



Monitoring and Evaluation Frameworks for the Common Agricultural Policy

Deliverable D2.4

Emerging ICT technologies for the agricultural domain



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Executive summary

The Common Agricultural Policy (CAP) post 2020¹ is targeted towards a wider range of objectives covering broader domains. The new technological developments are enhancing the capability of providing, retrieving and integrating new data sources that are called to achieve those new data requirements. Among the objectives of the MEF4CAP project is to evaluate the potential of the various ICT technological developments and to define a roadmap of the technical aspects of the future monitoring and impact evaluation of the EU agriculture policy.

An initial assessment of agricultural technologies that demonstrate the potential to support sustainable agricultural practices and to facilitate policy monitoring has been conducted and the respective results are document in “D2.1 Landscape of agri-food ICT technologies within EU”, “D2.2 Best practices on the adoption of ICT agricultural technological solutions”, and “D2.3 Identified new technological opportunities from collaboration with EU projects and initiatives”. This deliverable builds on these results and goes a step further aiming to assess future developments on selected ICT categories and their usability for the needs of CAP M&E. In this analysis future CAP objectives are also considered as these are defined through the specification of the respective indicators (documented in MEF4CAP - D1.3 Monitoring and Evaluation Needs of different stakeholders and Associated Indicators).

This deliverable initially provides an analysis on the future perspectives, existing drivers and barriers of key technological areas that are considered as the most relevant with future CAP, namely: satellite based Earth Observation, remote sensing based on UAVs, field sensor and advanced decision support, advanced agricultural machinery and robotics. It then proceeds with an analysis of existing environmental monitoring initiatives (also called Environmental Observatories) that are applying various methods for data collection focusing on aspects such as soil, water quality, greenhouse gas emissions, biodiversity, agricultural parameters monitoring, etc. Finally, a high level approach for a federated-distributed use of existing data repositories is proposed towards a stepwise integration of data sources on a differentiated scale-dependent approach (at local, sub-regional and regional levels).

¹ DG Agriculture and Rural Development

<https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/future-cap>

List of abbreviations

API - Application Programming Interface
 ARD - Analysis Ready Data
 CAMS - Copernicus Atmosphere Monitoring Service
 CAP - Common Agriculture Policy
 CHIME - Copernicus Hyperspectral Imaging Mission for the Environment
 CMEF - Common Monitoring and Evaluation Framework
 CSV - Comma-Separated Values
 DLS - Data Link System
 DOPA - Digital Observatory for Protected Areas
 EC – European Commission
 EO - Earth Observation
 EU - European Union
 FADN - Farm Accountancy Data Network
 FDIS - Field Data Information System
 FMIS - Farm Management Information System
 FSS - Farm structure survey
 GCS - Ground Control System
 GHGs - Greenhouse Gases
 GNSS - Global Navigation Satellite System
 GSS - Ground Station Server
 IACS - Integrated Administration and Control System
 ICT - Information and Communication Technologies
 IoD - Internet of Drones
 IoT - Internet of Things
 LPIS - Land Parcel Identification System
 MS – Member States
 NDVI - Normalised Difference Vegetation Index
 NIR - Near-Infrared
 NRT - Near Real Time
 NSP - National Strategic Plan
 PA - Paying Agency
 PMEF - Performance Monitoring and Evaluation Framework

RPA - Remotely Piloted Aircraft
 RS - Remote Sensing
 SDGs - Sustainable Development Goals
 UAS - Unmanned Aerial System
 UAV - Unmanned Aerial Vehicle
 VRA - Variable Rate Application
 WSN - Wireless Sensor Network

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1. Objectives and overview

Objectives

The main purpose of MEF4CAP project is to deliver an innovation agenda and roadmap for future monitoring of the EU agriculture policy. The Common Agricultural Policy (CAP) post 2020 is targeted towards a wider range of objectives covering broader domains – agriculture, sustainability, agri-environmental, food security among others. This fact implies that new data sources are required to measure the effects and performance of the Policy. Performance is the key idea in the new monitoring and evaluation framework of the CAP. At the same time, new technological developments, are enhancing the capability of providing, retrieving and integrating new data sources that are called to achieve those new data requirements.

WP2 “ICT Developments” of the MEF4CAP conducts an analysis aiming to identify and categorise technological solutions and trends with a proven success record (or a clear potential) that can be exploited for addressing the data needs of the future monitoring and evaluation frameworks for the agricultural policies. Towards this scope a review and assessment of established agricultural technologies has been conducted and the respective results are documented in “D2.1 Landscape of agri-food ICT technologies within EU” (2021) along with more recent research outcomes generated by ongoing projects documented in “D2.3 Identified new technological opportunities from collaboration with EU projects and initiatives” (2021). An elaboration on selected cases of digital agricultural technologies along with actual forms of the generated data logs that may act as ground truth evidences of performed agricultural practices is realised in “D2.2 Best practices on the adoption of ICT agricultural technological solutions” (2022). In addition, a high-level description of future CAP indicators is presented in “D1.1 Evolution of the CAP and related policies (the emerging sustainability agenda)” (2021) and “D1.3 Monitoring and Evaluation Needs of different stakeholders and Associated Indicators” (2021).

This deliverable builds on theses outcomes and proceeds with an analysis on the future evolution of the technological offerings that will be mature enough and available to support operations in the future agri-food domain from the perspective of the future policy monitoring and evaluation. As it is analysed in D2.2 digital agricultural technologies demonstrate the potential to concurrently serve two objectives:

- a. The implementation of good and sustainable agricultural practices that provide clear benefits for the farmers and for the climate.
- b. The provision of farm level ground truth evidence of the applied agricultural practices and their impact that can potentially be utilised for the monitoring and evaluation of agricultural related policies (CAP).

Hence, this deliverable focuses on selected categories of emerging ICT technologies for the agricultural domain that demonstrate a potential for wide utilisation across the EU but also demonstrate the potential for generating data evidence. The data products that will be

available from the use of these technologies and the respective drivers and barriers towards the large-scale adaptation of these technologies are analysed.

Another significant approach towards data collection for policy monitoring is realised by the various environmental monitoring initiatives. There are already significant initiatives of observatories that are applying complementary data collection mechanisms focusing on various aspects such as soil, biodiversity, rural development, etc. Given the importance of future CAP objectives in terms of implementing environmentally friendly and sustainable agricultural practices, it is critical to identify and align with current agro-environmental monitoring methods.

Overview

The sections of this deliverable are structured as following:

Section 1, presents the objectives and an overview of this deliverable.

Section 2, provides a generic introduction which sets the current context and the background on which this deliverable will elaborate.

Section 3, provides a report on future ICT technologies and CAP monitoring and evaluation

Section 4, presents an overview of initiatives of environmental monitoring observatories.

Section 5, provides the conclusions of this deliverable.

2. Introduction

There is currently an EU wide effort aiming to achieve environmental protection and optimisation of agricultural practices in a combined manner. These interrelated objectives are mainly pursued through the introduction of regulations like the new European Green Deal which also encompasses the Farm-to-Fork strategy, the Biodiversity strategy, the Soil and Forest strategy and the Climate Adaptation plan. Given that agricultural and forest land cover 80% of the EU, agricultural policies are expanding their reach in order to contribute to environmental goals set by the Paris Climate Agreement, and the Sustainable Development Goals (SDGs). To this end, relevant ambitious objectives for the European agriculture are set mainly through the new Common Agricultural Policy (CAP) and the New Delivery Model - established by Regulation EU 2021/2115 - which entails the introduction of National Strategic Plans (NSPs) for Member States further articulated at regional level. The NSP's implementation requires mechanisms for advanced data collection, storage and management in support of tracking the progress of the respective objectives, while also guaranteeing compliance with legal and regulatory requirements.

Traditionally, the collection of the information needed to conduct an assessment of any type of agricultural activity -including policy monitoring and evaluation- is a manual-intensive process that combines field data collection (e.g. for spot sample checks), the manual completion of questionnaires/ surveys as part of agricultural statistics (among others FSS and FADN) and incorporation of administrative data (i.e. IACS). This method - especially with regards to the manual data collection - has a number of limitations and it is difficult to include large samples because it is yet another overhead for farmers and auditors. On the same time, the manual provision of data by farmers can result in collecting inaccurate/biased information (Wollburg et al., 2021). It is evident that there is a need for improving current monitoring, reporting and evaluation mechanisms. The ongoing adaptation of digital agricultural technologies and mechanisms for agro-environmental observations can facilitate the development of a monitoring and evaluation framework that will serve policymakers and stakeholders in multiple purposes, including the control of beneficiary compliance, generating performance reports, and evaluations of the overall environmental impact and effectiveness of the applied policies.

Even since 2015, the EU has set the objective of integrating "farm level data with micro-data transmission, based on a modular approach with core variables, modules and satellites (<https://ec.europa.eu/eurostat/web/agriculture/methodology/strategy-beyond-2020>). In this context, EO data products have been introduced for agricultural assessment allowing the systematic and automated collection of environmental and agricultural related variables on a large scale. EO based tools and data products allow for the continuous, large scale and uninterrupted monitoring of some farm management activities that can be associated with sustainability and compliance with the CAP's agri-environmental objectives (e.g. cultivated crop type maps, grassland mowing events detection, analytics on vegetation and soil index time-series).

However, EO based monitoring comes with various limitations as it is mainly applicable for large parcels, affected by meteorological conditions, and it is not feasible to monitor precisely important sustainability related parameters in detail (e.g. use of pesticides & water, yield quantity/quality). With the current digital transformation trend in the agricultural production process, there is an enormous and underexplored potential for sensors and smart farming services that are increasingly being deployed by farmers and advisory service providers. In contrast with EO, field sensor based digital agricultural technologies can act as data sources capturing essential information, often in Near Real Time (NRT), from very detailed proximal sensing of crop characteristics (using e.g. in-situ sensors), over field-based mapping (e.g. soil scans or harvesters) to environmental conditions (e.g. weather stations). The benefits from upscaling (real-time) sensor data and exploitation of agri-environmental monitoring mechanisms on a wide level are also identified by the EU and relevant activities that are currently funded.

2.1 Background

This Deliverable D2.4 “Emerging ICT technologies for the agricultural domain” builds on the outcomes of D2.1, D2.2, and D2.3 combined with the elicitation of requirements of the evaluation frameworks of the future CAP by WP1.

“D2.1 Landscape of agri-food ICT technologies within EU” (2021) provided a review of technologies that already have or will have in the future a significant role in agricultural practices always considering data collection in the context of current and future CAP. Selected categories of technologies were analysed along with the information entities that can directly (raw data) or indirectly (inference/processing of data recordings) been extracted. In order to also include in our analysis relevant agricultural technological developments that are still on an early stage, but have the potential to be adopted on large scale in the years to come, a series of collaboration activities have been realised with the most prominent EU projects focusing on areas that are directly or indirectly related with the digitisation of monitoring and evaluation frameworks for the future CAP. The outcomes of these activities are documented in “D2.3 Identified new technological opportunities from collaboration with EU projects and initiatives” (2021).

Overall, the high-level key categories of technologies that were identified as important are: Telecommunications, Field Sensors, Farm Management Information systems (FMIS), Field Machinery, Earth Observation (EO), Livestock Management, Pasture Management and Financial management. Based on the conducted analysis, a first level outcome is that there is no one-fits-all technological approach that can provide all the necessary data for CAP monitoring and that it is more a synergetic/complementary use of generated datasets that needs to be facilitated. For example, recordings from digital field books (farmer’s calendar) escorted by ground truth evidences (e.g. sensor recordings, tractor’s navigation data, and invoices issued during the purchase of chemicals) can provide detailed insights on farm level. In addition, even if the various information items have been collected by the various ICT technologies utilised, it is also necessary to be shared in a meaningful manner. A framework for agricultural data sharing has

been identified as particularly important including the specification of a regulatory environment that will address issues of data ownership and data utilisation rights but also issues on data modeling harmonisation (e.g. semantics).

