Artificial intelligence in the agri-food sector

Applications, risks and impacts

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An increasingly digitised society involves recording human activity and monitoring products and processes. In the agri-food sector this gives rise to large quantities of data. At the same time, data is also generated for research and scientific experiments.

There is a growing interest in the applications of artificial intelligence (AI) in the agri-food sector to extract or exploit the information that can be detected in these data sets. Artificial intelligence algorithms, and the models derived from them, are used as support systems for better decision making or, in some cases, are implemented in automatic control processes and robotics, to alleviate drudgery.

In this study, sensing and data collection in different agri-food sectors are described, together with how the data can lead to better management and better decision making in crop and animal production.

As with other technological advances, AI in this domain comes with its own set of benefits, risks, ethical issues and societal implications. Questions raised with respect to AI include: how to balance potential benefits against potential risks; how to govern the use of these technologies; and how to incorporate socio-ethical value considerations into the policy and legal frameworks under development. Policies for training and education have to support potential users.

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Executive summary

Agri-food activities for delivering high-quality food or other products under sustainable production conditions involve many complex processes with many variables. These variables can have complex interactions, some of which are outside the control of producers or other actors in the value chain. Precision agriculture in field crops or animal production and highly automated greenhouse production are inherently linked to the continuous use of record keeping and sensing technology for plant growth, canopy development and animal behaviour. As a result, every day on a farm or in a food-processing facility, thousands of data points are collected. Artificial intelligence (AI) could be a powerful tool in helping organisations cope with this increasing complexity in modern agriculture.

Intensive data collection paves the way for growers, and all other actors in the value chain, to adopt artificial intelligence as a data-driven practice to gain more insights and, ultimately, better control the processes that affect producer income. Data collection is carried out manually by farmers or relies on equipment that is an important part of smart agriculture. While installed sensors deliver quantities of real time data, the ownership of the data and the exploitation of the models derived should be clarified.

In greenhouse production and animal husbandry, individual plants or animals, the in-house climatic conditions and their set-points are almost continuously monitored and recorded in highly local detail. This should lead to more efficient production and improve workers' wellbeing and animal welfare. In open fields, protected cultivation and animal sheds, machinery can execute management decisions made by a famer, based on AI advice or solely through AI-based electronic controls. AI is also an important tool for the automation and robotics that may relieve workers of drudgery. Potential risks should be addressed however, and the new technologies require proper testing in experimental settings (digital sandboxes and testing and experimentation facilities), to ensure that they are safe and secure against accidental failures, unintended consequences, and cyberattack.

Artificial intelligence algorithms make it possible to analyse and look for interactions in these large quantities of data, resulting from many sensors and observing many processes. To maximise benefit, high-quality data should be available and collected from robust, reliable sensors with low maintenance and low costs, and efforts made to specify the required quality of data. Data from multiple sources should be connected and the interoperability, or ease of data transfer, facilitated. As a next step, these algorithms make decision suggestions for the farmer or, even, implement certain decisions independently. The need therefore arises for ways to test the models' effects before they enter the market – both for their effectiveness and for flaws or unforeseen negative aspects. AI can solve the current scarcity of resources and skilled labour, but organisations and governments must make sure that training in digital skills is available for all agri-food participants. Legislation can help to avoid creating a digital divide within farming or food-processing communities. Monetising agricultural data and the rewards for users (farmers) and holders (machine or input suppliers) should be clearly explained. It may be appropriate to have some sector-specific regulatory objectives to handle the imbalance between the different stakeholders.

Large companies supplying AI software for analysis in agriculture can have an effect on the way agriculture evolves. On the other hand, retailers collect and analyse a massive quantity of data about the preferences and behaviour of their customers. A combination of these elements may create a potential for biased recommendations to farmers, to favour the optimisation of supplies being sent to specific food retailers. New start-ups could take a different view of the data and come up with new applications that may give more independent advice to farmers. European Union legislative initiatives should ensure that this does not lead to a reduction in agrobiodiversity. As algorithms are under continuous construction, and only a limited number of large companies can sustain such efforts, this may also lead to a small base for decision making and may lead to biased decision making.

Bringing the benefits of AI and digital agriculture to all farmers requires accessibility to networks and affordable broadband internet access, not only in residences, but also in the fields. Farmers or small and medium-sized enterprises (SMEs) must also make several complementary investments, such as installing specialised infrastructure for collecting and transferring data. Infrastructure policies may be needed here.

This study defines several issues that may require special measures or policy action to ensure all stakeholders have access to a fair and equitable participation in the benefits that AI may bring to agriculture:

- Rights and expectations for farmers, technology providers and the public.
- Regulation of the exploitation and governance of the European databases.
- Risk and liability for technology providers and users.
- Automation and the protection of farm workers.
- Transparency and quality assurance of AI models.
- Digital literacy and the digital divide.
- Legislation that prevents farmers becoming locked-in to corporate digital technology.
- Policies towards new market entrants which limit dominant positions of first movers.
- Affordability and accessibility of the data infrastructure and the information technology network.
- Supporting investment by farmers or SMEs to make use of potential AI benefits.

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List of abbreviations

AE	autoencoder, a form of unsupervised learning (a class of AI)
AFSC	agri-food supply chain
AI	artificial intelligence
ANN	artificial neural networks, inspired by biological neural networks
DL	deep learning, a subset of machine learning (a class of AI)
ET	evapotranspiration, total water loss from the soils and the crops
DSS	decision support system
GAN	generative adversarial network, a class of machine learning frameworks (a class of AI)
GPS	global positioning system, satellite-based radio-navigation system
GPU	graphical processing units that accelerate a range of scientific applications
HTP	high-throughput phenotyping technologies, to discover genetic traits that are desired or expressed
IoT	internet of things, digitally connected universe of everyday physical devices
KNN or (k-NN)	k-nearest neighbours algorithm, a non-parametric supervised learning method
LSTM	long short-term memory, an artificial neural network used in the fields of artificial intelligence
ML	machine learning, a method of data analysis that automates model building (a class of AI)
MLP-NN	a multilayer perceptron, a fully connected class of feedforward artificial neural networks
MRI	magnetic resonance imaging, a non-invasive imaging technology
OCT	optical coherence tomography, a non-invasive imaging test that uses light waves
PLSR	partial least squares regression, a statistical method
PLS	see PLSR
RFID	radio-frequency identification, small devices that use radio frequencies to transfer data
SVM	support vector machines (SVMs), a set of supervised learning methods used for classification, regression and outlier detection
TEF(s)	testing and experimentation facility
TCN	temporal convolutional networks for action segmentation and detection
VIS/NIR/IR	visible, near-infrared and infrared optical regions
ViT	vision transformer, a model for image classification
WSN	wireless sensor network, consists of spatially distributed autonomous sensing devices
1-MCP	synthetic plant growth regulator, structurally related to the natural plant hormone ethylene
3D-CT	three-dimensional computed tomography

1. Introduction

In this introduction, we first define the concept of smart agriculture. A short narrative illustrates the evolution of data collection, data availability and the need to use and combine all the data into information that helps farmers in making better decisions for more effective crop production, given a number of societal constraints. We draw attention to the agri-food chain, from the field to the consumer, although we limit further study to the production and storage steps. In a third, short, sub-section we introduce artificial intelligence as a tool to handle and combine data, in addition to scientific information to gain better insights and, hopefully, prepare or assist in future decision making and action. In the application domains, ethical and policy recommendations are given in subsequent sections of the study.

1.1. Smart agriculture

Agri-food production systems involve processes and processing conditions are very variable (e.g. the natural variability of biological processes, soils and climate). Furthermore, there are expectations from society, with respect to production conditions, inputs and the quality of the outputs. This also creates the need to document and register the activities.

Smart agriculture is a management concept that guides action towards safeguarding or increasing agricultural productivity and food security under variable physical and chemical constraints, a changing climate and increasing demands or expectations of transparency towards all actors in the agri-food chain.

Artificial intelligence (AI) is a tool that may allow smart agriculture to achieve objectives that are beyond the reach of human capabilities. The processing of a huge amount of data and transforming them into actionable items is one of the challenges for the future.

1.2. Changes in data collection in agriculture

Data from agricultural land, crop yields, and milk production have been collected or made available for some time. For example, research into the characteristics of soils and their effect on crop production were the basis of soil classification for the creation of soil maps that indicated the large variability of soils. Farmers knew to register the amount of grain produced on each field and found that it was related to weather, soil type and the amount of fertiliser applied. The milk production of each cow and the quality of the milk was registered through farm visits by advisors and the laboratory analysis of milk samples, on a regular basis.

Around 1980, it was realised that it would be better to try to adjust field management practices according to soil variability. This started the research and development into measuring local production within a field. From then on, a combine harvester has not only harvested grain but also automatically harvested data about the yield in a field.

Yield maps were – and still are – like colourful paintings. However, these paintings differ from year to year, depending on the weather conditions, fertiliser application, water availability or pests and disease during the growing period.

In a similar way to yield monitors, other measurement methods are still under development to assess the prevalence of diseases or nutrient and water stress during the growing period. Optical sensors were installed on machines to detect weeds and then a sprayer, or another mechanism, was instructed to destroy the weed. This is very similar to hand weeding, where a person sees a plant, decides that it is an unwanted weed (on the basis of knowledge and expertise) and then takes action to destroy the weed. Sensor-based data collection is an important component of automation, leading to robotic or autonomous systems for navigation, crop maintenance and harvesting.

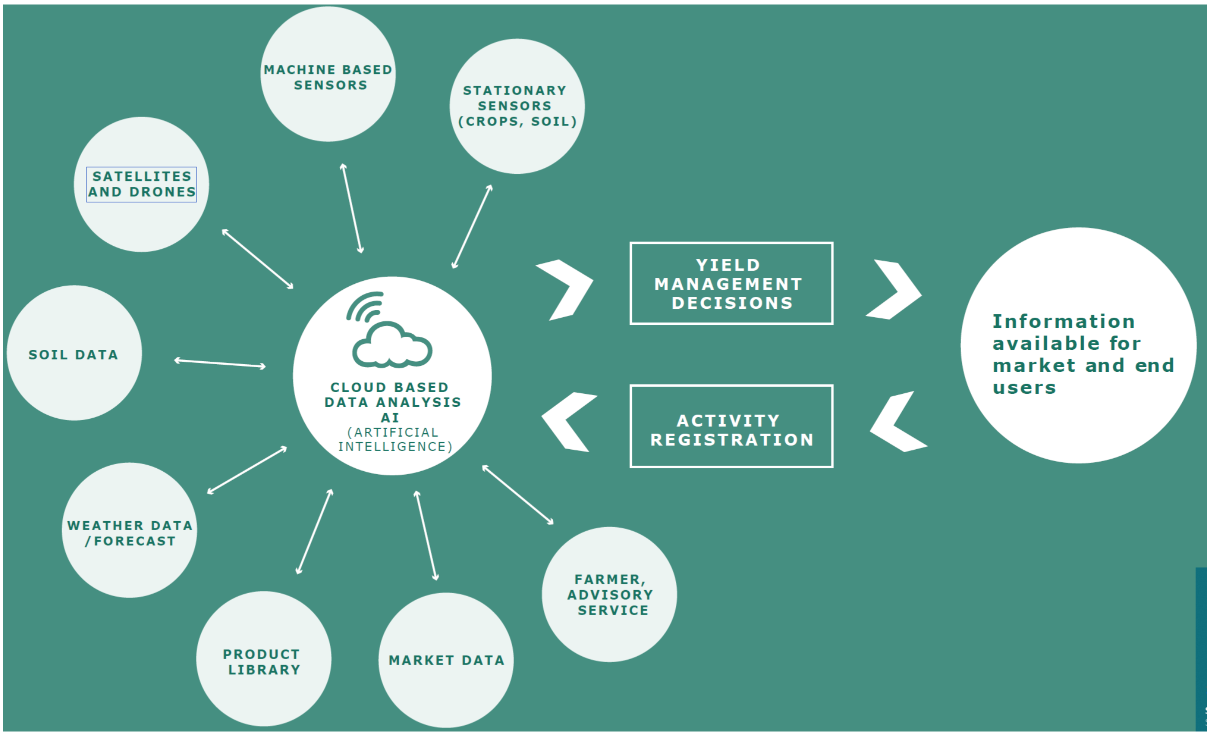
Gradually, more and more data became available on farms but using the data to enable better decision making, remains a challenge. First of all, the data relates to past seasons and the year to year variability implies that this year's data on yield are not a good predictor for next year's.

Secondly, all the different types of sensors can collect data in the fields over many years, but the question remains: how do these 'historic' data contribute to better decisions on crop management plans for the next growing season? One may wonder if there are ways to develop diagnostic tools (sensors and/or analytics) that can almost instantaneously help to formulate decisions and even start action for online management.

The next question which arises is: are there additional indicators that we can find and measure, on plants or animals, which contribute to improved decisions and more effective management? Here, one can expect more answers from the research.

Of course, management decisions have to respect environmental considerations and the expectations of society, as well as consumers, with respect to production methods, inputs in agriculture and product quality and safety.

Figure 1.1 Data can be collected in the field from crops soils and machines and are available to the end user.



1.3. Activities in the agricultural value chain

The agri-food system has four important components (Peters et al., 2020):

- On-farm production, where the production of plants or livestock interacts with soils, water, nutrients and microbes.
- After harvest, the packaging, storage, processing and distribution of food.

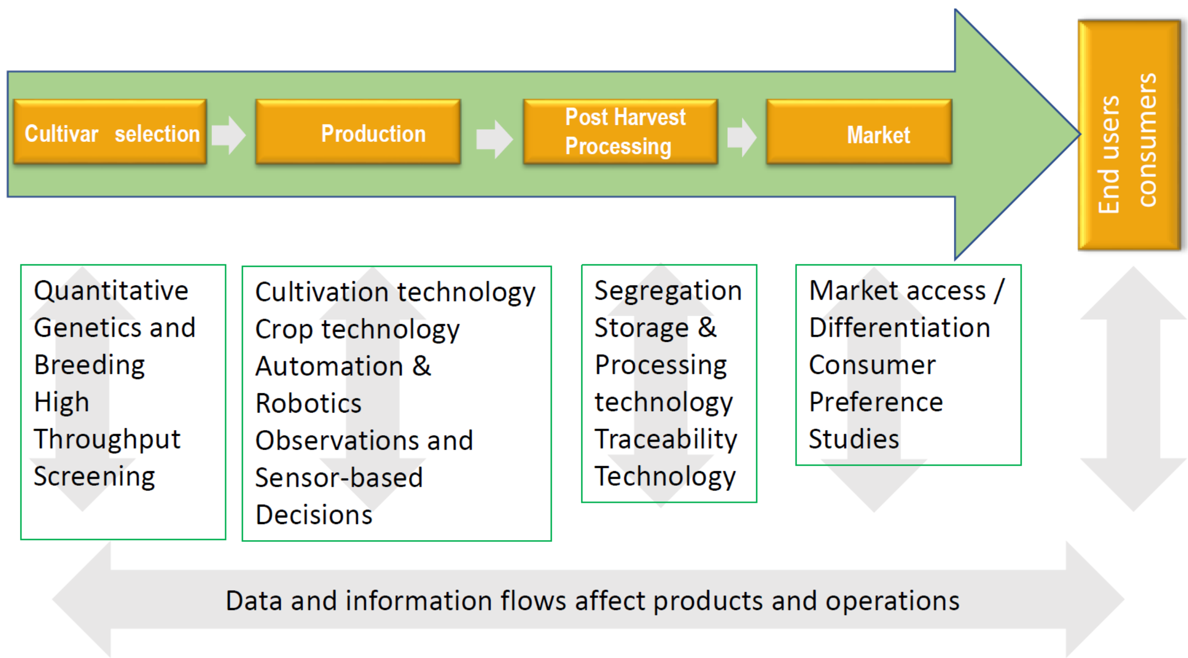
- Consumers, individuals and households have preferences, behaviour, knowledge, health considerations and budgets.
- Uncertainty and variability in all the above components associated with human activities, biotic factors (pests pathogens, diseases) and (difficult to predict) climatic conditions.

Artificial intelligence will play an increasing role in these components. A simplified, yet typical, agricultural supply chain comprises several steps, from the farmers' activities in the field, to intermediate storage or silos, transportation from storage to transformation plants and, from there, on to clients and consumers. In each step, data can be collected and will require multiple decisions to be made. The collected data must evolve from the field, up until the use of the product by processors or consumers, with the data being stored somewhere in the cloud, as presented in the simplified form in Figure 1.1.

There may be a need for further research into the underlying physical or biological processes, for a better understanding of the processes or to find better ways of observation and control.

There are many actors in this value chain and each may have a particular interest in certain data or store these at different locations. The data flow and information flow through different processes in the agri-food value chain is illustrated in Figure 1.2. The entire agri-food chain, with the different actors, can benefit from the digitisation and use of artificial intelligence tools because of the integrated flow of information, both upstream and downstream. At this point in the study, it is assumed that each actor in the chain is – or will be – able to deliver a product and the associated data or information to the next actor. In future, it may become clear that an overall analysis of the chain can offer advantages, albeit at the cost of larger investments in research on sensors, data collection and analytics.

Figure 1.2 Data and information flow for decisions in the agri-food-value chain (modified from a presentation by Ian Ferguson, ACPA 2017, Hamilton, New Zealand)



Differences in data quality, raw data formats, their accuracy and transmission challenges, paired with the high volume of data available at different times or location intervals, are among the many challenges that have hindered the rapid automation, use and reliability of artificial intelligence in the agri-food chain.

With so many actors, it is not clear where the data reside and how a smooth data flow can be made possible, whereby data ownership considerations, GDPR and efficient AI-based developments are possible. At many points in this flow, uncertain external events can occur.

1.4. Artificial intelligence for smart agriculture

In Article 3 of the proposed artificial intelligence act for Europe (EUR-Lex - 52021PC0206 - EN - EUR-Lex, 2021), the following definition is given:

'Artificial intelligence system' (AI system) means software that is developed with one or more of the techniques and approaches listed (in Appendix 1, here under *)[1] and can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with.

An Independent High-level Expert Group on Artificial Intelligence, set up by the European Commission (AI HLEG, 2018), proposed to use the following updated definition of AI:

- 'Artificial intelligence (AI) refers to systems designed by humans that, given a complex goal, act in the physical or digital world by perceiving their environment, interpreting the collected structured or unstructured data, reasoning on the knowledge derived from this data and deciding the best action(s) to take (according to pre-defined parameters) to achieve the given goal. AI systems can also be designed to learn to adapt their behaviour by analysing how the environment is affected by their previous actions.
- As a scientific discipline, AI includes several approaches and techniques, such as machine learning (of which deep learning and reinforcement learning are specific examples), machine reasoning (which includes planning, scheduling, knowledge representation and reasoning, search, and optimisation), and robotics (which includes control, perception, sensors and actuators, as well as the integration of all other techniques into cyber-physical systems).' See Figure 1.3.

Smart agriculture can be seen as a management concept that relies on data and insights obtained during research efforts, as well as during agri-food operations. The information can be structured in many different ways and results in decisions; sometimes automatically implementing these into actions towards safeguarding or increasing agricultural productivity and food security under variable physical and chemical constraints in a changing climate. Artificial intelligence is a tool that allows smart agriculture to achieve objectives that are beyond the reach of human capabilities. The processing of a huge amount of data and transforming them into actionable items is one of the challenges for the future.

[1] * in Appendix 1, the artificial intelligence techniques and approaches include:

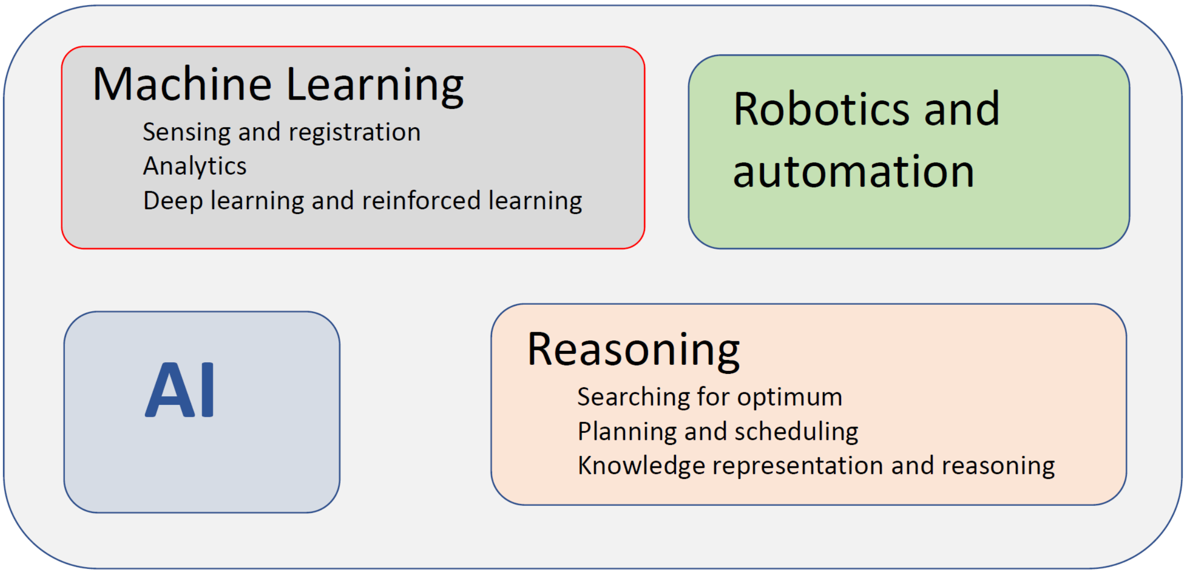
(a) Machine learning approaches, including supervised, unsupervised and reinforcement learning, using a wide variety of methods including deep learning;

(b) Logic and knowledge-based approaches, including knowledge representation, inductive (logic) programming, knowledge bases, inference and deductive engines, (symbolic) reasoning and expert systems;

(c) Statistical approaches, Bayesian estimation, searching, and optimisation methods.

There are several variables that farmers can control, such as variety selection, planting date, fertigation rate, pesticide application rate and interval times, machine usage and consumption. However, the interaction of multiple factors and the continuous variation of parameters can represent a huge obstacle to achieving the best combination of inputs. The aims are to ensure growth in production, control machine costs and reach predictable stability in the market. Furthermore, many variables are beyond farmers' control, such as environmental factors. Current and historical data analysis can provide a more predictable forecast for farmers. Of course, the final yield and the production costs are the result of all the efforts during the growing period. Business intelligence on available data can provide economic advantages for farmers. Data are increasingly collected by machine and field sensors, which are capable of importing high-quality data about critical factors in yield production, such as soil variation and quality, water and nutrient availability, plant health and disease control, as well as crop growth and evolution. In order to complement the expertise of farmers and operators, these data with high variance and uncertainty have to be analysed such that they can become an information base for making better decisions. External conditions, like local short-term weather changes, do not always have a degree of predictability that makes them reliable enough for short-term management decisions.

Figure 1.3 AI's sub-disciplines and their relationship



Observations, analyses and interpretation which enable the making of decisions and implementing them, occur at different scales in a field, single plant, farm or region. Timescales are often chosen based on the time horizon and they can be very short (a matter of minutes, in the case of protected cultivation), short (a matter of days, in the case of crop responses) or very long (over several seasons, in the case of soil changes).

A multifactor analysis of observed variables can be the basis for regional policy, advisory services and managing a farm or a field. The expertise of a farmer and his skills are important components in the decision making. When farmers rely on advice from consultants and advisory services, these also need to have been properly trained beforehand, in addition to farmers.

Disturbances in external conditions complicate the design and control of equipment and decision making, as well as the evaluation of the impact of these decisions and tools on the outcome, in terms of profit, as well as environmental effects.

In agriculture, improvements are expected or promised in many areas, based on the exploration and exploitation of data when these are available (Figure 1.4). Cost reductions, crop forecasting, and improved decision-making and efficiency are additional benefits directly benefiting farmers.

