AgriDataValue

Smart Farm and Agri-environmental Big Data Value

Deliverable D1.1

Definition & analysis of use cases and system requirements V1

Authors	Th. Zahariadis, O. Alvaniti, N. Afratis, A. Terpou. P. Athanasoulis, S. Rizou, I. Katris, M. Al Sayah, N. El Beyrouthy, Y. Oikonomidis, I. Chrysakis, R. Lazcano, P. Ramírez, N. Peiren, A. Turkmayali, J. Kiers, S. Bossuyt, E. Ampe, I. Salinas, E. Pardo, A. del Saz, F. José Lacueva-Pérez, V. Inglezou, G. Kokkinos, S. Neicu, K. Dmochowska-Dudek, P. Grzyś, M. Wójcik, P. Tobiasz-Lis
Nature	Report
Dissemination	Public
Version	V1.0
Status	Draft
Delivery Date (DoA)	M04
Actual Delivery Date	31 May 2023

Keywords	Use Cases, Functional Requirements, Non-Functional Requirements, Data Models, Interoperability,
Abstract	AgriDataValue is a comprehensive research project aimed at leveraging advanced technologies to revolutionize the agricultural sector. Through the integration of IoT, geospatial data, machine learning, and blockchain, AgriDataValue seeks to enhance the efficiency, sustainability, and productivity of farming practices. The project focuses on developing innovative tools and platforms for data collection, analysis, and decision-making processes in agriculture. By harnessing the power of IoT sensors, satellite imagery, and drone technology, AgriDataValue enables real-time monitoring and precise management of crops, water resources, and livestock. The utilization of machine learning algorithms facilitates data processing, pattern recognition, and predictive analytics, empowering farmers with actionable insights for optimizing resource allocation, crop treatment, and livestock management. Furthermore, the

	integration of blockchain technology ensures transparency, traceability, and data integrity throughout the food supply chain, fostering trust and accountability among stakeholders. The ultimate goal of AgriDataValue is to enable sustainable and smart farming practices that enhance food production, minimize environmental impact, and meet the challenges of a growing global population.

ACKNOWLEDGEMENT

The AgriDataValue project is funded by the European Union under Grant Agreement No. 101086461. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Executive Agency, while neither the European Union nor the granting authority can be held responsible for any use of this content.

	Participant organisation name	Short	Country
01	SYNELIXIS SOLUTIONS S.A.	SYN	EL
02	ATOS IT SOLUTIONS AND SERVICES IBERIA SL	ATOS	ES
03	SIXENSE ENGINEERING	SIXEN	FR
04	NETCOMPANY-INTRASOFT SA	INTRA	LU
05	SIEMENS SRL	SIEM	RO
06	SINERGISE LABORATORIJ ZA GEOGRAFSKEINFORMACIJSKE SISTEME DOO	SINER	SI
07	ALMAVIVA - THE ITALIAN INNOVATION COMPANY SPA	ALMA	IT
08	INTERNATIONAL DATA SPACES EV	IDSA	DE
09	SOFTWARE IMAGINATION & VISION SRL	SIMAVI	RO
10	SINGULARLOGIC S.A.	SLG	EL
11	EIGEN VERMOGEN VAN HET INSTITUUT VOOR LANDBOUW- EN VISSERIJONDERZOEK	EV ILVO	BE
12	ETHNIKO KAI KAPODISTRIAKO PANEPISTIMIO ATHINON	NKUA	EL
13	INAGRO, PROVINCIAAL EXTERNVERZELFSTANDIGD AGENTSCHAP IN PRIVAATRECHTELIJKE VORM VZW	InAgro	BE
14	UNIWERSYTET LODZKI	UL	PL
15	FUNDACION PARA LAS TECNOLOGIAS AUXILIARES DE LA AGRICULTURA	TEC	ES
16	DELPHY BV	Delphy	NL
17	INSTITUTO TECNOLOGICO DE ARAGON	ITAIN	ES
18	ZEMNIEKU SAEIMA	ZSA	LV
19	SOCIEDAD ARAGONESA DE GESTION AGROAMBIENTAL SL	SARGA	ES
20	AGROTIKOS KTINOTROFIKOS SYNETAIRISMOS KATOUNAS TO VIOLOGIKO AGROKTIMA	TBA	EL
21	SOCIETA ITALIANA DI VITICOLTURA EDENOLOGIA	SIVE	IT
22	NILEAS-SYNETAIRISMOS PISTOPOIIMENON AGROTIKON PROIONTON DIMOU NESTOROS MESSINIAS	NILEAS	EL
23	CONSEIL DES VINS DE SAINT-EMILION	CVSE	FR
24	ASOCIATIA OPERATORILOR DIN AGRICULTURA ECOLOGICA BIO ROMANIA	BIORO	RO
25	RI.NOVA SOCIETA COOPERATIVA	RI.NO	IT
26	AGRO DIGITAL SOLUTIONS	AgroDS	LT
27	NATIONAL PAYING AGENCY	NPA	LT
28	AGENZIA PROVINCIALE PER I PAGAMENTIDELLA PROVINCIA AUTONOMA DI TRENTO	APPAG	IT
29	AGENTIA DE PLATI SI INTERVENTIE PENTRU AGRICULTURA	APIA	RO
30	QUEEN MARY UNIVERSITY OF LONDON	QMUL	UK

DISCLAIMER

Document History

Version	Date	Contributor(s)	Description
V0.1	24/03/2023	SIXEN	Initial Draft
V0.2	09/05/2023	SYN	First working version
V0.3	17/05/2023	SIXEN	Contributions from partners
V0.4	18/05/2023	SIXEN	New working version
V0.5	21/05/2023	SYN	Integration of all input
V0.6	22/05/2023	SIXEN	Added partners UCs descriptions
V0.7	23/05/2023	SIXEN	Added final contributions
V0.8	25/05/2023	SIXEN	Added Introduction, Abstract and Conclusion
V0.9	29/05/2023	ILVO, ATOS	Reviewers comments
V1.0	29/05/2023	SIXEN	Final Version

Document Reviewers

Date	Reviewer’s name	Affiliation
26/05/2023	Nico Peiren	ILVO
29/05/2023	Raquel Lazcano	ATOS
25/05/2023	Naji El BEYROUTHY	SIXEN

Table of Contents

Definitions, Acronyms and Abbreviations

AD	Allowable Depletion
ADS	Agri-Environmental Big Data Space
ADS-C	ADS Core
ADS-M	ADS Marketplace
ADV	Agri Data Value
AI	Artificial Intelligence
ANN	Artificial Neural Networks
API	Application Programming Interface
API	Application Programming Interface
CAP	Common Agriculture Policy
CNN	Convolutional Neural Networks
CSP	CAP Strategic Plan
DLT	Distributed Ledger Technology
DoA	Description of Action
DIAS	Data and Information Access Services
DPO	Data Protection Officer
DSS	Decision Support System
EC	European Commission
EO	Earth Observation
EU	European Union
FAIR	Findability, Accessibility, Interoperability and Reusability
FDML	Federated Deep Machine Learning
FC	Field Capacity
GDD	Growing Degree Days
GHG	Greenhouse Gas Emissions
JAD	Joint Application Design
LL	Lower soil moisture Limit
LMAA	Lean Multi-Actor Approach
LSP	Land surface phenology
MAD	Maximum Allowable Depletion
MAP	Manure Action Plans
ML	Machine Learning
NDVI	Normalized Difference Vegetation Index
NIR	Near InfraRed
OGC	Open Geospatial Consortium
PWP	Permanent Wilting Point

RAF	Reference Architecture Framework
RF	Random Forest
SOS	Sensor Observation Service
TSS	Total Soluble Solids
UAV	Unmanned Aerial Vehicles
UC	Use Case
UGV	Unmanned Ground Vehicles
UN	United Nations
VS	Volatile Solid
WCS	Web Coverage Service
WFS	Web Feature Services
WMS	Web Map Service
WMTS	Web Map Tile Service

Executive Summary

One of the main objectives of AgriDataValue is to strengthen the capacities for smart farming and enhance the environmental and economic performance of the agricultural sector. Moreover, AgriDataValue aims to strengthen the capacities for climate monitoring, particularly soil & crop conditions in-line with UN Sustainable Development Goals [1]. To achieve the above objectives, AgriDataValue will work toward the development of the required technological innovations.

This Deliverable entitled “Definition & Analysis of Use Cases and System requirements” has twofold objectives: on one hand, it aims to update, refine, extend and analyse the project Use Cases (UCs) as they had been presented in the project Description of Action (DoA). On the other hand, it aims to provide an initial list of system requirements to be updated in the next months in parallel to the Agri Data Space (ADS) System specifications.

1 Introduction

By the year 2050, Earth is projected to be home to a population of over 10 billion people, signifying the urgent need for substantial increases in agricultural production, potentially as high as 65% to sustainably feed the global population. However, as we strive to accommodate this exponential growth, we face a significant challenge: most of the Earth's arable lands are already occupied, and approximately 70% of the available drinking water is being utilized for crop irrigation, with over 60% of this water being wasted due to inefficient irrigation practices.

The consequences of such wasteful irrigation techniques are multifaceted and far-reaching. Overirrigation not only leads to the proliferation of fungal and bacterial diseases, causing significant crop losses, but it also disrupts the delicate oxygen balance in the root zones, hampering plant water uptake and reducing soil temperatures. Moreover, this excess water application promotes nutrient leaching, diminishing the soil's fertility and further exacerbating the environmental impact. Additionally, the excessive use of fertilizers in Europe, exceeding 220,000 tonnes, poses a great risk of aquifer contamination, threatening the already fragile ecosystems and their associated services.

Furthermore, agriculture itself contributes significantly to greenhouse gas emissions, thus playing a dual role in climate change. On one hand, it serves as a contributor to global warming, while on the other hand, it is directly impacted by the adverse effects of climate change, such as reduced crop yields and structural and functional damage. Indirectly, climate change also affects crucial elements of agricultural systems, including soils, water resources, biodiversity, and overall productivity.

Given the escalating challenges of climate change, population growth, and limited land resources, it is imperative to embrace paradigm shifts in agricultural systems. The conventional approach of expanding cropped areas to meet the demand for food cannot be sustained without endangering biodiversity and further compromising the fragility of ecosystems. Therefore, the focus must shift towards optimizing agricultural production through the application of knowledge and innovative techniques.

This is where the concept of smart agriculture, supported by Big Data and Artificial Intelligence (AI), emerges as a promising solution. With the advent of advanced technologies, a wealth of data is being generated from various sources such as on-ground sensors, aerial platforms, satellite imagery, and wearable sensors. The processing and analysis of this vast amount of data, in conjunction with AI algorithms, have the potential to provide invaluable insights and information to guide decision-making processes and accelerate the transition towards a smarter and more sustainable form of agriculture. However, despite the immense potential of smart farming, several challenges hinder its widespread adoption. Foremost among these challenges is the issue of data availability, non-uniformity, and restricted access or sharing. The scarcity of reliable and comprehensive data complicates the training of AI models, thereby diminishing their perceived credibility among farmers and livestock raisers who remain sceptical due to the lack of tangible evidence of success. Consequently, a bidirectional feedback loop is created, with data restriction resulting from the absence of convincing success stories, while simultaneously impeding the generation of such success stories.

Another significant hurdle lies in the complexity of AI models themselves, rendering them difficult to comprehend for farmers, especially those who adhere to traditional or inherited practices. The intricate nature of AI algorithms, with their underlying statistical and computational complexity, poses a barrier to adoption, as farmers may find it challenging to fully trust and understand these sophisticated systems. Bridging this knowledge gap and fostering a sense of confidence and familiarity with AI technologies among farmers will be crucial for the wider acceptance and implementation of smart farming practices. The future of agriculture is intricately intertwined with the pressing challenges of population growth, climate change, and the limitations of land resources. To ensure food security for a burgeoning global population while preserving biodiversity and fragile ecosystems, a paradigm shift towards smarter and more sustainable agricultural systems is imperative. The integration of Big Data and AI into farming practices holds tremendous potential for optimizing agricultural production, but it also necessitates addressing key obstacles such as data availability and accessibility, as well as enhancing farmers' understanding and trust in AI technologies. By embracing these transformative changes, we can forge a path towards a resilient and efficient agricultural future, capable of meeting the needs of both present and future generations. One of the main objectives of AgriDataValue is to strengthen the capacities for smart farming and enhance the environmental and economic performance of the agricultural sector. Moreover, AgriDataValue aims to strengthen the capacities for climate monitoring, particularly soil & crop conditions in-line with UN Sustainable Development Goals [1]. To achieve the above objectives, AgriDataValue will work toward the development of the required technological innovations. However, the real impact will be achieved by the dissemination or the project results and the creation of a universal ecosystem that is aware of the technological and strategic achievements. Moreover, the AgriDataValue consortium partners are committed to promote the project outcomes among the relevant stakeholders and has developed a comprehensive dissemination and communication plan, which is targeted towards achieving smart farming and protection of the climate and the biodiversity.

The current version of Deliverable D1.1 aims at providing user-centric requirements reflecting both the views of the end-users as well as of other stakeholders that are located further down in the value chain, as explained later in section 1.1. The purpose of this version is to refine the requirements as had been described in the DoA, based on the experiences during the initial 4 months of the project. The document also provides insights from other initiatives and projects such as DataBio [2], IoF2020 [3], A-FarCloud [4] and DEMETER [5], and by that sets the foundations for a more detailed analysis of the requirements throughout the project life time until Ver. 2 at M30.

D1.1 is the first version of the User requirements capturing and analysis, while D1.2 will be the second version, where refinements and update of the end-user requirements will be provided as product of various discussions and feedback from the initial data capturing process. In addition, more end-users (not involved in the project) are expected to be interviewed and comment on the results of the first year’s demonstrations. Finally, the feedback in AgriDataValue’s social media channels will be analysed. The user requirements in this document will be reflected in T2.2 Architecture Requirements and definition work.

1.1 Intended Audience

The audience of the deliverable will be the various stakeholder groups that have been identified as AgriDataValue platform potential users. As such, at the first stage of the description of the user requirements, it was necessary to prioritize the end-users who will have the greatest impact on the definition and development of AgriDataValue platform during the project. These users are categorized into five main groups, namely: (1) individual farmers and/or farming companies, including both crop and livestock production, (2) farming (applied) and climate monitoring research institutes, including universities and scientists, (3) Specialized service and technology providers, such as SMEs that aim to offer services based on Agri-data and AgriDataValue technology, (4) Common Agriculture Policy (CAP) paying authorities though out Europe that aims to offer new tools to fairly apply the EU CAP 2023-2027 policy, and finally (5) EU policy makers and authorities that monitor implementation of the EU strategies towards a climate neutral economy, reducing the CO2 footprint and implementing the EU soil strategy.

Farming companies, especially those that provide the pilot sites for implementing and validating the AgriDataValue use cases and test scenarios, are considered to be the users with the highest priority, but it is necessary to consider that activities such as decision support and data analysis are in some cases outsourced.

Moreover, in our vision of farmers are future Agri-meteorology Data/ML models prosumers, the framing companies may in some cases overlap with agriculture development service providers SMEs.

In the first phase of requirements gathering we focused on users who were able to effectively provide feedback during the initial months of AgriDataValue project and will be included as testing cases of the AgriDataValue platform. These were users who are members of the AgriDataValue Consortium or have a direct link to the members of the consortium. Besides, with the advancing activities of the AgriDataValue project and the availability of dissemination materials, we have had the opportunity to focus on wider user base and update the user requirements after performing the first trials.

1.2 Document overview

The deliverable D1.1 structure is divided into 8 chapters.

Table 1 - Structure of AgriDataValue Deliverable D1.1

	Chapter title	**Summary**
Chapter 1	Introduction	By 2050, with a population of over 10 billion, agricultural production needs to increase by 65% to feed everyone. Challenges like limited land, water waste, fertilizer use, and climate change require a shift to smarter agriculture using Big Data and AI. AgriDataValue aims to enhance smart farming, disseminate results, and create a universal ecosystem.
Chapter 2	User-centred requirements methodologies	This chapter explores the methods of gathering end-user requirements for the AgriDataValue platform. Persona development is used to identify users, and the process progresses from use cases to meet their requirements. Accurate understanding of user needs is crucial for system development. Efficient requirement gathering methods are necessary for the platform's success.
Chapter 3	AgriDataValue Use Cases	In a user-centric approach, AgriDataValue introduces use cases to capture platform requirements. The Lean Multi-Actor Approach (LMAA) facilitates interactions and knowledge sharing among various actors. AgriDataValue implements LMAA through comprehensive use cases, co-creation of tools and AI models, pilot testing, and stakeholder feedback. The Agri-Environmental Big Data Space (ADS) platform is divided into the ADS Core (data storage, processing, AI/ML training, and decision support) and the ADS Marketplace (enabling innovative business models and data/ML model sharing).
Chapter 4	GAP Analysis in Agri-Environment Data Management, Processing & Storage	Digital transformation in the agrifood sector requires frameworks for data exchange, information organization, and clear responsibilities. Digital platforms should facilitate data access, foster data economy, and enable interoperability. Selecting the right platform is challenging due to the variety of options available. Aggregating existing platforms is crucial for data exchange. Addressing data interoperability, governance, and ownership is essential. The FAIR principles and data sovereignty play key roles. This section explores related projects and initiatives, focusing on data management.
Chapter 5	Climate change-agriculture nexus	In this chapter a summary of the climate change agriculture nexus in Europe is given. Trends of scientific literature will be evaluated, and an analysis of existing models and tools will be done. Through a

		classification by typology, advantages, disadvantages, limits and potential will be detailed.
Chapter 6	Data models and systems	This chapter focuses on data interoperability in the AgriDataValue project, emphasizing essential components and frameworks for seamless data exchange. Robust data models and systems are crucial for organizing and representing agricultural data consistently. The chapter provides insights and guidelines for effective data interoperability within the project, addressing challenges within the project's ecosystem and external dataspaces. The goal is to advance smart farming and sustainable agricultural practices.
Chapter 7	User and System Requirements	User requirements are generated aiming of addressing the specific needs and challenges and technical requirements for each use case
Chapter 8	Meta-Architecture Considerations	AgriDataValue adopts a multilevel architecture with a focus on data sovereignty, locality, and traceability. The project aims to develop a secure and trustworthy platform that leverages federation and decentralized processing. It will be an open-source, privacy-preserving, and federated AI-based platform capable of capturing and managing agri-environment data from diverse sources. The platform will enable secure and GDPR-compliant interoperability and data sharing among end-users, industries, and organizations.

2 User-centred requirements methodologies

The purpose of this chapter is to examine the different methods in gathering end-user requirements. End-user requirements are one of the vital pieces to ensure the success of a system, a platform, or a project, thus the success and the effectiveness of the AgriDataValue platform. To ensure the optimal requirements are received, the methods in which those requirements are obtained are equally important.

The first step into this process is to find out, identify and describe who the users of the AgriDataValue platform would be. One suitable technique for this task is the ***Persona development.*** The purpose of personas is to create reliable and realistic representations of the key audience segments for reference [6]. As such, personas are fictional, representative stand-in users for one segment of a systems target audience, who help with making sure that the system:

- Is designed for the user, not the technology provider or the scientist/researcher,
- See the target users as real people, with real stories and real needs,
- Implement a role-play end-user behaviour

This preliminary step would better shape the characteristics of the systems' users and ultimately improve the effectiveness of the user requirement gathering process which is the next step. Figure 1 provides a hierarchy of the different types of requirements. We start our research from the UCs that we have already identified in the project and provide very important but less details requirements, as they remain at user perception of the system. Then we move in a top-down approach to meet the end-user requirements. It should be emphasised that AgriDataValue "end-users" go well beyond the farmers and the farming companies to capture the complete farming & climate monitoring stakeholders' ecosystem. Finally, at the lower and most detail level, we meet the actual functional and non-functional ADS platform requirements, which WP2-WP4 will be requested to implement.

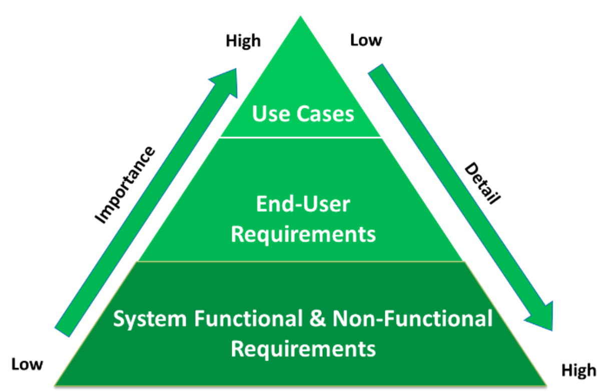


Figure 1: Hierarchical representation of the considered requirements

It is well agreed that insufficient efforts during the user and system requirements capture and analysis phase or the design phases of a system development life cycle often leads to errors in developed and deployed systems. Research in the industry indicates that the majority of problems encountered in complex ICT systems arise from poorly defined requirements. By comprehending users' needs accurately, the development team can provide a system that caters to their requirements. Hence, to ensure that the AgriDataValue platform succeeds and functions effectively, it is crucial to carry out the user requirement gathering process efficiently and coherently, while considering any limitations that may exist, to meet the AgriDataValue's user-centric demands. Thus, we initially provide an overview of the different methods for user requirement gathering.

2.1 AgriDataValue Actors

In order to gather inputs for D1.1, and more importantly, understand the needs of the different stakeholders, five actors' categories have been identified:

Category 1: Farming companies, cooperatives, and individual farmers. Most of the user requirements is focused on this category, who are considered as main users from our point of view and their requirements have the highest impact on AgriDataValue platform definition and development.

Category 2: Farming (applied) and climate monitoring research institutes, including universities and scientists. Entities in this category are also considered to be among the main users. In addition, personnel working at these entities may be involved in other projects in the agricultural or climate monitoring domain, which means that they have relevant perspectives in this regard.

Category 3: Specialized service and technology providers offering added valued services based on Agri-data and AgriDataValue technology. This category of entities refers to companies (mainly SMEs) that supply or support entities mainly in Category 1, which means that they do have a clear understanding of the challenges in agriculture processes. This category is highly relevant in this context since their success is closely linked with the emerging business opportunity, to some extent through innovations, connected with AgriDataValue platform. Services and products in this context may be software solutions, IoT/sensor manufacturers and various kinds of advisory, analytical, or other services to farms during or after the AgriDataValue project. The aim of the AgriDataValue is to increase overlapping between Category 1 and Category 3, converting farmers to data/ML models/farming advice/ warnings prosumers.

Category 4: CAP paying authorities. This category of entities refers to national or regional Common Agriculture Policy (CAP) paying authorities that aim to offer new tools to fairly apply the EU CAP 2023-2027 policy. Though in most cases the tools for 2023 are already in production phase, news policies and monitoring tools will be required the next years to realize and monitoring the CAP priorities.

Category 5: EU policy makers. This category of entities refers to stakeholders, EU policy makers, authorities that monitor implementation of the EU strategies and decision makers. towards a climate neutral economy, reducing the CO2 footprint and implementing the EU soil strategy.

Table 2. Explanation of the Actors categories and roles

Actor Categories	Role index	Role explanation
Category 1: Farming companies, Cooperatives, and Individual Farmers	1.a	**Company owner/manager.** This person makes strategic decisions for the company/cooperative, runs the company/ cooperative in an economically and environmentally sustainable manner, and maintains a good working environment.
	1.b	**An agronomist/livestock specialist.** This is a trained person, with a scientific background, who has knowledge of the production and based on his/her decision may apply a process or a sub-process to a specific crop or to the livestock.

Actor Categories	Role index	Role explanation
	1.c	**The Employee/worker.** This person offers hands on realization of the processes e.g., controls a machine or drives a tractor, flies a drone to collect data, feeds and inspects the animals.
Category 2: Farming (applied) and climate monitoring research institutes, including universities and scientists	2.a	**Project/group/Task leader** with objectives that correspond to a manager. This role has some similarity to 1.a, but refers to a person at the university or institute department that has reduced for decision capacity.
	2.b	**Senior researcher.** A person who drives the research, designs and coordinates experiments and other research activities, evaluates the result, etc. similar to 1.b.
	2.c	**Junior researcher or technical personnel**. A person who usually does hands on activities and routine research tasks, similar to 1.c.
Category 3: Specialized service and technology providers offering added valued services based on Agri-Environmental data and AgriDataValue technology	3.a	**Company owner/manager.** This is the company (SME) owner or the Technical Director and has a role similar to 1.a
	3.b	**Agriculture scientist, agronomist/livestock specialist domain specialist**. A person with strong knowhow and experience in the agriculture sector or with agricultural background working for service and technology providers. Corresponds to 1.b or 2.b.
	3.c	**SW/HW Engineer or Data Scientist**. A person who is involved in research and development of the added valued services, with a scientific background in SW/HW engineering, mobile Apps programmer, AI/ML and Big data analysis expert, geo databases, (satellite) image processing. S/He works in collaboration with people from 3.b to realize the ICT part of the offered service.
	3.d	**Assistant working with R&D&I**. A person who is involved in research, development and operation/support of the services. People with this role usually need assistance from 3.b and 3.c for at least part of their work and may perform ICT HW/SW services installations/ deployment/ maintenance at the farm/field.
Category 4: CAP paying authorities	4.a	**Authority General Manager.** This is the person that has the overall responsibility of the authority and has a role similar to 1.a
	4.b	**Domain Director**. A person with strong knowhow and experience in the CAP strategy and processes and has the responsibility for realizing specific sub-processes of the CAP e.g. monitoring, eco-schemes, IT support, on-site inspections.
	4.c	**SW Engineer/Data Scientist or Assistant**. An employee with a scientific background, who is involved in the day-by-day development, deployment and support of the authority's operations on CAP policies/strategies realization.

Actor Categories	Role index	Role explanation
Category 5: EU stakeholders/ policy makers	5.a	**Stakeholder, Strategy/Decision Maker.** This is a stakeholder that has the authority of decision making or voting for a strategy making at local, territory, country or EU level. In many cases, a member of a parliament or a political person with strong authority.
	5.b	**General/Domain Specific Secretary, Director or Advisor.** This is a person with scientific background and public administration expertise that has the responsibility to propose methods and procedures to realize a CAP policy, design and implementation of CAP strategic plans (CSPs)
	5.c	**Secretary/Director Assistant.** This is a person that communicates with the national or local CAP authority to supervise and coordinate the CAP implementation.

Note: In some companies one person may have multiple roles. Similarly, in some cases, one question may be relevant for several roles represented by different individuals.

2.2 Users' requirements gathering methods

There are many methods to collect information. This section describes some of the most widely adopted ones.

2.2.1 Interviews

Conducting interviews is a fundamental method of obtaining information about an information system. Interviews can provide a comprehensive understanding of the stakeholders' roles, the end users' requirements and how they consider interacting with the system. There are various types of interviews, such as structured, unstructured, or semi-structured, which can be conducted in either a group or one-on-one setting, or even a combination of both, along with observation. A good strategy for the reviewer to gather valuable insights about the platform and its essential capabilities is to ask questions that allow the collection of "stories". Employing this strategy can be advantageous in comprehending the project's value.

In general questions that an interview may include are categorized in two group:

- **Open-ended questions** are these types of questions that require the interviewee to explain or describe his/her thoughts and cannot be simply answered with a "yes" or "no". Open-ended questions allow consultants to ask follow-up questions or request for an example in order to obtain more detail. As an example, an open-ended question may be "*What are the main problems that you face on your daily routine?*"
- **Close-ended questions** can also be useful when the interviewer is looking for a specific answer. They can provide specific answers for the interviewee to choose from, in formats including true or false or multiple choice. Although close-ended questions do not provide as much detail as open-ended, they can be useful to cover more topics in a shorter amount of time. As an example, close-ended questions may be "What is the average amount of arable crop your produce per hectare?", "What is the average volume of fertilizers you annually use per arable crop per hectare?", "How many animals are treated per day?" Once the

questions have been established, it is a good practice to provide the questions to the interviewee prior to the interview, in the event that the interviewee needs to prepare them.

For privacy and GDPR issues, the interviewer should obtain permission from the interviewee that recorders may be used. This is especially important in case of open-ended questions to ensure that if details are missed while taking notes, they could easily be retrieved. At the end of the interview, the results should be provided to the interviewee, for confirmation of their responses.

Some general directions for an effective and successful interview could be:

- What are the biggest challenges in your day-by-day routine?
- To ensure focus on future and not current state, questions could be in the form: To your opinion, how would an ideal solution look like?
- Post interview questions could be in the form: What problems is the project technology trying to address? How might the project/platform meet this need? Where would the results be visible? Who will use this feature? What is the result of doing this? What's next?

Interviews may be organised wither in One-on-One base or as Group Interviews:

- **One-on-one interviews** is a frequently used method of gathering user requirements, construct use cases and represent one of the primary sources of requirements. To conduct an effective interview, preparation is essential, and the analyst should identify stakeholders to be interviewed, such as users, managers, directors, stakeholders, decision makers and actual end-users who are involved in day-by-day operation, interact with the current system and will be the users of the new one.
- **Group interviews** are similar, except there is more than one person being interviewed. Group interviews work well when the interviewees are at the same level or position. A group interview also has an advantage when there is a time constraint as the interviewees in many cases enter a brainstorm mode, complementing each other's answers. More thoughts and discussions can be generated, as someone in the group may state or suggest an idea that may have been overlooked by others, which in turn can lead to a discussion or provide more information on a particular issue. A major disadvantage can be scheduling the interview. When more than one person is involved, it may be difficult, or become time consuming, to establish a date and time that works well for all parties.

2.2.2 Questionnaires/Surveys

Questionnaires and Surveys are useful tools offering the advantage of gathering information from many persons in parallel in a relatively short time and of being less biased in the interpretation of their results. This technique is especially helpful when stakeholders are geographically dispersed, or when input from many respondents is needed to establish system requirements.

However, it is crucial to select the right respondents and design effective questionnaires to ensure successful information collection. As shown in Table 2, AgriDataValue considers different types of end-users, with quite different roles. Since users typically only use a subset of system functions, features, or processes, it is quite unlikely that a single questionnaire will fit all users. To conduct an efficient survey, the analyst should properly group the users and create different questionnaires for each group. While questionnaires and surveys are quantitative methods that offer less flexibility compared to qualitative methods like interviews, they can still be effective, as long as the analyst properly generate the questionnaires' structure. When constructing a questionnaire, the analyst can use general guidelines such as asking "how, where, when, who, what, and why" questions. For example, "How will you use this feature?" "How can we meet this business need?" "Where would the user access this feature?" When designing questionnaires, the analyst should consider at least the following issues:

- The ambiguity of questions. Is the question clear to the person that is fulfilling the questionnaire?
- Consistence of respondents' answers. Has the person taking the questionnaire the knowledge to answer?
- What kind of question should be applied, open-ended or close-ended?
- What is the proper length of the questionnaires?

2.2.3 End-users Observation

Obtaining reliable information from people can be challenging, even when they are sincere and try to be accurate. People may not always have a precise understanding of their actions or behaviours, particularly with infrequent events, past issues, or topics that generate strong emotions. Nonetheless, observation may provide the analyst with a immediate understanding of how users interact with current system and could interact with a future one. By observing users, the analyst can gain insights into how they perform their tasks, how their surroundings affect their interaction with the system, and what their requirements might be. This can be especially helpful when stakeholders struggle to articulate their needs clearly. Nevertheless, observation has some limitations, such as the potential for observation to influence people's behaviour and the time-consuming nature of this technique. Additionally, people may not behave as they typically would in the observed setting, leading to biased information. Last but not least, it is only specific end-user categories that may apply in this category, while many others, such as decision makers, may not even apply to this method. Therefore, when observation is utilized, it should be preferably performed in a complementary way to information gathered through other techniques.

2.2.4 Analyse existing system/solution documentation

By examining an existing system/solution, a system analysts can find out details about current systems and the processes that an organization uses today to solve a problem. Analysts can extract various valuable pieces of information from documents, such as issues with current systems, possibilities for meeting new requirements, organizational priorities that can impact system requirements, and reasons for the design of current systems.

However, it may be quite challenging for an analyst to understand in detail an existing system in short time. Moreover, there may be discrepancies between the systems documentation and the actual systems in use, as updates may have not been well reflected in the documentation. This is because of limitations in formal procedures, individual work habits and preferences, resistance to control, and other factors that contribute to the existence of informal systems. Thus, analysts should be aware of these potential discrepancies when reviewing official documentation.

2.2.5 Mock-up/Prototyping

Mock-ups and prototypes are means of exploring an idea before it is implemented. Most system developers believe that the benefits from mock-ups and early usability tests may be at least an order of magnitude greater than those from late usability data. Mock-ups and prototypes allow end users to see how their basic requirements are interpreted by the analysts and realized. After viewing and testing the prototype, the users usually adjust existing requirements to new ones. Instead of a simple mock-up, a more specialised approach is the so-called Joint Application Design (JAD), which is a facilitated, team-based approach for defining the requirements for new or modified information systems. The main idea behind JAD is to bring together the key users, managers, and system analysts involved in the analysis of a current system [7]. Though JAD may provide excellent results, it is not widely accepted in modern system design due to practical implementation constraints and increased cost.

The goal of using a mock-up or an early prototype to support requirement determination is to develop concrete specification for the ultimate system. Prototyping is mainly useful for analysing requirements which are ambiguous or not well-defined, and tools and data are readily available to rapidly build working systems. Though, prototyping is not a suitable solution in the AgriDataValue system context for all user categories, nevertheless, it can be a useful addition to enhance the effectiveness and accuracy of the final product (component, service) for technical and development-specific user teams.

2.2.6 Comparison of users' requirements gathering methods

When choosing a user's requirements gathering and determination method, there are various aspects that should be considered. [8]. Table 3 provides a comparison of the five previously discussed requirements determination methods based on these aspects.

Table 3: User requirements capturing methods comparison

Characteristic	Interviews	Questionnaires	End-user Observation	Existing system/ solution analysis	Mock-Up/ Prototyping
Information Richness	High	Medium to Low	High	Low	Medium to High
Time Required	Can be High	Low to Moderate	Can be High	Medium	Moderate to High
Expense	Can be high	Moderate	Can be high	Low to Moderate	High
Chance for Follow-up	Good	Limited	Good	Limited	Good
Confidentiality	Interviewee is known to interviewer	Respondent can be unknown	End-user and observer are known	Depends	End-user and analyst are known
Involvement of Subject	Interviewee is involved and committed	No clear commitment	Interviewees may not be committed	Depends	Users are involved and committed
Potential Audience	Limited Audience, but complete responses	Audience can be large, but no committed	Limited audience, type and detail	Limited Audience in volume and type	Limited Audience in volume and type

2.3 Gathering methods used in AgriDataValue

In AgriDataValue we used a combination of the aforementioned techniques to gather the first set of meaningful, useful and effective user requirements. First, one-on-one interviews were organised with the scenario leaders of the project pilots and the use cases. All pilots have presented their pilot locations, the daily problems and what AgcriDataValue could offer to them, Next, a number of questionnaires were prepared and sent to the partners in the project that fit under one of the user categories defined as AgriDataValue users in Table 2. Regarding users' observation, we consider that this input was covered by the category 2 (farming research institutes) and category 3 (service and technology providers) users that are part of AgriDataValue as they are used to working closely with farmers. Finally, existing solutions from the open market along with documentation from other projects and initiatives like DataBio, IoF2020 and A FarCoud were analysed.

For the refinement of the requirements, we plat to implement early mock-ups and prototypes and then perform additional interviews with farmers and stakeholders from all countries that are involved in the project. It should be considered that by including the pilot owners in the AgriDataValue project, we introduce combined approaches of capturing end users' requirements, which are finally converted end user needs.

2.3.1 Description of Questionnaires

Until this phase of the project, we had two inquiry rounds in which we asked the agricultural project partners questions about their pilots, use cases and technologies to be used.

For the **first round** we used Microsoft Forms as a tool to create a survey for the pilots. Microsoft Forms offers several advantages for conducting surveys:

1. Ease of use, as it allows users to create surveys quickly and easily
2. Integration with Microsoft Excel, so easy data collection and analysis
3. Microsoft Forms can be accessed from any device with an internet connection, including desktops, laptops, tablets, and smartphones. Respondents can conveniently complete surveys using their preferred devices.
4. Real-time response tracking: Forms provides real-time response tracking, allowing survey creators to monitor responses as they come in. This feature enables quick analysis and decision-making based on the collected data.
5. Microsoft Forms supports various question types, including multiple choice, text entry, rating scales, and more. It also allows for creating branching logic, where respondents are directed to different sections or questions based on their previous answers. These features enhance the flexibility and customization of surveys.

This survey was structured to get a good overview of all contact information, the overall status of the pilot, the expected technologies to be used and the expected timelines of pilot development.

The results of this first round were used to create a detailed Microsoft Excel file for the **second round** of inquiry. This spreadsheet provided a good overview of all pilots, use cases and agricultural partners. A separate tab was created for each pilot, and it had to be filled in by the pilot leader. At this stage it was important to seek confirmation of the findings from the first round, or to find further depth. This depth was requested on the following aspects:

1) type of crops or livestock

2) per use case the technologies used

3) per technology used the output in terms of data and information

4) per type of data/information the way it is available to the farmer and for professional use in an ICT context.

Based on these 2 rounds, an overview could be made of all the use cases covered in the pilots. This corresponds to the table of contents of sections 3.1 to 3.5. In addition, this outcome was used to create both tables in Section 3.8.1.

3 AgriDataValue Use Cases

In order to best capture the AgriDataValue platform requirements in a use centric approach, we introduce a number of Use cases that represent real needs of the involved end-users. As a methodological approach and based on lessons learnt, success methodologies and open innovation ecosystems supported by EC (both DG Agriculture and DG Connect) and Local Action Groups, AgriDataValue project will follow the **Lean Multi-Actor Approach (LMAA).** LMAA was introduced by H2020 project IoF2020 and further developed by EIP-AGRI [9]to foster the development of research, uptake innovations into operational applications and create real impact in agri-environment domain. It is worth underlining that most of the AgriDataValue consortium members have been IoF2020 partners and have participated in the definition or at least are already familiar with the LMAA methodology.

AgriDataValue LMAA will introduce new use cases, support new ideas and create a wide range of field tools, thanks to interactions between complementary actors, share of knowledge, expertise and capabilities. We plan to adopt LMAA as fully demand-driven approach, involving during each iterative cycle of AgriDataValue lifetime, various actors (i.e. farmers, farmers' groups and cooperatives, foresters and forestry groups, advisors, stakeholders, researchers, CAP paying authorities, decision making bodies, etc., as described in Table 2) to demonstrate on one hand, how the project fulfils the proposed objectives, needs, problems and opportunities of the full chain, from farmers to service advisors, suppliers and stakeholders, and on the other hand, how it complements existing research, innovation and best practices.