“D2.2 Best practices on the adoption of ICT agricultural technological solutions” (2022) attempts to go a step further than the high-level review of agricultural ICT developments (D2.1) and proceeds with the analysis of exemplar real-world cases of agricultural technologies utilisation that are concurrently serving two objectives:

- a) The implementation of good and sustainable agricultural practices that provide clear benefits for the farmers and the environment.
- b) The provision of farm level ground truth evidence of the applied agricultural practices that can potentially be utilised for the monitoring and evaluation of agricultural related policies (CAP).

D2.2 elaborates on selected technologies that have already achieved a significant penetration in agricultural production and hence demonstrate a clear potential for further utilisation on a large-scale. The example use-cases refer to the use of agricultural machinery and the implementation of Variable Rate Application (VRA) for agrochemicals, the use of Decision Support Systems in the context of FMIS for inputs optimisation and Earth Observation assisted pasture monitoring.

The respective benefits and remaining challenges for each of these use cases along with the respective conclusions have been identified. An overall high-level outcome is that new technologies require and generate extensive logs which in turn contribute in making the overall food production process traceable and quantifiable. For example, the VRA data logs and the farmers’ digital calendars (part of a FMIS) generated during various tasks execution, demonstrate significant potential for CAP monitoring and evaluation. On the other hand, significant challenges are remaining related with the accuracy/validity of the generated data logs along with issues on homogenisation and farm level data aggregation.

2.2 Technologies for monitoring

Based on the outcomes of D2.1, D2.2. and D2.3, there is a clear indication of the agricultural technologies that have been identified as the most relevant with future CAP monitoring. These technologies can be grouped in the following categories: Earth Observation (Satellite and UAV based), advanced agricultural machinery (implementing VRA), Farm Management Information Systems (interconnecting a variety of data sources and services e.g. in-situ sensors, geo-tagged photos, farm accountancy, advisory through decision support systems).

These core categories of technologies were also identified as the most important for collecting agro-environmental data during the second MEF4CAP’s stakeholder engagement workshop²

² <https://mef4cap.eu/news/stakeholder-workshop-exploring-new-data-and-technologies-to-measure-sustainability>

that was held on the 4th March, 2022. The workshop invited stakeholders to explore the potential of technology to meet the new data needs in the context of future CAP monitoring and evaluation (M&E). During the event, the MEF4CAP team shared findings and key learnings from the first year of the project and presented some of the potential pathways to improve sustainability measuring in agriculture. Among others, the workshop aimed to facilitate discussions between experts, farmers, and policy-makers around the role of data and technology in agriculture. During this two-hour online workshop, speakers and participants looked into the question of how technology and data sources can be best matched to improve the future monitoring and evaluation of the reformed CAP.

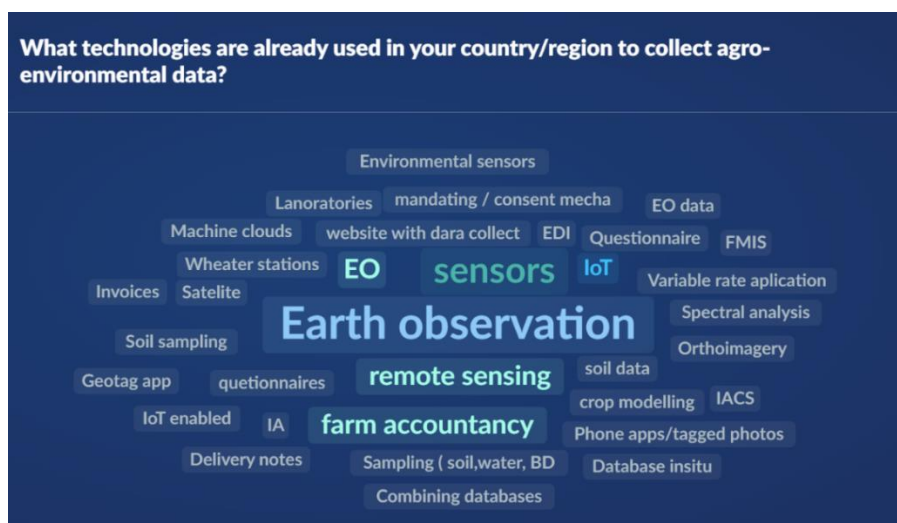


Figure 1. Promising technologies as new sources of data for CAP monitoring and evaluation

The workshop provided valuable insights on the digital agricultural technologies useful for CAP M&E, such as field sensors, Fam Management Information Systems (FMIS), Earth Observation and field machinery – to name just a few. During the workshop, the key findings from the assessment of current ICT developments in digital agricultural technologies were presented and comments were requested from the participants. The digital agricultural technologies can concurrently serve two objectives: First, existing and upcoming technologies can facilitate the implementation of optimised and sustainable agricultural practices with benefits for farmers, climate and the environment. Secondly, technology provides farm-level ground truth evidence of applied agricultural practices, allowing for easier monitoring and decision making in agriculture. Participants were asked to reply on which technologies are already used in their regions in order to collect agro-environmental data. A world cloud of the received replies is illustrated in figure 1. It must be noted that the feedback received from workshop participants matches the current outcomes of MEF4CAP analysis.

Besides the dataset generated on farm level through the use of the various agricultural technologies, there are already existing significant approaches on environmental monitoring³ that are applying complementary data collection mechanisms focusing on various aspects such

³ https://joint-research-centre.ec.europa.eu/scientific-activities-z/environmental-monitoring_en

as soil, biodiversity, water quality, rural development, etc. These initiatives can act as examples and useful outcomes can be extracted towards the realisation of a unified EU wide “Agri-Environmental Observatory” which will be capable to integrate -besides existing data sources - farm level data generated by the use of digital agricultural technologies. Towards this scope, a short summary of recent developments in EU observatories is presented on thematic areas that are relevant to the objectives of the future CAP.

This deliverable initially provides an analysis on the future perspectives of the identified key technological areas: Earth Observation (Satellite and UAV based), advanced decision support based on in-situ data sources, and agricultural machinery (including robotics). It then proceeds with analysis of future perspectives towards an Agri-Environmental Observatory. Based on the collected data, the Monitoring and Evaluation Framework of the future will prove to be feasible to monitor environmental and policy indicators on a farm, regional and national level with more accurate and frequently updated evidence.

3. Future perspectives on agri-tech for CAP monitoring and evaluation

The rapid emergence of advanced ICT technologies is currently causing almost all industries - including agriculture - to rethink and restructure their processes (Khan et al., 2021). According to various analyses (Liu et al., 2021) (Friha et al., 2021), four distinct major transformations have been experienced in agriculture, also mentioned as “revolutions”. As it is also illustrated in figure 2, the roadmap of transformations in agriculture is in relation to the respective technological developments. Briefly describing these transformations: 1) age of traditional agriculture featured by human and animal power, 2) age of mechanized agriculture featured by rumbling sounds, 3) age of automated agriculture featured by highspeed development, 4) age of smart agriculture featured by emerging technologies. The fourth industrial revolution (Industry 4.0) is developing and is characterised by a fusion of emerging technologies such as the Internet of Things (IoT), robotics, big data, artificial intelligence (AI), and blockchain technology.

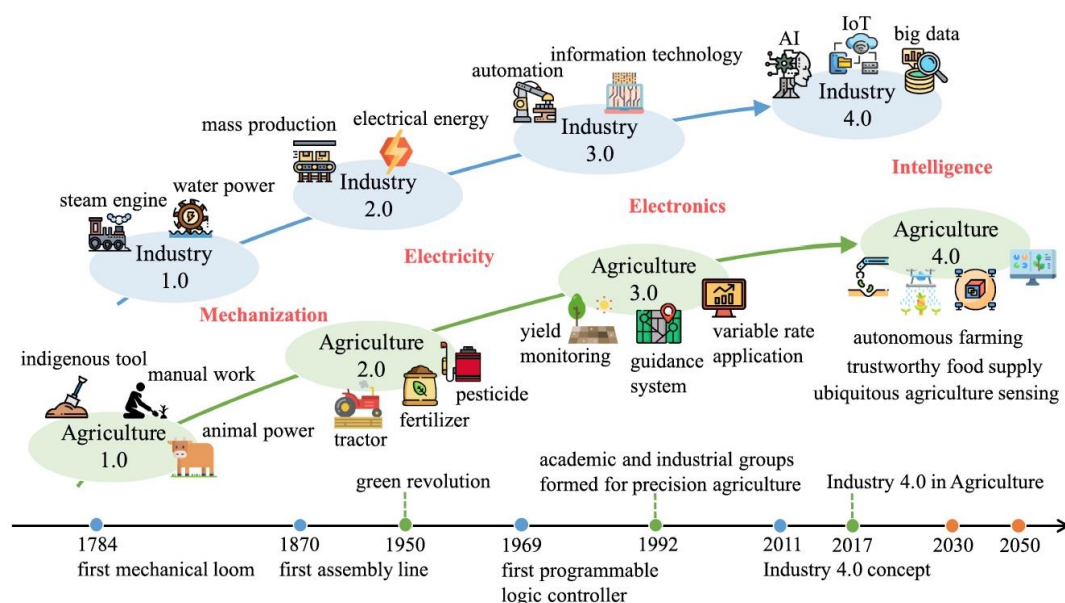


Figure 2. Development roadmap of industrial and agricultural revolutions (Liu et al., 2021)

There is currently strong interest in the research community and the industry in analysing the emerging needs and in developing new ICT solutions for the agriculture domain. Numerous state of the art reviews are presenting the ecosystem of agriculture technologies (Liu et al., 2021) (Khan et al., 2021) (Friha et al., 2021).

As it was analysed in the introduction of this document, advanced ICT technologies can serve the objectives of sustainable and optimised agricultural production but on the same time can generate useful evidences (in the form of data logs) that could potentially be utilised for the monitoring and evaluation of agricultural related policies (CAP). In the following subsections, an analysis is presented on the future of these technologies that are currently utilised in supporting both everyday agricultural practices but also CAP monitoring and evaluation.

3.1 Satellite based Earth Observation

The CAP has a relatively long history of using satellite technologies for checking agricultural subsidies. This was boosted even further in 2017 by the implementation of the Copernicus program⁴ which offers frequent, high resolution and free of charge satellite data (optical and radar) in order to support the monitoring of agriculture activities. The data from the Copernicus satellites, along with the NASA/USGS Landsat⁵ program offer very frequent imagery (for Sentinel 2 revisits occur every 5 days at the equator and 2–3 days at mid-latitudes) (Jian et al., 2017) which enable workflows for automated satellite image processing greatly benefiting

⁴ <https://www.copernicus.eu/en>

⁵ <https://landsat.gsfc.nasa.gov/>

farmers, administrations and the environment. The European Commission strongly encourages the use of these new imaging technologies while member states started deploying them and working towards post 2020 CAP monitoring.

Indubitably, the launch of Sentinel satellites which form the world's largest and most ambitious Earth Observation program, is a game changer in EO technology paving the way for a systematic and regular tracking and assessment of agro-environmental and climate variables. The Copernicus data services are currently bring even more data, and generate already meaningful agro-climatic indicators available through portals like the "Climate Advisory Services for Agriculture⁶".

The new CAP (2023-2027) will put into action the new monitoring approach as a key control system, using automated processes based on satellite imagery together with artificial intelligence algorithms for analysing large quantities of data. The PAs and their contractors will be developing coherent automated monitoring systems which will be fully interactive, transparent and facilitate access to satellite data and digital cloud processing services.

This will form the basis for further optimisation of these systems as space and AI industry technology continues to improve in the new decade. In this new space age, new advances and technologies will arise that enhance satellite capabilities cornering spatial, temporal and spectral resolution. Furtherly, the number of space missions will increase, satellite size will decrease and the value of satellite data will be maximised through the provision of Analysis Ready Data and cloud infrastructure environments.

