European Commission

AIA

Artificial Intelligence and EU Agriculture

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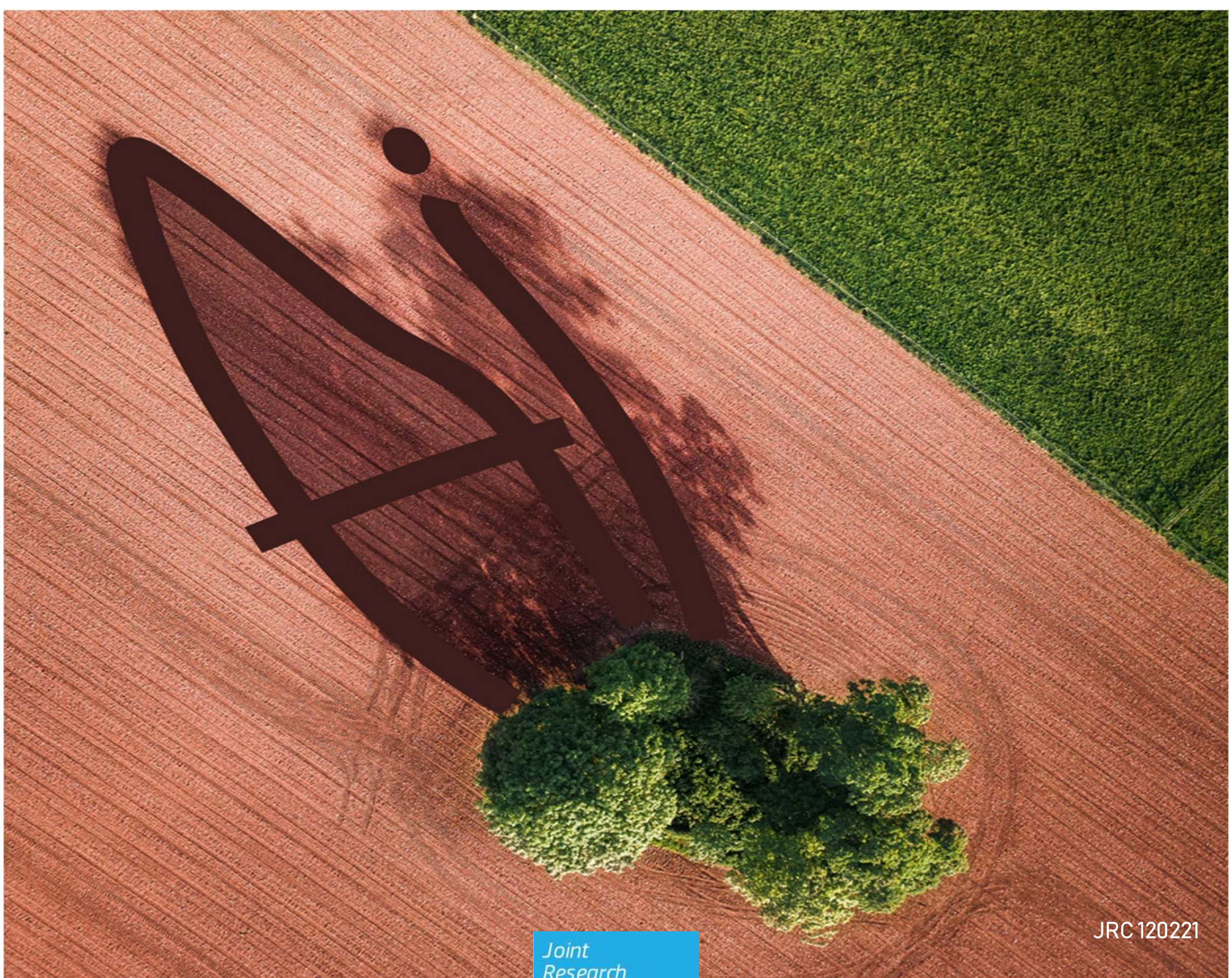
2020



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EU Science Hub
https://ec.europa.eu/jrc

JRC120221

How to cite this report: LOUDJANI P. *et al.*, AIA: Artificial Intelligence and EU Agriculture, 2020, JRC120221.

Contents

Forewords

The origin of this document lays in the contemporary challenge to foster knowledge and innovation to ensure a smart, resilient and sustainable agricultural sector necessary to respond to the main objectives of the next Common Agriculture Policy. Innovation can be defined as the introduction of new products and services to a whole community so that they are adopted by all stakeholders for their added values.

When one starts to read about Artificial Intelligence, even non-initiated persons, can immediately view a whole world of astonishing, or simply essential new possibilities for AI in the agriculture management domain. Thus, this document is meant to give a brief introduction on these possibilities, targeting decision-makers or stakeholders in agricultural administrations and accompany an oral presentation introductory to this topic.

Authors

Philippe LOUDJANI, Wim DEVOS, Bettina BARUTH and Guido LEMOINE.

Abstract

Artificial Intelligence (AI) is a broad field of computer science which started at the end of the 40's but became only popular today thanks to increased data volumes, advanced algorithms, as well as improvements in computing power and storage capacity. The activities, for which computers with artificial intelligence, are designed include speech and pattern recognition, machine vision, learning, planning and problem solving.

The scope of the current document, by no means exhaustive, is to discuss the innovation potential of Artificial Intelligence in the agricultural sector. After a short introduction of what is AI and what are its main advantages, a summary is made to show how AI can be a gamechanger, first in the agriculture private sector and then as a supporting tool for policy implementation by national administrations.

AI is still at its early stage and the possible broad use in agriculture policy needs to overcome several challenges discussed in the document. Much remains to be done and in such research and innovation areas, the JRC has an important role to play.

1 Introduction

Agriculture is one of the most ancient economic activities; therefore, it is generally identified as a traditional sector and – unfortunately – too often considered a conservative and static sector, which is unable to follow the pace of the other sectors. If one wants to look through these claims, one finds that agriculture embodies a strong dynamism; e.g. the EU Common Agriculture Policy (CAP), over its history, has been reformed several times to adapt to changing economic and social challenges.

Today, agriculture is again making a very sharp turn with challenge levels not encountered since after the second world war. Agriculture must adapt to many rapid changes due to external pressures that are growing even more rapidly. Population growth, natural resources availability, globalization, additional rules, competitive advantages, concern for animal welfare, environmental protection and climate change, rural development, consumer rights, energy consumption are all different aspects that impact on global agriculture, and aspects which are particularly sensitive within the European Union.