Figure 1.4 Promised areas of improvement of agriculture in the exploitation of the data

Mark, 2019

1.5. European initiatives for AI and is applications in agri-food

The European data act

The proposed data act aims to maximise the value of data in the economy by ensuring that a wider range of stakeholders gain control over their data and that more data is available for innovative use, while preserving incentives to invest in data generation (*Data Act | Shaping Europe's Digital Future*, n.d.). The data act should give the users of the connected products and related services the right to access data generated by those products and services.

For agriculture, the DIGITAl programme includes:

A common European agricultural data space: With the European data act, the European Commission is expected to support the implementation of a common European agricultural data space, facilitating the trustworthy sharing and pooling of agricultural data. The data space should increase the economic and environmental performance of the agricultural sector. This means enabling data sharing as well as practical, fair and clear rules on data use and access.

In precision agriculture, internet of things (IoT) analytics of data from connected equipment can help farmers analyse real-time data like weather, temperature, moisture, prices or global positioning system (GPS) signals and provide insights on how to optimise and increase yield. This should improve farm planning and help farmers make decisions about the level of resources needed. It would also protect farmers that use smart agricultural equipment against manufacturers who would use insights into farm yields to speculate on agricultural commodity pricing, essentially using farmers' data against them (Kogut-Czarkowska & Graux, 2022).

AI testing and experimentation facilities (TEF): the European Commission and Member States should develop world-class, large-scale reference testing and experimentation facilities (TEF) for AI in several sectors, including agri-food. There should be a boost in the uptake of trustworthy AI for the European agri-food sector. A call for the TEF for agri-food was launched in February 2022. Six proposals were submitted, but five were not eligible. It is expected that the contract will be signed in the first half of 2022 for a project duration of five years.

Digital Innovation Hubs (DHIs): These provide technological expertise and experimentation facilities to enable the digital transformation of the industry and the public sector. The experiences and lessons learned from the existing DIH SmartAgriHubs and AgroRobofood are good reference points.

Digital skills: Enhancing the digital skills of the farmers can be achieved via specialised education programmes or modules in key capacity areas which also includes the design and implementation of specific courses in digital technologies for professionals in the agricultural sector.

Horizon Europe

The European Commission has invested in research and innovation, including agri-food (European Commission, 2022). Cluster 6 'Food, bio-economy, natural resources, agriculture, fisheries, aquaculture & the environment' includes the use of digital solutions for the agricultural sector. In addition, under Pillar II, Cluster 4 'Digital, Industry and Space', innovative technologies such as IoT, cloud and edge computing, AI, robotics, and blockchain will be tested and validated in cases of agricultural use.

The following topics are listed:

- Development, testing and validation of innovative technologies through the use of cases in agriculture: IoT, AI, robotics, blockchain and edge computing;
- Apply advanced technologies in agri-food: drones, smart IoT, AI, upscaling real-time sensor data, 5G and edge solutions for remote farming;
- Cost-benefit analysis and increasing cost-effectiveness of digital solutions;
- Potential market exploration, roadmap for adoption of technologies.

The common agricultural policy (CAP)

The CAP has a cross-cutting objective on digitisation, knowledge and innovation which includes investment support for the European Innovation Partnership for Agricultural Productivity and Sustainability (EIP-AGRI).

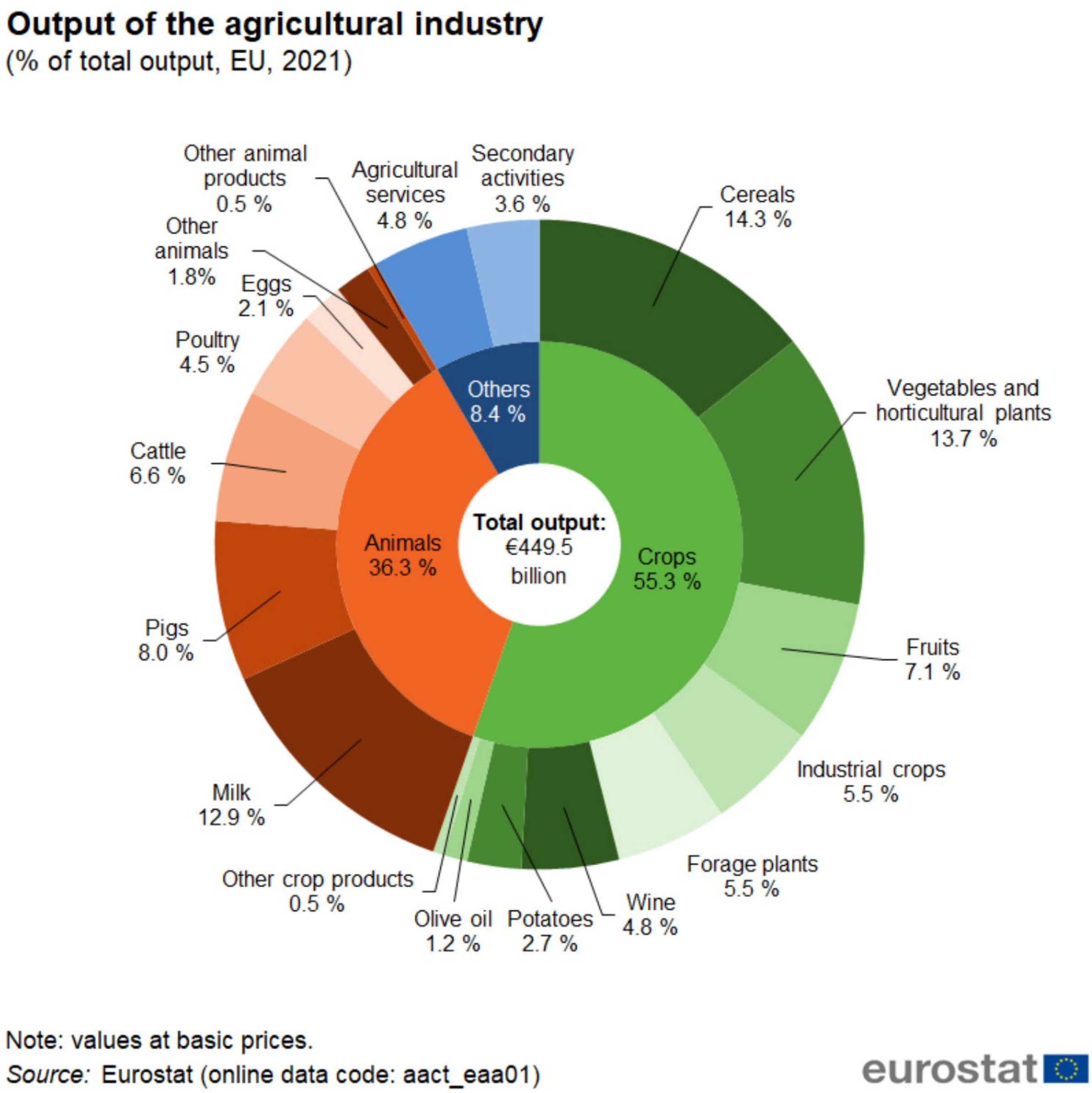
The 'Farm to Fork' strategy targets for sustainable food production are challenging and ambitious for the agricultural sector, in which digital technology is a key to success. Using IoT technologies offers a potential to optimise the use of pesticides on the land, minimising harmful chemicals in the environment and making crops safe for consumption.

1.6. Approach of the study

In the following sections, experts in different fields of agri-food reflect on the state of the knowledge in their area (measurement and automation tools in particular) and then look at how AI modelling and algorithms can contribute to better managing the agri-food value chain. The subdivision into the different domains was based on sectorial importance, as well as activities that are important for the whole of agriculture and agri-foods.

Figure 1.5 gives the output of the agricultural industry, whereby we see that crops are 55.3 % of the output and animals 36.3 %. In crop production, a large share of fruit and vegetables production is in protected cultivation (Eurostat, 2021). Protected cultivation is very intensive production on a rather small spatial scale but with high financial investment, high labour density and crop density per surface unit. It also has a high data density per surface area and per time unit. Crop production in the open air involves a rather large surface area and, more or less, follows the seasons because of annual production cycles. Between the Member States, there is a large variation in average farm size. Digital literacy may also show large variations between farms and it is, therefore, important that this digital divide does not increase or lead to uneven negotiating power when dealing with manufacturers, suppliers, retailers or other customers. Similarly, there are differences in farm sizes with respect to animal production. In addition, animal production has increasingly to cope with environmental constraints and greenhouse gas emissions.

Figure 1.5 Output of the agricultural industry sectors in Europe in 2021 in %



Furthermore, water availability and use is a common challenge across the sectors and across Europe. Post-harvest quality assessment, storage and transportation are important activities for the whole of the agri-food sector. An important concern is the reduction or avoidance of food waste. Therefore, post-harvest activities put an emphasis on advanced non-destructive methods for monitoring product quality in the value chain. The agricultural machinery industry is instrumental in data collection and automation and has close links with other industries for advanced tools that can be made for use in agriculture.

For the areas of agriculture that are considered as being exemplary for the potential of AI, we looked for experts who were familiar with the state of the art in the subject domain and who had technological expertise. An effort was made to include experts from different regions in Europe. After the initial contacts, and based on their availability, the experts or expert teams were asked to provide a state of the art, based on the literature and their own expertise, and also to formulate challenges as well as policy options. The latter were collected in the last section of this study.

- Protected cultivation (S. Hemming et al., Wageningen University and Research -WUR)
- Crop production in the open air (F. Rovira-Más, U.P. Valencia and D. Moshou, Aristotle University, Thessaloniki)
- The use of water for crop production (G. Wyseure, KU Leuven)
- Animal husbandry (T. Norton, KU Leuven)
- AI in the supply chain of horticultural products (B. Nicolai, KU Leuven and S. Hemming, WUR)
- AI and Agricultural Machinery (CEMA, the European Agricultural Machinery Association)

Section 8 contains reflections on ethical and societal impacts that the implementation of AI can have and on the risks that may arise for individual farmers, as well as regional or ecological developments. These are mainly based on the literature and informal discussions.

Section 9 analyses the barriers and their challenges towards the successful application of AI in agriculture. The challenge for better and more trustworthy algorithms is also discussed. All of the authors contributed.

In the final section, policy options and recommendations are formulated based on the authors' expert opinions and additional literature.

2. Artificial intelligence and protected cultivation

Greenhouse production processes are already highly automated and controlled but, similar to what is occurring in many sectors, AI systems are now taking control to unprecedented levels. Because of their potential ability to process large amounts of data and make tiny continuous adjustments, AI systems are beginning to provide greenhouse operators with myriads of production-related benefits (Treena Hein, 2021)

AI in protected horticulture can predict yield, ensure product quality from starting material to harvest, help decide on the planning of time-to-market and resources used and improve efficiency. It can, therefore, contribute to the economic profit of growers and the sustainability of their production. Both are important factors in industrialised production processes with large greenhouse compartments at different locations, a lack of skilled labour and increased demand for high-value food close to urban areas. In addition, the link between growing conditions and shelf-life processes needs to be elaborated, such that information from the end point (the consumer acceptance) is used as feedback to alter growing conditions.

2.1. Plant phenotyping of horticultural crops and the use of crop sensors

Plant phenotyping can be defined as the set of methodologies and protocols used to measure plant growth, architecture and composition with a certain accuracy and precision at different scales of organisation, from plant organs to complete crop canopies. The term is often restricted to plant breeding purposes, but it can also be used for plant production, specifically where measured plant features are used for precise crop maintenance and crop control in a controlled environment, such as (autonomous) greenhouses and vertical farms.

2.1.1. Digitalisation and artificial intelligence for crop morphology measurements

The shape and morphology of plants is related to variety, the underlying genetics and environmental factors (light, temperature, irrigation). Digital plant phenotyping refers to the use of computers for plant phenotyping where digital sensors are used to measure plant characteristics.

One of the most common digital phenotyping methodologies is image analysis, where cameras are used to record images and software is used to automatically extract the measurements from the images to access plant morphology (the shape of a plant), in a reproducible and accurate way (Van der Heijden & Polder, 2015).

Currently, many different types of cameras are available for measuring important plant features to characterise plant morphology. The most used camera is the RGB colour camera, which produces images in the visible spectrum, mimicking the human eye. To relate the images to real dimensions, 3D information is often needed, which resulted in RGB camera-based 3D sensors. The Intel Real-sense RGBD sensor is an affordable example of a RGB 3D sensor and is often used in horticultural phenotyping, e.g., for tomato fruit detection and counting (Afonso et al., 2020; Fonteijn et al., 2021). Other examples are LiDAR sensors. All of these might become low cost because of the development of smart phone cameras for consumers.

In greenhouse crop production, the plants may be intertwined, and so they cannot be easily imaged from all sides. This leads to occlusion and hampers the possibility of imaging important plant traits with a 3D camera. To overcome this problem, more advanced imaging solutions are needed. This can either be achieved by a moving trolley system with a mounted camera, flying drones inside the greenhouse or a robot that scans the plant with a 3D camera from many viewpoints. Using artificial intelligence algorithms, the point clouds from different single viewpoints are converted into a robust representation of the crop (Boogaard et al., 2020).

2.1.2. Digitalisation and artificial intelligence for crop physiology performance

Next to plant morphology, plant physiological processes are important for crop monitoring. In crop production, photosynthesis in the leaves yields important biochemicals, such as sugars, starch, chlorophyll and nutrients, that are transferred to the plant organs, flowers and fruits (Dieleman et al., 2018a).

Therefore, measuring the efficiency of plant photosynthesis directly and non-destructively is a desirable way for obtaining information on crop performance and for the early detection of deviations from optimal physiological conditions. Technologies like chlorophyll fluorescence imaging and thermal imaging are promising, especially if they can be applied to other parts of crop canopies, as well as individual leaves.

The chemical composition of the crop can be determined by sampling leaves or fruits, sending them to a laboratory and waiting for the analysis. Recent imaging spectroscopy was tested on a laboratory scale, to determine the composition of biochemicals in crops, with promising results (Dieleman et al., 2018b).

Imaging spectroscopy is an imaging technique for images taken using many narrow wavelength bands over a range extending across the visible spectrum (from ultraviolet to shortwave infrared) and compared to a standard camera, which only records red, green and blue light. In doing so, it creates an extremely detailed image of the reflection of light on plants or other objects. Imaging spectroscopy provides a lot of information on plant pigments, sugars, proteins, fats and water, as well as their distribution over the leaves or organs.

Regions of interest, such as the fruits or leaves, can be automatically extracted from the image. This opens the possibility of using this technique on mobile platforms (Mishra et al., 2020). Currently, a lot of research and development effort is going into the development of spectral cameras, making them less bulky, more robust, faster, and less costly.

Currently, AI techniques are explored to extract useful information from the massive amount of data collected by the spectral cameras (Mishra et al., 2021; Signoroni et al., 2019).

These developments suggest an outlook for the future, providing more information on different important plant features. Until now, most plant features could only be measured manually, destructively and/or very locally with scarce datapoints. Digitalisation of the measurement and use of modern sensors and camera systems will help to collect more datapoints. AI methods will largely help in the interpretation of variable data output. AI algorithms will also help to transform and combine the output of multiple sensors into useful information for growers.

2.2. Autonomous growing and the use of AI

Greenhouse horticulture is characterised by relatively high operational efficiency involving powerful managerial skills. However, demand for high vitamin and mineral food is increasing rapidly (Rabobank, 2018; Tilman et al., 2011). The volatile market demands, resource prices, scarcity of experienced labour (Brian, 2018), as well as uncertain weather and environmental conditions, make greenhouse farming a complex and risky endeavour. While encountering an environmental crisis (United Nations, 2019), food production systems need to become more productive, resource-efficient, and environmentally sustainable (Willett et al., 2019). The development of advanced and autonomous greenhouse production systems aims at realising the best possible production outcomes, considering quality and sustainability targets, with the uncertainties of resource availability, weather or market demand. The realisation of fully autonomous and intelligent horticulture entails three major components: remote sensing, remote control, and hands-free practices with robotisation.

2.2.1. Data for autonomous growing and production

Data regarding greenhouse production systems are becoming of increasing importance and are a means of deeper understanding and efficient management of the complex biological dynamic processes. Large and meaningful datasets about all growing aspects are sparse. The greenhouse climate is relatively well-monitored, resulting in a time series with short intervals. However, manual, subjective, time-consuming, often invasive, and costly measurements of traits of crop growth, development, pests, and pathogens result in fragmented weekly or bi-weekly data points (Bouzembrak et al., 2020). This implies considerable data uncertainty as a result of noise, missing data, inconsistent formats, and non-standard collection protocols, among others (Lezoche et al., 2020). Investment into integrating diverse and unstructured data is required before any additional meaningful insights are possible (Osinga et al., 2022).

Ongoing technological developments, computational power, and high-fidelity sensors offer new opportunities for automated, remote, and non-invasive sensing of growing parameters. The higher spatial and temporal resolution in the measurements and in the growing conditions allows for interpretation of the system's variability at coarser and granular levels and offers opportunities for sufficient information extraction towards more efficient adaptation of horticultural practices.

AI and machine learning can deal with the larger datasets and capture the nonlinear relationships present in the heterogeneous data sources in greenhouses.

2.2.2. Machine learning for yield prediction and resource use efficiency

Scalable and generic machine learning analytics are currently used to complement expert-based approaches for supporting yield predictions. Implementations of intelligent algorithms focus on predictions of indoor climate, microclimate (Ali & Hassanein, 2020; Taki et al., 2016, 2018), yield and quality aspects of vegetable crops and flowers (Alhnaity et al., 2020; Reissig et al., 2021; Xiao et al., 2021), as well as growth and development indicators. Descriptive and predictive models (Partial Least Squares (PLS)) (Li et al., 2016), Support Vector Machines (SVMs) (Fandel et al., 2021; Yan et al., 2010), Random Forests (RF) (Amir et al., 2021), Artificial Neural Networks (ANNs) (Ullah et al., 2020), and k-nearest Neighbours (KNNs) have developed yield forecasting tools and decision support systems (DSS) using predictors and outcomes from experience. In addition to ML, deep learning (Long Short-Term Memory (LSTM)) (Alhnaity et al., n.d.; Ali & Hassanein, 2020; Moon et al., 2020), Temporal Convolutional Networks (TCN) (Gong et al., 2021), and Multilayer Perceptron Neural Networks (MLP-NN) (Petrakis et al., 2022) have also shown significant advantages in processing time-series data to yield higher precision and better performance than other machine learning methods.

Reinforcement learning finds applications in selecting actions, based on continuous feedback, to maximise the system's performance. Current applications are aimed at learning the best operational decision for day-to-day climate optimisation, with fewer being aimed at irrigation control and crop management planning. Experiments for greenhouse control at a distance, using state-of-the-art artificial intelligence algorithms, yielded promising results in the cultivation of cucumbers (Hemming et al., 2019) and cherry tomatoes (Hemming et al., 2020), compared to references of experience-based manual growing. Different AI technologies have been shown to have the potential to contribute to predicting yield, as well as increasing yield and product quality and, at the same time, save resources such as energy, water and nutrients.

2.2.3. Deep learning for pest and pathogen management

In the future, the detection of plant pathogens and pests will become extremely important. Unless it is known what a plant is suffering from, nothing can be done about it. The earlier pests and pathogens are identified, the easier it is to control them. Automated systems are starting to play a greater part in this (Bauriegel et al., 2011; Polder et al., 2014; Rumpf et al., 2010).

Automatic detection of pathogens in plants, as early as possible and without damaging the plant, is an approach that is gaining ever more attention in horticulture. In automatic detection, the basic assumption is that a diseased plant looks different from a healthy one. For example, leaves can have subtle colour differences, which are often invisible to the human eye but can be captured using techniques such as spectral imaging. Spectral imaging, combined with deep learning techniques (described in the previous section), has the potential to become a powerful tool in pathogen detection in greenhouses and vertical farms.

Pest detection is often challenging because pests and their eggs are often located underneath the plant canopy and are, therefore, difficult to detect. They are often very small and show a very local distribution. Crops in general might suffer from multiple pests at the same time. Therefore, not only high-resolution detection but also local and organism specific detection is required. High-resolution imaging, in combination with deep learning techniques might have the potential for precision farming in greenhouses and vertical farms.

In both cases, large amounts of labelled images are required from different situations (locations, seasons, crop varieties) to sufficiently train the deep learning algorithms. More smart training is needed to overcome the lack of such real data and labelled images.

2.3. Digital twins and decision support for market-oriented production

Today's high-tech greenhouses are equipped with different standard sensors for monitoring light, temperature, humidity, and CO_2 and for actively controlling different actuators (e.g. lighting, screening, heating, ventilation, cooling, CO_2 dosing, fogging, dehumidification, irrigation, and fertiliser dosing) in order to control all growth factors important for crop production at every moment. Today's growers determine the climate, irrigation and crop management strategies based on experience and define the setpoints for climate and irrigation control manually. Actuators then operate based on the setpoints configured in a processing computer, while sensors give feedback on measured data for the control loop (Hemming et al., 2020).

The rapid pace of technological advancements, AI, cloud computing, and the uptake of the IoT produces an increasing data stream at high spatial and temporal resolution, almost in real-time.

In smart horticulture, the greenhouse grower can monitor and control operations at a distance, based on real-time digital information instead of direct observations and tasks on-site.

Large amounts of data can be leveraged for the design and implementation of advanced models, known as digital twins. A digital twin is equivalent to real-life objects mirroring the behaviour and states over its lifetime in a virtual space (C. Verdouw et al., 2021). As a digital representation of actual physical systems and technology integrators, digital twins offer a solution for complex systems analysis and can act as decision support tools (Pylianidis et al., 2021). Digital twins are increasingly adopted in the manufacturing, automotive, and energy industries (Caputo et al., 2019; Kritzinger et al., 2018; Sivalingam et al., 2018).

2.3.1. Digital twin of the greenhouse system

Dynamic climate models have been developed (Vanthoor et al., 2011) which act as digital twins of real greenhouses. An overview of today's greenhouse climate models was given in a previous study (López-Cruz et al., 2018). Since greenhouses differ from each other, an appropriate parameter determination or calibration is necessary for each model, to act as a digital twin of an existing greenhouse. These mechanistic digital twin models can be used to assist intelligent decision support on climate control actions. Simulations of past or future scenarios provide information on how different climate control in the past could have improved crop production and which actions are required to reach a certain crop production goal in the future. These models can also be coupled with intelligent algorithms to automatically determine climate setpoints, an action that is currently performed manually by the grower. In order to control crop production by an automated algorithm, mechanistic greenhouse climate and crop models are coupled to resemble a real greenhouse. The effects of changing set points can be tested on the digital twin and then, sent automatically to a processing computer to control the different actuators (Hemming et al., 2020).

2.3.2. Digital twin of the crop

The crop has a central role in every greenhouse production system. Crop management decisions and actions are mostly taken by the greenhouse staff. Since experienced and well-trained crop managers are scarce, crop simulation models can play a role in decision making. An overview of greenhouse crop models and modelling approaches are given in other studies (Kuijpers et al., 2019; Sarlikioti et al., 2011). Crop models can be used as virtual representations of reality (Marshall-Colon et al., 2017). They can be used to simulate different growing conditions and crop management strategies and to predict their effect on crop development and yield, as well as on fruit quality. Crop models can help to understand the crop behaviour under different growing conditions and can support the grower in making decisions. Additional sensors, monitoring crop status, can provide the grower with further information as described in the previous chapter. While automated greenhouse climate control algorithms have already been developed and are widely introduced in modern high-tech greenhouses, automated control procedures for crop status are still in their infancy (Hemming et al., 2020).

The available digital twins do not yet include all aspects for crop production. Typically, water and nutrient management could be described in more detail. Crop quality aspects are not described well and pest and pathogen management is lacking. More attention needs to be paid to the completion of mechanistic digital twins in future research.

2.3.3. Digital twins for decision support and AI

In general, complete digital twins (including greenhouse twins, the physical environment and crop twins) can facilitate operational and tactical management decisions, strategic design decisions, and predictive maintenance information. Preventive and corrective actions can be simulated and evaluated in the digital environment before the final actual intervention. Such complete digital twins are highly suitable for capturing available 'horticultural/green' knowledge and obtaining artificial training datasets for future system design and operation.