More satellite programs

By 2030, the number of satellites in space will also increase. New satellite market forecast anticipates 1,700 satellites to be launched on average per year by 2030 (Euroconsult "*Satellites to be Built & Launched*" report Dec. 2021)⁷. As regards the Copernicus program, six new satellite missions (Copernicus Expansion Missions) are prepared to expand the current capabilities of the Copernicus space component, see Figure 3. Especially, the hyperspectral and microwave missions are expected to boost the capabilities of agricultural monitoring from space.

⁶ <https://climate.copernicus.eu/climate-advisory-services-agriculture>

⁷ https://digital-platform.euroconsult-ec.com/wp-content/uploads/2022/01/Extract_Sat_Built_2021.pdf?t=61d89925c3e67

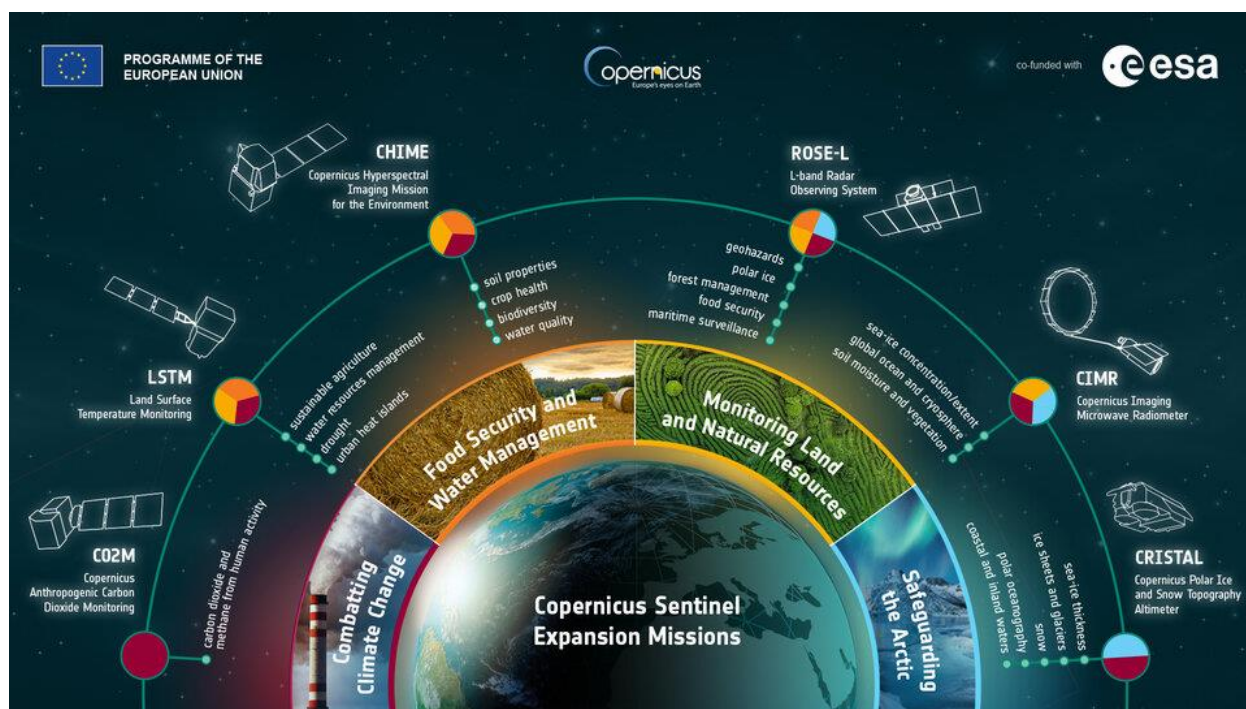


Figure 3. Copernicus Sentinel Expansion missions⁸

Spatial resolution

Besides new spectral fusion methods which can enhance the spatial resolution of satellite images, satellite sensors are constantly improving, offering at this moment spatial resolution as high as 20cm pixel e.g. Maxar Technologies⁹ 15cm. In the next decade, very high resolution imagery (<1m) will be the new norm increasing the positional accuracy of agricultural applications. Besides improving the spatial resolution of satellite imagery, new AI approaches will be developed in order to handle crop classification in small parcels. These new methods rely on multiple Machine Learning¹⁰ and Deep Learning¹¹ classifiers under an enable framework. That approach shows great potential of improving the accuracy of parcel- level crop mapping (Asawa et al., 2021) (Zhang et al., 2021).

Temporal resolution

The combination of Sentinel and Landsat satellite enables the rapid increase of temporal resolution having a revisit time of less than 4 days in almost all places in the earth. With the addition of new sensors, the temporal resolution is expected to increase even more, allowing for even daily observations.

Spectral resolution

The new generation of sensors are characterised by additional spectral bands covering the spectrum from the visible to thermal infrared. This enables unlocking new insight and applications for crop and soil health, plant stress and more. Figure 4 shows the 25 spectral

⁸ https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Copernicus_Sentinel_Expansion_missions

⁹ <https://blog.maxar.com/earth-intelligence/2020/introducing-15-cm-hd-the-highest-clarity-from-commercial-satellite-imagery>

¹⁰ <https://www.ibm.com/cloud/learn/machine-learning>

¹¹ <https://www.ibm.com/cloud/learn/deep-learning>

bands of Landsat Next which will be launched in 2029. Moreover, hyperspectral systems' development unleashes the next generation of satellites. Hyperspectral sensors have the ability to capture imagery across the whole reflective spectrum making the identification of various plant elements possible with excellent precision. ESA prepares the CHIME¹² mission (Copernicus Hyperspectral Imaging Mission for the Environment) which will provide systematic hyperspectral images to map changes in land cover and help sustainable agricultural practices.

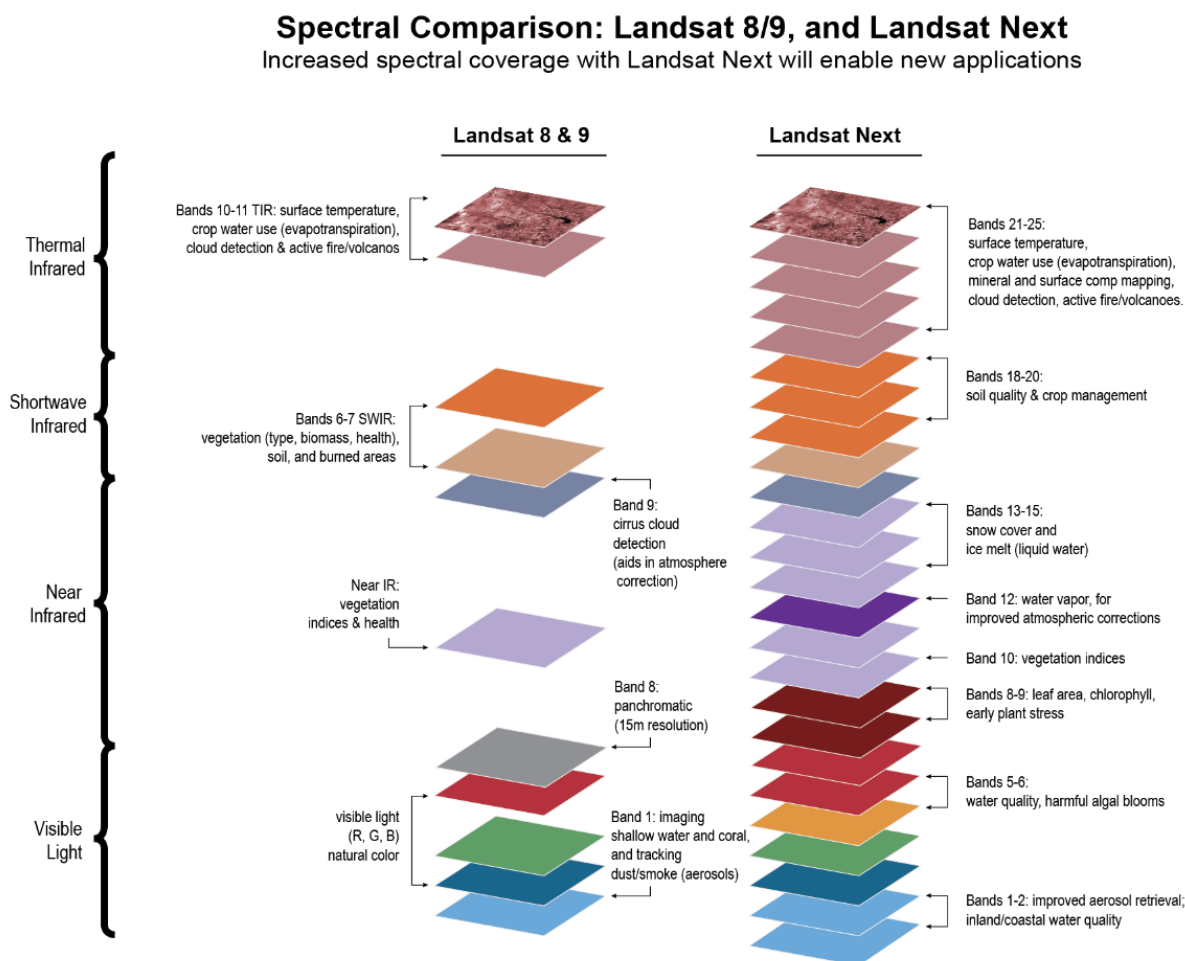


Figure 4. Spectral comparison of Landsat missions

Miniaturisation

Over the last few years, miniature satellites (nanosatellites) called CubeSats and SmallSats have been increasingly used to support innovative space programs. These satellites are much smaller and cheaper than the traditional satellites, having the potential to be a disruptive force to take the place of the large EO satellites. These tiny satellites can give low-priced access to EO data as their modular design allows to build and launch quicker than conventional satellites and according to the needs of each mission. As more CubeSats are launched, their temporal

¹² https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Going_hyperspectral_for_CHIME

resolution will tremendously expand providing information with less than one-day time lag. CubeSats can provide very cheap imagery and could open up EO to anyone (e.g. students, technology pioneers, community networks) putting forward new possibilities in research and technology development. In the coming years, these nanosatellites will be widely used for operational applications in agriculture, as they are now reaching the technological maturity required to provide reliable data. That will enable numerous powerful observations paving the way for new and more sustainable solutions.

Analysis-ready images

The advancement of data analytics will enable the standardisation of satellite data for the immediate analysis without additional user effort. New standards for Sentinel data will be introduced for the operational generation of ARD data in agricultural monitoring. Further, the adoption of advanced cloud services will transform the on-premise IT systems and allow for national to European up-scaling.

3.2 Remote sensing based on UAVs

Unmanned Aerial Vehicles (UAVs) are not a recent technology since the first attempt to construct a powered UAV was recorded in 1916 (Taylor et al., 1977). Though, the first use of remotely piloted aircrafts (RPAs) in agriculture was reported back to 1986 for monitoring Montana's forest fires (Ahmad et al., 2021). UAVs were initially exploited for military purposes; however, in recent years, their use has rapidly expanded to other types of applications (commercial, scientific, agricultural, etc.). The wider use of UAVs was led by the huge technological advancements and the miniaturisation of the associated hardware during the 1980s and 1990s (Tsouros et al., 2019).

Several categories of unmanned aerial vehicles exist and are used for different applications. The most common UAVs that are used in agriculture are shown in Figure 5 (Mogili et al., 2018). Rotary-wing UAVs are more stable fliers as they are capable of a vertical take-off and landing; however, they are slower and cannot cover as much area during their battery life (Saiz-Rubio et al., 2020). Fixed-wing platforms, on the other hand, can cover more area per flight and carry larger payloads, but tend to be more expensive, are more complex to fly and can break more easily after multiple landings (Yinka-Banjo et al., 2019).