Resolving that complex puzzle can be tentatively described as looking into ways to produce more for all with less resources and in a sustainable manner ensuring sufficient nutritional quality and diversity and contributing to huge environmental and climate-related challenges. The ever-increasing demand for production can no longer be ensured only through traditional farming methods. Thus, changes should be introduced across the entire agricultural value chain up to the behaviour of the end consumer. Direct and indirect technical drivers of change have accelerated during last decades (e.g. positioning technology (GNSS), sensors, machines, computer capacity, Internet of things, data analytics, etc.). Among these drivers, Artificial Intelligence techniques are very fast increasing and showing great potential as cross-cutting solutions for many sectors.

Designed during the after war years, the common agriculture policy has been created to ensure a stable supply of affordable food in Europe. Today, the role of a common "food security" policy is even more necessary to respond to the exceptional conditions triggered by climate and environment developments.

Thus, the scope of the current document, by no means exhaustive, is to identify and discuss the innovation potential of Artificial Intelligence in the agricultural domain and especially investigate its application as a supporting tool for policy implementation by national administrations. This involves research and innovation areas where the JRC can have an important role.

2 What is Artificial Intelligence (AI)?

Artificial intelligence (AI) is a wide-ranging branch of computer science dealing with building smart machines that are capable of performing tasks that typically require human intelligence. Some of the activities, computers with artificial intelligence are designed for, include speech recognition, machine vision, learning, planning and problem solving.

Artificial Intelligence is one of the recent fields in the history of science and engineering. Developments started at the end of the 40's and the term artificial intelligence was invented in 1956 (John McCarthy). However, AI became very popular in recent times thanks to the increase of data volumes, the emergence of advanced algorithms, as well as improved computing power and storage capacity.

Machine learning and deep learning are currently the two dominant technologies of AI.

In Machine learning, a computer is fed with data and it then uses statistical techniques to "learn" how to get progressively better at a particular task, without having been specifically programmed for that task. Machine learning can consist of both supervised learning (using labelled data sets) and unsupervised learning (using unlabelled data sets).

Deep learning is a special type of machine learning that runs input data through a biologically-inspired neural network architecture. These networks are made out of a number of generated hidden layers through which the data is processed, allowing the machine to iterate "deep" in its learning, making dynamic connections and weightings on the input data until the best results are achieved.

There are other technologies within AI that are also very fast growing. They are listed in the figure 1 below and will be touched upon latter in the document.

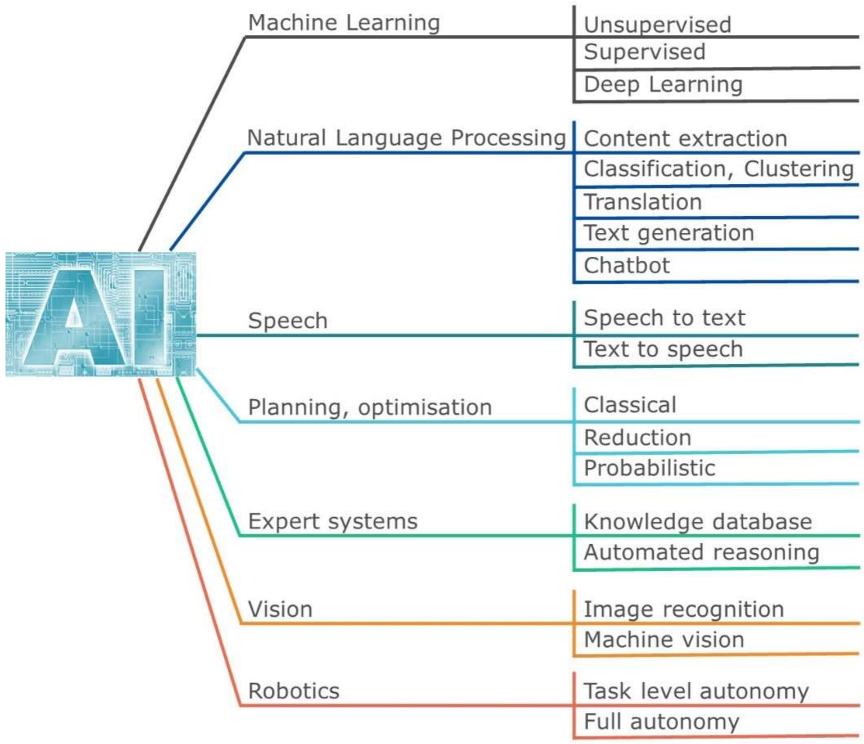

Figure 1: Main technologies used in Artificial Intelligence

3 What are the main advantages of AI?

Artificial intelligence, if coded properly, helps in reducing the error and increasing the chance of reaching accuracy with a greater degree of precision and higher speed compared to humans. Indeed, AI allow logical applications without emotions, making rational decisions with less or no mistakes; Machines, unlike humans, do not require frequent breaks. They are programmed for long hours and can continuously perform without getting bored, distracted, or even tired.

AI allows handling multi-dimensional and heterogeneous sources of data and discovering specific trends and patterns that would not be apparent to humans; AI adapts through progressive learning algorithms to let the data do the programming. AI finds structure and regularities in data so that the algorithm acquires a skill.

AI can help predicting what a user will type, ask, search, and do. They can act as assistants and recommend actions/solutions. In many situations, the complete absence of emotional side, makes the robots “think” logically and take the right program decisions.

4 What are the main disadvantages of AI?

Artificial intelligence requires huge development costs. AI is based on software programs which may need frequent upgrading to cater to the needs of the changing environment. In the case of severe breakdowns, the procedure to recover lost codes and reinstating the system might require time and cost. In addition, there is often a need to fill a knowledge gap and the necessity to acquire skill competencies though new staff or staff training.

Artificial Intelligence cannot fully replace/replicate humans. Machines do not have the multi-perspective skills of humans, as they are typically programmed to perform specific tasks in constrained conditions. Furthermore, since AI knowledge is often learned from patterns in large training data sets, such knowledge is based on deduction, not reasoning, e.g. with understanding of the physical processes that underlie that knowledge. AI applications do not include emotions and moral values. They perform what is programmed and cannot make the judgment of right or wrong and cannot take decisions if they encounter a situation unfamiliar to them. They perform incorrectly in such situations. Machines cannot replace the intuitive creative abilities of the human brain and its possibility to think out of the box.

As seen partially with smartphones and other technology already, humans can become too dependent on AI and impair their thinking and judging abilities.