Convergence between digital and physical greenhouse production systems has been pursued as an essential goal for data-driven horticulture. In the domain of process systems engineering, Reinforcement Learning (RL) has been applied to resolve stochastic optimal control challenges with the uncertainties of the highly non-linear and complex processes. As real-world data is augmented in mechanistic algorithms that comprise the digital twin, the virtual environment can act as a learning environment that generates adaptive control actions with statistical significance, instead of the conventional hardcoded control logics of deterministic conditions.

Deep RL networks require finite learning iterations. To explore the potential of such data-greedy networks for horticultural challenges in a practical, timely and economically feasible manner, data from the digital twins can be used as it is repeatable, inexpensive, and clean. In view of conditional, highly automated and high-fidelity twins, interventions suggested in the digital twin can be directly implemented without the grower's inspection or physical proximity. The twins are able to self-diagnose and adapt to users' preferences (C. N. Verdouw et al., 2016). The benefits can result in cost savings of recourses, improved product quality, faster actions with lower risks, and increased production (Pylianidis et al., 2021; C. Verdouw et al., 2021).

2.4. Challenges for AI in protected cultivation

2.4.1. Challenges of digitalisation in crop phenotyping

The current challenge is to give meaningful interpretation to sensor data and to transform that into decision support systems or even autonomous control for growers. To achieve this, high quality data must be made available from multiple sources and connected. Data must be collected from robust, reliable sensors with low maintenance and low costs. The more data points that can be collected, the more information is available for smaller areas, down to individual plants, and this contributes to a higher resolution of information within a complex system of highly variable and fast changing dynamic biological processes. Indeed, there are a number of important crop parameters and processes that may ultimately affect AI algorithms, even if there are no data or insufficient data is available (seen Annex 1). Knowledge about this may lead to interpretable AI models that also come closer to reflecting natural processes.

2.4.2. Challenges of artificial intelligence in autonomous growing

Given the complexity of greenhouse production, the use of different technological tools in an integrated approach is the key for optimum crop management to reach optimum yield, while minimising the use of resources, including the reduction of energy and water use and pest and pathogen management.

Many developments have been demonstrated at a small laboratory scale or in a research environment but translation and integration into commercial applications is lagging behind. Currently, real data, especially on different aspects of crop performance, pests and pathogens, are scarcely available or not publicly shared. Artificial data might be obtained by mechanistic crop models but typically do not cover all growing aspects and often show a gap between the mechanistic model (artificial data) and reality, especially in the description of real crop management. Future research must focus on obtaining more knowledge from the digitalisation of crop management and performance and translating that knowledge into more detailed mechanistic crop models for better artificial training datasets. More labelled datasets should be created and publicly shared, in the field of pest and pathogen management. In addition to this, better physical-based AI models must be developed, validated in applied trials and translated for commercial situations.

More applications of robotisation in human-performed tasks will accelerate the realisation of fully autonomous systems and can be a future source of data collection as well. A systems-thinking approach is necessary for the development of integrated solutions. Monitoring, control, and automation challenges in multi-faceted dynamic greenhouse systems must be addressed by engaging experts in a holistic and multidisciplinary process for better understanding and tackling of interrelationships and uncertainties.

Besides gaining more fundamental knowledge, more effort is needed for the validation of single technological solutions and the integration of multiple solutions into a new integrated high precision horticultural farming system. For that, more field-laboratories with a research-like high-tech data infrastructure, but close-to-practice crop growing system, are needed to facilitate such technology validation and integration.

2.4.3. Challenges for digital twins in market-oriented production

Current challenges lie in the high dimensionality of greenhouse growing systems due to the various designs and various crops. Associated costs of the development of high fidelity digital twins are high and a selection of minimum assets covering the market demands is required. A balance between highly detailed information and more general twins can lower development costs.

Interactive interfaces with techniques of augmented and virtual reality make the twins more coherent and attractive, although they require a high level of information infrastructure. More research and development is needed in this field. The development of detailed digital twins to describe reality, with a small gap between the twin and reality, is needed. In addition, user acceptance and confidence is needed. More research on social aspects will help the development of interactive interfaces and user-friendly solutions.

Overcoming barriers for the application and policy options would require one or more demonstration sites where digital twins of a greenhouse crop production facility can be tested in a safe environment for different crops and conditions. This would give growers confidence in the power of data and artificial intelligence-driven control of crop production systems.

3. Artificial intelligence in field crop production

The benefits of artificial intelligence (AI) for crop production may be focused, in general terms, on making agricultural equipment more intelligent and on making farm operations more efficient and sustainable. Vehicle automation can be enhanced with AI algorithms that improve productivity and safety. Farming operations will be improved by the deployment of AI-based expert systems**,** providing support for decision making and paving the way for data-driven agriculture, if massive field data become accessible.

3.1. Vehicle automation and smart field operations

3.1.1. Status of intelligent equipment for agricultural production and the advent of robots

An overview of smart and AI-driven machinery developments

Equipment manufacturers, the technological vanguard of field mechanisation, have made –and are still making– a significant effort to evolve state-of-the-art vehicles into intelligent machines by the introduction of smart behaviour, automation, and data-collection devices. By robotising existing products, manufacturers have avoided designing machines from scratch while using the already-validated features of popular models. This upgrade typically includes automatic steering or safety functions that make daily work safer, less tiring and more efficient. Recent examples of such smart tractors are the New Holland T4.110F (with an autonomous NHDrive (2018) navigation system), the Kubota AgriRobo (based on Series-L tractors, with capabilities to generate crop maps and auto-steer (2018)), and Yanmar driverless tractors.

Even though the process of digitisation in agricultural equipment started by furnishing top-of-the-line models with sensors and processors (Figure 3.1) to acquire data and automate basic functionalities, leading manufacturers have also contributed to the advancement of farm robotics by conceiving, developing, and showing, in public events, eye-catching concept prototypes that demonstrate their industrial leadership. These prototypes are fully autonomous vehicles without a driver's seat, which are similar in size to conventional tractors, and enabled to show technologically advanced behaviours. However, as they are concept vehicles, they are not yet commercially available and, therefore, unprepared to hit the market. The examples illustrated in Figure 3.1 shows the concept vehicles launched by principal manufacturers.

The interest in agricultural robots has grown strongly in the last decade, although its worldwide distribution is not uniform. The areas of application of robotics in agriculture are (in decreasing order of magnitude) field farming, dairy management indoor farming, horticulture, and others.

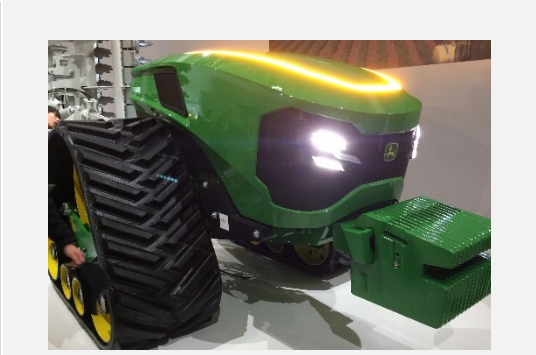
The global agricultural robotics market is anticipated to reach USD 8.82 billion by 2025 with a CAGR of 24.7%. By comparing the growth with robotics market (CAGR 10.5%), the penetration of robots in the field of agriculture will be stronger (Mege et al., 2019) . Overall, the USA has dominated the market during the first two decades of the 21st century. For the next decade, however, the Asian market is expected to grow at the highest rate due to increasing government support and increasing technological advancement, whereas the European market will expand at a lower rate. Unless there is a strong European initiative, the ever-growing market of farm robotics will be in the hands of Asia and America for the next 20 years, resulting in a heavy toll to pay for European agribusinesses and entrepreneurs.

Figure 3.1 Concept robotic tractors: a) John Deere (1997); b) CNH (2016); c) Kubota (2020); and d) John Deere (2019) (pictures by F.Rovira-Más).

a

b

c



d

Since a sustainable professional agriculture is not conceivable without machines, the smarter the better, it seems that Europe cannot ignore the need to stimulate European technological development in agriculture. Indeed, the stated goal of a greener agriculture, from field to fork, can only be achieved in a competitive way when European farmers can make use of the advanced tools that can be delivered by knowledge-driven equipment.

Automation and AI by large machinery manufacturers versus independent service consultancies

Manufacturers of agricultural equipment have devoted important resources to develop intelligent machines that may substitute conventional tractors soon, leading to the advanced concepts in Figure 3.1. However, the complexity and size of such machines has prevented their commercial release hitherto, due to reliability, safety, and legal reasons. Manufacturers themselves are reluctant to launch forward-looking products that might get involved in an accident and, thus, jeopardise their long-time reputation. This situation has resulted in the sprouting up of small enterprises that have focused their resources on solving a specific problem with robotics. Most of them are –or have initially been– start-up or spin-off companies, which have circumvented safety issues by reducing the size of robotic platforms. By doing so, not only have they diminished the risks inherent in automation in open fields, but they have also reduced the environmental footprint, by changing conventional diesel engines for electric propulsion systems. In an attractive business model end-users do not need to worry about machine maintenance and liability. It may be that the successful deployment of robotic solutions occurs before full autonomy becomes a practical reality.

Another approach can be that mechanised activities on farms, and in the postharvest, are increasingly offered as a service by companies or by cooperatives rather than on-farm ownership of the equipment. This can result in a rapid and continuous modernisation of the equipment that is adapted as new needs arise.

3.1.2. Crop health management

Crop health management involves detection and actuation. Detection might be further enriched by prediction but the extreme complexity of weeds, disease and pest dynamics has not resulted in many widespread commercial solutions yet. However, it is on the agenda of many corporations, such as Bayer, which has made large investments to develop prediction tools for mobile telephones (*Digital Farming | Bayer Global*, 2022) since 2017. Smart actuation, by delivering an adjusted spray rate only to places where weeds are located, has recently seen successful solutions with a combination of artificial intelligence and computer vision (https://bluerivertechnology.com). The following examples provide a few representative cases of advanced machines for the delivery of crop protection products or the mechanical removal of weeds, but many more are on the way as new smart machines are continuously emerging.

Is smart crop health management possible with limited available molecules?

Crop protection is a fundamental stage in food production and it may become a serious problem if it is mishandled; its relevance deserves a few lines of discussion. To begin with, weeds and pests pose different scenarios and require different solutions. Surprisingly, in Europe this carries geopolitical implications. Northern states, with milder summers, more rain, and extensive production are mostly affected by losses caused by weeds. Southern states, with the changing climate increasing the occurrence of heatwaves and intensive production of specialty crops, are mostly hit by devastating pest invasions or diseases spread by pests (Schneider et al., 2020). As a result, when a common policy for the reduction of legal crop protection products is proposed, a careful analysis should be conducted for all users, from cereals to high value fruits. For example, it remains the case that markets and consumers prefer perfect fruits, with no tiny blemishes in the skin. In a climate change context, immaculate fruits cannot be produced without practical resources to combat pests and diseases. Research resources can help professional chemists develop molecules that are totally respectful to the environment, in combination with equipment developers that may construct intelligent sprayers (Ortí et al., 2022), capable of delivering the right amount of product to the targeted leaves and reducing drifts to the atmosphere and drips to the soil. Weed control can also be expected from physical technologies, like the selective electrocution of undesired plants. Such environmentally friendly equipment can be implemented after sufficient testing under many different conditions. The data gathered from such extensive tests are the basis for AI-based algorithms, which are implemented in smart field equipment. The competitive agriculture of the 21st century requires smarter machines and cleaner products; feeding 9.5 billion people by 2050, without state-of-the-art machines and without effective products, seems unfeasible.

Robotic solutions for mechanical weeding

The moratorium on glyphosate, set by many European states, has motivated the return of mechanical weeding which, in turn, has spurred on the development of small-size weeding robots powered by electric drives. The reduced size of these robotic platforms has mitigated some of the objections related to reliability and safety. In addition, the fact that these solutions are highly specialised limits the system complexity, as only one task (weeding) is performed at a time. Figure 3.2(a) shows robot Oz with a mass of 150 kg (Naïo Technologies, France) for mechanical weeding in horticulture, with 70 units sold in 2018, most of them in France. Figure 3.2(b) shows the Vitirover (Saint-Émilion, France) for mechanical weeding in vineyards. It represents a business model based on services, by which a fleet of robots executes the requested weeding task according to the instructions set by the in-field operator assigned by the company. This model releases the growers from operating and maintaining the robots because that is done by the company.

Figure 3.2 Robots for mechanical weeding: courtesy of a) Naio Technologies: Oz b) Vitirover.

a b

Smart weed control by spraying

The elimination of weeds with smart spraying requires the application of herbicides only where weeds are present, avoiding any spray on the soil or the cultivated plants. Artificial intelligence tools like machine learning techniques, and deep learning in particular, have significantly amplified the scope of computer vision and improved the detection success of weeds in crops. The US company Blue River Technology developed the technology 'see & spray' to remove weeds in lettuce production with machine vision. This technology gained a lot of attention, after the acquisition of the company by the leading manufacturer John Deere. (*Our Mission - Welcome | Blue River Technology*, n.d.)

Figure 3.3 Autonomous blast sprayers: a) GUSS (USA); and b) Jacto JAV II, Brazil (with permission).

a b

Data-driven precise spraying robots for high-value crops set in orchards and groves

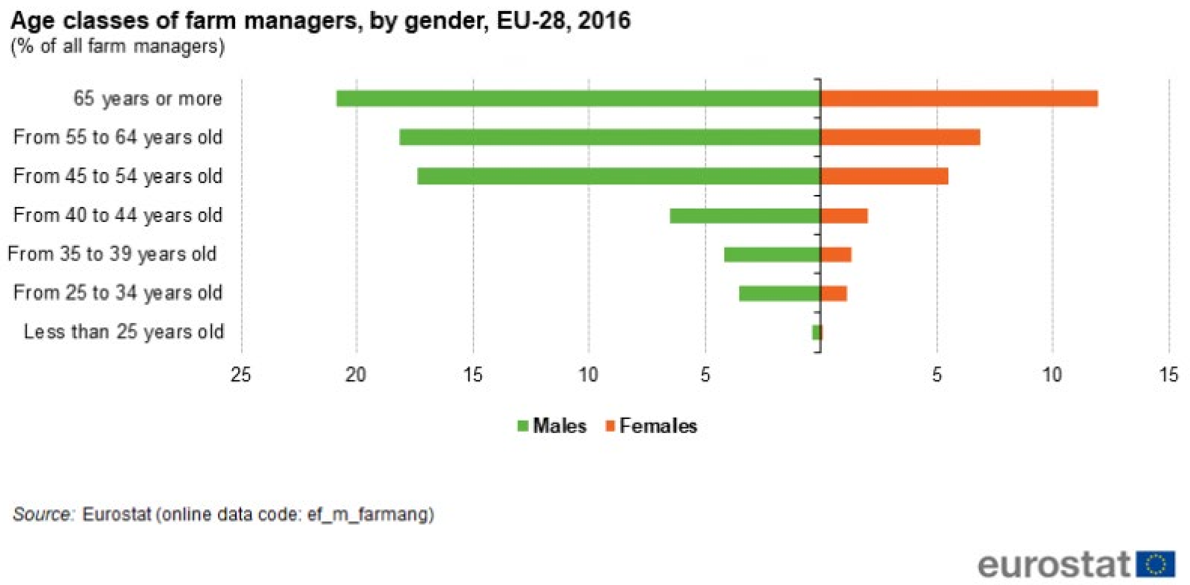
The delivery of crop protection products to fruit trees requires moving a tank with spray liquid around the fields and the actuation of a turbine that forces airflow to transport spray droplets to the targeted trees. These requirements pose a minimum threshold for power and size, complicating automation and the use of electrical power. To autonomously guide the large sprayer in Figure 3.3(a), he American firm GUSS (Global Unmanned Spray System, Kingsburg, CA, USA) possesses a fleet of large autonomously guided sprayers that can be stopped by a remotely controlled switch. A supervising team (stationed in a van nearby) follows the operation, granting both safety and quality of work. Similarly, Figure 3.3(b shows the Brazilian version of this idea with a sprayer built by Jacto (Pompéia, SP, Brazil). The autonomous vehicle can reach 15 km/h and discontinues spraying when vegetation is absent.

3.1.3. Barriers, limitations, and risks for future expansion

Alleviate high cost of advanced equipment by sharing

The successful deployment of AI throughout agricultural equipment, with the purpose of making it become 'intelligent' and efficient to execute automated functions, may be threatened and hindered by the following challenges, which can limit or even ruin their practical implementation and acceptance. The higher cost inherent in advanced technology, monetary cost of purchasing and time cost of learning, may be compensated by equipment sharing in farmer associations or cooperatives, but there are still many professionals who are not willing to share their equipment. Service providers have been effective in the introduction of sophisticated equipment. Nevertheless, the introduction of digital technologies that can embody AI applications is not always linked to unaffordable costs of machinery or the size of the holding. What may hinder a larger expansion of these technologies stems from other problems, such as the complexity of solutions, the age of the farmers, and uncertainty about the expected results or fear about a potential lack of returns. The following paragraphs examine some of these barriers more closely.

Figure 3.4 Age classes of farm managers in Europe in 2016 (includes UK)



Source: Eurostat*Farmers and the Agricultural Labour Force - Eurostat*, 2018

The challenge of an aging farming population

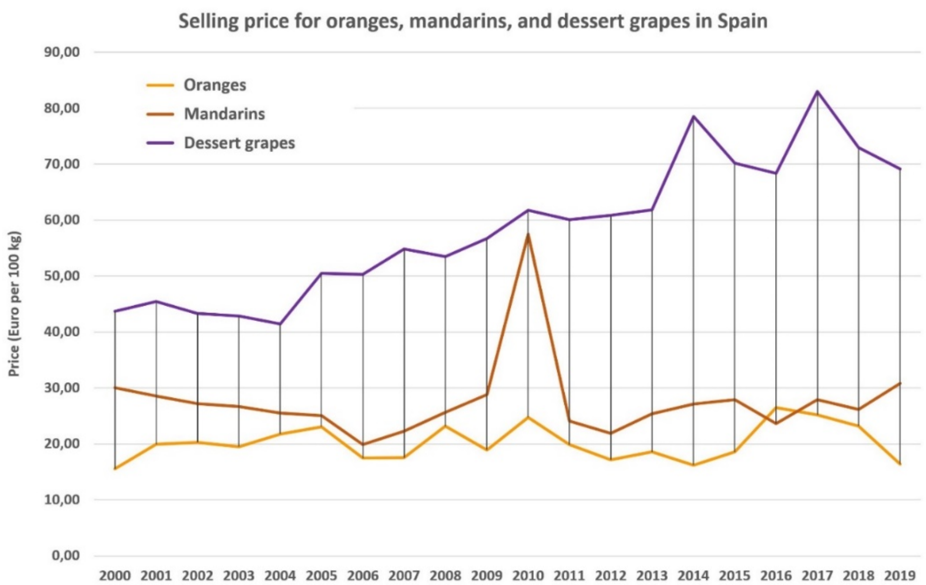
Eurostat statistics on farmers and the farm labour force show that, in Europe, farm managers are typically male and relatively old. Seven in every ten (71.5%) farm managers on the EU's 10.5 million holdings were male and a majority (57.9%) were 55 years of age or more. Only about one in every ten (10.6%) farm managers was a young farmer under the age of 40 (see Figure 3.4) and this share was even lower among female farmers (8.6%) (*Farmers and the Agricultural Labour Force - Eurostat,* 2018). The share of older farmers varies between countries but, in general, older farmers work on smaller farms, in terms of economic size.

Most farm managers in the EU only have practical experience; this was the case for seven in every ten (68.3%) of them in 2016. Less than one in ten (9.1%) farm managers had full agricultural training and the rest (22.6%) had basic agricultural training. In some member states, the level of agricultural training among farm managers was particularly low.

The age structures and the level of agricultural training underline the need to encourage a new generation of farmers that are well trained, including the digital training that allows them to get the most benefit from advanced technologies in hardware and software.

However, human resources may become an important barrier for the wide dissemination and actual implementation of digital applications advanced solutions relying on AI such as automation, robotics, and decision support systems. Twenty first century growers need professional instruction in the use of digital tools and vehicle operation. The fact that the average age of farmers is very high at present (makes a rapid transition quite difficult. An articulated *extension* network will be necessary to implant both novel technologies and new production concepts, such as sustainability and circularity. With the farms workforce in one track, and the policy-making representatives in the other, they will not find a meeting point unless the right intermediary agents are properly involved and endowed with the required resources. Education and training is, as a result, the key for a seamless transition towards the sustainable production of food, feed, and fibre in the digital age.

Figure 3.5 Selling price in Spain for citrus and dessert grapes (2000-2019)



Source: Eurostat

Lack of available labour makes crops disappear

Labour costs for the production of fruit in the USA often ranges between 40% and 60% of total production costs (Burks & Schmouldt, 2008), and the situation in Europe is quite similar, According to a recent study by the Valencian Association of Agricultural Producers (AVA-ASAJA), the average production costs of citrus fruits in Spain reached 0.23 € / kg for oranges, 0.28 € / kg for mandarins, and 0.20 € / kg for lemons in 2020. In addition to labour, farmers require fuel for machinery, good quality seeds, fertilisers, irrigation water, and crop protection products, whose cost is constantly on the rise due to tightening restrictions motivated by environmental regulations. These production costs have been increasing over recent decades, while farmers' profits have remained stagnant, or even decreased, for many products. Such low profitability has resulted in the younger generation giving up on agricultural activities as career opportunities. This has been the case in citrus production in Eastern Spain. Figure 3.5 establishes a comparison among selling prices for oranges, mandarins, and table grapes in Spain between 2000 and 2019. While grape prices have been increasing with consumer price indices, the prices of mandarins and oranges have been mostly stagnant over the last 20 years. This divergence, between increasing prices for production inputs (such as labour, fuel, or chemicals) and flat prices for produce values, has put the Spanish citrus sector under severe pressure.

Automation replaces labour?

The vision of robotics as the ultimate link in agricultural mechanisation, by which not only the physical drudgery of farmers, but also their mental effort in decision making, will be complemented by AI-driven intelligent machines, seems natural within the current technological trends. However, there is an always-present anxiety that remains unsettled, and which has its roots in the early beginnings of the industrial revolution: 'Are farming robots going to drastically reduce employment in agriculture taking farmers to extinction?' This is a non-trivial question that should be addressed with care, to avoid drawing unfounded conclusions. If the goal of digital agriculture is to ensure the sustainability of agricultural activities, it is obvious that the idea is not the elimination of farmers but just the opposite; grant them long-term permanency and welfare. The analysis of the impact from introducing robots in agricultural fields must rely on the use of data from trustworthy sources and the fact that the specific case of agriculture has needs, with problems and background conditions different to other industrial sectors. Unfortunately, given the novelty of farm robotics, there are not many sources available.