Figure 5. Most common types of UAVs for agriculture applications

This technology in the agriculture sector is still developing, with many possible uses yet to be explored (Hassler et al., 2019). In order to produce more detailed images with high spatial resolution at a low cost, cameras mounted upon UAVs were utilised with promising results (Matese et al., 2015). As these UAVs began to incorporate more peripheral technologies - such

as robotics, big data, artificial intelligence, internet of things etc. (Swamidason et al., 2022) - and grew in complexity, a new term was developed to describe the whole system together, that is Unmanned Aircraft System (UAS) (Gupta et al., 2013). Along with this new technology, came many new challenges such as processing of geospatial data (Chang et al., 2017) and lower temporal resolutions when applied to large areas of land (Marino et al., 2019). Therefore, it should be noted that UAS technology is not meant to replace satellite data, as there are trade-offs for using one over the other and in several situations, both UAS and satellite imagery are used in conjunction (Gevaert et al., 2015).

Areas of use

UAVs have a remarkable potential in the agriculture sector and have proven to be a valuable tool for farmers - for crop monitoring, for improving resources efficiency, for performing field activities - since their use allows better, simpler and faster farm management. These systems are able to produce soil and field three-dimensional models, collect data, monitor crop growth as well as perform spraying or planting applications (Miranda et al., 2019) (Fountas et al., 2020). Collected high-quality data are processed in order to provide useful insight into crop development and highlight ineffective practices; such as track changes in crop health and maturity and/or identify parts of a field experiencing hydric stress. It is also worth pointing out that UAVs have even been used in the context of livestock management and more specifically to monitor and protect sheep¹³. Currently, UAVs have quite a wide range of usage, which is expected to expand due to the advancement in cutting edge technologies. Intensive research has been conducted and findings regarding their application are presented as following:

- crop monitoring and health assessment (Ahmad et al., 2021) (Rahman et al., 2021)
- field mapping (Hassler et al., 2019) (Kim et al., 2019) (Santos et al., 2019)
- disease surveillance (Ahmad et al., 2021) (Santos et al., 2019)
- biomass and field nutrient estimation (Hassler et al., 2019)
- soil and field analysis (Ahmad et al., 2021) (Rani et al., 2019)
- plant species detection/identification/counting (Uddin et al., 2018)
- irrigation management (Devi et al., 2020) (Hassler et al., 2019) (Rani et al., 2019)
- fertiliser application (Ahmad et al., 2021) (Devi et al., 2020) (Hassler et al., 2019)
- pesticide and herbicide application (Devi et al., 2020) (Yinka-Banjo et al., 2019)
- mechanical pollination (Ahmad et al., 2021) (Sun et al., 2020)
- weed management (Hassler et al., 2019) (Rani et al., 2019)
- phenotyping (Hassler et al., 2019)
- crop harvest (Ahmad et al., 2021) (Herrmann et al., 2020) (Rani et al., 2019)
- crop insurance (Ahmad et al., 2021) (Rani et al., 2019)
- seed plantation (Fountas et al., 2020) (Yinka-Banjo et al., 2019)
- forestry applications (Ahmad et al., 2021) (Sudhakar et al., 2020) (Torresan et al., 2017)
- livestock management (Rahman et al., 2021) (Sun et al., 2020) (Vayssade et al., 2019)
- economical aspects (Ahmad et al., 2021)

¹³ <https://concisesoftware.com/agritech-driving-the-future-of-agriculture-with-technologies/>

With regards to UAV applications, there are references of successful usage in the following cultivations (Velusamy et al., 2022) (Cuaran et al., 2021):

- Rice
- Maize
- Wheat
- Soya
- Barley
- Sugar beet
- Sugarcane
- Sunflower
- Cotton
- Sorghum
- Canola/Rapeseed
- Potato
- Onion
- Eggplant
- Grapevine
- Pine
- Citrics
- Olive
- Peach
- Banana

Advantages and Limitations

UAVs offer better resolutions and flexibility of use (revisit time of satellites) over satellite imagery (Martos et al., 2021). Such features help to monitor important crop parameters such as nitrogen (N) and chlorophyll contents (Maes et al., 2019). One of the prominent features of this technology is its higher resolution than the satellite imagery—offering up to 0.2m of spatial resolution, which is approximately 40,000 times better resolution that means more and high-quality information can be extracted from these images. UAVs offer lower operational costs; however, for large amounts of data (to cover larger areas), data processing costs increase exponentially (Ahmad et al., 2021). Another drawback is that certain UAV machine vision applications may require flying at midday in order to avoid vegetation shadows on the ground which could cause errors with imagery data (Saiz-Rubio et al., 2020). Moreover, data post processing and image mosaicking could often be quite challenging.

Weiss et al. (2020) summarise that the main constraints of UAVs are the impeding meteorological conditions (rain, snowfall, clouds, wind and fog), the local and national regulations, the limited spatial coverage due to limited battery life or payload limits, along with the lack of standard procedures for inflight calibration of the UAV sensors. Fountas et al., (2020) point out other important issues such as accuracy, interoperability, data storage and computation power that need to be addressed for effective use of these technologies in the agriculture domain. Data security is also an important issue to cope with in the forthcoming years and large ICT companies are already researching this issue. A study undertaken from Chinnaiyan, R. et al. (2020) offers the implementation of blockchain and smart contracts in order to safeguard data, which are then archived through IoT-enabled UAVs and sensors, with their respective deployment considerations.

Future Perspective

It is clear that the potential of UASs in agriculture is very high and the market is growing rapidly. According to an estimate, UASs and the agricultural robotics industry could be worth as much

as \$28 billion by 2028 and up to \$35 billion by 2038¹⁴. The trend is for drones to become smaller, lighter, more efficient and cheaper (Vergouw et al., 2016). According to Radoglou-Grammatikis et al. (2020), the combined use of UAV technology and big data analytics could be very promising in dealing with the most pressing problems of agriculture.

This new era is of the Internet of Drones (IoD), where fleets/swarms of drones will be deployed and controlled through a ground station server (GSS) via a wireless channel in order to collect the desired data (Martos et al., 2021). Currently, research is being conducted to further explore possibilities for remote areas, where there is no internet connection availability. A recent study examined the possibility to use a cellular network for this purpose (Martos et al., 2021). The next generation of UAV sensors could provide on-board image processing and in-field analytic capabilities, which will give instant insights to the interested parties, without the need for cellular connectivity and/or cloud connection (Shakhatreh et al., 2019).

There are many applications where research is lacking or non-existent currently. For example, the development of agricultural image databases would provide a massive aid in the creation of machine vision algorithms to run from UAS, as many researchers find themselves having to create their own datasets which can be very time consuming and costly (Kamilaris et al., 2018). The field of deep learning appeals promising and extensive research is taking place; many models applied to agriculture are still in their infancy (Hassler et al., 2019).

Already some H2020 projects are researching the integration of UAV and satellite footage. For example, projects CALLISTO¹⁵ and DIONE¹⁶ complement the available data from satellites with targeted high quality UAV imagery and link them with open geospatial data, and in-situ sensor data. This combination of technologies is beginning to power or enhance new and existing methods and tools, and have already been deployed on farms.

With regards to the future CAP new monitoring and evaluation needs, the advanced capabilities of UAVs in collecting extensive data logs could be a game changer since it will allow to monitor local land use in real time and to ground truth satellite information (Global Food Security)¹⁷. Tracking and assessment of agro-environmental and policy indicators on a farm, regional and national level will be enhanced with more accurate and frequently updated evidence. To conclude, UAVs' applications have great potential to become an integral part of the agriculture domain but there are still challenges to be addressed.

3.3 Field sensor and advanced decision support

Field sensors are sophisticated devices that are installed in cultivations and enable the detection, monitoring and recording of various parameters. Different types of sensors are used in agriculture enabling crop, soil and atmospheric monitoring (Navarro et al., 2020). Field sensors in agriculture are usually part of a smart farming system and provide the necessary input in order to proceed with decision making that will guide applied agricultural practices. With regards to CAP monitoring, sensor recordings can be considered as additional evidences of recorded farm practices. For example, recorded alterations in soil moisture can be

¹⁴ <https://www.electricvehiclesresearch.com/articles/13908/agricultural-robotics-and-drones-diversity-of-functions-forms>

¹⁵ <https://callisto-h2020.eu/>

¹⁶ <https://dione-project.eu/>

¹⁷ <https://agri-tech-e.co.uk/wp-content/uploads/ultimatemember/20190812/game-changing-technologies-agriculture.pdf>

considered as ground truth evidences that escort a recorded irrigation event on the farmers' calendar field book also allowing to infer the actual amount of water applied. In general, FMISs when combined with emerging technologies and data sources like IoT and Remote Sensing can offer predictive insights in farming operations and drive real-time operational decisions (Wolfert et al., 2017). This functionality is also associated with the term Agricultural Decision Support Systems (ADSS). Smart farming systems and ADSS are currently operate on a rather centralized manner which can be described by the following three main phases (Dahane et al., 2020):

- a) Data recording using sensors deployed in an agricultural field.
- b) Collected data are transferred to a centralized data repository, cleaning and storage of data takes place. Knowledge extraction and decision support using advanced data processing methods e.g. Artificial Intelligence.
- c) Useful knowledge is transferred back to the farmers e.g. in the form of advice on cultivation practices.

The ongoing widespread use of the Agricultural IoT has led to the explosive growth of sensors and the increasing number of data. Following the centralized approach, the large amount of data increases the load on the cloud server, which in turn increases data transfer/storage/processing cost and complexity and reduces the response speed (Zhang et al., 2020). At the same time field sensors are getting more robust with additional capabilities for data collection and processing. In order to address the problem of data explosion and network delay, the "Edge Computing" model has been introduced (Satyanarayanan et al., 2017) which enables computing and storage resources to networks closer to mobile devices or sensors. "Edge computing" provides intelligent services at the edge of the networks which are closer to the data source, enabling each edge of the IoT to have data collection, analysis, computing, and intelligent processing capabilities. In addition, local decision making and processing can meet key requirements of network capabilities and resource constraints, security and privacy challenges. The concept of allocating data processing closer to the end devices is also described by the terms "Fog computing" introduced by Cisco¹⁸ and "Mobile Edge"¹⁹ computing introduced by the European Telecommunications Standards Institute (ETSI). A conceptual illustration of the terms "Edge", "Fog" and "Cloud" is available in figure 6.

¹⁸ <https://www.cisco.com/c/en/us/solutions/computing/what-is-edge-computing.html>

¹⁹ https://portal.etsi.org/portals/0/tbpages/mec/docs/mobile-edge_computing_-_introductory_technical_white_paper_v1%2018-09-14.pdf

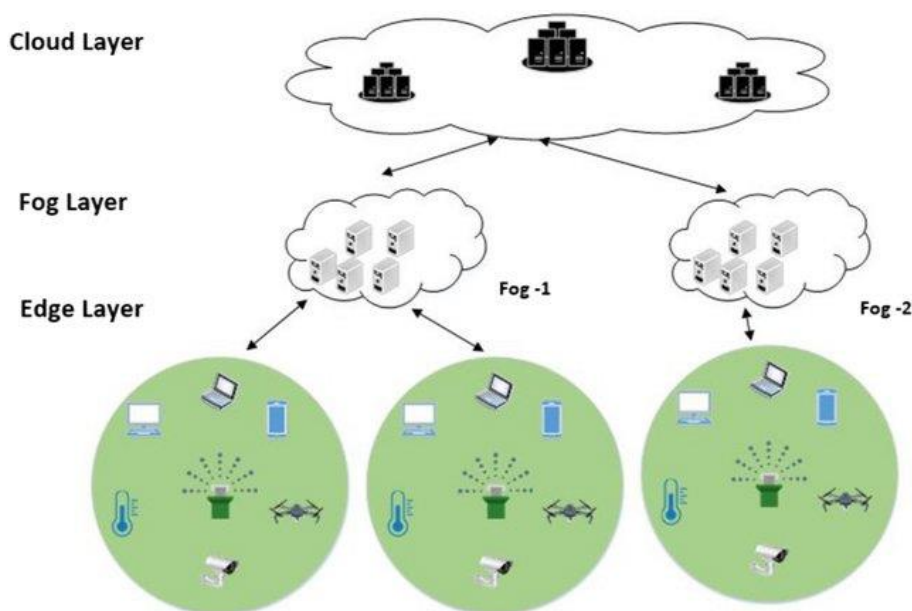


Figure 6. Illustration of “cloud”, “fog” and “edge” layers (Qureshi et al., 2021)

With regards to agriculture application domain the adoption of Edge Computing can be considered as enabler for the further implementation and optimization of various state of the art technologies such as Artificial Intelligence (AI), Computer Vision and Virtual/Augmented Reality.