Figure 2: LMAA adapted to AgriDataValue concept

The AgriDataValue MAA is implemented through requirements and specifications extracted from comprehensive use cases originating from AgriDataValue end-users (WP1), a complete set of tools and AI models co-created with technological partners and end-users (WP2-WP3) and fully tested and validated through the project pilots (WP4). Feedback from pilots via the human interaction with all stakeholders is further utilized to extend and upgrade sensors and pilots (WP5) and create real impact, not only to agriculture, but also to the greater public (WP6).

In the analysis that follows, we organize the Use Cases (UC) in Clusters based on the crop or livestock that they target. Moreover, we offer an interaction analysis of each UC in a UML-like [10] Use Case Diagram approach. For better analysing of the UC analysis, **Agri-Environmental Big Data Space (ADS)** is logically split in two main components: a) the **ADS Core (ADS-C)** and b) the **ADS Marketplace (ADS-M)**.

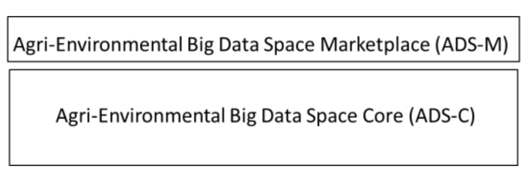


Figure 3: Agri-Environmental Big Data Space (ADS) platform High level logical separation

- The **ADS Core** (ADS-C) is the logic segment where all data is stored and processed. It follows by definition a distributed architecture and multiple logical instances may be hosted by different actors, i.e., end-users or services providers. Besides the heterogeneous data repositories, the ADS-C also includes AI/ML training logic and the Decision Support System (DSS).

- The **ADS Marketplace** (ADS-M) is the logical segment that enables the realization of innovative business models and turns end-users (e.g., farmers) to data/ML models prosumers. The ADS-M includes mechanisms, such as blockchain technology/inter-DLT and smart contracts for exposing available data/ML models/advice and enables traceability and sharing under specific conditions (e.g., a monthly or per usage fee).

Detailed considerations based on the Use Cases analysis and System requirements is provided at chapter 7.

3.1 Use Cases Cluster 1: Arable Crops

The UC Cluster 1 is focused on Arable Crops and aims to optimize the quality and quantity of the crops, while lowering the environmental footprint.

Objectives: In detail, the objective of UC Cluster 1 are to:

- Optimize the quality and quantity of the arable crop production
- Reduce environmental footprint and increase environmental sustainability of the crop production
- Optimize the natural resources utilization by reducing the wasted irrigation water, reduce or replace chemical fertilizers with organic ones, reduce or replace chemical the pesticides with organic ones, reduce the consumed energy and/or increase the renewable energy mix.

Approach: The approach to realize the UC cluster 1 objectives is to combine agricultural knowledge, historical data, (real-time) ICT systems and Big Data processing technologies such as IoT sensors, edge cloud, drones/satellite visual/multispectral images and AI models and train ML-based Decision Support Systems (DSS) and applications to provide advice on improved crop production.

3.1.1 UC 1.1: Reduce Wasted irrigation water

Objective: The main objective of UC1.1 is to increase crop production, while reducing wasted water and improving the automation of the irrigation zones through interoperable remote-control systems and robust management. Real-time monitoring and control of water supply adapted to the conditions required by the irrigated crop and the environmental conditions/forecasts to balance water consumption, reduce wasted water and energy consumption based on informed decisions and crop automation.

3.1.1.1 State of play

One of the most common irrigation models is the *mass balance method* (also called *scientific irrigation scheduling*), where irrigation schedule is determined by calculating how much water is needed based on accurate soil moisture readings and the soil properties. Parameters that are considered in irrigation schedule are:

- **Soil saturation** where all the soil pores are filled with water. This occurs in the unsaturated zone above the water table after a heavy rain or irrigation event.
- **Field Capacity** (FC) refers to the amount of water left in soil after gravity drains saturated soil. Soil moisture values above field capacity will drain downward recharging the aquifer/water table.
- **Permanent Wilting Point (PWP)** refers to the amount of water in soil that is unavailable to the plant. When the soil water content reaches this point, plants die.

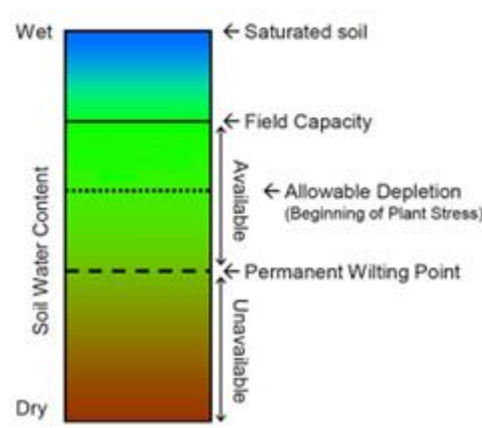


Figure 4: Soil Water Content [12]

- **Allowable Depletion** (AD) represents the amount of soil moisture that can be removed by the crop from the soil before the crop begins to stress.
- **Maximum Allowable Depletion (MAD)** is the fraction of the available water that is 100% available to the crop. MAD can depend on soil or crop type (Table 4) [11].
- **Lower soil moisture Limit** (LL) is the soil moisture value below which the crop will become stressed because it will have insufficient water. When the lower limit is reached, it is time to irrigate. The LL is a very important value because dropping to or below this value will affect the health of the crops.

The equations below show how to calculate the lower soil moisture limit and the soil moisture target for irrigation optimization.

$$AD = (FC - PWP) \times MAD$$

$$LL = FC - AD$$

It should be underlined that the soil type/texture and the crop root depth play a very important role in defining the FC, PWP and AD (Table 29) [12].

Crop	Maximum Allowable Depletion (MAD)	Effective Root Depth (Inches)
Apples	75%	36
Blueberries	50%	18
Carrot	50%	18
Cauliflower	40%	18
Cucumber	50%	24
Grass	50%	7
Green beans	50%	18
Leafy greens	40%	18
Peppermint	35%	24
Potatoes	35%	35
Strawberry	50%	12
Sweet corn	50%	24
Table beet	50%	18
Winter squash	60%	36

Table 4: MAD and Effective Root Dept per Crop

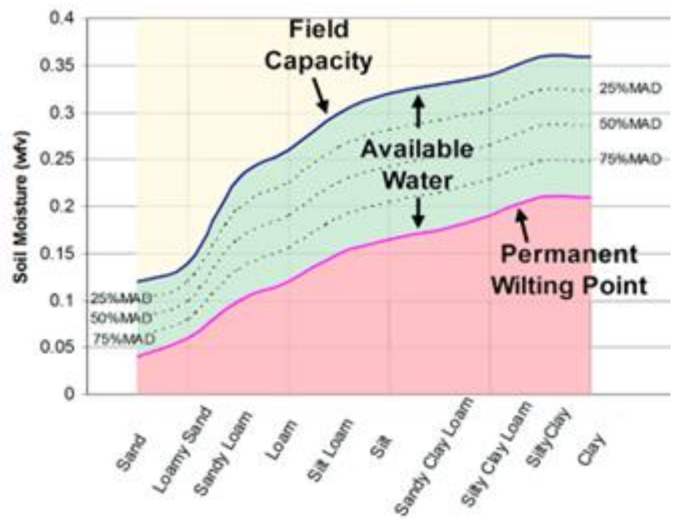


Figure 5: Soil Texture

Today, there are many commercial or experimental irrigation systems that offer remote control and irrigation management, aimed in an optimized water management. However, most of these irrigation systems are closed or proprietary solutions that do not share software or hardware elements, limiting their options of modification or extension with new features. In some cases, they may offer a proprietary API for extracting some historical data, though in most cases, they do not meet any interoperability or data sharing standard as they are designed not to be interoperable, or interwork with 3rd party applications.

In addition, the majority of these irrigation systems have a limited lifespan of around 8 to 10 years, making them highly susceptible to obsolescence. As a result, upgrading these systems can be challenging and expensive, often requiring identical equipment to ensure compatibility, further exacerbating the economic burden. Moreover, due to lack of openness and interoperability, irrigation components (i.e. pumping stations, irrigation branches and hydrants) do not exchange useful information to optimize exploitation.

3.1.1.2 Target Scenario and Approach

Most commercial and off the shelf irrigation control systems are developed by specific manufacturers which are reluctant to allow external users and other 3rd parties to modify their configuration or operation mode. Though, most of these systems do not follow specific interoperation standards, they may offer APIs so that gathered historical data may be extracted. This fact may allow farming companies and irrigation communities to expand their irrigation system with different vendors' devices, having a heterogeneous environment but with the capability of interoperating with all the devices responsible for the irrigation.

The use of open and standard technologies provides a significant advantage regarding how systems can interact and interoperate. Though nowadays there is still no consolidated standard for remote monitoring and control for irrigation, there is a number of ISO stable standards [13] [14] that specify irrigation techniques.

In AgriDataValue approach, we plan to use an extended set of real-time and historical IoT sensor data (e.g. soil, leaf, air data), weather forecast and drones'/satellites visual and multi-spectral data to extract indices such as NVDI and degree days, calculate evapotranspiration and automate irrigation in a closed loop approach.

3.1.1.3 Interaction Analysis

Figure 6 provides the interaction analysis of UC 1.1 in a UML like Use Case Diagram approach. All main

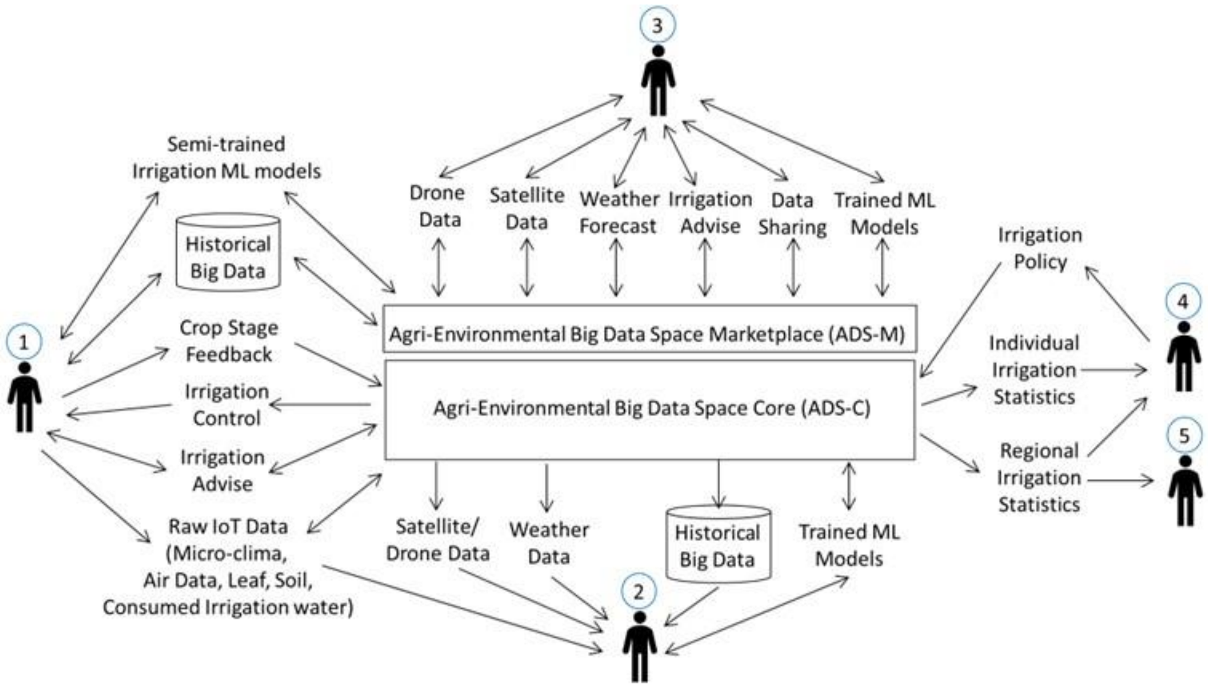


Figure 6: UC 1.1 Interaction Analysis

The UC interaction Analysis is quite similar to other UCs. Actor 1 provides to ADS-C: a) ***raw IoT Data***, such as local micro-climate data (rain volume and Precipitation data, wind direction and volume, air temperature and humidity), soil moisture and temperature, leaf wetness, along with volume and schedule of the consumed irrigation water and b) ***crop stage feedback,*** informing the system on the crop growth stage and feedback on irrigation advice. Moreover, via the ADS-M may offer ***historical Big Data*** and ***semi-trained irrigation ML models***, under specific incentives/ fee. The ADS platform responds with ***Irrigation Advice*** and if available may offer ***automatic Irrigation control***. Actor 2 (farming and climate monitoring research institutes) receives any type of ***historical data***, ***weather data*** and ***drones/satellite data***, along with ***trained ML models***. In return, Actor 2 offers more advanced or experimental ML models, which may be utilized by Actors 1 and 3. Actor 3 (Specialized service and technology providers offering added valued services based on Agri-data and AgriDataValue technology) access the ADS platform only via the ADS-M component. Via specific smart contracts may retrieve or provide any type of shared data, information or advice, including ***historical shared data***, **drones' and satellite's data**, ***irrigation advice*** and ***ML trained models***.

Actor 4 (CAP paying authorities) directly via the ADS-C module imposes to the platform specific ***irrigation policies*** (such as eco-schemes) and retrieves ***individual irrigation statistics*** to be used when calculating the CAP national/ regional supporting funding. Finally, persona from both Actor 4 and Actor 5 (EU stakeholders/ policy) retrieve ***regional irrigation statistics*** to evaluate the fulfilment level of specific CAP policies/strategies, including soil strategy objectives.

3.1.2 UC 1.2: Reduce Fertilizers

Objective: The main objective of UC1.2 is to reduce fertilizers without reducing crop production or quality. The ideal fertilization of the soil is highly dependent on the specific needs of the crop, soil characteristics and environmental conditions. An approach to reduce fertilizers should take these parameters into account and be flexible to accommodate unpredicted changes.

3.1.2.1 State of play

Growth and yield of the crop are limited by the nutrient that is least available in the soil or by environmental conditions such as water, light and temperature (Liebig's law, Figure 7) [15]. Providing plants with more nitrogen when they are limited by another nutrient is therefore futile. Excess quantities of a nutrient can be detrimental for crop growth, as they may inhibit uptake of other nutrients. Farmers are therefore encouraged to take soil samples that provide a full chemical analysis of all nutrients present [16].

Figure 7: A schematic representation of Liebig's law

Fertilization increases crop yield but this is not a linear response. When extreme high quantities of fertilizer are added, the crop yield will no longer increase (Figure 7). The yield could even decrease, when adding excess nitrogen to plants, they become more vulnerable to diseases and plagues. Adding higher concentrations, especially of nitrogen and phosphorus, than needed by the crop is detrimental to nature. These compounds are mobile in the soil and move to the aquifer and surrounding water bodies. This can enable microalgae to bloom, a phenomenon called eutrophication that is harmful for biodiversity and aquatic life [17, 18].

During the growing season plants take up nutrients from the soil. When these crops are harvested, these nutrients are permanently removed from the soil. [19] When these nutrients are not replenished by fertilizer, we risk depletion of our fertile soils and progressive yield losses in subsequent years [20]. One measure that can reduce the use of fertilizers and the risk of nitrogen leaching is working towards higher organic carbon concentrations in the soil. Soils with higher organic carbon concentration have a higher buffering capacity for nutrients. Higher organic carbon stimulates the mineralization process, needing less nitrogen fertilization. Another advantage of carbon farming is the fixation of greenhouse gas, carbon dioxide, from the atmosphere. However, working towards a higher organic carbon concentration takes time [21].

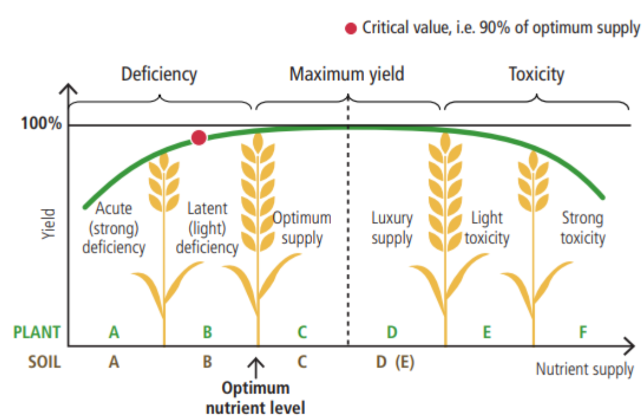


Figure 8: Yield response to nutrient supply

Another measure that can optimize or potentially reduce the use of fertilizers is precision agriculture. In precision agriculture, the fertilizer is not evenly distributed across the field but is applied zone-specific based on task maps. The zones that are deemed to need more fertilization, receive higher concentrations. There is still some discussion about the strategy for this place specific fertilization. Some advice to fertilize more on the less developed places in the field, this is called the Kings scheme. A common argument for this strategy is that this will make the field more homogenous. You can also apply the opposite strategy, wherein you fertilize more on the more developed places in the field, called the Robin Hood scheme. Nitrogen is not always the reason for lesser crop growth, so applying more could result in higher nitrate leaching instead of higher yield. Task maps are often based on satellite imagery, crop scans, soil scans, yield maps or soil texture maps. The companies that offer these scan services, often provide services to render task maps. However, combining data sources, especially from different providers, proves difficult. This data is often spread across different agridata platforms in varying data formats or geographical projections and farmers face difficulties to combine these information sources [22, 23, 24, 25].

3.1.2.2 Target Scenario and Approach

We plan to improve the current fertilisation advice by taking into account satellite imagery and weather forecasts. With satellite imagery, we can assess crop growth and adjust the fertilization advice to the actual nutrient needs. The weather forecasts can predict the future crop growth, based on historical data. The fertilisation advice should include a long-term vision for carbon farming, improving soil properties and microbial life.

Farmers have many available data layers of each field, such as satellite imagery, drone imagery, soil scans, crop scans and yield maps. Viewing and comparing each layer is not only a time-consuming activity but also a difficult one. There are geographical software solutions with which you can view these layers, but these have a steep learning curve. Often the data is delivered to the farmer as pdf rapports or with an online platform by the provider, making it impossible to load the data into other platforms. In AgriDataValue we plan to create a platform in which the data layers can be accessed by the farmer and clustering methods can be applied to define management zones. This can allow the farmer to make task maps and optimise or reduce fertilisation usage.

3.1.2.3 Interaction Analysis

Figure 9 provides the interaction analysis of UC 1.2 in a UML like Use Case Diagram approach. Actor 1 provides the ADS-C with a) **raw IoT Data**, such as local micro-climate data (rain volume and Precipitation data, wind direction and volume, air temperature and humidity), soil or tissue nutrient balances and the schedule with fertilisation rates that were applied and b) **crop stage feedback**, informing the system on the crop growth stage and feedback on the fertilisation advice. The ADS-M can provide **historical Big Data** and **semi-trained fertilisation or clustering ML models** under specific incentives or fees. The ADS platform may in turn provide **fertilisation advice** that accounts for seasonal or geographic variation in crop nutrient needs.

Actor 2 can interact directly with the ADS-C and receive **historical data, weather data, remote sensing data** and **crop- or soil scan data**. **Trained ML models** can also be shared, which Actor 2 may improve or expand. These can improve models can be used by Actors 1 and 3.

Actor 3 (Specialized service and technology providers) access the ADS platform only via the ADS-M component. Via specific smart contracts may retrieve or provide any type of shared data, information, or advice, including **historical shared data**, **drones' and satellite's data**, **Fertilisation advice** and **ML trained models**.

Actor 4 (CAP paying authorities) imposes to the platform specific **fertilisation policies** and retrieves **individual fertilisation statistics** to be used when calculating the CAP national/ regional supporting funding. Finally, persona from both Actor 4 and Actor 5 retrieve **regional fertilisation statistics** to evaluate the fulfilment level of specific CAP policies/strategies, including soil strategy objectives. This information is very sensitive and will/can only be shared if agreed to by the farmer.

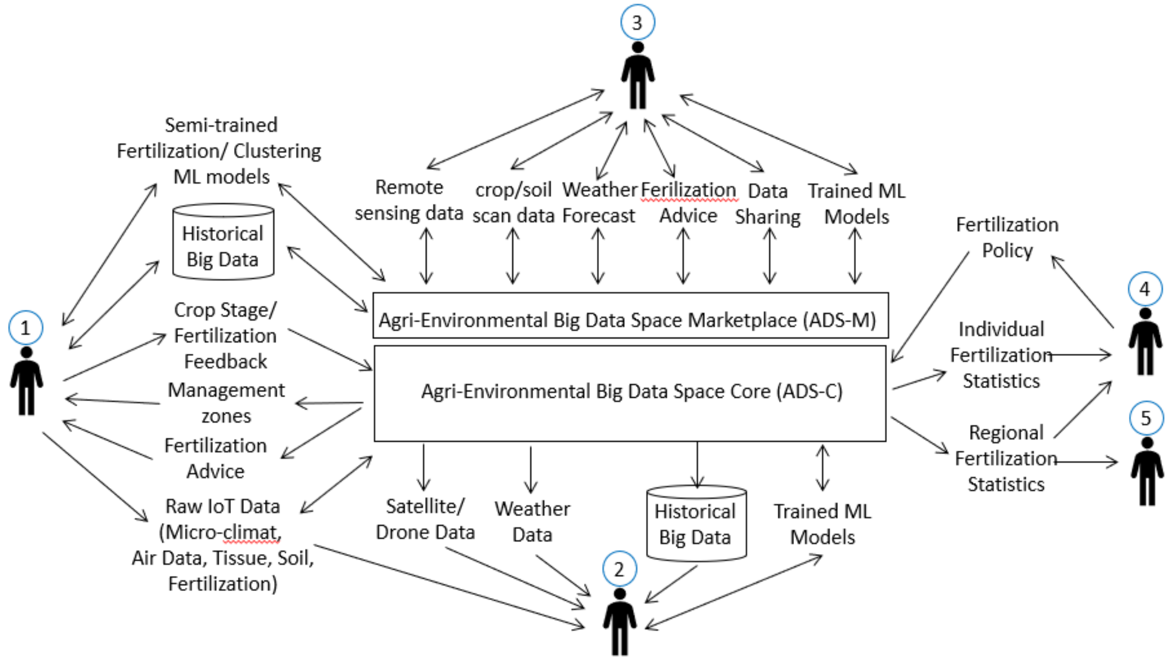


Figure 9: UC 1.2 interaction analysis

3.1.3 UC 1.3: Reduce Pesticides

Objective: Analysis of usage tactics and disease prediction based on yield growth, temperature, wind volume, rain/humidity, and heating/cooling degree days to utilize pesticides only when needed.

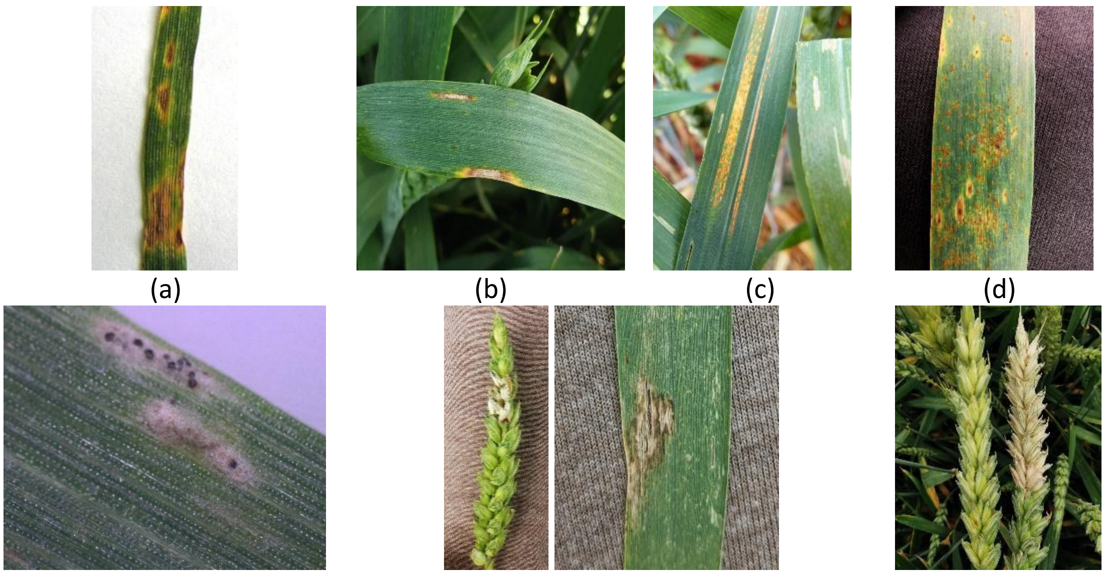
3.1.3.1 State of play

Today, it is very important to grow healthy crops with as little adverse impact on agroecosystems as possible and to promote the use of smart control mechanisms. One of the most difficult aspects in winter wheat cultivation technology is the spread of leaf and ear diseases. The need to control diseases is determined by the dynamics of their development and impact on winter wheat yield and, consequently, on the level of profitability.

The time and dose of the fungicide in a given year should be chosen depending on the prevalence of diseases, which depends on several factors, including meteorological conditions. Main wheat diseases (at least in Latvia are:

- **Tan spot (Pyrenophora tritici-repentis).** The first symptoms of wheat leaf yellowing are small, brown spots with a light centre. From the very beginning, a pale-yellow band forms around the spot. Later it becomes darker yellow. The spots become larger and grey in the middle, but a small dark spot forms in the centre. The fungus requires 6-24+ hours of moisture to infect a leaf. This means that rain, significant dew, or high canopy humidity are factors that can lead to infection. Optimal temperatures for symptom development range from 16 to 28 °C
- **Septoria leaf blotch (Zymoseptoria tritici).** The first symptoms of wheat leaf spotting in winter wheat usually appear on the lower leaves already in autumn as grey-brown spots with black dots (pycnidia). Later, grey, elongated, veins-limited spots with black pycnidia appear on the leaves. Favourable conditions for Septoria leaf blotch: Humidity on the leaves, which lasts for more than 20 hours; The rains over 10 mm fallen within 24 hours, or the sum of the precipitations fallen during 3 consecutive days which exceed 10 mm of rain favours the development of disease; Rainy weather at the early stages; Susceptible varieties; Wheat after wheat; Minimum tillage; Infected plant debris on soil surface.
- **Wheat yellow rust (Puccinia striiformis).** Yellow rust infects all above-ground parts of the plant. Signs of the disease are bright yellow pustules arranged in straight rows, parallel to the veins of the leaves. The disease

usually occurs early in the growth season, when temperature ranges between 2 and 15 °C; but it may occur to a maximum of 23 °C. High humidity and rainfall are favourable conditions for increasing the infection on both leaf blade and leaf sheath [26], even on spikes [27], when in epidemic form. Symptoms are stunted and weakened plants, shrivelled grains, fewer spikes, loss in number of grains per spike and grain weight. Losses can be 50%, but in severe situations 100% is vulnerable. Since yellow rust can occur whenever the wheat plants in green and the environmental condition conducive for the spore infection, yellow rust is a severe problem in the wheat-producing regions worldwide. Temperatures during the time of winter wheat emergence and the coldest period of the year are crucial for epidemic development in winter-habit wheat crops.



(a) (b) (c) (d) (e) (f) (g)

Figure 10: Wheat diseases. From left to right a) Pyrenophora tritici-repentis, b) Zymoseptoria tritici, c) Puccinia striiformis, d) Puccinia triticina, e) Blumeria graminis, f) Parastagonospora nodorum, g) Fusarium spp

- **Wheat leaf rust (Puccinia triticina).** Brown rust infects the leaves and spikes. The signs of the disease are orange to brown pustules, chaotically distributed over the entire leaf plate. The germination process requires moisture and works best at 100% humidity. Optimum temperature for germination is between 15–20 °C. Before sporulation, wheat plants appear completely asymptomatic.
- **Powdery mildew (Blumeria graminis).** Powdery mildew can be observed on the leaves, stems and ears of plants. The first signs of the disease are white web-like frost. At first, they are individual pustules (pads), but later they can cover the entire leaf. Later, in the light frost, dark balls are visible - fruiting bodies, in which asci spores develop. Powdery mildew is an obligate parasite with a narrow specialization. Each cereal species has its own form of powdery mildew. Powdery mildew of wheat thrives in cool, humid climates and proliferates in cloudy weather conditions. The pathogen can also be an issue in drier climates if wheat fields are irrigated. Ideal temperatures for growth and reproduction of the pathogen are between 16 °C and 21 °C with growth ceasing above 25 °C. Dense, genetically similar plantings provide opportune conditions for growth of powdery mildew.
- **Parastagonospora nodorum.** Wheat leaf spot mainly damages the spikelet's and can also penetrate the grain. Symptoms of the disease also appear on the leaves as grey (brownish grey) spots with brown dots (pycnidia).
- **Fusarium head blight (Fusarium spp).** The symptoms of Fusarium head blight are very visible when the wheat is ripe. Damaged areas are lighter. In the case of a strong infection, an orange plaque of various shades can be observed on the spikes. In some cases, it can also be seen on the grain. It is a fast-growing fungus, usually able to grow up to 8-8.8 cm in diameter within four days. Its optimal growth temperature ranges from 22.5–27.5 °C, with the minimum and maximum temperatures required for growth being 2.5–7 °C and 35 °C, respectively. The minimum humidity level required for vegetative growth is 88%.

Factors affecting the development of diseases ¨The development of winter wheat diseases is influenced by a number of factors, among which are the following [28]

- Crop phase and development stage (BBCH): please refer to Figure 11.
- Agrometeorological parameters (the amount of precipitation, air temperature, humidity, number of rainy days by time period, etc.);
- Previous crop (wheat / another crop);
- Soil tillage type (tilling / no-tilling);
- Wheat variety (Skagen, Edvins, Brons, Mariboss, Talsis, Rotax, KWS Malibu, Fredis, Ceylon, Creator, Zeppelin, Fenomen, Patras, SW Magnifik, Famulus).

Steam Extension	Heading	Flowering	Ripening

30-49	51-59	61-69	70-79
9 stages of cereal development: 30, 31, 32, 33, 37, 39, 45, 47, 49	4 stages of cereal development: 51, 55, 57, 59	3 stages of cereal development: 61-63, 65, 69	stages of cereal development: 70-79

Figure 11: Development Phases of Wheat

3.1.3.2 Target Scenario and Approach

This Use case will focus on the most popular in Latvia variety - Skagen. The farmers by implementing preventive measures that ensure the normal growth and development of plants (plant change, soil treatment, variety selection, optimal sowing or planting time, fertilizing), can reduce multiplication of harmful organisms and crop infection or even prevent. By observation stage – crop monitoring in order to observe the appearance of the harmful organism and the dynamics of its spread, taking into account also the distribution of its natural enemies, and to make a correct decision on the necessary measures to control harmful organisms at a certain stage of development of the crop and the harmful organism. Direct plant protection measures provide justified use of plant protection products based on the data obtained from field observations on the appearance of harmful organisms, development dynamics and multiplication at a critical level.

Within AgriDataValue, we plan to study and analyse IoT data and images from various sources in order to forecast/detect Winter wheat diseases and adapt fungicide spraying recommendations.

3.1.3.3 Interaction Analysis

Figure 11 provides the interaction analysis of Winter wheat pest control UC in a UML like Use Case Diagram approach. All main actors/ end-users participate at the specific UC.

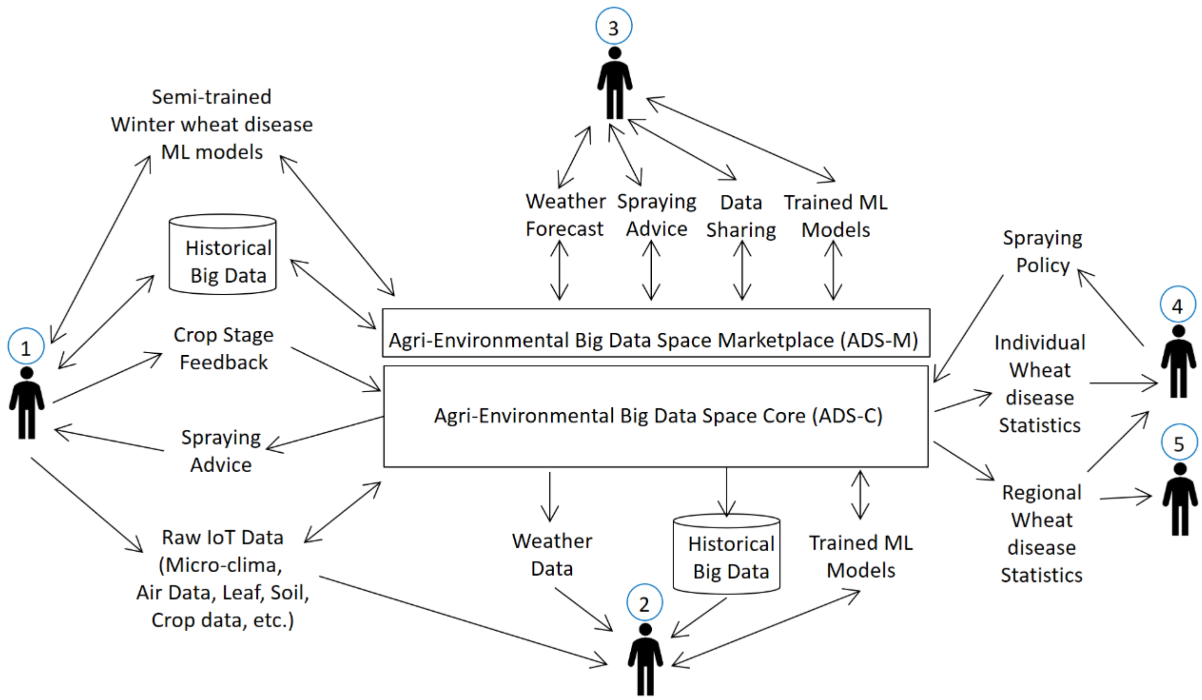


Figure 11: Winter wheat pest control UC Interaction Analysis Diagram

As can be seen, Actor 1 interacts both directly with the ADS-C and the ADS-M logical components. Actor 1 provides to ADS-C: a) ***raw IoT Data***, such as local micro-climate data (rain volume and precipitation data, wind direction and volume, air temperature and humidity, leaf wetness), possible soil data (soil moisture and temperature), wheat growing phase and stage, previous crop (wheat or other crops), soil tillage type and b) **Crop *stage feedback***, informing the system on the Wheat disease stage and feedback on spraying advice. Moreover, via the ADS-M Actor 1 may offer ***historical Big Data*** and ***semi-trained winter wheat disease detection ML models***, under specific incentives/ fee. The ADS platform responds with ***Spraying Advice*** and potentially ***pest control strategy***. To facilitate research and experimentation, Actor 2 (farming and climate monitoring research institutes) is allowed to interact directly with the ADS-C and receive any type of ***historical data***, ***weather data***, along with ***trained ML models***. In return, Actor 2 offers more advanced or experimental ML models, Wheat disease detection and control experiments at laboratories, which may be utilized by Actors 1 and 3.

Actor 3 (Specialized service and technology providers) access the ADS platform only via the ADS-M component. Via specific smart contracts may retrieve or provide any type of shared data, information or advice, including ***historical shared data***, ***spraying advice*** or ***services*** and ***ML trained models***.

Actor 4 (CAP paying authorities) imposes to the platform specific ***spraying policies*** (such as volume and type of fungicides) and retrieves ***individual wheat disease statistics*** to be used when calculating the CAP national/ regional supporting funding (e.g., in case of AgriDataValue certified wheat disease, sampled physical inspections may be reduced). Finally, both Actor 4 and Actor 5 (EU stakeholders/ policy) retrieve ***regional winter wheat diseases statistics*** in order to evaluate the fulfilment level of specific CAP policies/strategies, including soil strategy objectives.

3.1.4 UC 1.4: Increase potato production/quality

Objective: Optimizing the potato crop cultivation and quality using hyperspectral measurements to measure potato quality, allowing for modifications in the production processes to mitigate losses due to quality issues.

3.1.4.1 State of play

Potato crops are an essential part of the European agriculture. In 2020, 55 million tonnes of potatoes were harvested across the European union, with an estimated value of EUR 12.3 Billion. This represents 3.1% of the total EU agricultural output of 2020 [29]. Climate change is one of the biggest challenges for the potato crop cultivation. Due to its shallow root system, potatoes are particularly sensitive to continued droughts. The more prevalent droughts during the potato growing season have led to significant crop losses [30, 31]. These more prevalent droughts can lead to a higher occurrence of black spot in potatoes as dehydrated tubers are more susceptible to these bruises. Blackspot is caused by mechanical impact during harvest and handling. Without peeling, blackspot is difficult to detect but can cause significant quality reduction. This black discoloration is responsible for considerable economical losses [32].

Spectroscopy has been increasingly used in food and agriculture as the absorption characteristics are related to chemical properties, composition and structural characteristics. It can be used in both pre and post- harvested crops. The range of the spectral imaging system can range from the ultraviolet (UV) to the shortwave infrared (SWIR) region [33]. There are multispectral imaging systems consisting of multiple bands within this spectrum or hyperspectral imaging systems with continuous narrow bands. Hyperspectral imaging can simultaneously detect the spectral and spatial properties of an object. While traditional detection methods are often destructive and time consuming, hyperspectral imaging is a non-destructive and fast detection method [34]. Hyperspectral imaging has been suggested to be able to detect black spot in potatoes (Figure 12) [35].

Figure 12: Black spot in potatoes, only visible when peeled [32]

3.1.4.2 Target Scenario and Approach

In this Use Case we will improve the production quality of potatoes. We will use the newest technologies such as hyperspectral imaging to detect the quality of potatoes. Large quantities of data are generated with these imaging techniques and this data will be linked to the quality of the potatoes. Detecting the quality is the first step to improving the potato production processes. Based on the hyperspectral images, an advice can be created with machine learning techniques. For example, detecting black spot in the first potatoes that are harvested can warn farmers to take precautions with future harvesting and handling of potatoes to prevent damage.

The objective determination of quality allows farmers to prove that their products are of a good quality and negotiate a better price. Detecting the subpar products can prevent them from being processed with the healthy ones and reduce waste and loss of confidence among consumers [35].

3.1.4.3 Interaction Analysis

As can be seen, Actor 1 (Cooperatives, and Individual Farmers) interacts both directly with the ADS-C and the ADS-M logical components. Actor 1 provides to ADS-C: a) **raw IoT Data**, such as local micro-climate data (Precipitation, air temperature and humidity), soil moisture and temperature, leaf tissue or soil analyses, along with the schedule of the relevant field activities and b) **Potato stage feedback**, informing the system on the crop growth stage and feedback on advice. Moreover, via the ADS-M may offer **historical Big Data** and **semi-trained ML models**, under specific incentives/ fee. The ADS platform responds with **Advice**.