Use of robotics creates opportunities for crops and workers

In 1910, 18% of the USA's workforce was employed in agriculture. By 2012, this figure had decreased to 1%, mostly due to mechanisation (Stone, 2014), with similar trends in Western Europe. What happened to all that labour force? As mechanisation became established, the primary sector readjusted and many workers who could no longer find a job in the field were employed in the (agricultural) machinery manufacturing industry. The straightforward cause and effect relationship between the extinction of certain jobs and the rise of unemployment rates is not always valid because we should always take into consideration the elasticity in the market and its innovation capacity. As a matter of fact, data might prove the opposite. In the case of robots, the International Federation of Robotics declared that Japan had 323 robots per 10,000 workers in 2013, which is significantly higher than other industrialised countries like the USA, where the rate was 152 robots per 10,000 workers for the same year. Surprisingly, the unemployment rate for Japan in 2013 was 4%, which is much lower than most of the countries with clearly less automation implanted in their industry (Jordan, 2016). For instance, the manufacturing industry in Spain reported 160 robots per 10,000 workers in 2016, with an unemployment rate of 18.6% for that year. Nonetheless, each specific sector carries its own distinctive features and to draw meaningful conclusions, this analysis should concentrate on the agri-food sector. According to Burks and Schmouldt (2008), the introduction of robotics in agriculture can create more employment in the overall economy than it might initially destroy. It is not realistic to only consider the substitution of workers by machines because there are many crops for whose production there is not much skilled labour available, such as pruning in French vineyards, harvesting strawberries in Spain, or picking asparagus in Germany. For these situations, the dilemma is either automation or disappearance of the crop, with a strong impact on small family-owned businesses, which are dominant in Europe. On the other hand, the digitisation of agriculture can and will involve the creation of novel companies to manufacture and maintain intelligent equipment, provide consulting for data analysis and decision making, or assure the presence of extension agents to instruct end-users about digital tools. Indeed, end users will need assistance in operating such equipment, either because of training needs or because they may take insufficient time to read manuals or watch tutorials. As stated by Brynjolfsson and McAfee (2014), the progress conveyed through the digital revolution may enrich our lives as never before but at the expense of acquiring the basic knowledge that will allow the effective use of new advances. In this regard, 21st century farmers will have to cultivate a set of new skills, in accordance with today's available technology, as well as that to be developed soon. Agricultural robots may carry out the toughest tasks on the farm, those that nobody wants to get involved with, and which, as a result, often end up in the hands of immigrants. However,, what is 'rough' for locals is equally rough for immigrants. These hard tasks have a dissuasive effect on young people at the time of starting an agricultural business. It is likely that, in some cases, one will see robot-assisted activities that take the drudgery out of several tasks.

However, not every task in agricultural production is physically demanding and harsh; there will always be a need for planning, management, decision making, and strategy envisioning, for whose optimal delivery the producer remains unreplaceable. After all the evidence accumulated in the first two decades of the 21st century and despite the opportunities already introduced –and yet to be deployed– for the advanced management of modern agriculture, there is still a direct rejection of these technologies by a small group of practitioners, who feel the threat of progress to their status quo. This hostile opposition to technology is not new at all; it first appeared in England in 1785 when the first weaving machine was built. The same happened again in 1837, with the development of the steel plough by blacksmith John Deere because the steel, apparently, ruined soil fertility. Even today, there is a hesitation to embrace, or willingly reject, technology, including agricultural robots. The appearance of anti-robotic groups is possible, in the same way there are anti-vaccine groups.

3.2. Expert systems and decision support applications

3.2.1. The cycle of data management

Precision agriculture as a start

The concept of Agriculture 5.0 includes the farms that are following Precision Agriculture principles and using equipment with advanced features, such as variable rate technologies or decision support systems, often involving the use of robots and AI (Zambon et al., 2019). Raw measurements from crops need to be efficiently processed such that numbers or images unambiguously turn into valuable information for farmers. Crop management based on field data evolved with the advent of Precision Agriculture but it has been deeply transformed by the present digital era.

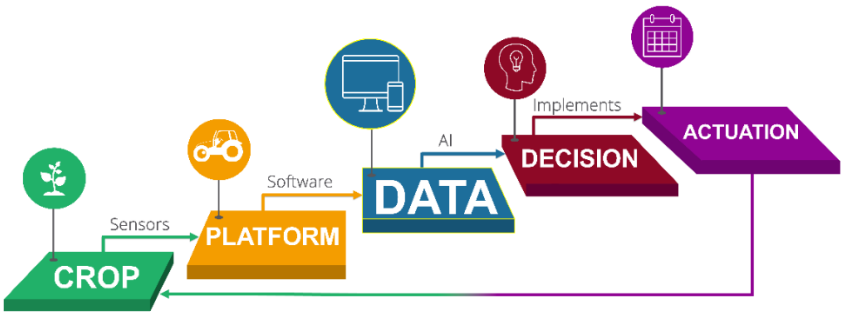
Farmers' observations or objective measurements

In traditional farms, where sensing technology has not arrived yet, field management relies on the visual inspection of crop development to diagnose problems and make the required correcting decisions. This approach requires field experience and is subjective because information is perceived through the eyes of farmers. Alternatively, in farms where advanced technology is available, field management may be systematically structured according to the operating cycle given in Figure 3.6 (Saiz-Rubio & Rovira-Más, 2020). This management system is based on objective field data and smart decision-making, in what is known as *data-driven agriculture*. In particular, it starts from the actual *crop* to manage, taking advantage of its inner variability, both spatial and temporal. The *platform* refers to the physical means with which information is acquired, mostly non-invasive sensors through which objective data are obtained. *Data* includes the information directly retrieved from the measurements taken from the crop, soil, or ambient conditions.

From data to decisions to response data

The nexus between the data and the *decision* stage involves filtering routines and AI algorithms for simplifying and interpreting the data, to help the grower make optimal decisions. Finally, *actuation* refers to the physical execution of an action commanded by the decision system and it requires the use of advanced equipment that can receive orders from a computerised control unit. Each action takes place during crop growth; therefore, the cycle in Figure 3.6 starts again when the response of the crop is registered by sensors and the loop continues systematically, until harvesting time, which marks the end of the crop life cycle.

Figure 3.6 Cycle of data management



Source: Saiz-Rubio & Rovira-Más, 2020

3.2.2. The lack of massive data: route to Big Data conditions

How to get the high-density data available

One of the fundamental differences between traditional and modern farming, apart from the mechanisation level, is the data collected directly from the crops. In traditional farms, where growers judge by visual assessment, decisions are relative and subjective. Modern farming, on the contrary, focuses decision making on quantitative data to grant objective decisions. However, the excess of data can become a challenge to cope with, as vital information may be masked by noise. The popularisation of the global positioning system (GPS) and precision farming, in conjunction with the availability of affordable sensors, has revolutionised the way farms are managed; an important, central role is played by field data in decision making. Nevertheless, despite the increased interest in data-driven agriculture (Saiz-Rubio & Rovira-Más, 2020), the reality in farms is far from being *big data driven*, mostly due to the lack of field data with the proper *density*, *precision*, and *frequency*. In fact, the acquisition of field data is often based on manual sampling, such as the assessment of fruit maturity to determine harvesting time. These manual data acquisitions can only be performed a limited number of times per season, for practical and economic reasons, resulting in scanty sampling that also risks introducing the subjectivity of each operator.

Where are the best available data on the crops

An initial effort to make the acquisition of field data more efficient has led to remote sensing images, either from Earth observation satellites or airplanes –both manned and unmanned– equipped with sophisticated optical systems. However, some physiological phenomena mostly depend on the environmental conditions surrounding each plant. The lateral portion of trees, where fruits are typically carried, often provides richer information than zenithal measurements, e.g., the relative humidity enveloping a tree canopy for estimating its vapour pressure deficit. Thus, it is often more convenient to monitor the status of each tree than airborne images taken far above canopies. Unfortunately, hiring an operator for monitoring orchards is not cost-effective either. The EU-funded VineScout project (2017-2020) faced the challenge of data collection in vineyards by designing and building a robot to systematically monitor grape vines and their surrounding environment. In particular, the VineScout robot (Figure 3.7(a)) senses the right side of the trellised canopies every two rows, acquiring leaf and air temperature, relative humidity, atmospheric pressure, and the spectral indices NDVI (Normalized Difference Vegetation Index) and PRI (Photochemical Reflectance Index), with the purpose of better understanding and tracking the water status and growth rate of the vines. Figure 3.7 shows the robot mapping a commercial vineyard at high resolution with speeds around 2 km/h, to achieve massive sampling. For the vineyard in Figure 3.7(b), for instance, the robot scanned 14 rows in 71 minutes to cover an area of 0.65 ha with a map of 14,856 data points, yielding a 'density' of 2.3 points per m^2 (Rovira-Más et al., 2021). For the sake of comparison between massive sampling and regular sampling, water status was manually measured for the monitored rows with a pressure chamber to perform ground truth correlations, distributing 36 measurements over the 0.65 ha, which resulted in a data density of 0.0056 points per m^2. Although the robot can navigate without GPS (Rovira-Más et al., 2020), global positioning is necessary for building the high-resolution crop maps.

Figure 3.7 VineScout robot for monitoring olive groves (a) and vineyards (b) at high resolution. (source F.Rovira-Más)

a b

3.3. Intelligent crop planning

3.3.1. On farm planning

Lately, technologies such as the use of Big Data, Cloud Computing, Remote Sensing, Agri-robotics and the Internet of Things (IoT) sensors, combined with the use of AI, are increasingly used in every aspect of the agri-food supply chain (AFSC). These technologies have contributed to the accumulation of an explosive volume of data and information and the transition to the new farming era, the so-called Agriculture 4.0 (de Clercq et al., 2018; Liu et al., 2020; Zambon et al., 2019; Zhai et al., 2020). Nevertheless, the level of the exploitation of these data in the agricultural sector is still relatively low (Wolfert et al., 2017; Kamilaris et al., 2017), neglecting a tremendous opportunity for disruptive data-driven innovation with regards to more optimised and sustainable production and consumption practices in the long-term.

Data analytics for agri-food supply estimation

In this light, big data analytics can play a key role in the transformation of data into added value for agri-food stakeholders, through its capacity to efficiently aggregate, process and visualise large and complex datasets. Despite being an emerging technology, big data is a domain that is expected to have a high impact in the organisation of this new agricultural era. By leveraging high-volume, multi-source, real-time and historical data with processing, forecasting, and tracking capabilities, it is expected that farm management and operations will change drastically, promoting the continuous improvement of business models. Beyond more common applications, such as optimising production yield by finding optimal parameters (e.g. temperature and rainfall) based on large, historical, multi-site datasets (Majumder et al., 2019) , big data analytics also opens doors for other more complex and less common cases. An example of this is the estimation of food availability in developing countries, to address the challenge of sustainable food security, enabled by the analysis of land use and production data from more than 13,000 farm households, across multiple sites in 17 countries across sub-Saharan Africa (Frelat et al., 2016).

Machine learning and integrated farm planning

Combined with cloud computing and IoT, AI (and particularly machine learning (ML)) has been identified as one of the main driving forces towards integrated farm planning. Recent studies highlight ML as being one of the most promising techniques currently being explored in this regard (Kamilaris et al., 2017; Liu et al., 2020). ML has applications in the areas of food availability and security, weeds, soil, crop and animal monitoring and management, as well as weather and climate change. ML algorithms have been used to maximise crop yield and minimise input costs, since they can identify complex patterns, trends and relationships in the multidimensional, heterogeneous agricultural data. They can make accurate predictions and provide a strong foundation for improved agricultural decision-making and operations management (Shi et al., 2019). In a recent review by Liakos et al. (2018), it is mentioned that 61% of published agriculture sector articles using ML approaches were from crop management, 19% from livestock management, 10% from soil management and 10% from a perspective of water management. Within Agriculture 4.0, a number of different approaches are emerging from the scientific community, including privacy-preserving mechanisms to deal with the cyber-security and privacy issues of the digital era.

Decision support systems

A Decision Support System (DSS) is an indispensable tool in many different sectors and the agricultural sector is a perfect candidate, since agricultural activities are often complex (due to the many physical, chemical, and biological processes involved) and require a large amount of data to be processed for proper management. A DSS is a software mechanism which aids an end-user to easily and quickly leverage complex data to improve decision-making processes. Hence, both raw data and the output of analytical tools can be converted into knowledge and presented through a user interface in an interpretable way. A DSS can help decision-makers make more effective decisions, when dealing with poorly defined and complex data. However, one of the characteristics of an agricultural DSS is that, typically, it has a low autonomy level. Given that, farmers have total responsibility for taking the final decisions (i.e. actions) by validating (or not) the suggestions/instructions provided by the DSS (Zhai, et al., 2020) which, in turn, can show some kind of autonomy level within clearly defined system boundaries.

3.3.2. Planning by producer organisations or cooperatives

Market forecasting

Market demand fluctuates quite rapidly, which means that agri-food companies must be one step ahead to act in time. Facing this, companies have been pursuing predictive analytics techniques to improve their supply chains and optimise marketing operations. Due to its ability to effectively discover trends and patterns in large datasets, ML methods allow predictive analysis that can support not only agricultural operations, but also retail (Huber & Stuckenschmidt, 2020). Thus, considering financial constraints to make an accurate market demand forecast, and an automated inventory control system is a game changer for the retail sector. In addition, ML methods can also predict market prices and the tendencies regarding the agri-food sector that will be in the pipeline soon, by understanding the behaviour of market demand. With this, AI-based techniques have become very popular among producer organisations and cooperatives, to efficiently boost supply chain performance, increase productivity and profit, optimise stock management and resource allocation, reduce costs and waste and increase customer satisfaction.

Reliable and trusted food supply

It is known that, in recent years, consumers have been increasingly concerned with how agri-food products are produced, handled, packaged, stored and distributed, in the same way they want to know the authenticity and origin/traceability of the same products. Additionally, global shocks and disruptions in supply chains (e.g. those caused by the COVID-19 pandemic) have made it evident that robust agri-food systems are crucial. There is a huge need for a resilient, functional, equitable, fair and transparent AFSC that will benefit farmers, involved stakeholders (including the processing industry, suppliers, retailers, etc.) and consumers. Besides that, a sustainable circular bio-economy can serve to mitigate the socio-economic impacts caused by global crises, especially with regard to food security and safety for those in greater need.

Logistics from producer to consumer

Therefore, the logistics domain is also of great importance within the context of agricultural organisations and cooperatives and refers to the physical flow of entities and related information from producer to consumer, in order to satisfy consumer demand (Talavera et al., 2017). It is present in all stages of the 'Farm to Fork' journey and each stage has the challenge of maintaining product integrity, efficiency and quality (Nukala et al., 2016). Until they reach the 'Fork', agri-food products are exposed to different conditions that can potentially degrade their quality. Lack of, or weak, temperature and/or humidity control, incorrect physical handling and delays, as well as the increasing threats to food security and the inevitable food loss and waste, have led to the tremendous need for a traceability system. These systems are considered an important quality control mechanism that guarantees the safety of agri-food products, throughout the cycle from farming to consumption (Prashar et al., 2020).

Internet of Things and wireless sensor networks

In this regard, advances in Agriculture 5.0 have provided new opportunities for the digitalisation and automation of the entire AFSC, by promoting IoT-related applications and data-oriented technologies and offering new and effective services for end-users. For instance, IoT-based systems using WSNs can provide continuous, automatic and up-to-date information on crop product storage, allowing managers to make decisions about what products should be given priority to be handled and/or removed, in order to avoid losses or deterioration.

Blockchain and transaction integrity

Blockchain, the distributed ledger technology behind Bitcoin and other cryptocurrencies, also has a big role in AFSC management, as it can be used to know who is performing which actions, including the time and location of the same actions. Blockchain can provide end-to-end traceability and integrity of all transactions and ensure that all information produced along the AFSC is auditable, if all agri-food parties implement transparency measures in their processes (Kamilaris et al., 2017; Wolfert et al., 2017). Transport operators will be able to monitor important parameters (time, temperature, humidity, etc.) inside the containers in real-time, by using adequate sensors. Whenever a value exceeds the established safety limit, an alarm is immediately triggered (Galvez et al., 2018; Kshetri, 2018). In addition, it is possible to predict delays in product delivery and, in this way, react through active cooling or decide on a faster route. In turn, by analysing the transportation data reports, retailers will be able to accept or reject the goods, which is of great importance when dealing with sensitive and refrigerated products. In addition, they will be able to manage the goods stock based on their current condition. Blockchain can also be used to prevent food fraud, which causes enormous economic losses and reduces consumer trust, by tracking and authenticating the AFSC and understanding the provenance of products (Galvez et al., 2018).

Detect and predict problems

If the right tools for monitoring are used, allied with advanced data analysis, it is possible to accurately detect problems in the AFSC, predict them before they occur and make faster and better decisions, to improve the resilience and sustainability of AFSCs. In fact, Agriculture 4.0 allows more intelligent management of AFSCs, with the vision of reinforcing logistical efficiency, addressing food safety and security, mitigating inherent risks and complying with certifications and regulations. Additionally, it aims to promote provenance traceability and food authentication, increasing the relationship between stakeholders and ensuring consumer confidence that the products are genuine and of high quality, among other aspects.

3.4. Challenges of AI in field crop production

3.4.1. Infrastructure resources required

The successful implementation of AI techniques in daily operations at field level requires important human and technical resources. Many AI algorithms are not practical, either because they demand an unavailable, high flow of field data, or because they require high computational power. The real-time transmission of field data to the cloud is not ensured in most rural areas where crops are typically grown and 5G or the internet, if available, can be unreliable. On-board computation and data storage is a convenient way to alleviate expensive infrastructure requirements while avoiding the loss of critical field data. Technical resources, therefore, may be demanding but cost-effective solutions are already accessible.

3.4.2. System wide challenges

Some of the challenges of AI in agriculture can be framed at a system-wide level, meaning that they encompass general characteristics of the system that do not pertain to a singular layer of the architecture at an individual level, but should emerge from the system. These include aspects such as the scalability of the solutions and their flexibility, meaning the capacity to adapt to changing conditions or requirements dynamically, in a robust manner. These aspects, along with the real-time capability of the service layer, are crucial in coping with the real-time and ever-changing dynamics of the global economy. As the system grows and adapts, it can also become increasingly complex, making it important to find ways to keep this complexity in check.

3.4.3. System dynamics and continuous improvement

A major point that relates to this system dynamics is the aspect of continuous improvement and engineering, which is enabled by the system's combination of real-time data and capacity to learn and adapt through AI. New approaches should leverage data collected in real-time, not only to ensure that the system performance can be improved but, most of all, that it can be at least maintained in the face of these dynamic conditions inherent to real-world environments. In the case of ML applications, this entails dealing with aspects such as concept drift, which refers to instances in which the distributions of data may have changed from those with which models were initially trained. As such, integrated approaches for seamless and automated monitoring, adaptation and validation of deployed solutions should be explored.

3.4.4. Concept drift

The use and modification of innovative deep learning (DL) techniques, such as the different variates of Autoencoders (AE) or Generative Adversarial Networks (GANs) could, potentially, be a way to reduce the aspect of concept drift. This can be succeeded by the augmentation of the training set with data that are generated by the aforementioned DL models and that can be processed in such a way that they will include possibly distractive parameters or noise and will expand the range of the training set distribution.

3.4.5. Model generalisations or overfitting?

Integration into deep learning algorithms has recently been introduced in the field of agricultural AI techniques. However, the attention mechanism applied in most cases has been case-specific, with a lack of model generalisation; only using a single attention mechanism can potentially cause overfitting of the model. A multi-head attention mechanism can establish a long-distance dependence of the input image, providing different attention to different positions of the image.

3.4.6. A convincing reliability

Farmers worry about the reliability of the machines, in terms of their correct operation, as well as reliable mechanics and electronics. Indeed, they are afraid that a breakdown at a key moment in the season (for example, at harvest time) puts part or the whole crop at risk. Here, testing sandboxes for integrated mechanical, electronic and AI systems can increase confidence.

3.4.7. Training the farming population

The age structure and the level of agricultural training underline the need to encourage a new generation of farmers that are well trained, including the digital training that allows them to fully profit from the advanced hardware and software technologies. Demonstration activities and small field trials can help to convince farmers. Furthermore, demonstrators where the weaknesses or failure risks are shown are also necessary as learning tools before a full scale deployment can be successful.

3.4.8. Mechanisation as a service

Custom operators or specialised machinery operators should also be made aware of the importance of the data being collected during their field work. Every operator should be able to explain his qualifications and the type of service he delivers to his customers.

3.4.9. Crop protection

The efficiency of crop protection can be improved by the intensive use of aerial images, ground based information, weather conditions and forecasts, as well as a history of prevalence in the field. In epidemiological models for weeds, pests and diseases, AI based on data can contribute to more sustainable crop protection.

4. AI in soil and water management and irrigation

Soil and water management has a number of new challenges. Climate change has made the weather more unpredictable and, therefore, forecasting is becoming more difficult. Periods with storms and high rainfall alternate with dry periods. More crop stress, caused by higher temperatures or by excessive rain or floods, is to be expected. Heat resistant varieties are one of the options but intelligent long term (longer than one growing season) water management is another necessity. During summers with high temperatures, flooding and the submergence of crops during longer periods can be detrimental. At the same time, temperatures are higher and more droughts are expected; the crops need more water, either fed by rain or irrigation.

Challenges from a crop growth perspective are important, but the role of the agricultural land in groundwater recharge and flood reduction also needs to be optimised as an ecosystem service to society.

Using AI, we can combine real-time information from sensors, weather forecasts and crop soil modelling. In addition, spatial information from drones and satellites is accessible. In this way, climate adaptive management becomes feasible by taking into consideration the temporal and spatial variability of the soil and crop status in the field. It allows fast responses and reacts proactively to forecasts.

Finally, AI decision support should be a combination of real-time sensors feeding data and imagery into crop growth and soil water balance models for the most optimal decisions. In general, the local level focusses on the farm and crop productivity, while the water resources require a regional dimension at the level of entire river basins and aquifers.

4.1. Water budgeting at local or regional level

4.1.1. Real-time crop stress identification and prevention

A whole range of sensors can now be connected by the Internet of Things (IoT). Small solar panels and widespread internet coverage IoT has become feasible in the field, even at a distance from farmhouses and main power supplies. Although prices for the IoT are affordable, the sensors themselves are still expensive and in a dense network. AI needs to integrate this continuous stream of information into a decision support system.

There is a lot of tradition and experience with irrigation scheduling in many parts of Europe, especially in the South (e.g. Spain) (García et al., 2020). Planning irrigation applications is normally based on crop evapotranspiration (ET) estimations, rainfall measurements and soil water accounting, ideally updated by soil water sensing and weather forecasting. Farming tends to aim at the highest productivity, which often leads to supplying the average crop with more than the total water requirement. Large efficiency gains are possible. One cause is that the application of water has a degree of non-uniformity and, therefore, if the farmer wishes to give an adequate dose for the entire field, the farmer needs to over-irrigate most of the field. The higher the uniformity of an irrigation system, the less over-irrigation is needed. Crop water productivity (i.e. the amount of yield per volume of water consumed) is important. A shortage of water to about 70% to 80% of the water requirement (depending on several factors) often results in the highest crop productivity per unit of water. However convincing farmers to apply deficit irrigation, or less than 100%, remains an important challenge (Alcon et al., 2014).

The water for plant growth is taken up by the roots. The consequence is that the entire root zone needs to be considered and not just the top few centimetres. Also, the growth stage is very important. For example, pears in Belgium need careful irrigation depending on the growth stage (Janssens et al., 2011).

Measuring meteorological data by automatic weather stations connected to the internet is now reliable and low-cost. Measuring rainfall, temperature and humidity by low-cost internet-connected meteorological stations is highly reliable, provided the station is well installed and located. However, estimation of evapotranspiration (ET) by the recommended Penman Monteith method also requires proper wind-speed and radiation data. Low-cost sensors for the last two variables (wind and sunshine) are less reliable, and need to be calibrated and/or continuously cross-checked with nearby high-quality more costly stations or even research stations and advisory services. An AI-based management model should have proper data-assimilation procedures to integrate low cost meteorological stations and combine them with higher quality ones.

Soil water accounting models with rainfall and estimated crop evapotranspiration have already been used for some time. Adding AI can combine more sources of information, and check and update it by using real time soil water sensing. One particular challenge is the variability of the field in space and depth. Such sensors are to be placed in several places in the field at a minimum of two to, preferably, three depths. Therefore, a large number of low cost sensors could be preferred more than a low number of expensive but more accurate sensors. The 3D variability within the field can be captured in this way.

In agriculture, soil water monitoring (Evett et al., 2012) by in situ sensors can involve tensiometers, TDR, capacitance measurements or electrical conductivity. Measuring temperature within the same sensor is often carried out and allows a temperature correction.

The electrical conductivity-based sensors have the lowest cost and are easy to monitor. Commonly, an outer coating porous material is used around inside electrodes. The water content inside the porous material is in equilibrium with the soil water. The electrical conductivity between the electrodes relates well to the soil water content if the salt level in the soil is not too high.

