the adoption of several new technologies in different sectors such as Web 3.0, edge cloud, extended and mixed reality, and generative artificial intelligence. They have contributed to the transformation of many areas, including precision agriculture. During 2021–2022, investment into these technologies reached record levels, and market validation continues to grow, fostering sustainable innovation, especially for agricultural productivity. This reflects both accelerated tech adoption along with addressing current rising concerns for food security and agricultural sustainability. The purpose of this section is to take a closer look into the contributions of those emerging technologies in the precision agriculture area.

Generative AI has the potential to redefine the horizontal tech stack across any field of application, including agriculture. Its uses can focus on enhancing existing technologies in the agricultural space by addressing use case specifics, including crop type and user location navigation, as well as relevant data to be crawled or ingested to fine-tune the underlying models. Furthermore, its contribution goes beyond data ingestion by automating any creative or repetitive tasks, including data preparation, visual and text content creation, product copy generation, etc. AI can also assist in the design of more efficient models, solving NP-hard combinatorial optimization problems with the appropriate training. Such models can support practical problems across the precision agriculture domain, including variable rate application for fertilizer and seeding, crop planning, as well as product delivery.

2.7.2. Policy and Regulation Considerations

As precision agriculture increasingly relies on Artificial Intelligence (AI) to enhance digital remote sensing capabilities, enhancing sensor data management, as well as AI algorithms, increasingly become centralized with major private digital service platforms. While this may greatly de-risk underlying business in deploying various novel types of applications for farmers in supporting decision-making, it does run the risk of creating some monopolistic nature of the market that can potentially disadvantage farmers either via high rents or loss of ownership of their data. Moreover, the use of AI for digital service provision does not alleviate the need for government intervention in creating incentives for the provision of public goods. For instance, while remote sensing can provide more accurate information about the environmental footprint of certain farming actions, it cannot alone assure farmers take action to reduce the potential negative externality of land runoff from fertilizer uses that pollute nearby watersheds with algal blooms detrimental to water quality. Government intervention is critical in not only monitoring behaviors but also in providing incentives that shape behaviors toward better environmental management. Regardless of policy action by the public sector, there is still the need for a regulatory environment that allows for a rapid yet secure rate of digital technology adoption. This calls into question current liability insurance regimes that define responsibility in cases of technology-driven failures or damages, as AI in precision agriculture can potentially reduce risk-aversion behavior by farmers, thus requiring wider coverage at lower costs. Regulatory frameworks need to be altered to incentivize innovation and adaptation of AI in precision agriculture. For example, lifting regulations around data storage and usage, especially confidentiality agreements between farmers and digital service providers, could increase the ability to pack different types of private data into one big package which could then be used to build or enhance novel tools with a wider market appeal.

2.7.3. Sustainability and Environmental Impact

AI has gained popularity due to its tracking capabilities and ability to reduce the human workload related to farm management. Utilizing AI approaches in PF models makes them more scalable and flexible, but answers to questions regarding sustainability and environmental effects remain unanswered. Examining empirical results on how AI improves resource use efficiency, farm income, labor and technical costs, carbon footprint, CO2 emissions, organic matter content, and crop yield, we suggest finish-up courses of action for better-addressing sustainability and environmental concerns regarding agricultural decision-making. Subsequently, we emphasize how incorporating some specific types of prior knowledge and additional requirements into the AI-enabled PF approach would help to shed light on various aspects of sustainable development. Given that one predictive task may produce opposite results for two different farms, we propose using specific approaches tailored for particular variables and indicators when estimating resource use efficiency.

AI, adopting ML, DL, and ANN models, is certainly a solution to various problems PF models face. Consequently, policymakers and researchers have started promoting the use of AI technologies in PF models so that farmers improve their production while simultaneously aiming at reducing the environmental effects of such production. In this regard, it is recommended to seek a balance between PF models supported by AI and the aspect of output resource use efficiency. The primary focus of the necessary policies should be the relevance of AI technologies to resource use efficiency, economic development, environmental efficiency, and social responsibility. Numerous studies note that the advanced pace of progress in AI development indicates that its use in PF models can help accomplish previously announced goals regarding resource use efficiency, thus allowing the farmers to contribute to sustainable development.

2.8. Conclusion

Crop production is important for food security worldwide. As the population reaches nine billion in 2050, demand for food security increases, and resource access is restricted. Agricultural practices negatively impact the climate by generating carbon dioxide and methane emissions, but incentives toward more sustainable actions are expected to affect positively the environment. Current practice recommendations mainly cover a small number of aspects of precision farming. Additionally, policies are being developed to implement recommended practices. Novelty in our schedule aims at providing a working integrated computational framework of everything related to precision agriculture that anyone involved in precision agriculture might need, and provide to those involved the means of developing more efficient future algorithms.