Replacement of some human activities with machines can lead to unemployment or necessity to ensure professional reorientation programs or redeployments. Nevertheless, for employment the picture is not fully negative. Usually when technological innovations take place, it occurs in two forms, process and product, these being capable of creating new industries, new assemblies and subsequently, new jobs.

5 Why AI is necessary in agriculture?

The global population growth is increasing demand in quantity and quality of all resources. However, land availability is restricted, so there is a need to produce more with less and to do so in a sustainable manner (the so-called sustainable intensification).

CAP2020+ has as scope to tackle these challenges and this reflects in its set of nine specific objectives:

> 1) Support viable farm income and resilience across the EU territory to enhance food security;
>
> 2) Enhance market orientation and increase competitiveness including greater focus on research, technology and digitalisation;
>
> 3) Improve farmers' position in the value chain;
>
> 4) Contribute to climate change mitigation and adaptation, as well as sustainable energy;
>
> 5) Foster sustainable development and efficient management of natural resources such as water, soil and air;
>
> 6) Contribute to the protection of biodiversity, enhance ecosystem services and preserve habitats and landscapes;
>
> 7) Attract young farmers and facilitate business development in rural areas;
>
> 8) Promote employment, growth, social inclusion and local development in rural areas, including bio-economy and sustainable forestry;
>
> 9) Improve the response of EU agriculture to societal demands on food and health, including safe, nutritious and sustainable food, as well as animal welfare.

To reach most of these objectives, technological innovation is mandatory. With its potential to boost automation, knowledge gaining, productivity and efficiency, AI will play a major role in agriculture domains, even if not used standalone but in combination with other technologies (enhanced GNSS, adapted practices, Internet of Things (IoT), cloud based solutions, new sensors …).

6 Current and potential developments in private sector

AI is very fast growing in the private sector, where it proposes solutions and services to farmers and food/feed production companies to ease their workload and to enable smart farming.

The main areas, where AI development is a strong asset, are:

1. AI and robotics

AI Algorithms are trained to analyse images from cameras on drones or robots to recognize specific patterns on the crop, fruit or even animal condition.

The information so detected allows to launch alerts (automatic identification of a plant disease) and to do automated farming (Fruit harvesting with robots, automatic milking, robot weed killer/uprooting, automatic animal counting …).

For example, machine vision systems can recognize crop diseases and pest damage. Such AI tool can automatically detect diseased cassava plants with 98 percent accuracy. The neural network that powers this AI tool runs entirely on a smart-phone, without the need for an expensive processing architecture, making it easily accessible to farmers (Ramcharan *et al.*, 2017).

In another example, a robotics company developed an automated apple picker, to identify the fruit, determine whether it is ripe and then use a vacuum system to pick the apple without damage (Abundant Robotics). This requires sensors and cameras to collect data to provide automated decision-making in real time to actuate robotic components. The same system approach is also being developed/adapted for other fruit such as oranges and strawberries (Agrobot, Dogtooth, Harvest CROO Robotics) or vegetables like lettuce (Vegebot: Birrell *et al.*, 2019).

Figure 2: Test of automatic apple harvesting by FFRobotics Company

As a last example, in the well-developed precision farming domain, there are self-driving tractors that can autonomously navigate the farm holding (Case IH, New Holland). The self-driving vehicles have data collection devices to capture navigation routes along with sensor data relating to internal components and the external environment. Thus, they can ensure works such as automatic planting with high accuracy and reducing seed losses; automated grassland mowing, and even automated weed removal (Ecorobotic). These precision farming techniques allow to reduce if not eliminate herbicide (pesticide) spreading.

It is still anecdotal, but in 2017, researchers from Harper Adams University (U.K.), managed to harvest about 5 tons of spring barley from the world's first robotically tended farm. Everything from start to finish — including sowing, fertilizing, collecting samples and harvesting — has been done by autonomous vehicles on the farm (Teresa Pultarova, 2017).

Figure 3: 'Bonirob' robot developed by [Deepfield Robotics] to automatically pick out weeds in crops

2. AI and Internet of Things

The IoT defines devices that are able to connect to and receive and transfer data via the Internet.

In a traditional farming business, many decisions are usually based on experience, historical data and 'feel' of the farmer. These decisions govern the use of fertiliser, irrigation, pesticides and harvesting.

Alternative solutions are under development where the IoT collects data and the AI processes these data into meaningful information.

At field level, information from above ground imagery can be combined with data coming from other sensors and sources (temperature, rainfall, soil texture …) to provide cognitive and innovative solutions for precision farming (spreading good quantities of products/water at the right place and the right time) or SMART agriculture. These solutions can recommend calibrated doses of fertiliser, targeted irrigation and early identification of diseases or substandard conditions. The SEMIOS or CROPIO solutions are examples of this.

Substantial progresses are observed also in the domain of animal monitoring. IoT and AI start to provide tools to help farmers in monitoring, forecasting, and optimising the farm animal husbandry.

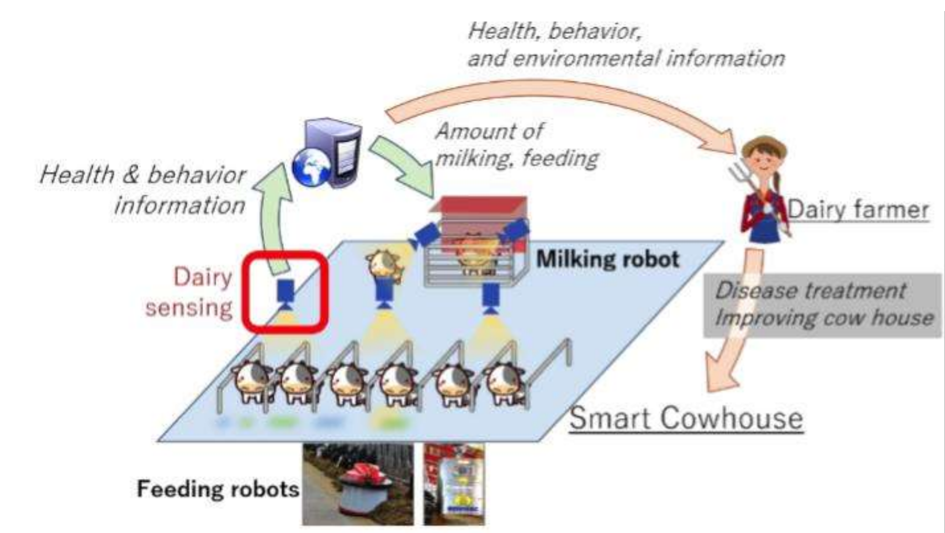

Figure 4: Smart cowhouse using imaging and AI to monitor milk cow health (Osaka University)

AI can allow to accumulate and analyse data of each individual animal to optimise its diet or monitor its behaviour. For instance, a Dutch company has developed a motion-sensing device attached to a cow's neck to transmit its movements to a program driven by AI. Daily sensor data, compared to long time series, serve to generate alerting messages to the farmer e.g., that a particular cow is ill, has become less productive, or is ready to calve.