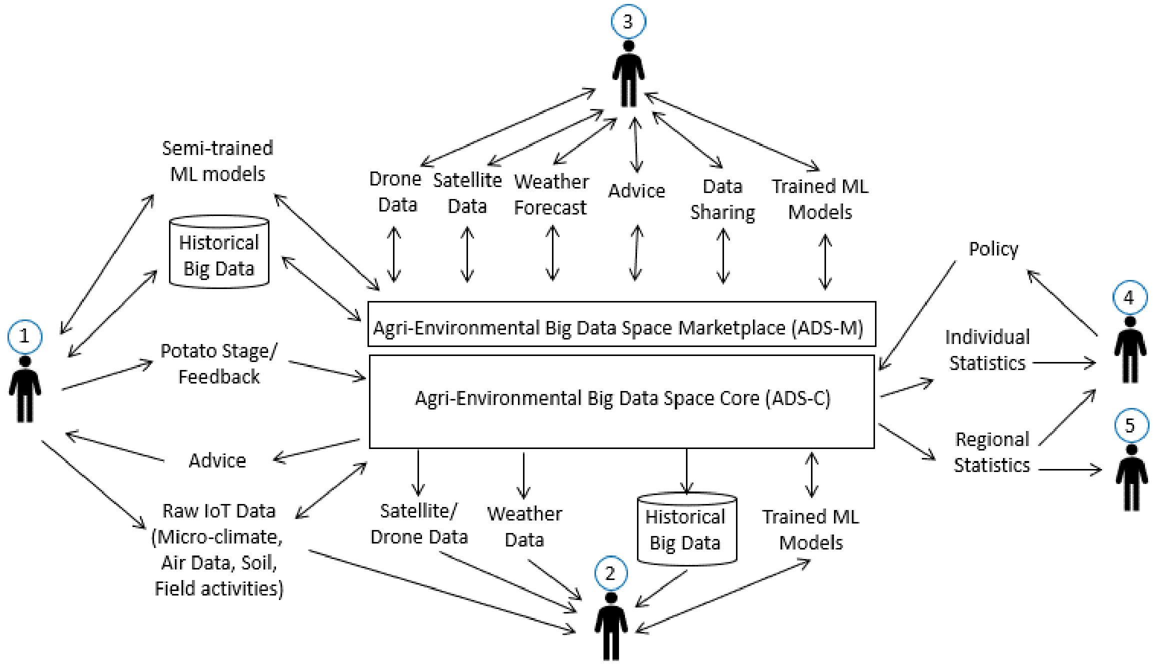


Figure 13: UC 1.4 Interaction Analysis

To facilitate research and experimentation, Actor 2 (farming and climate monitoring research institutes) is allowed to interact directly with the ADS-C and receive any type of **historical data, weather data** and **drones/satellite data**, along with **trained ML models**. In return, Actor 2 offers more advanced or experimental ML models, which may be utilized by Actors 1 and 3. Actor 3 (Specialized service and technology providers offering added valued services based on Agri-data and AgriDataValue technology) access the ADS platform only via the ADS-M component. Via specific smart contracts may retrieve or provide any type of shared data, information, or advice, including **historical shared data, drones' and satellite's data, advice,** and **ML trained models.** Actor 4 (CAP paying authorities) directly via the ADS-C module imposes to the platform specific policies (such as eco-schemes) and retrieves **individual potato statistics** to be used when calculating the CAP national/ regional supporting funding. Finally, persona from both Actor 4 and Actor 5 (EU stakeholders/ policy) retrieve **regional statistics** to evaluate the fulfilment level of specific CAP policies/strategies, including soil strategy objectives.

3.2 Use Cases Cluster 2: Vegetables

The UC Cluster 2 is focused on the Vegetables Crops and aims to optimize the quality and quantity of the crops, while lowering the environmental footprint.

Objectives: In detail, the objective of UC Cluster 2 are to:

- Improve precision irrigation and fertilization, mainly via automatization of irrigation and fertilization.
- More accurately predict harvesting time to crop increased production/diseases prediction for vegetables/arable.
- Involve IoT sensors, edge cloud, radiation/chlorophyll/pH metering, multiple data platforms with geotagged photos alone with drones/satellite multispectral imagery.

3.2.1 UC 2.1: Precision open field/greenhouse Irrigation/Fertilization

Objective: Compare open field and greenhouse yields, focused on tomato and cucumber via an innovative fully automated sensing/decision/irrigation system.

3.2.1.1 State of play

Protected cultivation of vegetables is constantly evolving to improve production both in quantity and quality and to establish strategies that minimize costs per unit of crop. In these production systems, **the use of water and fertilizers is closely linked**, and the application of techniques that increase the efficiency of water use will also result in a better use of fertilizers; although it should not be forgotten that the consumption of water and nutrients are two different physiological processes.

In this context, **the development stage of the crop and the climatic conditions that surround it will determine its nutritional needs**. **The greenhouse allows the climate inside to be modified within certain margins** in terms of radiation level, temperature, humidity, and CO_2 content, so the scenarios that are generated are multiple and the possible interactions between climate and plant will have to be considered when establishing nutritional guidelines. The quality of the products is obtained in the field and is not improved by post-harvest, understanding by quality both the intrinsic characteristics (colour, flavour, nutritional content, etc.) and the extrinsic characteristics, which are becoming increasingly important, such as obtaining products free of residues and in a sustainable way with non-polluting techniques, including the reuse of leachates and the reduction in nitrogen input. Factors that increase crop quality, such as water stress and salinity, normally reduce yields, so it will be necessary to establish a compromise between yield and quality. Nutrient management must ensure a profitable level of production as well as safe, nutritious, healthy, and tasty products.

3.2.1.2 Target Scenario and Approach

The profitability of protected cultivation of horticultural crops is increasingly associated to the efficiency in the use of resources (mainly water and fertilizers) **than to the aim of obtaining a high production**. The increase in the price of water and fertilizers, the environmental burden involved in obtaining them and the need to control soil and groundwater pollution have contributed to the search for strategies that contribute to increase this efficiency without negatively affecting fruit production. The conditions generated under greenhouse cause physical-chemical properties of the soil to change rapidly due to high temperatures and high inputs of both water and fertilizers, to maintain an intensive crop with considerable nutrient extraction. **The soil solution under greenhouse is easier to control than in the open field**, due to the absence of rainfall and the usual practice of simultaneous water and fertilizer inputs throughout the crop cycle. In many cases the Ca, Mg and S content in the soil and water and sometimes even the immobilized P in the soil are sufficient to compensate the crop needs. In the initial phase of the crop cycle is when the greatest N losses occur due to the contribution of organic matter and the first planting irrigations. Substrate crops are usually open systems with a washing fraction ranging between 30 and 50% and represent one of the sources of groundwater pollution and eutrophication, so the reuse of leached solutions is presented as an alternative to increase the efficiency in the use of fertilizers while contributing to the reduction of environmental pollution, especially by nitrates.

On the other hand, **the use of sensors and processes automation provides an additional advantage in terms of input savings, yields and fruit quality, because the real needs of the crops are known.** In this context, tomato and cucumber are two relevant crops in Southeast Spain, where, under protected cultivation and the adoption of some sensors, we can highlight:

- **Tomatoes** grow at relatively warm temperatures, making them the perfect crop for greenhouses. Compared to growing tomatoes at open field, growing in a controlled greenhouse increases yield and quality, reduces pests and diseases, and increases the growing season. As concrete data, there are yield averages for tomato plants, which are as follows: quantity of tomato per hectare in open-air plantations is 50-75 tons, vs approximately 120 tons under greenhouse (approximately, 50% more).
- The main objective of protected cultivation of **cucumber** and the control of the parameters described (irrigation, fertilization, climate…) is to achieve off-season harvesting, in other words, that plants produce in

winter periods. However, there are also other advantages: increase in crop earliness, shortening its vegetative cycle; increased yields (with increases of 70% in comparison to open field); higher crop quality, producing healthier and more uniform fruit; and better control of pests and diseases, with stronger and healthier plants.

3.2.1.3 Interaction Analysis

There are several technologies available to the farmer (Actor 1) to support irrigation and fertilization management. The irrigation operation in farms can be automated using programmers, but there are recommendation systems through the web and other channels that can provide the irrigator with an estimate of the needs in his plots. Actor 2; farming and climate monitoring research institutes, will provide working tools to Actors 1 and 3.

Similarly, the advance of ICTs facilitates the use of sensors, their processing and visualization regardless of geographical location, but the application of optimal irrigation is limited by the laboriousness and excessive knowledge required by irrigators. Moreover, in commercial irrigation plots, the distribution in irrigation sectors and the spatial variability further accentuates the complexity of decision making. A reasonable objective would be to provide the farmer with tools that facilitate and even free him from making decisions on day-to-day irrigation practices, supported by available technological innovations. Here, Actors 4 and 5 will benefit of different irrigation and fertilizers usage statistics.

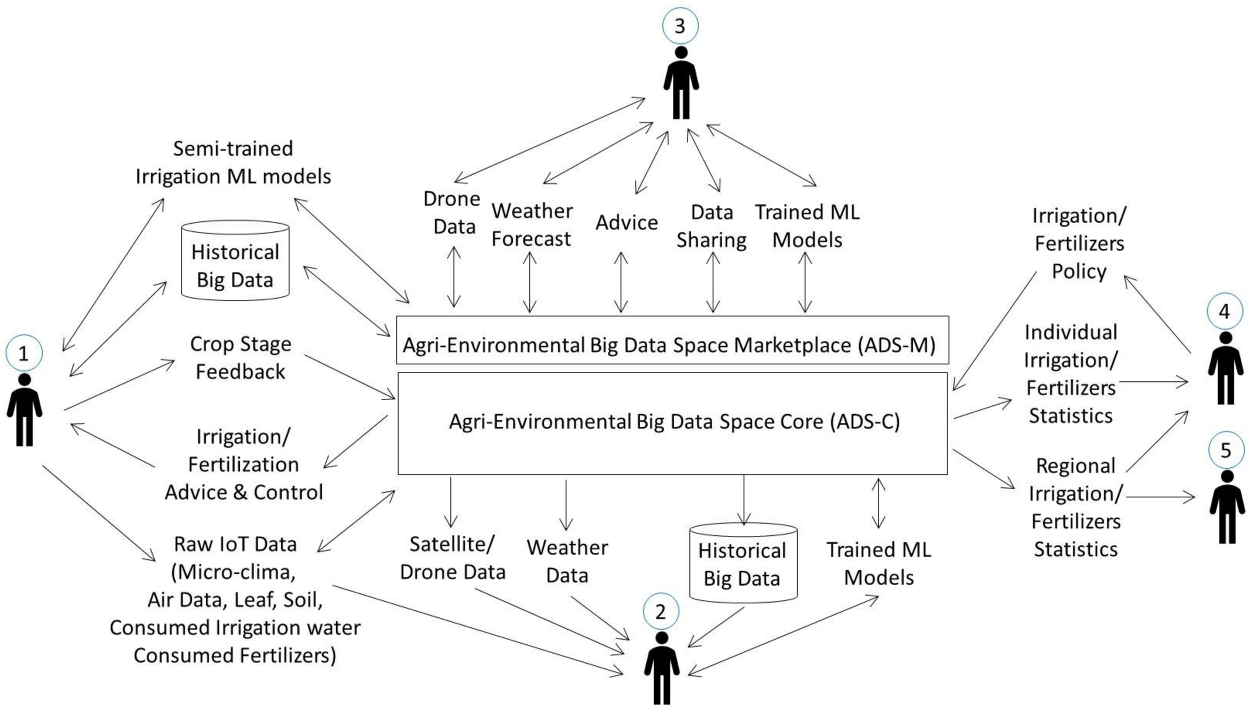


Figure 7. UC2.1 Interaction Analysis Diagram.

3.2.2 UC 2.2: Increase leek /root-crops(carrots) production/quality

Objective: Validate and improve the simulation model for fertilisation rates in leeks (ECOFERT model) by analysing historical data and applying the model to a new scenario.

3.2.2.1 State of play

About thirty years ago, the European Commission placed a limit on the amount of nitrate in surface and groundwater of 50 mg NO_3 L^{-1} to prevent both detrimental effects on the environment and human health. Today, the limit is still exceeded in many regions, especially those with intensive vegetable production (e.g. leek, cauliflower etc.). The combination of the shallow rooting system of vegetables and excessive fertilizer usage frequently results in many cases in high mineral N residues [36, 37, 38].

To reduce nitrogen leaching, soil-based recommendation systems were introduced, such as KNS [39], N-expert [40] and N-min [41]. Besides the fertilisation rate, the application method (e.g. site-specific application with variable fertilizer rates) also affects the effectiveness of the fertilization. Nkebiwe et al. [42] identified three advantages of localised fertilizer application compared to broadcasting: (i) higher yield, (ii) higher nutrient concentration in the above-ground biomass, (iii) higher nutrient uptake.

However, several simulation studies concluded that year-to-year weather variation leads to considerable variation in the effectiveness of the improved N-management. Therefore, the aim of the WikiLeeks project (HBC.2017.0819, funded by the Flemish Agency of Innovation and Entrepreneurship, 2019-2023) was to investigate the effectiveness of a soil-based advisory system, applied specifically to leek production, to reduce fertilizer use, residual soil nitrate and so nitrate leaching, while maintaining similar biomass production levels compared to a fixed high fertilisation rate under varying weather conditions using a simulation model. Therefore, the ECOFERT simulation model was used to accurately simulate leek cultivation under varying fertilisation rates, application methods and weather conditions. This study showed that soil-based fertilizer recommendations and localised fertilizer application have the potential to reduce the environmental impact of intensive vegetable production [43]. However, variable weather conditions can indeed affect the effectiveness of the advisory system as the fertilizer dose calculation depend among other on assumptions regarding crop N-uptake and mineralisation. So, further analysis of the available data, including multispectral drone data (Figure 14), is crucial to predict accurate these properties, with the aim to further improve the effectiveness of the advisory system.

Figure 14: Multispectral drone flight in leeks

3.2.2.2 Target Scenario and Approach

To reduce nitrogen leaching without quality or yield losses, a correctly calculated fertilisation is a necessity. Not only the dosage is of importance but also the timing. The nitrogen release should match the plants growth. The existing models take into account soil characteristics but not weather forecasts and remote sensing imagery such as satellite imagery and drone imagery. In AgriDataValue we will analyse historical data. This includes sensitive data so permission from the farmers who own the data is essential. We will validate the current advice generated by the model and if necessary, improve the model by including remote sensing imagery and weather forecasts.

The AgriDataValue project will monitor leeks to provide new data, including soil scanning, multispectral drone imagery, climate data and soil analyses. With this new data, the model can be improved and validated.

3.2.2.3 Interaction Analysis

As can be seen, Actor 1 (Farming companies, Cooperatives and Individual Farmers) interacts both directly with the ADS-C and the ADS-M logical components. Actor 1 provides to ADS-C: a) ***raw IoT Data***, such as local micro-climate data (air and soil temperature, precipitation), soil moisture and temperature, along with rate and schedule of the applied fertiliser and b) ***crop stage feedback,*** informing the system on the crop growth stage and feedback on fertilisation advice. Moreover, via the ADS-M may offer ***historical Big Data*** and ***semi-trained Fertilisation ML models***, under specific incentives/ fee. The ADS platform responds with ***Fertilisation Advice***.

To facilitate research and experimentation, Actor 2 (farming and climate monitoring research institutes) is allowed to interact directly with the ADS-C and receive any type of ***historical data***, ***weather data*** and ***drones/satellite data***, along with ***trained ML models***. In return, Actor 2 offers more advanced or experimental ML models, which may be utilized by Actors 1 and 3.

Actor 3 (Specialized service and technology providers offering added valued services based on Agri-data and AgriDataValue technology) access the ADS platform only via the ADS-M component. Via specific smart contracts may retrieve or provide any type of shared data, information, or advice, including ***historical shared data***, **drones' and satellite's data**, ***fertilisation advice*** and ***ML trained models***.

Actor 4 (CAP paying authorities) directly via the ADS-C module imposes to the platform specific ***irrigation policies*** (such as eco-schemes) and retrieves ***individual fertilisation statistics*** to be used when calculating the CAP national/ regional supporting funding. Finally, persona from both Actor 4 and Actor 5 (EU stakeholders/ policy) retrieve ***regional fertilization statistics*** to evaluate the fulfilment level of specific CAP policies/strategies, including soil strategy objectives. This information is very sensitive and will/can only be shared if agreed to by the farmer.

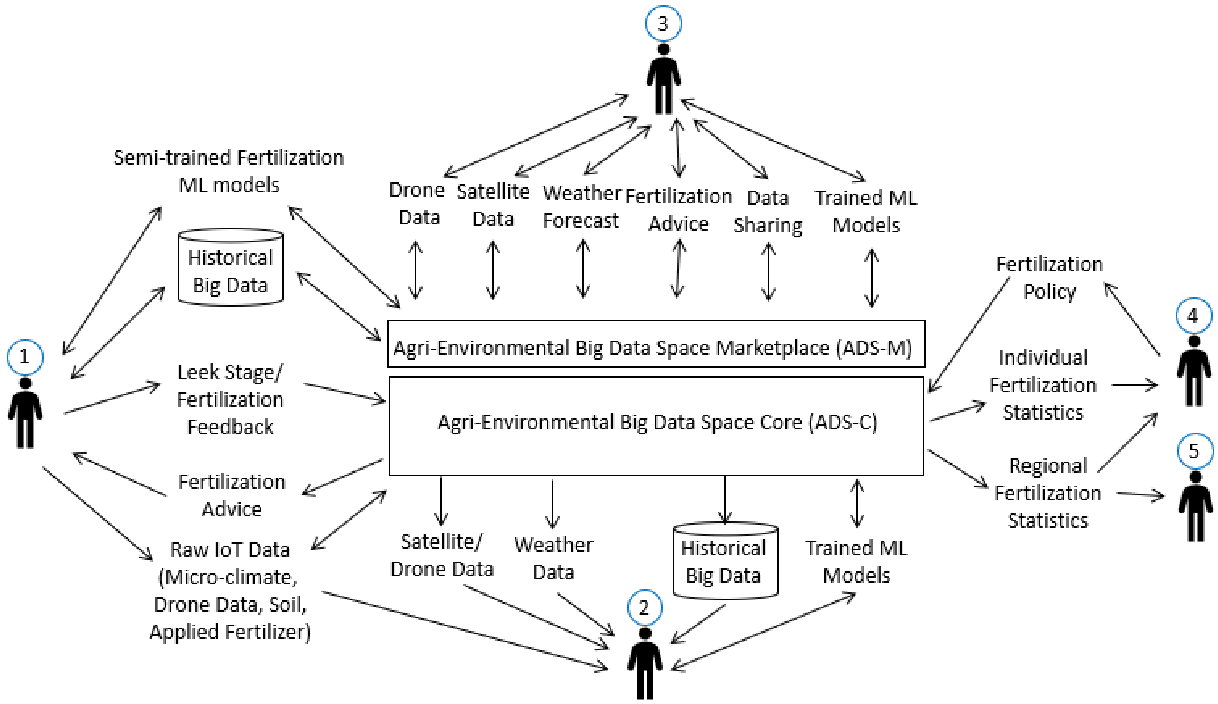


Figure 15: UC 2.2 interaction analysis

3.2.3 UC2.3: Optimization of Soluble Solids Content

Objective: Detection of soluble solids content focused on tomatoes through non-destructive methods in situ (non-harvested fruits) may have significant impact in quality (°Brix).

3.2.3.1 State of play

Total Soluble Solids content, parameter expressed as °Brix, today is a fruit quality parameter today commonly quantified with an **optical digital refractometer** (Figure 16). This is a destructive technique due to the juice must be extracted from the fruits evaluated. This parameter is used to determine the content of soluble solids (usually sugars) dissolved in a liquid. For example, a solution of 30 °Brix contains 30 grams of soluble solids dissolved per 100 grams of solution or liquid phase. The Brix scale is routinely used in the food industry to quantify the approximate sugars amount in different types of drinks such as fruit juices, wine or soft drinks.

Figure 16: Optical (left) and digital (right) refractometer to measure Total Soluble Solids content in fruits (°Brix).

3.2.3.2 Target Scenario and Approach

In addition to the technique described above, **NIR (near infrared) spectrometry** is an innovated option frequently used in Agriculture. Spectrometry is the measurement of the amount of energy absorbed by a chemical system as a function of wavelength. The infrared region of the electromagnetic spectrum comprises the area between the visible range and microwaves and is divided into three regions: near, middle and far, depending on the wavelength. In the case of NIR spectrometry, the wavelength ranges from 780 to 2,500 nanometers (nm).

NIR spectrometry is based on the application of infrared radiation on a matrix or sample to be analysed. Depending on the nature of the bonds (-CH, -NH and -OH) of the molecules that make up the sample to be analysed, it will absorb a certain amount of energy. This technique is based on the Lambert-Beer Law, i.e., the amount of energy absorbed by the sample is directly proportional to the concentration of the sample components. Both qualitative and quantitative information can be obtained with this technique, although the most widespread analysis is the quantitative one. This is performed by developing calibrations in which, with a reference method, the spectral value, and the values of an attribute of the samples are confronted: for example, fat, moisture, acidity. In this way, with the calibration and the spectral information we can predict the value of the attribute of interest of an unknown sample. In Agriculture, this technology is used to control fruit ripening, which guarantees the commercialization of products with optimum quality.

3.2.3.3 Interaction Analysis

Temperature is the most influential factor on fruit quality parameters as total soluble solids (TSS), acidity (A), colour and fruit size.

The interaction diagram provides the interaction analysis of the data extraction, analysis and availability process, where: farmers (Actor 1) measure the TSS content in fruits and, through the Actors 2 and 3 labours, who process and analyse the collected data, Actors 4 and 5 can obtain references and implement improvements in terms of fruit quality and, specifically TSS content improvements (Figure 9). They could make decisions not only in terms of management strategies, but also through the application of innovative technologies and sensors.

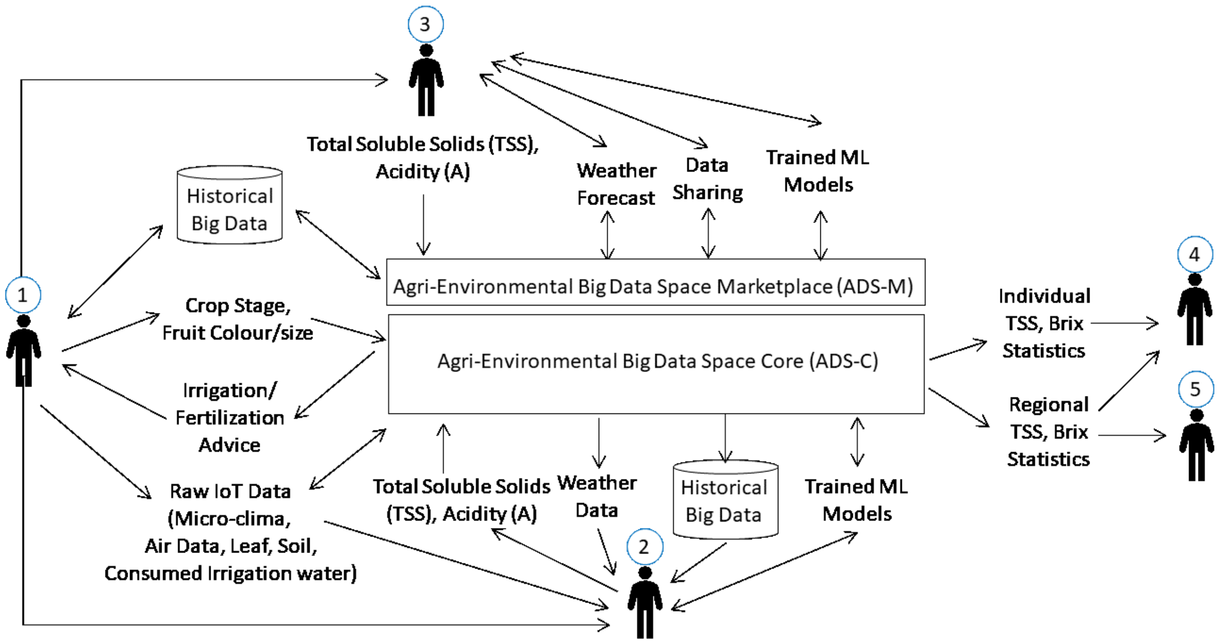


Figure 17. Interaction Analysis Diagram

3.2.4 UC2.4: Automatization of greenhouse windows for climate control

Objective: Control the greenhouse climate from the selection of the best position of the greenhouse windows.

3.2.4.1 State of play

Ventilation is the key process of climate control and plays an essential role in shaping the greenhouse climate. It must be borne in mind that any action on the level of ventilation simultaneously modifies the concentration of CO2, the temperature and the humidity of the air in the greenhouse. On many farms, it is the only means available to the farmer to gain some control over the greenhouse climate under situations where the solar load is high. An efficient ventilation system must meet the following criteria:

- Induce the mixture of indoor and outdoor air.
- Generate an adequate level of air speed to promote the exchange of energy and mass between the plants and the indoor air.

The movement of air under the greenhouse can be generated by means of fans (forced, mechanical or dynamic ventilation), or by using natural ventilation. Ventilation is called "natural" when only natural external forces act on the exchange of indoor air with outdoor air. Natural ventilation is achieved with the installation of windows, whose driving force is the difference in pressure established between the two sides of the window. This pressure difference originates from two different processes:

- The influence of the wind, which generates a distribution of pressure on the surface of the greenhouse.
- The influence of the difference in temperature between the interior and the exterior, which generates a difference in density and, consequently, in pressure.

The main problems with greenhouses are the low climate control provided by these structures, so that in most cases the interior microclimate is far from optimal. The desired increase in the quality of production requires an improvement in greenhouses to achieve greater control of the interior microclimate, and within climate control techniques in warm countries, ventilation is surely the most important.

Until now, most of the climate controllers designed and used in greenhouses are associated with a single control variable, temperature, giving rise to single variable controllers. Generally, the control of this equipment is based on the experience acquired over the years in the production area, making use of a series of setpoint parameters. However, in most cases these systems cannot reveal stress phenomena in the plantation, not easily detectable by the human eye, such as high evapotranspiration, incorrect relative humidity, or poor ventilation management; Although they do not cause the crops to die suddenly, they greatly affect their quality of life, and therefore their productive yield and the quality of the fruits.

3.2.4.2 Target Scenario and Approach

The developments that are intended to be carried out have as their main objective to achieve better climatic conditions from a more precise climate control that can control the temperature and humidity of the greenhouse, with the premises of being technically efficient.

As a novelty in the sector, the development of a climate controller based on a non-linear optimization algorithm is proposed, which will determine the state of the greenhouse windows that maximizes the photosynthesis rate of the crop, in relation to the climatic variables of temperature, humidity and radiation. The algorithm will implement crop growth or photosynthesis models. The objective of this algorithm is to execute a non-linear optimization sequence, marking as a restriction to obtain the highest photosynthesis value, so that through iterations, identify the best combination of window opening values that achieves the highest photosynthesis and, in this way, set the new temperature, humidity and radiation setpoints. In this algorithm you can set preferences in the actuators that you want to use in relation to others (for example, use roof windows rather than side ones). It is important to find the best combination with the least number of iterations and time, to reduce the computational cost.

3.2.4.3 Interaction Analysis

The following Interaction Analysis (Figure 18) helps to explain the analysis process. There are several technologies available to the farmer (Actor 1) to support windows climate control management. The climate control operation in farms can be automated using programmers. Actor 2 (farming and climate monitoring research institutes), will provide working tools to development of growth models that allow the identification of the most suitable climatic conditions within the greenhouse to Actors 1 and 3.

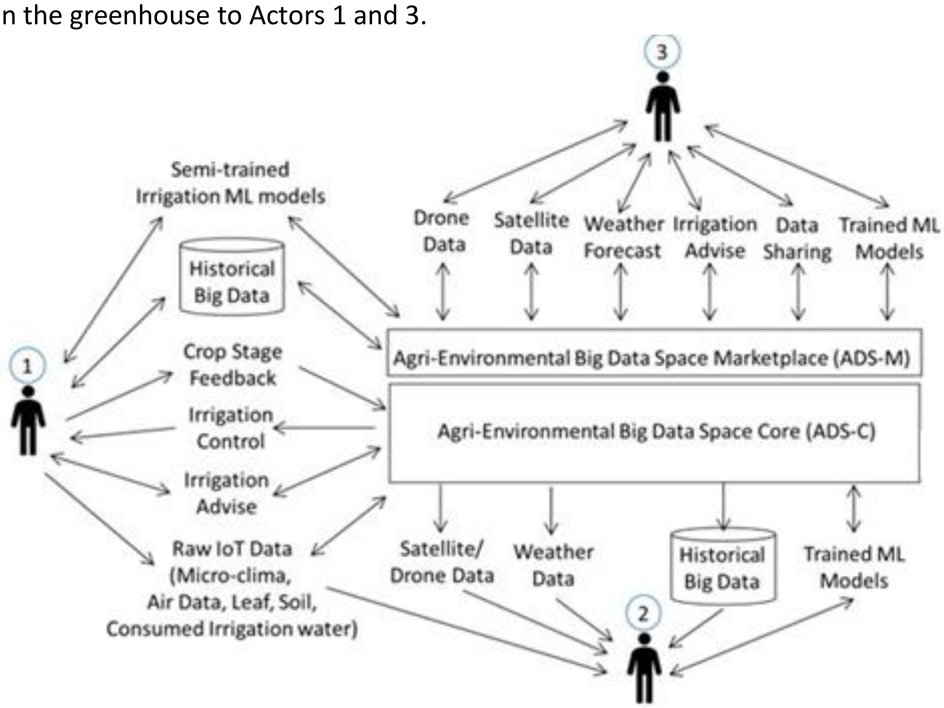


Figure 18: Greenhouse windows' control Interaction Analysis Diagram

UC 2.5: Increase control of agri-environmental for organic farming

Objective: The main objective of UC2.5 is the real-time monitoring and control of agri-environmental conditions adapted to different crops.

3.2.4.4 State of play

Monitoring agri-environmental conditions is crucial for the transformation of agricultural production from conventional to organic, characterised by high product quality, while minimising negative environmental impact. Its aim is the continuous (year-round) production of organic food, featured by a complete absence of chemical fertilisers and synthetic pesticides. Fertilisation of the soil in this case is achieved naturally by providing composts and other organic matter from plants and animals in order for the soil to naturally nourish the plants. Sustainable crop production (permaculture) is a method of growing or harvesting food in an environmentally and ethically responsible manner. It involves following agricultural and food production practices that do not harm the environment, ensure fair treatment of workers and support local communities.

Permaculture agriculture is based on the natural conditions provided by a selected area. The basic principle of farming in such an area is not to change it, but to adapt to the current conditions, e.g. if there is an alkaline substrate, it should not be acidified, but to plant basophilic plants. Permaculture agriculture also has a positive impact on water management. It is not only an ecological trend, but a field for scientific research, especially **the study of the impact of agro-environmental parameters on indigenous crop conditions.**

Most of Poland's soils are light, with sandy, permeable ground. Climatic conditions are also unfavourable for agriculture (shorter growing season and lower rainfall). The productivity of a site is influenced by, among other things: humus content and quality, soil pH, nutrient abundance. The right fertilisation can determine the yield by as much as 40 - 50%, so it is important on organic farms to systematically monitor the soil nutrient content by performing differentiated analyses of the above factors. Taking measurements each time before sowing is very time-consuming and not very precise, and does not allow for long-term, more extensive analyses.

The principle of organic farming is to continuously improve soil fertility and prevent soil degradation. Correct fertilisation on an organic farm should take into account the following factors:

- regulation of the soil reaction, which is a basic condition for the availability of nutrients (including calcium) to the pH level resulting from the agronomic category of the soil,
- increasing the humus content of the soil to a state defined as medium, i.e., about 1.5-2%, through the use of natural and organic fertilizers and a proper crop rotation,
- balancing nutrients such as phosphorus, potassium, magnesium to a medium class level.

The expenditure incurred on chemical analyses of soil abundance pays off in the form of:

- proper plant nutrition and health, resistance to frost, as well as improved quality and increased fruit yield,
- considerable savings on fertilisers,
- avoidance of the over-fertilization effects (salinisation and contamination of soils, ground and surface water),
- lower production costs

Sustainable crop production differs from industrial crop production, which is generally based on monoculture farming (growing only one crop in a large area), intensive use of commercial fertilizers, intensive use of pesticides and other factors harmful to the environment, communities and farm workers. In addition, sustainable crop production practices can lead to higher yields over time, with less need for expensive and environmentally harmful inputs. This production model, combined with mechanisation and automation, guarantees a quality product that meets the quality expectations of the modern consumer.

Vegetables on raised beds grow much faster, thanks to the higher moisture content, better soil temperature, and the decomposition of organic matter allows the crop to grow earlier, extending the growing season. The use of weed seed-free substrate means that there is almost no need to weed. In addition, the soil in the boxes is not trampled, giving it more airiness. This is a very convenient solution when growing many different vegetables with completely different fertiliser requirements. The soil in the box can be replaced at any time, making it easy to avoid soil diseases and pests. Therefore, monitoring the condition of the soil and other agro-environmental conditions is crucial in organic farming.

3.2.4.5 Target Scenario and Approach

The rapid technological development of the agricultural sector requires constant updating of knowledge and skills in order to maintain the economic efficiency and competitiveness of farms, especially in the area of advanced technologies for quality products. We assume that the implementation of the above objectives will have a significant impact on increasing the awareness of rural inhabitants, through the promotion of natural farming methods. Developing and then implementing agricultural investments may resolve a problem of optimising an agricultural production in local scale and thus helping farmers to run their businesses more efficient and effective. Furthermore, creating know-how for organic farms will make organic production even more important on the Polish market and thus increase the quality of life in rural areas.

The environmental monitoring system we aim to develop is designed to continuously measure, i.e., temperature and humidity at the most sensitive points. If pre-set alarm thresholds are exceeded, the system should inform the user in a manner specified during the device's configuration. It should allow the connection of many other types of sensors, and its hardware configuration should be flexible enough to allow the set-up to be tailored to the individual user's needs. In AgriDataValue approach, we plan to use an extended set of real-time and historical IoT sensor data (e.g. soil data) and weather forecast.

3.2.4.6 Interaction Analysis

Figure 19 provides the interaction analysis of UC 2.5 in a UML like Use Case Diagram approach.

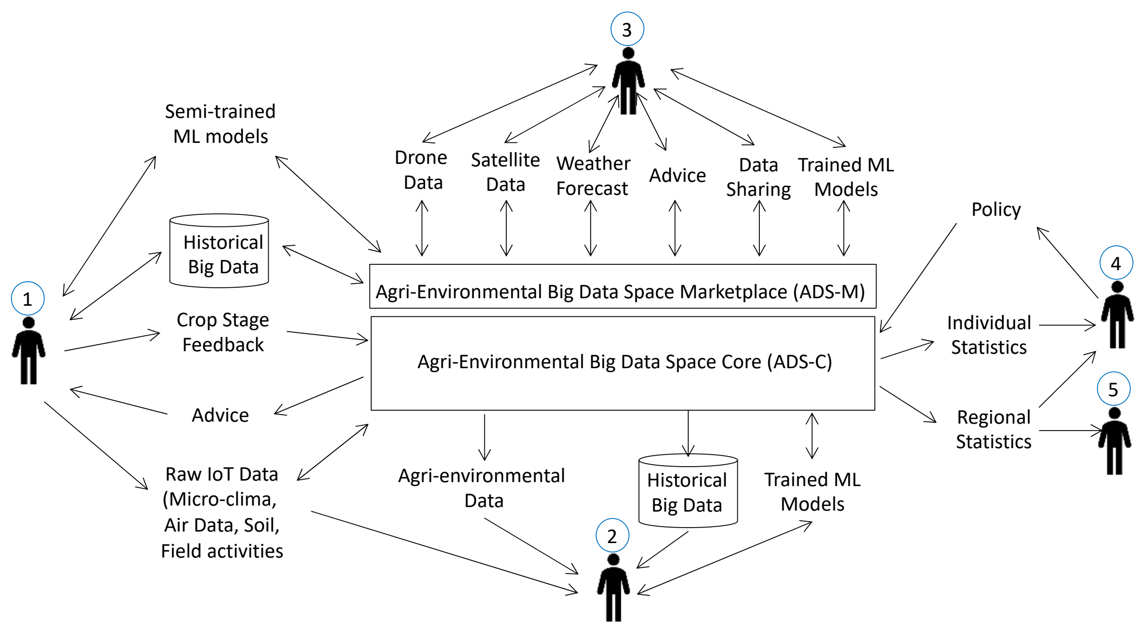


Figure 19: UC 2.5 Interaction Analysis

Actor 1 (Cooperatives, and Individual Farmers) provides: a) **raw IoT Data**, such as local micro-climate data (precipitation, air temperature and humidity), soil moisture and temperature or soil analyses, along with the schedule of the relevant field activities and b) **Crop stage feedback**, informing the system on the crop growth stage and feedback on advice. Moreover, via the ADS-M may offer **historical Big Data** and **semi-trained ML models**, under specific incentives/ fee. The ADS platform responds with **Advice**. Actor 2 is allowed to interact directly with the ADS-C and receive any type of **historical data** and **agri-environmental data**, along with **trained ML models**. In return, Actor 2 offers more advanced or experimental ML models, which may be utilized by Actors 1 and 3. Actor 3 access the ADS platform only via the ADS-M component. Via specific smart contracts may retrieve or provide any type of shared data, information, or advice, including **historical shared data, drones' and satellite's data, advice,** and **ML trained models.** Actors 4 and 5 can obtained individual/regional statistics to support the decision-making process and to evaluate the fulfilment level of specific CAP policies/strategies.

3.3 Use Cases Cluster 3: Trees/Vineyards

The UC Cluster 3 is focused on Tree/Vineyard crops and aims to focus on use cases related to disease/frost detection, improve quality of Vegetables Crops and aims to optimize the quality and quantity of the crops, while lowering the environmental footprint.

Objectives: In detail, the objective of UC Cluster 3 are to:

- Protect the health and quality of fruit trees and vineyards crop.
- Increase quality and quantity, avoid diseases with less pesticides
- Foresee and mitigate frost and heil.

The UC Cluster 3 involve IoT weather/soil sensors, edge cloud, diverse geotagged photos' datasets, and drones/ satellite multispectral imagery.

3.3.1 UC 3.1: Fruit trees disease forecast/detection

Objective: The main objective of UC3.1 is to reduce the use of phytosanitary treatments on woody crops (apple, peach, pear) using ML models to support farmers decisions. Different data sources will be used to train and use the ML models. Field observations of the phenological evolution of plants and of the presence and degree of affectation of pest, climatic real, estimated and forecasted data, multispectral images from the Copernicus Sentinel 2 satellite constellation will constitute the core of the data. Nevertheless, other data sources, such as Spanish Cadastral Registry, will be used during the transformation of the raw datasets from the main data sources into the data used to feed the models. We will create phenology and pest risk prediction models because of the relationship of the phenology stage at which a phytosanitary treatment is applied and its effectiveness.