Tensiometers provide some of the most useful measurements because they measure the water potential, which is directly related to the ease of water extraction by roots. However, tensiometers need continuous attention. Now, they can also be monitored digitally in real time and malfunctions can be identified quickly. The digital tensiometer also extends the measurement range to -150 kPa, which is almost double the range of the manual equivalent.

Time Domain Reflectometry (TDR) and Frequency Domain (FDR) sensors are quite expensive for economic agriculture. They use more sophisticated measurements of the dielectric constant of the soil. As the dielectric of water is much larger than the mineral or organic fraction and the air, this is a very precise method which, for most applications does not require calibration. Ideally, a sensor is not impacted by the salinity of the soil water; the higher the frequency, the less the impact.

The FDR can contain the electronics inside the sensor and the minimum cost is about 150 €. The TDR works at a higher frequency and is not so affected; it can even be used to simultaneously measure soil water content and electrical conductivity. Unfortunately, TDR measurements commonly require multiplexing of the connection to a specific TDR monitor. This makes it less practical for large fields and is the most costly method.

It is important to stress that remote sensing radar or microwave techniques only measure a shallow top layer of soil, to about 1 cm, and most methods depend on modelling of the deeper layers.

The low cost amateur sensors for use in gardens are also installed in the top layer and, in most cases, they do not measure the entire root zone. They are commonly based on electrical conductivity measurements, as explained earlier in this text. As already mentioned earlier, the roots take up water. So, the entire root zone should be measured.

Depending on the rooting depth of the crop, this means that the deepest sensors need to measure the water at 60 to 90 cm below the surface.

Monitoring the above ground crop status by remote sensing has more recently been developed. Stress can be detected by thermal and multi or hyperspectral imaging. Although these methods are very useful for remote sensing and research, when water stress is detected, it is often too late for irrigation scheduling. Remote sensing by drones or by satellites (with regular passing intervals) is useful, although NDVI methods still suffer from cloudiness, they are most useful to follow the biomass growth and detect differences in growth within the field. Most irrigation managers agree that sensing stress in the vegetation as a trigger for irrigation scheduling is often too late and not as reliable. However, remote sensing is still useful. A regular follow-up of the spatial distribution of biomass within a field is necessary information for precision crop management. It is important to identify the reasons for differences in biomass production. Although the harvest can often be related to the biomass, the harvest index (harvest per biomass) is not necessarily identical within a field.

Methods following the turgor in cells and/or the sap flow in orchard trees are very useful for research but less so in the practice of commercial farming.

Irrigation scheduling, along with soil water accounting in the entire root zone, benefits from real-time in situ measurements. AI is needed to assimilate the measured online data for correction of the root soil water balance and improving the scheduling accuracy. A combination of low-cost sensors and the spatial 3D root zone monitoring, together with vegetation monitoring, is needed.

A more efficient and rational water use for crop growth is possible by a combination of modelling, soil water sensing in the root zone, remote crop biomass monitoring and weather forecasting. Irrigation scheduling requires a good follow-up of the water in the root zone of the crop. All these data sources should be integrated into the AI approach.

4.1.2. Water supply monitoring

Flow data in irrigation pipes or canals can also be monitored in real-time by IoT because of solar panel powered internet connected sensors. This allows us to follow the quantity of water at any place in the irrigation system by wireless means. Typically, for pressurised irrigation there can be continuous detection of leaks and a very quick response. The volumes of water can be administered to the crop more precisely and accidental losses avoided.

Hydraulic structures should be installed on canals. The water levels are monitored by pressure transducers or by ultra-sonic sensors.). The latter is often preferred as it is without contact with the water. Currently, they are also low cost and easy to integrate to monitor continuously. In addition, as costs have been reduced, extra sensors can be installed downstream of the hydraulic structure, to control possible backwater effects and prevent faulty interpretations. A hydraulic structure always implies a (small) loss in hydraulic head.

Similar possibilities exist for pipes. Measuring the pressure drop along a Venturi allows monitoring of the discharge in a pipe. The small pressure drop occurs in the Venturi needs to be compensated by the pump, to obtain the required pressure and discharge for the irrigation system.

Propeller meters have traditionally been used for monitoring volumes of water. This is common practice, especially for water accounting of flow through pipes. Nowadays, they are also available with digital connections to the internet.

The transit time of an acoustic signal between two or more points in the pipe is more expensive. Such a measurement does not imply pressure loss and the need for a Venturi or an orifice restriction inside the pipe. Also, magnetic flow meters on flow pipes are possible.

In a similar way, either velocity radar sensors or acoustic dopplers can be installed on irrigation canals without the need for hydraulic structures and without loss of hydraulic head. The velocity radar sensor has the advantage of being non-contact, which is a major advantage for flow with a high sediment load.

While pressure transducers and ultra-sonic level sensors have become low cost (25 to 50€ for the sensor and approximately 100€ for the internet link), the acoustic dopplers cost at least 5000€ for one sensor. So, for a dense measurement network on pipes and canals at different levels within an irrigation system, the lower cost systems could be preferred. Precise and spatially detailed information from the irrigation system can be integrated in the management of the entire system using AI. Any malfunction and/or leak can be quickly alerted, in order to save water. Along with the real-time monitoring of flow valves and weirs, the irrigation system can be operated by IoT.

4.1.3. Reduction of water use by smart irrigation and smart micro-irrigation

In many countries in Europe, a flexible reel machine with a moving rain gun (Figure 4.1) is used. This is, however, a method requiring high pressure (energy costs are a linear function of the pressure for equal application rate) and suffers high wind-drift losses. Rain guns can be equipped with a solar-panelled GPS, pressure and spray-angle control connected to remote control over the internet. As an example, the rain gun can be stopped automatically or remotely if the wind becomes too strong.

Replacing the rain gun (Figure 4.1) by a spray boom (Figure 4.2) already allows for an important water saving, especially under windy conditions. In addition, the much lower pressure for a spray boom implies an important energy saving. The spray boom, which irrigates much more uniformly, also allows for monitoring of pressures and discharges within the system. A spray boom is, however, more expensive compared to a rain gun. If water and energy savings are not perceived as being important, farmers will not be eager to convert to the more efficient spray boom, which can also allow for differential and more precise irrigation within a field. As mentioned before, the more uniform the irrigation equipment is, the more water efficient it becomes.

Figure 4.1 Rain gun attached to a reel machine (not in the photo) (source Guido Wyseure)

Even more saving can be realised by drip-irrigation. This system supplies the root zone directly and avoids wind drift losses and soil evaporation. While a reel machine with a spray boom is highly flexible and can be used for different fields, a drip irrigation system is a permanent installation and, therefore, not as flexible. This poses more challenges for land cultivation and crop rotation. An additional advantage is that a drip irrigation system can be remotely controlled and pressures can be measured inside the system. As such, a high level of automation is possible, in conjunction with soil and water monitoring. Drip irrigation requires water quality control and allows for "fertigation". This means that a very precise, timely and more efficient demand for fertiliser is possible with less nutrient losses to the underlying aquifer. Sensing the pH and the EC of the irrigation water is important for proper functioning.

An AI system for the spray boom or the drip-irrigation that measures the water supply and combines this with the soil water monitoring, increases the efficiency and reduces excess water delivery. This should improve the management at the field, farm, and irrigation system level.

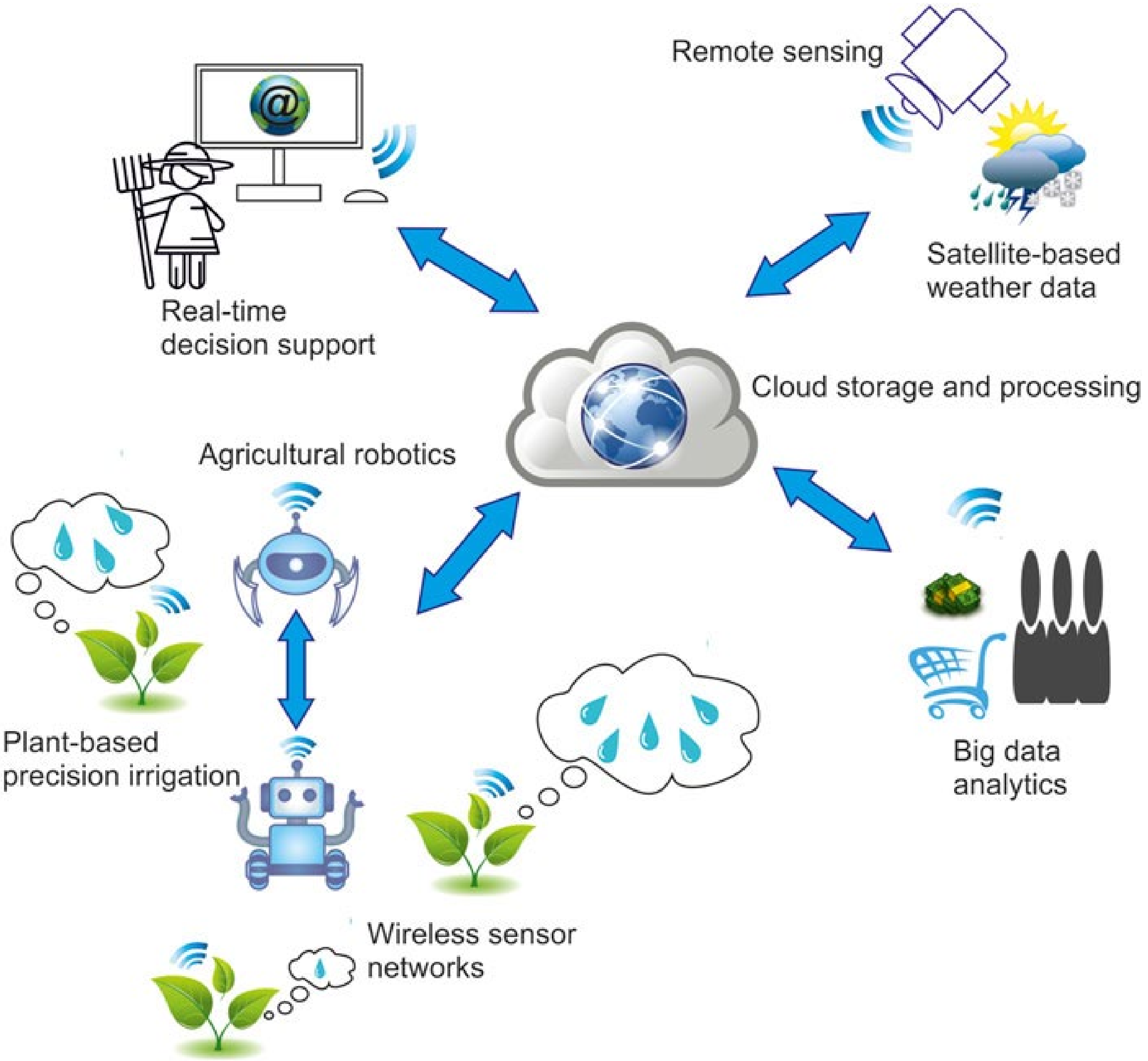
Figure 4.2 Spray boom attached to a reel machine (source Guido Wyseure)

4.1.4. Improving the efficiency of water use

Variability in soil properties and soil profiles within fields implies that there is a spatiotemporal variability in soil water content and water stress experienced by plants. This may mean that, under a uniform irrigation regime in a particular field, the crop water use efficiency can be very variable, leading to non-uniform crop growth and yields. Scheduling the timing and volume of irrigation can be improved if there is a better estimate of the forecast irrigation needs in different field locations, based on a combination of local sensing of the crop and soil indicators, as well as water loss due to evapotranspiration.

A monitoring system that captures several plant, soil and weather parameters can feed enhanced models for the dynamics of water use and water needs. These can be physics models enhanced by AI with data processing of all the available data and their temporal, as well as spatial, variability. Such a system ensures that most local disturbances are incorporated for predictive accuracy. A novel irrigation control strategy, based on a hybrid model of predictive control can, after suitable field evaluation, results in improved water use efficiency and water productivity (Bwambale et al., 2022). Efforts have been made to include rooting depth in the irrigation technology, thereby changing the depth in the soil where water is delivered, to have the best uptake efficiency (Liao et al., 2021). Much of the stress and burden of irrigation can be reduced for farmers and users. In some cases, farmers can also remotely visualise and monitor their cultivation environment, to see the performance and state of their plant and soil conditions, as well as control the status of actuators using mobile phones and computers (Abioye et al., 2022). Reducing water consumption will have to consider the soil variability and the response of the plants to make a more efficient use of every applied drop of water. Plant-level sensors can give individual plants or plant monitoring units the ability to communicate their needs in real time. After all, the best-placed entity to answer the question "how much water is too much water" is the individual plant, communicating its needs. real time and determining when it wishes to be watered, how much water it requires, and how much thirst it can take before compromising the final expected yield (Owino & Söffker, 2022). Artificial intelligence combining plant and soil and weather data with accurate, dynamic growth models can look at specific scenarios in the management of the available water as well as the expectations of yield quantity and yield timing (Figure 4.3). Efficient precision irrigation technology supplies the water to each field or part thereof according to the growing season and these expectations. In the next step, improvements of the irrigation management can be expected from the use of digital twins. This also opens opportunities for precision "fertigation".

Figure 4.3 The future of precision irrigation control, with cloud-based data storage and processing, real-time communication between plant-based sensors, intelligent agents (including robots), supported by weather data and market analytics. (Owino and Söffker, 2022)



4.2. Management of aquifers and river catchments

Integrating the local management at a regional scale is important in managing the water resources in aquifers and river catchments.

4.2.1. Monitoring water level in soils and rivers

Most countries in Europe have a network of river and aquifer monitoring. We do not elaborate this detail here but the measurement of water resources is fairly standard in most member states. Several existing water information systems allow real time access to data by the public including the farmers, especially to river and canal levels and discharges.

Real-time access to groundwater levels is less common and those levels change more slowly. But more real time sensors connected to the internet would also be very useful for following the groundwater reserves in real-time.

The integration of regional water resource levels and the forecast of water resources availability into irrigation and drainage management opens up new possibilities for intelligent proactive management under drought conditions.

4.2.2. Information on phreatic water table for run-off management and groundwater recharge

Some water managers blame the draining of agricultural fields in many parts of Europe for water shortages. It is important to understand that most agricultural drainage systems are meant for workability and trafficability during early spring, to allow field operations and grazing, but not for summer conditions. Also, during harvest in the autumn and early winter, machinery might damage the soil structure of very wet soil. At the same time, it should be well understood that roots for almost all crops (rice is an exception) grow in aerobic conditions and not in saturated conditions. Crops with shallow roots will suffer more severely during dry periods. Also, during the summer, the excess of evapotranspiration over rainfall reduces the groundwater recharge to zero, regardless of whether there is a pipe or ditch drainage system or not.

Figure 4.4 Level controlled drainage with higher water level and lower outflow. The manhole on the collector drain is blocked (courtesy of https://www.boerennatuur.be/peilgestuurde-drainage-en-subirrigatie/).

Shallow phreatic water can contribute to root zone water supply by capillary action. Therefore, level-controlled drainage (Figure 4.4) lowers the water table when needed for workability/trafficability and keeps water levels higher during the growing season in the summer. This is often done manually by controlling the water level in the manhole of the collector before discharge into the ditch.

It is important to stress that level-controlled drainage is only feasible in flat low lying areas with shallow groundwater. In sandy areas, the control of the water level by ditches is sufficient and there is no need for the installation of tile drains. In medium textured soil with shallow phreatic water, drainpipes have added value. The fine textures, like heavy clay, have too low a conductivity for effective drainage.

Measuring groundwater levels in a drainage system allows us to adjust the groundwater level automatically in a climate adaptive way. In combination with distance controlled, adjustable weirs and levels in the manholes, climate adapted drainage is possible.

Higher demands of ET during the dry and hot periods can steer a rise in water so that more capillary rise can reach the bottom of the root zone.

Alternatively, forecasts of heavy rain can be a signal to lower the table in order to create an extra buffer in the root zone to store more rain and to reduce runoff. Immediately after, storm levels can rise again. AI can contribute to climate-intelligent groundwater level management with advantages for local crop growth and regional water management at the same time.

4.2.3. AI based weather forecasts for drought or water excess

Weather forecasting has been improved by the use of supercomputers and cooperation between weather services. In general, predictions for the next 5 to 7 days are accurate, especially for temperature and general weather conditions. However, the amount of rainfall is still more difficult to predict. Therefore, local weather stations are still useful and should be integrated.

For agricultural drought, it is important to stress that it is the storage of soil water in the root zone that matters.

4.3. Challenges for AI in soil and water applications

4.3.1. Macro-management of the water supply

The AI will allow the integration of several sources and a large quantity of data to proactively and quickly react to multipurpose management of the crop, along with the conservation of water resources. The online connection through the IoT of a large and diverse sensor network is important for soil water balance models that drive irrigation and drainage scheduling. It leads to the climate adaptive control of phreatic water levels for sustainable and economic crop growth. At the same time, the water supply and phreatic level control can be monitored and integrated within the local water balance models. Data assimilation algorithms need to update the models with the observed variables. With a high number of sensors, monitored simultaneously by IoT and with a very short time interval, a continuous automatic data check and correction is essential. In addition, spatial images of crop biomass from satellites or drones can be integrated. Ideally, the models can consider the status and forecasts of regional water resources, to preserve the quality and quantity of the resources.

Careful regional and local water table management in low lying areas, by AI-steered phreatic water level control, should replace the former simplistic view of agricultural drainage.

4.3.2. When and how to irrigate

AI based management of aquifers and all water supply sources and precision irrigation systems that incorporate crop soil and weather information allows farmers to increase water-use efficiency.

Variable irrigation within a single crop or field must be achieved based on models for forecasting water needs and data analysis from previous seasons. A major challenge here is the integration of crop-soil-water models with real-time data-acquisition and weather forecasting. Capturing the monitored spatial variability of the available water in the entire root zone is important for managing the water supply to the crops. Also, providing irrigation appropriate to the growth stage of the crop is paramount.

In the foreseeable future, irrigation decisions will be based on ever smaller sections of a field, perhaps down to a single plant. In these operations, the seed selection and the root development potential of varieties is an important decision for farmers. With increasing problems of water scarcity and environmental impact, a policy leading to high water productivity (maximum yield per unit of water) and minimal environmental impact should be implemented. This means maintaining low-cost water, up to the maximum productivity, but substantial incremental costs for over-irrigating. With AI, a lot of water can be saved by more precisely targeting the maximum water productivity, rather than the maximum yield, which includes attention for the growth stage. The irrigation timing and the use of water only when required can increase the water productivity and the crop yield resulting in 'more crop per drop'.

4.3.3. Storing surface water for long dry spells

In recent years, there has been the phenomenon of periods with heavy rains, alternating with long dry and hot spells. This can be within a single year or it may be that wet and dry years alternate on an irregular basis. Not all the excessive rain can percolate into the soil but should be captured in reservoirs. Deciding on the size and location of these reservoirs can best be done based on all the information about water storage capacity of the soils, the types of crops planted and the crop rotation, as well as the long-term weather forecasts. AI can be a useful tool in preparing such plans.

Weather forecasts, in combination with water levels in storage basins, can alleviate the risk of floods and may also offer opportunities to divert water to other regions where expected rainfall is lower. Such dynamic use of storage capacity can reduce flood risks and also avoid much water going into rivers (in the short term) while there may be a shortage (in the long term). The regional topography has to be taken into account in such management strategies.

In addition, soil water levels can also be dynamically changed through drainage control. This is another component of dynamic water storage management, in combination with reservoirs and basins. Artificial intelligence is a useful tool for such management.

5. AI in animal production

Livestock farming is a key part of the food production and supply chain. By 2030, the demand for animal products is projected to increase by more than 20% globally (OECD-FAO, 2021). From this perspective, it seems that there will be continued motivation to intensify animal production in the coming years. However, changing eating patterns and environmental concerns across the EU are acting to restrict expansion of the animal sectors. Greater attention is now being directed at resource efficiency, animal health and welfare rather than at the volume of production. As a consequence, EU livestock farms are consolidating with the smaller, less efficient producers struggling to survive. For those that remain, staying competitive is still a challenge and technologies are needed to enhance the sustainability of their operations (Anonymous, n.d.).

In modern livestock farming, there are many different technologies which allow farmers to manage their production processes more easily and accurately than before the widespread availability of computers. For example, on a basic level, bookkeeping software allows a farm's overall economic performance to be tracked, while climate and feeding control systems remove the need for repetitive manual labour. However, the most important aspect of livestock farming, namely the monitoring of the animals themselves, is still a significant effort requiring both time and skill on the part of the farmer. In recent years, steps have been made towards developing technologies for monitoring animal health, welfare and productivity with the aim that farmers better understand and act on their animals' needs within an appropriate time frame. While there have been some successes, e.g. the dairy sector, there are nevertheless, remaining challenges in trying to realise robust technology to do this on the farm. These include biological challenges, i.e. time-varying behaviour of animals, environmental challenges (conditions that interfere with the quality of collected data), as well as the challenges in handling the volume of data produced by sensor technologies. Therefore, while sensors, data storage and networking components are already sufficiently developed, new data analytical methods are now needed to make further progress (Norton et al., 2019).

Artificial Intelligence is the science and engineering of making intelligent machines and is infiltrating many industries globally. It is not surprising that the link between livestock farming technology and AI is building in importance day-by-day. Advances in the application of AI techniques to process data provides the opportunity for software to become more intelligent and accurate in the extraction of information on the health and welfare and productivity of animals, from a wide range of data sources. There is no denying that the future of farming will be more automated, intelligent, and data-driven than it is today. The question is how exactly will it look and what influence will AI, IoT, and, perhaps, virtual reality have on the new generation of livestock farming? Will these technologies be the core of the realisation of more resource and labour efficiency in the future.

5.1. Why are AI technologies impacting animal production?

AI and associated technologies have been around for many years now and infiltrated many industries. However, in recent years it has suddenly gained hype and is now a commonly used buzz-word that attracts wide-spread attention in the agricultural research community. When considering the range of applications in the animal production sector, the following reasoning can be derived for this popularity:

- The performance/price ratio of currently available computing power has never been so high. This makes it interesting for researchers or companies that want to exploit the power of deep learning in the modelling of large data-sets. The key to this is the rapid development of graphical processing units (GPUs) which enable large scale parallel computations to be implemented on a standard desktop machine. Such broad availability of computational power is spurring an explosion in the application of AI.

- There is a large volume of data being produced by modern sensor technologies and this needs to be processed into valuable information. In animal farming there are a plethora of data sources, such as cameras, microphones, and sensors (such as 3D accelerometers, temperature sensors, skin conductivity sensors and glucose sensors). Fortunately, AI based algorithms need large datasets for model training before they become robust enough to make smart decisions. The complementarity is contributing to their broadening applications in the field.
- The AI algorithms of today are more accurate and perform better than ever before. Because of the availability of (pre-trained) deep neural networks, more accurate classifications or correlations can be made than were previously possible.
- Industry and governments start to see the opportunities with AI technology and the level of investment in research and innovation is increasing concomitantly. Moreover, traditional livestock input companies (e.g. producers of feed, pharmaceuticals, building technology) are starting to expand within this knowledge.

5.2. Hardware for AI processing on livestock farms

A major aim in the utilisation of data-driven technology to monitor farm animals is to do it the cost effectively, in as robust a way as possible. This does not mean that because sophisticated and expensive hardware systems are available, they will be cost effective for farmers. Appropriate hardware and software components must be carefully chosen to achieve a favourable price/value ratio. In this respect, there is always a choice to be made between body-worn and remote sensing solutions. While the cost of individual hardware units to the farmer should be kept cost-effective, this is limited by the price/quality ratio. Therefore, the added value of the technology should be derived via intelligent data processing. For this, AI technologies such as deep learning, are becoming increasing important. Some of the most interesting technologies producing data on livestock farms include:

Farm equipment: Almost all standard farm equipment, whether it be for climate control, automated feed mixing, or milking, collects information that can give important clues on the productivity of the animals, energy use and general welfare. More high-tech machinery, such as automatic milking machines, can also collect information on animal health and productivity on an individual level. The opportunity to combine these different data sets is now evident and some companies are now producing platforms that enable different datasets to be combined.