3. Specific case of drones

While still limited in their spatial range of action, UAVs (Unmanned Aerial Vehicles), commonly known as drones, combined with AI technics can offer many solutions at parcel and holding level such as precision seeding, precision irrigation or even precision protection plant products spreading. The versatility of drones with the possibility to mount different sensors (visible, thermal, infrared …) to capture up to centimetre resolution images provides many opportunities to improve farming processes. Drones exist now that carry small tanks (5 to 10 litters or kilograms) and be directly used as precision product spreader. For more information, see the Digital transformation Monitor report on Drones in agriculture.

Figure 5: UAV used for precision Plant Protection Product spreading over a corn field

4. Decision support services

Decision support systems (DSS) in agriculture are information technology (IT) resources that are designed to tackle complex problems in crop production, utilising the best available data and knowledge about scientifically-sound best practices. AI plays an increasing role in the development of these Knowledge systems that are now predominantly delivered in the form of Apps to help farmers taking decisions in different domains. Among these, one can cite:

a. E-calculators / Agriculture apps

E-calculators are smart applications that can help farmers to choose the most appropriate solutions for their farming activities. Some calculators are based on computer vision and deep-learning algorithms to process data captured by drones/smartphones and/or software-based technology to monitor crop and soil health (e.g. CropDiagnosis). Others are based on machine learning models and developed to track and predict various environmental impacts on crop yield such as weather changes (e.g. FarmShots). Some are more focused on price prediction and market guidance. They are designed to help farmers better facing the increasingly more severe and volatile weather impacts. A wider range of software at farmers' disposal can be found under the following link:

https://www.capterra.com/farm-management-software/

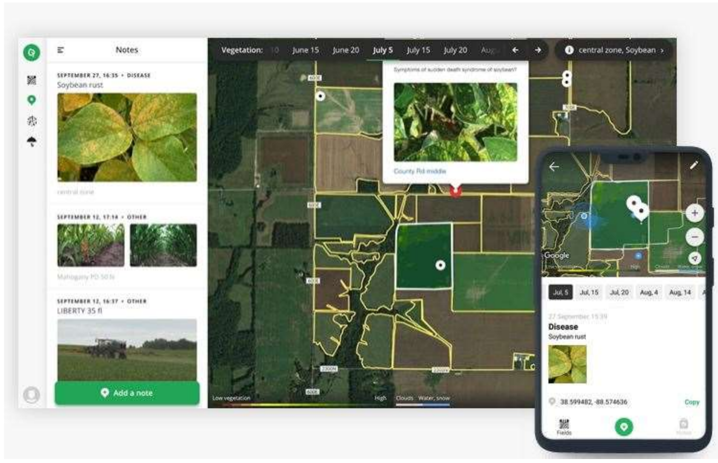

Figure 6: Screenshot of the field scouting option of the OneSoil Company platform

As for example of the wealth of developments occurring in the App domain, the below infography provides an overview of existing smartphone Apps in the plant production sector.

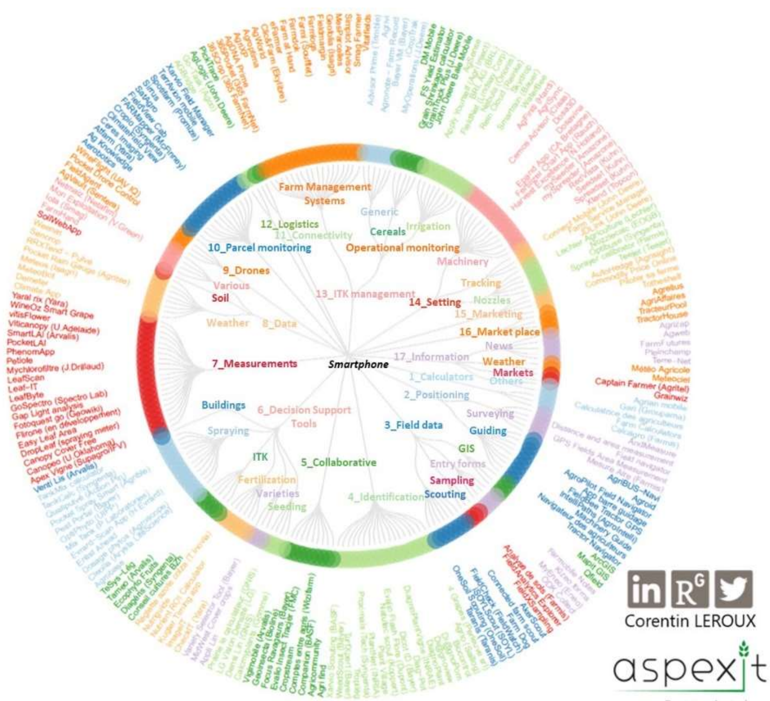

Figure 7: Dendrogram of smartphone apps in the plant production domain (Source: Aspexit).

b. Chatbots

Chatbots (sometimes referred to as a chatterbots) are evolutions of Apps with the aim to provide fast solution to simple, urgent problems and being much easier and cheaper to develop. They are AI powered computer programs which conduct an artificial conversation via auditory or textual methods. They use AI technologies, including deep learning, natural language processing and machine learning algorithms. The bot is programmed to self-learn. As a chatbot receives new words and dialogues, the number of inquiries that it can reply to and the accuracy of each response will increase. Chatbot virtual assistants are increasingly used as they allow to save time and gain in knowledge by providing answers on-the-fly. In the agricultural sector, chatbots are still very few but have great potential to provide farmers with fast answers and recommendations on specific problems (e.g. plant or animal disease identification and treatment).

7 Potential for the CAP and public administration

As seen above, vast opportunities are already offered by private sector using AI. These solutions developed independently without a specific intervention from, or link to, the common agriculture policy.