AI has a place in agricultural application technologies and is currently primarily employed in video/image analysis. The evolution of Edge Computing in combination with AI (also called Edge Intelligence) is expected to make easier and more effective the operational use of technologies like unmanned agricultural machinery, plant disease diagnosis, pest/weed identification, plant species identification and pesticide recommendations (Zhang et al., 2020) (Fountas et al., 2020).

With regards to data collection in the context of CAP monitoring and evaluation, the advanced processing capabilities of sensing devices can support the real time analysis of generated datasets on the device level, the extraction of useful summaries and the direct transfer to the desired data repositories. This process can support a more direct data collection and reporting process bypassing current flows which include data monitoring, off-line analysis and reporting. For example, a future agriculture machinery (tractor) implementing VRA may have the necessary processing capabilities on generating and transferring a data report of the executed task in a near-real-time mode. On a similar manner, a UAV mission for crop type identification will be able to near-real-time process and analyse captured images and transmit only the processed final outcomes.

In the context of On-The-Spot Checks (OTSC) and Checks by Monitoring (CbM) the use of digital photographs with spatial (latitude and longitude coordinates) information is under investigation and experimental use (Sima et al., 2020). These photos are also known as “geotagged photos” and can be captured with the use of most smartphones and cameras with a built-in GNSS (Global Navigation and Satellite System) antenna that enables automatic retrieval of time and positioning from the antenna. This is a promising approach and it is highly

probable to start being implemented habitually by farmers resulting on a substantial amount of photos that will need to be processed by CAP administrators. Edge computing combined with machine learning techniques on image content recognition becomes a realistic solution offering real time processing that will allow the confirmation of alleged crop types and activities depicted in the photo.

3.4 Advanced agricultural machinery and robotics

For six decades automation has played a fundamental role in increasing efficiency while reducing the cost of industrial production and products. In the past twenty years, a similar trend has started to take place in agriculture, with GPS- and vision-based self-guided tractors and harvesters already being available commercially. Robotic systems have found fertile ground in agriculture tasks, due to the progress of ICT technologies, mainly advanced sensing, actuation, and AI. The increasing demand for accurate field operations, while reducing the farming inputs and environmental impact, constitutes robotic platforms as the alternative of conventional tractors and implements (Fountas et al., 2020). The development of robotic technologies and their application in agriculture is becoming a growing topic of interest and consideration (Marinoudi et al., 2019) with an increasing amount of research work being perceived in the last decades. Several literature reviews focusing on agricultural robots confirm the ongoing interest from both the research community and the industry (Fountas et al., 2020) (Ramin et al., 2018). As it is stated in the report of the technical committee for Agricultural Robotics & Automation by IEEE²⁰, this is just the beginning of what will be a revolution in the way that food is grown, tended, and harvested.

With regards to agricultural operations and based on existing published results (Bac et al., 2014) (Slaughter et al., 2008) (Zhang et al., 2019) (Bechar et al., 2017), farmers have started to experiment and, in some cases, have fully adopted in their everyday operations small sized, electrically driven autonomous platforms that automate or augment operations such as:

- transplanting/seeding
- pruning
- thinning
- light ploughing
- mowing
- harvesting
- disease monitoring
- spraying
- weed control

According to Zhang et al. (2019), robotic solutions regarding crop monitoring and harvesting are already beyond the experimental stage and are considered to have significant beneficial effects on production profits, enabling faster and easier automated harvest while increasing crop quality and yield. With regards to robotic applications that target specific **crops**, there are already references of successful integration in the following cultivations:

²⁰ <https://www.ieee-ras.org/agricultural-robotics-automation>

- cotton (Fue et al., 2020)
- strawberries (Defterli et al., 2016)
- arable farming (Aravind et al., 2017)
- apple harvesting (Bulanon et al., 2010)
- generic orchards management (Zhang et al., 2019)
- grapes^{21,22}
- citrus^{23, 24}

There are also examples of successful integration of robotics in several applications in livestock production, with more prominent evidence such as autonomous milking robots, manure scraping, and feeding platforms, combined with individualised care and health monitoring using identification technologies like RFID.

An extensive list of commercial agricultural robotic platforms is provided in a report from H2020 - BACCHUS project²⁵ where it is evident that strawberries cultivation is currently highly supported by such platforms. For example, "Berry 5"²⁶ automated harvester for strawberries may perform with a harvest time of 8 seconds per berry and harvesting 8 acres per day. Similarly, other reported strawberry robotic harvesters are developed by "Dogtooth"²⁷ in UK, Agrobot E-Series²⁸ in Spain and Octinion²⁹ in Belgium and Netherlands.

There are still important challenges to be addressed that prevent robotics from reaching their full potential. According to Fountas et al. (2020), the existing prototype and commercial platforms are limited to task-specific operations, whereas the scalability to different crops or environments is questioned. For example, robots may operate efficiently for greenhouse production, due to the controlled environment conditions and structured cultivation properties. Expanding the capabilities of robots from the lab and greenhouse environment to the outdoor conditions is crucial, when it comes to sensing under harsh environments and operating under unpredicted conditions. There is still room for improvement - and extensive research is taking place - regarding issues such as slow harvest rates, low crop recognition accuracy and high damage rates during the harvesting process.

Use of robotics and automation in agriculture also raise social, economic and ethical issues. On one hand, robotics and automation can help to mitigate labor shortages by reducing the reliance on manpower and can improve agricultural productivity to support sustainable economic development and growth. On the other hand, labor shift from repetitive tasks to high-skilled engineering jobs and the imbalanced adoption of agri-technologies by farmers is expected to create social implications. Advanced intelligence and decision-making capabilities

²¹ <https://advr.iit.it/research/april/table-grape>

²² <https://venturebeat.com/2020/06/24/autonomous-farm-robot-burro-assists-human-workers-with-grape-harvest/>

²³ <https://www.energicid.com/company-news/robotic-citrus-harvester-to-be-developed-by-energicid-with-funding-by-u.s.-department-of-agriculture>

²⁴ <https://www.cambridge.org/core/journals/robotica/article/abs/robotic-picking-of-citrus/C84664DD820503C31CE4158C1FD03E44>

²⁵ <https://bacchus-project.eu/>

²⁶ Harvest Croo Robotics. <https://harvestcroo.com/> - last accessed February 2022

²⁷ Dogtooth. <https://dogtooth.tech/> - Last accessed: February 2022

²⁸ Agrobot E-Series. <http://agrobot.com>

²⁹ Octinion. <http://octinion.com/products/agricultural-robotics/rubion>

of robots results in debates about moral aspects and, overall, responsibility issues for the respective actions taken. Moreover, expensive technologies and the demand for resources and infrastructures to launch robotics in the field will challenge their effective adoption from the economic feasibility point of view (Fountas et al., 2020).

Overall, robotics and automation demonstrate the required potential for playing a significant role in agricultural production of the future. Most robotic systems require mechanisms for the management and analysis of large data sets during their operation i.e. for the optimised sensing and detection required for visual-based guidance of the applied robotic agricultural systems. At the same time, extensive data logs are generated and act as ground truth evidence of the performed operations allowing the further automation of data collection that are also ideal for future CAP monitoring and evaluation. For example, a robotic harvester may generate data logs which can act as evidence on the date/amount/type of harvested yield that will automatically escort the fruit products supporting a more transparent food chain. Besides the reported remaining operational barriers of the robotic platforms, there are many data interoperability and standardisation problems that need to be resolved towards the further exploitation of the generated data recordings.

4. Environmental Observatories

A future agro-environmental policy monitoring and evaluation framework needs to employ heterogeneous data sources and data channels that will allow the controlled data flow and data aggregation. Based on the collected data it will be feasible to monitor environmental and policy indicators on a farm, regional and national level with more accurate and frequently updated evidence. On the same time, useful information will be feasible to be provided to interested parties (e.g. farmers, farmers associations, advisor, regional policy administrators) based on extracted/aggregated outcomes on a regional level, including parameters related with environment (e.g. carbon footprint, nitrates, pesticides use), agricultural processes (e.g. pests infestation, average harvested yield, crop types in the area, phenological stages) and financial aspects (e.g. average income, yield prices, agricultural inputs prices).

Such an integrated data collection approach has not only been identified as useful for CAP monitoring but also for other domains. There are already significant initiatives of observatories that are applying complementary data collection mechanisms focusing on various aspects such as soil, biodiversity and rural development. These initiatives can act as examples and useful outcomes can be extracted towards the realisation of an EU-wide federated ecosystem of “Agri-Environmental Observatories” which will be capable to integrate -besides existing “traditional” data inputs - farm level data generated by the use of digital agricultural technologies. Towards this scope, a short summary of recent developments on EU observatories is presented on thematic areas that are relevant with the objectives of the future CAP.

4.1 Soil Observatory

The EU Soil Observatory³⁰ has been established on 2021, aiming to support sustainable soil management strategies and to become the principal provider of reference data and knowledge at EU-level for all matters relating to soil. EUSO builds on the existing European Soil Data Centre³¹ (ESDAC) which is a thematic centre for soil hosting relevant soil data and information at European level. Until today, monitoring of soil parameters is mainly based on “Land Use/Cover Area frame Survey” (LUCAS) which is a statistical survey managed by Eurostat and performed every three years in the EU. LUCAS objective is to obtain harmonised data on land cover and land use, as well as other landscape channels (e.g. grasslands, grass margins, trees, stone walls). Since 2006, five LUCAS surveys have been conducted (2006, 2009, 2012, 2015, 2018) (R. d’Andrimont et al., 2020) in which information for 106 variables have been collected. The most recent 2018 LUCAS survey is based on 337,854 sites/observations, out of which 238,077 were in-field and 99,777 were photo-interpreted in office. It should be noted that in various cases LUCAS soil sample outcomes are combined with Earth Observation data including Google Earth images, interpretation of historical high resolution aerial images, Street View terrestrial images, etc. (Borrelli et al., 2022).

³⁰ https://joint-research-centre.ec.europa.eu/eu-soil-observatory-euso_en

³¹ <https://esdac.jrc.ec.europa.eu/>

EUSO aims to improve the current data collection mechanism and to proceed with the collection of high-resolution, harmonised and quality-assured soil information (showing status and trends) in order to track and assess progress in the sustainable management of soils and the restoration of degraded soils in EU. The realisation of this vision is organised through the following five functions:

1. Support the development of an operational EU-Wide Soil Monitoring System.
2. Establish an EU Soil Dashboard that reflects the state of soil health and trends in pressures affecting soil health.
3. Further consolidate and enhance the capacity and functionality of the European Soil Data Centre (ESDAC) to support evolving knowledge needs and innovative data flows.
4. Support research and innovation through the implementation of Horizon Europe's Mission on Soil Health and Food.
5. Provide an open and inclusive forum that supports the drive towards a societal change in the perception of soil.

With regards to the actual data collection mechanisms, the EU wide Soil Monitoring System will be based on a harmonised soil monitoring system for the EU following a federated data collection approach including national or regional soil monitoring activities. A centralised European Soil Data Centre (ESDAC) will be developed in order to manage data flows (both inputs and outputs) which will integrate outcomes of the various national and regional soil monitoring outcomes. The monitoring system will focus on the automated calculation of specific indicators that reflect policy targets (e.g. Soil Pollution Watch List, biodiversity, erosion, etc.). The European Soil Data Centre will be INSPIRE compliant supporting the collection, transmission, sharing and dissemination of qualitative and quantitative soil sampling parameters along with relevant meta-data (e.g. geographical location, time). Through the implementation of the EU Soil Strategy and the Work Programme of the Soil Mission, the EUSO will support member states in establishing and operating national or regional monitoring systems to support the exchange of harmonised information about the state of soils (indicators), to be integrated at EU level. Visualisation and rendering of outcomes will be supported by user friendly dashboards that will reflect both the state of soil health and trends in pressures affecting soil health. Key policy messages will be developed through indicators that are populated by a range of data flows (e.g. monitoring, modelling, Copernicus, citizen science, big data, etc.).