RFID: The identification and tracking of objects throughout a supply chain using RFID tags has been quite a success for many sectors. In animal production, these tags have also been used to identify individual animals so that the provenance of the animal can be verified along the supply chain. These tags can also be used to derive information on the animal health and welfare. However, commercial applications of this are scarce.

Wearable sensing technology: welfare sensors, such as accelerometers, can be fixed to the animals, usually in the form of neck and leg-worn devices. There is quite a body of research demonstrating the success of such devices in the dairy sector, where cow activity increasing around the beginning of oestrus can be successfully detected using these devices. Given the clear added value to dairy farmers, these systems are now adopted in the industry. The value has not been so clear for other sectors.

Computer Vision technology: Computer vision is a technology that is proving to be extremely relevant to animal production, health and welfare monitoring. With advances in machine learning for image processing there has been an explosion in the range of application fields but this technology is still at the research stage, with limited success when being applied (Chen et al., 2021).

Sound monitoring technology: For animal monitoring research, sound analysis technology has been directed to measuring animal sounds that are indicative of compromised health and welfare status of the animals. In past decades, a lot of attention has been given to measuring and analysing animal vocalisations and other environmental sounds in livestock houses but, so far most of the applications are mainly based on experiments at a laboratory scale or research farms and the ones that use real field measurements are still scarce.

5.3. AI for improving animal productivity

Tools to monitor animal productivity have long been utilised in the different livestock sectors. Automatic weighing devices are regularly used in the dairy, pig and poultry sectors. Milk and egg production monitoring is also a highly automated process on modern farms. However, apart from the dairy sector, which is leading the way with automated milking systems, the exploitation of modern technologies to optimise the growth and productivity of animals through automated feed management are only just beginning to emerge. Feeding management represents an interesting development as standard feeding strategies typically offer animals the same feed amount and composition (e.g. some animals can receive too much and others too little nutrients). Consequently, the field of 'Precision Feeding' has emerged during the last 15 years, giving rise to technology driven methods that optimise the growth and body composition of individual animals by automatically controlling the quantity of feed energy and amino acids being offered. The technology is sophisticated; underlying physiological processes should be quantified and married with appropriate sensing and actuation in order to provide continuously targeted individual feeding. Researchers from Canada have also demonstrated that such an approach can realise a 27% decrease in Lysine intake and 27% reduction in Phosphorus excretion, when compared to three-phase feeding (Pomar et al., 2011). While zootechnical benefits of this technology have been validated, the market pull has not yet been strong enough to stimulate further innovation, despite the possibility to reduce feed costs by 10% (Pomar et al., 2011).

5.4. AI for improving animal welfare

Enabling real-time management of animal welfare is a core ambition of precision livestock farming. This aligns with the current focus of the European Commission's Green Deal to enhance the welfare of production animals ((*A European Green Deal | European Commission*, n.d.)). Data-driven technologies have strong benefits above current approaches of welfare monitoring, which are either focused on identifying 'Iceberg indicators' at the end of a production round or else are infrequently observed (typically once or twice) by auditors during the production round itself. Data-driven animal husbandry can, on the other hand, enable a more welfare-optimised way of animal management. Instead of the farmer managing animals based on economic indicators alone they have the opportunity to adjust the conditions based on welfare indicators, which also have a production value. Realising this objective requires different AI technologies. For example, processing of the multiple sensor data to automate the estimation of welfare indicators requires novel machine learning methods, the optimisation of conditions around the animal to improve their welfare requires optimisation techniques, and the selection of appropriate actions based on the reasoning engines. These must come together to offer another level of AI driven decision support beyond current practices.

5.5. AI for improving animal health

AI based technologies are becoming more frequently used to detect and diagnose diseases in farm animals. Examples include the detection of respiratory issues as well as abnormal physiological or behavioural signals. Some examples already exist on the market, whereas many more are actively being pursued by the research community with the aim of reducing antibiotic usage on farms. Respiratory health monitoring is a good example of where AI technologies have made an impact on animal health monitoring. From the past, it is known that, through audio processing, the automatic detection of pig coughs, a good indicator for respiratory problems in pigs, could be accurately detected. A study by Berckmans et al. (2015) showed that an automatic detection tool could give warnings up to 2 weeks earlier, compared to a situation where the pigs were observed by the farmer and the veterinarian. While this is just one example, there are many interesting opportunities for AI in animal health monitoring. Being able to identify high-risk animals on an individual level in large herds is still a significant challenge and opportunity. The follow-up opportunities then include the continuous follow-up of diseased animals following treatment and quantifying the risk of disease spread not only on the farm itself but on a regional level.

5.6. AI for improving animal breeding

Animal breeding is the process of selecting and breeding with those animals in a herd which express favourable genetic traits. These traits can be expressed physically (e.g. body geometry and size), physiologically (e.g. stress response) or they may be behavioural (e.g. temperament). Phenotyping comprises the tools and methods to measure parameters associated with these traits and can range from laboratory-based assays to non-invasive sensor systems. While the range of these animal phenotyping technologies is broad, the requirement to record objectively and in a non-biased manner, in order to infer information on the targeted traits, is universal. Of course, the speed of throughput of the phenotyping is of vital importance in order to capture a representative volume of information that can be used in the breeding programme. This has led to the development of what are called high-throughput phenotyping technologies (HTPs), which use data-driven technologies to measure many physical and biochemical traits of animals, quickly and accurately (Silva et al., 2021a)

The measurement of many phenotypic traits in a high-throughput manner allows for a more efficient selection of animals with desired characteristics. As noted by Silva et al. (2021), the recent advances in sensors and data analytics have enabled and promoted the application of high-throughput phenotyping in animal breeding and genetics research. Pérez-Enciso and Steibel (2021) explained that this has two main reasons: (1) novel traits can now be measured using new animal monitoring technologies, and (2) classical traits can be measured continuously and objectively over longer periods than were previously possible. Nevertheless, they also see that these steps forward have given rise to new challenges that need further consideration, e.g. large volumes of unstructured, noisy, partially redundant, and partially incomplete data.

5.7. Challenges for AI solutions on livestock farms

While the integration of digital technology is now happening across EU livestock farms, the full exploitation of the potential illustrated in Figure 5.1 has yet to be achieved. Some key challenges, which are expanded below, still need to be addressed.

5.7.1. The diversity of farming systems.

There is enormous diversity in the way animals are farmed, which does provide significant opportunities for product marketing and differentiation. However, the development of AI tools requires a degree of uniformity to reach successful deployment. Therefore, it is not surprising that data driven tools work best on larger farms where standardised layouts have been adopted. The future challenge is to develop technologies that are robust and scale independent without the need for new research and development.

5.7.2. Computing power.

Given the volume of data that needs to be processed and the sophistication of the AI algorithms, there is a need for expensive computing power on the farm to run these algorithms. Farmers should not be expected to purchase and maintain such computing resources, in order to adopt AI on a farm. Furthermore, the transfer of large volumes of data for processing on the cloud should not be relied on, given the threats from hackers and internet connectivity. Therefore, further research on developing techniques that can work on the edge of IT networks is required.

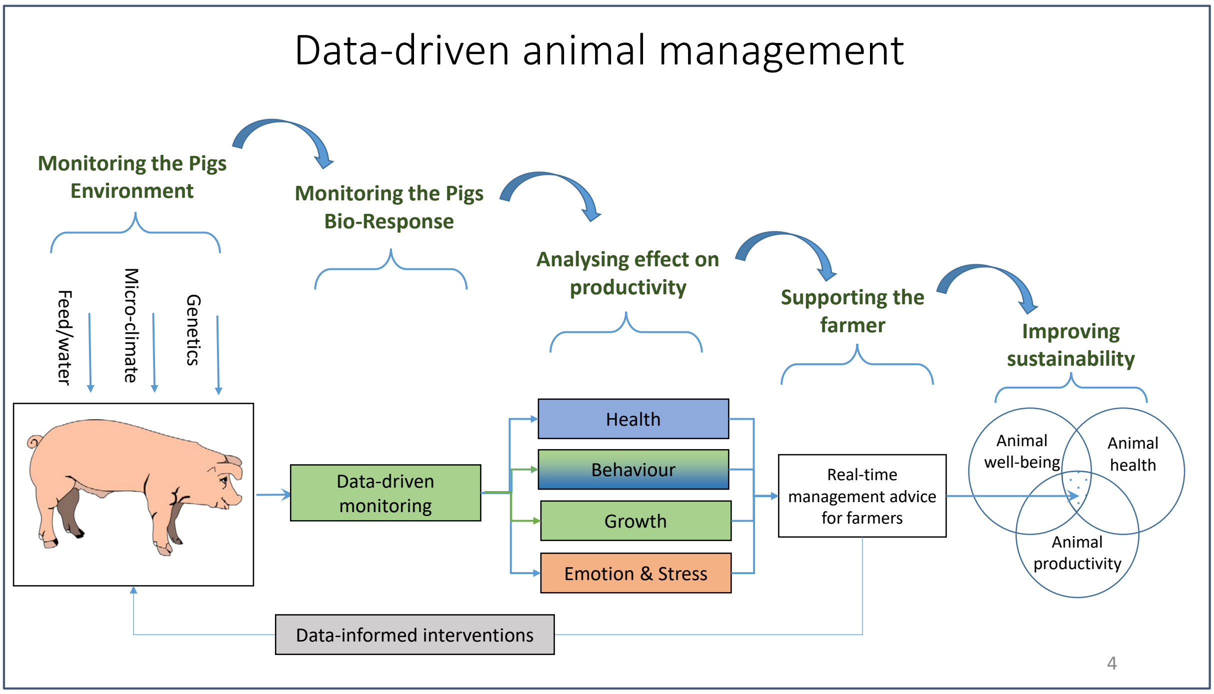
5.7.3. Maintaining farmer trust.

As AI technology becomes more widely adopted by farmers, the reliance on the technology increases concomitantly. Achieving reliable AI algorithms require training with large volumes of data. Moreover, it also requires thorough scrutiny of the type of decision support offered to the farmer by the technology. This brings risk to the early adopters of these technologies, which have to have a sufficient maturation period and can act to reduce the trust in the technology when they fail. Therefore, appropriate design standards, governed by the appropriate bodies, should be met before this technology is released to farmers.

5.7.4. Business models.

While the development of AI applications is regularly done in isolation from other technology, the integration of different data sets can realise opportunities beyond what was foreseen with the initial application. Business models that stimulate interaction between different companies should be explored to maximise synergies between applications and, in turn, avoid farmers being overloaded with multiple applications.

Figure 5.1. Schematic on the linking of animal monitoring with management actions in a data driven framework (Source: Tomas Norton)



6. AI in supply chain management of horticultural products

Horticultural products such as fruit, vegetables, nuts and flowers are perishable by nature and remain highly prone to pests and pathogens. Once harvested, their quality during the supply chain depends on ambient conditions, notably temperature, relative humidity and atmosphere composition (O_2 and CO_2 levels, ethylene). While, in general, quality decreases during the postharvest life of many horticultural products, so-called 'climacteric fruit' are harvested unripe and their quality actually improves during postharvest ripening in controlled conditions. Inefficiencies in the supply chain can lead to significant quality decay, food safety issues and food and nutrition loss. Estimated losses of fruit and vegetables can be as much as 40% (FAO, 2019). Postharvest technology aims at providing solutions to support quality management, from harvest to the consumer, and includes technologies such as low temperature and controlled atmosphere storage, packaging, and treatments with fungicides, plant growth regulators (such as ethylene or 1-MCP), coatings and waxes. Therefore, product quality management by appropriate postharvest technologies plays a key role in all segments of the horticultural supply chain (Rong et al., 2011; Trienekens & Zuurbier, 2008). AI sensing technologies and data-driven innovations can play an important role in monitoring the quality and safety of horticultural products throughout the chain, timely decision support, market linkages and supply chain resilience (Lezoche et al., 2020; (Popa et al., 2019). The remainder of this section focuses on fruit and vegetables but AI offers similar opportunities in the postharvest handling of nuts and flowers.

6.1. AI in online sorting and grading of fruit and vegetables

One of the common operations in the supply chain is quality based grading and sorting where the quality attributes are visually perceivable such as size, weight, colour and presence of external defects. Images are captured using colour cameras and the choice of AI approaches range from traditional machine learning methods (Zhang et al., 2014), to more recent deep learning algorithms ;) (Yang & Xu, 2021; Zhou et al., 2019). Their advantage, compared to more traditional image processing techniques, is that the former do not require relevant features to be defined upfront and take the raw images as input, thereby greatly reducing development time. A multitude of AI based solutions have been developed to monitor the quality of external attributes for a variety of fruit and vegetables (Elakkiya et al., 2018; Nturambirwe & Opara, 2020; Zhou et al., 2019) and are being implemented by major sorting line manufacturers.

Over the last two decades, novel measurement technologies have appeared, that allow the online sorting and grading of fruit and vegetables based on internal quality attributes, such as sugar and dry matter content, firmness, and the presence of internal disorders, pests and diseases (e.g. internal browning or worm holes). It is often impossible to observe these attributes from the outside. A multitude of non-invasive sensing technologies, such as NIR spectrometers, spectral imagers, Raman spectroscopy, fluorescence imaging, backscattering imaging, acoustic sensing devices, e-noses and e-tongues, X-Ray devices, MRI, and OCT, among many others (see the comprehensive surveys by (Nicolaï et al., 2014; Walsh et al., 2021) have been considered. Near infrared (NIR) spectroscopy is amongst the most popular technologies, as it allows online measurements of quality attributes such as the soluble solids content at typical commercial speeds of 10-15 fruit per second per lane. It relies on the measurement of absorption and scattering of NIR radiation (780-2500 nm) by the fruit, through reflectance or transmittance measurements. Multivariate regression models are then established between the variable of interest, such as the sugar content and the NIR reflectance or transmittance spectrum. These so-called calibration models are typically constructed using well-established chemometric techniques, such as partial least squares regression analysis (PLSR) (Saeys et al., 2019). Recently, deep learning networks are becoming more popular. Researchers have found relatively small advantages in deep learning networks for calibration, with respect to traditional chemometrics or other nonlinear models, such as support vector machines

(SVM). The advantage that deep learning networks have is that they can easily be adapted to take into account additional information, such as the origin of the product, season, and all other data that sensor networks in orchards or greenhouses may collect during production, e.g. weather conditions, leaf area index, irrigation, etc. This could potentially increase the robustness and general applicability of the calibration models and increase sorting and grading accuracy. A further development is hyperspectral imaging, which combines machine vision with spectral analysis. It has been used to evaluate the spatial distribution of quality attributes on or below the surface of the fruit. The output is a hyperspectral image: a data cube that has two spatial and one spectral dimension. The size of this data cube is challenging, both in terms of bandwidth on the sorting line and computational resources. Hyperspectral images are often analysed on a pixel by pixel basis, thereby losing information on spatial patterns. Much more valuable information may be obtained by means of deep learning networks. The state of the art of VIS/NIR/IR spectroscopy for measuring fruit and vegetable attributes has been reviewed extensively in Walsh et al. (2021).

Although NIR transmission spectroscopy is being used for the detection of internal quality defects that do not generate externally visible symptoms, its accuracy is limited by the relatively small penetration depth of NIR radiation. The potential of X-ray radiography and tomography is now being investigated as the penetration depth of X-radiation is much better than that that of NIR radiation. X-ray radiography is easy to implement but suffers from limited contrast and optical path-length effects, which are due to the fruit's size and shape. X-ray tomography reconstructs a 3D image of the product from a large number of transmission images at various angles. It provides high resolution 3D-images but is more difficult to implement online because of both hardware and software constraints. In both cases, deep learning can be used for segmentation and classification as it avoids the manual selection of image features (van de Looverbosch et al., 2021). One problem is the difficult and time consuming annotation of datasets, combined with the need for large amounts of training data. The potential of combining 3D CT images with X-ray projection simulations and data augmentation techniques to compute large virtual datasets of X-ray radiography images, which are suitable for training radiography systems for internal quality detection, is currently being investigated. Also, novel deep learning-based 3D reconstruction techniques are being developed to reduce reconstruction time, so it is compatible with commercial sorting line speeds (Janssens et al., 2018).

6.2. AI for linking postharvest quality to pre-harvest conditions

The incidence of storage diseases and disorders, such as superficial scald of pome fruit, typically increases during postharvest storage. Meanwhile, quality attributes change as well. In developed countries, the majority of fruit and vegetables are sorted and graded online just before commercialisation. These systems provide a continuous data-stream of quality attribute measurements that are currently under-utilised. AI techniques can be used to detect patterns in these changes, throughout the storage season, and use this information as early warning systems for cool store managers. For example, the susceptibility of pome fruit to superficial scald –a storage disorder that causes brown discolouration of their skin– varies between seasons and is difficult to predict at harvest. When superficial scald is detected early in the season, this may mean that pome fruit that are not stored under very low O_2 atmospheres or are not treated with plant growth regulators, such as 1-MCP, are susceptible to the disorder. By monitoring how superficial scald evolves during the storage season, based on the output of sorting lines, an AI based system of decision support may advise to commercialise susceptible fruit as soon as possible.

In the next step, the output of sorting and grading machines could be related to orchard data, weather conditions or greenhouse indoor climate, soil condition, fertiliser application, pesticide application, satellite and drone data, and other data collected by field robots and sensor networks. In this way, the industry then becomes the laboratory. In contrast to designed experiments, where well-defined levels of factors are imposed to optimise the information content of the experiment, this is compensated by the availability of massive datasets. Deep learning networks are particularly suited to such analyses. They can be incorporated into AI systems that can be used to advise farmers and cool store operators for adapting production systems and cold storage protocols, to improve quality. A major issue is that all those data are distributed among the different stakeholders. This implies that data formats need to be standardised. Also, confidentiality issues should be considered. Large companies and co-operatives are now developing in-house data management and AI systems. Appropriate application programming interfaces (APIs) should be developed to enable communication with the software used by other parties.

6.3. Digital twins of horticultural supply chains

Digital twins for horticulture were discussed in Section 2. Here, the discussion is focused on quality as the product moves through the chain from harvest to consumer. A digital twin is then a digital representation or mathematical model of the fruit or vegetable and its environment. It is linked to the real-world products by sensors supplying data of the environmental conditions near the target fruit or vegetable (Defraeye et al., 2021; Verboven et al., 2020). The digital twin is typically a mechanistic model based on physical conservation laws and kinetic equations. For example, cool stores or shipping containers can be modelled by means of computational fluid dynamics; the fruit is modelled as a biochemical reactor with inputs, outputs and source terms such as heat and CO_2 production by respiration. Alternatively, deep learning networks can be used, as well as hybrid approaches.

Digital twins of fruit or vegetables can be used for the management of cool store complexes for long term storage, such as those for pome fruit. These complexes often include hundreds of cool stores, each with a capacity of several hundred tonnes of fruit. The energy costs for storage accumulate while quality decreases with increasing storage time and, at the same time, the market price typically increases towards the end of the season because of imbalances between supply and demand. Given the current increase in energy costs, decisions on when to commercialise the fruit in the storage season have a large impact on profits. The commercialisation date is based on prior experience but is often suboptimal. Digital twins for postharvest storage operations that allow the prediction of postharvest quality changes, based on data from an extended array of sensors (O_2, CO_2, ethylene, fermentation volatiles, etc.), may feed AI systems that advise when farmers or cool store managers should commercialise fruit.

Figure 6.1 illustrates the digital twin concept for the shipment of fresh horticultural products in containers. The digital twin can be used to simulate the behaviour of the fruit when subjected to the conditions that exist in the shipping container and that are available from the cloud. These computations are done in real time and, at each moment, give a realistic description of how the quality of the fruit in the container is evolving. The simulations may be used to diagnose quality problems during shipping. The shipping manager can also perform a 'what-if' scenario analysis to optimise a container's climatic conditions within technically feasible limits or to change the shipping route. In the end, an additional AI layer may interpret the simulation results and advise on the proper actions to be taken by the shipping manager.

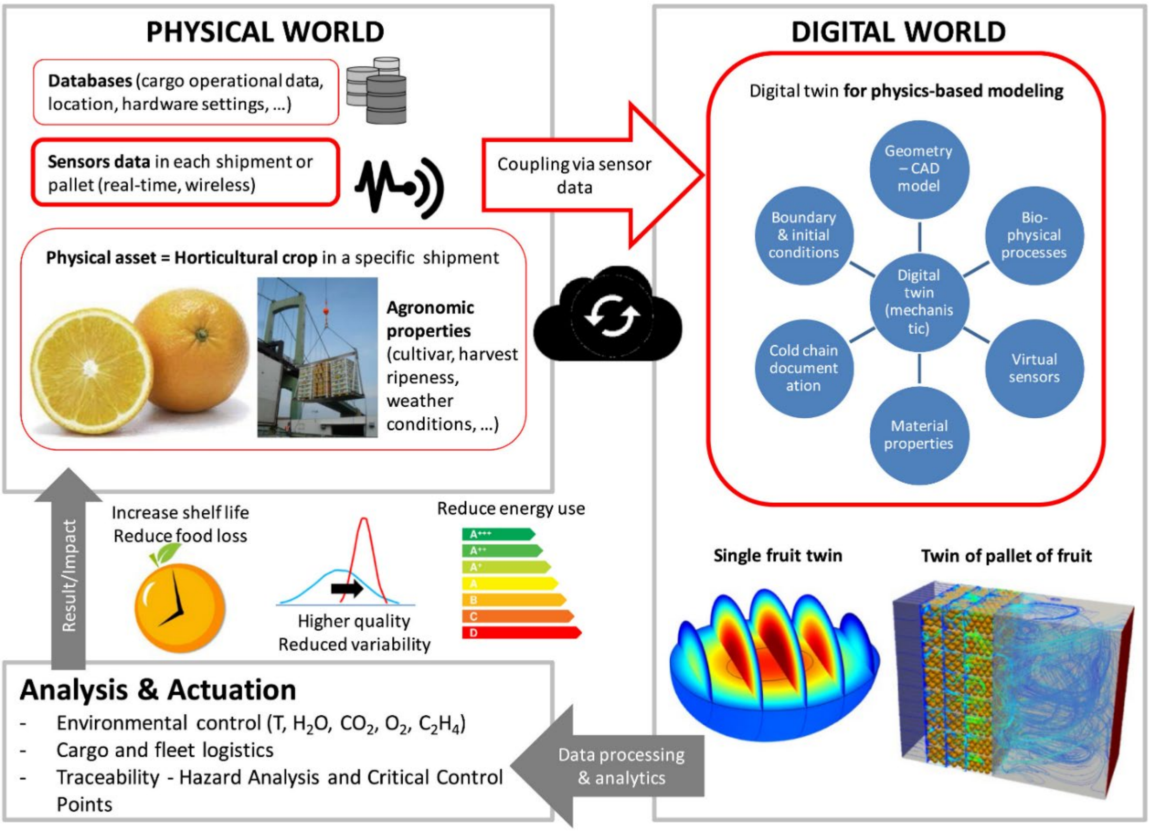
6.4. Challenges in supply chain management of horticultural products

A lot of insight and technology has been proposed and tested under controlled laboratory conditions for advanced supply chain management. In order to translate laboratory-scale solutions to commercial applications, robust and low-cost sensors are required, which should be compatible with new IoT-based solutions to monitor and control crop quality from production to retail.

At the moment, it appears that data from crop monitoring during production and crop monitoring in the postharvest value chain are not really coupled. Therefore, AI offers an opportunity to link crop growing conditions to postharvest behaviour.

In a further step, it can give information to growers on how to adapt variety selection and growing conditions to deliver a product that satisfies market expectations, in terms of harvest moment, shelf life quality and reduction of losses and waste.