3.3.1.1 State of play

Phenology, the timing of cyclical and seasonal natural phenomena such as flowering and leaf out, is an integral part of ecological systems with impacts on human activities like environmental management, tourism, and agriculture. As a result, there are numerous potential applications for actionable predictions of when phenological events will occur. However, despite the availability of phenological data with large spatial, temporal, and taxonomic extents, and numerous phenology models, there have been no automated species-level forecasts of plant phenology. This is due in part to the challenges of building a system that integrates large volumes of climate observations and forecasts, uses that data to fit models and make predictions for large numbers of species, and consistently disseminates the results of these forecasts in interpretable ways.

Numerous phenology models have been developed to characterise the timing of major plant events and understand their drivers [44]. These models are based on the idea that plant phenology is primarily driven by weather, with seasonal temperatures being the primary driver at temperate [45, 46]. Because phenology is driven primarily by weather, it is possible to make predictions for the timing of phenology events based on forecasted weather conditions. The deployment of seasonal climate forecasts [47], those beyond just a few weeks, provides the potential to forecast phenology months in advance. This time horizon is long enough to allow meaningful planning and action in response to these forecasts. Numerous phenology models have been developed to characterise the timing of major plant events and understand their drivers.

Phenological modelling may benefit from advancing parameterisation approaches such as machine learning techniques and data assimilation, while at the same time addressing issues related to nonlinear and discontinuous phenomena. Furthermore, the introduction of more nonlinearities into model simulations could further reduce uncertainties and bias.

Plant phenology at species-specific level is the consequence from two opposing factors [48]:

- ***Intrinsic factors of plants***, or characteristics of an individual plant (e.g., genome, age, and evolution within a plant community), are associated with biotic potential, photosynthetic activity, absorption of nutrients, constructive metabolism, etc.
- ***Environmental component*** is representative of the restraints imposed by competition, limited resources, stress, respiration, aging, and geospatial factors. Figure 20 summarizes them. Factors in the triangle show the affecting components and factors to control plant phenology. Factors outside the triangle display the tempo-spatial dimension of plant phenology to address all scale issues related to plant.

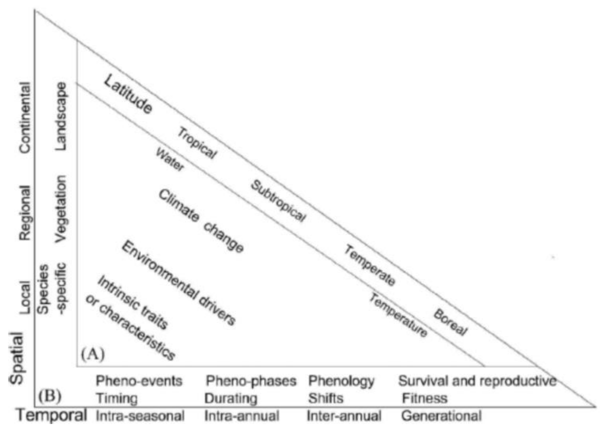


Figure 20. Factors controlling plant phenology

Regarding environmental factors, historically phenological models were created based on the statistical search of correlations between observed phenological state signals and land surface phenology (LSP). Because of the difficulties to integrate more variables in human driven calculations [49] modelling efforts have generally relied on functions (usually linear) of meteorological drivers, such as average temperature and precipitation, growing degree days (GDDs), light and temperature, minimum temperature, photoperiod, vapor pressure deficit, or minimum relative humidity.

Nevertheless, there is a lack of understanding on number of important aspects, such us the multivariate influence of meteorological variables (temperature, precipitation, solar radiation) driving phenology, or the effect of additional drivers in the modelling of autumnal phenophases. A deeper mechanistic understanding of phenology, its variability and drivers across multiple scales, and its link to other physiological processes is needed to be able to develop predictive models. Although not fully understood, most species in temperate climates adopt a mix of signals that fall into three categories: (1) solar signals (photoperiod, irradiance), (2) past seasonal experience signals (winter chilling [49]), and (3) current or very recent past signals (concurrent temperature and/or water conditions).

Most studies of LSP analyse trends in phenological events across years. More recent studies present process-based models to uncover cause–effect relationships between long-term trends in phenology and its key driving variables. These studies focus on trends in phenology produced by trends in weather (mainly warming). However, interannual variation in LSP arising because of the inter-annual variability in weather are less studied, with model-based studies of this phenomenon being scarce. Moreover, many studies investigating the sensitivity of phenological events to climate variation use calendar seasonal or monthly mean climatic variables, which operate on fixed human calendar scales with a start date of 1 January, instead of using biological scales, for example, time relative to the growing phase of plants [50] or considering where Julian date representation to continuous representation of time.

As current phenology models are based on accumulated temperature forcing, making forecasts requires information on both observed temperatures (and other variables) as well as, forecast temperatures (and other variables). However, the modelling of inter-annual variation in LSP considering its potentially complicated relationship with climate in a multidimensional feature space might not be possible using traditional linear regression models. In this sense, phenological modelling may benefit from machine learning techniques such as the random-forest (RF) method, reducing uncertainties and bias. RFs have the potential to identify and model the complex non-linear relationships between phenology and climate, being able to handle a large number of predictors and determine their importance in explaining phenology. RFs have been applied with very promising results to other fields of ecology and biological sciences, as well as to the simulation of phenological shifts under different climatic change scenarios, but the potential for modelling climate-driven inter-annual variation in phenology is still to be explored.

3.3.1.2 Target Scenario and Approach

Currently, there are a lot of web services providing information of the climatic conditions, both observed and forecasted, together with the derived indexes that can support the decision making of farmers based on the location of stations. In addition, the use of multi-spectral satellite images has been tested to remotely monitor the development of arable crops and forests. Finally, public authorities, farmers associations and farming organizations own datasets of field observations of phenology and the presence of pests. However, these observations datasets are not shared to enable their merge with climatic (raw or derived) data or multispectral images in order to create ML models to predict phenology of crops or the risk of pest in a more accurate way than the derived indexes.

The goal of UC3.1 is to use the methodology created by ITAINNOVA to create ML models, and existing developments to predict the phenology evolution and the pest risks in vineyards to other woody crops. The idea is to be able to obtain field observations, climatic data and Sentinel 2 multispectral images of other areas and crops through the ADV data space to train and use ML models. We will use data of the crops in Aragón of an example of the process.

3.3.1.3 Interaction Analysis

Figure 21 shows the interactions between the actors of the UC3.1 at high level. It identifies 4 main actors. First, they are the data service providers (actor stereotype 3). These are entities which can provide (open) data of required datasets such as multispectral satellite images (i.e., Copernicus Sentinel 2), meteo-data (either real observations, real estimations, or weather forecasts) or geographical descriptions of the area of interest (i.e., the fields under monitoring and prediction).

The second type of actors are the Farming Entities (actor stereotype 1). They represent farmers associations, cooperatives, private companies, or public authorities which can provide historical field observations. That is phenology records or the presence of pest records. These entities are expected to have agronomist as members of their staff. They can also play the role of final users: they can take advantage of the intermediate data and ML predictive models although they will be interested in high level inspections.

The third kind of involved entities are the ones being able to train and provide ML models (actor stereotype 3) using the data provided by data service providers and the knowledge provided by Farming entities. They are the Model Developers, that is Data scientist. These actors can transform raw data into intermediate data which can be used to create the models (either from scratch or from existing models) to fit the data of a given area and crop.

They will produce both model and intermediate valuable data to be used either by the Farming Entities or by the Farmers.

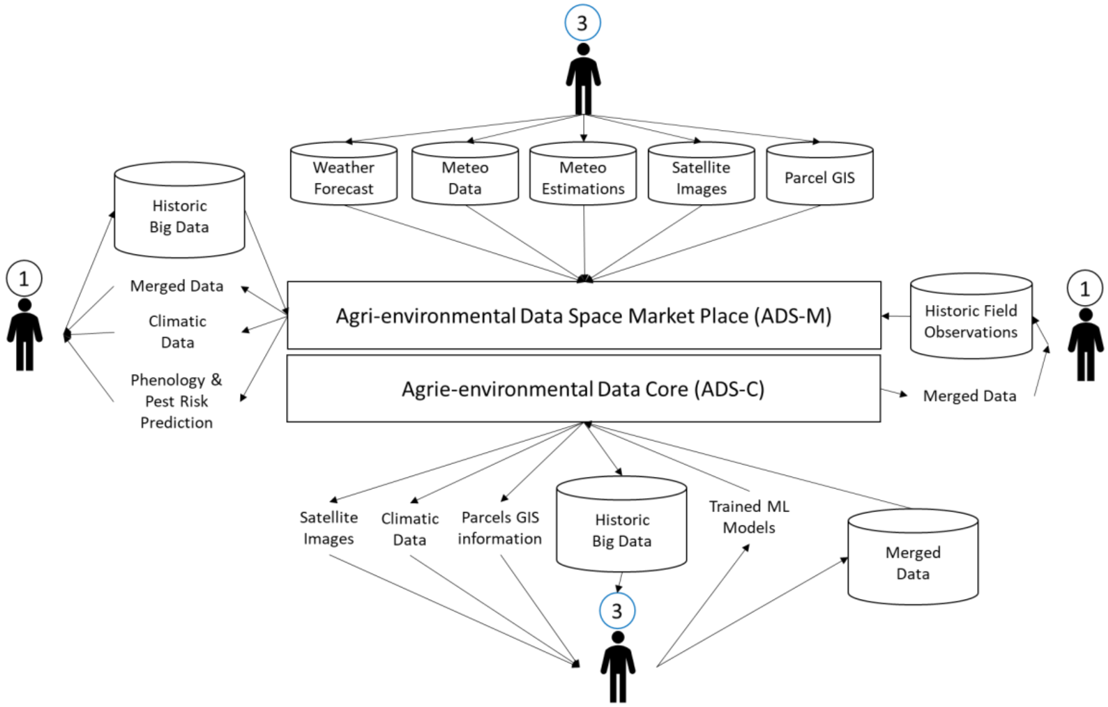


Figure 21. High Level Interactions Between Actors of UC3.1 using ADV Data Space

Farmers represent the (final) users of the UC3.1 (1). They will use the trained ML models to make data-based decisions on the application of a phytosanitary treatment or not. To get the phenological and the pest risk predictions, they will provide the system with information about the fields they are interested in together with information of the field observations of the current season. These data will be transformed in the same way as the data used for training the models by processes implemented by the data scientists. They will receive both the results of the predictions as well as the climatic data which will support them.

3.3.2 UC 3.2: Anti-frost control

Climate change threatens vineyards in different ways. Global warming, heavy rain in the flowering season, hail and frost can affect wine production and quality. Among them, hail is one of the biggest threats that winegrowers are facing. A hailstorm can destroy a vineyard in just few minutes. It affects not only the current year but also the following year's growth of the vine.

3.3.2.1 State of play

After two years of studying different solutions with different experts to protect vineyards, the Saint-Emilion winegrowers voted at the end of January 2021 to set up a community-led hail mitigation system (Selerys system). The solution covers the area of 7500 hectares and protects the Lussac Saint-Emilion, Puisseguin Saint-Emilion, Saint-Emilion and Saint-Emilion Grand cru appellations. The system is a self-operating instrument remotely controlled for aerial cloud seeding.

The Selerys system is based on 3 components: the hail-risk detection (SKYDETECT RADAR), the physical mean to seed the cloud (LAÏCO solution based on self-operating balloons launcher) and the nature of the agent (hygroscopic Salt) used to reduce the risk of hailstorm formation.

Figure 22. Existing community-led hail mitigation system components

This system is based on a highly competitive short-range X-Band radar able to provide for local or large territories:

- A real-time total monitoring of the total half sphere
- Displaying each cloud's maximum reflectivity in high definition

This radar is associated with a data processing algorithm that allows to follow minute by minute the evolution of all potentially dangerous clouds in a radius of 30 kms around the radar and to give sufficiently precise information to help the winegrowers to intervene or not.

This system alerts twenty-seven volunteer winegrowers, which are ready for the remote activation of the 37 semi-automatic balloon launchers spread across the area. Biodegradable balloons inflated with helium are then released and sucked up by the updrafts generated by the storms. Once they are in the middle of the cloud, a torch releases *hygroscopic salt* (200g in each balloon), which reduces or prevents the formation of hailstones and causes precipitation of rain instead. The whole system is powered by photovoltaic panels. Up to 6 balloons can be pre-loaded. Additional functions include:

- Remotely commanded balloons launch through SMS
- Checks the flares connected to each balloon for safe flights
- Transmits flight plans to the smart seeding balloons
- Inflates the balloons with the optimum quantity of helium
- Launches the balloons automatically once the inflation is over
- Remote global monitoring (gas, flares & balloons stocks, security checks…).

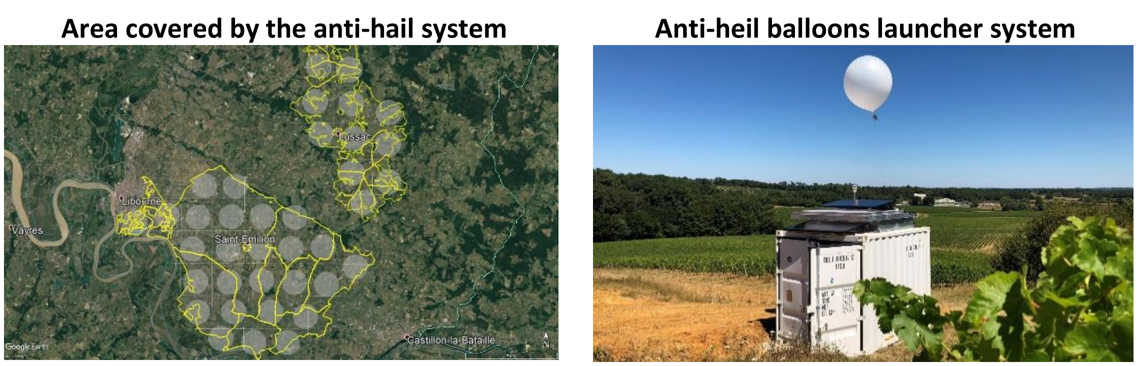


Figure 23. Existing community-led hail mitigation system components

The 37 SOBLI are equipped with weather stations. Each station indicates: wind direction, wind strength, precipitation and precipitation types, temperatures, pressures.

3.3.2.2 Target Scenario and Approach

The anti-frost/anti-hail system already installed in the vineyards of Saint-Emilion since 2021. Each year, between 200 and 300 balloons are released and so far, no hail damage has been observed. However, the hail detection system is a quite expensive short-range X-Band radar able to provide for local or large territories, offering a real-time total monitoring of the total half sphere and displaying each cloud's maximum reflectivity.

Within AgriDataValue, we will try to study the weather characteristics and combine it with satellite images to consider alternative ways of detecting the potentially dangerous clouds, potentially in an even larger geographical area.

3.3.3 UC 3.3: Pest Control on Mediterranean Fruit Fly

Objective: *Ceratitis capitata*, known as the *Mediterranean fruit fly*, or ***Medfly*** is one of the most destructive fruit pests in the world, infecting more than 200 fruits types. Medfly's existence in agricultural fields must be monitored systematically for effective combat against it. We plan to install IoT and automated capture traps to detect existence and build models to predict pest tracking/mitigation.

3.3.3.1 State of play

Medfly is one of the world's most destructive fruit pests. Though "Mediterranean", the pest lives in Africa, Asia, West Australia, Central America, Caribbean and South America. In Europe, it is found in Albania, Azores, Balearic Islands, Canary Islands, Corsica, Croatia, France, Greece, Italy, Madeira Islands, Portugal, Southern Russia, Sardinia, Serbia, Sicily, Slovenia, Spain. Because of its wide distribution over the world, its ability to tolerate cooler climates better than most other species of tropical fruit flies, and its wide range of hosts, it is ranked first among economically important fruit fly species. Its larvae feed and develop on many deciduous, subtropical, and tropical fruits and some vegetables. Although it may be a major pest of citrus, often it is a more serious pest of some deciduous fruits, such as peach, pear, and apple. The larvae feed upon the pulp of host fruits, sometimes tunnelling through it and eventually reducing the whole to a juicy, inedible mass. In some of the Mediterranean countries, only the earlier varieties of citrus are grown, because the flies develop so rapidly that late season fruits are too heavily infested to be marketable. Some areas have had almost 100% infestation in stone fruits. Harvesting before complete maturity also is practiced in Mediterranean areas generally infested with this fruit fly [51].

Figure 24: Mediterranean Fruit Fly Life Cycle. From left to right a) Egg b) Larvae, c) Pupae in soil, d) Adult Male

Medfly life cycle takes 28-34 days to complete in summer and 60-115 days in winter [52]. Eggs hatch in 2 to 3 days at 26°C, which is optimum temperature. The larvae tunnel throughout the pulp of the host fruit to feed for 6 to 10 days. Generally, the fruit falls to the ground during or after larval development. The third instar larvae normally emerge from the fruit to pupate in the soil. However, pupation may occur anywhere; it is not necessary for the larvae to enter the soil to pupate. Adults emerge from the pupal cases in 6-15 days at 26°C. The lifecycle between two generations under favourable conditions is 18-33 days.

Fly activity and numbers are greatest during warmer months. Adult Medflies become active when temperatures exceed 12°C. As the temperature rises in spring, increased numbers of adults emerge from the ground and flies become active. Adult Medfly may live for two to three months and are often found in the foliage of fruit trees, especially citrus. As long as fruit is present, most Medfly will not move more than 50 metres. The males form groups underneath leave and call for females to mate.

If control is not started at this time, Medfly populations will grow and cause problems later in the season. Today, there are available special traps in the field to catch Medflies. Baits can be used in combination with Delta traps and funnel traps (Figure 25). The older version of traps used protein baits that captured large numbers of non-target insects, while new versions use combinations of chemicals to attract male and female fruit flies. Other baits traps are equipped with pheromone bait-dispenser for Medflies, for attracting and mass trapping the pest.

Figure 25: Various types of Mediterranean Fruit Fly Traps [53]

Pheromone baits for Medflies should be checked from time to time and their dose should be reduced or increased depending on the density of pests in the controlled area. Several technologically supported automated remote monitoring system have been proposed in the literature aiming to eliminate the frequent site visits as a more economical solution [54] [55], however their penetration in the market is minimal.

3.3.3.2 Target Scenario and Approach

Based on the Medfly lifecycle, studies have shown that insect development is temperature dependent. The egg, larval, and adult development is influenced by air temperatures; the pupal development depends on soil temperatures [56]. In both environments, a minimum temperature exists below which no measurable development takes place. For Medfly, these thresholds are 9.7°C in soil and 17°C in air. In the literature, several temperature models for Medfly insect development stages have been proposed to predict their entire life cycle [57]. Most temperature models consider the number of days necessary to complete the cycle, the mean monthly temperature, and the threshold temperatures to calculate the number of necessary “degree days” to have adult insects, with optimal conditions 25±1°C and 65±5% relevant humidity [58]. Additional factors, such as light intensity or biotic ones, such as vegetational properties, distribution of resources, or predator pressure may drastically modify the evolution of Medfly populations [59].

Within AgriDataValue, we aim to reduce the volume of pesticides by implementing ML algorithms to accurate predict the Medfly lifecycle and spread, while increasing the confidence of the farmers to the insect prediction system. In order to achieve the goal, we plan to utilize existing and install new IoT agri-meteorological stations to collect and process air, leaf and soil parameters such as temperature and relevant humidity, along with light intensity, to build ML models that will calculate the probability of Medfly appearance. The presence of adult Medfly insects as feedback of the ML models will be reported manually, while automated traps that utilize cameras to automatically identity adult Medfly insects will be considered. Moreover, in case of Medfly appearance in a region, larger geographical models combining wind speed and direction, along with weather prediction models and satellite images will be considered to predict the direct of pests spreading.

3.3.3.3 Interaction Analysis

Figure 26 provides the interaction analysis of Medfly pest control UC in a UML like Use Case Diagram approach. All main actors/ end-users participate at the specific UC.

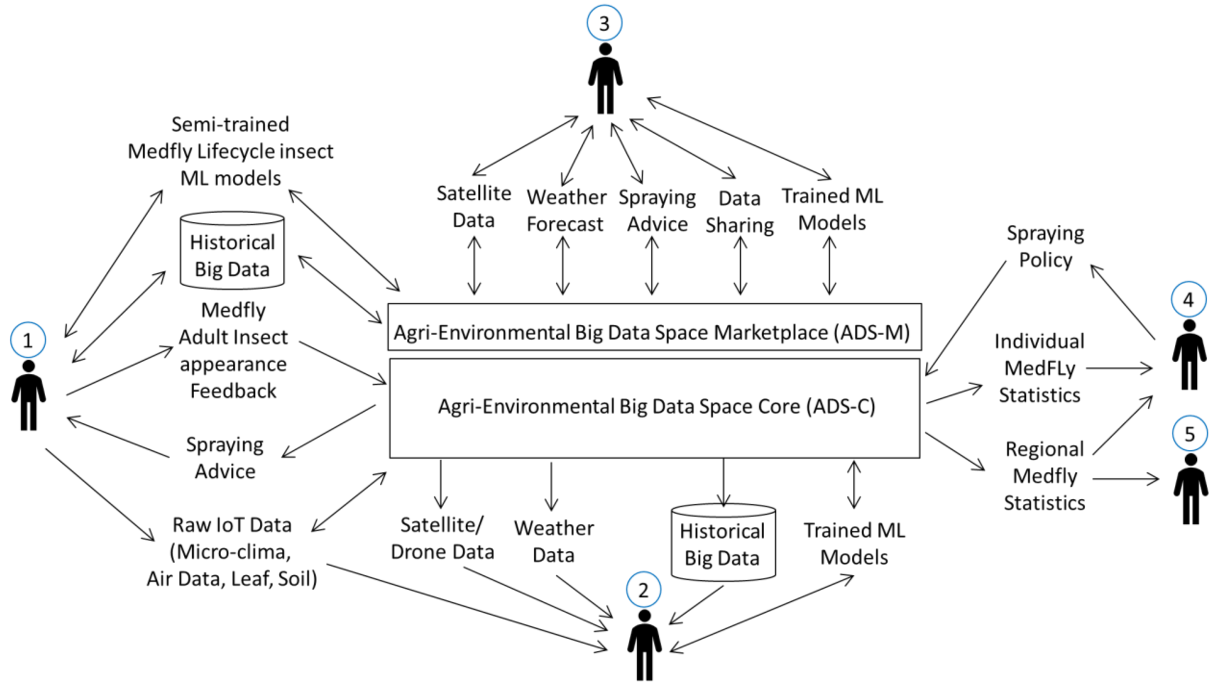


Figure 26: Medfly pest control Interaction Analysis Diagram

As can be seen, Actor 1 (Farming companies, Cooperatives and Individual Farmers) interacts both directly with the ADS-C and the ADS-M logical components. Actor 1 provides to ADS-C: a) ***raw IoT Data***, such as local micro-clima data (air temperature and humidity, rain volume and precipitation data, wind direction and volume), soil moisture and temperature, leaf wetness and b) ***Medfly adult insects appearance feedback,*** informing the system on the Medfly lifecycle stage and feedback on spraying advice. Moreover, via the ADS-M may offer ***historical Big Data*** and ***semi-trained irrigation ML models***, under specific incentives/ fee. The ADS platform responds with ***Spraying Advice*** and potentially ***pest control strategy***.

To facilitate research and experimentation, Actor 2 (farming and climate monitoring research institutes) is allowed to interact directly with the ADS-C and receive any type of ***historical data***, ***weather data*** and ***satellite data***, along with ***trained ML models***. In return, Actor 2 offers more advanced or experimental ML models for Medfly lifecycle and Medfly population experiments at laboratories, which may be utilized by Actors 1 and 3.

Actor 3 (Specialized service and technology providers offering added valued services based on Agri-data and AgriDataValue technology) access the ADS platform only via the ADS-M component. Via specific smart contracts may retrieve or provide any type of shared data, information or advice, including ***historical shared data***, **satellite's data**, ***spraying advice*** or ***services*** (e.g., using specialized drone-based spraying) and ***ML trained models***.

Actor 4 (CAP paying authorities) directly via the ADS-C module imposes to the platform specific ***spraying policies*** (such as volume and type of insecticides) and retrieves ***individual Medfly statistic*** to be used when calculating the CAP national/ regional supporting funding (e.g., in case of AgriDataValue certified Medfly, sampled physical inspections may be reduced). Finally, both Actor 4 and Actor 5 (EU stakeholders/ policy) retrieve ***regional Medfly statistics*** to evaluate the fulfilment level of specific CAP policies/strategies, including soil strategy objectives.

3.3.4 UC 3.4: Pest Control on Olive Fruit Fly

Objective: *Bactrocera oleae*, known as *Olive Fruit Fly,* is a species of fruit fly which belongs to the subfamily Dacinae [60]. It is phytophagous species, whose larvae feed on the fruit of olive trees, hence the common name. It is considered as one of the most serious pests in the cultivation of olives. We plan to install IoT and capture traps to detect existence and build ML models to predict pest tracking/mitigation.

3.3.4.1 State of play

The Olive Fruit Fly has been reported in Europe, Africa, the Canary Islands, the Middle East, China, California, Mexico, Central America [61]. The predisposition to the flies' attacks is tied to several factors, both intrinsic and extrinsic. The main ones are climatic (temperature and rainfall), so marked differences can occur from year to year. However, other genetic or agronomic factors should not be overlooked.

The life cycle of Olive Fruit fly start when the adult females lay their eggs in the summer when the olive is at least 7–8 mm in diameter. Egg-laying is done by making a puncture with the ovipositor into the skin of the olive, leaving only one egg in the hollow below. The bite has a characteristic triangular shape, it is visible to the naked eye and is known as “fly bite”. A puncture has a dark green colour, whilst older bites have a yellowish-brown colour because of wound healing. The Olive fruit fly egg has elongated and cylindrical shape with approximate dimensions of 0.7×0.2 mm. Like other dipterans, larvae are transparent-white, with spindle shape, with very small head and the end of the broad abdomen and reach a size of 7-8 mm. Puparium is reddish brown-brown and similar to that of a barrel of wood. Finally, the adult olive fly has a length of only 4-5 mm and is somewhat smaller in size of the common fly. The body features a varied range of brown tones with a light-coloured triangle on the back somewhat yellowish [60]. The size of the females is larger than that of the males and they have an oviscapto (an egg-laying tubular structure organ) very appreciable.

Figure 27: Olive Fruit Fly. From left to right A) Egg b) Puparium, c) Adult Male. d) Adult Female

The life cycle of the olive fruit fly is closely linked to the seasonal development of its main host, the cultivated olive (*Olea europea*), and to the local climate. By late June to the beginning of July as the new olive crop develops, females begin to lay eggs and are attracted to the fruit. Although eggs may be laid in small fruit, the larvae do not successfully develop until the ripening fruit grows to sufficient size. Eggs hatch in 2 to 3 days, and larvae develop in about 20 days during summer and fall. in spring. Pupal development requires 8 to 10 days during summer but may take as long as 6 months in winter, as larvae produced during fall, leave the fruit and pupate in the soil where they spend the winter; however, some maggots overwinter in fruit left on trees and pupate. Multiple generations occur throughout summer and fall. In summer the flies can complete a generation in as little as 30 to 35 days, given optimum temperatures (20°C to 30°C). The olive fruit fly has no true period of dormancy, and all stages of the insect can occur during winter. Hot (35° to 40°C), dry conditions reduce the build-up of olive fruit fly populations [62]. Fruit fly eggs and first instar maggots can experience relatively high mortality during hot, dry weather. Adult flies also may die during periods of high temperatures if adequate water and food are not available. High olive fruit fly populations have been observed in both coastal and inland areas.

Similarly, to UC3.3, within AgriDataValue, we aim to reduce the volume of pesticides utilized for Olive Fruit Fly by implementing ML algorithms to accurate predict their lifecycle and spread, while increasing the confidence of the farmers to the insect prediction system. To achieve the goal, we plan to utilize existing and install new IoT agro-meteorological stations to collect and process air, leaf and soil parameters such as temperature and relevant humidity, along with light intensity, to build ML models that will calculate the probability of Olive Fruit Fly appearance. The presence of adult Olive fruit fly insects as feedback of the ML models will be reported manually, while automated traps that utilize cameras to automatically identity adult insects will be considered. Moreover, in case of insects’ appearance in a region, larger geographical models combining wind speed and direction, along with weather prediction models and satellite images will be considered to predict the direct of pests spreading.

3.3.4.2 Target Scenario and Approach

Within AgriDataValue, we plan to study and analyse IoT data and images from various sources in order to predict the existence and population spreading of Olive Fruit fly. The interaction analysis diagram is almost identical to the Medfly interaction analysis diagram (Figure 26). Again, we consider Actor 1, who interacts both directly with the ADS-C and the ADS-M logical components and provides: a) ***raw IoT Data***, such as local micro-clima data (air temperature and humidity, rain volume and precipitation data, wind direction and volume), soil moisture and temperature, leaf wetness and b) ***Olive Fruit Fly adult insects appearance feedback,*** informing the system on the Olive Fly fly lifecycle stage and feedback on spraying advice. Moreover, via the ADS-M may offer ***historical Big Data*** and ***semi-trained irrigation ML models***, under specific incentives/ fee. The ADS platform responds with ***Spraying Advice*** and potentially ***pest control strategy***.

Actor 2 receives any type of ***historical data***, ***weather data*** and ***satellite data***, along with ***trained ML models***. In return, Actor 2 offers more advanced or experimental ML models for Olive Fruit fly lifecycle and population experiments at laboratories, which may be utilized by Actors 1 and 3.

Actor 3 via specific smart contracts may retrieve or provide any type of shared data, information or advice, including ***historical shared data***, **satellite's data**, ***spraying advice*** or ***services*** (e.g. using specialized drone-based spraying) and ***ML trained models***.

Finally, Actor 4 imposes to the platform specific ***spraying policies*** (such as volume and type of insecticides) and retrieves ***individual Olive Fruit fly statistics*** to be used when calculating the CAP national/ regional supporting funding, while both Actor 4 and Actor 5 (EU stakeholders/ policy) retrieve ***regional Olive Fruit fly statistics*** to evaluate the fulfilment level of specific CAP policies/strategies, including soil strategy objectives.

3.4 Use Cases Cluster 4: Livestock

The UC Cluster 4 is focused on livestock and aims to focus on use cases related to reduction of gas emissions, reduction of nitrogen deposition, and proactive livestock health/welfare and calving monitoring.

Objectives: In detail, the objective of UC Cluster 4 are to:

- Use edge cloud and real-time IoT sensor data (e.g. neck collar, feeders, emission sensors) together with GPS location data to monitor the cattle/pig health, activity, feeding and calving
- Proactively control milk and meat quality
- Reduce the GHG emissions and nitrogen deposition.

3.4.1 UC 4.1: Reduce Greenhouse gas emissions

Objectives: Methane is the major greenhouse gas is livestock. The first source is enteric emissions and the second is manure. To tackle the enteric emissions, we implement nutritional strategies that have a potential to reduce the methane production. The possible reductions are measured with methane sensors, such as GreenFeeds and other multi-gas analysers. Emission calculation is expressed as absolute methane emissions, Methane yield (CH_4 production divide by Dry Matter Intake (DMI)) and methane intensity (CH_4 production divide by milk production or meat production). We will collect, process and corelate feed, milk, and emissions data in one flow aiming to significantly reduce the enteric emissions mainly on cattle. In a latter phase the same can be done for manure emissions mainly on pigs.

3.4.1.1 State of play

The European Green Deal sets out the EU's commitment to shift into a climate neutral economy by 2050, where all sectors shall contribute. The 2021 European Climate Law turns this climate neutrality objective into a legal commitment to reduce greenhouse gas (GHG) emissions by at least 55% by 2030. Today, livestock producers in European union (EU27) 220 Mt CO_{2e}, 163 Mt CO_{2e} comes from CH_4 from enteric emissions and 57 Mt CO_{2e} from manure management.

Within AgriDataValue, we aim to reduce the enteric emissions mainly from cattle by nutritional measures by implementing ML algorithms to accurate predict the emission reduction of the feed measures. To achieve the goal, we plan to utilize existing measurements from existing sensors such as emission measurement, feed intake and analysis and milk production parameters, and measurements that become available in the near future, to build ML models that will calculate these enteric emissions.

The same approach will be used for manure, mainly from pigs. To achieve the goal, we plan to utilize existing measurements from existing sensors such as emission measurement, feed intake and analysis and manure analysis, and measurements that become available in the near future, to build ML models that will calculate these manure emissions.

3.4.1.2 Target Scenario and Approach

Within AgriDataValue, we plan to study and analyze sensor data from various sources in order to predict the major greenhouse gas emission from livestock. Enteric methane prediction studies have shown that enteric emissions are total feed intake, fiber intake and additive concentration dependent.

Unfortunately, historical Big Data of different emission trials are not available. Thus, to achieve the goal, we plan to utilize few existing historical data and measurements from existing sensors such as emission measurement, feed intake and analysis and milk production parameters, and new measurements as they become available in the near future, to build ML models that will calculate the emissions. Additionally, project partners have some semi-trained ML models that will be further trained in the course of this use case.

3.4.2 UC 4.2: Reduce nitrogen deposition

Objectives: The element nitrogen (N) is ubiquitous and necessary for life, but bio reactive components such as ammonia, nitrous oxide and nitrate are harmful for the environment when expelled in excess. Therefore monitoring these molecules in agriculture is of upmost importance to have an agricultural system that is in equilibrium with the environment. We will collect, process and corelate feed, manure and water parameters fine tune and improve future manure action plans (MAP).

3.4.2.1 State of play

78% of the atmosphere is composed of nitrogen gas (N2) and nitrogen is a necessary building block of all life on earth. It is an essential element in plant fertilizers and animal feed. Yet it also causes some intractable environmental problems. To be available as a nutrient, it must be converted into a reactive form. The last decades, there has been an increase in the formation of reactive nitrogen, through the production of ammonia (NH3) for fertilizer, among other things, and through the formation of nitrogen oxides (NOx) from combustion processes (energy, industry and transportation). About twice as much reactive nitrogen is now formed annually as would be without human intervention.

As more reactive nitrogen is formed, there are also more nitrogen losses to the environment. A high concentration of nitrate (NO3-) in groundwater and surface water can have a negative impact on drinking water quality. Together with phosphates, it causes toxic algal blooms and biodiversity loss in watercourses and coastal areas (eutrophication). Nitrogen oxides (NOx) and ammonia (NH3) are air pollutants in themselves that also contribute to the formation of particulate matter and ozone. In addition, these substances have a fertilizing effect on nature, affecting nitrogen-sensitive habitats. Nitrogen pollution also contributes to climate change: nitrous oxide (N2O) is a powerful greenhouse gas.

Because agriculture is an economic activity that largely takes place in an open system that interacts with soil, water and air, it is an important contributor to nitrogen pollution. Because the system is open, emissions reduction in agriculture is more challenging than in other sectors. In addition, there is also a risk of problem shifting: a reduction in emissions of one substance (e.g., ammonia) is sometimes accompanied by an increase in emissions of another (e.g., nitrous oxide). The nitrogen efficiency of food production is therefore of crucial importance. It is defined as the ratio of nitrogen in the final product (meat, milk, etc.) to the nitrogen in the input (the fertilizers or feed). The higher the nitrogen efficiency, the less nitrogen is lost to the environment.

Agriculture has a small share in nitrogen oxide (NOx) emissions, but a large share in ammonia (NH3) emissions. The main sources of ammonia emissions are barns, manure storage, field application of manure, and manure processing. Ammonia is a major contributor to nitrogen deposition in nature reserves. To achieve the European nature goals, it is therefore important that the emission of ammonia decreases. The most important measures to reduce ammonia emissions are as follows: Feeding measures (supplements in feed, reducing protein content in feed; Animal housing (low ammonia emission stall systems and floors, air scrubbers); Manure storage (covering manure, acidification of manure); Manure application (manure separation, low emission manure application, reduced urea fertilizers, urease inhibitors).

Within AgriDataValue, we aim to reduce mainly the ammonia emissions from cattle and pigs by the above-mentioned measures by implementing ML algorithms to accurate predict the emission reduction. To achieve the goal, we plan to utilize existing measurements from existing sensors such as emission measurement, feed intake and analysis and manure analysis, air scrubber data, and measurements that become available in the near future, to build ML models that will calculate these manure emissions.

3.4.2.2 Target Scenario and Approach

Within AgriDataValue, we plan to study and analyze sensor data from various sources in order to predict the major nitrogen emission from livestock.

Unfortunately, historical Big Data of different emission trials are not available. Thus, to achieve the goal, we plan to utilize few existing historical data and measurements from existing sensors such as emission measurement, feed intake and analysis and milk production parameters, and new measurements as they become available in the near future, to build ML models that will calculate the emissions. Additionally, project partners have some semi-trained ML models that will be further trained in the course of this use case.

3.4.1 UC 4.3: Proactive cattle/pig health/welfare monitoring

Objective: A modern farm has already many sensors that were not initially intended to monitor health and welfare of the animals, such as activity sensors, neck belts, RFID tags, temperature and humidity sensors, scales, feed intake/concentrate intake, milk production, fat and protein content of the milk. Screening and linking these data can lead to predictions before clinical symptoms become detectable.

3.4.1.1 State of play

Animal welfare and health is getting more and more attention from livestock producers, consumers, and policymakers alike. Therefore, there is a tendency to continue improving the health and welfare of our livestock. Even though there is still disagreement on how animal welfare can be objectively measured, there are sufficient sensors present on most livestock farms.~~,~~ Although most developed to monitor production parameters, if linked and processed in the right way can be used to predict and monitor animal health and welfare.

Within AgriDataValue, we aim to enhance animal health and welfare for the targeted livestock species by implementing ML algorithms to identify changes in behaviour and production parameters that indicate changes in health and welfare. To achieve the goal, we plan to utilize existing sensor measurements from feed intake and production parameters, weight (gain), temperature, humidity, moving behaviour, and measurements that become available in the near future, to build ML models that will predict changes in production parameters and behaviour that can be correlated with health and welfare issues.

3.4.1.2 Target Scenario and Approach

Within AgriDataValue, we plan to study and analyze sensor data from various sources in order to indicate changes in animal health for cattle and pigs. To achieve the goal, we plan to utilize existing measurements from existing sensors such as emission measurement, feed intake and analysis and milk production parameters, and measurements that become available in the near future, to build ML models.

Historical Big Data for this kind of work are non-existent, therefore a platform that can easily collate and integrated data. This would allow to better train ML models that they become more advanced to be used in practice.

3.4.2 UC 4.4: Calving monitoring

Objective: Calf losses are often result of dystocia (difficult calving). Losses may be reduced by sending calf birth alarms as the earlier help is sought the greater the survival rate of both cow and calf.