4.2 Biodiversity Monitoring

With regards to biodiversity monitoring, the “Knowledge Centre for Biodiversity” (KCBD) has been established by the European Commission aiming to track and assess progress in relation to implementation of biodiversity-related international instruments; to foster cooperation and partnership of climate and biodiversity scientists; and to underpin policy development. In this context, the Biodiversity Information System for Europe³² (BISE) platform has been developed

³² <https://biodiversity.europa.eu/>

which acts as a single-entry point for biodiversity data and information in Europe. The platform provides generic useful information e.g. on relevant policies, legislation and supporting activities related to EU directives along with important EU-wide research projects related to biodiversity and ecosystem services.

A more complete - in terms of data richness - biodiversity monitoring approach is provided by the “Digital Observatory for Protected Areas”³³ (DOPA). DOPA provides a set of web services and applications that can be used primarily to assess, monitor, report and possibly forecast the state of and the pressure on protected areas at multiple scales. The data, indicators, maps and tools provided by the DOPA are relevant to a number of end-users including policy makers, funding agencies, protected area agencies, and researchers. The information can be used, for example, to support spatial planning, resource allocation, protect area development and management, and national and international reporting. Using global reference datasets, the DOPA supports global assessments but also provides a broad range of consistent and comparable indicators at country, ecoregion and protected area level. One significant feature of DOPA approach is that it has been developed using open standards for spatial data and a number of web services are accessible to third parties allowing the direct reuse of results through databases queries.

With regards to progress monitoring of biodiversity actions on EU scale, the “EU Biodiversity Strategy Dashboard”³⁴ is available by DOPA showing progress of the EU and its Member States towards the targets set for 2030. The dashboard mainly incorporates and visualises datasets provided by European Environment Agencies (e.g. on nationally designated areas) and the EC (e.g. Natura 2000 data - the European network of protected sites). Provided datasets are rather static with an update frequency of one year.

The “DOPA Explorer”³⁵ (figure 7), provides a web-based information system on the world's protected areas, which helps the European Commission and other users to assess the state of and the pressure on protected areas at multiple scales. Using global reference datasets, the DOPA supports monitoring and reporting through a broad range of consistent and comparable indicators at country, ecoregion and protected area level. These indicators are particularly relevant for Aichi Biodiversity Target 11 (Protected Areas) of the Convention on Biological Diversity, and the UN Sustainable Development Goals 14 (Life below Water) and 15 (Life on Land).

Finally, DOPA provides a web service that ensures transparency and reusability of data collection, using open standards for spatial data and open-source programming languages. A number of web services are accessible to third parties allowing others to directly embed the results of the DOPA's analyses web applications or simply to query the databases. The REST

³³ <https://dopa.jrc.ec.europa.eu/dopa/>

³⁴ <https://dopa.jrc.ec.europa.eu/kcbd/dashboard/>

³⁵ https://dopa-explorer.jrc.ec.europa.eu/dopa_explorer

service is available only for non-commercial use. The REST web service end-point is available here: <https://dopa-services.jrc.ec.europa.eu/services/>

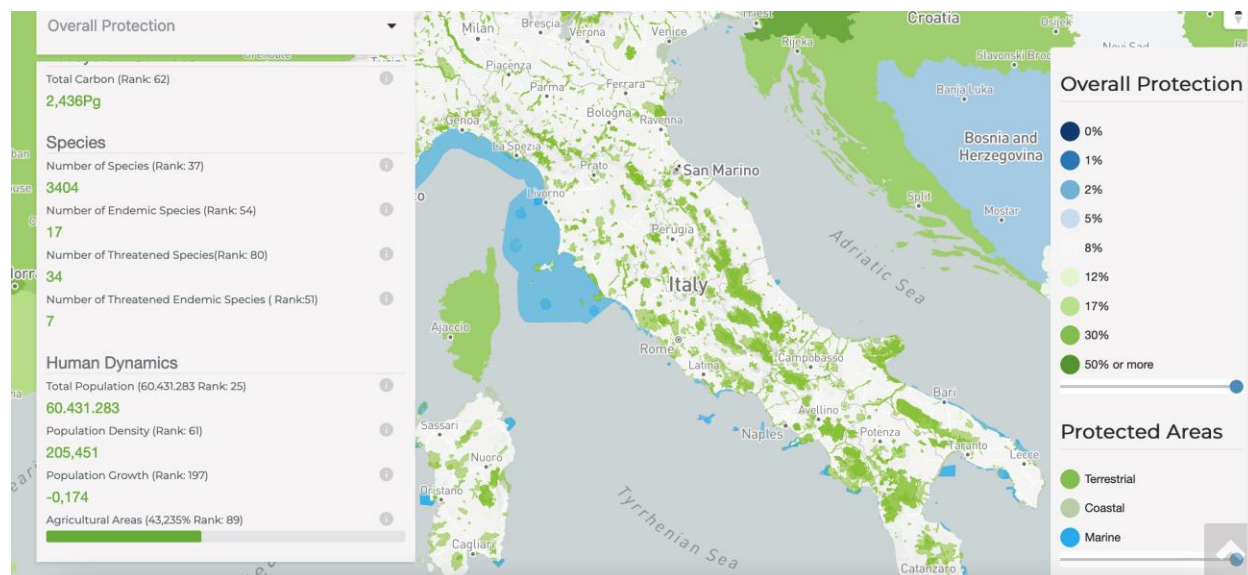


Figure 7. The Digital Observatory for Protected Areas (DOPA) Explorer

Next generation biodiversity monitoring aims to further integrate data collection towards a more dynamic integration of relevant data sources. As it is analysed by Skidmore et al. (2021), monitoring global biodiversity from space through remotely sensing geospatial patterns has high potential to further enhance existing knowledge acquired by field observation. Authors of this scientific article provide a comprehensive, prioritised list of remote sensing biodiversity products and essential biodiversity variables (EBVs) that can further improve the monitoring of geospatial biodiversity patterns, enhancing the existing essential biodiversity variables framework and its applicability. Authors provide an experts' review process of the most relevant, feasible, accurate and mature for direct monitoring parameters (e.g. biological effects of disturbance, habitat structures) from satellites.

With regards to in-situ monitoring, there is a plethora of IoT based approaches aiming to monitor biodiversity (Zapico et al., 2021) capturing for example camera trap insect images and sound fingerprints in a non-intrusive manner, automatically analyse and label them with deep learning and edge computing mechanisms and transmit this information to scientists in a timely manner (Zapico et al., 2021). Other approaches (Brüggemann et al. 2021) include regional monitoring of selected bird species as a method to analyse the causality and detect changes given that their presence is a good indicator of ecosystem health and integrity. Cost-efficient, long-term monitoring mechanisms are developed through Wireless Acoustic Sensor Systems for automated remote bird identification, census, and localisation. Such systems are able to record and transmit the audio samples combined with a classification framework for automated evaluation.

4.3 Greenhouse gas emissions monitoring

There are various initiatives for monitoring greenhouse gas (GHG) emissions on EU level. The European ‘Integrated Carbon Observation System³⁶’ (ICOS) provides standardised and open data from more than 140 measurement stations across 14 European countries. The stations observe greenhouse gas concentrations in the atmosphere as well as carbon fluxes between the atmosphere, the land surface and the oceans. The ICOS community consists of more than 500 scientists in both its current member and observer countries supporting policy and decision-making through highly standardised, in situ data and elaborated data products referring to greenhouse gas emissions and sinks across Europe.

ICOS utilises linked open-data technology, which allows data sharing via internet links in a standardised manner (INSPIRE compliant), associating data measurements with meta-data descriptions, and supporting machine-to-machine communication of datasets. Three levels of data products are provided through the ICOS data portal:

Level 0 - Raw data

Raw data directly obtained from human measurements or automated sensors that have not undergone any transformation expressed in physical units either directly provided by instruments or converted from engineering units (for example, mV, mA, Ω) to physical units.

Level 1 - Intermediate observational data

Near Real Time data that are developed for fast distribution using only automated quality control within a certain short time interval (typically 24) hours of the measurement. NRT data are defined as a high-quality data set that will be distributed in the default way to the users. These data sets have their own provenance metadata that describe the raw data used, the versions of the software and the scripts, the settings and the results of the automatic quality control.

Level 2 data - Final quality controlled observational data

Level 2 data are the main product of ICOS and form the final, quality-checked dataset, published by the Central Facilities, to be distributed through the Carbon Portal.

Level 3 data - Elaborated products

All kinds of products elaborated by scientific communities that rely partly or completely on ICOS data products are called Level 3 data. The Carbon Portal will provide resources to integrate and disseminate Level 3 products, which will be provided on a voluntary basis by the research community and/or, if agreed upon, by collaborative projects.

Datasets are available for use through the following SPARQL endpoint:

<https://meta.icos-cp.eu/sparqlclient/?type=CSV>

and are also available through an online data portal (figure 8): <https://data.icos-cp.eu/portal/>

³⁶ <https://www.icos-cp.eu>

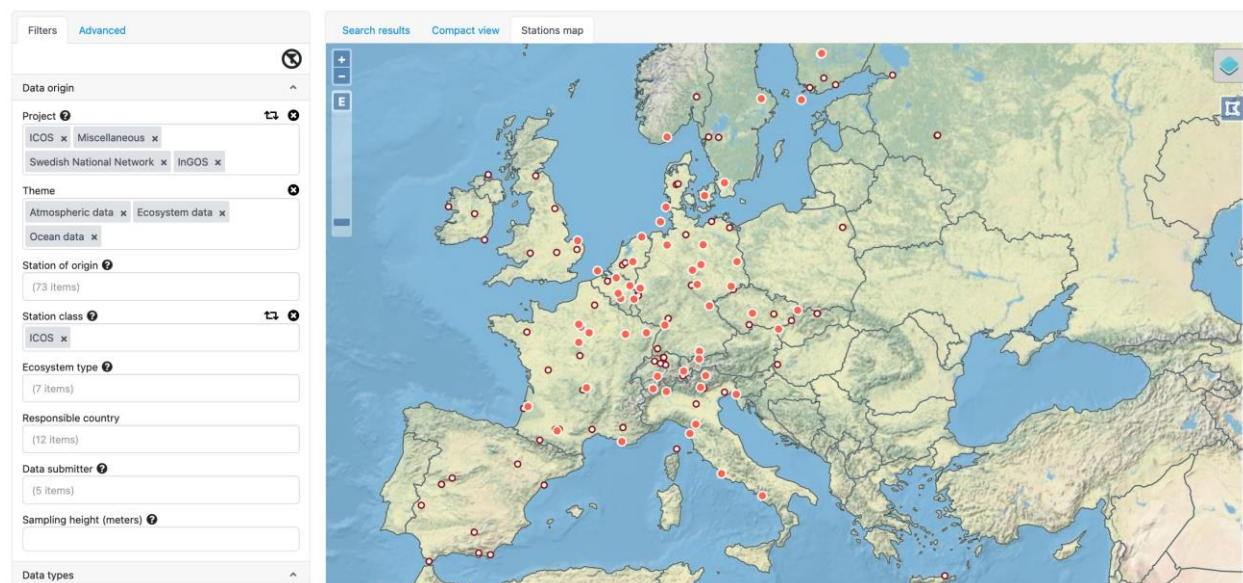


Figure 8. Snapshot of ICOS data portal illustrating the various air quality monitoring stations.

