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Artificial Intelligence applied to agriculture for the optimization of production, revenue and reduction of waste

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Sommario

Overview of the thesis

A. General Context on the Importance of Sustainable Agriculture

Agriculture is the very foundation of our existence, providing the food that sustains the lives of billions of people around the world. However, the increasing demographic pressure, climate change, and intensive agricultural practices have posed significant challenges to the sustainability of this vital sector. In this context, the adoption of sustainable agricultural practices emerges as an indispensable imperative to ensure global food security and mitigate the environmental impacts resulting from decades of unregulated exploitation.

Sustainable agriculture is not simply a fashionable concept, but a necessary response to the environmental and social challenges that our society must face. Recognizing the intrinsic value of the land and natural resources, sustainable agriculture aims to maintain and improve soil productivity over time, reduce the use of harmful chemicals, and preserve biodiversity. Moreover, it seeks to mitigate greenhouse gas emissions, promote ethical practices in the treatment of animals, and ensure economic equity for farmers.

B. Problem Statement

Despite the vital role that agriculture plays in our society, the management of agricultural resources currently faces a series of complex and interconnected challenges. The increasing demographic pressure, climate changes, soil erosion, and intensive agricultural practices have generated a series of problems that threaten the long-term sustainability of this fundamental sector and thus the ability ensure food security to an increased world population.

Focusing on production, we notice that the cause of the reduction in production and therefore the greater losses, as a consequence, come from pathogens and weeds. Weeds consistently reduce the expected profit and yield of farmers[1].

A report confirms a 50% reduction in yield for dried bean and corn crops if weed infestations are not controlled. There is a loss of about 48% in wheat yield due to weed competition[2] [3] These losses can sometimes reach up to 60%.

Demographic Pressure and Food Security: With a continuously growing world population, the demand for food is set to significantly increase in the coming decades. This puts unprecedented pressure on agricultural resources, requiring an increase in food production. However, inefficient resource management can lead to a decrease in soil fertility, threatening long-term food security.

Climate Changes and Meteorological Variability: Agriculture is particularly sensitive to climate changes and meteorological variability. Extreme weather events, such as droughts, floods, and heatwaves, can compromise agricultural production and negatively affect soil quality. The lack of accurate forecasts and advanced tools to address these climate changes represents a significant challenge.

Depletion of Natural Resources: Intensive use of fertilizers, pesticides, and other chemicals has led to the depletion of natural resources and environmental pollution. The lack of prudent management of such agricultural inputs can cause irreparable damage to surrounding ecosystems, with negative impacts on biodiversity and human health.

Limited Access to Advanced Technologies: In many regions of the world, limited access to advanced agricultural technologies represents a significant barrier to the

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[1] K. N. Harker, "Survey of yield losses due to weeds in central Alberta", Canadian Journal of Plant Science, Vol. 81, No. 2, pp. 339–342, 2001

[2] M. Khan, N. Haq, "Wheat crop yield loss assessment due to weeds", National Agricultural Research Cen intensification tre, Vol. 18, No. 4, pp. 449–453, 2002

[3] S. Fahad, S. Hussain, B. S. Chauhan, S. Saud, C. Wu, S. Hassan, M. Tanveer, A. Jan, J. Huang, "Weed growth and crop yield loss in wheat as influenced by row spacing and weed emergence times", Crop Protection, Vol. 71, pp. 101–108, 2015

adoption of sustainable practices. This creates inequalities in agricultural efficiency and hinders the implementation of innovative solutions to address the sector's challenges.

C. Purpose of the Report: How AI and Satellite Data Can Contribute to More Efficient Management

The main goal of this report is to explore how Artificial Intelligence (AI) and the use of satellite data can merge to create an innovative and highly efficient approach in the management of agricultural resources. Through the detailed analysis of data collected by satellites and the application of advanced artificial intelligence algorithms, we aim to revolutionize agricultural practice, optimizing resource allocation and reducing waste.

Optimization of Agricultural Practices: The primary objective is to examine how AI can be employed to analyze satellite data and provide detailed information on the state of the soil. This allows for the optimization of agricultural practices, adjusting decisions on fertilization, fertilization, and irrigation in real-time based on the actual needs of the soil.

Reduction of Waste and Improvement of Sustainability: Through the implementation of intelligent systems, we aim to reduce resource waste, limiting the excessive use of fertilizers and pesticides. AI can contribute to targeted resource management, ensuring that only the areas that need it receive specific treatments. In this way, we promote a more sustainable and environmentally friendly agricultural practice.

Real-Time Monitoring and Predictive Decisions: The report proposes to explore how AI, through the analysis of real-time satellite data, can provide predictive information on crop growth, weather conditions, and potential challenges. This would allow farmers to anticipate the needs of their crops and make timely decisions to maximize yield.

Development of Integrated Systems: A further aim is to examine how AI and satellite data can be integrated into complex systems, collaborating with other advanced agricultural technologies to create a holistic approach to resource management. This will include assessing the interaction between AI and on-site technologies, such as agricultural drones and ground sensors.

Through this exploration, we propose to demonstrate how AI and the use of satellite data can not only solve current challenges in the management of agricultural resources but also open new possibilities for more efficient, sustainable, and ecologically responsible agriculture.

Chapter 1: Foundations of Artificial Intelligence

Artificial Intelligence (AI) refers to the simulation of human intelligence in computers that are programmed to think like humans and mimic their actions. The term can also be applied to any machine that exhibits traits associated with the human mind, such as learning and problem-solving. The roots of AI can be traced back to ancient myths of mechanical automata that mimic human life and function. However, as an academic field, AI was founded in 1956 at a conference at Dartmouth College, where the term "artificial intelligence" was coined for the first time. AI branches into various subfields, each focusing on specific areas of learning and capabilities. Some of these include:

Machine Learning (ML):AI learns to make decisions based on data.

Deep Learning: A subcategory of ML that uses neural networks with many layers to analyze large volumes of data.

Natural Language Processing (NLP): AI processes and understands human language.

Robotics: AI applied to robots, enabling them to perform tasks autonomously.

Computer Vision: AI that interprets and understands the visual world.

Machine Learning in Agriculture

In the field of agriculture, AI finds significant application through machine learning, a branch that allows systems to improve their performance by analyzing large amounts of data and autonomously recognizing patterns. This process is crucial for interpreting satellite data, allowing the identification of specific soil conditions, such as moisture, composition, and the presence of nutritional deficiencies, without the need for specific programming for each type of analysis.

Computer Vision

Computer vision represents another important field of AI application, enabling systems to process and interpret images and videos similarly to the human eye. In agriculture, this facilitates the monitoring of crops, from analyzing growth status to the early detection of diseases or infestations, providing a valuable tool for maintaining high standards of plant health and productivity.

Natural Language Processing (NLP)

AI, through Natural Language Processing (NLP), also extends to the understanding and generation of human language, enabling the processing and synthesis of large amounts of text. This technology can transform collected data into comprehensible reports, simplifying the interpretation of agricultural data and allowing farmers to make decisions based on clear and concise information.

Expert Systems

Expert systems, leveraging AI capabilities, implement sets of logical rules to emulate human reasoning in specific fields. In agriculture, they can provide recommendations on optimal measures for cultivation, irrigation, and crop management, based on a detailed analysis of environmental and meteorological data.

Predictive Analysis

Finally, predictive analysis emerges as one of the most transformative aspects of AI, anticipating trends and future conditions. In agriculture, this means being able to predict climatic variations, soil conditions, and crop evolution, allowing farmers to plan targeted interventions in advance to maximize yields and minimize risks.

Through these applications, AI is positioned as a fundamental lever for innovation in the agricultural sector, offering advanced tools for analysis, management, and optimization of agricultural practices. Its ability to handle huge volumes of data and provide predictive and personalized insights opens new frontiers for more sustainable, efficient, and productive agriculture.

Artificial Intelligence (AI) is one of the key research areas in computer science; with its rapid technological progress and wide field of application, artificial intelligence is becoming pervasive very quickly due to its robust applicability, particularly in solving problems that cannot be well addressed by humans and traditional computing structures. Agriculture is an area of extreme importance where 30.7% of the world's population is directly engaged on 2781 million hectares of agricultural land.[4].

The application of computers in agriculture was first reported in 1983.[5]. Several approaches have been suggested to solve existing problems in agriculture, ranging from databases to [6] to decision support system [7].