3.4.2.1 State of play

Good herd management is one of the major contributors to optimized reproductive performance and farm net return. Calving monitoring and assistance represent a weak point worldwide; although sometimes neglected, parturition is a crucial event for both the dam and the new-born. Prolonged or difficult calving (dystocia) and untimed (both late and early) assistance can compromise welfare, fertility, and milk production of the dam, together with survival, growth and future performance of the calf. Dystocia is a great concern in dairy cattle, with an incidence ranging from 10.7 to 51.2% in USA, and from 2 to 22% in Europe. In that case, the health of both the mother and the calf is at risk. In beef cattle, the incidence of difficult calving is usually lower and ranges from 3 to 7.7%. Moreover, 6-10% of new-born beef calves are lost at birth and/or very soon after birth. Half of them are lost as a result of calving complications. Incidence of calf mortality within 48 h of life ranges from 5.3 to 13.2% in USA with the majority of events occurring in calves born from primiparous cows; in Australian beef pasture-based systems, it reaches 20% in primiparous dams.

Animals tend to give birth at night when they feel safest. Only 50% of primiparous and 70% of older lactating cows are able to give birth on their own. On farms with management problems, almost every cow loses at least one calf in her lifetime due to delayed assistance and/or lack of human presence at birth.

Awareness of the effects of dystocia on dam and calf welfare, survival and farm net return is growing among farmers and stakeholders. Improved calving monitoring and assistance are essential to timely recognition and resolution of dystocia and colostrum administration to new-borns. However, the identification of the exact beginning of parturition is challenging. The majority of farms rely on software to calculate the expected date of calving based on the day of the last insemination, but length of gestation varies. In systems where natural breeding is used or when the date of the last insemination was not recorded, the date of calving can only be presumed with approximation of 10 days.

Pre-calving changes in behaviour in cattle are represented by increased restlessness, reduced feed intake and rumination, seeking for isolation associated with frequent postural changes, tail raising and greater frequency of lying bouts. Those changes in behaviour become more frequent in the last hours before calving. Visual observation of periparturient animals could be carried out through video recording by cameras placed on the maternity pen, but this method is time-consuming and rarely used. The frequent presence of an observer could also induce discomfort in periparturient animals, induce the release of catecholamines and interfere with the calving process. With the use of precisely designed algorithms, it is possible to monitor the movements and posture of cows in real time before giving birth, which allows to make a decision on further action. The second phase (stage II) of the calving process, or the expulsion of the fetus, is the most important. It usually lasts less than one hour. This is the time when help should be given if necessary and the time when the calf is most likely to suffocate or develop respiratory acidosis, which causes prolonged wasting due to non-absorption of immunoglobulin. Research shows that automated sensors are much more accurate compared to visual observation. Timely calving assistance and initial neonatal care reduce the incidence of postpartum uterine diseases such as retention of fetal membranes, metritis and neonatal mortality, uterine infections, but improve the insemination outcome. Ensuring colostrum intake in the first 6 hours of life is essential for calf survival. Information on the exact time of calving also helps improve calf immunity and growth through a more successful colostrum management option [63].

3.4.2.2 Target Scenario and Approach

There are already commercial solutions for calving monitoring. The animal is equipped with a collar that provides monitoring of the moment of calving. Based on changes in the behaviour of the cow, with the help of an accelerometer and algorithm, the received information is automatically evaluated according to the physiological state of the animal, and using automatic data exchange is sent to the attached smart device (host's computer, telephone). Animals are constantly monitored both in the barn and on pastures. This system is very simple to use – the collar needs to be put on only once in the life of the animal, and the **service is provided for the entire life of the cow**. It helps to reduce your mental load: less stress, more confidence in what is happening and less unnecessary manipulation of animals.

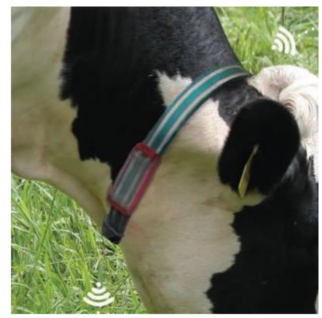


Figure 28: Vel'Live® Cattle calving detection system

The system analyses parameters such as the rumination time, standing time, number of steps, sleeping time and number of times lying down, tail lifting, as well as activity and behaviour changes to precisely identify the beginning of the expulsive phase, thus warning farm personnel and encouraging timely intervention [64]. As an example, the duration of stage II of calving has been reported to average 64.0 min for unassisted primiparous, 42.7 min for assisted primiparous and 20 min in multiparous cows. Methods for the identification of the beginning of expulsive phase are phone alerts and relative time of alarm reception could be used to schedule intervention in case time interval from alert and calving progression exceeds the median.

However, manufacturers of existing calving monitoring systems are reluctant to allow external users and other 3rd parties to get access or modify their configuration or operation mode. In AgriDataValue approach, we plan to study and analyse IoT data from various sources:

- Statistical data from the beef animal groups with and without the calving sensors;
- Data from the National Animal Data register;
- CSV file from the database.

According to the National legislation and in compliance with the CAP requirements the animal data should be recording, and the data transferred to the National Animal Data register. At this stage the compliance with the different registers causes big challenges. Finally for the end users – other farms the recommendations will be elaboration on the parameters which should be followed for the increasing the survival rate of both cow and calf.

3.4.2.3 Interaction Analysis

Figure 29 provides the interaction analysis of Calving monitoring UC in a UML like Use Case Diagram approach. All main actors/ end-users participate at the specific UC 4.4.

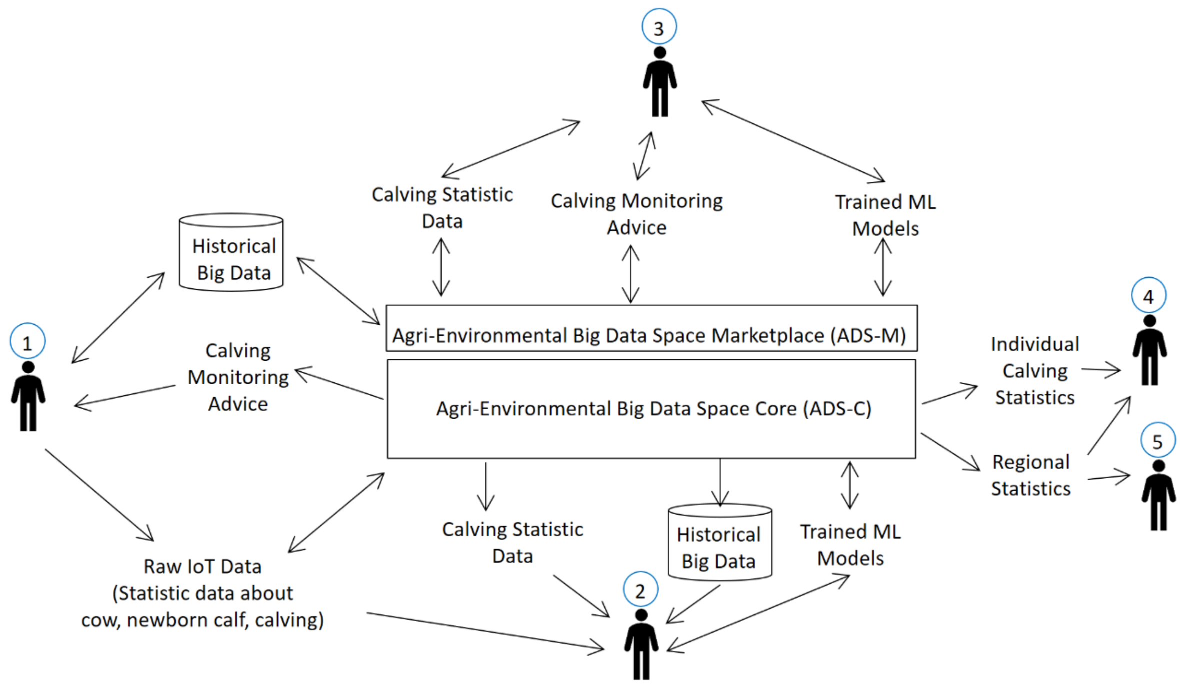


Figure 29: Calving monitoring UC Interaction Analysis Diagram

As can be seen, Actor 1 (Farming companies, Cooperatives and Individual Farmers) interacts both directly with the ADS-C and the ADS-M logical components. Actor 1 provides to ADS-C: a) ***Raw IoT Data*** (statistic data about cow, new-born calf, calving). Moreover, via the ADS-M may offer ***Historical Big Data*** and ***Semi-trained calving monitoring ML models***, under specific incentives/ fee. The ADS platform responds with ***Calving Monitoring Advice***. To facilitate research and experimentation, Actor 2 (farming and livestock research institutes) is allowed to interact directly with the ADS-C and receive any type of ***historical data***, ***calving monitoring data***, along with ***trained ML models***. In return, Actor 2 offers more advanced or experimental ML models, for calving monitoring, which may be utilized by Actors 1 and 3.

Actor 3 (Specialized service and technology providers offering added valued services based on Agri-data and AgriDataValue technology) access the ADS platform only via the ADS-M component. Via specific smart contracts may retrieve or provide any type of shared data, information or advice, including ***calving statistic data***, ***historical shared data*** and ***trained ML models***. Actor 4 may retrieve ***individual calving statistics*** on livestock data to calculate the farmer CAP national/ regional supporting funding. Finally, both Actor 4 and Actor 5 (EU stakeholders/ policy) retrieve ***regional statistics*** in order to evaluate the fulfilment level of specific CAP policies/strategies.

3.5 Use Case Cluster 5: Cross Sector

The UC Cluster 5 is focused on Cross Sectors' applications and aims to underline AgriDataValue focusing on a business-oriented dimension.

Objectives: In detail, the objective of UC Cluster 5 are to:

- Validate cross domain use cases (fruit, vineyards, livestock, milk, oil, biogas, manure, energy)
- Address both supply and demand sides of the supply chain, including interoperability and traceability of platforms, electricity production and waste management.

Though all Use Cases have been selected to create significant impact in the agriculture domain, AgriData Space will also experiment with a unique case of combining multiple pilots in a single circular economy case (UC5.1), along with meat/milk traceability (UC5.3/UC5.4). It will be realized by TBA, member of Agrinio Union, one of the largest agricultural cooperatives in Greece with more than 20.000 members [65]. The approach to realize the UC cluster 5 objectives is to combine historical, (real-time) and Big Data processing technologies such as IoT sensors, edge cloud, drones/satellite visual/multispectral images and AI models and train ML-based applications to provide advice on improved cross sector, added valued services.

3.5.1 UC 5.1: Fully Circular ecosystem

Objective: Experiment and model the correlation of IoT data, ranging from forage crop production, cattle feed, welfare and manure handling, biogas generation, electricity production and utilization of solid and liquid waste in biological fertilization and irrigation of crops (including forage).

3.5.1.1 State of play

It is well known that fertilizers represent an important cost of the crops, while the cost of the feeding the animals is the most important cost of the livestock farmers, which is constantly increasing. Depending on the mix of organic animal by-products/wastewater and agricultural residues and silages in an area (e.g., cattle farms, other livestock units), the mineral content of the digestate may be more suitable for agricultural use. This has the consequence of reducing the need for chemical fertilizers and thus saving farmers money.

Manure is the most abundant source of organic material within the animal sector, which is correlated with the animal type. About 23 kg of cattle manure are produced per animal per day [66], which has 3% nitrogen, 2% phosphorus, and 1% potassium (3-2-1 NPK), making it the right type of fertilizer for almost all types of plants and crops. That's because it brings back nutrient balance to fields organically. Despite the Circular Economy Regulations, which not allow untreated animal manure incineration, in many cases, manure is used on farms without proper treatments, releasing carbon dioxide (CO_2), methane (CH_4), and ammonia (NH_3) contributing to GHGs emissions, while sometimes, it can contain dangerous pathogens and bacteria, such as EColi [67]. So, an aging or decomposition process is necessary to break down the organic matter and eliminate the harmful substances before the manure.

Cow and pig manure contains a high amount of carbohydrates and proteins respectively with a theoretical amount of 469 and 516 Liquid CH_4 (LCH_4)/kg VS [68]. Recent studies from the Danish Institute of Agricultural Sciences propose that the application of treated waste as a soil conditioner to one hectare of grasses ensures savings of at least 34 kg of nitrogenous fertilizer. Beyond environmental and soil protection, this may result in a farmer profit of €20, thus a reduced production cost of up to 40%. A small biogas unit produces an amount of liquid or solid organic fertilizer (as a free by-product), enough to cover the organic fertilization of 5,000 – 10,000 acres, which can be given free to farmers.

3.5.1.2 Target Scenario and Approach

UC5.1 is based on combination of use cases and pilots and will be mainly realized by TBA, an AgriDataValue beneficiary and member of the Agrinio Union cooperative [65]. As it is shown in in Figure 30, we consider a fully circular economy example. We may start from cattle which are mainly fed for their meat, without underestimated milk. Various farm and animal wearable sensors will be used to monitor animals' welfare, activity, feed, calving and emissions, and are part of UC cluster 4. Meat traceability and Milk/Dairy traceability are considered in UC5.2 and UC5.3 respectively.

In this UC example, manure, dairy factory waste and crop waste (including local olive mill waste) will be used to feed two anaerobic digesters already available by TBA to produce biogas. Biogas will be consumed by an 5MW electricity generator, which provides electricity to the grid. The anaerobic residual digesters waste material left after the digestion process is called *"Digestate"* and it is composed of liquid and solid portions. These are often separated and handled independently, as each have value that can be realized with varying degrees of post processing. Within AgriDataValue digestate will be utilized as organic fertilizers in the form of compost (solid waste) and irrigation water (liquid waste).

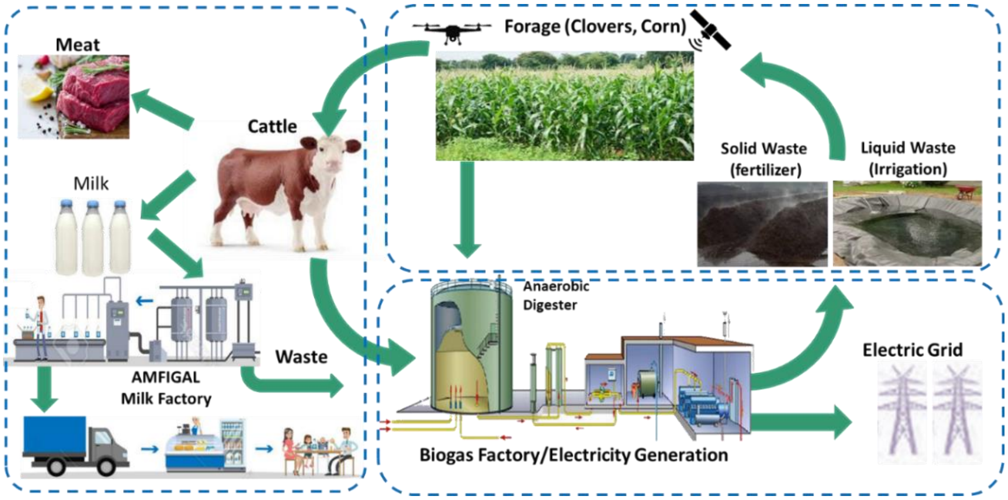


Figure 30: Circular Economy and Meat/Milk traceability Pilot

As it is shown in Figure 30, IoT sensors, geotagged cameras and satellite multispectral data supported by edge cloud processing will be utilized to improve the forage crop production and inspect climate change. We plan to study and analyze IoT data and images from various sources to calculate the economic profit of the circular economy experiment and the impact in the climate, along with GHG reduction. We plan to calculate the average manure produced per animal, based on species, feed mixture and age, using various farm (e.g., Synelixis SynAir product) and wearable sensors which will be used to monitor animals' welfare, activity, feed, calving and emissions. The produces manure will be injected to the anaerobic digesters and the biogas generated will be calculated. As a next step, we will measure the produced liquid and solid waste (compost), along with their influence in forage production. It is known that the soils in Greece, after the reckless use of chemical fertilizers for several years, have a serious fertilization problem. Finally produced forage will be feed to cattle.

3.5.1.3 Interaction Analysis

Figure 31 provides the interaction analysis of Circular Economy UC in a UML like Use Case Diagram approach. All main actors participate at the specific UC. As can be seen, Actor 1 interacts with AgriDataValue system and provides: a) ***raw IoT Data***, such as local micro-clima data (air temperature and humidity, rain volume and precipitation data, wind direction and volume), soil moisture and temperature, leaf wetness, air quality data, manure and animal waste produced, animal welfare, activity, feed, calving data, generated Biogas/Energy, liquid/solid digestate and b) ***Feedback on volume and quality of generated secondary (sub-)products***. Moreover, via the ADS-M may offer ***historical Big Data*** and ***semi-trained circular economy ML models***, under specific incentives/ fee. To facilitate research and experimentation, Actor 2 is allowed to interact directly with the ADS-C and receive any type of ***historical data***, ***weather data*** and ***satellite data***, along with ***trained ML models***. In return, Actor 2 offers more advanced or experimental ML models along with financial analysis and investment advice of circular economy establishments sustainability, which may be utilized by Actors 1 and 3. Actor 3 may retrieve or provide any type of shared data, information or advice, including ***historical shared data***, **satellite's data**, ***statistics*** and ***financial analysis and investment advice of circular economy establishments sustainability***.

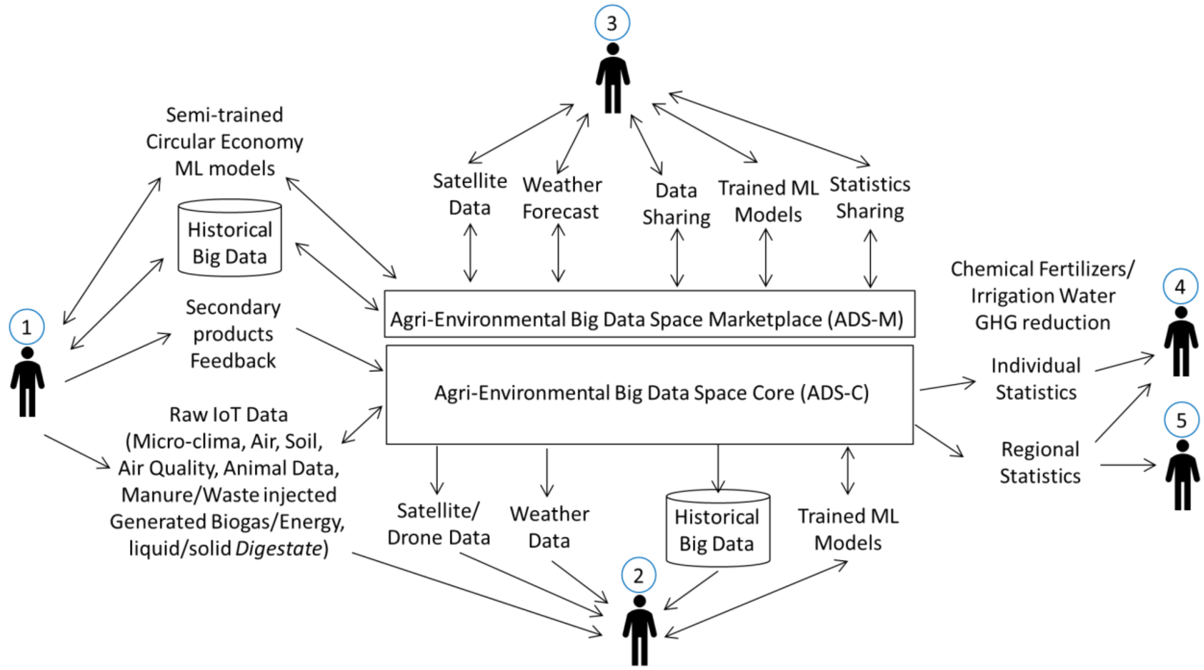


Figure 31: Circular Economy Interaction Analysis Diagram

Actor 4 may retrieve ***individual statistics*** on biogas/energy and liquid/solid digestate produced, to calculate the **reduction in chemical fertilizers applications and in clean water consumption** for irrigation, which may be used when calculating the CAP national/ regional supporting funding. Finally, both Actor 4 and Actor 5 retrieve ***regional statistics*** to evaluate the fulfilment level of specific CAP policies/strategies, including soil strategy objectives.

3.5.2 UC 5.2: Supply Chain transparency for Winemaking

Objective: Experiment and model both on-farm and post-farm activities, from technical and business perspectives related to orchards/vineyards harvesting, fruit processing/wine production and supply chain traceability, including data business models.

3.5.2.1 Target Scenario and Approach

Many stakeholders in the wine/vineyards supply chain already have some sort of data gathering system in place. In some cases, there are even silos of data stored in private databases. Within UC5.2, we plan to research by corelating grapes and wine production data in AgriDataValue platform blockchain facility. However, the objective is to trace up to the wine fermentation/ageing at cellars rather than all the way to the consumers table.

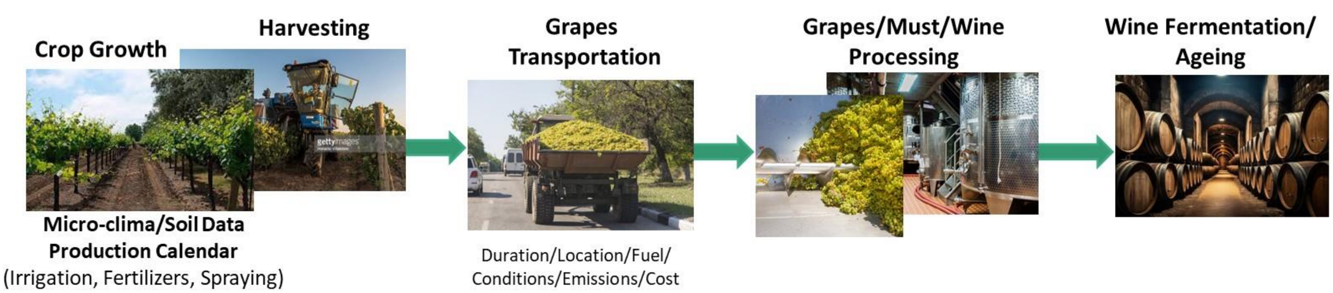


Figure 32: Winemaking Traceability Scenario

As can be seen in Figure 32, the scenario starts from the vineyards, where grapes are growing and gathers data related to weather and micro-clima, satellite/drones, soil and leaf, along with crop production calendar, including any type and volume of irrigation/water consumption, application of any type of fertilizers or pesticides spraying (if any), or any other farming activity (e.g. anti-frost actions). Additional data related with the crop growth history are added, farmer feedback along with AgriDataValue system advise on best practices up to crop harvesting. The timing of the harvest is crucial as it affects the sugar, acid, and flavour levels in the grapes.

As the harvested grapes are transported to the winery additional information on conditions (e.g. temperature, light, humidity), transportation duration and cost may be collected. At the winery, harvested grapes are crushed to release the juice and may also undergo destemming, which removes the stems from the grape clusters. The crushed grapes, along with their skins, seeds, and juice are placed into fermentation vessels, typically stainless-steel tanks or oak barrels. Yeast is added to the mixture to convert the sugars in the grapes into alcohol through the process of fermentation. This can take anywhere from a few days to several weeks, depending on the desired style of wine. After fermentation, the mixture is pressed to separate the solids (grape skins, seeds, etc.) from the liquid (wine). The liquid is transferred to a different container, while the solids are usually discarded or used for other purposes such as making grape pomace oil or for distillation. Whatever remains may be provided as waste to circular economy UC. The wine is often aged, from a few months to several years, depending on the type of wine being produced, in oak barrels or stainless-steel tanks to develop complexity and enhance flavours. To remove any remaining solids or impurities, the wine may undergo a process of clarification and filtration. Finally, once the winemaker is satisfied with the wine's flavour and quality, it is ready for bottling. Aging in bottle at winery's cellar allows the wine to further develop and evolve over time.

Nevertheless, as a full traceability use case from farm to fork for grapes/wine supply chain is beyond the AgriDataValue scope, we concentrate on the farm to winery steps, which may be latter extended to cover the complete supply chain.

3.5.2.2 Interaction Analysis

Figure 33 provides the interaction analysis of the Grapes/Wine supply chain traceability UC in a UML like Use Case Diagram approach.

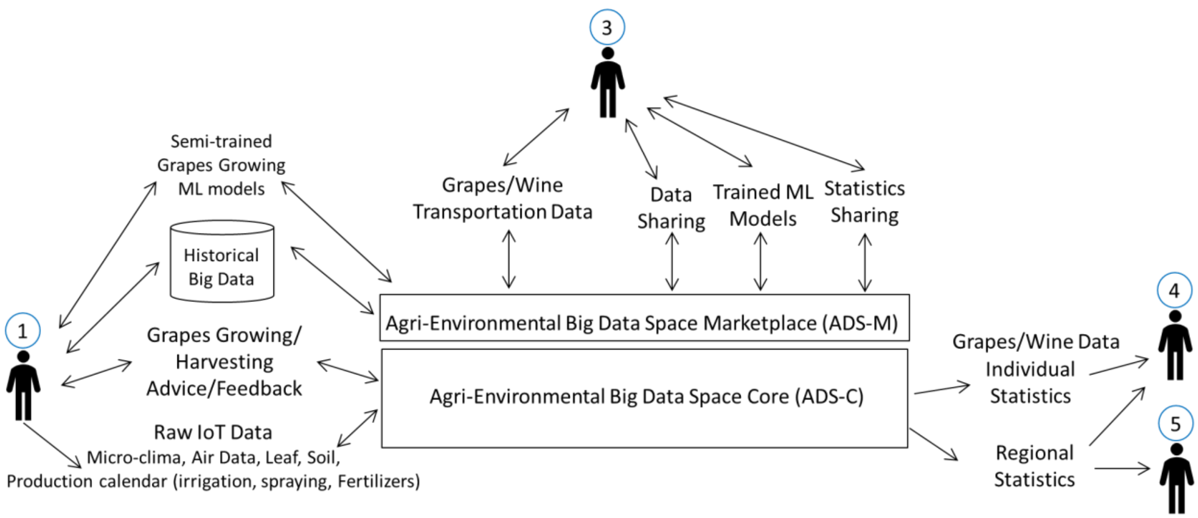


Figure 33: Grapes/Wine supply chain traceability Interaction Analysis Diagram

The UC can be considered in relation to other UCs such as reduction of irrigation, fertilizers or spraying. Though all main actors could participate at the specific UC, we focus on the Actors 1, 3, 4 and 5. As can be seen, Actor 1 interacts with AgriDataValue system and provides: a) ***raw IoT related Data*** (micro-clima, air-data, Leaf and Soil data), b) ***Production calendar*** data (i.e., dates and volume of irrigation, spraying, fertilization) and c) ***Feedback on production*** to receive ***advice on best practices***. Moreover, via the ADS-M, Actor 1 may offer ***historical Big Data*** and ***semi-trained grapes production ML models***, under specific incentives/ fee. Actor 3 may retrieve or provide any type of shared data, information or advice, including ***grapes/wine transportation data***, ***statistics*** and ***financial analysis***. Actor 4 may retrieve ***individual statistics*** on grapes/wine data to calculate the farmer CAP national/ regional supporting funding. Finally, both Actor 4 and Actor 5 retrieve ***regional statistics*** to evaluate the fulfilment level of specific CAP policies/strategies, including soil strategy objectives.

3.5.3 UC 5.3: Supply Chain transparency for Meat traceability

Objective: Experiment and model both on-farm and post-farm activities, related to cattle/pig meat production, by interoperable farm, slaughterhouse, and supply chain traceability.

3.5.3.1 State of play

Meat traceability is a concept which is becoming increasingly discussed and have recently emerged on most consumers' radars. Traceability in meat production is the ability to trace an individual cut of meat from field to fork. This means that any beef, lamb, pig or animal produce that ends up on customers' plate, can be tracked all the way back to the farm and the animal, which it came from. By following traceability processes at each stage of a supply line, it is possible to achieve full meat traceability. Similarly in case of milk/dairy traceability, any bottle/carton of milk, piece of cheese, yogurt or dairy in general should be able to be tracked all the way back to the farm and the animal, which it came from. This also includes the animal related information and the way it has been fed.

Agri-food traceability is part of the EU regulation 2017/625, on "enforcing EU rules for the agri-food chain" [69]. The regulation establishes common rules for EU official controls to ensure that agri-food chain legislation for the protection of human health, animal health and welfare, and plant health, is correctly applied and enforced and introduces a better harmonised and coherent approach to official controls and enforcement measures along the agri-food chain and strengthens the principle of risk-based controls. To ensure that the Union agri-food chain legislation is correctly enforced, the competent authorities should have the power to perform official controls at all stages of production, processing and distribution of animals and goods concerned by that legislation. Moreover, to ensure that official controls are thoroughly conducted and effective, the competent authorities should also have the power to perform official controls at all stages of production and distribution of goods, substances, materials or objects which are not governed by Union agri-food chain legislation insofar as it is necessary to fully investigate possible infringements of that legislation and to identify the cause of any such infringement.

For transparency reasons, the national authorities must publish annual reports on traceability, along with rules for calculating fees to ensure that EU countries properly finance their control system and that the fees do not exceed the cost of performing official controls [70].

3.5.3.2 Target Scenario and Approach

Many stakeholders in the meat supply chain already have some sort of data gathering system in place. However, currently most of the data gathered is mainly being used for food safety purposes. In some cases, there are even silos of data stored in private blockchain to offer cattle traceability. The potential of structured large-scale data collection for the improvement of resource efficiency, animal welfare and product transparency in the beef supply chain is still largely unexplored. Within UC5.3, we plan to research by corelating animal production, feed and traceability from the stable to the local slaughterhouse, including animal feeding, wellbeing and growth data in AgriDataValue platform blockchain facility.

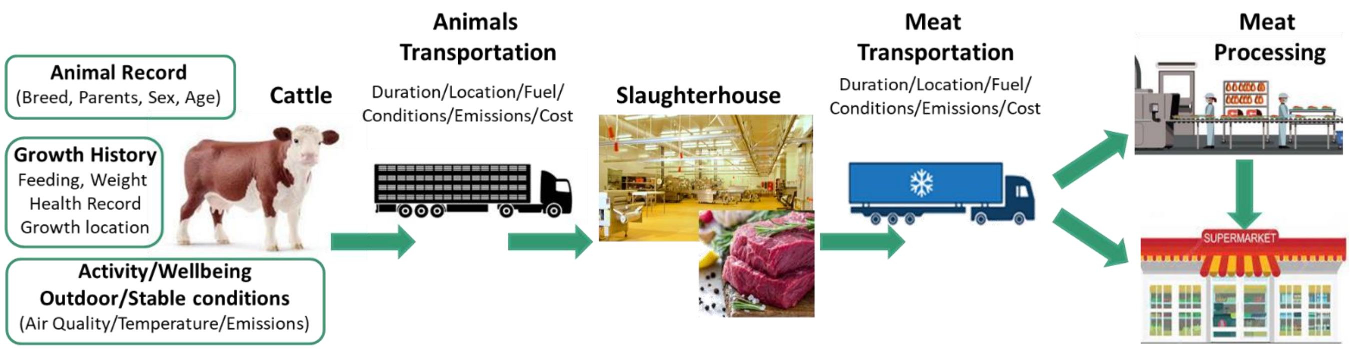


Figure 34: Meat Traceability Scenario

As can be seen in Figure 34, the scenario starts from the initial animal record/genealogical tree including the animal breed, parents, sex, age etc. Additional data related with the animal growth history are added, including the feeding history, weight, growth location, health record along with any medication or feed supplements. Finally, animal habits, movement, wellbeing and (outdoor/indoor) living conditions are added.

As the animal is transported to the slaughterhouse additional data related to transportation duration, location, conditions along with truck emissions, fuel and cost are added. At the slaughterhouse, additional information related with the animal health and process is added. The next step includes meat supply chain, transportation to the store or processing at meat factory and intermediate storage.

Nevertheless, as a full traceability use case from farm to fork for meat supply chain is beyond the AgriDataValue scope, we concentrate on the farm to slaughterhouse steps, which may be latter extended to cover the complete supply chain.

3.5.3.3 Interaction Analysis

Figure 35 provides the interaction analysis of the Meat supply chain traceability UC in a UML like Use Case Diagram approach. Though all main actors could participate at the specific UC, we focus on the Actors 1, 3, 4 and 5.

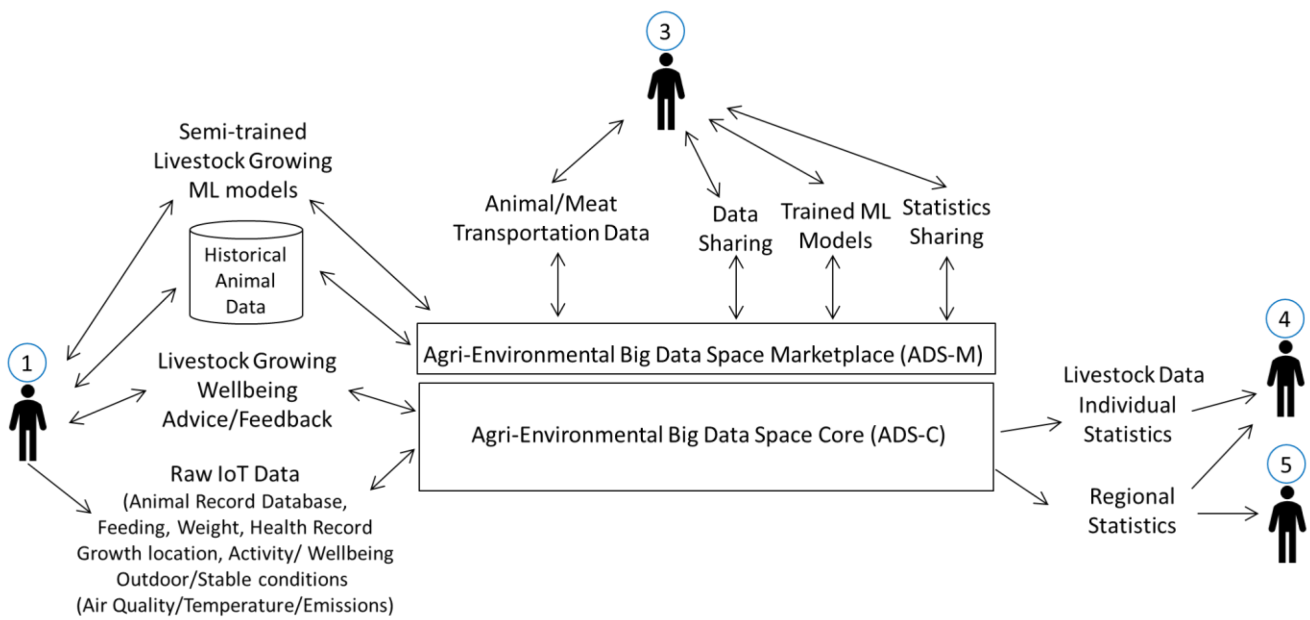


Figure 35: Circular Economy Interaction Analysis Diagram

As can be seen, Actor 1 interacts with AgriDataValue system and provides: a) ***raw Animal related Data*** (animal breed, genealogical tree/parents, Sex, Age), b) **Growth History** (all feeding information, animal weight record, health record, growth locations etc), c) **Activity/Wellbeing** of the animal, including **Outdoor/Stable conditions** (Air Quality/Temperature/Emissions). Moreover, via the ADS-M, Actor 1 may offer ***historical Big Data*** and ***semi-trained irrigation ML models***, under specific incentives/ fee. Actor 3 may retrieve or provide any type of shared data, information or advice, including ***animal/meat transportation data***, ***statistics***, ***financial analysis and investment advice of livestock production***. Actor 4 may retrieve ***individual statistics*** on livestock data to calculate the farmer CAP national/ regional supporting funding. Finally, both Actor 4 and Actor 5 retrieve ***regional statistics*** to evaluate the fulfilment level of specific CAP policies/strategies.

3.5.4 UC5.4: Increase farmers' digital independence

Objective: Increasing farmers' digital independence in precision farming and IoT applications

3.5.4.1 State of play

Precision farming techniques can potentially optimize or even reduce the required inputs such as fertilisation, irrigation, crop protection and labour. Precision agriculture can potentially be a mechanism to meet food production needs while reducing environmental impacts [71]. Variable rate technologies can match the actual need for fertilizer or crop protection in that specific place of the field. These variable rate task maps are often based on scans, drone- or satellite imagery. IoT technology has transformed agriculture with providing farmers real time data (Figure 36).

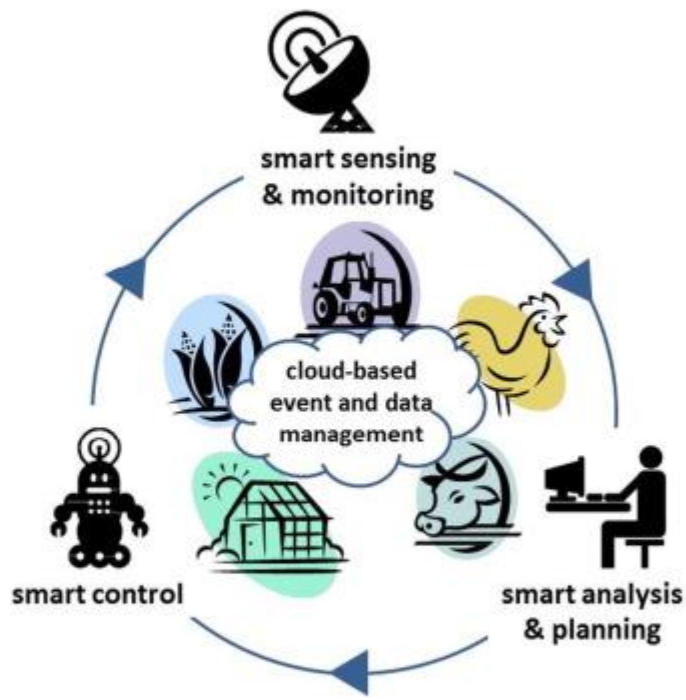


Figure 36: Data management in smart farming [85]

By using these newest digital technologies farmers could produce higher yields, reduce waste and practice more sustainable. It could improve their decision-making, increase their profits, improve working conditions by automatization and increase transparency. But despite all these potential advantages, there is still some reluctance to use these technologies, especially in smaller farms. Some reasons for this reluctance include connectivity issues, unawareness of the benefits, incompatibility between platforms, lack of digital skills, high initial investment cost and privacy concerns. Farmers prefer easy-to-use technologies such as automatic steering, section control and forecast apps and tend to stay at their current technology level [72, 73].

Challenges in adopting Big Data are often characterized by the 4 Vs: Volume, velocity, variety and veracity. To solve problems, large **volumes** of data are needed, these large volumes can be overwhelming for the farmer. Farmers need the decision making to be fast. When they receive data of their field, they want to handle on it quickly, this is implied by the second V: **velocity**. The data that is gathered on the farm consists of a large **variety** of data types and they often need to be processed together. Farmers need to be certain of the **veracity** of this data for it to be considered in their decision making. Faulty data could have an impact on their quality and yield [74].

3.5.4.2 Target Scenario and Approach

In this use case we will host a learning network of farmers. This network will allow collaboration between the farmers and interchanging of knowledge and experience. The network will be guided by agronomists who can aid when digital skills of the farmers are insufficient and provide training to further the farmers digital independence.