However, the CAP is entering a new era with its main challenge of sustainable intensification of production and with a variety of performance obligations (soil, biodiversity, climate impact mitigation, energy saving …). At the same time, larger and larger amounts of data are produced and often made available free of charge (Like COPERNICUS data). The use of AI should attract interest from agriculture policy makers and public administrations since it offers new opportunities to automatize processes of administration and management of farmer's aid applications. AI can also contribute to the learning processes, knowledge acquisition and exchange regarding the agricultural practices implied in these aid applications.

1. Already in use: checks by monitoring

The introduction of free Sentinel data has provided the opportunity to replace the On-The-Spot Checks (OTSC) by a proactive and preventive method of checks by Monitoring (CbM). CbM have been officially introduced in 2018 by Article 40a of Regulation (EU) No 809/2014 as amended by Commission Implementing Regulation (EU) 2018/746.

The applicability of this method is validated by Sentinel satellites 1&2 automated processing using machine learning technology to detect eligibility conditions or farming activity evidence. On these aspects, one can see the Technical guidance on the decision to go for substitution of OTSC by monitoring) and for further details on Check by Monitoring method, read the "discussion document on the introduction of monitoring to substitute OTSC".

In the proposal for the next CAP regulation the CbM method should be substituted by an Area Monitoring system AMS) (Art. 64 of the proposed so-called CAP 'Horizontal' Regulation). Like CbM, AMS will assess agricultural activities and practices on agricultural areas by Copernicus Sentinel satellite data but, unlike CbM, the AMS enables MS to expand the range of application contexts to include, among others, the provision of services to farmers, the quality assurance of indicators in the context of the post-2020 CAP, and the collecting of data for novel indicators and statistics. In either system, automated processing using machine learning technology, together with other AI technologies, are expected to play a major role.

5. Already in use: support to LPIS update

While developing methods of Sentinel data automatic processing to support the checks by Monitoring, it rapidly became obvious that similar principles could be used for other components of the integrated system (IACS). It is particularly the case for the update process of the Land Parcel Identification System (LPIS). Managed by Member Sates paying agencies, LPIS record and geo-locate the lands eligible for CAP payments. LPIS information content should permanently reflect the actual situation of land eligibility on ground. This means that regular screening should be done to identify and report changes (e.g. house or road construction, conversion of grassland to arable land, land abandonment …). This is commonly done through visual interpretation of Very High Resolution imagery (often aerial) acquired regularly in Member States.

The use of AI techniques like machine learning and image segmentation have a great potential to improve and speed up the LPIS update processing. Automatic detection of changes using Sentinel data can be used for instance in the frame of risk analysis. By spotting areas of higher change occurrence, it can help administrations to decide on zones where (aerial) VHR imagery should be renewed in priority.

Automatic identification of changes using Sentinel data can also be used to flag reference parcels for potential need for update. Once flagged, visual interpretation of the parcel on VHR imagery will allow to confirm or no the change and proceed to the update if necessary.

Another approach has been used 2019 by Belgium-Flanders administration to automatically identify and digitise specific ineligible elements over the whole territory (i.e. greenhouses and horse tracks/horse carousels) using training samples. See Figure 8 and Figure 9 below.

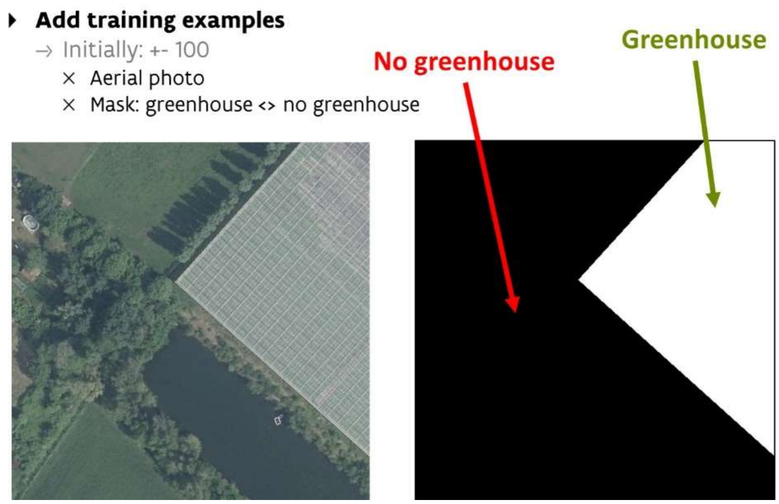

Figure 8: Example of automatic identification and border detection of greenhouses using VHR aerial imagery in Belgium-Flanders (Courtesy: Department Landbouw & Visserij).

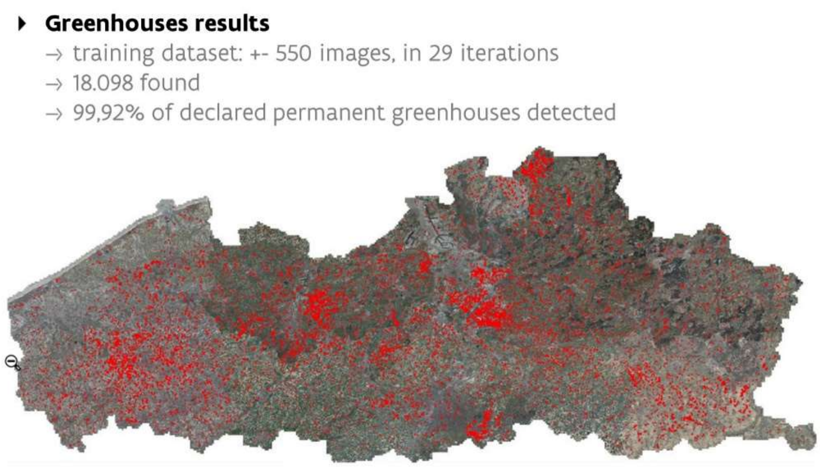

Figure 9: Belgium Flanders map locating greenhouses automatically identified on VHR aerial imagery (Courtesy: Department Landbouw & Visserij).

6. Handling geotagged photos

As part of a monitoring system, farmers (or other actors) may provide the administration with geotagged photos to evidence land use or land cover elements. The quantity of such photos can rapidly grow making an individual visualisation unworkable.

With the recent advances in computer vision and machine learning techniques, image content recognition has become a realistic solution. It allows not only to confirm/reject the crop type/activities depicted in the photo but also to filter out photographs of objects that are defined as not of interest. The geolocation attributes, which are based on precise, untampered GNSS signals (e.g. from the Galileo system) are essential both in the monitoring context, but also to increase the location specificity of machine learning algorithms.