An initiative with similar objective is the Emissions Database for Global Atmospheric Research (EDGAR³⁷) supported by JRC. EDGAR offers an online inventory of global past and present day anthropogenic emissions of greenhouse gases and air pollutants by country and on spatial grid. It provides global emission trends in a comparable and consistent manner to analyse energy, climate and air pollution policies for industrialised and developing countries. Emissions are calculated using a technology-based emission factor approach consistently applied for all world countries. Emissions are calculated with a use of a mathematical formula - on an annual basis - through the incorporation of various factors characterising the targeted area/country such as human activity, country-specific activity data, technologies utilised, and country-specific emission factors. Calculated emissions are spatially allocated on 0.1 degree by 0.1 degree grid cells. A geographical database is available using spatial proxy datasets with the location of energy and manufacturing facilities, road networks, shipping routes, human and animal population density and agricultural land use, that vary over time. National sector totals are distributed with the given percentages of the spatial proxies over the country's area. Input to EDGAR are international annual statistics that have been collected since 1970. Emissions are calculated for the following substances:

- Direct greenhouse gases: Carbon Dioxide (CO₂), Methane (CH₄), Nitrous Oxide (N₂O), Hydrofluorocarbons, Perfluorocarbons Sulfur Hexafluoride (SF₆), Nitrogen Trifluoride, and Sulfuryl Fluoride (SO₂F₂).
- Ozone precursor gases: Carbon Monoxide (CO), Nitrogen Oxides (NO_x), Non-Methane Volatile Organic Compounds (NMVOC) and Methane (CH₄).
- Acidifying gases: Ammonia (NH₃), Nitrogen oxides (NO_x) and Sulfur Dioxide (SO₂).

³⁷ <https://edgar.jrc.ec.europa.eu/>

- Primary particulates: Fine Particulate Matter (PM10 and PM2.5) and Carbonaceous speciation (BC, OC).
- Mercury: total mercury (Hg) and mercury forms: Gaseous Elemental Mercury (Hg0), Particle-bound Mercury (Hg-P) and Gaseous Oxidised Mercury (Hg2+)
- Stratospheric Ozone Depleting Substances: Chlorofluorocarbons (CFC-11, 12, 113, 114, 115), Halons (1211, 1301, 2402), Hydrochlorofluorocarbons (HCFC-22, 124, 141b, 142b), Carbon Tetrachloride (CCl4), Methyl Bromide (CH3Br) and Methyl Chloroform (CH3CCl2).

Datasets available for download are available here:

https://edgar.jrc.ec.europa.eu/emissions_data_and_maps

also including GHG emission sources related with Agricultural activities (Agricultural soils, Agricultural waste burning, Manure management, Rice cultivation).

The Copernicus Atmosphere Monitoring Service³⁸ (CAMS) provides consistent and quality-controlled information related to air pollution and health, solar energy, greenhouse gases and climate forcing, through the use of satellites.

CAMS mainly focuses on satellite-based observation on carbon dioxide (CO₂) and methane (CH₄) natural fluxes and anthropogenic emissions and their trends but also includes in situ data in a complementary manner. Satellites measure carbon dioxide and methane throughout the entire depth of the atmosphere and cover the whole globe; however, their data are currently less accurate than in situ measurements. In situ instruments sample the lower parts of the atmosphere with a high accuracy and are mostly found in easily accessible parts of the globe, mainly in more developed countries. In situ observations are also vital for improving the accuracy and long-term consistency of the CAMS estimates, providing highly accurate data close to the sources and sinks at the interface between the Earth's surface and the atmosphere. CAMS draws on a number of European and international infrastructures for its in-situ data. For instance, data from the ICOS pan-European research infrastructure with data from more than 100 stations are measuring atmospheric levels of greenhouse gases as well as their fluxes. The datasets are updated on a yearly basis (since 2002) with each update cycle adding (if required) a new data version for the entire period, up to one year behind real time.

Access to CO₂ datasets:

<https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-carbon-dioxide?tab=overview>

Access to CH₄ datasets:

<https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-methane?tab=overview>

³⁸ <https://atmosphere.copernicus.eu/about-us>

4.4 Water monitoring

Water monitoring mechanisms aims to assess water quality and to evaluate the impact of pollutants and chemicals, to monitor water and marine ecosystems, to provide early warnings and risk management, to monitoring of floods and droughts and the monitoring of water quantity. Currently a “Knowledge Hub on Water and Agriculture³⁹” is provided by JRC which aims to support scientific knowledge and mechanisms towards the implementation and integration of agricultural and water policy objectives in the European Union. The hub provides a “Water and Agriculture Information Tool” which visualises data from the following sources: “Land cover and fertilization” by CAPRI model - Corine land cover, “Surface water quality” by EEA Waterbase - Water Quality, and “Groundwater quality” - EC DG ENV and “Ecological and chemical status of water bodies” by WISE WFD distributed by EEA V01 R03. Data are available under the following thematic categories:

- Land cover and fertilization
- Surface water quality – Nitrates
- Groundwater quality - Nitrates Directive
- Surface water quality – Phosphates
- Ecological status of water bodies
- Chemical status of water bodies
- Irrigation

The data portal is available at the following link:

<https://water.jrc.ec.europa.eu/portal/apps/MapJournal/index.html?appid=0f4003b4f72547f5ab03d7f356b5888d>

A snapshot of the dashboard on water quality and the concertation of Nitrates on surface waters is illustrated in figure 9.

³⁹ <https://water.jrc.ec.europa.eu/>

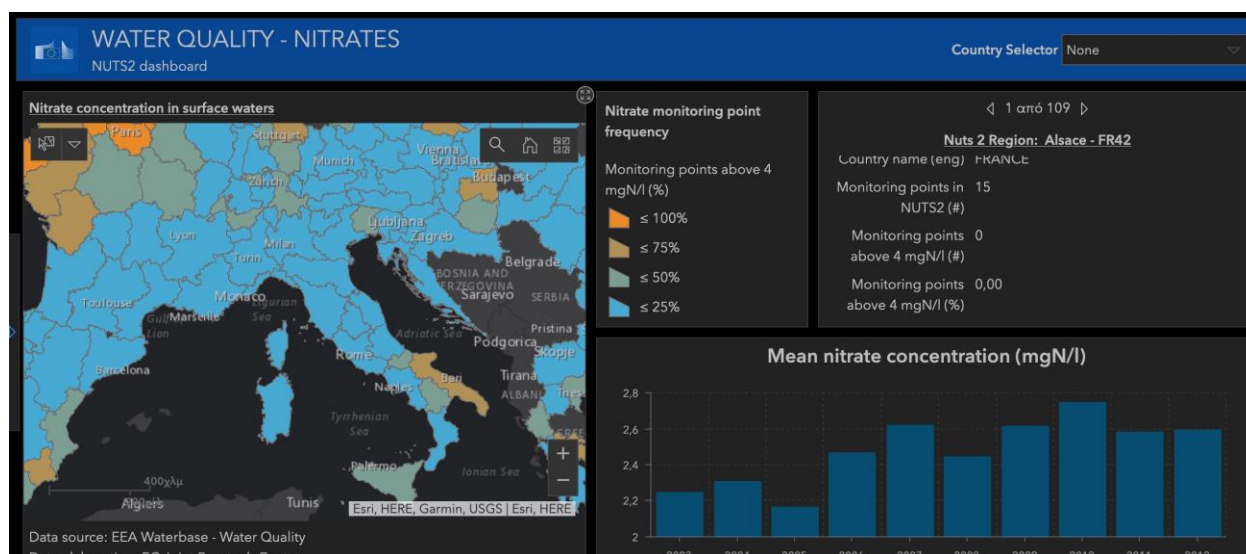


Figure 9. Nitrate concentration in surface waters

Numerous EU projects and initiatives aim to further improve the water quality data collection process through the use of IoT sensor networks. Based on research from Manjakkal et al. (2021), Olatinwo et al. (2019), Cloete et al. (2016) and Hsu et al. (2016), there are already available well-designed and robust sensors that can continuously monitor water quality during transport and identify contaminants in the watershed. The main approaches employed include colorimetric, electrochemical, and optical sensing enabling sensors to estimate the amount of dissolved oxygen, nitrates, chlorine, and phosphates. However, there is no dominant near-real-time water quality monitoring approach making the respective measurements openly available.

4.5 Towards a unified Agri-Environmental Observatory

One of the main mechanisms for monitoring and evaluation of the CAP is the Common Monitoring and Evaluation Framework⁴⁰ (CMEF) which identifies a set of performance indicators in four categories: context, output, result, and impact. The indicators are combined with further information (such as on trade and quality schemes) into 13 thematic presentations at EU and Member States level. Context indicators (figure 10) provide information on agricultural and rural statistics as well as general economic and environmental trends. Some of this information drills down to regional level (NUTS 2-3). Data from CMEF are also available through a data explorer (web dashboard) but also through the Agri-food Data Web API: https://agridata.ec.europa.eu/extensions/DataPortal/API_Documentation.html

⁴⁰ https://agridata.ec.europa.eu/extensions/DataPortal/cmef_indicators.html



Socio-economic indicators

C01 Population
C02 Age structure
C03 Territory
C04 Population density
C05 Employment rate (*)
C06 Self-employment rate
C07 Unemployment rate
C08 GDP per capita (*)
C09 Poverty rate (*)
C10 Structure of the economy
C11 Structure of the employment
C12 Labour productivity by economic sector



Sectoral indicators

C13 Employment by economic activity
C14 Labour productivity in agriculture
C15 Labour productivity in forestry
C16 Labour productivity in the food industry
C17 Agricultural holdings (farms)
C18 Agricultural area
C19 Agricultural area under organic farming
C20 Irrigated / Irrigable land **NEW**
C21 Livestock units
C22 Farm labour force
C23 Age structure of farm managers
C24 Agricultural training of farm managers
C25 Agricultural factor income (*)
C26 Agricultural entrepreneurial income (*)
C27 Total factor productivity in agriculture (*)
C28 Gross fixed capital formation in agriculture
C29 Forest and other wooded land (FOWL)
C30 Tourism infrastructure



Environmental indicators

C31 Land cover
C32 Areas facing natural and other specific constraints (ANCs)
C33 Farming intensity
C34 Natura 2000 areas
C35 Farmland birds index (FBI) (*)
C36 Conservation status of agricultural habitats (grassland)
C37 HNV (high nature value) farming (*)
C38 Protected forest
C39 Water abstraction in agriculture /WEI+ (*) **NEW**
C40 Water quality (*)
C41 Soil organic matter in arable land (*)
C42 Soil erosion by water (*)
C43 Production of renewable energy from agriculture and forestry
C44 Energy use in agriculture, forestry and food industry
C45 Emissions from agriculture / GHG per LSU & GHG per ha (*) **NEW**
C47 Sales/Use of antimicrobials in food producing animals (*) **NEW**
C48 Risk, use and impacts of pesticides (*) **NEW**

Figure 10. Common Monitoring and Evaluation Framework indicators

The CAP instruments are transforming from Common Monitoring and Evaluation Framework to the new performance, monitoring and evaluation framework⁴¹ (PMEF) which foresees greater reliance on EU country notifications and statistics. New mandatory indicators on biodiversity, pesticides and animal health are introduced while new satellite area monitoring systems and more detailed data collection and data sharing on farming practices are currently developed. The indicators will be monitored through annual performance reports and a biannual review of the performance of CAP strategic plans to assess the progress of EU countries in reaching their targets and the objectives of the CAP.

Based on the conducted analysis regarding the mechanisms for environmental monitoring, it is evident that there is a similar need for employing state of the art data collection mechanisms across various domains. This need is also apparent for the future CAP monitoring and evaluation mechanisms. Currently there are various initiatives - sometimes in parallel - that deploy their own data collection networks. These initiatives need to be aligned towards a common EU wide dataspace where data collections will be feasible to be consumed for various purposes. Data interoperability and data reuse are key enablers towards an optimised exploitation of the monitoring infrastructures that may have initially been deployed to serve different purposes. In many cases, the environmental monitoring initiatives that are presented

⁴¹ https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/new-cap-2023-27_en

in these sections are allowing access to the respective data sets through standardised APIs (REST or SPARQL). A best practice towards a federated agro-environmental data repositories ecosystem of the future is that data repositories will be compliant with the FAIR⁴² principles, supporting data availability through interoperable/standardised mechanisms.