Figure 6.1. Framework of a digital twin in a transport chain of fresh horticultural produce



Source: Defraeye et al., 2021. The left part represents the physical world and includes known details of the container and cargo. Weather conditions and other relevant variable shipping data are continuously recorded. All product properties have been determined at shipping time, including cultivar, sugar or dry matter content, firmness, and colour. Sensors inside the container measure temperature, relative humidity and gas composition in the box. Sensor and GPS data are transferred to cloud storage via a wireless connection and fed to the mathematical model of the product and its environment in the right part of the figure. The model can be mechanistic or data driven (deep learning network) or a hybrid combination of both.

7. AI and the agricultural machinery industry: collecting data and decision deployment

The industry (CEMA and others) formulates some views and has experience in trying to answer the following questions:

- How robust must an AI controller be?
- What are the different possible scenarios in which AI can be deployed in farm decision making, fleet management, functional optimisation, or machine-driven decision making?
- What quality level of data is required for AI?
- Who/what is liable when decisions are taken by an AI system?
- Legal and safety framework
    - for autonomous agricultural robots and machinery
    - for data collection decision deployment

Within the European institutes, the call for 'human-centred AI' is still strong but implies that humans need to be protected from AI, and this leads to the proposal that AI regulation is treated more like a consumer and citizens protection tool than as a true AI regulation. In several cases, AI is perceived as an additional uncontrollable dependency for the agricultural sector. However, man, machine and progress are linked: people build and use machines to improve or simplify life. In this sense, AI is just another step in making machines better and reaching production, savings and quality objectives that would otherwise require a longer period or not be reachable at all.

The approach of the AI Regulations, in terms of the requirements for high-risk AI, is correct overall but the application needs to be differentiated. The concept of risk as the basis of the draft AI Regulations treats all applications in the same way. The general AI that treats personal data and grants access to critical services is treated in the same way as the narrow-scoped AI that operates on the field to protect a crop.

The scope of the regulation is so enormous that collateral damage seems inevitable; the machinery sector might be one of the most affected. Still, there are ways to build in more gradients for the specificities of sectors like agriculture. Agriculture presents different phases and aspects in production that may require more automation and AI applications without a substantial increase in the risk, compared to actual human-steered operations. Indeed, in field operations, most health and safety risks concern the operator of the machine.

Non-exhaustive examples of AI use in agriculture:

- Autonomously driving vehicles/machines
- Agricultural robots/operations for field work
- Automated fleet coordination/management
- Farming simulation protocols
- Soil management, e.g. soil analysis and optimised prescription treatment, soil charting for specific applications
- Crop management from seed to harvest (disease and mould detection, pest detection and solutions, micro nutrient/targeted nutrients)
- Weed and pest management
- Weather and environmental input optimisation
- Human work coordination
- Animal breeding, feeding and health management
- Predictive analysis of multiple factors
- Decision support – a big difference compared to a pure advice function

- Coordination of all the previous functions in one production chain
- Overall knowledge and decision support in economic, financial and organisational aspects of the business

The use of AI offers undeniable economical, production and sustainability advantages when it comes to operational efficiency (e.g. the reduction of pesticide and weed control, targeted application of fertilisers etc.), cost in design, and time to market. This tool provides a key to solve the 'Gordian knot' arising from growing production, increased sustainability, environmental requirements and a growing complexity of systems, paired with a more costly and/or reduced availability of means.

Thus, the requirement for AI advancement in agricultural operations may require different and more sector-targeted evaluation of the risk, compared to the benefits that AI's restrictive requirements may bring to society.

When a machinery manufacturer uses AI within its own internal design process and its own controlled data sets, they are in control of the risks, including those unique to AI, and they have full liability.

While AI algorithms are quite well known and available, the main game changer comes with the availability of a large amount of data to be evaluated and related to each other. The amount of inputs and the building of new statistical relations cause a feeling of loss of control as not every step can be controlled by humans at the same pace. However, heterogenic quality in data sources may require the systems to treat and assess data quality and value, to yield a trustworthy result.

Security is also an upcoming key element for creating trust in such schemes.

An example of an interesting project within GAIA-X is Agri-GAIA, that exclusively focusses on AI applications (https://www.data-infrastructure.eu/GAIAX/Redaktion/EN/Artikel/UseCases/agri-gaia.html).

Besides the basic data provided to the machine at the start (by the producer), the machine continues to evolve throughout its lifetime. The self-learning systems are still improving after being placed on the market (maps), by using locally available data and statistical data extrapolated from other machines (e.g. Adaptive traffic systems). The results from individual AI machines are a product of usage and given localised factors, such as terrain, soil quality, geographical position, water availability, weather, etc. Thus, the results can be quite different from the aggregated statistical data from different machines and, under the control of a manufacturer, they are used for software updates for all machines.

It must still be noted that, in many cases, the AI driven function will still need to behave between certain boundaries but the related risks for the entire machine and its environment, might not be fully understood/covered in advance.

7.1. Challenges for agricultural machinery development in Europe

With growing intelligence and complexity in control systems, more and more intelligent systems are being integrated into machinery, with the operator/driver being replaced by such systems. With a growing number of 'extended' vehicle features/functions/services, that require connectivity and cooperation, there is a growing need for controlled data sharing and cybersecurity measures. For industry, that would mean access via a platform and not direct access to machines, to protect IP/ trade secrets and product compliance.

CEMA and AEF (the agricultural industry electronic foundation, a global organisation funded by industry and combining some of the brightest electronic and software experts in the industry) are working on the necessary strategy for interoperability networks and technical requirements and standards.

The main message from industry can be summed up as: *Differentiate the legislation in relation to AI on technology based on the risk arising from the application.*

8. Barriers, challenges, and outlook for AI adoption in agri-food

Agriculture is in the early days of yet another revolution, at the heart of which lie sensors, hardware, and connectivity, in conjunction with data models and connectivity. Artificial intelligence in agri-food is evolving as an important tool, together with many technologies, hardware, and software, all of which are interconnected and can lead to added value activities and services. They gather data from multiple resources and sensors, apply learning methodologies and prepare decision making or, even, execute the decisions. Artificial intelligence, analytics, connected sensors, and other emerging technologies could further increase yields, improve the efficiency of water and other inputs, and build sustainability and resilience across crop cultivation and animal husbandry. Lutz Goedde et al., 2020). There is a need for further development of the hardware for sensing and executing decisions but a lot of work and attention must also be given to data, analytics, and models. The digital twins are a combination of virtual reality and the real physical processes for improving efficiency and sustainability in the agri-food chain.

A list of problems that need further attention is given below; they need to be overcome if artificial intelligence is to be used as a tool in agri-food.

8.1. Technical developments to reduce barriers for AI in agri-food

Advances in machinery have expanded the scale, speed, and productivity of farm equipment, leading to more efficient cultivation of more land. Seeds, irrigation, and fertilisers have also vastly improved, helping farmers increase yields. This section gives the most urgent AI-related hardware needed for advancing the efficiency and sustainability of field operations, production in modern greenhouses and in buildings for indoor farming or storage, as well as for consumer oriented postharvest operations:

- Robust and low cost sensor technologies and monitoring solutions, to generate precision data and actuators for the implementation of daily decision-making
- New high-tech sensor technology, low costs for dense use in crop production and the detection of crop vigour and crop health
  - in greenhouses
  - in vertical farms
  - directly in fields
  - on mobile machinery and robots
  - on drones
- Robust and reliable environmental sensors for monitoring
  - health and well-being of animals
  - in-house climate in greenhouses or vertical farms
  - Near-field or in-field environmental conditions that have direct effects on plant growth or health
- Soil sensors for in-field data or off-line soil composition and soil health monitoring
- Animal monitoring technologies, such as animal health or diseases
- The Internet of Things (IoT)
- Network and connectivity
  - Agricultural operations, farms and data collection and actuation (including manual registration) can be distributed over a large geographic area
  - Local availability of data at each location is not sufficient to use advanced digital tools
  - For full advantage of digital tools, good connectivity or equipment would help to turn these data into valuable information as a basis for actions

- Autonomous or automatic controllers, including automated tractors and robots with actuators, to carry out the decisions made towards optimal management and with registration of activities
- Weather services
- Satellite services
- Develop new IoT based solutions, which are required to monitor and control crop quality from production to retail

8.2. Challenges for models, data, and analytics

Since data can be generated from sensors, activities or historical events, there is a need to look at the requirements that these data should satisfy, to make reliable use of them.

8.2.1. Quality and availability of data for reliable AI development

- Availability of large data sets with high variability and high quality; these data should be findable, accessible interoperable and reusable (FAIR)
- High density data points for high-density information on small areas and small time steps, down to individual plants. This contributes to a higher resolution of information within a complex system with highly variable and fast changing dynamic biological processes
- Availability of metadata
- Reliable labelling of data for deep learning applications
- Application programming interfaces to facilitate communication between existing and novel AI systems
- Novel data augmentation methods for training deep learning networks
- Novel AI methodologies to interpret 3D or 4D data
- Novel and fast 3D reconstruction techniques for tomographic images of agricultural products
- Sufficient data bandwidth in real-time data dense applications such as online sorting and grading of horticultural products
- Meaningful interpretation of sensor data, from raw data to grower usage
- Software and data analytics services and learning methodologies
- Quality assurance of the data from sensors or manual registration
- Interpretation of the data coming from multiple sources
- Make use of physical or interpretable models
- Data-driven black-box models, to look for potential connections between processes
- Optimisation and decision support
- Easy access to high performance computers for training of deep learning networks
- Transformation of data into decision support systems for growers
- Usage of data for autonomous control
- Protocols for maintaining confidentiality of data and consideration of data ownership issues

8.2.2. Development of digital twins in combination with AI

- Consider different aspects of the crop production system to reach optimum yield by optimum crop management, while minimising resource use, including the reduction of energy and water use and pest and pathogen management
- Obtain more real data, especially on different aspects of crop performance, but also pest pathogens, which are scarcely available or not publicly shared
- More labelled datasets should be created and publicly shared, especially in the field of pest and pathogen management
- Usage of more artificial data obtained by mechanistic models
- Extend knowledge and implementation of more detailed and complete mechanistic crop production models, including more knowledge on crop and product quality, pests and pathogens

- Better physics (physiology) based models of the production and postharvest environment, including greenhouses, fields, storage facilities and shipping containers
- Bridge the gap between mechanistic models and reality, thus digitalisation of green-finger knowledge to facilitate AI
- Develop interpretable deep learning modes that allow insight into the physiology or physics hidden in the models. Create more complete digital twins with highly detailed information on crop management, resource management and pest and pathogen management
- Use and demonstrate digital twins in combination with AI for decision support for growers on the design and operation of systems
- Develop and apply more techniques of augmented and virtual reality to make the twins more coherent and attractive

8.3. Some concerns, expectations, and recommendations

8.3.1. User acceptance of AI

- Include user acceptance and confidence with social research, including supply industry liability and operational safety aspects
- More development of robotisation of human-performed tasks to accelerate the realisation of fully autonomous systems
- Create more field-laboratories with a research-grade high-tech data infrastructure but close-to-practice crop growing system to facilitate such technology and AI validation and integration
- Training of growers and their staff in the use of AI and, also, the limitations that can arise. Make growers and their staff confident to interact with automated AI based process control.

8.3.2. Develop trust and equal opportunities

The further adoption of AI technologies in agriculture requires that farmers and consumers trust the services that are offered. Transparency of the supply chain and of the way information is collected and used is very important. Some points of caution are given below.

Data collection of information about validity, integrity, precision, reliability, timeliness, and the range of data.
Encourage organisations to ensure that data collection is accompanied by such meta-data that can help towards more reliable data analysis and resulting models. This meta-information can also be added to the product documentation when commercialising AI based models or decision making.

Encourage transferability of data collected by machines and in research organisations.
Of course, these data collection tools must be sure of the quality of the data, as well as the readability of the data. This has implications on the ownership of data and on the right of competitors to use it or for new research and development initiatives.

Have mechanisms or initiatives to monitor or compare the results coming from different suppliers in terms of:

- Model drift over time
- Regional usability or performance
- Performance with respect to agricultural or food policy: does the policy affect the model or is it the other way around?

Equal opportunities for using the results of digitalisation in agri-food.
Monitor the use of models by small and large farmers and counteract the risk of a widening of the digital divide.

Pay attention to the impact AI might have on female farmers(Gwagwa et al., 2021):
How will AI contribute to gender parity in agriculture participation? For example, will it improve the terms on which women participate in agriculture given the current shifts within markets and agricultural value chains; if so, how? In what ways are the current disfavouring of women by data and algorithm biases reflected in agriculture? Are the algorithms trained on biased data? What policies are needed for the intentional inclusion of women, to redress discriminatory anomalies and provide safety nets, while utilising AI technologies to include them in new forms of work, entrepreneurship, and innovation?

8.3.3. Expectations from and for applied research and development (R&D)

Researchers and companies want to bring their results, or their new technology, to the market. However, it is the experience of many that the road from the laboratory to the introduction to the market can be long, difficult and, above all, expensive.

Under the Digital Europe Programme (DIGITAL) there are calls for setting up Testing and Experimentation Facilities (TEFs). In the DIGITAL 2021-2022 programme year, there was a call for a Testing and Experimentation Facility for Agri-Food (TOPIC NAME: Testing and Experimentation Facility for Agri-Food General Information Programme: Digital Europe Programme (DIGITAL), 2022.) At the time of writing, a project has been selected and contract negotiations are ongoing for a launch in the spring of 2023.

It is expected that more calls for TEFs in different applications or technological areas will be forthcoming. The contributors to this study make some suggestions for testing in such facilities.

- Facilitate the use of high-tech sensors of other industries for horticulture, agriculture, and animal husbandry (cross-overs)
- Combine engineering, IT and crop-experts' knowledge into an integrated approach, add social components as well (multi-disciplinary approach)
- Combine different technological solutions into integrated approach (integration)
- Translate small laboratory scale or research environment results into scalable demonstrators, as a step towards commercial application (implementation)
- Validate technologies in applied demonstrator trials that can be translated towards commercial situations that are meaningful for end-users (validation)
- Create more field-laboratories with a research-grade high-tech data infrastructure but close-to-practice crop growing system, to facilitate such technology and AI validation and integration (safety)
- Train growers and their staff in the use of AI and also in the limitations that can arise. Make them confident to interact with automated AI based process controls (education)
- Treat greenhouse horticulture as a separate 'agricultural system' because of its highly industrialised characteristics

Furthermore, scientific insight and advanced analytics can be a powerful tool in building the AI models using large sets of high-quality data and can make use of such virtual facilities to look at effective procedures for:

- Management of food wastes
- Management of animal disease outbreaks
- Pest and disease management in crop production: AI based models and calibration with past data can then look for the effects of limiting or withdrawing some crop protection. It is important that these (virtual) studies yield long term effects for the food supply, the agrobiodiversity and the environmental and human health effects

8.3.4. Concerns about regulation and standardisation

The approach of the AI Regulations, in terms of requirements for high-risk AI, is generally correct but the application needs to be differentiated. The risk concept at the basis of the AI draft Regulation treats all applications in the same way. The general AI that treats personal data to grant access to critical services is treated in the same way as the narrow-scoped AI that operates in the field to protect crops.

The scope of the regulations is so enormous that collateral damage seems inevitable; the machinery sector might be one of the most affected. Still, there are ways to build in more gradient for the specificities of sectors like agriculture. Agriculture presents different phases and aspects in production that may require more automation and AI application without a substantial increase of the risk in comparison to the actual manually steered operations. Indeed, in field operations, most health and safety risks concern the operator of the machine.

8.3.5. Concerns about risks and liabilities

In the review of the agricultural sectors, it has become clear that AI will be able to better organise or optimise current processes, reduce waste of inputs and outputs and animal welfare. It also offers new opportunities like autonomous mechanical weeding (instead of chemical use) or new harvesting and storage technologies. There is a risk of the spreading of crop disease that is not detected by the agricultural AI but that may reduce food availability (an example of this is mycotoxins). There is a risk of zoonoses (diseases transmitted from animals to humans). The question then arises as to what the risks are and what the role can be for AI applications in agriculture.

Some examples:

- Black box machine learning models are currently being used for high stakes decision-making, However they can only tell what happened in the field or to the animals and may cause considerable harm. Explaining black box models still leaves them as hindsight models. Models based on insight (and process knowledge) have some inherently interpretable value and are considered as being better in a foresight (decision making or planning) context. The value (and risks) of the AI for agriculture models can be tested in a sandbox using trustworthy validation procedures
- Autonomous vehicles operating in fields where manual workers are also present
- Systems where animal welfare can be at risk or where a human/animal interaction can pose dangerous situations for workers
- AI based diagnostic systems and subsequent recommendations/prescriptions for animal health
- Long term effects of the introduction of new varieties/breeds on biodiversity and natural flora or fauna
- The comparison of AI advisory systems developed by large industrial groups for bias, including the risk of a digital divide in agriculture
- The use of smart crop protection methods on the development of chemical and mechanical weed resistance
- Evaluate the long term effects of new practices introduced under CAP
- Sandboxes as a testbed for a combination of physical systems, to transparently test new technologies and contribute to evidence-based adherence to the objectives of some CAP requirements while adhering to AI regulations
- Sandbox greenhouse for experimenting with AI based technologies of indoor crop production towards green production methods (CO_2 reduction or absorption, no pesticides)
- Test the implications of the Artificial Intelligence Act when other EU Directives may be involved (e.g. the Machinery Directive), like those for certification and standardisation (ISO)

- AI systems developed outside Europe can test if they comply with the EU Artificial Intelligence act (and the Data Protection Act, among others)

The use of AI in areas that matter to human life (agriculture, forestry, climate, health, etc.) has lead to an increased need for trustworthy AI with two main components: explainability and robustness. One step toward making AI more robust is to leverage expert knowledge in what can be called human-centred AI (HCAI); it is a combination of 'artificial intelligence' and 'natural intelligence' to empower, amplify, and augment human performance, rather than replace people (Holzinger et al., 2022).

9. Policy options for the use and simulation of AI in the agri-food sector

Artificial intelligence is considered to be one of the tools that will allow new insights to improve or optimise existing technologies or processes in the agri-food chain; such as for farm decision making or optimal control of plant growth. Furthermore, the set of techniques available in AI will lead to new opportunities and technologies, such as autonomous agricultural robots, and automated crop protection or fruit harvesting. A combination of scientific discoveries may result, as well as insights derived from the analysis of (massive) quantities of data.

Worldwide smart information systems (based on 'Big Data' and AI) are being hailed as a possible solution to help better and more effectively manage plants, seeds, harvesting and farms in the agricultural industry. An exponential growth in data has accompanied the digitalisation of agriculture through the proliferation of mobile technology, remote-sensing technologies and distributed computing capabilities. According to the World Bank, the effective management of data will open new opportunities to improve the lives and livelihoods of smallholder farmers by lowering costs and reducing information asymmetries. However, the lack of experience in data management or adoption of data driven services can limit the possibilities of digital transformation (Robert Townsend et al., 2019).

In the following sections, some of the key issues are discussed as they relate to liability and risks or to ethical and societal concerns from researchers and stakeholders. Thereafter, some options or possibilities for action and expected effects are given.

9.1. Issues with the application of AI in the agri-food sector

The use of AI-based solutions may give rise to several concerns about the concentration of power in the hands of large corporations, i.e. agricultural technology providers with a strong and dominating technological capability. The technology users or farmers are variable in size and may have concerns about their privacy, confidentiality, and the ownership of their data. They may want to know how to protect themselves, in the case of unexpected usage, undesirable or, even, physical or financial damage. Even more so, since the technology and its applications in agriculture are rather new and many developments are ongoing with considerable activity in well-established ICT companies, as well as new start-ups; end users are rather unfamiliar with the technology.

Some of the ethical issues raised by AI in agriculture intersect with ongoing controversies about agricultural policy in general. This includes whether governments should try to protect 'small farms' from being outcompeted and bought up by larger concerns; the appropriate role of the market vis-à-vis food security; the ethics of intensive animal production; the relative merits of large-scale versus small-scale farming; and the genetic modification of crops and animals (Sparrow et al., 2021).

9.1.1. Ethical and societal issues

Dara et al. (2022) proposed an ethical framework for the design and development of AI-based technologies with an ethical legitimacy and accountability that also gains the trust of farmers as stakeholders. In this framework, there are six considerations: 1) fairness, 2) transparency, 3) accountability, 4) sustainability, 5) privacy, 6) robustness. Some or most of these should be the responsibility of the technology providers, but it may be an option to have legislative initiatives to clarify the rights and expectations of farmers, technology providers or the public.

Fairness and transparency

'Black box' models are created directly from data by an algorithm. Trusting the black box model implies trust in the entire data set on which it was built (Rudin & Radin, 2019). However, every (large) data set may contain imperfections due to missing data or errors in the coding of manually recorded data, etc. These risks introduce bias and reduce the fairness of the AI models. The implementation of such models may lead to serious problems or to enabling actions that cannot be implemented or tolerated. The training, validation, and testing of data sets should be sufficiently relevant, representative, free from error and complete, in view of the intended purpose of the model and its calibration. The need for high quality data is also recognised in the Artificial Intelligence Act (EUR-Lex - 52021PC0206 – EN). Transparency of AI algorithms and models can be an important factor when enabling farmers to understand, trust and finally adopt systems based on AI or machine learning. It is also important that both farmers and their advisors receive suitable training.

In several cases, efforts are made to explain the behaviour of the black box models. Explanations often do not make sense or do not provide enough detail to understand what the black box is doing (Rudin, 2019). However, creating or designing models that are inherently *interpretable* in the first place, can help provide a better understanding of and trust in the autonomous decisions made and they often become more (and not less) accurate.

Digital literacy, digital divide and data ownership

Agri-food companies have started to extract value from the data they collect and to use digital technologies to lock farmers in to their own product ecosystems (e.g. through farm inputs or machinery). In a report by the Centre for European Policy Studies and the Barilla Centre for Food & Nutrition Foundation (Renda et al., 2019) it is noted that the digital transformation has the potential to empower small-scale farmers. However, in the absence of dedicated public policy, they may be excluded from the supply chain or left in a new situation of economic dependency, in which they own their land but rent their data and digital equipment from larger agri-food companies, or even tech giants.

There is also a discussion on data ownership by farmers, the technical support they receive from companies for collecting data and rewards for the intellectual property claimed by companies that use data from many farmers to develop AI based algorithms for farm advice and decision making. A Code of Conduct on agricultural data sharing by contractual agreement has been agreed between farmer organisations, agricultural technology corporations and agricultural suppliers and cooperatives (Ader, 2021). The farmer remains at the heart of the collection, processing, and management of agricultural data.

The Code of Conduct between farmer organisations, agricultural technology corporations and agricultural suppliers and cooperatives contains non-binding guidelines and is not to be used as a legal document. It refers to legal documents and relevant EU legislation.

Traceability and monopoly

Digital tech companies, in combination with retailers, are becoming ever more important and are also increasingly shaping the production and consumption of food. 'Going digital' or 'smart' is becoming a hegemonic model of economic and social development, in the agri-food system and beyond (Prause et al., 2021).

Standards and regulations driven by concerns over the climate crisis and food safety, particularly in the EU, might become a further driver towards digitalisation of 'climate-smart' agriculture. Using digital technologies is a way for farmers and food traders to prove their compliance with complex national or EU policies and with bi- and multilateral trade agreements. This may help retailers to intensify their control over food producers and commodity chains. Together with large e-commerce companies, these actors are also increasingly shaping the production and consumption of food. This may affect the agro-ecology and the (bio)diversity of agricultural production without facing effective government regulation.

9.1.2. High-risks and liabilities from the application of AI

In agriculture, three types of risk stemming from AI or machine learning are considered: (1) risks relating to data, including acquisition, access, quality, and trust; (2) risks emerging from the narrow optimisation of models and unequal adoption of technology during design and early deployment of ML systems; and (3) risks associated with deployment at the scale of ML platforms (Tzachor et al., 2022). How can users be informed about the potential risks for their farm or business?