The idea of using artificial intelligence techniques in crop management was first proposed in 1985 by McKinion and Lemmon in their article "Expert Systems for Agriculture[8]

More recently, convolutional neural networks (CNN), a specific type of deep learning model commonly used with images, have been employed to improve the performance of quality classification models in corn.[9]

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[4] Artificial Intelligence in Agriculture: A Literature Survey: https://www.researchgate.net/profile/Gouravmoy-Banerjee/publication/326057794_Artificial_Intelligence_in_Agriculture_A_Literature_Survey/links/5b35ab970f7e9b0df5d83ec6/Artificial-Intelligence-in-Agriculture-A-Literature-Survey.pdf

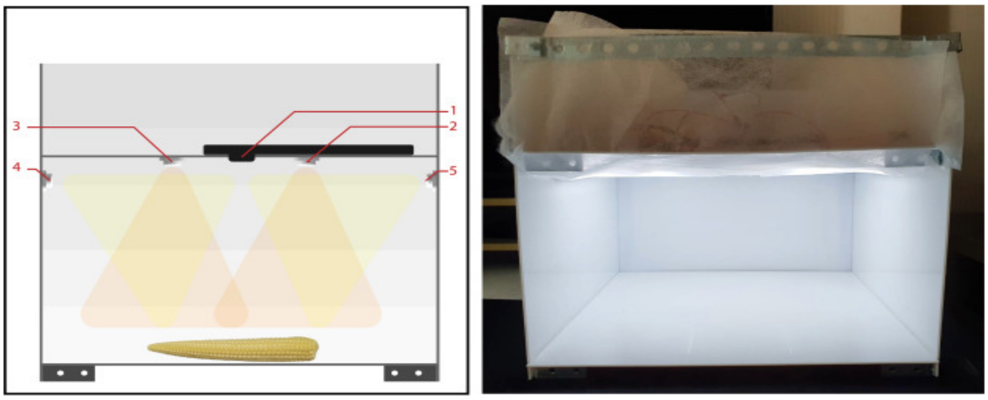
[5] D.N. Baker, J.R. Lambert, J.M. McKinion, ―GOSSYM: A simulator of cotton crop growth and yield,‖ Technical bulletin, Agricultural Experiment Station, South Carolina, USA, 1983

[6] P. Martiniello, "Development of a database computer management system for retrieval on varietal field evaluation and plant breeding information in agriculture," Computers and electronics in agriculture, vol. 2 no. 3, pp. 183-192, 1988.

[7] K. W. Thorpe, R. L. Ridgway, R. E. Webb, "A computerized data management and decision support system for gypsy moth management in suburban parks," Computers and electronics in agriculture, vol. 6 no. 4, pp. 333-345, 1992.

[8] J. M. McKinion, H. E. Lemmon. "Expert systems for agriculture," Computers and Electronics in Agriculture, vol. 1 no. 1, pp. 31-40, 1985

[9] Kris Wonggasem, Pongsan Chakranon, Papis Wongchaisuwat, Kris Wonggasem, Pongsan Chakranon, Papis Wongchaisuwat, Automated quality inspection of baby corn using image processing and deep learning, Artificial Intelligence in Agriculture 11 (2024) 61–69.



In fact, in the study, sensors were placed inside a white box that selected images of corn, which were then automatically analyzed by deep learning algorithms for validation and then the final test.

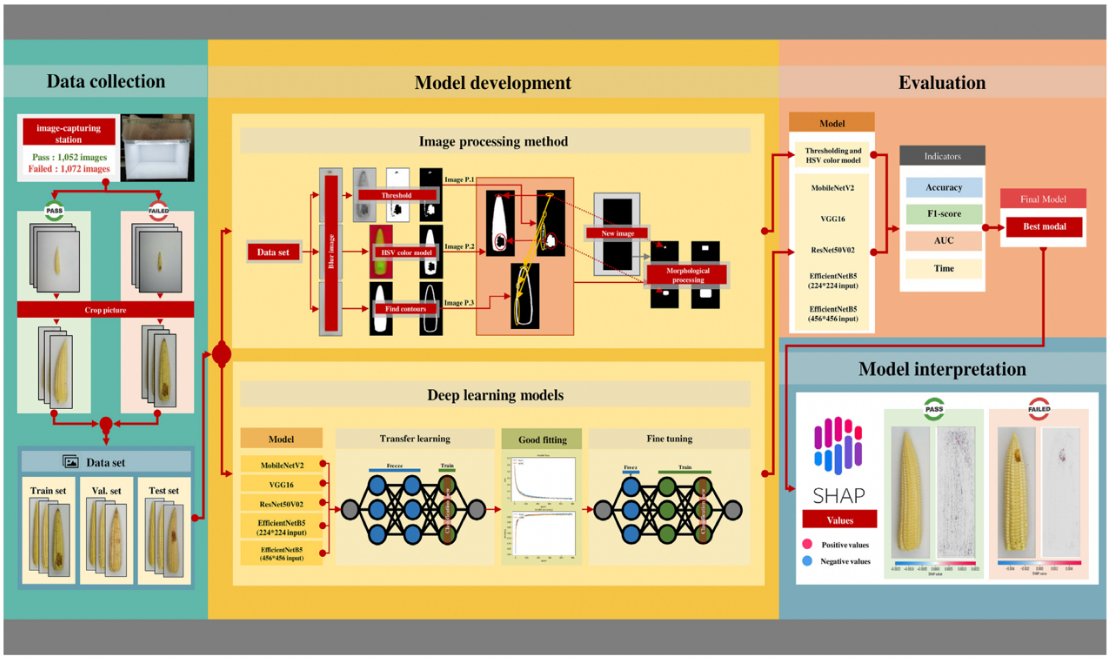


Fig. 3. The flow process chart.

A portion of the samples was used to train the algorithm to recognize features that would either pass the test or reject the corn sample, while the rest of the samples were subjected to the algorithm.

In this study they utilized the standard Mobilenet, VGG16, and EfficeintNetB5, ResNet50V2 network structures.

Table 2
Overall accuracy and F1-score of experimented methods on train, validation and test set.

Method	Model	Train		Validation		Test	
		Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
Image processing	Thresholding and HSV color model	95.54	95.50	95.12	95.10	95.28	95.33
	MobileNetV2	99.85	99.85	97.91	97.89	98.11	98.13
	VGG16	99.48	99.47	97.74	97.70	97.64	97.65
Deep learning	ResNet50V2	100.00	100.00	98.26	98.23	98.13	98.10
	EfficientNetB5 (224 × 224 input)	100.00	100.00	98.26	98.23	98.58	98.59
	EfficientNetB5 (456 × 456 input)	100.00	100.00	98.78	98.77	**99.06**	**99.07**

The table 2, is referred to the different part of the study, showing the different phase of the analysis, the conclusion show that the final test gave interesting results from the system based on Deep learning more than normal image processing, showing the maximum accuracy with system EfficientNetB5 (456 × 456 input).[10]

[10] Kris Wonggasem, Pongsan Chakranon, Papis Wongchaisuwat, Kris Wonggasem, Pongsan Chakranon, Papis Wongchaisuwat, Automated quality inspection of baby corn using image processing and deep learning, Artificial Intelligence in Agriculture 11 (2024) 61–69.

The Role of AI in the Agricultural Sector

Resource Optimization: AI, leveraging high-resolution satellite data, has shown a significant impact on resource management. According to a study conducted by the National Institute for Space Research (INPE), the application of machine learning algorithms has led to a 20% reduction in water use in corn crops in some regions.

Increase in Productivity: The benefits of machine learning in crop management are clearly evident. Savitha and UmaMaheshwari (2018) have also developed the concept of an efficient and automated irrigation system using remote sensors that employ Arduino technology, which can increase production by up to 40%[11]

Waste Reduction: AI can optimize supply chains, improving logistics and reducing post-harvest waste.

Timely Response to Environmental Conditions: AI, integrating satellite data with machine learning models, enables a timely response to environmental variations. According to a report from the Group on Earth Observations (GEO), this timeliness in response can reduce the risk of crop damage by up to 35%.

Labour and Time Savings: A 20% increase in operational efficiency was recorded by the implementation of AI-driven technologies, as highlighted in a study conducted by the Food and Agriculture Organization (FAO) - Harnessing Artificial Intelligence for Global Food Security [12]

Environmental Sustainability: Projects like "Sustainable Farming using AI" in Australia have demonstrated a 25% reduction in greenhouse gas emissions through more targeted and sustainable agricultural practices [(Australian Farm Institute - AI in Agriculture)].[13] **Predictive Decisions and Plant Disease Prevention:**Predictive analysis by AI, based on satellite data and climatic models, allows for early prevention of diseases.

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[11](https://www.sciencedirect.com/science/article/pii/S258972172030012X#bb0415)
[12] (http://www.fao.org/3/cb1308en/cb1308en.pdf)
[13] (https://www.farmtable.com.au/sustainable-farming-using-ai/).

Chapter 2: The Reasons Behind Precision Agriculture

The environmental sustainability of Agriculture is one of the main challenges that humanity must face. We cannot stand still in the face of this challenge; instead, we must respond by producing in an efficient and sustainable manner.