The farmers are allowed to pick a precision agriculture topic of their choice, ensuring the practical relevance of the topic. Providing support will stimulate the farmers to test new technologies and farm management strategies. These new strategies can optimize or reduce fertilisation and pesticide usage.

These use cases can highlight issues and barriers with using precision farming techniques. These issues can be brought to the attention of the technology providers. With permission of the host farmers, the successful cases could serve as an example to other farmers and improve precision farming adoption levels.

3.5.4.3 Interaction Analysis

Figure 37 provides the interaction analysis of UC 2.5 in a UML like Use Case Diagram approach.

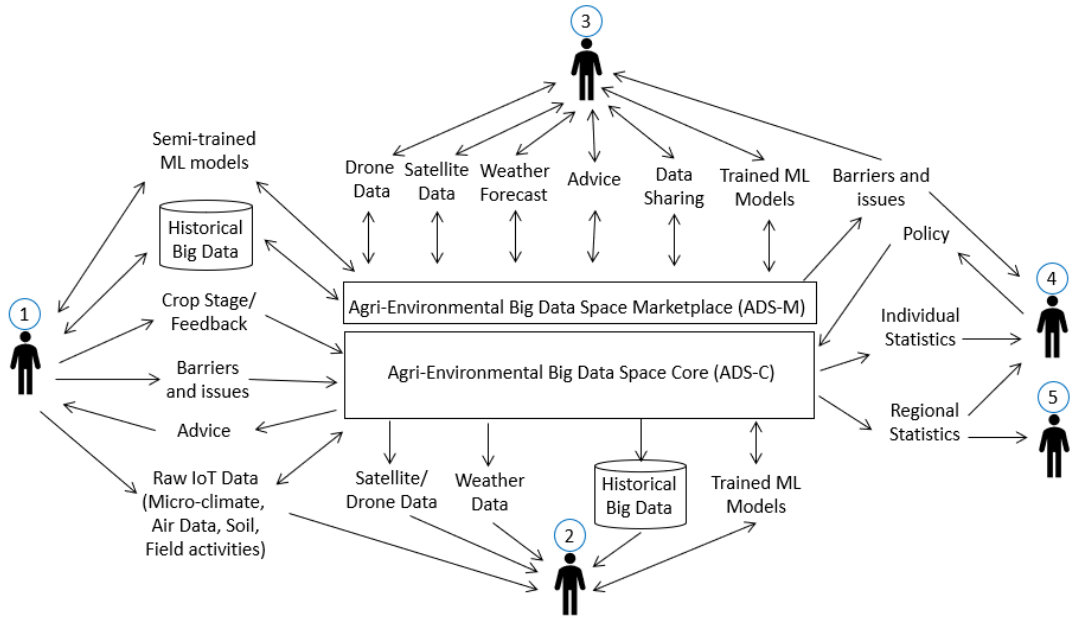


Figure 37: UC 2.5 Interaction Analysis

As can be seen, Actor 1 (Farming companies, Cooperatives and Individual Farmers) interacts both directly with the ADS-C and the ADS-M logical components. Actor 1 provides to ADS-C: a) ***raw IoT Data***, such as local micro-climate data (rain volume and Precipitation data, wind direction and volume, air temperature and humidity), soil moisture and temperature, along with a schedule of their relevant field activities and b) ***crop stage feedback***, informing the system on the crop growth stage and feedback on the advice. Moreover, via the ADS-M may offer ***historical Big Data*** and ***semi-trained ML models***, under specific incentives/ fee. The ADS platform responds with ***Advice*** concerning a specific activity such as fertilisation.

To facilitate research and experimentation, Actor 2 (farming and climate monitoring research institutes) is allowed to interact directly with the ADS-C and receive any type of ***historical data, weather data*** and ***drones/satellite data***, along with trained ML models. In return, Actor 2 offers more advanced or experimental ML models, which may be utilized by Actors 1 and 3.

Actor 3 (Specialized service and technology providers offering added valued services based on Agri-data and AgriDataValue technology) access the ADS platform only via the ADS-M component. Via specific smart contracts may retrieve or provide any type of shared data, information or advice, including ***historical shared data, drones' and satellite's data, advice*** and ***ML trained models***. They can also receive feedback from the farmers on the current barriers and issues, so that they may improve their products.

Actor 4 (CAP paying authorities) directly via the ADS-C module imposes to the platform specific policies (such as eco-schemes) and retrieves ***individual statistics*** to be used when calculating the CAP national/ regional supporting funding. Finally, persona from both Actor 4 and Actor 5 (EU stakeholders/ policy) retrieve ***regional statistics*** to evaluate the fulfilment level of specific CAP policies/strategies, including soil strategy objectives. The policy makers can also receive the current barriers and issues so they can take these into consideration when making new policy decisions. This information is very sensitive and will/can only be shared if agreed to by the farmer.

3.6 Use Cases Cluster 6: CAP realization

The UC Cluster 6 is focused on CAP realization tools/applications and aims to underline AgriDataValue focusing on a CAP monitoring tools.

Objectives: In detail, the objective of UC Cluster 6 are to:

- Assess and manage the risk through modern ML, aiming to reduce the use of pesticides, fertilisers, and antibiotics.
- Bring forward modern crop monitoring technologies (e.g. automatic pixel classification of satellite images, automatic processing of data received from in-situ sensors)
- Benchmark eco-scheme monitoring tools to support the new CAP towards fair income, land use protection and environmental care.

3.6.1 UC 6.1 Economic risk assessment

Objective: Assessing and managing the risk through modern machine learning (ML), that help farmers to adopt "external" recommendations in collaborative production and predicting the yield quality. In parallel, the National contribution to EU objectives are to reduce the use and risk of pesticides, fertiliser and antibiotics.

3.6.1.1 State of play

By the year 2050, planet Earth will be the home to more than 10 billion people, and we need to increase agricultural production for as much as 65% to feed all inhabitants. Today, we are already cultivating almost every piece of land we can, ***consuming more than 70% of drinking water for crops' irrigation (and more than 60% of this water is wasted due to overirrigation)*** [1] and use more than 220.000 tonnes of synthetic fertilisers and pesticides annually only in Europe, further aquifer contamination via deep infiltration, while jeopardising our fragile eco-system and causing climate change. Beyond water waste, overirrigation increases the potential of crop yield loses from fungal and bacterial foliar, disturbs the oxygen balance of the root zone, reduces plant water uptake, causes a decrease in soil temperature, thus reduces root growth, increases energy use for pumping, causes leaching of nitrogen and other micronutrients, roots rotting diseases. Similarly, livestock plays a significant role in balancing climate ecosystem. In Europe (EU27), the agricultural sector is responsible for 11% of total greenhouse gas emissions [2], while an excessive concentration of greenhouse gases, such as carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) from livestock enteric fermentation, raises the average annual temperature, contributing to the global warming. In parallel, according to FAO ***climate change is emerging as a major challenge to agriculture and biodiversity***.

The last couple of years, modern farms are creating a huge amount of data. Smart terrestrial sensors on the fields measure the micro-climate, the air humidity and temperature, the rain volume, the irrigation water usage and examine the soil conditions and pest developments; GPS-guided tractors and farming machines, flying drones and satellites with multi-spectral cameras produce data about the exact field irrigation, fertilising and pesticides needs;

wearable sensors provide valuable information for livestock health, growth and wellbeing. By applying Big Data and Artificial Intelligence (AI) technologies on combinations of diverse agricultural data, we can provide significantly knowledge, ultimately support farmers in their decision-making processes, help them run their businesses more efficient and have the potential to enable sustainable innovation and growth.

The European Green Deal, introduced in 2019 by the EC (EC, 2019), sets ambitious targets for the European food and agricultural system for 2030, several being quantitative with a reduction in the use of pesticide, fertiliser, and antibiotics by 50%, 20%, and 50%, respectively. Additionally, a quantitative target has been set to increase agricultural areas under organic farming (25%), agricultural areas under high-diversity landscape features (10%), and protected areas.

The EU Biodiversity Strategy for 2030, as part of the European Green Deal, specifically aims at protecting nature and reversing the degradation of ecosystems, addressing the impacts of climate change, forest fires, food insecurity and disease outbreaks.

CAP Strategic Plans contribute to the objectives of reducing greenhouse gas emissions and increasing carbon sequestration, by protecting and increasing carbon sinks, and addressing emissions from mineral fertilisers and livestock. For the first time, CAP basic standards (conditionality) protect EU agricultural wetlands and peatlands to reduce carbon release. Climate mitigation efforts are stepped up thanks to e.g., restricted tillage, a ban on conversion, drainage, burning or extraction of peat. To remove more carbon, farmers need to further change production methods. The Plans will incentivise land managers to store carbon in soil and biomass and reduce emissions on 35% of the EU's agricultural area through appropriate management practices, such as extensive grassland management, growing of leguminous and catch-crops, organic fertilisation, or agroforestry.

Farmers protect soils and preserve soil potential thanks to crop rotation. All Strategic Plans include this as a new basic condition for farmers instead of new GAEC obligation and the rotation will take place on around 85% of the arable land supported by the CAP. Crop rotations will also help disrupt pest and disease cycles and thus reduce use of pesticides. In addition, the CAP Strategic Plans will help farmers restore soil fertility, reaching up to 47% of EU agricultural land such as through enhanced crop rotation, conservation agriculture, catch crops or vegetation cover in orchards. This also helps increase the water retention capacity and resilience to drought.

Targeting water resilience, specifically, the Plans include support for action on cultivating drought-adapted crops, establishing or restoring landscape features like ponds and hedges, stimulating agroforestry, improving irrigation equipment and infrastructure.

To reduce pollution from fertilisers and pesticides, all farmers receiving support must create buffer strips along water courses of at least 3 metres, sometimes with special provisions for small fields surrounded by water. The Strategic Plans provide for support that aims at reducing emissions during different stages of the nutrient cycle, from feeding and animal housing, to manure storage and application of ammonia. To reduce the use and risk of pesticides, more than 26% of EU agricultural land will receive support e.g., by banning use in certain specific areas, adopting integrated pest management, and using non–chemical methods for pest control such as precision farming. Reduction of pesticide and fertiliser use will also be achieved also through increasing the area of organic production. The size of the area that receives specific CAP support for organic production in 2027 will almost double, reaching close to 10%, compared to the area funded in 2020 (5.6%). This will significantly help Member States' reach their national ambitions for increase in organic areas. The ambitions for those areas across Member States range from 5 to 30% in 2030.

3.6.1.2 Target Scenario and Approach

Transformative changes such as the ones required within the Green Deal and the new CAP may have a significant environmental and economic performance of the agricultural sector. Though the irrigation water pricing does not follow a consistent pattern between member states and the overall level of prices is relatively low, the climate change, especially in countries such as Spain and Greece with large, irrigated areas, is expected to change the irrigation pricing model in the near future. Moreover, irrigation cost is significantly increased by the energy cost of pumping, especially in case of greater depth, while overirrigation increases the potential of crop yield loses from fungal and bacterial foliar, disturbs the oxygen balance of the root zone, reduces plant water uptake, causes a decrease in soil temperature, thus reduces root growth, causes leaching of nitrogen and other micronutrients, roots rotting diseases. Similarly, pesticides usage, only when and if it is really needed, does not only protect the environment and our lives, but has a significant impact in the farmers. In case of livestock, animals' health/welfare, feeding, activity and calving status, play a significant role in climate ecosystem, while affecting economic performance of the farmer.

AgriDataValue will strengthen the capacities for smart farming, and thus enhance the environmental and economic performance of the agricultural sector *via knowledge*. By upscaling (real-time) data from IoT sensors, drones, and agricultural robots (KER-1, KER-5, KER-7) with interoperable, already available dataset and satellite EO data, along with Big Data and Artificial Intelligence (AI) technologies, AgriDataValue will enable to enter the Smart Farming 4.0 era and ***enable sustainable food systems and traceability from farm to fork*** (KER-8).

3.6.1.3 Interaction Analysis

As can be seen, Actor 1 (Farming companies, Cooperatives and Individual Farmers) interacts both directly with the ADS-C and the ADS-M logical components. Actor 1 provides to ADS-C: a) ***raw IoT Data***, such as local micro-clima data (rain volume and Precipitation data, wind direction and volume, air temperature and humidity), soil moisture and temperature, along with volume and schedule of the consumed irrigation water, pesticides/fertilization and b) ***irrigation/ pesticides / fertilization stage feedback,*** informing the system on irrigation/pesticides/ fertilization feedback on advice. Moreover, via the ADS-M may offer ***historical Big Data*** and ***semi-trained economic risk assessment ML models***, under specific incentives/ fee. The ADS platform responds with ***irrigation/ pesticides / fertilization advice*** and if available may offer ***automatic irrigation/ pesticides / fertilization control***.

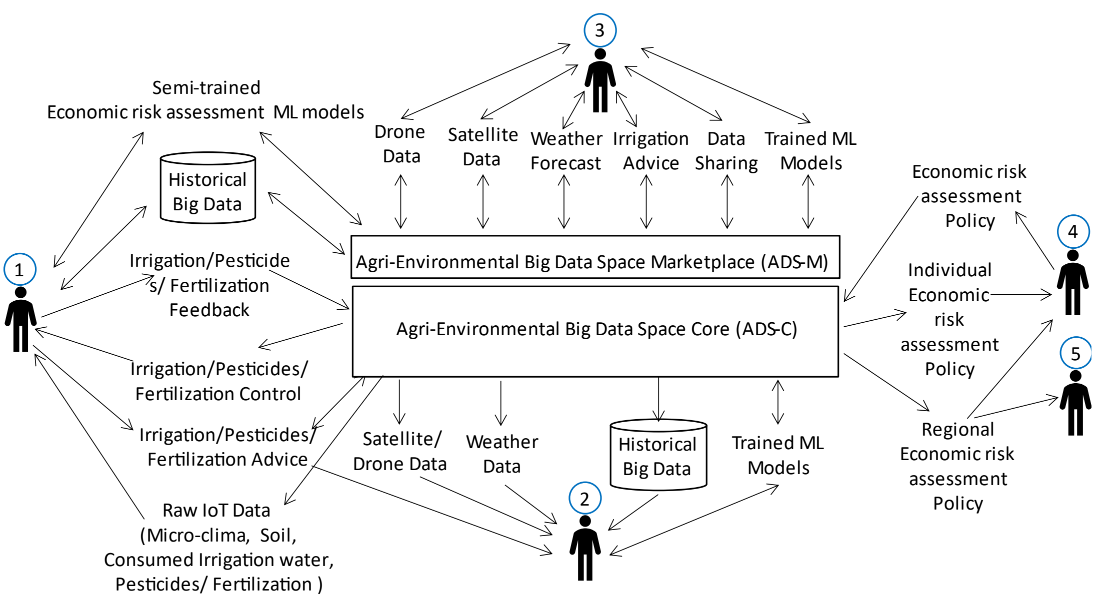


Figure 38: UC 6.1 Interaction Analysis

To facilitate research and experimentation, Actor 2 (farming and climate monitoring research institutes) is allowed to interact directly with the ADS-C and receive any type of ***historical data***, ***weather data*** and ***drones/satellite data***, along with ***trained ML models***. In return, Actor 2 offers more advanced or experimental ML models, which may be utilized by Actors 1 and 3.

Actor 3 (Specialized service and technology providers offering added valued services based on Agri-data and AgriDataValue technology) access the ADS platform only via the ADS-M component. Via specific smart contracts may retrieve or provide any type of shared data, information or advice, including ***historical shared data***, **drones' and satellite's data**, ***irrigation advice*** and ***ML trained models***.

Actor 4 (CAP paying authorities) directly via the ADS-C module imposes to the platform specific ***economic risk assessment policies*** and retrieves ***individual economic risk assessment policies*** to be used when calculating the CAP national/ regional supporting funding. Finally, persona from both Actor 4 and Actor 5 (EU stakeholders/ policy) retrieve ***regional economic risk assessment policies*** to evaluate the fulfilment level of specific CAP policies/strategies.

3.6.2 UC6.2 Real-time input for pilot (satellite images, data sensors, weather forecast)

Objective: The main objective of UC6.2 is to bring forward modern crop monitoring technologies, such as: automatic pixel classification of satellite images, automatic processing of data received from in-situ sensors, weather forecast, in order to help the farmers to make faster and more efficient decisions in the distribution of inputs and treatments on their crops.

3.6.2.1 State of play

The last couple of years, modern farms are creating a huge amount of data which could be used for training ML models and make decisions based on AI algorithms. However, one of the most important hinders is the agricultural data availability and heterogeneity. Sensors' data generated locally is often more precise and valuable, in comparison to global, EU-wide, national, or regional datasets. On the other hand, the combination of local data with datasets from a broader area, allows for comparison of crop and stock raising conditions, automated identification of crop or stock diseases or production delays, well before it could be observed in the area of interest, while it offers significant support for informed decisions related to agricultural production adaptation to climate change or for market analyses. Moreover, the utilization of AI models for combining and upscaling heterogeneous agricultural data, for example local weather or soil measurements with drones' or satellites' multispectral vegetation indices, such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Green Normalized Difference Vegetation Index (GNDVI) and Chlorophyll Vegetation Index (CVI), could generate more accurate knowledge, covering larger areas with reasonable overall cost.

3.6.2.2 Target Scenario and Approach

AgriDataValue aims to establish itself as the "Game Changer" in Smart Farming digital transformation and agri-environmental monitoring, and strengthen the smart-farming capacities, competitiveness, and fair income by introducing an innovative, open source, intelligent and multi-technology, fully distributed Agri-Environment Data Space (ADS). To achieve technological maturity, fast and massive acceptance, AgriDataValue adopts and adapts a multidimensional approach that combines state of the art Big Data and data-spaces' technologies (BDVA/ IDSA/ GAIA-X) with agricultural knowledge, monetization, new business models and agri-environment policies, leverages on existing platforms, edge computing and network/ services, and introduces novel concepts, methods, tools, pilot facilities and engagement campaigns to go beyond today's state of the art, perform breakthrough research and create sustainable innovation in upscaling (real-time) agricultural sensor data, already evident within the project lifetime.

Many farmers already collect data from the sensors installed on their lands. Within UC6.2, we plan to correlate all the data in order to optimize of inputs, water and energy resources for the crops. For this reason, the data it manages cover the following aspects:

- Geospatial data: location, Geographical Information System (GIS) and GPS
- Satellite imagery: Sentinel 2, Proba-V (RGB, NDVI)
- Climate data: Historical meteorological data and forecast
- Agrometeorological data: air temperature, air humidity, wind speed, wind direction, the amount of precipitation, soil temperature, soil humidity
- In situ data: Farm crop - phenological phase, plant height, degree of plant development

For a selected field and period, UC6.2 will provide a diagnosis field and view processed data with plant stress detection derivate information. UC6.2 will display the results in map containing the NDVI images under the crop fields and the output table containing processed data from the NDVI image, crop parameters and resulted meteorological data. The users can identify based on the results the crop situation and recommendations for each selected field. The result will also provide Pie Charts that display the level of soil moisture % (Drought and Flood) and additional bar chart Graphs will contain Scorching Heat Intensity or Winter Harshness (mutual exclusive).

3.6.2.3 Interaction Analysis

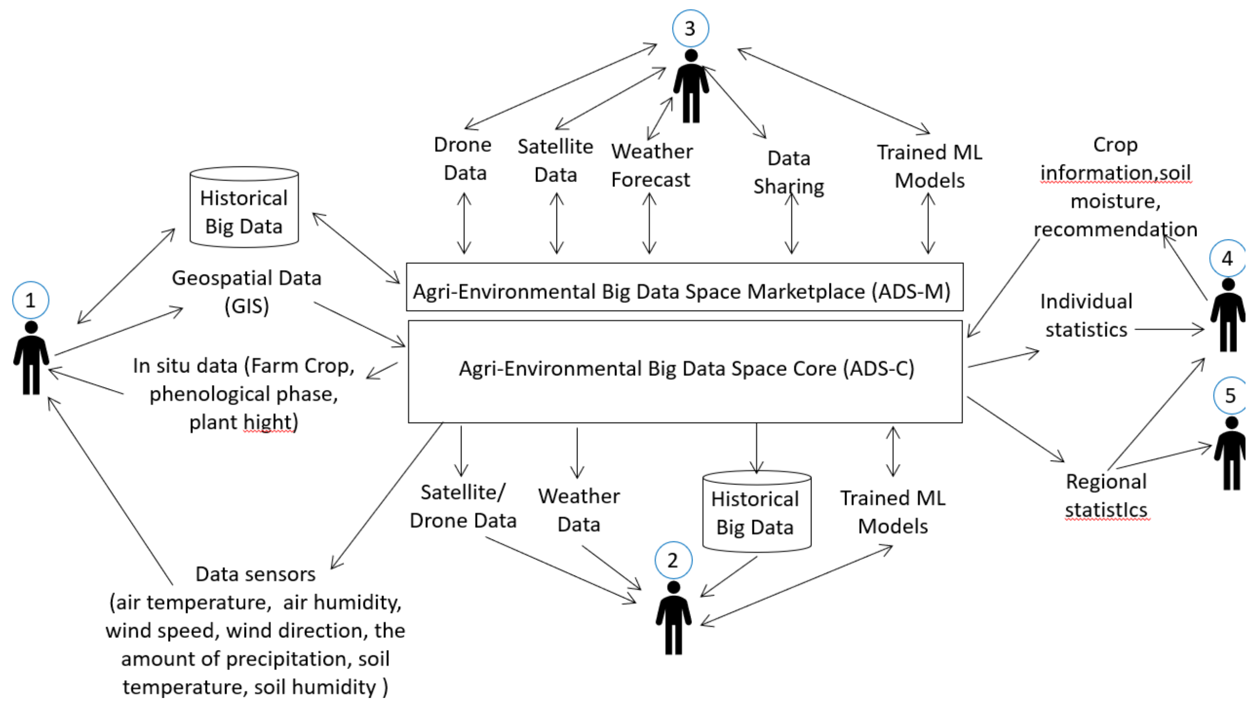


Figure 39: UC 6.2 Interaction Analysis

Actor 1 (Farmers) interacts with AgriDataValue system and provides:

- Geospatial data location, Geographical Information System (GIS)
- Climate data
- Agrometeorological data: air temperature, air humidity, wind speed, wind direction, the amount of precipitation, soil temperature, soil humidity
- In situ data: Farm crop - phenological phase, plant height, degree of plant development

Actor 2 (farming and climate monitoring research institutes) receives any type of historical, weather and drones/satellite data, along with trained ML models. In return, Actor 2 offers more advanced or experimental ML models, which may be utilized by Actors 1 and 3.

Actor 3 provide any type of shared data, including satellite imagery, historical meteorological data and weather forecast. Actor 4 processes all the data through ADS and provides on the results the crop information and recommendations for each selected field, like: level of soil moisture % (Drought and Flood). More information to farmers (correlated data: weather, soil properties and hybrid maturities, geo-location, etc.) will facilitate faster and more accurate decisions. Also, statistical reports can be obtained regarding the variation of climatic parameters and soil fertility over a period, for a certain plot. The statistical reports are important to evaluate the fulfilment level of specific CAP policies/strategies. Both Actor 4 and Actor 5 (EU stakeholders/ policy) retrieve ***regional statistics*** to evaluate the fulfilment level of specific CAP policies/strategies, including soil strategy objectives.

3.6.3 UC 6.3 Benchmarking and Eco-scheme monitoring tools for new CAP

Objective: Eco-scheme monitoring tools to support the new CAP towards fair income, land use protection and environmental care

3.6.3.1 State of play

Through the support granted through Pillar I of the CAP, the aim is to revitalize the animal breeding sector and stimulate the users of agricultural areas to practice sustainable agriculture by exploiting the areas through grazing. Through the Ecoschemes in Pillar I, farmers are stimulated to adopt agricultural practices beneficial for the climate and the environment, respectively: improving the quality and protecting the soil through the rotation and diversification of crops, including leguminous crops, the sustainable management of nutrients, the contribution to the protection of biodiversity, the maintenance and adoption of extensive agricultural practices, non-productive investments to ensure anti-erosion protection of the soil, efficient management of natural resources, protection of water resources against pollution and increased biodiversity. At the same time, the major focus on increasing the degree of resilience of holdings will reduce the negative impact of climate factors, through the integrated approach of some risk management tools financed from both pillars of the CAP.

By means of the implementation of ecoschemes, a better protection is desired and maintaining the potential of soils (avoiding desertification phenomena), but also increasing biodiversity, decreasing carbon dioxide emissions, increasing the areas occupied by protein crops in order to increase the nutritional quality of the soil, increasing soil fertility and humus content. At the same time, the aim is to maintain water quality as a result of compliance with the Water Framework Directive no. 91/676/EEC, maintaining the quality of meadows, increasing the diversity of agricultural crops but also maintaining the vitality of villages and sustainable agriculture practiced at the level of small traditional households. The following eco-schemes contribute to the environmental objective of climate change adaptation and mitigation, including by storing carbon in the soil and reducing greenhouse gas emissions:

- ECOSCHEMA: *Environmentally beneficial practices applicable in arable land*,
- ECOSCHEMA: *Practicing environmentally friendly agriculture in small farms, respectively traditional households*.

Through the requirements of these two ecoschemes, farmers will make their contribution to increasing the carbon storage capacity in the soil, reducing soil erosion by reducing the impact of agrotechnical works and increasing natural fertilization by planting proteinaceous crops. Eco-schemes also contribute to the improvement of soil and air quality by reducing the consumption of chemical substances in fertilization.

Also, through the application of ecoschemes:

- ECOSCHEMA: *Environmentally beneficial practices applicable in arable land*,
- ECOSCHEMA: *Practicing environmentally friendly agriculture in small farms, respectively traditional households*
- ECOSCHEMA - *Learning the interval between rows in orchards, vineyards, nurseries and orchards*,

- *ECOSCHEMA -reducing the use of pesticides*,

the contribution of farmers to the achievement of the environmental objective regarding the promotion of sustainable development and the efficient management of natural resources (water, soil and air) is ensured, including by reducing dependence on chemical substances. The application of the requirements set out in the 4 ecoschemes will lead to the improvement of soil quality and the reduction of erosion by protecting the soil and covering it for a prolonged period, diversifying crops and establishing proteinaceous crops. Also, the practices promoted in the ecoscheme contribute to increasing the nitrogen content in the soil, increasing the soil's carbon sequestration capacity and improving the biocenosis and soil structure, the main natural resource in agricultural activity. In order to stop and reverse the decline of biodiversity, improve ecosystem services and preserve habitats and landscapes, the requirements for ECOSCHEMA - Environmentally beneficial practices applicable in arable land and ECOSCHEMA - The spacing between rows in orchards, vineyards, nurseries and orchards that have a high degree of crop diversification, keeping a percentage of the holding area for non-productive and landscape elements and the obligation to keep the land between the rows covered with grass in vineyards and orchards

3.6.3.2 Target Scenario and Approach

The eco-schemes aim at providing financial incentives to farmers for their contribution to the achievement of general objective 2 of the CAP - Consolidation of actions to protect the environment and those against climate change and the contribution to the fulfilment of the European Union's environmental and climate objectives, closely following the achievement of all 3 objectives strategies with a focus on:

- ✓ mitigating climate change,
- ✓ improving biodiversity
- ✓ ensuring high-quality, safe, nutritious food produced by sustainable methods.

The ecoschemes address the protection of natural resources managed by farmers in the agricultural production process, characterized by their contribution to reaching the action areas of the new CAP, respectively:

- ✓ mitigating climate change, including reducing greenhouse gas emissions from agricultural practices, as well as maintaining existing carbon stocks and increasing carbon sequestration capacity;
- ✓ adaptation to climate change, including actions to improve the resilience of food production systems, as well as to increase animal and plant diversity, for greater resistance to disease and climate change;
- ✓ preventing soil degradation, restoring soil, improving soil fertility and nutrient management and soil biocenosis;
- ✓ protecting biodiversity, conserving or restoring habitats or species, including the maintenance and creation of landscape elements or non-productive areas;

Conservative agriculture promotes technologies that involve minimal intervention on the soil (renunciation of a large number of passes on the soil: plowing, harrowing and the other work of preparing the germinal bed or caring for the crops). One of the specific practices defined by the ecoscheme will stimulate conservative crop establishment technologies through no-tillage, strip tillage or minimum tillage systems. In general, a degree of soil coverage with these conservative practices in weight of more than 50% contributes to increasing the ability of the soil to adapt to the effects of climate change, by preventing erosion and moisture loss from the soil. Thus, the quality of the soil is maintained and augmented and aims to increase the biodiversity in the soil, while ensuring a favorable habitat for the development of fauna. At the same time, as a result of the conservative technology, an improvement in the texture and structure and the biota of the soil will be obtained, the increase in organic matter in the soil.

3.6.3.3 Interaction Analysis

Figure 40 provides the interaction analysis of the Eco-scheme monitoring UC in a UML like Use Case Diagram approach.

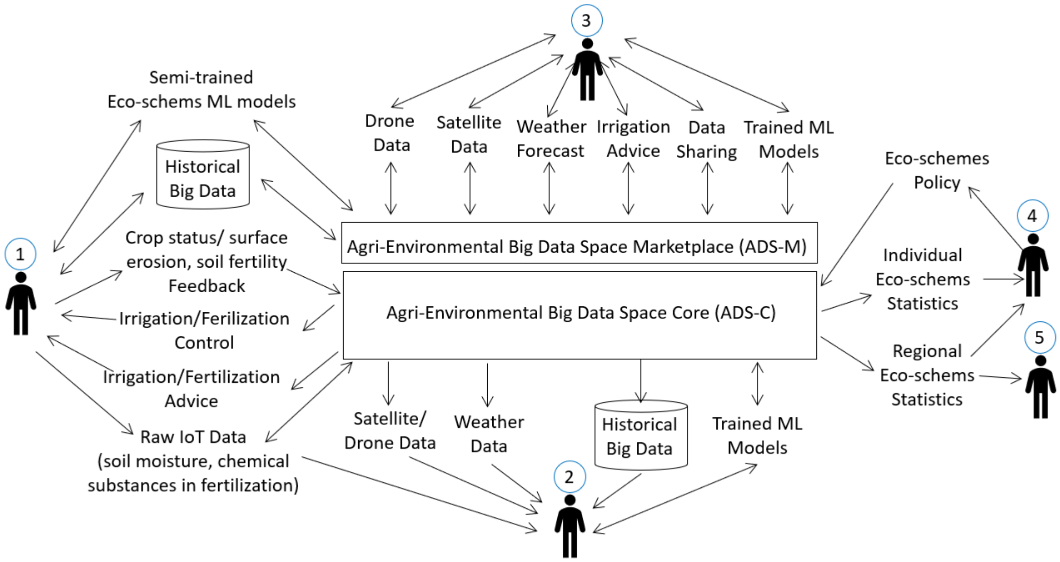


Figure 40: UC 6.3 Interaction Analysis

As can be seen, Actor 1 interacts with the AgriDataValue system and provides: a) raw data related to soil moisture (local microclimate data), b) feedback on crop status, informing the system about the stadium of crop growth, c) feedback on the consumption of chemical substances in fertilization, d) feedback on surface erosion of agricultural land and e) feedback on soil fertility. Moreover, through ADS-M can provide big historical data and semi-trained circular economy ML models under specific incentives/fee. To facilitate research and experimentation, actor 2 (agricultural research and climate monitoring institutes) is allowed to interact directly with ADS-C and receive any type of historical data, meteorological data and drone/satellite data along with models . ML trained. Instead, Actor 2 provides more advanced or experimental ML model that can be used by Actors 1 and 3.

Through certain smart contracts, Actor 3 can retrieve any type of data, shared advice information, including shared historical data, drone and satellite data, eco-scheme advice, and ML trained models. Finally, Actor 4 directly through the ADS-C module imposes the policy platform for eco-schemes and retrieves individual eco-schemes statistics to be used in the calculation of national/regional CAP support funding. Finally, the person from both actor 4 and actor 5 (stakeholders/EU policy) retrieves regional statistics on eco-schemes to assess the level of achievement of CAP-specific policies/strategies.

3.7 Use Cases Cluster 7: Climate monitoring

Climate change poses significant challenges to the agricultural sector, impacting crop growth, livestock production, and overall farm productivity. To effectively adapt to these changing conditions and build resilience, farmers and policymakers rely on climate monitoring as a crucial tool. Climate monitoring refers to the systematic observation and analysis of weather patterns, atmospheric conditions, and long-term climate trends. This essay explores the role of climate monitoring in agriculture, its importance, the advantages it brings to the sector, and real-life use case examples showcasing its potential in improving agricultural practices and outcomes.

Climate monitoring plays a vital role in agriculture by providing valuable information about weather patterns, climate variability, and climate change impacts on crop growth, pests, diseases, and water availability. It involves collecting data from weather stations, satellites, remote sensing technologies, and climate models. This data is analysed to generate climate indicators, forecasts, and early warning systems that guide farmers in making informed decisions regarding planting schedules, irrigation management, pest control, and other agricultural practices.

Climate monitoring is crucial in agriculture for several reasons:

- **Enables farmers to anticipate and adapt to climate-related risks**, such as extreme weather events, droughts, and shifts in temperature and rainfall patterns. By monitoring climate indicators like temperature, precipitation, and humidity, farmers can make timely adjustments to their farming practices, ensuring optimal crop growth and minimizing losses.
- **Helps farmers identify long-term climate trends and predict future conditions**. This information is invaluable for strategic planning, allowing farmers to choose suitable crop varieties, adjust planting dates, and implement irrigation strategies tailored to changing climatic conditions. By proactively adapting to the changing climate, farmers can enhance productivity, reduce vulnerability, and maintain long-term sustainability.
- **Facilitates precision agriculture**, enabling farmers to apply inputs like water, fertilizers, and pesticides more efficiently. By using climate data and sophisticated technologies, farmers can precisely target areas in need, minimizing resource wastage and environmental impact.
- **Supports optimal water management.** By monitoring rainfall patterns and soil moisture levels, farmers can implement effective irrigation strategies, ensuring that water is used judiciously, and crops receive adequate hydration. This enhances water-use efficiency, saves resources and mitigates the impacts of water scarcity.
- **Aids in pest and disease management.** By tracking temperature and humidity conditions, farmers can anticipate the emergence of pests and diseases, enabling timely interventions and reducing the risk of crop damage. Early warning systems based on climate monitoring data help farmers take preventive measures, such as adjusting planting schedules or applying targeted treatments, minimizing yield losses and the need for excessive chemical inputs.

However, as climate change is a mid- to long term process, even within AgriDataValue it is quite difficult to define specific Use Cases that have tangible results within the project lifetime. Instead, we define a number of Climate related use cases that mainly target Climate Monitoring and their influence in various activities of the project. In the following we highlight some UC already applied at different locations in the world, which would be of AgriDataValue interest. However, specific implementation and validation needs further analysis:

- **UC 7.1: Use of Climate Monitoring in Precision Farming.** In Netherlands, Farmers may utilize climate monitoring data, along with advanced technologies like remote sensing and drones, to optimize nitrogen fertilization [77]. By monitoring climatic conditions and nitrogen levels in the soil, farmers precisely tailor fertilizer applications, reducing nitrogen runoff and environmental pollution.
- **UC7.2: Climate Monitoring for Water Management.** In Australia, the Murray-Darling Basin Authority uses climate monitoring data to manage water allocations in response to changing climatic conditions [78]. By monitoring rainfall patterns, river flows, and evaporation rates, the authority can allocate water resources more effectively, balancing the needs of agricultural production and environmental sustainability.
- **UC7.3: Climate Monitoring for Disease Management.** In the United States, the Integrated Pest Management (IPM) program utilizes climate monitoring to forecast the spread of pests and diseases. [79] For instance, the program uses climate data to predict the risk of late blight disease in potato crops. By monitoring temperature and humidity conditions, farmers receive timely alerts and can implement preventive measures, such as adjusting irrigation practices or applying fungicides, to mitigate disease outbreaks and minimize crop losses.

- **UC7.4: Climate Monitoring for Crop Planning.** In India, the Indian Agricultural Research Institute (IARI) uses climate monitoring data to develop crop planning tools [80]. By considering historical climate data, rainfall patterns, and temperature trends, the institute provides farmers with guidance on suitable crop varieties and ideal planting dates. This helps optimize crop yields, reduces the risk of crop failure, and improves overall farm profitability.
- **UC7.5: Climate Monitoring for Livestock Management.** In New Zealand, farmers use climate monitoring to manage livestock health and well-being [81]. By monitoring temperature, humidity, and heat stress indices, farmers can implement measures to prevent heat stress in dairy cows, such as providing shade, proper ventilation, and access to cool water. This ensures the welfare of the animals and maintains milk production during periods of extreme heat.
- **UC7.6: Climate Monitoring for Soil Health.** In Brazil, the Agricultural Research Corporation (EMBRAPA) employs climate monitoring data to assess soil moisture conditions and develop irrigation strategies [82]. By combining climate data with soil moisture sensors, farmers can make informed decisions about irrigation timing and volume, optimizing water use efficiency and preventing soil degradation.
- **UC7.7: Climate Monitoring for Crop Rotation.** In Germany, farmers utilize climate monitoring data to determine the most suitable crop rotation patterns [83]. By considering temperature, rainfall, and soil moisture conditions, farmers can optimize the sequence of crops planted, promoting soil health, pest management, and nutrient balance.
- **UC7.8: Climate Monitoring for Agroforestry Systems.** In Kenya, climate monitoring data is used to guide the implementation of agroforestry systems. [84] By assessing rainfall patterns, temperature ranges, and soil moisture levels, farmers can select appropriate tree species that complement agricultural crops, enhancing biodiversity, soil fertility, and microclimate regulation.
- **UC7.9: Climate Monitoring for Greenhouse Management.** In the Netherlands, climate monitoring is crucial for greenhouse farming. [85] By tracking temperature, humidity, and CO2 levels, farmers can create optimal growing conditions for crops, facilitating year-round production, reducing disease risks, and maximizing crop yields.
- **UC7.10: Climate Monitoring for Livestock Feed Management.** In Australia, climate monitoring data helps farmers manage livestock feed resources [78]. By monitoring rainfall patterns and pasture growth rates, farmers can make informed decisions regarding grazing rotations, supplementary feeding, and drought management, ensuring optimal nutrition for livestock.
- **UC7.11: Climate Monitoring for Pollination Management.** In the United States, climate monitoring is utilized to enhance pollination management in orchards [86]. By tracking temperature and rainfall patterns, farmers can accurately predict the timing of bloom and coordinate pollination services, maximizing fruit set and yield.
- **UC7.12: Climate Monitoring for Integrated Pest Management.** In Thailand, climate monitoring is used to implement integrated pest management strategies [87]. By monitoring temperature and humidity conditions, farmers can anticipate pest outbreaks, deploy beneficial insects at the appropriate time, and minimize the use of pesticides, promoting sustainable pest control.
- **UC7.13: Climate Monitoring for Aquaculture.** In Norway, climate monitoring supports the aquaculture industry [88]. By tracking sea temperature, salinity levels, and oxygen concentrations, fish farmers can optimize fish health, feeding practices, and water quality management, ensuring sustainable aquaculture operations.
- **UC7.14: Climate Monitoring for Food Supply Chain Management: In** the United Kingdom, climate monitoring data is utilized to manage the food supply chain [89]. By tracking weather conditions, including temperature

and precipitation, throughout the growing season, retailers and distributors can anticipate crop availability, adjust storage and transportation logistics, and ensure the timely delivery of fresh produce to consumers.