Health risks for people and animals

In the review of the agricultural sectors, it has become clear that AI will be able to better organise or optimise current processes, reduce waste from inputs and outputs and improve animal welfare. It also offers new opportunities like autonomous mechanical weeding (instead of chemical use), or new harvesting and storage technologies. There is a risk of the spreading of crop disease that is not detected by the agricultural AI but that may reduce food availability, such as mycotoxins or the risk of zoonoses (diseases transmitted from animals to humans). The question is how to manage these in AI applications in agriculture.

Furthermore, AI in the agri-food sector needs sufficient robustness against hacking or other inappropriate use. Animal and crop health can have major implications for human health, as well as for the food supply. Therefore, the highest level of security should be considered.

Accountability and loss of income from AI implementation

AI providers of crop protection services can include the detection and recognition of diseases. The strategy for dealing with this can be advice on chemical crop protection and the timing of it, taking weather forecasts into account. Erroneous weather forecasting could lead to erroneous treatment advice that ultimately results in crop loss. Similarly, damage or loss of animals can happen after treatment recommendations.

In a similar way, autonomous farm equipment or robots can cause damage to the crop or to neighbouring crops or installations or farm workers.

9.1.3. Concerns from stakeholders and society

Production methods in agriculture and agri-food often raise concerns from consumers, related to their potential impact on health and on the environment. The use of AI must be clarified, in the sense that the production methods remain based on solid biological and agronomic principles, but that one can improve on these practices to really make use of all the available information. On the other hand, some new technologies and tools, like automation and robotics, raise concern about the interaction of a farmer with his products. Furthermore, it may not always be clear who the beneficiaries are, or where the control over food production resides. Some of these concerns are given here.

AI, automation, and protection of farm workers

Automation in agriculture, including autonomous plant production in greenhouses or plant factories, has the potential to bring both opportunities and risks to working conditions. On the other hand, the application of automated technologies to the job market brings physical and psychosocial risks. As a follow up to Deshpande et al. (2021), attention should be paid to the way that (fully) autonomous systems can comply with labour regulations and the risks to workers that must be avoided. It can include minimal investment in technology and computer literacy as part of education and training, to create a more economically resilient workforce.

Overcoming barriers for application and policy options would require one or more demonstration sites, where digital twins of a greenhouse crop production facility can be tested in a safe environment for different crops and workers. This would give growers, as well as workers, confidence in the power of data and the AI-driven control of crop production systems. This policy option/initiative also relates to options on automated production facilities. Testing and experimentation facilities, as well as digital sandboxes, could be suitable tools.

Water resources protection policy

Operators or users of the software should establish a policy on how to deal with potential water shortages, such that there is consent on how the water priorities are established. In case of expected shortages, users should receive an advanced warning such that they can alter their production plans to cope with limited supply. Regulators should be informed about possible limitations in the supply of drinking water or of water for industrial use. These uses should also be included in the AI models that manage or forecast regional water supplies.

A digital sandbox must be installed, in which long-term effects of AI models can be simulated. The hierarchy effect of these models must be tested for the long-term effects of water collection, run-off avoidance, water storage and water supplies to the different users. This is to ensure that the effect of the yearly short-term recommendations does not lead to depletions of the water reservoirs or the available ground water, with all the subsequent damage to the environment and the economic activities in the long term.

Animal welfare and the CAP

Data-driven technology should be integrated in the official animal welfare standards – these solutions will reduce the subjective point-in-time assessment that is now ongoing.

Labels on animal-derived products should include objective data derived from on-farm sensors.

ISO standards on the design of animal monitoring technologies should be adopted by the industry.

The storage and collection of data and monetisation in the agri-food value chain

The presence of sensor networks contributes to novel procedures to supervise or evaluate the performance of equipment in the field or on the farm, like in animal housing or product storage. It is offered as a service for preventive maintenance of equipment and to give the farmer advanced warnings of potential break downs.

Some of the data that are collected in this way are very machine-specific and would serve only the manufacturers of those specific tools. However, the data transmission bandwidth is usually large enough that additional data can be collected, not only for machinery maintenance, but also relating to farm management. The manufacturers can benefit if they intend to use the data for production line evaluation. A farmer may not be aware of this practice, or they may not be capable of detecting or evaluating this 'semi-hidden 'data collection. There may also be privacy issues here.

One expects that when such a practice is implanted in animal housing and in cases of mechanisation, then the farmer or customer must be fully informed about the extent of the data being collected by the operator and how these data will be used or passed on to ICT providers or developers (and what the monetisation of these data looks like). In any case, the farmer could ask to receive a free copy of the data in a readable form without the need for additional software.

A broader approach is largely missing for estimating the impacts of digitalisation on the organisation of the agri-food system, since the current debate's tendency is to focus on digitalisation at the input and farm level. One reason for this might be that digitalisation along the food commodity chain seems to be discussed under different terms and in different strands of the literature. Automation, robotics, IoT, AI and digitalisation in the food-processing and packaging sector are referred to as Industry 4.0, while similar technologies at the farm level are referred to as smart farming or Agriculture 4.0 (Prause et al., 2021). The Horizon Europe and digital programmes are examples of multi-financial framework initiatives and should become a policy initiative for further development.

Affordability of AI and concerns about the digital divide

There is no doubt that there is a cost to farmers who benefit from the new technology and opportunities from digital agriculture. However, caution should be employed so that this does not widen the digital divide in farming communities.

Bringing the benefits of AI and digital agriculture to all farmers requires accessible networks, data bases and machine learning or state of the art analytics algorithms. This accessibility includes the possibility to upload and collect data from wireless sensors in the field and from machines operating in the field. This implies affordable broadband internet access, not only in residences, but also in the fields. Another complicating factor may be that some (or most) platforms on machines for data acquisition or for the automation of actions, are proprietary (Chaterji et al., 2020).

The CAP and data collection down to farm level

In the report by the European Court of Auditors on Data in the Common Agricultural Policy (*Special Report Data in the Common Agricultural Policy*, 2022), the following excerpts indicate that more and more data are becoming available in national CAP-related databases. For a better evaluation of the CAP and the European Green Deal, it follows that the evolution of these databases extends down to the farm level and, in some cases, to field level.

Under the 'Farm to Fork' strategy, the European Commission intends to convert the farm accountancy data network (FADN) into a farm sustainability data network (FSDN), with a view to collecting farm-level data on the 'Farm to Fork' and biodiversity strategy targets, as well as other sustainability indicators. The Commission published a roadmap in June 2021 and plans to present a proposal for a regulation in the second quarter of 2022.

The Commission has expressed the need for a common unique identifier for agricultural holdings (farms) that would make it possible to link farm-level data from various data sources (e.g. administrative registers and surveys). The identifier would have to take account of the different Member State systems and complex farm structures with different combinations and locations. This requires a common definition of a farm, and such a definition has an impact on financial indicators like farm income.

Using a digital field book, where farmers register their activities, would be a step forward in digitising farms and improving the monitoring of consumption and impact, with regards to pesticides, fertilisers, water, and soil. The Commission's proposed FaST (Farm Sustainability Tool for Nutrients) platform is a tool with a flexible architecture that provides modern analytics and interoperability with many data sources. FaST builds on several data sources, which are either connected (live sources) or imported (static sources) on the platform. To provide farmers with access to their own data, FaST connects to the regional/national integrated administration and control system (IACS – or equivalent farm registry), where the farmers' data are stored. The access to these databases is not clearly described, although DG AGRI and the Joint Research Centre (JRC) seem to be the primary candidates for exploiting and analysing these available data. However, it appears that farmers should also have access to data related to their farm.

9.2. Action and regulation

In the previous section, several issues were defined that may require special measures to ensure all stakeholders a fair and equitable participation in the benefits that AI may bring to agriculture. Farmers and SMEs in agri-food are, mostly, rather small independent operators, while technology providers and retailers have considerable economic power, which gives them the capacity to impose rules on their suppliers and, to some extent, their clients. Legislators can play a role here, to set the guidelines and the rules to balance the interaction between stakeholders.

9.2.1. Regulatory policy options

Farmers, large and small, see the introduction of new technologies as a potential source for improving their operations and /or making their farms (more) profitable. On the other hand, there is a cost related to the use of AI and the benefits are not always clear. Technology providers are usually large software developers or equipment manufacturers. This results in an uneven knowledge and expertise background between farmer and supplier. Regulation can play a role in levelling the ground between these different parties or stakeholders.

Regulations on the rights and expectations of farmers, technology providers and the public

Artificial intelligence applied to agriculture promises data-informed ways to support farmers' traditional practices, while mitigating the challenges. However, the drive toward precision agricultural technologies is focused on large-scale monoculture practices that are unsustainable and economically risky for farmers. Agri-tech companies tend to focus more on the technological aspects than on the agricultural aspects. The solutions provided become increasingly capable of collecting data that can yield important information to the farmer as well as to agri-tech companies.

When crops are produced under widely varying agricultural, environmental and management conditions, the data collected can become the basis for models that provide information to the farmer for use in making decisions on crop management and planning future crops. In this respect, tech providers would like access to the agricultural data and, if possible, in an exclusive way.

At present, no EU legislation specifically regulates the question of ownership of data (*Agri Data Regulation (EU GDPR and US) - Enveve S.A.*, n.d.). However, in the proposed EU digital data act, data users are defined (e.g. the farmer who harvests his grain) versus the data holder (e.g. the combine manufacturer). For farmers generating the data to remain in control, the data has to be readable by the farmer in an open-source format. Also, the data should be transportable, so that a farmer can use the data when they move to a different technology provider. Farmers should be able to enforce copyright on their data. The proprietary data about the machine itself can then be part of the copyright of the manufacturer.

Legislative initiatives may be called upon to clarify the rights and expectations of farmers and technology providers. This may include specifications for making data available in a defined format while access rights to data can also be regulated.

A legislative regulation on data ownership and database consultation could specify that the farmer that collects or enters the data is the owner of the data and that they can transport these data to third parties in a readable format and units. These third parties may be consultants, certification schemes or equipment manufacturers. The limitation to this is that it only applies to agricultural data, and specific machine data or database codes are proprietary to the scheme owner or equipment supplier.

One policy option is to specify a data retention regulation. When a technology provider, consultant or other external agent is given access to the farmer's data, then the user-agreement must specify how the data will be archived, how long it will be kept, and how it will be removed or returned to the farmer, in addition to how the farmers can access the data themselves. It should also define what happens to the data once a contract is terminated.

A risk and liability regulation

In global agriculture, three types of risks stemming from AI or machine learning are considered: (1) risks relating to data, including acquisition, access, quality, and trust; (2) risks emerging from the narrow optimisation of models and unequal adoption of technology during design and early deployment of machine learning systems; and (3) risks associated with deployment at the scale of machine learning platforms (Tzachor et al., 2022).

The question then arises as to how users can be informed of the potential risks to their farm or business. Insurance companies also want to know what risks they should cover.

A possibility for meeting these needs would be establishing a risk assessment body, in conjunction with the model and data quality evaluation policy described in Section 9.2.2.

Another option would be to allow insurance companies to take the initiative for risk assessment related to AI applications in machinery, as farm management tools or in the value chain. This could lead to an insurance framework which insurances companies, AI providers and users can use to set coverage and premium levels.

However, some obligations related to liability determination, in the case of accidents, could also be considered for a legal framework.

- It may be interesting to separate machine functions that are under the control of a human operator (the motion of the carrier) from those that have been automated, e.g. the functioning of some instruments (spray application in the case of crop protection), which are controlled by AI software. Separate insurance clauses have to be envisaged for the driver, the manufacturer of the machine and, if that is the case, the software supplier. Changes to the hardware or the software that are not authorised by the manufacturer or supplier can transfer the responsibility (and insurance requirements) to the owner of the machine.
- It would then become necessary to include an obligation for the preservation of discoverable information that may be relevant evidence or useful for adversaries in incidents related to damage to crops, property, or the environment. However, this may also imply the need to access data or even a proprietary code.
- Another option would be leaving the insurance responsibility entirely to the operator, who would have to sign an agreement with the manufacturer so that, the latter would in no situation be held responsible for any incident or damage that results from operating the equipment. Also, the manufacturer may also be asked to preserve discoverable information and the provide possibility to read proprietary data and code.

Automation and the protection of farm workers

Automation in agriculture, including autonomous plant production in greenhouses or plant factories, has the potential to bring both opportunities and risks to working conditions. European agriculture depends, to a large extent, on migrant workers, many of them undocumented, who take up a significant proportion of tasks, such as picking fruits and vegetables, as well as packing and processing food. In this context, it is also significant that more than a third of EU farmers are over 65 years old, while less than 5 % are under 35, and few have had training in the use of digital technologies. For untrained workers or farmers, automated technologies may bring risks or diminished job opportunities.

Farmers and farm workers need to be equipped with the skills that prepare them for the digital aspects of farming. The European Federation of Food, Agriculture and Tourism Trade Unions (EFFAT) is already, with the support of the European Commission, looking into the opportunities and risks of digitisation and the impact of digital transformation on labour, labour markets, social protection and related institutions (N.N., 2021). Training programmes must be developed as part of the digital education of farmers, but vocational training must also be made available for migrant workers.

It may be an appropriate policy for mandatory training of workers in operating machines that have built-in AI and digital automation functions. This training should include basic information on the machine operations and the controls that the operator can supervise or manipulate. Emergency situations should be part of the training. In the case of (fully) autonomous systems, attention should be paid to how (fully) autonomous systems can comply with labour regulations and the risks to workers that must be avoided.

Overcoming barriers to the application of these policy options could require one or more demonstration sites, where digital twins of a greenhouse crop production facility could be tested in a safe environment, for different crops and workers. This would give growers, as well as workers, confidence in the power of data and AI-driven control of crop production systems. These training sites could be organised through a tender for a digital agriculture training site and linked to the risk assessment bodies mentioned above.

9.2.2. Policy options for knowledge creation and management

Artificial intelligence in agri-food makes use of data collected from growers, either manually or by machine. It is possible to extract models containing relationships between many factors in food production, by looking at the data collected from a large number of farmers with different products or production methods. These models can help farmers to understand ongoing processes in the field and make effective decisions in crop or animal management. Providing farmers with the proper training improves their interaction with technology suppliers, while helping them gain insight into the biological and agronomic processes, raising awareness on the importance of the quality of the data they collect.

Regulation on the exploitation and governance of the European databases

The use of databases for the evaluation of the CAP and the European green deal by EU institutions (DG AGRI or JRC), can be fully supported. However, the issue of regulating access to these databases should also be carefully considered.

Databases generated using public funding and resources should be publicly accessible while respecting privacy. Therefore, farmers should be able to access their own data, as well as anonymised or aggregated data for the same region or same type of farm. Research institutes can apply to the relevant database managing authority for temporary access to a database for research purposes, under the condition that only aggregated results are given and no individual farm can be traced in reports. They should be wary of personally identifiable information that can be found through GPS tags or georeferenced data.

Whether the use of and access to the databases should also be made possible for commercial companies (consultants, financial institutions, machinery companies) in an anonymised way, so that individual entries cannot be traced back to individual farms, should also be discussed. Whether these companies have to pay a fee, relative to the number of datapoints used should also be considered.

Transparency and quality assurance of AI models

The transparency and quality of the AI models used in decision-making depends on the modelling algorithms and the quality of the data used as the basis for the AI models. Since these models are used as vehicles for the decisions made when implemented for equipment operations or for farm management, then it is only fair that users enjoy a certain level of quality and trustworthiness. One option for knowledge management is passing legislation that forces the model developer or implementer to provide the user with information containing the description of the underlying model approach, according to categories such as: biophysics based mathematical models, interpretable modelling, or black box models. In addition, the supplier should state which database was used for building the model and on which database a validation test was run, together with the outcome of this validation. In that case, a history of the evolution of the models with the different releases should also be provided.

In addition to the above policy, and since the quality of the data is important for the quality of the models, a model developer may be asked to submit the database that was used for quality evaluation and testing by a proper control body (e.g. the JRC could assume this role). An advisory panel could be created within that control body, which would specify the rules and procedures for the quality evaluation, including a quality scale to be given as result of the evaluation of the database. The control body may contract third parties to run the evaluation.

Additional legislation can stipulate a more in-depth evaluation that does not restrict itself to the databases but also considers the performance of AI models. The criteria may include the model outcome over a specified range of testing data, the level of interpretable results or the underlying assumptions and biophysical models. The reporting method for the results of those tests could be decided by the control body (e.g. JRC together with an expert team from other research institutes and industry). The outcome of the evaluation should also include a sensitivity analysis for small or unexpected deviations or errors in the data. Such a policy should become effective after a preparatory and installation period of about three years. In any case, the confidentiality of the information supplied by the model developer must be guaranteed.

Digital literacy and the digital divide

Every user or person that is confronted with AI in agri-food should receive suitable training in their own language. A number of programs are in place in several commercial institutes and at university level. However, enrolling in these or other training programs must be made attractive, including to small farmers. High prices for digital technologies make it unaffordable to many farmers and, thereby, create or reinforce a digital divide. A way to address this problem begins with providing the appropriate training. This training should start at the level of education the person has received previously but should be extended, to bring general education to a higher level. During the education period, young farmers and future workers in the sector should be part-time employed in an agriculture-related occupation, while their salaries are complemented by a study grant from a professional or vocational training program established by the EU. The scope of the training must focus on the business model of the specific sector first of all, but pay special attention to new technologies as well.

The development of robust AI models that can adapt to the farm size has to be encouraged. Technology developers must indicate if their products are, indeed, also applicable to small farms and can deliver an improvement in farm management; otherwise they must clarify the effect that the size of the exploitation has on the performance of the model. The use of demonstrators, like digital sandboxes and test and experimentation facilities (TEFs) established under the CAP for training programmes, must be encouraged or even made mandatory.

COPA (the Committee of Professional Agricultural Organisations), qualified technology federations and commercial organisations can apply to administer the training programs and are then made responsible for the quality of the training and for the number of participants that successfully complete the training. For this purpose, cooperation with EFFAT (the European Federation of Food, Agriculture, and Tourism Trade Unions) is encouraged.

9.2.3. Policy options towards AI based agricultural economy

Data collection and data entry can be time-consuming for a farmer and they should not be forced to enter the same data again, if different governmental agencies or commercial operators need it.

When, under certain rules, data can be accessed by different organisations, then it is very likely that new start-ups will take a different look at the data and come up with new applications that may give more independent advice to farmers. In all cases, the availability of a reliable data network is necessary in all rural areas.

Legislation that prevents the lock-in of farmers in corporate digital technology

There are several private organisations and public authorities that demand or oblige farmers to contribute data on their farming practices and activities.

Hence, many databases are almost completely based on data entered or owned by the farmers (input manually or by using sensors on the equipment operating on their farm), as well as that collected through public funds. It follows that new legislation can encourage the development of non-proprietary technologies and software for open access and open source solutions, that lead to the technological sovereignty of farmers. This legislation prevents the lock-in of farmers in terms of corporate digital technology. On the other hand, it will give opportunities to new entrants in the software development market and independent consultancy services. It also gives new entrants the opportunity to participate in the monetisation of agricultural data. It can be expected that corporations may consider this as hampering their innovation strategy.

In all cases, it may be of interest that data (collected by machines or manually entered), as well as meta-data, are readable by open-source software. This would overcome the complicating factor that some (or most) platforms on machines for data acquisition or the automation of actions, are proprietary.

Policies towards new market entrants and to limit dominant positions of first movers

The availability of a large network of farmers that contribute to large databases with quality data, combined with publicly available databases, is almost a prerequisite for developing some AI tools in agriculture. When the number of participants increases, then it can be expected that the models become better and the first technology provider that operates with these data has a competitive advantage over later entrants and can generate substantial profits that may be used to prohibit new entrants. The first mover can, in some cases, claim intellectual property rights even on the output type and format of the models.

It can be an option that potential new entrants can obtain financial support to cooperate with public technological institutions, in order to co-develop new applications and compete as start-ups with the incumbents in some applications of AI in agriculture. For this co-development, they are also granted access to publicly available databases and can make an agreement with the institutions on the use of basic AI tools.

This regulation can also imply that rules are set to make it possible for a user (farmer, SME) to switch to a new technology provider at a reasonable cost, including the transfer of data in a readable format.

Affordability and accessibility of the data infrastructure and of the IT network

Bringing the benefits of AI and digital agriculture to all farmers requires the accessibility of networks, databases and machine learning or state of the art analytics algorithms. This accessibility includes the possibility to upload and collect data from wireless sensors in the field and from machines operating in the field. Hence, it implies affordable broadband internet access, not only in houses, but also in fields.

The policy options should specify the granularity of the telecommunication infrastructure in Europe, that must be such that the required data transmission rates for using artificial intelligence and automation in agriculture is also possible in remote rural areas, at a cost that does not discriminate between remote areas, rural areas, or more populated areas. When licenses are sold or granted to the ICT providers this should be an obligatory requirement.

Policy to support investments by farmers or SMEs to make use of AI potential benefits

Besides the investment in machinery and equipment that have built-in technologies for data collection or autonomous operations, there are also other complimentary investments that farmers or SME's have to make, like specialised infrastructure for collecting and transferring the data to the appropriate database or the temporary hiring of specialised workers who know how to use the data. In addition, switching to AI for making use of the presence of AI in new equipment (whether purchased or used by contractors or custom operators) may require changing the process or the overall strategy.

One policy option is to encourage the specific set-up of regional user organisations that receive financial support for technological investment. These can be producer organisations that are operating under the CAP. On the other hand, policies can also encourage targeted investment in selected vertical industries that could benefit all players, where individual farmers or SMEs could not afford to invest alone.

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Annex

Commercial companies that offer AI services in agriculture (non exhaustive list)

- according to the size of the companies and the regions (Artificial Intelligence in Agriculture Market by Technology (Machine Learning, Computer Vision, and Predictive Analytics), Offering (Software, Hardware, AI-as-a-Service, and Services), Application, and Geography - Global Forecast to 2026, n.d.) :
    - By Company Type: Tier 1 – 35%, Tier 2 – 40%, and Tier 3 – 25%
    - By Region: Americas – 40%, Europe – 30%, Asia Pacific (APAC) – 20%, and Rest of the World (RoW) – 10%

The largest companies that are the prominent players in AI in the agriculture market are: International Business Machines Corp. (IBM) (US), Deere & Company (John Deere) (US), Microsoft Corporation (Microsoft) (US), Farmers Edge Inc. (Farmers Edge) (Canada), The Climate Corporation (Climate Corp.) (US), ec2ce (ec2ce) (Spain), Descartes Labs, Inc. (Descartes Labs) (US), AgEagle Aerial Systems (AgEagle) (US), and aWhere Inc. (aWhere) (US).

- Start-ups active in AI in Agriculture (AI in Agriculture Start-ups | Tracxn, 2022)
    - USA 175
    - United Kingdom 39
    - Israel 36
    - The Netherlands 27
    - Brazil 23
    - France 19

Source: Top 25 Agri-Tech Companies in 2021 | by Reetika | appengine.ai | Medium

A list with 14 important start-ups for AI in Agriculture is given in Top 14 Startups Developing AI for Agriculture (2022). Most of the start-ups in this are in the USA.

- Within the framework of EIT, a report was prepared describing the situation of digitalisation and AI maturity among small and medium sized enterprises (SME) from manufacturing and food industries (Baruchelli et al., 2020).
- In this report, a number of the above-mentioned companies are briefly described: what they provide and how it is done (pp15-17), in agricultural production. Commercial activities by companies in the food processing and manufacturing industries form the main part of the report.
- At the time of writing this report, there was no information from other countries or regions about the evolution of AI services offered to agriculture.

There is growing interest in the applications of artificial intelligence (AI) in the agri-food sector, to extract or exploit the information in datasets resulting from the monitoring of products and processes. Artificial intelligence algorithms, and the models derived from them, are used as support systems for better decision making or, in some cases, are implemented in automatic control processes and robotics, to alleviate drudgery.

In this study, sensing and data collection in different agri-food sectors are described, together with how the data can be curated to achieve better management and decision making in crop and animal production.

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