Why must agriculture be sustainable? Firstly, it lends itself to more decisive policies on land management since it is the only activity that reaches every corner of our territory. However, numerous problems threaten its sustainability.

45% of European soils have soil quality issues, highlighted by low levels of organic matter. Moreover, a quarter of the lands suffer from moderate to high degrees of erosion, putting at risk soil fertility and its capacity to support crops.

In the last 20 years, bird populations in agricultural habitats have decreased by 20-25%, while common butterflies have even decreased by 70%. Pollinators, such as bees, are threatened by this decline, with severe consequences for biodiversity and food production.

Additionally, 40% of agricultural lands are exposed to nitrate pollution, posing significant risks to water resources and the environment. The agricultural sector is also responsible for 9% of greenhouse gas emissions, thus contributing to climate change The reduction of available agricultural lands is another challenge. The FAO estimates that to feed the world in 2050, agricultural production needs to be increased by 70% compared to today. This means that cereal production must grow by 43%, mainly for animal feed and bioenergy, while meat production must increase by 75% to meet the demand of developing countries.[14]

However, simultaneously, there is an annual loss of agricultural land due to desertification, urbanization, and other land uses. Moreover, in recent years, there has been a trend towards a slowdown in productivity increases in developed countries, leading to the loss of competitiveness of the most marginal and poor lands.

[14] https://terraevita.edagricole.it/macchine-agricole-trattori/lagricoltura-precisione-unintensificazione-davvero-sostenibile

All these phenomena make it clear that there is a need for Sustainable Intensification this time, achieving a simultaneous improvement in productivity and sustainable management of agricultural lands. "More knowledge per hectare" means having greater knowledge and information to produce food while increasingly safeguarding the environment.

Precision Agriculture

It is the tool that allows for the full achievement of the concept of sustainable intensification of agricultural production. It has been available to the industry for about 20 years, but it has struggled to spread: [15]

- the reasons do not lie in the size of the investment, but in understanding its real benefits;
- scarce knowledge among operators in its use;
- among the most advanced countries, Italy is where precision agriculture has had the slowest spread. Internationally, the USA, Australia, Germany, and France stand out.[16]

[15] Gabriele Chiodini, (2018), Cerealicoltura tra agricoltura di precisione e digitale; La stima dei danni da avversità atmosferiche su uva da vino e cereali a paglia
[16] Angelo Frascarelli, (2017), Effetti sui costi e ricavi dell'agricoltura di precisione - WORKSHOP: Innovazione e precisione nell'era dell'Agricoltura 4.0

The Spread of Precision Agriculture Worldwide

Let's begin by analyzing the current state of precision agriculture worldwide, with a special focus on the United States, the largest user of this technology. Currently, in the United States, the level of adoption of precision agriculture is significant: 60% of farms operate at a basic level, 35% at an intermediate level, and 12.3% at an advanced level. These figures highlight a growing awareness and adoption of more precise and targeted agricultural practices.

Moving to developing countries, such as Brazil, Argentina, India, and Malaysia, we witness a rapid spread of precision agriculture. These countries are increasingly embracing this technology, recognizing its benefits in terms of increased productivity and reduced environmental impacts. Another key player to watch is China, where it is estimated to become the world's largest user of precision agriculture. Rapid development and growing awareness of environmental challenges are pushing China towards the adoption of more sustainable and targeted agricultural practices.

Turning to Europe, we note that the highest levels of adoption of precision agriculture are recorded in the northwestern part of the continent. However, even in countries like Italy, adoption is gradually increasing. Currently, in Italy, the adoption of precision agriculture does not exceed 1% of the Utilized Agricultural Area (UAA), but the government is taking steps to promote its adoption, indicating a concrete commitment towards more sustainable and innovative agricultural practices.

The 5 levels of precision agriculture, based on company equipment and signal precision level:

1. Assisted guidance,

2. Assisted guidance with section control;

3. Automatic steering;

4. Automatic steering with section control;

5. Use of maps and variable rate distribution.

Difficulties on spread of PA

Precision agriculture (PA) represents an innovative frontier in the agricultural sector, promising to optimize resource use, improve sustainability, and increase productivity through the use of advanced technologies. Despite these promises and the availability of such technologies for over twenty years, the spread of PA in Italy remains limited, with minimal adoption among farmers. The reasons for this hesitation and resistance are multiple and complex.

Firstly, there is significant resistance from farmers to invest in PA technologies without concrete guarantees of economic return. This caution is understandable in a context where initial investments can be considerable, and the lack of familiarity with the long-term benefits makes it difficult to justify such expenses. Despite international and national studies highlighting the economic advantages of PA, from the use of assisted guidance technologies to more complex mapping and variable rate systems, the perception of risk remains a significant obstacle.

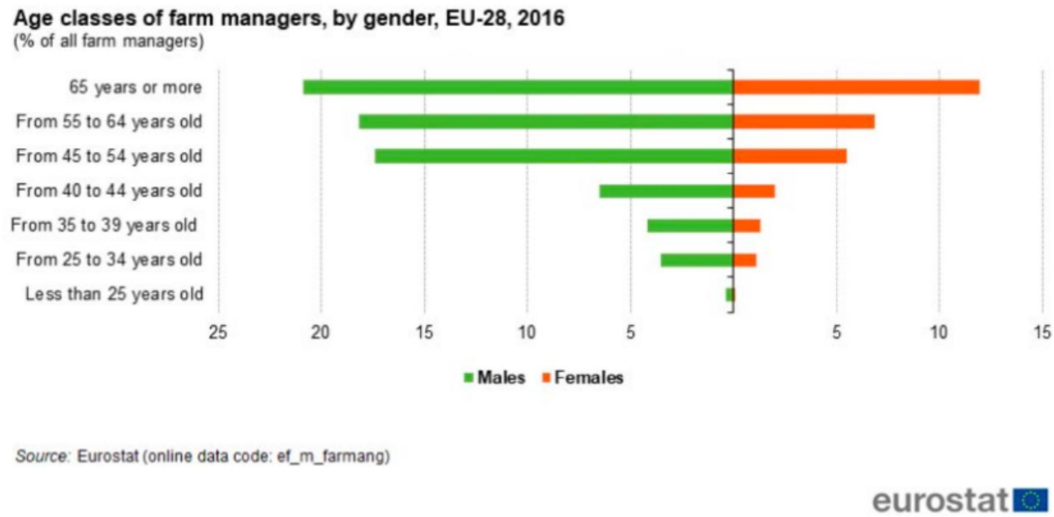
Economic profitability is a key factor for the adoption of any agricultural innovation. Therefore, assessing the economic benefits of PA is essential to promote its spread. However, resistance to adoption stems not only from concerns about the initial investment but also from the difficulty in understanding the concrete advantages over traditional practices. Moreover, there is a marked reluctance to move away from established techniques and traditional mechanization, highlighting a general reluctance towards learning and integrating new technologies.

Another critical point is the obsolescence and oversizing of the existing agricultural machinery fleet. Many farmers have outdated equipment, which, despite being in excess of the power required by the cultivated lands, are considered sufficient for current needs. Introducing PA would require a substantial update of this machinery fleet, as well as a profound cultural change, shifting the emphasis from traditional manual and mental skills to advanced digital and technological competencies.

The professional growth of agricultural entrepreneurs and the human resources involved is crucial to overcome these barriers. Education and training play a key role in increasing awareness of the benefits of PA and reducing resistance to innovation. Furthermore, some farmers show a particular interest in investments in agricultural mechanization, often continuing to increase the power of their machines without valid technical or economic justifications. This attitude reflects a fascination with the more tangible aspect of technological innovation, at the expense of a more holistic approach that includes PA.

Another major problem hindering PA and its development, as can be seen from the following figure, is the average age of farm managers, which according to the European Union in a 2016 study, has over 20% of male subjects over the age of 65.

Eurostat statistics on farmers and the agricultural workforce show that, in Europe, farm managers are generally men and relatively old. Seven out of ten agricultural managers (71.5%) in the EU's 10.5 million firms were men, and the majority (57.9%) were 55 years or older. Only about one in ten agricultural managers (10.6%) was a young farmer under the age of 40..[17]



[17] European parliament, (2023), Artificial intelligence in the agri-food sector

Another significant difficulty in leveraging Precision Agriculture, especially in the application of satellite imagery such as spectral images and all similar types, lies in the great challenge of interpreting and exploiting the data they provide. The slow pace of analysis and the difficulty in timely interpretation prevent farmers from being able to use it to make their operations more productive and, above all, more cost-effective in terms of using the right amount of fertilizers and manure, a crucial aspect for reducing costs in farm management.

Economic Aspect Analysis

The economic analysis of precision agriculture (PA) highlights how this technology involves a substantial initial investment but is justified by significant long-term benefits, both in terms of operational efficiency and cost reduction and revenue increase.