Navigating the jungle of events, algorithms, practices, services, and research, is possible with help from an expert board, a help-desk service, a brainstorming room, and the appropriate tools. Precision Agriculture means collecting, and properly interpreting all data that relate to soil monitoring, plant monitoring and crop modeling, micro-weather forecasting, planning, and decision-making. Many problems on which to develop, and report solutions are present: spatial and temporal heterogeneous field maps, crop models, decision-making models, crop market evolution, economic aspects, and policies. In the agricultural world characterized by a valley of death between fundamental research, experimental tests of many different aspects in different conditions, and implemented products and services, one solution is to choose a few specific areas, optimize them, and common independent integrated processes and services.

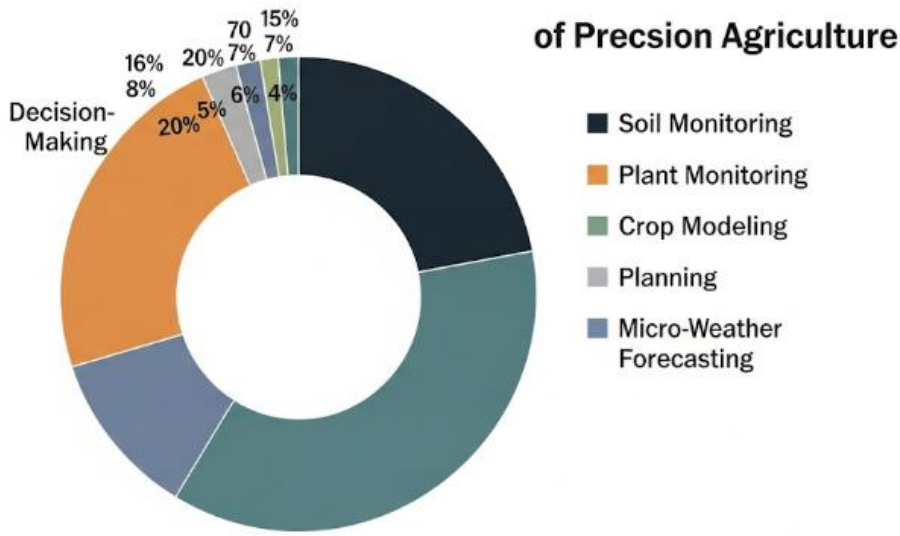

Fig 2 . 3 : Precision Agriculture: A Holistic Approach

2.8.1. Summary and Implications for Future Agricultural Practices

This work leveraged a range of artificial intelligence and data analytics methods, including unsupervised and supervised machine and deep learning and process simulation models, to extract insights from relational, image, video, and simulation datasets collected from precision agriculture on farms. Applications included estimating corn nitrogen needs, predicting pest infestation and damage, predicting corn market prices, and simulating the relationship between fertilizer inputs and corn outputs. The work aims to combine new algorithms and remote sensing capabilities with traditional agricultural models to address practical problems relevant to producers. Applications were designed for producers' use, combining model-based data fusion with user-friendly software. Precision agriculture, and in particular data-driven decision support for variation in inputs and management, has the potential to improve the sustainability of agriculture by increasing productivity in areas with favorable growth conditions and decreasing resource use or increasing quality in areas with less favorable conditions. Increasing concerns from consumers about emissions, pollution, and fertilizer use could translate into marketing advantages for technology adopters, and agri-businesses, lenders, and governments are already promoting the use of such new technologies. The question is what it will take to see rapid adoption, and whether policy implementation can increase that adoption. Despite the potential benefits, barriers to adoption remain. Producers have questions about return on investment, whether new technologies will work under their conditions, and for whom.

References

Liakos K.G., Busato P., Moshou D., Pearson S., Bochtis D. (2018). Machine Learning in Agriculture: A Review. Sensors, 18(8), 2674. https://doi.org/10.3390/s18082674

Kamilaris A., Prenafeta-Boldú F.X. (2018). Deep Learning in Agriculture: A Survey. Computers and Electronics in Agriculture, 147, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Mishra A., Singh V.P., Pandey R.P., Khedun C.P. (2020). Precision Agriculture and Artificial Intelligence: A Perspective. Current Science, 119(6), 984–992. https://doi.org/10.18520/cs/v119/i6/984-992

Jha K., Doshi A., Patel P., Shah M. (2019). A Comprehensive Review on Automation in Agriculture Using Artificial Intelligence. Artificial Intelligence in Agriculture, 2, 1–12. https://doi.org/10.1016/j.aiia.2019.05.004

Zhang Y., Wang G., Wang J. (2021). Applications of AI and Big Data in Smart Agriculture: A Review. IEEE Access, 9, 75999–76020. https://doi.org/10.1109/ACCESS.2021.3083991