Figure 10: Example of automatic recognition of image content.
Geotagged photo of an Alfalfa field and automatically classified as Alfalfa with 99.4% confidence (work and courtesy of Aleksandra Sima, JRC D5)

One weak aspect is that deep learning technologies operate on tagged (e.g. categorized) data. The crucial phase of tagging/labelling requires experience and expert judgement. This is still mainly done manually and therefor very resource intensive. Comprehensive tagging automation is thus a great challenge that is currently strongly addressed.

Thus, apps are now available to help to identify plants providing a picture (e.g. Pl@ntNet, PictureThis, PlantSnap …). For Pla@ntNet for example, the user help focusing the automatic recognition specifying which part of the plant has been captured. In addition, if a plant has been correctly identified, the picture can be uploaded in the APP database with the corresponding label/tag thus users are permanently enriching categories of training set (i.e. flowers, leaves, barks and entire plant). There is currently a need to build and organise (free and open) databases targeting the needs for land use and land cover identification specific to the agriculture domain and some Member States have already started to do so.

Furthermore, AI, through augmented reality solutions in dedicated apps, could guide camera users to take pictures on predefined locations and guarantee prerequisite conditions (zoom, panorama, camera tilting …).

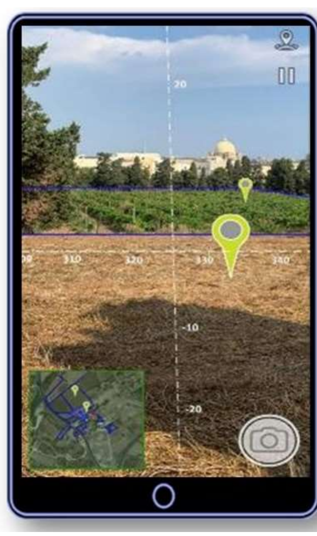

Figure 11: "SITI Land AR" App facilitating geotagged imagery capture.
Augmented reality is used to direct the user to the targeted parcel with camera tilting, parcel borders and parcel identifiers displayed real-time (Courtesy of Abaco Company, IT).

For more information, please refer to the JRC technical report on the use of Geotagged imagery in the frame of CAP checks (JRC120223).

7. Potential support for CAP Strategic Plans

The Commission's legislative proposals on the future of the CAP introduced the concept of CAP Strategic Plans at the level of individual MSs. MSs will have to identify their own priorities for intervention and, in accordance with targets set out at the EU level, select, justify and elaborate their measures from the given set of instruments. The EC will approve the CAP plans and monitor their results in accordance with the set objectives and indicators.

AI technology could help addressing several challenges resulting from this legislative proposal.

- Text mining, natural language processing (NLP)

These technologies, applied in the domain of literature review and meta-analysis, could help gathering knowledge in specific domains (farming practices, biodiversity, soils, water quality & quantity, energy …) and could help MS reducing subjectivity in decision-making and justifying the proposed measures in strategic plans or could support the EC approving these plans.

Indeed, the creation of knowledge depends upon the ability to find, understand, and synthesise research that has been done before. Up to now this has always been a very time (and cost) consuming task relying on the common involvement of several experts on a dedicated thematic field. To date, the use of Natural Language Processing paves the way to automated review of immense collections of research papers or studies: performing keyword searches, browsing articles to discern what is most relevant, determining whether a paper is worth reading, and even prioritising articles. One can read, out of many others, the paper from Marshall and Wallace (2019). Text mining / Natural Language Processing can allow to discover information out of multilingual sources and to provide results in a specific language. This 'polyglot' ability can substantially facilitate the knowledge accrual and the knowledge dissemination within and among all Member States.

- Machine learning, deep learning, IoT

The use of image time series, standalone or together with other data (climate, soil …), could be used for spatial mapping, object identification, image segmentation and pattern recognition. This could improve rural area delimitations and farm landscape zoning to better target areas of a specific intervention. It may also support the creation of reference baselines from which evolution will be measured and delivery of results/performance evaluated.

8. Potential support for Farm Advisory Systems/Services

As part of the CAP legislation, all Member States must operate a farm advisory system (FAS). This FAS is a system for advising farmers on land management and farm management.

In the future CAP, such FAS is expected to play a more prominent role since farmers will face an increased need for knowledge and skills in a wide range of domains (water, soil, biodiversity, climate change, precision farming …). For this reason, the legal proposals consider it is essential to set up stronger agricultural knowledge and innovation systems (AKIS). AKIS is used to describe whole knowledge exchange systems: the ways people and organisations interact within a country or a region and can include farming practice, businesses, authorities, research, etc.

AI integrated into decision support systems could impact advisory services in substantial ways. AI tools can be used to analyse and select relevant information from voluminous and varied data with the aim to learn and implement. This simplification capacity is indispensable for the complex problems where the environment exceeds the human ability to identify and comprehend the relationships between variables.

As mentioned above, decision support tools are fast growing in the private domain. Farmers could use them in combination with the FAS. Furthermore, GIS tools, computer capacities, computer power, cloud computing possibilities are now developed to a point where MS administrations could consider building and providing some decision support mechanism as part of their integrated management systems.

For instance, when a farmer makes his/her aid application and considers the choice of crop for the location where it will be grown (vulnerable zone, protected zone, erosion risk zone …), relevant information could be sent to the applicant providing/reminding any legal rules/requirement linked to each specific crop/parcel combination. This information could include the list prohibited plant products, the maximum plant products authorised, or even the legal compliant period for spraying.

9. Potential support for crop yield forecasting

Accurate and timely estimations of yields of the main European crops are of the upmost importance for EU food policies and international markets and trade.

Since the early 90’s, the MARS Crop Yield Forecasting System, ran by the JRC, is the official system providing crop monitoring and yield forecasting for the EU. The so-called “bulletins” are also scrutinised by the market operators. The forecasting system uses near real-time data like observed weather, weather forecasts and medium spatial resolution remote sensing data. Static input data consists of soil maps, crop calendar and historical administrative yield statistics. With these inputs, data crop conditions for the ongoing season are simulated and yield estimates are updated on regular intervals to finally make crop specific end-of-season yield forecasts.

However, these parametric models based on the season’s deviation from an averaged years’ crop growth suffer from weaknesses since they imperfectly capture some factors (e.g. genetic and environmental impacts) and interaction with other factor. Without the use of the high-resolution Sentinel data, signals and trends are not disaggregated at the parcel level. The impact of these shortcomings is increasing under the influence of climate change and the higher frequency of extreme weather events.