The initial investments in PA mainly cover fixed capital, such as agricultural machinery, additional components, and software. Despite the high cost of these technologies, which rarely falls below €50,000 per machine, the impact of the initial investment does not represent the main barrier to adoption. This is because the improved efficiency of the machines reduces the cost of use, offsetting the initial fixed costs.

The introduction of PA leads to a change in costs related to the use of machines, with a general trend towards decrease due to the optimization of operations. For example, fuel costs are reduced thanks to more efficient passes that minimize overlaps and increase work speed. These savings partially offset the increase in fixed costs due to the initial investment in PA technologies.

PA significantly improves the efficiency in the use of resources such as seeds, fertilizers, and agrochemicals. The reduction of waste through variable application and assisted guidance allows for the optimization of input use, reducing variable costs. For example, variable rate application technology allows savings of up to 15% on fertilizers and agrochemicals.

Although PA requires more specialized labor, potentially leading to higher costs for training and external consulting, it also reduces work times and improves working conditions. The savings in terms of labor hours, due to the reduction of overlaps and increased efficiency, not only lower labor costs but also improve the quality of life for operators.

The increase in revenue, resulting from higher yields and reduced production costs, along with indirect benefits such as improved quality of productions and environmental advantages, makes PA economically advantageous. A concrete example of this advantage is seen in the increased productivity of a medium-sized corn farm, which recorded an annual income increase of €155 per hectare thanks to PA.[18]

Capitolo 3: Tecnologie Satellitari per il Monitoraggio del Terreno

Satellite technologies are essential for soil monitoring in agriculture, providing detailed data that support informed decisions. We will explore some of these technologies, offering detailed descriptions and references to studies and practical applications demonstrating their effectiveness.

Currently Used Satellite Technologies

Optical Satellites:

Operating Principle: Use optical sensors to capture visible and infrared light, providing high-resolution images of the Earth's surface.

- [18] Frascarelli A. (2016), Valutazione economica dell'agricoltura di precisione, in Casa R. (a cura di), *Agricoltura di Precisione. Metodi e tecnologie per migliorare l'efficienza e la sostenibilità dei sistemi colturali*, Edagricole, Bologna, pag. 213-228

Practical Example: The Sentinel-2 satellite from the Copernicus program offers high-resolution multispectral images, ideal for monitoring details such as the state of vegetation.

Radar Satellites:

Operating Principle: Use radio waves to measure reflectivity from the Earth's surface, penetrating through clouds.

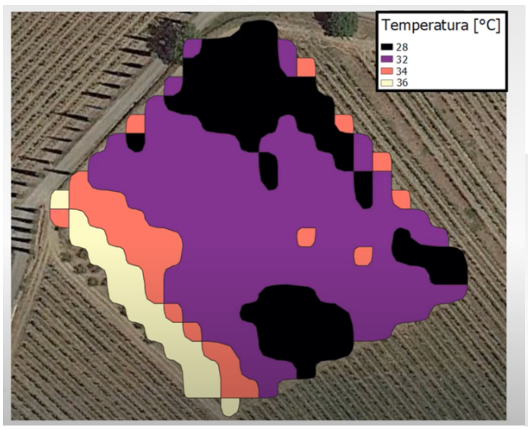
Practical Example: The Sentinel-1 satellite, part of the Copernicus program, has been used to monitor altimetric changes and soil deformations.

Hyperspectral Satellites:

Operating Principle: Capture data across a wide range of wavelengths, allowing detailed analysis of soil and vegetation characteristics.

Practical Example: The PRISMA satellite, operated by the Italian Space Agency,[19] provides high-resolution images for analyzing biogeochemical soil parameters. A study by M. Boschetti and colleagues (2021) used PRISMA data to estimate chlorophyll concentration in crops.

Thermal sensors can easily detect water stress and diseases, with the related issue of the influence of environmental and weather conditions.



[19] https://www.asi.it/scienze-della-terra/prisma/

Integration of Multi-Sensor Data:

Operating Principle: Combines data from various satellite technologies to obtain a comprehensive view of the terrain.

Multispectral sensing with RGB (Red-Green-Blue) sensors is a common technique used in satellite and aerial image analysis to obtain detailed information about terrain features and vegetation. Here's an insight into how it works and what advantages it offers:

- Vegetation analysis

- Crop mapping

- Terrain evaluation and coverage

- Monitoring environmental changes

Operating Principle

RGB sensors, commonly used in satellites for image acquisition, are designed to capture light in three main color bands: red (Red), green (Green), and blue (Blue). They are designed to record light reflected from the Earth's surface in three main color bands: red, green, and blue. These bands correspond to specific wavelengths of visible light in the spectral range of 400 to 700 nanometers.

When the satellite passes over a particular area, the sensors record the amount of light reflected in each of these color bands. Each pixel in the image corresponds to a specific area on the Earth's surface and contains information about the light reflected in each band.

These data are then combined using an additive color synthesis technique, where the red, green, and blue bands are overlaid to form a color image. This image represents the terrain and vegetation characteristics, with various shades and colors indicating different materials and conditions.

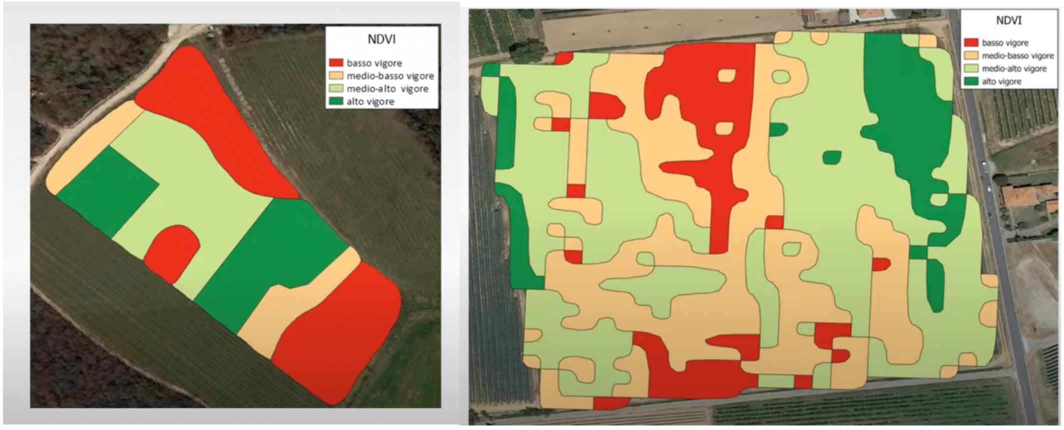
The image acquisition cadence depends on the type of satellite and its orbit. Some satellites can capture images daily or even multiple times a day, while others may have a longer cadence, weekly or monthly. The frequency of acquisitions is determined by user needs and the characteristics of the sensor and satellite platform.

The spatial and temporal resolution of the images is a crucial aspect to consider. Spatial resolution refers to the minimum size of the object that can be distinguished in the image, while temporal resolution indicates the time interval between two consecutive acquisitions. These factors influence the quality and utility of the images for different applications, such as agriculture, natural resource management, and environmental monitoring.

Vegetation Analysis:

The analysis of vegetation using RGB sensors and multispectral sensing is essential for understanding the health and condition of agricultural crops. This method provides detailed information on plant conditions, allowing farmers to intervene promptly to enhance production and minimize losses. RGB sensors, equipped on satellites and planes, capture light reflected off the Earth's surface in three primary color bands: red, green, and blue. These bands, matching specific wavelengths, allow for the generation of a color image that reflects the terrain and vegetation's features.

Through the analysis of multispectral images, changes in the colors and shades of plants can be detected, signifying stress, diseases, or nutrient shortages. For instance, drought-stressed plants might appear in lighter colors, while diseases could alter leaf shades. It is possible to segment different areas based on the soil's "vigor" status, as illustrate in the subsequent images.



According to many, it has been shown that multispectral analysis of RGB images has enabled the early identification of diseases in corn crops, allowing timely interventions that have reduced production losses. Furthermore, the use of multispectral sensors allows for precise mapping of crops, identifying the different types of vegetation present in an agricultural area. This enables farmers to plan agricultural activities more effectively, optimizing resource use and maximizing yield. Multispectral analysis of RGB images has allowed for the assessment of the health of wheat crops, identifying areas with nutrient deficiencies and supporting targeted decisions on fertilization.

Crop Mapping

Through multispectral analysis using RGB sensors, an important tool for farmers in monitoring and managing their production is represented. This approach allows for a detailed view of crop distribution over large agricultural areas, enabling farmers to plan and manage agricultural activities more efficiently.

Different crops have unique spectral signatures, i.e., specific responses to light at different wavelengths of the electromagnetic spectrum. These spectral characteristics allow for distinguishing between crops and identifying them through the analysis of multispectral images. For example, wheat fields may appear in intense green, while vineyards may have darker green shades.