Climate monitoring plays a vital role in agriculture, providing farmers with crucial information to adapt to the challenges posed by climate change. By tracking weather patterns, predicting climate trends, and assessing the impact on crops, livestock, and water resources, climate monitoring empowers farmers to make informed decisions and implement sustainable agricultural practices. The advantages of climate monitoring, such as precision agriculture, optimal water management, and improved pest and disease control, contribute to enhanced productivity, reduced environmental impact, and increased resilience in the face of climate variability. Real-life UCs examples demonstrate the practical application and benefits of climate monitoring, highlighting its potential in improving agricultural outcomes and ensuring the long-term sustainability of farming systems. As climate change continues to pose challenges to agriculture, the integration of climate monitoring will be crucial for building resilient and adaptive agricultural systems worldwide.

3.8 Captured Data/Information

On the main line, there are three categories of use cases in this project:

- Agricultural Use Cases (Cluster 1 to 5) that are executed by agricultural partners' pilots
- Climate monitoring Use Cases
- CAP realization Use Cases

This section lists the partners involved for each Use case category. It then gives an overview of the data/information collected and from which source it is collected.

3.8.1 Agricultural Use Case, partners, and pilots

The table below gives an overview of the Agricultural Use Cases, indicating in which pilot a UC occurs and which project partner is responsible for execution of the pilot.

	UL	DELPHY	ZSA	TBA	Ri.NO	BioRO	InAgro	ILVO	TEC	SAGRA	CVSE	NILEAS	SIXEN	SIMA	ALMA	SINER	SYN	NPA	APPAG	APIA
UC 1.1: Reduce Wasted irrigation water		X		X		X	X													
UC 1.2: Reduce Fertilizers			X	X		X	X													
UC 1.3: Reduce Pesticides	X	X	X			X	X													
UC 1.4: Increase potato production/quality							X													
UC 2.1: Precision open field/greenhouse Irrigation/Fertilization							X		X											
UC 2.2: Increase Leek /carrots/root-crops production/quality	X						X													
UC 2.3: Optimization of Soluble Solids Content									X											
UC 2.4: Automatization of greenhouse windows for climate control									X											
UC 2.5: Increase control of agri-environmental for organic farming	X																			
UC 3.1: Fruit trees disease forecast/detection					X					X		X								
UC 3.2: Anti-frost control											X									
UC 3.3: Pest Control on Mediterranean Fruit Fly			X		X															
UC 3.4: Pest Control on Olive Fruit Fly												X								
UC 4.1: Reduce Greenhouse gas emissions								X												
UC 4.2: Reduce nitrogen deposition								X												
UC 4.3: Proactive cattle/pig health/welfare monitoring			X	X				X												
UC 4.4: Calving monitoring			X					X												
UC 5.1: Fully Circular ecosystem			X	X																
UC 5.2: Supply Chain transparency for Winemaking				X											X					
UC 5.3: Supply Chain transparency for Meat traceability			X	X											X					
UC 5.4: Increase farmers' digital independence							X													
UC 6.1: Economic risk assessment														X				X	X	X
UC 6.2: Real-time input for pilot (satellite images, IoT, weather)														X	X	X	X	X	X	X
UC 6.3 Benchmarking and Eco-scheme monitoring tools for new CAP														X	X	X	X	X	X	X
UC 7.x Climate monitoring													X							

The tables below show an overview of all data/information collected and from where it was collected.

Captured Information (part 1 of 2)	Use Case / Technology used	1.1	1.2	1.3	1.4	2.1	2.2	2.3	2.4	2.5	3.1	3.2	3.3	3.4	4.1	4.2	4.3	4.4	5.1	5.2	5.3	5.4
AI-algorithm 3rd party	Drone images			X																		
Air flow control	Ventilation sensors														X							
Air Humidity	Air sensor										X			X								
	Soil sensor	X																				
	Weather Forecast										X	X	X									
	Weather station	X	X	X		X			X	X	X	X	X	X							X	X
Air Temperature	Air sensor										X			X								
	Soil sensor	X																				
	Thermostates														X							
	Weather Forecast										X	X	X									
	Weather station	X	X	X		X			X	X	X	X	X	X							X	X
Ammonia content	Air scrubber															X						
Ammonia emission (g/day)	Ammonia sensor															X						
Ammonia emissons (g/day)	Ammonia sensor															X						
Animal behavior	Activity/tracking sensor																X					
	Camera system																X					
Animal identification	RFID														X	X	X					
Animal indentification	identity collar RFID															X						
As applied information	PWM-spot spray system			X																		
Blossom map	Drone images			X																		
Calving behavior	Activity/tracking sensor																X	X		X		
Calving date	Artificial insemination																	X				
CH4	Air sensor														X							
CO2	Air sensor														X							
Conformity	Body condition score																X					
Drinking uptake																	X					
EC	Soil scan		X			X	X														X	
	Soil sensor										X	X	X									
Energy	Energy Measurement sensor																		X			
Evapotransiration	Weather station										X	X	X									
FAPAR	Satellite images		X	X		X	X														X	
Feed uptake																	X					
Flow control	Ventilation sensors															X						
FTIR emisson (g/day)	Greenhouse FTIR sensor														X							
Health monitoring	Medication registration																X					
Heat detection	Activity/tracking sensor																X			X		
Hyperspectral signal	Harvest scanner				X																	
Irrigation	Soil sensor										X	X	X									
Leaf wetness	Weather station										X	X	X									

table continues...

Captured Information (part 2 of 2)	Use Case / Technology used	1.1	1.2	1.3	1.4	2.1	2.2	2.3	2.4	2.5	3.1	3.2	3.3	3.4	4.1	4.2	4.3	4.4	5.1	5.2	5.3	5.4
Meat Supply Chain data	RFID																			X		
Methane emission (g/day)	Methane/CO2 sensor														X							
Milk production	Milk robot/parlor														X							
N-content	Manure analysis															X						
NDRE	Drone images		X			X	X														X	
NDVI	Drone images		X			X	X														X	
	Satellite images	X	X	X		X	X				X										X	
NIR/Chem. Analysis	Feed Quality analysis														X	X						
OC%	Soil scan		X			X	X														X	
Pest	Field observation data										X											
pH	pH meter					X															X	
	Soil scan		X			X	X														X	
Phenology	Field observation data										X											
Plant nutrients	Selective ion sensor					X															X	
PLS model results	Harvest scanner				X																	
Production data	Biogas																		X			
Radiation	Weather station								X		X	X	X								X	
Rainfall	Soil sensor	X																			X	
	Weather Forecast										X	X	X									
	Weather station	X	X	X		X					X	X	X	X							X	X
Salinity	Conductivity meter					X															X	
Soil humidity	Soil sensor										X	X	X									
Soil moisture	Satellite images	X	X			X	X														X	
	Soil sensor	X	X	X		X				X	X		X	X							X	X
Soil pH	Soil sensor									X												
Soil temperature	Soil sensor	X	X	X							X	X	X	X							X	X
Solar radiation	Weather station											X										
Temperature	Thermal Measurement sensor																		X			
Thermal mag	Aircraft Thermal map											X										
TIF-files	Drone images			X																		
Total Soluble solids	Refractometer							X													X	
Ureum content	Ureum analysis															X						
Walking behavior	Pressure sensors																X					
Water potential 20cm	Soil sensor										X	X	X									
Water potential 40cm	Soil sensor										X	X	X									
weight of animals	Load cells														X							
Weight of feed	Load cells														X							
Wind direction	Weather station														X							
Wind speed	Weather station	X	X	X		X			X		X	X	X								X	X
Yield potential	Drone images		X			X	X														X	
	Satellite images		X	X		X	X														X	

end of table

4 Technological GAP Analysis

Provision of digital frameworks, fostering vendor-neutral data exchange, business-oriented organisation of information, and assignment of responsibilities for data and service management, needs to be specified and provided by any initiative aiming to promote Digital Transformation in the agrifood sector. This is considered the foundation for value chain information sharing and exploitation practices, including all relevant economic and legal implications involved in data ownership and confidentiality.

As high-level requirements, the AgriData Space Digital Platform (DP) should provide:

- data-driven mechanisms and solutions to ease access and exploitation of data (data management),
- fostering data economy and digital business,
- vertical and horizontal interoperability[1] to boost technological diffusion, to create new services and applications, throughout the whole value chain, and potentially create new markets or extend/generalise the current ones.

There are several of Digital Platforms available for the development of intelligent systems, each supporting both vertical and horizontal interoperability among datasets, services, and applications. However, this poses an inherent difficulty for the decision-making processes of many business owners and system designers; evaluate the right platform(s) to find the best fit which will solve their business needs. Also, there specific aspects of these needs that must be considered such as scope, maturity, ownership of components, privacy, standards supported, implied business models, etc. The various needs lead to more and more technical solutions being brought to the market by open-source software communities and eco-systems.

Currently the landscape of existing data platforms including four main sources of Agri data: data from machinery suppliers, alliances and data sharing platforms, open data (e.g., sat and weather data) and other data sources, as displayed in Figure 41 below.

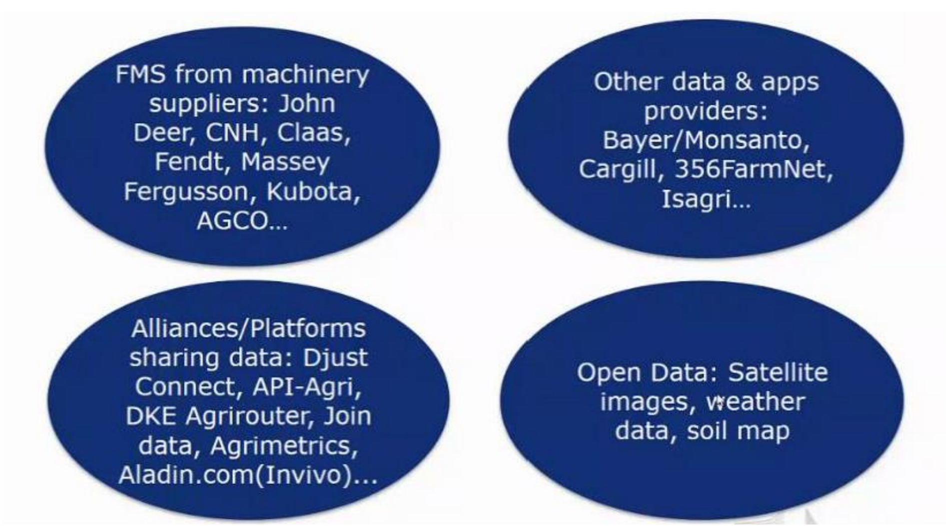


Figure 41. The landscape of existing data platforms

[1] Horizontal: interoperability between substitutable entities (services, platforms, etc)
Vertical: interoperabilty between complementary entities (services, platforms, etc)

A key objective, in general, is the drive to aggregate or federate all these data platforms to facilitate data exchange, to increase end-user flexibility and to better use the potential of data in the agricultural sector. In order to address this, issues like data interoperability, data governance, and business models about the usage and procurement of the data is necessary; in addition, resolving challenges that deal with incentivizing actors to be willing to share their data and participate in this data space must also be addressed.

Quite important is regarded the necessity of using the FAIR (findability, accessibility, interoperability, and reusability) principles when it comes to the access, management and use of data. Key in the usage of data is the data sovereignty aspect: e.g., companies want to stay in control over the flow of their data and there is a lot of potential also in linking data at a cross-domain level. Therefore, focusing on the sovereignty aspect, IDSA emphasised an imbalance: on the one hand everyone talks about interoperability, about data exchange, about data sharing, about data-centric services, but the topic of data ownership, data security and data value, in general “the ability of a natural or legal person to exclusively and sovereignly decide concerning the usage of data as an economic asset” has not been sufficiently addressed.

In this section, we introduce the work from other European projects and initiatives that has been undertaken by educational, public, and commercial organizations, and includes the principles and main concepts of Large-scale pilot Reference Architectures coming from the smart-farming and agricultural data management domain. We focus mostly on data management aspects.

4.1 Review of data management and privacy focused projects

Among various initiatives, we highlight some that we consider to be the most important and/or the most relevant to AgriDataValue project.

4.1.1 GAIA-X

The **GAIA-X** project [90] aims towards the creation of a federated, open European data infrastructure, enabling the interconnection of centralised and decentralised data infrastructures to turn them into a homogeneous, user-friendly system. Thus, GAIA-X will define the technical principles which foster the implementation of the European Data Strategy. Data Sovereignty, i.e., the execution of full control and governance by a data owner over data location and usage, is one of the core principles of GAIA-X. The requirement of data sovereignty has led to the following high-level requirements for a GAIA-X implementation:

- **Openness and transparency:** specifications will be accessible to all GAIA-X participants, technical steering and roadmap definitions are conducted in a public process.
- **Interoperability**: participants can interact with each other in a defined way. Self-description and policies are used to manage interactions between data providers and data consumers.
- **Federation:** standardized access and multiple decentralized implementations operated by autonomous providers.
- **Identity and trust systems** to manage the interaction between GAIA-X participants, without building upon the authority of a single corporation or government.

The core architectural elements in GAIA-X are *assets, participants,* and *catalogues*. Participants are natural or legal persons that can act as a provider, consumer, data owner, and visitor. Providers can host multiple user accounts. Assets can either be a *Node,* a *Service*, a *Service Instance,* or a *Data Asset*. Hereby, a node is in general a computational resource like a data centre or an edge computing device, and nodes can be organized in hierarchies. Services can be deployed on nodes and describe a cloud offering. A service instance is the concrete realization of a service running on a node. All nodes, services, and service instances are associated with a provider. Data assets are data sets that can be either searched, provided, or consumed by either another service or a participant, are hosted on a node, and are owned by a participant. GAIA-X data assets are content- and structure agnostic and provide metadata and a self-description. Self-descriptions contain the characteristics of assets and participants, and catalogues are the elements that implement the publication and discovery assets and participants.

The architecture of GAIA-X fosters the development of digital ecosystems and structures them into *Infrastructure Ecosystems* and *Data Ecosystems*. The infrastructure ecosystem comprises hereby services to transfer, process, and store data. Stakeholders of the infrastructure ecosystem can be cloud service providers, edge clouds, HPC providers, etc. Under the data ecosystem, actors along the data value chain are summarized. This could be for example data providers, data owners, data consumers, or smart service providers.

Following the global European data strategy, GAIA-X aims to become a Data Ecosystem and Infrastructure covering in that way the European values and standards and its architecture is being driven by the overall mission. GAIA-X's architecture utilizes both information technology and digital processes to realize the connection among all participants belonging to the European digital economy. Through the leverage of standards that now exist, open technology, and concepts, it realizes easy-to-use, open, quality-assured, and consistent services and data that are characterized by innovation. GAIA-X aims to become a facilitator bringing interoperability and interconnection among the several participants both for data and services.

As known, Digital Sovereignty characterizes the ability or power to make decisions concerning digital processes, infrastructures, digital processes, or the way that data are moved, structured, built, and managed. The GAIA-X architecture provides technical solutions to establish Digital Sovereignty following EU standards. Digital Sovereignty, which is a case of Data Sovereignty, represents full control, execution, and governance by a Data Owner on fields such as data location and usage. GAIA-X can enable the participation of Providers and Consumers in a digital sovereignty ecosystem via the application of core architectural principles that are described below. GAIA-X, as shown in Figure 42, uses technological approaches such as:

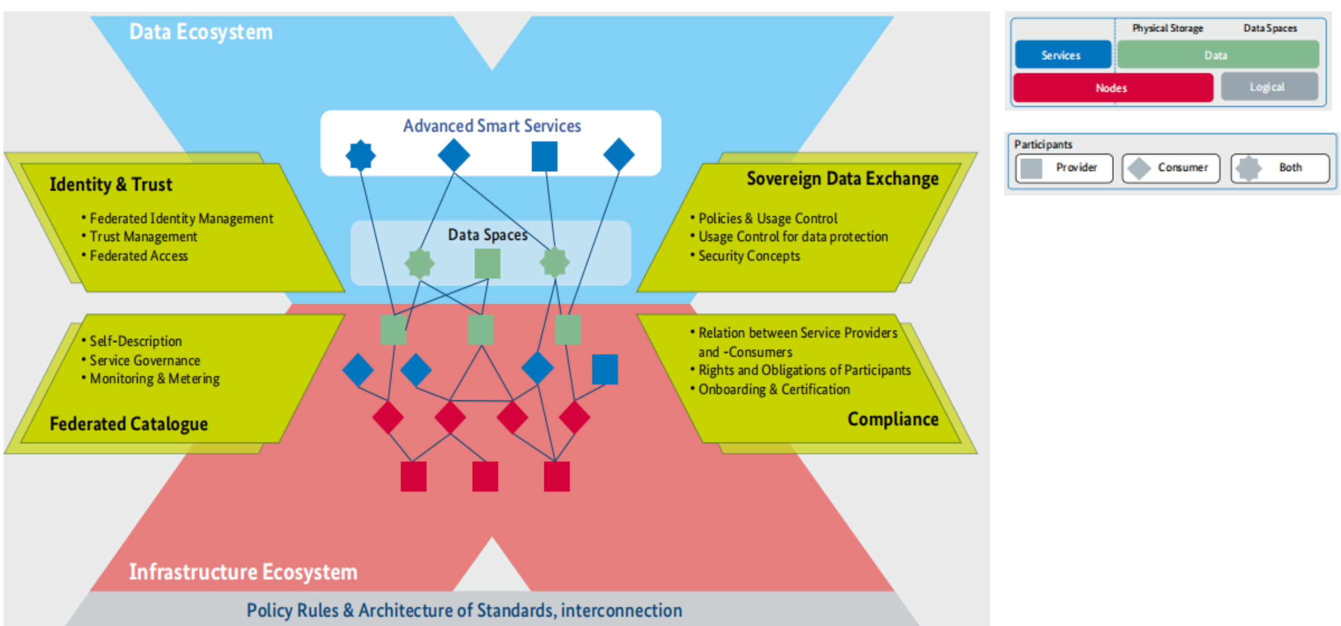


Figure 42. High-level representation of GAIA-X architecture that shows the major architecture components and functions that are followed by the Federation Services.

a) Federation, supporting standardized access to GAIA-X and implementations in a decentralized way, providing a rich digital ecosystem. Each component enhances security policies in the different resources and endpoints of the system.

b) Self-Descriptions and Policies, providing the common elements on a technical level related to the selection, coordination and initiation of the interactions between Consumers and Providers. More specifically, the Self-Descriptions stand for GAIA-X offerings and Policies the stand for requirements. If those two matches, then they can start to interact with the GAIA-X ecosystem.

c) Identity and Trust, helping GAIA-X Participants to verify if their interaction with others and also the services they use is reasonable, authentic, and backed by Self-descriptions and Policies.

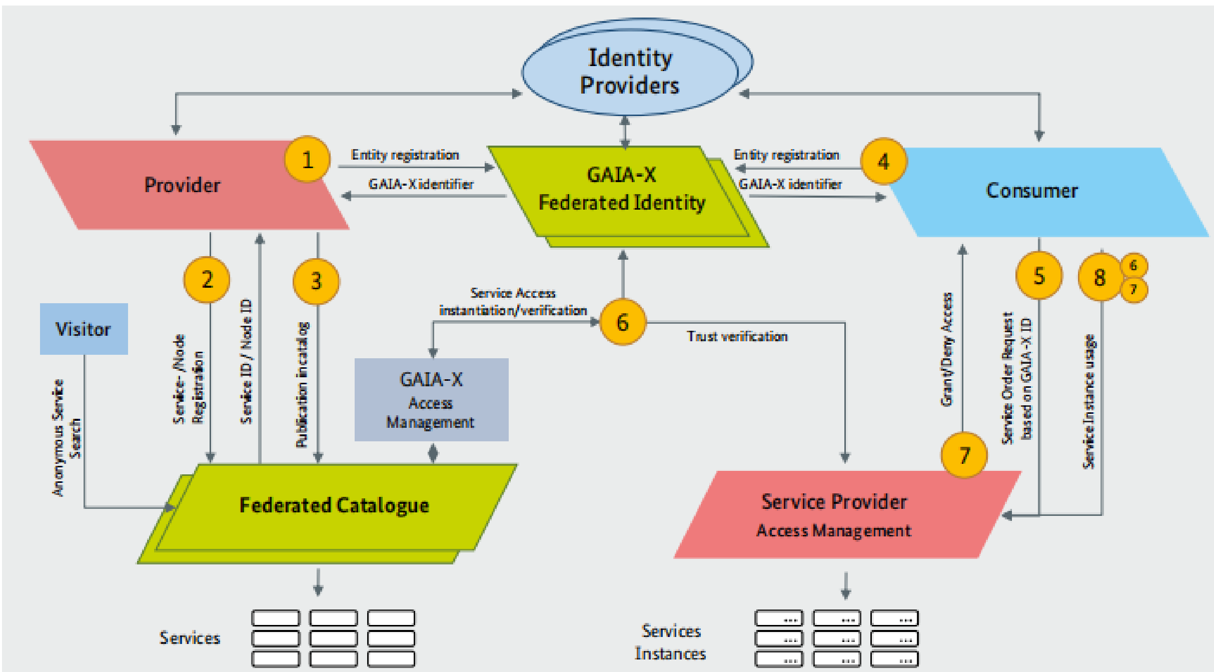


Figure 43. High-level description of the Federated Identity Model

As far as the architecture principles is concerned, Figure 43 shows the essential principles gathered from the architectural vision and objectives and stand for the main (core) that this architecture follows:

1) **Openness and Transparency:** The documentation of GAIA-X technologies and the documentation and architectures could be accessed in a worldwide level from the Participants. Everything, such as the roadmap of GAIA-X, technical steering of GAIA-X takes place in public and the cooperation with private sector players will be uncovered.

2) **Interoperability:** Each participant will interact with all the other participants in a well-specified way. Although the architecture describes the technical means to succeed in that, it is questioning and operates far from the specific implementations.

3) **Federated Systems:** GAIA-X (Figure 3) clearly identifies a federated system that comes from autonomous Providers, connected with a specified set of standards, legal rules and frameworks. Federation also includes decentralization and distribution.

4) **Authenticity and Trust:** A secure digital environment can be enhanced without building upon the authority of the government or a single corporation. This can be achieved with an identity management system with a specified declaration, revocation of trust, and mutual authentication.

4.1.2 OpenDEI – Reference Architecture for Platform Interoperability

OPEN DEI is an EU-funded project, which aims to detect gaps, encourage synergies, support regional and national cooperation, and enhance communication among the Innovation Actions implementing the EU Digital Transformation strategy [91]. The cross-Industry Digital Platforms federation of the OPEN DEI project [92] provides useful insights to the most relevant work in the field of Reference Architecture for building Digital Platforms to support the Digital Transformation journeys in the four sectors targeted by OPEN DEI (i.e., manufacturing, agriculture, energy, and healthcare).

The OPEN DEI Reference Architecture Framework (RAF) is built upon 6 main ***underlying principles*** as follows:

- **Interoperability through data sharing**: Syntactic interoperability between two or more systems is achieved by means of using common data formats and communication protocols. Semantic interoperability between two systems is achieved when the information exchanged can be interpreted meaningfully and accurately at both ends, producing useful results as defined by the end-users of both systems.
  Recommendation 1: *OPEN DEI RAF should foster technical interoperability at syntactic and semantic levels, via the use of data sharing mechanisms, grounded on well-established standards and design/implementation patterns.*

- **Openness**: In the context of data-driven services, the concept of openness mainly relates to data, data/API specifications and software.
  Recommendation 2: *OPEN DEI RAF should ensure a level playing field based on open-source datasets/software/standards and demonstrate active and fair consideration of the coverage of functional needs, maturity and market support and innovation.*

- **Reusability**: Reuse means that system architects confronted with a specific problem seek to benefit from the work of others by looking at what is available, assessing its usefulness or relevance to the problem at hand, and where appropriate, adopting solutions that have demonstrated their value elsewhere. This requires the involved stakeholders to be open to sharing its interoperability solutions, concepts, frameworks, specifications, tools and components with others.
  Recommendation 3: *OPEN DEI RAF must support reusing and sharing of data and solutions, enabling cooperation in the collaborative development of data models and solutions when implementing Digital Transformation pathways.*

- **Avoid Vendor Lock-In:** When establishing Digital Platforms, system architectures should focus on functional needs and defer decisions on technology, if possible, to minimize dependencies on vendors, to avoid imposing specific technical implementations or products on their constituents and to be able to adapt to the rapidly evolving technological environment. The OPEN DEI RAF should be able to support the adoption of concrete open standard technologies to use for the effective sharing of data for example, while at the same time choose technologies that will not impose any specific technical implementation and avoid vendor lock-in. The functioning of an implementation-independent technology requires data to be easily transferable among different sub-systems independently of how and who has implemented those subsystems, to support the free movement of data. This requirement relates to data portability - the ability to move and reuse data easily among different applications and systems, which becomes even more challenging in cross-border scenarios.
  Recommendation 4: *OPEN DEI RAF should foster access and reuse of their digital services and data irrespective of specific technical implementations or products.*

- **Security and Privacy:** To establish trust between different security domains requires a common data-sharing infrastructure based on agreed standards, policies and rules that are acceptable and usable for all domains. In addition to secure solutions, it is necessary to build a trusted ecosystem that includes identification, authentication, authorization, trust monitoring and certification of solutions.
  Recommendation 5: *OPEN DEI RAF must define a common security and privacy framework and establish processes for digital services to ensure secure and trustworthy data exchange between the involved stakeholders and in interactions with organization and businesses.*

- **Support to a Data Economy**: Common data sharing infrastructures should come with marketplace functions enabling data providers to publish their offerings associating terms and conditions which, besides data and usage control policies to be enforced, may include different formulas for payment: single payment, subscription fees, pay-per-use, etc. To support monetization of data, it should also include the necessary backend processes supporting data usage accounting, rating, payment settlement and billing. Standards enabling the publication of data offerings across multiple compatible marketplaces will be highly desirable.
  Recommendation 6: *OPEN DEI RAF must define a data marketplace framework enabling parties to publish open and priced data, supporting the creation of multi-side markets and innovative business models which bring support to the materialization of a Data Economy.*

The Reference Architecture Framework (RAF) proposes reusability as a driver for interoperability, recognizing that the data-driven services for DT should reuse information and services that already exist and may be available from various sources inside or beyond the organizational boundaries of the adopting organizations. Information and services should be retrievable and be made available in interoperable formats (e.g., adhering to FAIR principles [93]). To this end, the core reusable Model Building Blocks (MBBs), mainly representing information sources and services, should make their data or functionality accessible through well-defined services supporting data-oriented and event-driven interactions. The reusable building block approach finds a suitable application by mapping solutions against the conceptual building blocks of a Reference Architecture that allows reusable components to be detected, which also promotes rationalization.

The OPEN DEI project has defined the approach for designing a common Reference Architecture Framework able to describe the Cross-Domain Digital Transformation.

The extensive use of sensors and connected devices is a common scenario in the implementation of many Digital Transformation solutions and in many industrial sectors. The huge amount of available data is able to cover many business scenarios. Data-driven pipelines and workflows management is nowadays crucial for data gathering, processing, and decision support. To deal with this complexity OPEN DEI has adopted the following 6C architecture, adapted from the one suggested by the German *Industrie 4.0* initiative [94], and based on the following pillars (using a bottom-up reading):

- **Connection**, making data available from/to different networks, connecting systems and digital platforms, among several IT cultures and cross organizations' boundaries, start from the capability to make data available from/to different physical and digital assets. Different devices or sensors are used to acquire a variety of IoT data, but also many systems are based on unstructured or multi-media files. Data and information may also come from existing IT systems, using sector-specific protocols or more common standards coming from the Internet of Things (IoT) world used to realize data transfers.

- **Cyber**, modelling in-memory based solutions to convert data into information, leveraging several information conversion mechanisms. Digital representations (of assets, data, and information) will be then shared with upper layers of the pyramid to improve the self-healing properties of the overall system.

- **Computing**, storing, and using data on the edge or on the cloud. Many of modern digital platforms use a combination of cloud and edge computing models, based on driving factors for establishing more centralized and powerful computation capabilities, or faster, connectivity friendly and secure computing at the edge of the digital networked platform. The forces fuelling the demand for distributed computing technologies are advancing rapidly. This will create a paradigm shift for organizations moving along new digital transformation pathways, with potential changes affecting all players in the target business ecosystem.
- **Content/Context**, correlating collected data for extracting information, creating a digital space for data-information continuum, not something to push out to one side of the adopted information architecture. Modern businesses need a comprehensive approach with the end goal of driving the data (processing) and information needs. However, exploiting data is not as straightforward. Thus, data needs to be acquired (captured, entered via a data pipeline) and processed with a goal and context in mind, making it information, which essentially is about processed data, before moving to the next levels.
- **Community**, sharing data between people and connecting stakeholders for solving collaboration needs. Networked organizations will be able to collect and share knowledge and opportunities in the widest number of sectors so that its members can make the right decisions. The community around organizations could become increasingly important to collect and share information in a push-pull fashion.
- **Customization**, personalizing by following each user's perspective creates added value to data and at the same time match their expectations. Multiple strategies can make it possible to address all aspects of the end-user expectations and empower an individual to progress through platform functionalities in a natural way. Democratizing access to data is a promising approach to help unlock the value of data, but even the most advanced technology is of little value if people do not embrace it. This is a lesson that many businesses have learned the hard way; to avoid pitfalls, it is crucial to properly understand end-user expectations and build the platform from the ground up while keeping in mind that the intended audience, even within a single organization, can be diverse and must be properly segmented and with specific and varying needs.

In this scenario, complex systems based on distributed intelligence will be increasingly designed and operated based on accurate data sharing and analysis techniques. But as one of the upper layers is showing, the "smart" functions of the platforms will gain more power by using the network and community effects, such that organizations' habits are changed while their dimensions of business are expanded.

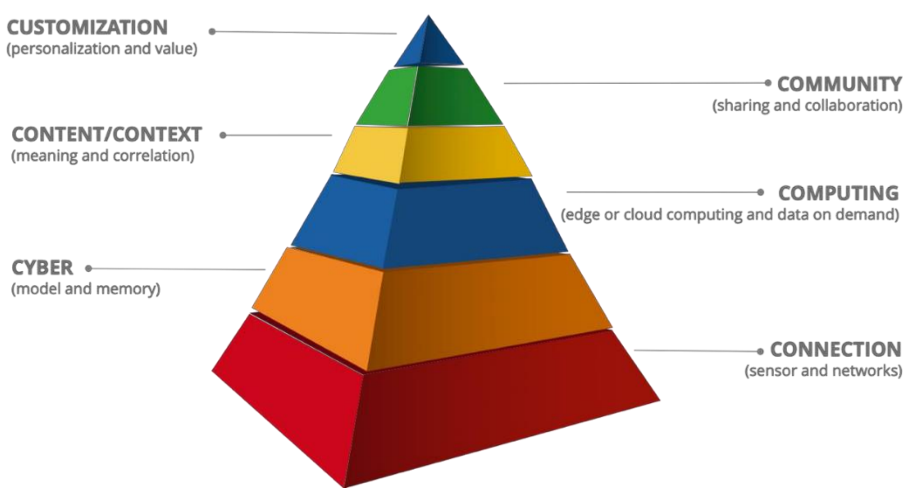


Figure 44. 6C Architectural Model

4.2 Review of Reference Architectures in Smart Agriculture projects

The Reference Architectures briefly described below come from recent large scale projects which also involved many pilot applications. These projects adapt their research architecture leveraging on Reference Architectures from past research projects and initiatives, such as those coming from IoT reference models and from the Big Data frameworks. Then, they customize these architectures, as their goal is to deploy systems based on these Reference Architectures to address large scale (and numerous) pilot applications. A main aspect of all these Reference Architectures is the data management and how this is achieved taking (data, user) privacy into account.

4.2.1 DEMETER

There are a variety of smart farming systems and platforms already deployed, employing many different communication, sensing, and data processing technologies. DEMETER [5] proposes an overarching approach that integrates heterogeneous technologies, platforms, and systems, while supporting fluid data exchange across the entire agri-food chain, addressing scalability and governance of data ownership. In this way, it offers a way for the integration of already deployed smart farming and platforms, which could employ several different communication, sensing, and data processing technologies.

The proposed approach enables existing Agriculture Knowledge Information Systems (AKISs) to continue their operation, but also allows those systems to both make available and consume data from other cooperating systems. Additionally, newer technologies and services can be exposed and included in updated applications that may be of interest to the cooperating AKISs. This is more realistic and viable in terms of usability, market adoption, and sustainability. Furthermore, another goal is to facilitate the exchange and interoperability of data, from various sources and in different formats potentially, which is needed to create advanced applications. DEMETER proposed architecture consists of services available from DEMETER Providers and to DEMETER Consumers, and is loosely based on the architecture model introduced by the Industrial Data Space (IDS) [95], then further specified by the International Data Space Association (IDSA), which is the continuation of IDS. This model is also consistent in general with more recent initiatives such as GAIA-X.

As data interoperability is of critical importance, the proposed solution provides the necessary data translation mechanisms combining the use of a semantic data model (Agriculture Information Model — AIM) developed by DEMETER, along with the respective data translation/management/inference mechanisms adopting widespread standardised solutions such as NGSI-LD, Saref4Agri [96], ADAPT [97], etc. To enable interoperability of heterogeneous data handling approaches, the DEMETER provider-consumer services, deployed on various AKISs, translate and exchange data based on the AIM common data format with the use of lightweight data wrappers/translators. For this conversion to be feasible, each AKIS needs to provide the specifications of the utilized data model and semantics, or it should parse returning content in the AIM format. The AIM is not built ab initio but incorporates and extends existing ontologies and vocabularies already available for this domain.

4.2.2 DataBio

The DataBio project [2] follows the BDVA Reference Architecture. An exhaustive list of all the 91 components have been defined by the DataBio platform. In the DataBio Architecture, the top layer has the data visualisation and UI tools (e.g., 2D, or 3D visualisation). This sits on top of the data analytics layer that generated data for the UI using techniques such as neural networks; this layer uses components for descriptive analytics, which analyse past (or historical) data to understand trends and evaluate metrics over time, predictive analytics aim to predicts future trends based on past data, and prescriptive analytics which showcase viable solutions to a problem and the impact of considering a solution on future trends. Below that sits the data processing architecture which allows batch, interactive or real-time processing of data and include the relevant technologies and databases (e.g., Apache).

The data management layers are responsible for the collection, preparation and curation of data and they include the agrifood data marketplace. At the bottom of the architecture sits the layer of the actual infrastructure used such as the cloud, 5G, IoT etc., which enables the connection to devices that provide the data used in the other layers.

4.2.3 IOF2020

Building upon the IoT reference model (see standard recommendation ITU-T Y.2060 dated 06/2012) which is presented in the figure below, and its evolution which is the functional view of the IoT-A ARM, the IoF2020 [3] use case pilots utilize customized architectures, one for each specific use case.

For example, in the next figure, we present the functional view a IoF2020 Use Case. More specifically, the application layer sits at the top of the architecture, with the device layer at the bottom. On top of the device layer sits the connectivity layer (see “Communication” layer in the IoT-A Architectural Reference Model) and between this and the application layer there is the service support and application support layer (the components of which correspond loosely to the other layers in the IoT-A Reference Model); for example, clearly the IoT service layer corresponds to the equivalent layer in the IoT-A Reference Model. The only exception seems to be the information mgmt. layer (also referred as data layer in other figures) part of which seems to correspond partly to the business process management layer and part to others in the IoT-A Reference Model. Finally, Management and Security (at the sides) apply to all layers.

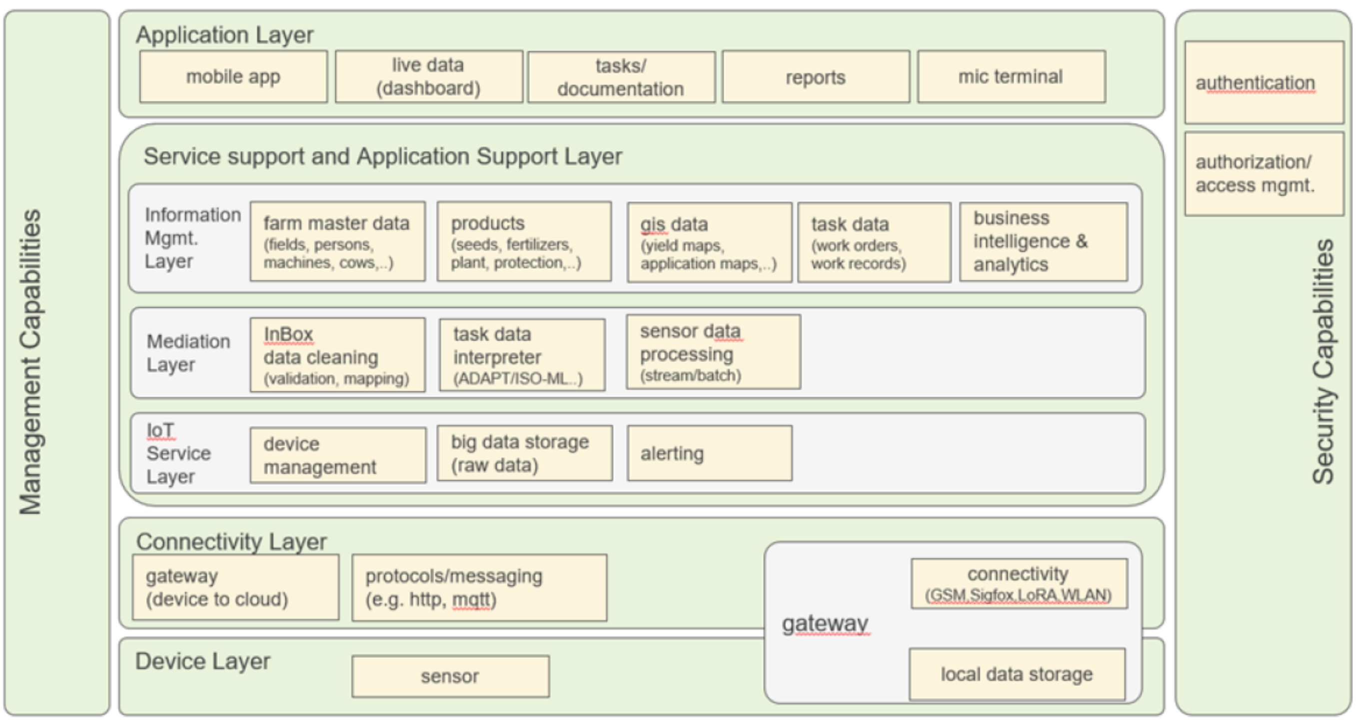


Figure 45. IoF2020 use case 1.4

What the IOF2020 approach and its architectures lack, their main drawback, is semantic interoperability. More specifically, it would be far more desirable that the architecture should allow different services to be used and input into the same platform on a need basis. To achieve this, the architecture should incorporate common data management tools and common data frameworks for storing, processing, and transmitting the knowledge collected through raw input data, or processed data by various services and tools. It should also employ a portfolio of communication protocols as appropriate to receive the input data from various sources (mainly devices but also human user if appropriate). Furthermore, it should provide services that “translate” between data formats (e.g., those used by devices that input data into the platform) to maintain semantic interoperability. Finally, ideally the services used should use a common standard so that they can be used and composed together on demand for the different application domains and problems without the need for expensive and time-consuming customization.