Neural network and deep learning tools can simultaneously cope with complex nonlinear relationships in high-dimensional datasets and the increased number of high spatial and temporal resolution satellites (e.g. Sentinel fleet). As a result, they are very promising to improve predictive aspects (Guimarães Nobre *et al.*, 2019; Nari K. *et al.*, 2019) and to increase the knowledge gain (Khaki s., and Wang L., 2019). Ultimately, this should improve the efficiency and performance of crop yield models.

8 Challenges

The use of AI for agriculture is only at an emerging stage and to explore its full potential, several challenges still have to be overcome.

1. Data availability and use

As already mentioned in Geotagged imagery chapter, AI systems need a lot of appropriate data to train machine and to improve predictions and output accuracy. It is necessary to create database, access them and ensure interoperability between data and computing tools. Different databases are already available publicly, some with wide research/application scopes and other more thematic specific (e.g. image-net, leafSnap, leafNet: Barré P. *et al.*, 2017).

Citizen science and crowdsourcing can play a major role in data collection. The word crowdsourcing is a self-explanatory combination of crowd and sourcing, and was first created in 2006 (Howe J., 2006). Despite the multiplicity of definitions for crowdsourcing, the generic concept involves the broadcasting of problems to the public, and an open call for voluntary contributions (through Internet, mobile phones) to help solve that problem.

If suitably organised, farmers, on voluntary basis, could obviously be knowledgeable information providers on agriculture land and activities. Such information could be gathered though, as best candidate, the Geospatial Aid Application (GSAA); the mandatory IACS online aid and payment claim application. Novel approaches could, for instance, consider the output of farm machinery as acceptable evidence, especially for more complex schemes (e.g. extensive grassland management, precision farming practices that lower environmental impact).

To date, the quality of the inputs collected through crowdsourcing as well as the data quality procedures that are needed to improve them draw some criticism (i.e. biased information). Nevertheless, AI algorithms are promising to filter the noisy results and produce more precise and accurate insight from those big data sets. For a review of crowdsourcing for agricultural applications see Minet F. *et al.*, 2017.

It is necessary to push forward the ongoing efforts towards combining social, economic, climate and environmental data and extend their link to agriculture. Combining that information will help improving the overall knowledge on rural areas and enable making more informed decisions aiming at their smart management. The specific potential of these developments as support within the CAP strategic plan process is reiterated here.

2. Cybersecurity and privacy protection

As any other technological innovation, AI applications may have adverse consequences for farmers and farming companies. Recently, the Consultative Committee of the Convention for the Protection of Individuals with regard to the Processing of Personal Data published its Guidelines on Artificial Intelligence and Data Protection (https://rm.coe.int/guidelines-on-artificial-intelligence-and-data-protection/168091f9d8). These guidelines assist policy makers, developers, manufacturers and service providers in ensuring that AI applications do not weaken the privacy rights and the data protection rules.

Both elements should seriously be examined since the trend is that AI domain will more and more depends on the use of algorithms on data in open source environment.

3. Building confidence and trust in AI systems

Many AI tools that rely on vast amounts of data are usually not self-explanatory (black box concept). At the same time, any algorithm carries with it an inherent possibility for error. The lack of capability of the algorithm to explain its business logic and decision rules invites scepticism on its results. Doubts persist whether the results can actually be considered as fair, aligned to human values and relevant to the problems they claim to tackle. This triggers concerns as to the amounts and type of data handled by AI systems, as to those who produce them and as to those who may maliciously distort them.

So ensuring transparency in AI systems and occasionally succeeding in explaining a black-box operation will be an asset to build confidence in such technique.

4. Societal and ethical implications

It is not straightforward to predict the societal and ethical implications of AI introduction in agriculture. Some authors even warn that some farmers might not consider the use of AI and may prefer instead to keep depending on their empirical expert knowledge (Rose D.C., and Chilvers, 2018).

AI developments imply that the agriculture workforce transits to a new job environment and learn new skills. This is both a challenge and an opportunity for rural economies. While AI applications grow fast, administrations lack skilled professionals who can design and work with this technology. They need to train their professionals to unlock the benefits, or hire new AI skilled staff and reorient existing ones. Some stakeholders fear that AI advances will bring unemployment and social turmoil, especially in the agriculture sector.

This is not new; in the twentieth century, the proportion of the workforce in EU agriculture decreased from 40% in 1900 to some 2% after the introduction of more efficient tools, specialised machines, and a better application of scientific progress.

Even if AI might further reduce or replace the labour on agriculture land (farm robots), it may free time for farmers and dedicate it to other tasks or even tackle the problem of lack of harvesting workforce for some fruit and vegetable products. Also AI may well increase job opportunities for consultants to farmer businesses and IT specialists in Member States administrations.

5. General development of digital agriculture – digital market

Organizations will need robust data capture and governance processes as well as modern digital capabilities. For these, they must be able to build or access the necessary infrastructure. Cloud computing and "massively-parallel" processing systems seem unescapable. Technologies like GNSS and telecommunication are essential enablers for future AI-based take up.

AI in agriculture can and will be more and more deployed through apps on smartphones. Accessibility for all EU farmers requires seamless mobile connectivity which still remains a challenge for many rural areas. Existing broadband infrastructures must keep pace with the growing demand of data capture, transfer, and exchange necessary for AI and digital agriculture as a whole.

To address this shortfall, the Commission has proposed a set of measures to ensure everyone in the EU will have internet connection. In its Digital Single Market strategy, the Commission adopted initiatives and legislative proposals so that, among others, all European households, rural or urban, should have access, by 2025, to networks offering a download speed of at least 100 Mbps, which can be upgraded to 1 Gigabit/s.

9 The role of JRC

The new CAP delivery model shifts emphasis from compliance to performance, and rebalances responsibilities between the EU and the Member States, while improving coherence across the future CAP with other EU policies.

In that context, Member States will define intervention measures in CAP Strategic Plans to target policy measures to national conditions. The Commission will assess and approve the Strategic Plans to confirm they adhere to EU policy parameters. Member States and the Commission will share responsibility for monitoring progress and evaluating effectiveness.

Specific requests were made for JRC involvement in collecting knowledge on the effectiveness of interventions, accompanying the Member States in the design of their CAP Plans and supporting AGRI in assessing the CAP Plans. JRC support is also welcomed concerning the policy preparation, simplification, integrated System Methodology and quality assessment, monitoring of yields and sharing expertise in the agriculture – environment – climate nexus where the CAP now has to deliver more and better.