Another study conducted by [Gao et al. (2020)] utilized multispectral analysis to monitor the health of wheat crops in an agricultural region of the United States. The study's findings highlighted that multispectral images accurately identified areas with water stress and nutrient deficiencies in wheat crops, allowing farmers to take targeted corrective measures.

Evaluation of Land Cover

The assessment of land cover through the use of RGB sensors and multispectral detection represents an important methodology for understanding the distribution and characteristics of soil and vegetation in a specific area. This approach provides valuable information to farmers and natural resource management experts, allowing them to assess land use, identify areas of interest, and plan land management activities.

RGB sensors, mounted on satellites and aircraft, capture high-resolution images of the Earth's surface, enabling precise distinction of various terrain and vegetation characteristics. Through the analysis of multispectral images, it's possible to assess the distribution and extent of different land covers, including vegetation, water bodies, urban areas, and uncultivated zones. One of the most common uses of land cover assessment is in planning and managing agricultural activities. For instance, farmers can use information from multispectral images to identify the best areas for cultivating different crops, assess the degree of land cover, and plan irrigation and fertilization.

Furthermore, the evaluation of land cover is also crucial for planning and managing water resources. Through the analysis of multispectral images, areas with higher or lower water availability can be identified, and the distribution of watercourses and wetlands can be assessed. This information is vital for the sustainable management of water resources and the prevention of phenomena such as desertification and soil aridification.

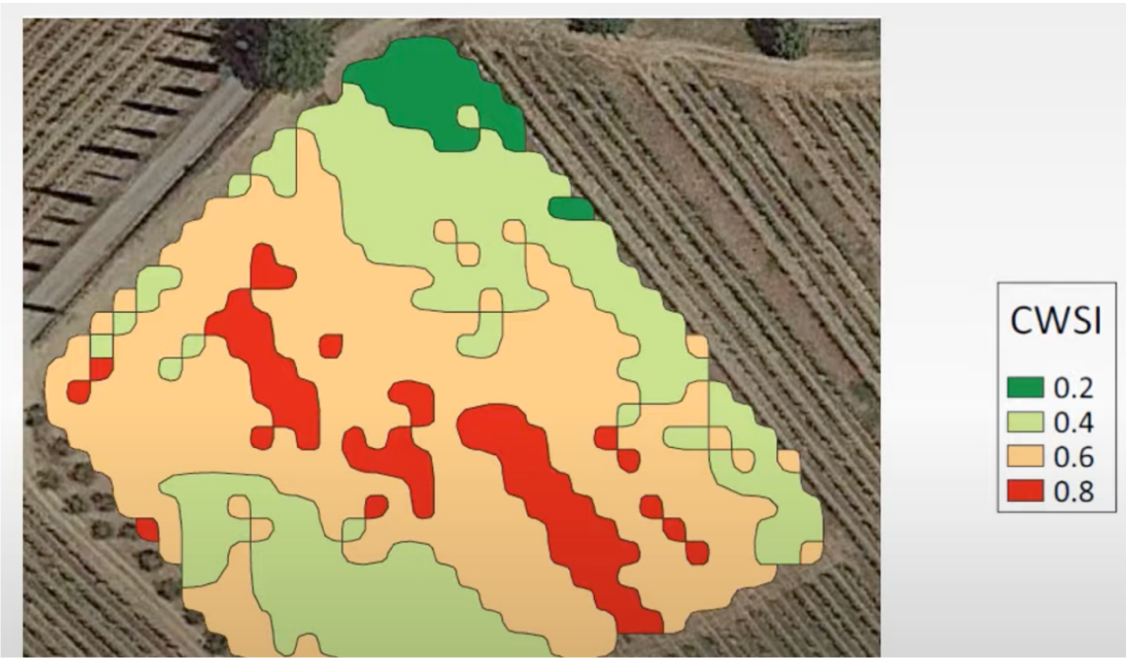
By effectively using this information, it's possible to optimize land use, protect the environment, and ensure sustainable and high-quality agricultural production.

Environmental Change Monitoring

Multispectral detection with RGB sensors can also be used to monitor environmental changes over time, such as deforestation, urban expansion, or the loss of natural habitats. By analyzing color variations in RGB images captured at different times, it's possible to identify and assess the impact of such changes on the environment. Monitoring environmental changes through the use of RGB sensors and multispectral detection is a crucial aspect in evaluating and managing natural resources and ecosystems. This approach provides scientists and conservation experts with an important source of information to understand the impacts of human activities on the environment and implement mitigation and adaptation measures. RGB sensors mounted on satellites and aircraft acquire high-resolution images of the Earth's surface, allowing the assessment of changes in land use, vegetation cover, and environmental characteristics over time. Through the analysis of multispectral images, it's possible to identify and map environmental changes across large geographical areas, enabling experts to assess impacts and plan corrective actions. A significant example of environmental change monitoring application was reported in a study by Jones et al. (2019), where multispectral analysis of RGB images was used to assess urban expansion and the loss of natural habitats in a coastal region. The study's results highlighted rapid land-use change and significant loss of natural habitats, providing valuable information for conservation planning and land management.

Groundwater Level Assessment

The assessment of groundwater level is a critical aspect of agriculture and water resource management. Using RGB sensors and multispectral detection can be an effective method to monitor and evaluate groundwater levels. RGB and multispectral sensors can detect variations in light reflectance in the near-infrared spectral band, sensitive to the presence of water in the soil. This allows experts to identify and map areas with different soil moisture levels. Through the analysis of multispectral images, it's possible to assess the distribution and variation of groundwater levels over time. For example, images can show areas with excess moisture, indicating potential drainage problems, or areas with low moisture, signaling the need for irrigation. Furthermore, the use of RGB and multispectral sensors can be combined with data from weather stations and soil moisture sensors for a more accurate and detailed assessment of groundwater levels. This integrated approach enables effective monitoring of variations in groundwater levels over time and space, supporting informed decisions on water resource management. Since the 1980s, with the introduction of the Crop Water Stress Index (CWSI) by Idso in 1981, this crop water stress indicator has been primarily used for irrigation scheduling. However, recent studies have highlighted limitations in measuring canopy and air temperature to calculate the CWSI in irrigation management practices. For this reason, the importance of adopting a new approach, based on the use of satellite images to process the CWSI, has emerged. Estimating the CWSI is crucial as it represents one of the fundamental parameters for evaluating a crop's environmental interaction and defining its yield potential. Moreover, recent research in 2021 has emphasized the importance of the CWSI as a tool for water savings in irrigation practices.



These advancements represent a significant breakthrough in optimizing irrigation management practices and addressing challenges related to water availability, allowing for greater precision in assessing crop water stress and improving their yield. Ultimately, the adoption of new paradigms provides us with concrete opportunities to effectively address the environmental and climatic challenges affecting agriculture, while promoting the sustainability and efficiency of practices.[20]

Assessment of Soil Nutritional Aspect

A crucial element in understanding the state of vegetation is its green color, which is closely related to the presence of chlorophyll. An index that allows the analysis of this characteristic is the TCARI/OSAVI, a complex index influenced by the amount of chlorophyll present in plant tissues.

This index provides valuable information on crop health, enabling the identification of areas in the agricultural field affected by chlorosis. This phenomenon can be caused by nutritional deficiencies or attacks of phytopathies, and it is essential to compare the results of TCARI/OSAVI with those of the NDVI to obtain a comprehensive and detailed analysis.

TCARI, belonging to the CARI index family, is influenced by chlorophyll content but can be distorted by soil reflectance, especially if the vegetation is poorly developed (low LAI). For this reason, it is combined with OSAVI, an index that corrects the soil effect.

[20] https://iwaponline.com/ws/article/23/3/1390/93626/Estimation-of-crop-water-stress-index-and-leaf#

What makes chlorophyll-related indices unique is their ability to integrate the Red-Edge band, which is particularly sensitive to variations in chlorophyll content and leaf structure. This approach offers a detailed view of the health and status of vegetation, allowing farmers to intervene promptly and optimize the management of their agricultural fields.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Summary of collectible data that will become inputs for AI:

Satellite or drone data, for the remote monitoring of crop vegetative vigor and some biophysical parameters; These tools offer considerable potential for remote crop monitoring and the acquisition of significant biophysical data. First, the use of drones and satellites enables constant and detailed monitoring of crops over vast agricultural lands. This continuous observation capacity allows farmers to promptly identify any anomalies or problems, such as water stress, nutritional deficiencies, or plant diseases. Thanks to this constant monitoring, interventions can be planned and implemented in a timely manner, contributing to improving crop health and productivity. The collection of multispectral data by drones and satellites enables detailed information on the state of crops. This information goes beyond the visible spectrum, allowing the calculation of vegetative indices such as the Normalized Difference Vegetation Index (NDVI) or the chlorophyll index. These indices provide valuable insights into plant vigor and the overall health of crops, allowing farmers to accurately and thoroughly evaluate crop growth and development.