Based on current paradigms, the main data sources of an agro-environmental observatory of the future that will allow near-real-time monitoring can be grouped in the following categories:

- In-situ data sources
This category includes data from deployed sensor networks and services (e.g. FMIS, agricultural machinery).
- EO data products and open datasets
Various data repositories are currently available relating to environmental, climate, soil and social parameters provided by research institutions (e.g. JRC) and/or regional/national administrative entities (statistical authorities), e.g. the Agri-food Data Portal. According to the analysis in section 3.1 spatial and time granularity of the respective data products will be further enhanced.
- Questionnaires, surveys and manually added data especially referring to farmers' related characteristics and opinions.

A high-level objective for a long-term agro-environmental monitoring system is to realise methods for the stepwise integration of data sources on a differentiated scale-dependent approach (at local, sub-regional and regional levels). Such a system should realise a complementary use of local level data sources with data repositories reflecting regional parameters (e.g. FADN/FSDN, IACS, LPIS) and other data repositories with relevant environmental observation metrics (e.g. land use/cover change, water and soil quality, biodiversity index, territorial data). Relevant innovative knowledge inference/forecasting methods (e.g., social-media analytics) can also support the collection of evidence on social aspects e.g., Quality of Life in rural areas.

As it was analysed the current landscape of agro-environmental data repositories and agricultural technologies is highly fragmented where data are modelled heterogeneously and access to data collections is facilitated through APIs specified in non-uniform ways. According to the literature, data heterogeneity can be addressed with the use of data translators (Roussaki, et al., 2021) (Kalatzis, et al., 2019) that act as interoperability enablers. Interoperability enablers are usually software components that retrieve data items from the various sources and convert/model them according to the specifications of a dominant or even standardised data model. With regards to data provision the use of information systems known as Data Brokers that are compliant with the standardised data model and are providing standardised APIs⁴³ are currently among the best practices⁴³. To this end, figure 11 illustrates a conceptual view of federated data sources aiming to address the issue of interoperability and

⁴² <https://www.go-fair.org/fair-principles/>

⁴³ <https://www.fiware.org/community/smart-agrifood/>

to facilitate data access from multiple repositories. The objective of a unified agro-environmental data ecosystem is currently pursued from various EU initiatives including the “European Strategy for data⁴⁴” and various H2020 actions^{45,46}.

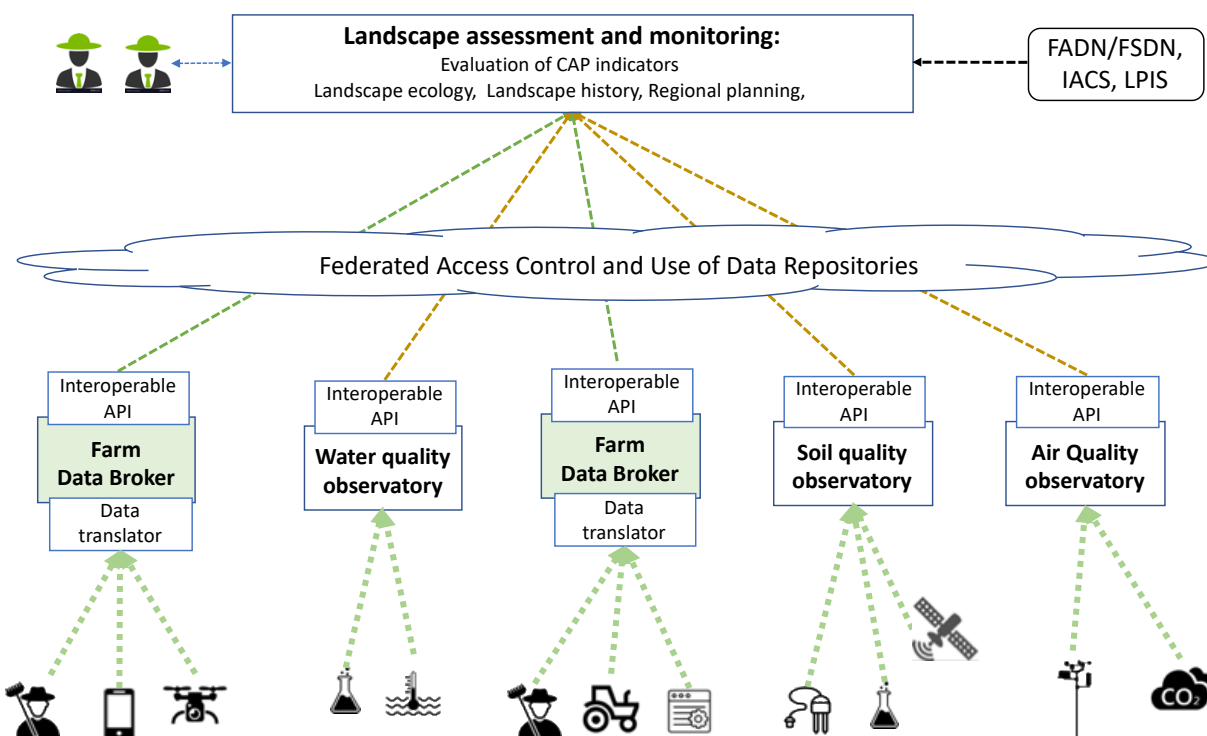


Figure 11. A high-level conceptual illustration of a federated ecosystem of agro-environmental data sources

⁴⁴ <https://digital-strategy.ec.europa.eu/en/policies/strategy-data>

⁴⁵ <https://www.atlas-h2020.eu/>

⁴⁶ <https://h2020-demeter.eu/>

5. Conclusions

Digital agricultural technologies, besides transforming the applied cultivation practices, demonstrate the potential to provide farm level ground truth evidence which also impacts the mechanisms for monitoring and evaluation of agricultural policies (CAP).

This deliverable focuses on the future evolution of selected technological offerings that are projected to be mature enough and available to support operations in the future agri-food domain considering also the perspective of the future policy monitoring and evaluation. As it was also stated at the conclusions of “D2.1 Landscape of agri-food ICT technologies within EU” there is no one-fits-all technological approach that is capable to provide all the necessary data for CAP monitoring. It is more a synergetic/complementary use of available data sources that needs to be realised. This conclusion is further supported through the conducted analysis of this deliverable.

The following technologies have been analysed and the following conclusions are extracted:

Satellite based Earth Observation

Satellite based Earth Observation is expected to have an even more significant role in future agriculture as well as CAP monitoring and evaluation systems. The main current barriers are related with spatial resolution (e.g. not possible to analyse small parcels), spectral resolution (more spectral information is some time needed to identify some crop types) and dependence on weather conditions (e.g. decreased quality of observations on cloudy days). In the future, these barriers will be partially resolved through the use of new satellite missions with increased capabilities (e.g. hyperspectral monitoring systems) combined with big data analytics algorithms. Access to processed EO data products and services and inferred outcomes (e.g. calculated indexes, crop types, identification of specific cultivation activities) is expected to be easier with a reduced processing and storage need through the use of digital cloud processing services and infrastructure.

Remote sensing based on Unmanned Aircraft Systems (UASs)

It is clear that the potential of Unmanned Aircraft Systems in agriculture is very high and the market is growing rapidly. The field of operation for UASs is expected to improve and expand for additional agricultural activities and cultivations. The main current operational constraints of UASs are the impeding meteorological conditions (rain, snowfall, clouds, wind and fog), the local and national regulations of UAS operation, the limited spatial coverage due to limited battery life or payload limits, along with the lack of standard procedures for inflight calibration of the UAS sensors. The capabilities of UASs are expected to expand in the future with more powerful engines and batteries. Additional constrains such as low accuracy, lack of interoperability, needs for increased data storage and computation power are also expected to be addressed especially when the use of UAS will be combined with advanced analytics (e.g. AI algorithms and Edge Computing). Such an approach will provide processed outcomes in a near-real-time mode avoiding delays of current lifecycle of operation (e.g. execute mission -

collect & store data - process data offline - extract results). UASs are not currently utilised for CAP monitoring and evaluation, however there is a clear potential especially with regards to on-the-spot-checks operations for selected areas.

Field sensor and advanced decision support

The ongoing widespread use of the Agricultural IoT has led to the explosive growth of sensors and monitored data. At the same time field sensors are getting more robust with additional capabilities for data processing. New computing paradigms like “Edge Computing” combined with machine learning will enable decision making in a distributed manner closer to the sensing layer. This approach will eliminate the need for transferring large amounts of data to cloud based data repositories and the commitment of substantial processing power facilitating the realization of intelligent decision making in additional domains of agriculture production. With regards to data collection in the context of CAP monitoring and evaluation, the advanced processing capabilities of sensing devices can support the real time analysis of generated datasets on the device level, the extraction of useful summaries and the direct transfer to the reporting agencies. For example, a future agriculture machinery tractor implementing VRA will have the necessary processing capabilities on generating and transferring a data report of the executed task in a near-real-time mode. In addition, image content recognition of geotagged photos captured by the farmers’ mobile phone will be possible to be realized on a non-centralized manner facilitating the confirmation of alleged crop types and activities depicted in the photos.

Advanced agricultural machinery and robotics

With regards to autonomous platforms (agricultural robots) that automate or augment operations there are already promising first assessments but for a limited area of agricultural needs and for limited cultivations. However the achieved benefit is substantial optimising in many cases significantly the performance of the operations. For example, according to the published results automated harvesting of strawberries demonstrate significant improvements which results to the adoption of this technology in operational-commercial environments. There are still important challenges to be addressed that prevent robotics from reaching their full potential. Expanding the capabilities of robots from the lab and greenhouse environment to the outdoor conditions is crucial, when it comes to sensing under harsh environments and operating under unpredicted conditions. Overall, robotics and automation demonstrate the required potential for playing a significant role in agricultural production of the future. Extensive data logs are generated and can potentially act as ground truth evidence of the performed operations allowing the further automation of data collection that are also ideal for future CAP monitoring and evaluation. For example, a robotic harvester may generate data logs which can act as evidence on the date/amount/type/quality of harvested yield that will automatically escort the fruit products supporting a more transparent food chain. To our knowledge, there is no evaluation yet on the use of agri-robotic platforms in the context of CAP M&E.

Environmental Observatories

Based on the conducted analysis there is an EU-wide need for data collection through heterogeneous sources in order to monitor and evaluate indicators related with the implemented agro-environmental policies. There are already significant initiatives of observatories that are applying data collection mechanisms focusing on various aspects such as soil, biodiversity, water, agricultural monitoring, rural development, etc. In many cases, these approaches are still fragmented and operate in parallel, dedicating significant efforts to collect data from similar sources and for similar purposes without fully exploiting the gathered data collections. In many cases, the monitoring initiatives are still in a proof of concept stage e.g. part of an experimental project, while regulations dictating data access to third parties are rather strict or not clear. Semantic and syntactic data interoperability issues prevent the ease use of accessing and processing the available data collections. In some cases, best practices are already applied and access to data repositories is provided through standardised mechanisms (e.g. SPARQL endpoints) which is a significant step for their further exploitation. Semantic interoperability is also still an issue because there is still no widely accepted dominant data model (ontology) for semantically annotating agro-environmental observations. Given the increased need for sharing data collections and the significant efforts that are currently invested towards standardisation of data models (e.g. relevant H2020 actions and the work of standardisation bodies like ETSI), the issue of data interoperability is expected to be resolved to an extended degree in the near future. In most of the cases data collection of the existing observatories is realised through satellite EO (e.g. Copernicus) and/or IoT based sensor networks deployed for a specific scope. There is a need to develop mechanism that will allow the complementary use of these data collection and enable data sharing among the various existing operational- even private/commercial- sensor networks.

As a next step and in the context of MEF4CAP's demonstration cases, innovative mechanisms for collection and sharing of agro-environmental data will be realised allowing to evaluate such approaches and extract significant outcomes towards the future CAP M&E.

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