As described in the document, the AI technology trends (e.g. big data analytics and machine learning, intelligent sensors, surveying and rural digitization) hold the promise of driving the move to the new delivery model. It nevertheless needs to be matured enough to provide MSs with the necessary guidance on rules and working methods. This is where JRC fully finds its mandate as the Commission's science and knowledge service.

10 Conclusions

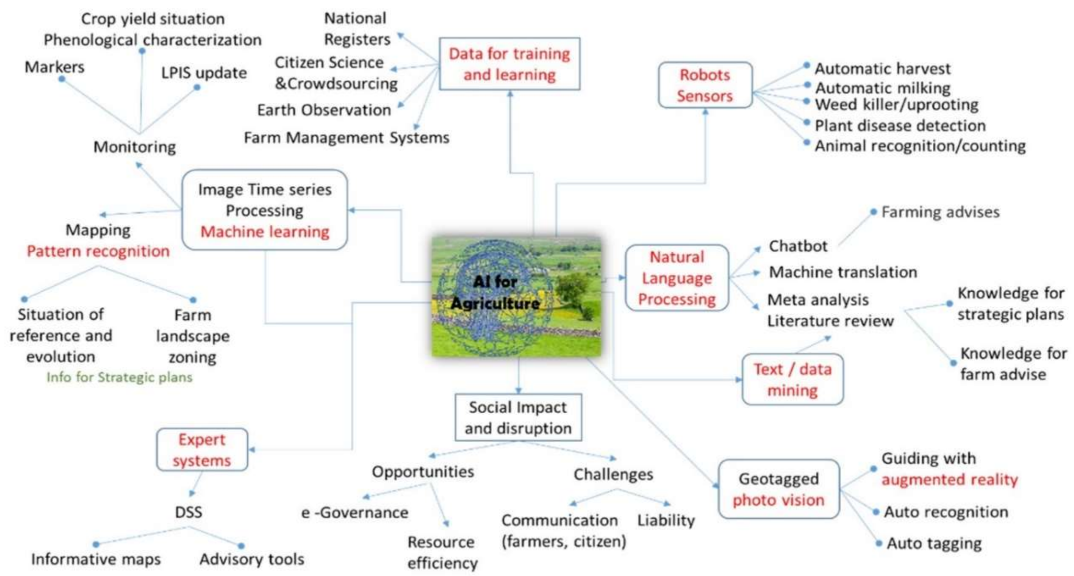

Figure 12: Mind map of Artificial Intelligence applied in agriculture

As result of the recent progress in computing capacity and a surge of digital data availability, artificial intelligence technology, which existed since the late 40's, is now becoming a strong option to analyse complex systems like agriculture and farming.

Private companies have taken the first steps to deploy artificial intelligence (AI) together with big data analytics, and even the Internet of Things (IoT) to gain insights into and offer solutions in the farming business. Current AI solutions combine weather/land/soil/health of crop information to allow farmers to grow the appropriate crop with best yield, with time, money and work savings in any given season. The deployment of AI-driven robots to support some farm activities, reducing, replacing human labour, is also growing very fast.

While many of these private-sector solutions are aimed at agri-businesses and enterprises, some have also potential for the public sector. Policymakers dealing with agriculture face new agri-environment, climate, energy, social, food quality and safety challenges and so might benefit from new insights offered by data analytics. In the CAP payments domain, the first important step has been made by the introduction of the checks by monitoring. It paves the way for more efficient climate-aware cognitive farming and for advanced systems of crop monitoring. In the frame of the future CAP, AI promises opportunities for the strategic plans setup and the deployment of advisory services and the sound management of rural areas as a whole.

Nevertheless, AI deployment is still at its early stage and the possible broad use in agriculture policy needs to overcome several challenges. First, AI systems need a lot of data to train machines and to make precise and robust predictions, especially in location specific contexts. For agricultural land and activities, consistent temporal series only start to be established, and even though spatial data can be gathered more easily, some suffer from inconsistency and inaccuracy. Second, data infrastructures need to mature in their way to organize data capture, sharing, harmonization, labelling, security and safety. At the same time, public administrations need to build confidence and trust in AI, develop the necessary procedures and make the investments and changes in workforce and skills if not the way to approach agriculture supervision.

Future developments will depend and should benefit from actions and incentives from EC policies/initiatives (e.g. Single digital market) and from active research and exchange of information (e.g. AKIS).

Today's AI systems are primarily software-only systems. Developing hybrid architectures by coupling algorithms, data from multiple sources (satellites, drones, field and machinery sensors), and applications (precision farming) will improve decision making for farmers, agronomists and public authorities and pave the way to the agriculture of the 21st century.

In such framework, the JRC has an important role to play as the one recently fulfilled in the development and implementation of the Checks by Monitoring methods. For this, and for the AMS to come, there is still a lot to do to fully automate processes (e.g. to address various environmental aspects as part of Rural Development measures and conditionality) and the use of AI with VHR, Sentinel and geotagged imagery will be essential.

Alan Turing's (1950) essay on Computing Machinery and Intelligence concluded that: "We can see only a short distance ahead, but we can see that much remains to be done". This is definitely applicable to AI in agriculture.

Last but not least, AI should not be investigated as an aside research and application domain. For instance, coupling artificial intelligence with blockchain technology holds great perspectives. While AI will help in sustainable and performant farming management, blockchain will ensure that data are distributed in a transparent manner to evoke confidence and transparency in the future Farm to Fork system; but this should constitute a different report.

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List of abbreviations and definitions

AI	Artificial Intelligence
AKIS	agricultural knowledge and innovation system
AMS	Area Monitoring System
CAP	Common Agriculture Policy
CbM	Checks by Monitoring
CMYF	Crop Monitoring and Yield Forecasting
DSS	Decision Support Systems
EC	European Commission
EU	European Union
FAS	Farm Advisory Service/System
GAEC	Good Agriculture and Environmental Conditions
GIS	Geographic Information System
GSAA	Geo Spatial Aid Application
IACS	Integrated Administration and Control System
IoT	Internet of Things
IT	Information Technology
JRC	Joint Research Centre
LPIS	Land Parcel Identification System
MARS	Monitoring Agriculture ResourceS
MS	Member State
NLP	Natural Language Processing
OTSC	On-The-Spot-Checks
UAV	Unmanned Aerial Vehicle

List of figures