Moreover, the use of drones and satellite data enables mapping the spatial variability of crops on a large scale. This is particularly useful for identifying areas with lower yield or specific problems, allowing farmers to adopt targeted management strategies to optimize yields and reduce resource waste.

Weather data, both real-time and historical; are fundamentally important in precision agriculture. These data provide crucial information for farmers to make informed decisions and optimize their agricultural practices. Real-time weather data allow farmers to monitor current atmospheric conditions and adjust their cultivation activities accordingly. Information such as temperature, humidity, wind speed, and direction are essential to assess the risk of frost, drought, or other extreme weather conditions that could affect crop health. This real-time monitoring enables farmers to make quick and targeted decisions to protect their crops and maximize yields.

Furthermore, access to historical weather data allows farmers to analyze climate patterns over time and identify significant trends or anomalies. This historical analysis can be valuable for predicting future weather conditions and proactively planning agricultural activities. For example, knowledge of seasonal climate patterns can help farmers determine the optimal timing for seeding, irrigation, or protecting crops against diseases and pests.

Proximal sensing: soil moisture sensors, salinity sensors, soil temperature sensors, rain gauges, leaf wetness, solar radiation, etc.; These sensors provide a wide range of data, from soil moisture and salinity levels to temperature, leaf wetness, and solar radiation, offering a comprehensive overview of environmental conditions and crop needs.

Soil moisture sensors allow farmers to accurately assess the moisture level present in the soil, essential for planning irrigation efficiently and optimizing water resource use. Knowledge of soil moisture helps avoid water wastage and reduces the risk of water stress for crops; soil salinity sensors provide crucial information on the concentration of salts in the soil, allowing farmers to monitor and manage salinity levels to preserve soil fertility and crop health.

Soil temperature is another key parameter monitored through specific sensors. These sensors assess the thermal conditions of the soil, providing useful indications for optimizing seeding times, seed germination, and crop development throughout the agricultural season.

Rain gauges are used to measure the quantity and intensity of precipitation, allowing farmers to assess natural water input and integrate irrigation based on crop needs. Leaf wetness is another critical parameter monitored through specific sensors, allowing the assessment of the efficacy of phytosanitary treatments and optimizing spraying operations to maximize efficacy and reduce waste of phytosanitary products.

While solar radiation sensors provide information on crop exposure to sunlight, allowing farmers to assess photosynthetic efficiency and optimize cultivation practices to maximize crop production and quality.

Soil parameters, through the acquisition of pedological maps, the execution of chemical-physical sampling, or the use of soil electrical conductivity sensors; Indeed, acquiring pedological maps provides a detailed view of soil distribution in a given area. These maps identify variations in soil composition, including factors like texture, structure, pH, and nutrient presence. This information is fundamental to understand the specific characteristics of the soil and appropriately plan agricultural activities, for example, selecting the most suitable crops or applying fertilizers in a targeted manner.

Regarding the execution of chemical-physical soil sampling, it provides detailed data on the chemical composition and physical properties of the soil. These samplings allow the assessment of soil fertility, nutrient availability, and contamination level, providing farmers with the necessary information to plan fertilization operations and optimally manage soil resources, and for this, we can also combine the analysis of conductivity sensors.

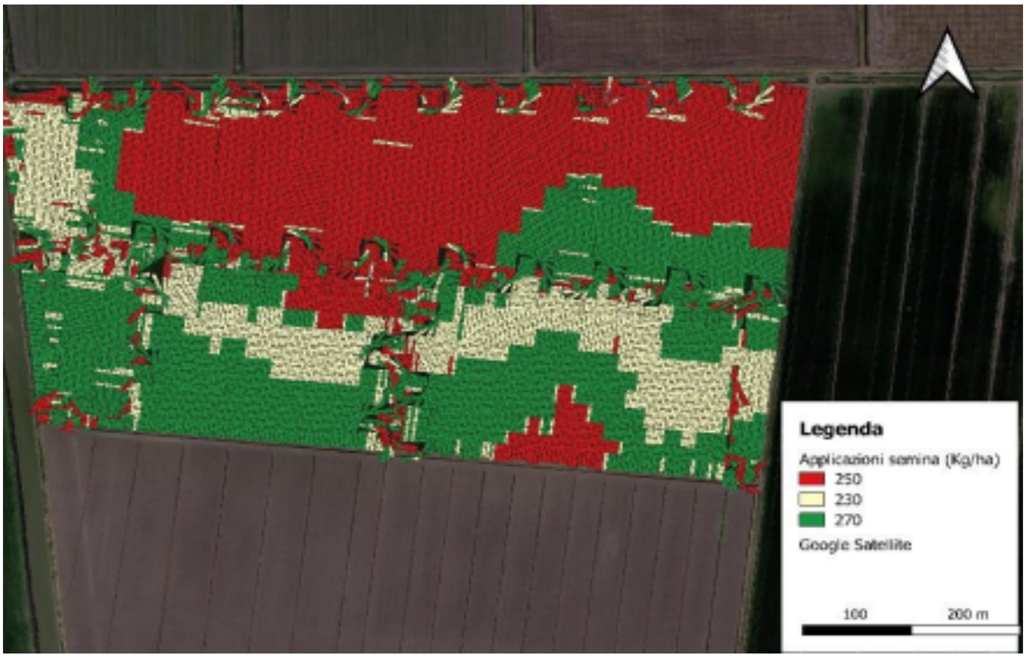
Predictive modeling for pathogen risk or water stress, This methodology allows farmers to anticipate and manage potential crop health problems timely and efficiently, minimizing negative impacts on yields and crop quality. Predictive modeling is based on the analysis of historical data and environmental parameters to develop predictive models capable of estimating the likelihood of pathogens or water stress conditions in certain geographical areas and time periods. These models consider a variety of variables, including weather conditions, the presence of pathogens in the soil or air, and crop susceptibility factors, to provide accurate and reliable predictions of potential risks to crops. The use of predictive modeling enables farmers to take preventive or corrective measures in advance to minimize the negative impact of pathogens or water stress on crops

Chapter 4: Practical Applications of AI with Satellite Data

Part 1: Data Collection for the Farmer

Every farmer should have a file containing all their owned lands, possibly unified and divided by fields rather than only by unique parcels, to make the differentiation and creation of the map referring to such surfaces more effective. A business digitization, as shown in the following image,

The next step that can be the construction of a cartographic file containing the historical and updated crop plan. Each macro-area should have its weather station available, which is essential for evaluating soil-related conditions such as moisture and data obtainable from proximity sensors. The subsequent image shows the application of different seed quantities based on the different parts of the soil derived from satellite images.



An interview should then be conducted at the company to retrieve data on equipment, management, crop plans, and needs, accompanied by a field notebook. This interoperable tool is capable of consulting data collected preparatory to the management of agricultural systems and compliance with regulatory constraints. Moving on to the monitoring and transfer part, we use the vigor and vegetative state map starting from satellite images, vegetation vigor indices (NDVI and MSAVI, in particular) will be processed. The analysis of the indices will visually identify areas within the field presenting issues, so that company technicians will have a tool to qualitatively evaluate intra-field variability and remotely monitor crop progress throughout the entire vegetative cycle. Subsequently, yield data collection provided by the client will proceed, to populate the set of information levels preparatory to the provision of advanced services.

Part 2: Data Detection and Processing

Subsequently, data analysis will be carried out thanks to satellite images and then specific samples, thus a detailed soil analysis to understand the chemical characteristics of the soil. This activity is preparatory for identifying areas with different characteristics where selective soil samplings will be performed, followed by the characterization of variability and creation of homogeneous zones (MUZ), creation of maps dividing the field into stable homogeneous zones over time (MUZ).

Each MUZ will be associated with the reference soil class and its physicochemical characteristics. The collected data aim to support decision-making, more specifically, the analysis through multi-source data will allow defining the cultivation aptitude of various fields. The same analysis aims to develop prescriptions for pre-sowing and coverage fertilization at a fixed or variable rate to optimize crop yield by making resource use more efficient.

The analysis will also aim to manage the seeding density to handle areas of different suitability considering varietal characteristics and variability between fields for crop cultivation.

A subsequent step would be to exploit environmental data and proximal sensors to measure soil moisture and provide for the exploitation of the best irrigation plan, continuing with the generation of early warning models for the risk of pests that can damage the harvest.

The availability of satellite images (Sentinel – 2);

Processing and determination of VIs and biophysical parameters provide an indication of the crop's physiological state;

Weather data from weather stations;

Smart scouting with proximal sensors capable of quantifying chlorophyll and flavonoids content; This information allows having all the data necessary for our in-depth study. The part that has most hindered precision agriculture, as mentioned in the previous chapter, concerns, in addition to initial costs and training in the use of PA, the ability to analyze data and make decisions; at this moment, AI implementation comes to support.

At this moment, we can exploit the various possibilities that technology provides us at this historical moment. Starting with machine learning, we could provide past satellite data and images to start making estimates, comparing for companies that have yield data in the past, also comparing periods when vegetation states typically changed thus assessing any diseases that affected the various soil particles.

Also evaluating when various treatments such as fertilizers and fertilizations were carried out and in what state the crops were to start accumulating past data as well, also evaluating on average for each geographical area the periods when there were the best conditions for the soil, combining our analyses of the weather data of the area, in order to understand thanks to the use of neural networks any more precise recurring patterns for each area as to the best states of vegetation.

To be able to understand for each area which is the most effective moment based on the crops for when to sow. Based on the evaluation in sync with the weather station that is enriched with related data from agronomy experts on the best temperatures for each type of crop also thanks to satellite images thus finding the best moment to sow, for example, in each area more precisely and efficiently.

It would be necessary to create an AI, based on a derivation of ChatGpt, for example, or as other AIs that are now coming out, that thanks to the collection of all historical data, parameters of the various indicators named previously, information related to agronomic analyses can analyze autonomously the inputs that we provide. Even better would be to dedicate a platform-application where everything is already complete, both the data related to the farmer's lands, therefore company files. Already automatically on each land, with all the data detected by satellites or drones in addition to proximity sensors, thus creating a unique management system, automatically inserting prescription maps on each land based on various identified deficiencies thanks to all the inputs that will arrive automatically to the AI

Part 3: Operational Section

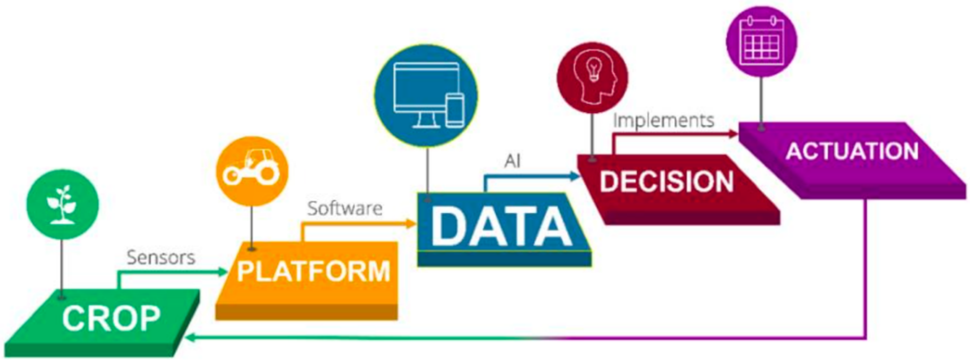
The final part will involve the end operator, namely the farmer, who will be the only one required to interact with the AI system. From here, they will have their entire business situation at their fingertips, able to manually check various fields but, most importantly, without the need to consult agronomists to evaluate different situations like vigor indices, vegetation, water stress, etc.

The platform will automatically analyze and instantly start notifying the farmer with notifications on standard and customizable parameters about the situation of their lands. They can query the system with specific questions about what to do and how, as the system will have been pre-populated with all possible scenarios, both by collecting past data and by setting strategies in advance by a team of expert agronomists.

This will be possible primarily due to the definition of objective data such as various indices since the system will automatically be able to promptly notify the farmer in case of irregular outputs from control bands and, especially relying on predictive algorithms, will benefit from advanced analysis that could lead to various water stress situations, for example, or specific weather conditions that could favor the appearance of particular pathogens. In this way, the farmer will be able to simplify control over their company, without the need to frequently consult experts or have excessive difficulty in controlling indices or images.

They will also be able to utilize and employ prescription maps automatically by connecting the platform with variable rate AP equipment (e.g., increasing the density of seeding, reducing the amount of fertilizer on areas not subject to pathogens), making it possible and easy to achieve the maximum possible result in terms of efficiency and effectiveness of agricultural management.

In this way, the farmer becomes master of their data with extreme ease of analysis thanks to an ecosystem that analyzes situations for them, thanks to a system that can also respond to questions and queries the farmer makes, becoming almost an agronomist at the service of the farmer who, by mastering data and analysis of indices, can be more objective and quick in analysis, allowing the farmer to have a clear picture of their agricultural situation. The maximum interconnection created will give life to an almost entirely automatic system, hypothesizing in the distant future, that the AI will collect all the data, analyze it, make prescriptions, and automatically provide to the machinery which, in turn, based on their commands and functions, will operate in complete autonomy.



Chapter 5: Case Study and Optimized Resource Implementation

The interviewed company is located in the province of Avellino and is among the companies that most embrace and integrate the developments of Precision Agriculture and a part of AI. It is a relatively young company; the owner is an agronomy graduate passionate about agriculture, who decided to dive into the cultivation of chestnuts, hazelnuts, bee hives for honey, and olives right after finishing his studies.

He started 7 years ago with a few small lands and now manages about 40 hectares, distributed between arable lands, chestnut groves, and orchards with about 300 bee hives attached to the company. Despite being the youngest farmer in the area, the company has been growing significantly in recent years, with an average annual revenue growth of around 20%, becoming one of the largest in the cultivation sector in the area, with the goal of doubling the cultivated plots improving production and doubling the turnover in the next 5 years especially thanks to PA combining AI.

He could move to more favorable and flat areas but to enhance the territory, he decided to stay in the town where he lives (Solofra), where some of his holdings hold various production certificates (e.g., organic farming) and protected parks that significantly enrich the quality of the products supported by the choices that computerized systems are making to improve with efficient and more effective treatments.

The company was selected based on its reputation in the territory, based on the results obtained and the recognitions that are allowing it to be used by coldiretti as a case study and example of a Digital 4.0 company, with the proposal to elect the owner as a trainer in courses with chestnut producers throughout Campania to train other farmers and entrepreneurs in the conscious use of existing technology.

The interview took place first by phone and then in person, lasting over five hours with open questions that allowed learning about all the technology used, delving into currently used systems, systems in development, up to the final challenges that are developing, listing in advance the topics of interest, starting from its corporate history, reaching the crops used, the management of processes with various computerized methods converging in particular on the topic of greatest relevance such as the impact of AI and PA in his company, on how he exploits it and how he manages to benefit from it.

The company, being in a very mountainous territory with most of the plots difficult to reach by normal means, indeed, only uses small-sized machinery for some works due to the difficulty in processing.

The entrepreneur started by illustrating the company's surfaces, which were in two protected parks and have particular characteristics given their location and give added value in terms of product quality. Currently, the company deals with different high-income crops, thus cultivating olives, chestnuts, hazelnuts, and owns bee hives from which it obtains more than five different types of honey depending on the area.

Given the territory and the culture, it is not possible to use all the PA tools; prescription maps are useless since, in addition to predominantly manual performances, there is no direct land processing. The company is working to implement the Drones department to perform phytosanitary treatments on crops for diseases, for example, but currently, in Italy, they are banned, so it is waiting for regulation for use.

Diseases are monitored thanks to the extensive use of sensors, as there are weather stations, soil sensors measuring parameters related to temperature, water, etc., along with sensors for diseases. In fact, it uses predictive algorithms, based on these latest data, that can communicate instantly when conditions for the development of pathogens are present, thus alerting in advance, allowing instant control and action on crops.

Currently, several predictive algorithms for diseases and pathogens are active, and at this time, new sensors are being installed to work on creating new algorithms to understand when to treat a new pathogen that has recently arrived in Italy, the "Asian stink bug."

Focusing on the more managerial aspect of the software, this allows the detailed insertion of all information related to various products used on each plot of land, ensuring meticulous control over the use of products up to the kilogram for each specific treatment. Recording the duration of each treatment for each crop and the use of precise quantities of products or seeds creates a detailed historical archive on the use of materials in processing. This allows a post-harvest analysis to evaluate the exact quantities used and, reflecting on previous productions, identify any errors to be able to intervene correctly the next period.

This approach produces a comprehensive report of all inputs, facilitating year-over-year comparison and incorporating data into a sort of business income statement for each plot of land. This account is updated daily with new operations performed, ensuring accurate management of each plot, as illustrated in the following figure,

This consequently allows for assessing the true profitability of a single plot over time, enabling managerial background evaluations to support investment decisions, for example, when considering leasing lands or attempting to cultivate some lands and then evaluating whether it is efficient to continue or not. Specifically, in the processing phases, plant protection processes are optimized, operating at the moment when the notification arrives from the algorithm by the sensor stations. For the harvesting phases, there is no possibility of having an automatic yield map, but it arrives interconnected in the field by the operator who enters the results of each plot directly into the economic management system, also classifying the quality that will determine the price and consequently the variation for each plot for its economic account. Irrigation management is monitored thanks to leaf wetness sensors and other interconnected ones that measure electrical transmission, automatically measuring water stress for each area to evaluate where there is a deficiency and where there is therefore a need for irrigation, bringing the level to parameters established based on soil permeability, thus adapting each soil based on its composition to perfect irrigation.

As for the economic benefits and results, below we show an economic overview of the economic results of yield for two of the crops, namely hazelnuts and chestnuts per hectare.

HAZELNUT			
AVERAGE PRODUCTION DIFFERENCE (three-year period 2021-2023)			
2021	**2022**	**2023**	
Average Production with AI and AP(kg/ha)			**Average 3 yr**
3000,00	2870,00	3120,00	2996,67
Average production competitor (kg/ha)			**Average 3 yr**
2750,00	2430,00	2910,00	2696,67
Delta production (kg/Ha)			**300,00**
Average price of products with AI and AP(€/kg)			**Average 3 yr**
3,20 €	2,50 €	3,50 €	3,07 €
Average price of products with standard procedure (€/kg)			**Average 3 yr**
3,00 €	2,20 €	3,20 €	2,80 €
Total gross revenue Company using AI(€/ha)			9.189,78 €
Total gross revenue normal company (€/ha)			7.550,67 €
Delta revenue (€/ha)			**1.639,11 €**

Focusing on hazelnut before, we can see that during the three-year production from 2021 to 2023 there is an average of delta of production from the farm in question compared to other competitors of 300 kg for each Ha that is approximately and average of 10% more in terms of production.

And already from this point we can see the first big difference from traditional way to using all new technologies , but another thing to consider is that not all fields are to full production because some of them are new since the company is new and some fields were born not so much time ago, in the next year surely this parameter will grow more and difference in production for Ha will go higher.

Now focusing on price of products, products made with greater attention to pathogens or diseases, will have better quality based on their “care” , infect based on the data that we took from the entrepreneur during the year the average price were 3,07 euro versus 2,80 euro so this difference of more than 9.5% of price in case of AI company give to us another confirmation to our thesis that using AI in process will help us to have more net profit , more production and quality.

We see at the end of the table a delta of gross revenue of 20% more in case of company that use AI.

CHESTNUT			
AVERAGE PRODUCTION DIFFERENCE (three-year period 2021-2023)			
2021	**2022**	**2023**	
Average Production with AI and AP(kg/ha)			Average 3 yr
2600,00	2870,00	2720,00	2730,00
Average production competitor (kg/ha)			Average 3 yr
2310,00	2130,00	2210,00	2216,67
Delta production (kg/Ha)			**513,33**
Average price of products with AI and AP(€/kg)			**Average 3 yr**
2,15 €	1,75 €	3,70 €	2,53 €
Average price of products with standard procedure (€/kg)			**Average 3 yr**
1,80 €	1,50 €	3,20 €	2,17 €
Total gross revenue Company using AI(€/ha)			6.916,00 €
Total gross revenue normal company (€/ha)			4.802,78 €
Delta revenue (€/ha)			**2.113,22 €**

In case of chestnut the difference is bigger in terms of percentage arriving a delta production close to 20% more in case of company that has AI process and a Delta gross revenue of 44% more.

Of course all this revenue aren't net, but the cost for this is more in terms of taking care adding every day the work done in every fields and installing the metrological station that is an investment that has an amortization during the year and in case of company in this study they have 3 only in all the fields and with full sensor the cost in total can go close to 8.000 euro including all sensor and algorithm who can provide to give a predictive information for better decision and better results.

The fam is currently in its digital transition phase, showing great interests in innovation and technologies in order to keep reducing production costs and generate higher revenues and market prices.

The analysis confirms the overall gains generated by the investments made so far both in terms of quality and also in terms of phytosanitary costs reduction.

At the same time, the farm is currently planning further expansions of the AI technologies. More particularly, the use of drones might generate additional applications which are currently missing such as image acquisition with higher resolution compared to the status quo that mainly relies on satellite images. Moreover, subject to phytosanitary legislation, the drones can also assist the farm with more targeted applications of plant protection products (PPPs), arial spraying and optimization of PPP use.

This technology will help the farm especially in areas of the farm with natural constraints and difficulties of access with tractors and machineries (e.g., mountain areas).

The data management is centralized via a software called "X-Farm" that is subject to a yearly subscription paid by the farm to manage relevant information generated by the AI technology.

In terms of challenges identified, the farm is confronted with upscaling problems of technologies in order to cover all processes carried out at farm level.

For the moment, this limited to phytosanitary treatments, although further applications (e.g. block-chain, traceability, etc.) can be still explored.

The inter-operability of systems will become key to allow shifting technologies, optimization of data use and freedom by the farm to decide the way forward.

Secondly, the accessibility by all farm employees constitutes an additional challenge. Everything is managed by one person and this brings quite a big burden. The farm will have to consider involving other employees in the long run.

Third, the upscaling of AI technologies will also generate additional investments both in terms of financial resources and learning and knowledge acquisition. A proper assessment will have to be carried out to understand the costs and benefits generated by a full AI farm system.

Chapter 6: Final Conclusions and Future Challenges

The COVID pandemic, the Russian invasion of Ukraine, and the consequences of climate change are putting the EU food system under serious pressure. Developing a more resilient food system capable of absorbing shocks and coping with increased risks should be a key priority for the European Union. Linked to this, the increased world population will also require more food production (e.g., according to the FAO, +70% by 2050) with fewer natural resources (e.g., water, land) and a more sustainable intensification of production systems.

On the other hand, access to healthy diets and quality meals poses a challenge for low-income households which, considering the high food inflation, are shifting to diets rich in energy and poor in nutritional quality, with consequences related to obesity and non-communicable diseases, cancers, etc.

There is, therefore, a need to reconcile high-quality products at an affordable price for all consumers.

In this context, adopting the latest technological solutions to make agriculture more efficient becomes an indispensable necessity. Here is where Artificial Intelligence (AI) comes into play. Robotics and autonomous systems (RAS) are revolutionizing many global industries, and agriculture is no exception. These technologies promise to have a significant impact on sectors of the economy with relatively low productivity, such as the agri-food sector, which is a vital component of national economies.

Besides the current uses of Artificial Intelligence in agriculture, it is important also to consider the future developments and advanced prospects of this technology.

One of the most promising research areas involves the application of AI in the precision of agricultural decisions. Currently, AI is used to optimize agricultural operations, such as water and fertilizer distribution, but future developments aim to create artificial intelligence systems that can make decisions autonomously, based on real-time data from sensors, drones, and other sources.

Moreover, the fusion of emerging technologies such as Artificial Intelligence, the IoT (Internet of Things), and robotics could lead to the creation of fully automated and interconnected agricultural systems, known as agriculture 4.0. These systems could revolutionize the entire agricultural process, from irrigation to harvesting, improving efficiency, reducing costs, and minimizing environmental impact.

Another significant development involves the application of machine learning (ML) in the analysis of agricultural data. Machine learning algorithms can analyze vast amounts of data from sensors, satellite images, and other sources to identify hidden patterns and trends. This can help growers make informed decisions on when to plant, irrigate, fertilize, and harvest, thus optimizing yields and reducing waste.

Finally, Artificial Intelligence could play a crucial role in mitigating climate change and adapting to environmental challenges. AI algorithms can be used to develop predictive models of the climate and weather conditions, allowing growers to anticipate and mitigate the effects of extreme weather events, such as droughts and floods.

Nevertheless, there are some challenges that need to be highlighted and followed very closely in the near future, which will make AI a true revolution or something partially exploited.

First, rural areas depend on access to broadband and high internet connections. Today, on average at the EU level, 70% of rural areas are covered by such service. However, work is being done to reach full coverage.

Second, especially for small-scale farms, the costs of implementation, acquisition of knowledge, and difficulties in managing sophisticated technologies remain a key barrier that needs to be assessed against the benefits generated in the long term.

Third, the interoperability of systems is another element limiting the freedom of farmers to shift from one technology to another. It is also important to remember that farmers are already squeezed today between input supplies (seeds, fertilizers, and pesticides) and processors and retailers on the other side, representing the weakest part in the value chain with limited power to influence market price. So, AI technology should rather help farmers to reinforce their position in the value chain.

In conclusion, the future of Artificial Intelligence in agriculture is extremely promising. Future developments could lead to fully automated agricultural systems, more precise and sustainable agricultural decisions, and greater resilience to climate change and environmental challenges, as well as greater upstream and downstream integrations of the agri-food supply chain, shortening the distances between farmers and consumers. Investing in the research and development of these technologies is essential to ensure a sustainable food future for the planet.

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