4.2.4 AFarCloud

AFarCloud (Aggregate FARming in the CLOUD) [4] is an ECSEL project whose goal is to provide a distributed IoT platform for early adopter farmers and rural professionals willing to use agriculture real-time computer systems to increase efficiency, productivity, animal health and food quality, and also to reduce agricultural labour costs. This platform is integrated with farm management software and supports monitoring and decision-making solutions based on Big Data and real time data mining techniques.

The AFarCloud platform consists of three main functional components: (i) the *Farm Management* System, (ii) the *Semantic Middleware* and (iii) the *Deployed Hardware* layer. Besides, the AFarCloud platform interconnects with other data sources like 3rd Party legacy systems databases.

The *Farm Management System* offers: a Mission Management Tool (MMT) to plan cooperative missions involving Unmanned Aerial Vehicles (UAV) and ground vehicles ranging from fully autonomous UGVs to legacy systems; a Decision Support System (DSS) to make decisions pre-, during- and post-mission; a system configurator to configure the above-mentioned systems, including their key hardware components (mission relevant sensors and other component important for performing a mission); and, applications for the user to manage and monitor the whole system.

The *Semantic Middleware* offers among others, components for: data storage and retrieval from the Cloud; managing and cataloguing images; registration of IoT devices, animals, and vehicles in the farm; data flow management inside the platform; managing, controlling and acquiring data from IoT devices and missions involving ground and aerial vehicles; data processing and knowledge extraction. The Semantic Middleware implements a software layer that hides the underlying complexity of the deployed hardware, so that the Farm Management System can access to that hardware in a unified way.

The *Deployed Hardware* layer provides means to deploy and integrate the services and data related to unmanned aerial vehicles, semi-autonomous ground vehicles, actuators, sensors and other IoT devices.

Something that is still missing (since it was not in the scope of that project) from this architecture is the support for the interoperability between several farm platforms (FMS) and their offering services and not just repositories.

4.2.5 DjustConnect

DjustConnect is a neutral data exchange platform, managed by the Institute for Agricultural, Fisheries and Food Research (ILVO), available for all data users in the Agrifood sector. DjustConnect originated as an EFRO (European Fund for Regional Development) project, called Datahub for AgroFood, with the support of its founding companies (AVEVE, Boerenbond, CRV, DGZ and Milcobel) and grew into a fully mature platform, successfully connecting data receivers and farmers, enabling data-driven applications to thrive.

The mission is to stimulate data exchange in the Agrifood sector with respect for the different stakeholders; the usage and valorisation of data, eliminating repetitive, boring data entries, unlocking the full potential of applications and creating benefits throughout the value chain. DjustConnect wants to provide a means of data exchange respecting data ownership, farmers and providing decision power, regarding the data exchange, to the different parties involved.

DjustConnect is for everyone who wants to contribute to innovative agriculture through data sharing with respect for farmers. Farmers and horticulturist produce quality products, but also quite a lot of data. A lot of these company data are shared with others, such as the government, suppliers, buyers, producer organisations or cooperations. This data sharing has great advantages because they get smarter digital tools, optimal service or less administration in return. However, as a company manager it is not always easy to keep a clear overview of who has access to which part of your data. DjustConnect provides agricultural business the control over their data. They decide to whom and why they share their data. This way they can safely manage their data and safely enjoy all the benefits of their data. Also suppliers, buyers, producer organisations or agricultural cooperations have access to data. This are either their own company data or data managed from farmers. These data can have great additional value for data receivers. They can use this data to improve their services and products or to develop new digital products. DjustConnect ensures that these data receivers find the data providers, that they don't need to invest in an own data sharing infrastructure, that the data transactions are easily managed and that everything is handled correctly through one DjustConnect contract. Companies that want to expand their products or services by using data-input from the agrifood sector, act as data receivers. They find an overview of available data on the DjustConnect marketplace [98]. If present, DjustConnect will make sure their data-request will end up with the right owner. This way data sharing goes 100% according to the Code of Conduct without they need to manually manage permissions. When granted permission they will get access to the data with one connection. The legal side is also simplified as DjustConnect makes sure all transactions are performed in a legally correct manner. This way data sharing is safe, transparent and simple for everyone.

4.2.6 Summary

In the table below, the key components or design features of each one of the architectures described in the previous subsections are present in the following table:

Table 1. Examples of Large-scale Pilot Reference Architectures analyzed

Organisation	Description
DEMETER	The key benefits of DEMETER are that it connects a human-focused interaction space with the actual digital implementation space. This ensures the fact that DEMETER remains fully human-centric and human-driven – delivering digital enablers that are fully aligned to the needs expressed by the farmers and based on the knowledge and wisdom captured through structured mechanisms. All communication with external third parties is based on the DEMETER Agriculture Information Model (AIM), a common semantic data model used for information exchange across the DEMETER ecosystem. Moreover, the notion of the DEMETER-enhanced Entity (DEE) is that a service, application, platform, or thing is being wrapped with DEMETER enabler functionalities to act as a DEMETER consumer and/or producer. Many of these DEEs interoperate with each other to form an application solution.
DataBio	DataBio has the following layers, starting from top-to-down approach: 1) Data visualisation and User interaction, 2) Data Analytics, that uses neural networks, 3) Data Processing Architectures, in order to process interactive, batch or real-time data, 4) Data Management layer that collects, prepares and curates data, 5) Infrastructure, that uses technology solutions in order to connect devices.
IOF2020	IOF2020 builds upon the IoT reference model and its evolution the functional view of the IoT-A ARM; this is a layered architecture where the devices sit at the bottom, with

	communication facilities on top of them linking them to the service and app support layer, while at the very top sit the applications. Security and data management are present as vertical slices that cover all the layers. IOF2020 customizes this architecture for each of its use case pilots, therefore each one utilizes a slightly different, customized architecture, depending on the needs of the specific use case; without having generic interoperability facilities (without customization).
AFarCloud	AFarCloud provides a distributed IoT platform for farmers and professionals so that they can increase efficiency, animal health, productivity and food quality, and reduce the costs on labouring. The basic elements of the AFarCloud are the following: 1) Farm Management System, 2) Semantic Middleware, 3) Deployed Hardware. It can also connect to other data sources such as 3rd Party data or legacy systems DB.
DjustConnect	DjustConnect stimulates data exchange in the Agrifood sector with respect for the different stakeholders; the usage and valorisation of data, eliminating repetitive, boring data entries, unlocking the full potential of applications and creating benefits throughout the value chain. DjustConnect provide a means of data exchange respecting data ownership, farmers and providing decision power, regarding the data exchange, to the different parties involved.

5 Climate change-agriculture nexus

5.1 Review on climate change-agriculture nexus and impact in EU

The climate change agriculture nexus refers to the intricate relationship between climate change and agriculture. It recognizes the significant impact of climate change on agricultural systems and, in turn, the influence of agricultural practices on climate change. This concept highlights the interconnectedness and mutual dependency of these two domains.

Climate change affects agriculture in several ways. Rising temperatures, changing rainfall patterns, increased frequency of extreme weather events (such as droughts, floods, and storms), and altered pest and disease dynamics pose significant challenges to agricultural productivity, food security, and rural livelihoods. These changes can disrupt crop growth cycles, reduce yields, degrade soil fertility, increase water stress, and threaten the overall stability of agricultural systems.

Conversely, agriculture exacerbates climate change diversely. Deforestation for agricultural expansion releases carbon dioxide (CO_2) into the atmosphere, reducing carbon sinks and exacerbating GHG emissions. Additionally, agricultural practices such as livestock rearing, rice cultivation, and the use of synthetic fertilizers generate methane (CH_4) and nitrous oxide (N_2O), potent GHGs. Furthermore, soil erosion and degradation resulting from unsustainable farming practices can release stored carbon, further contributing to climate change.

The climate change agriculture nexus highlights the need for a comprehensive approach that addresses both adaptation and mitigation strategies. Adaptation focuses on developing resilient systems that withstand climate-related stresses and continue to provide food security. This involves implementing techniques like climate-smart agriculture, crop diversification, improved irrigation methods, and climate-resilient crop varieties usage.

Mitigation efforts aim to reduce GHG emissions from agricultural activities. This includes promoting sustainable farming practices, precision agriculture, agroforestry, and the adoption of renewable energies. Additionally, reducing food waste and improving efficiency along the agricultural value chain can contribute to climate change mitigation.

Understanding and managing the climate change agriculture nexus is crucial for sustainable development, ensuring food security, and minimizing the environmental impact of agriculture. It requires interdisciplinary collaboration, policy support, technological advancements, and the active involvement of farmers, researchers, policymakers, and other stakeholders to address the complex challenges posed by climate change in this sector.

The climate change-agriculture nexus in Europe has profound implications for the agricultural sector, food security, and rural livelihoods. Here is a review of some key impacts and examples illustrating the relationship between climate change and agriculture in Europe:

- ***Changing Growing Seasons:*** Rising temperatures and altered precipitation patterns are disrupting the traditional growing seasons in Europe. Warmer winters and earlier springs can lead to changes in crop phenology, affecting flowering, pollination, and fruit development. For instance, in some regions of Europe, grape harvests for winemaking have shifted to earlier dates due to warmer temperatures.
- ***Shifts in Crop Suitability:*** Climate change is causing shifts in the suitability of crops across Europe. As temperature and rainfall patterns change, some areas may become less suitable for certain crops, while others may open up new opportunities. For example, olive groves in southern Europe are facing increased

risks due to more frequent heatwaves and droughts, while regions in northern Europe are exploring the viability of growing olives as the climate becomes more favourable.

- ***Increased Water Stress:*** Changing precipitation patterns and increased water scarcity pose significant challenges for European agriculture. Reduced water availability impacts crop growth, livestock production, and irrigation practices. In regions like the Mediterranean, drought conditions are becoming more frequent, leading to decreased crop yields and challenges in maintaining livestock.
- ***Pest and Disease Dynamics:*** Climate change influences the distribution and behaviour of pests and diseases, affecting agricultural productivity and crop health. Warmer temperatures can facilitate the expansion of pests and the emergence of new diseases. For example, the spread of the European corn borer (a pest) northward into new regions in Europe has been linked to warming temperatures, posing risks to maize production.
- ***Impacts on Livestock:*** Livestock farming in Europe is vulnerable to climate change impacts. Heat stress on animals can reduce productivity, affect reproduction rates, and increase mortality rates. For instance, heatwaves have led to significant losses in dairy cow productivity in some regions. Additionally, changing pasture availability and quality can impact livestock nutrition and forage availability.
- ***Coastal Vulnerability:*** Climate change-induced sea-level rise and increased coastal flooding pose risks to agricultural areas in low-lying coastal regions. Saltwater intrusion can contaminate agricultural lands and compromise soil fertility. The Netherlands, for example, has implemented innovative measures such as floating farms to adapt to rising sea levels and safeguard food production.

These examples highlight the complex and varied impacts of climate change on European agriculture. Efforts to address the climate change-agriculture nexus in Europe involve implementing adaptation strategies, such as adjusting cropping patterns, promoting resilient crop varieties, improving water management, and enhancing livestock husbandry practices. Mitigation measures include reducing greenhouse gas emissions from agricultural activities through sustainable farming practices, agroecology, and renewable energy adoption. It is essential for policymakers, farmers, researchers, and stakeholders to collaborate and prioritize climate-smart agricultural approaches to ensure food security, sustainability, and resilience in the face of climate change.

As an example, in France the effect is shown in the following areas:

1. ***Vineyard Shifts:*** Climate change is influencing the suitability of wine grape cultivation in France. Warmer temperatures are affecting grape varieties and wine quality. A recent study [99] found that wine-growing regions in France are experiencing shifts in suitability, with some traditional wine regions facing potential declines in grape quality due to increasing temperatures. This has led vineyard owners to explore new grape varieties and adapt their cultivation practices. Another study [100] focuses on modelling the impacts of climate change on grapevine growth in Bordeaux vineyards, examining potential yields, phenology (timing of growth stages), and canopy density, while another study [101] provides a comprehensive review of the impacts of climate change on viticulture (grape cultivation) in France, covering aspects such as grapevine growth, grape quality, and wine production.
2. ***Heat Stress on Livestock:*** Rising temperatures and heatwaves pose challenges for livestock farming in France. Heat stress affects animal welfare, reproduction, and milk production. A recent study [102] examined the impact of heatwaves on dairy cow performance in France and found that heat stress led to reduced milk yield and increased somatic cell count, indicating compromised udder health.
3. ***Water Management Challenges:*** Changing precipitation patterns and water availability affect agricultural water management in France. A recent study [103] assessed the vulnerability of French agricultural areas to water stress. The research highlighted the risks of water scarcity in different regions, particularly in

Mediterranean and Atlantic coastal areas, and emphasized the need for improved water management practices to adapt to changing climate conditions. Another study [104] assesses the impact of climate change on agricultural water resources in the French Mediterranean region, using indicators to evaluate the potential consequences of changing climate conditions.

4. ***Shifts in Crop Phenology***: Changing temperature and rainfall patterns influence the phenology of crops in France. A recent study [105] investigated the impact of climate change on the flowering dates of major fruit trees in France. Other studies have found that apple, cherry, and pear trees have experienced earlier flowering dates over the past few decades, which can have implications for pollination, fruit set, and crop yields. Another study [106] examines the impact of climate change on the phenology (timing of growth stages) of ***wheat crops*** in France throughout the 21st century.
5. ***Summer crops vulnerability to climate change:*** Another study [107] investigates the vulnerability and adaptation potential of European summer crops, including those in France, to climate change using observational data and crop model simulations.

5.2 The use of Smart Farming in Europe

Smart farming refers to the application of information and data technologies to the practice of farming. Although relatively new, this practice is starting to take hold throughout Europe. Smart farming involves the collection of data across a farm, which is then utilized to enhance farming operations. This approach employs advanced technologies such as internet-enabled sensors, robots, and satellites to revolutionize agriculture. By utilizing these technologies, farmers can identify ways to increase their yield while utilizing fewer resources. Precision agriculture is a complementary practice to smart farming that is also known as agriculture 4.0. This approach considers the slightest variables involved in running a farm. By making small adjustments, farmers can ensure that they optimize every aspect of their farming processes.

5.2.1 The main technological evolutions involved in Smart Farming

In this section we analyse some of the most interesting technological evolutions, which are involved and create real impact in Smart Farming.

5.2.1.1 Unmanned Aerial Vehicles (UAVs)

UAVs are used to inspect health and monitor the growth of large field of crops through remote sensing, crop estimation, weed detection, water management, and spraying. UAVs primarily contribute through remote sensing [108]. UAVs capture images using visible, near-infrared, thermal spectrum cameras and laser scanners. These images provide valuable information to farmers for making informed decisions about their crops and land.

UAVs are also used in crop estimation by creating a 3D reconstruction of the cultivation through acquired images. This is achieved through programming techniques that enable the creation of a 3D model of the vegetation structure, allowing for precision analysis [109]. Using multiple UAV flights throughout a growing season can provide a historical overview of vegetation growth [110]. Weed mapping is another valuable application of UAVs in agriculture, as it can reduce the need for chemical inputs and labour from farmers. Multispectral cameras, a primary component of UAVs, can also be used in water management techniques [111] by providing information on the humidity levels of crops. Lastly, UAVs are being tested for spraying operations [112] with the goal of reducing pesticide inputs by acting precisely where and when needed.

Table 5: Comparison of UAV technologies [113]

	Fixed Wing 	Rotary Wing 
Speed	High	Low
Coverage	Large	Small
Resolution	cm/inch per pixel	mm per pixel
Take-off and landing area	Large	Small
Flight time	High	Low
Wind resistance	High	Low

Image processing in UAVs: Image processing techniques are employed to create two-dimensional maps using images captured by UAVs in various spectrums. These maps are highly valuable for crop monitoring and yield estimation, two of the most critical applications in agriculture. Several vegetation indices are used in the literature for these purposes, including NDVI, GNDVI, and SAVI for crop monitoring, and ARI, MARI, RGI, ACI, MACI, CI, and GRVI for estimating leaf pigments [114].

Table 6: Vegetation Indices [114]

Index name	Formula
Normalized Difference Vegetation Index	$NDVI = \frac{NIR-Red}{NIR+Red}$
Anthocyanin Reflectance Index	$ARI = Green^{-1} - RedEdge^{-1}$
Modified Anthocyanin Reflectance Index	$MARI = (Green^{-1} - RedEdge^{-1}) \times NIR$
Red–Green Index	$RGI = \frac{Red}{Green}$
Anthocyanin Content Index	$ACI = \frac{Green}{NIR}$
Modified Anthocyanin Content Index	$MACI = \frac{NIR}{Green}$
Chlorophyll Index	$CI = \frac{NIR}{RedEdge} - 1$
Green-Red Vegetation Index	$GRVI = \frac{Green-Red}{Green+Red}$
Soil-Adjusted Vegetation Index	$SAVI = \frac{(NIR-Red)\times(1+L)}{NIR+Red+L}$
Green Normalized Difference Vegetation Index	$GNDVI = \frac{NIR-Green}{NIR+Green}$
Difference Vegetation Index	$DVI = NIR - Red$

ML application in UAVs: ML and Deep Learning techniques are used in various tasks in agriculture and are expected to bring significant improvements. For example, they are used in crop monitoring [115], in water management [116] to identify diseases [117] and to classify weeds [118].

The main advantaged of UAVs are that they 1) give the farmer a bird's eye view of their field in a short time; 2) lower the operational cost and 3) are more flexible and less expensive that other monitoring technique such as manned airborne and satellite inspection.

Since 2019 (revision in 2022), EU Regulations 2019/947 and 2019/945 [119] set out the framework for the safe operation of civil drones in the European skies. They adopt a risk-based approach, and as such, do not distinguish between leisure or commercial civil drone activities. What they consider is the weight and the specifications of the civil drone and the operation it is intended to conduct. However, there are still no fixed regulations in all EU countries, which may hinder UAVs development and use.

5.2.1.2 Unmanned Ground Vehicles (UGV)

The use of UGV is still at an experimental phase but is promising. An UGV can perform various tasks in the field like seeding, harvesting, weeding, spraying, pruning, and crop monitoring [120]. Existing UGVs have been tested on numerous crops including grapes, peppers, cucumbers, tomatoes, asparagus, sunflowers, sugar beet, and hazelnuts. Researchers aim to develop UGVs which can work in swarms or cooperate with UAVs to perform complex tasks [121]

Figure 46: Exampled of UGVs in smart Farming

The main advantaged of UGVs are they reduce the required labour effort and boost accuracy of the operations in the field, while they decrease in operational cost. Moreover, they offer precise appliance of fertilizers and pesticides and reduce the environmental impact. Finally, the small size of the UGVs comparing with the existing heavy machinery will avoid the massive soil compaction and reduce energy consumption.

5.2.1.3 Wireless Sensor Networks (WSNs)

Various wireless technologies have been used during the last decades, like Bluetooth Low Energy (BLE), WiFi, 3G/4G, SigFox, Narrowband IoT (NB-IoT), and LoRa. The following table provides a comparison of wireless sensor networks applied to smart agriculture.

Table 7: Comparison of Wireless Sensor Networks

	BLE	ZigBee	WiFi	3G/4G	SigFox	NB-IoT	LoRa
Frequency band	2.4 GHz	868/915 MHz 2.4 GHz	2.4 GHz 5 GHz	865 MHz 2.4 GHz	433 MHz 868 MHz 915 MHz	–	433 MHz 868 MHz
Data rate	2 Mbps	20–250 kbps	1.3 Gbps	1 Gbps	100 bps	250 kbps	50 kbps
Transmission range	100 m	20 m	100 m	Cellular Coverage	40 km	15 km	20 km
Energy consumption	Low	Low	High	Medium	Low	Low	Low
Cost	Low	Low	High	Medium	Low	High	Low

5.2.2 Adoption of smart farming technology, benefits, and barriers in Europe

This sub-section offers an overview of the adoption of smart farming technologies in European countries along with the benefits of using smart farming technology, and the barriers to increasing the adoption rate.

A 2020-study led across Europe on the adoption of smart farming technologies identified that the larger the farms, the greater the adoption rate [122]. Farms under 10 ha have significantly less adopters than farms that are 101 ha and larger. Farms that are over 500 ha were exclusively adopters. The difference in adoption rate significantly varies between countries, the farm size, and the cropping systems. For example, both Greece and Serbia had lower rates of adoption than Germany, the Netherlands, and the UK. Further, arable farmers had a significantly higher rate of adoption than both tree crop and vineyard farmers, which was interrelated with farm size differences. Training in agricultural technologies also appear to be crucial for increasing adoption rate of smart technologies. However, in some countries, such as France, the raise of education level of farmers faces a structural standstill with the lack of accessible options within the French education system for farming-oriented higher education level diploma for future farmers [123].

Overall smart farming technologies offer improved farm practices related to better communication, better surveillance system, a more optimized practice, better execution, better knowledge spill over, and better environmental performance. This section focuses on the economic and environmental benefits. In their PhD dissertation, Hanitravelo reviewed 34 studies that discussed environmental benefits of digital technologies (2020). Table 32 at Annex section 11.1 offers a summary of this scoping review. The review identified that the use of digital technologies in farming allows a decrease in energy consumption, water and pesticide use. The idea is that digital technologies allow farmers to optimize input use and thus emit fewer pollutants that have negative impacts on the environment. Although digital technologies seem to have a positive impact on the environment, there is a gap in research on impacts on the entire agricultural sector, notably towards whether digital tools in agriculture improve knowledge about environmental practices [124].

5.3 Economic performance

Researchers have highlighted the challenge of low adoption rates for digital technologies in agriculture. When only a few large farms adopt these technologies, it is difficult to predict the same benefits for medium-sized and small farms. The issue is exacerbated by the fact that the primary factor distinguishing users and non-users of digital technologies is their attitude toward them. For instance, a survey of 971 farmers who grew wheat, potatoes, and cotton in five European countries (Belgium, Germany, Greece, The Netherlands, and the UK) revealed that adopters were motivated by the economic return, while non-adopters were more sceptical [73].

Several studies have examined the economic impacts of digital technologies in agriculture, with some concluding that their costs are too high to be profitable for farmers. For instance, the aforementioned survey [73] identified economic cost as a major barrier to adoption. In the USA, a study found that the profitability of variable nutrient availability in a rotation of rice and soybean was highly sensitive to factors such as residual phosphorus and percentage of clay in a field’s soil [125]. Similarly, two studies in China on the adoption of RFID technology suggested that digital technologies were too costly for farmers [126]. Overall, the challenge for farmers in benefiting from digital technologies is that they must invest in the entire package of recording, guidance, and execution technologies to make them operational and profitable. This often makes the investments prohibitively expensive for small or medium-sized farms.

Some studies suggest that digital technologies can have economic benefits for farmers. For instance, sensor-based variable rate nitrogen application could result in farmers losing up to €30 per hectare or gaining up to €70 per hectare. Additionally, increased turnover due to the use of ICT or an 80% reduction in on-farm labour due to milking robots could also lead to economic benefits. However, more research is needed to fully understand how digital technologies can improve the economic performance of farmers. It is important to note that digital technologies are likely to become more affordable, intelligent, and better suited to farm needs in the future.

There has been limited research on the impact of digital technologies on farm profits, but the available evidence suggests that before 2019, small and medium-sized farms may not have benefited from such technologies due to high investment costs. Trust is also a significant issue that must be addressed to increase their adoption rate. Table 33 offers a summary of these studies and the key insights on economic benefits from digital technologies used in agriculture. Contrary to the studies on the environment where there was a certain consensus on the positive impact of smart technologies, there is a lack of studies illustrating the profitability of digital technologies in agriculture [124].

5.4 Barriers to adoption of smart farming technologies

Although all farmers broadly perceive smart farming technologies as useful to farming and generally expect smart farming technologies to continue to be so, when it comes to specific on-farm challenges, farmers are less convinced of smart farming technologies potential. Both adopter and nonadopter groups are hesitant regarding smart farming technologies adoption, such that adopters are somewhat disillusioned about the smart farming technologies that they have experience with, and non-adopters because they are not convinced that the appropriate technologies are available and accessible. Several barriers on the adoption of smart farming technologies in Europe have been identified [122].

Some of the most common barriers are:

- **High investments costs:** a characteristic that inhibits the trialability and evaluation of each smart farming technologies relative advantage
- **Lack of neutral advice:** Lack of information about existing innovative technologies as well as individual and impartial advisory services for farmers
- **Technological incompatibility:** Many farmers deplore technological incompatibility of smart farming technologies with existing technologies as devices are not interoperable. With digital technologies farmers no longer have the possibility to rely on “do it yourself” strategies when mending or adjusting devices, which is directly related to compatibility. Farmers would not only need very specific knowledge, but even risk illegal practices as software are protected as intellectual property.
- **Lack of end-user’s participation in the innovation process:** Smart farming technologies are based exclusively on technological advances. In this context, the technology customization on the farmers needs appear to be quite limited. The role of farmers in the innovation process is not clearly defined, or even denied. Proposed solutions (software, innovations, data involved, and decisions via a “black box”) are often proprietary. The farmer is just considered as end-user more than an innovation actor, which would promote their autonomy.
- **Lack of suitable options that are context-specific:** Farmers generally must adapt to standard solutions suited for the greatest market share. Consequently, the proposed solutions do not fully suit the local heterogeneous agricultural needs. Unfortunately, customized solutions realized by businesses would be too expensive.

Table 8. Barriers to smart farming technologies adoption in Europe [122]

Non-adopters	Adopters
High investment costs	High investment costs
Too complex to use	Too difficult to interpret data
Technology not appropriate for farm context and size	Devices are not interopera-ble and not precise enough
Added value is unclear	Added value is unclear
Lack of access to live demonstrations of SFT use with neutral contact	Lack of neutral advice

Especially in France, livestock farmers, especially dairy farmers, are among those who use technology the most. They have the highest adoption rate of Decision Support Systems (DSS) and are the third largest group using internet for professional purposes (10%) after cereal farmers (17%) and meat breeders (12%).

Use of digital technology by sampled dairy farmers in France as of 2020:

- 77% use the Internet as communication technology
- 50% use DSS
- 18% use the Electronic Monitoring Tool
- 11% use the Automatic Milking System
- Effect of new technology on dairy farmers in France:
  - 15% increase of milk production thanks to internet use (technology improves farmers' connection with their peers, keeping them informed about new innovations, techniques, and practices)
  - The use of Automatic Milking System increases milk production by approximately 25%.
  - The use of DSS increases production by approximately 22%
  - the Electronic Monitoring Tool (EMT) increases production by around 38%

Effect of these technologies are higher for low and medium yielding farms (compared to already very high yielding farms). Although the technologies are more adopted by farmers on the most intensive farms, the effects on production are more beneficial for the less intensive ones. Table 9 offers an overview of the different tools, software, experimentation, and institutional efforts towards smart farming in France.

Table 9: Current adopted smart-farming technologies in France and surrounding countries

Name	Description	Location	Source
360 viti	Web platform for agronomic decision management in viticulture	France/ USA	[127]
Agricolus	Complete platform for precision agriculture, Idroplan helps you to manage the irrigation, to define the best moment to act and the right quantity of water to use.	Italy/ International	[128]
Agricultural robots	The French startup Naïo Technologies is using Galileo to develop autonomous robots that can perform a variety of agricultural tasks, such as weeding, harvesting, and crop monitoring. The robots use sensors and machine learning algorithms to navigate fields and make decisions on crop management	France	[129]

Name	Description	Location	Source
AgroClim by Promété	Offers a range of 30 OADs against diseases or pests in viticulture, arboriculture, market gardening or field crops. From the application, estimate the level of protection of your plot and the ideal time to re-intervene thanks to the spraying windows	France	[130]
Agroptima	A software program that offers modules for crop management, livestock management, and financial management	France/ International	[131]
Agroptimize	A cloud-based software that allows farmers to manage their farm data, including crop management, precision farming, and livestock management	Belgium	[132]
AgroStart	A software suite that includes tools for crop management, inventory management, and financial management	BASF France division	[133]
Bouquet Farmlife	Animal collars to monitor all their life cycle	France	[134]
Climate FieldView	A software program that provides tools for crop management, field mapping, and yield analysis. by the Climate Corporation	France/ International	[135]
Corhize	A suite of tools to help keep a global vision on the water management of a parcel, a farm or a territory, and in particular the support to irrigation	France	[136]
Decitrait	Decision Support Tool (DST) that allows to follow the level of infection of diseases (downy mildew and powdery mildew) on vineyard plots	France	[137]
Ekylibre	A software platform that provides tools for crop management, field mapping, and financial management	France	[138]
Farmi	Application that offers agronomic support, and agroeconomic tools by Avizio and Crop Observer:	Switzerland	[139]
FarmWorks	A software suite that includes modules for crop management, livestock management, and financial management.	France/ international	[140]
Flexio	Connected greenhouse	France	[141]
Irré-Lis	Allows to calculate in real time the state of the water reserve of the soil and the forecasted dates of the stages which impact on the sensitivity to the hydric stress of the crop	France	[142]
Irribet	Indicates when irrigation is necessary for sugar beet crops	France	[143]
Mileos	Daily anti-mildew tool for potatoes	France	[144]
Move and Connect	connected sensors stream data around the world for smart farming	France	[145]
Movida	Risk assessment of mildew and powdery mildew in vineyard	France/ International	[146]
MyEasyFarm	software platform that offers tools for crop management, field mapping, and yield analysis.	France	[147]
Next Farming by FarmFacts	A software program that includes modules for crop management, livestock management, and field mapping	Germany	[148]
Rimpro	DST for the management of pests and diseases in fruit and wine crops	France	[149]
ruitweb	Offers many forecasting models for diseases and pests, which are important in fruit growing (e.g. scab, hoplocampus, fire blight,		

Name	Description	Location	Source
	codling moth, sooty mould disease, etc.). They offer two different weather forecast models (yr.no, meteoblue)),		
Scan Bean	Sclerotinia risk assessment on beans	France	[150]
Sencrop	The French company Sencrop is using weather data from EGNOS and other sources to develop a platform that provides farmers with real-time information on weather conditions.	France/ International	[151]
Sensing Labs	Provides sensors and software for monitoring environmental conditions in agricultural settings. The platform collects data on temperature, humidity, soil moisture, and other factors, which can be used to optimize crop growth and yield.	France	[152]
SpaceSense	Provides farmers with information on soil moisture, temperature, and other variables. The platform can be used to optimize irrigation and improve crop yields, as well as to monitor the impact of climate change on agricultural production	France	[153]
SynField/ SynAir	Synelixis offers a complete HW/SW/cloud platform, which may monitors more than 30 different parameters on air, soil, leaf and water, combines weather data from local meteorological stations and 3rd party sources and offers irrigation advice, spraying advice, air and water quality monitoring, remote control of irrigation and farm automation.	Greece/ Italy/ International	[154]
VigiMAP	Tool for the control of potato blight at plot level	Belgium	[155]
VitiMeteo	Follow the evolution of the main vine diseases	Germany	[156]
Wago by Terranis	Based on a water balance model developed in the framework of research projects, Wago calculates the daily water reserve of the soil from plot data, meteorological data (rainfall) and satellite images that update the water balance according to the real development of crops throughout the season	France	[157]
Weenat	Connected meteorological sensors and high-precision agronomy devices for agricultural professionals	France/ International	[158]
Xarvio Field Manager	Decision Support Tool (DST) that allows to monitor wheat, barley and oilseed rape crops with predictive models of stages, diseases and pests, as well as satellite image analysis.	France	[159]
Yara CheckIT	A software platform that provides tools for crop monitoring, nutrient management, and yield analysis	France	[160]

5.5 Publications, contributions, and trends in Europe

In order to study publications related to smart farming and precision agriculture, a corpora search was performed using the SCOPUS database. The query TITLE-ABS-KEY (“smart farming”) AND TITLE-ABS-KEY (“precision agriculture”) yielded 506 documents. As can be seen in Figure 47, the first publication dates to 2015. Most probably, this link relates to the ratification of the UN Sustainable Development Goals agenda, where the need for paradigm shifts in agriculture was stressed. Since 2015, a steady increase in publications’ number can be seen with a clear peak in 2022. Despite the increase, the number of publications is still relatively low with only 125 publications of smart farming and precision agriculture. This could be due to the relatively recent nature of these disciplines but also to its limited extent and adoption. Accordingly, significant research efforts are still needed for this emerging discipline.

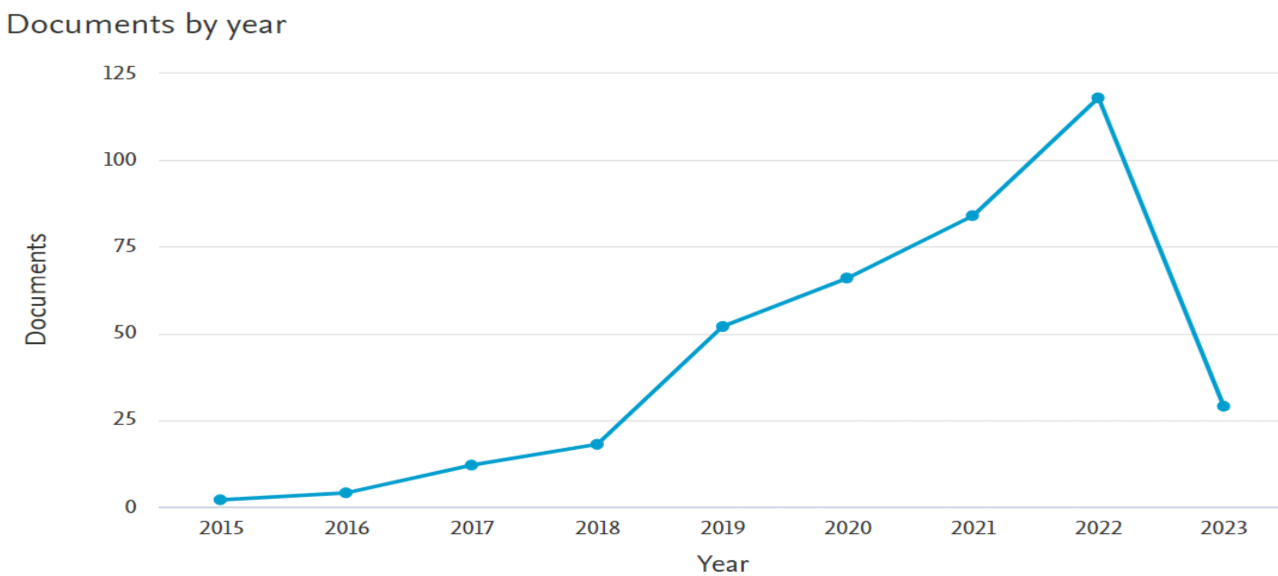


Figure 47: "Smart Farming" and "Precision Farming" publications at SCOPUS Database

In terms of contributions, a detailed analysis per country was performed. A non-EU aggregated analysis reveals that India is leading in terms of publications on smart agriculture and smart farming with 115 documents, followed by Italy with 33, Greece with 23, Spain with 22, Germany with 17 and France with 11 (Figure 48). When EU counties are aggregated, the ranking changes to 151 documents by the EU followed by 115 for India (Figure 49).

The presented curves rather show that publications on smart farming and precision agriculture are somehow restricted to particular geographies with Europe leading on the subject. In this vein, the European Commissions (EC)' Horizon, H2020 and FP7 programmes were found to be the leading funding parties for most studies. Under this context, the following precision agriculture and smart farming projects from the EC's programmes were found (Table 10) though a more detailed list of more than 520 past projects in smart farming are available at the following Link.

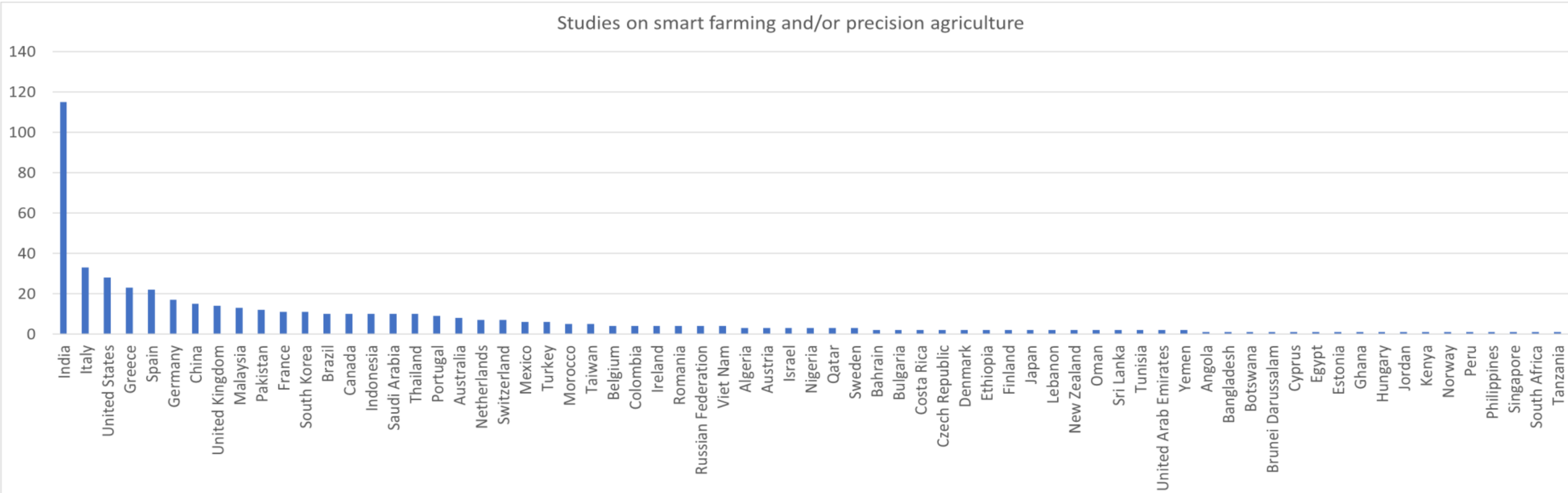


Figure 48: Studies on Smart Farming and Precision Farming (non-EU aggregated analysis)

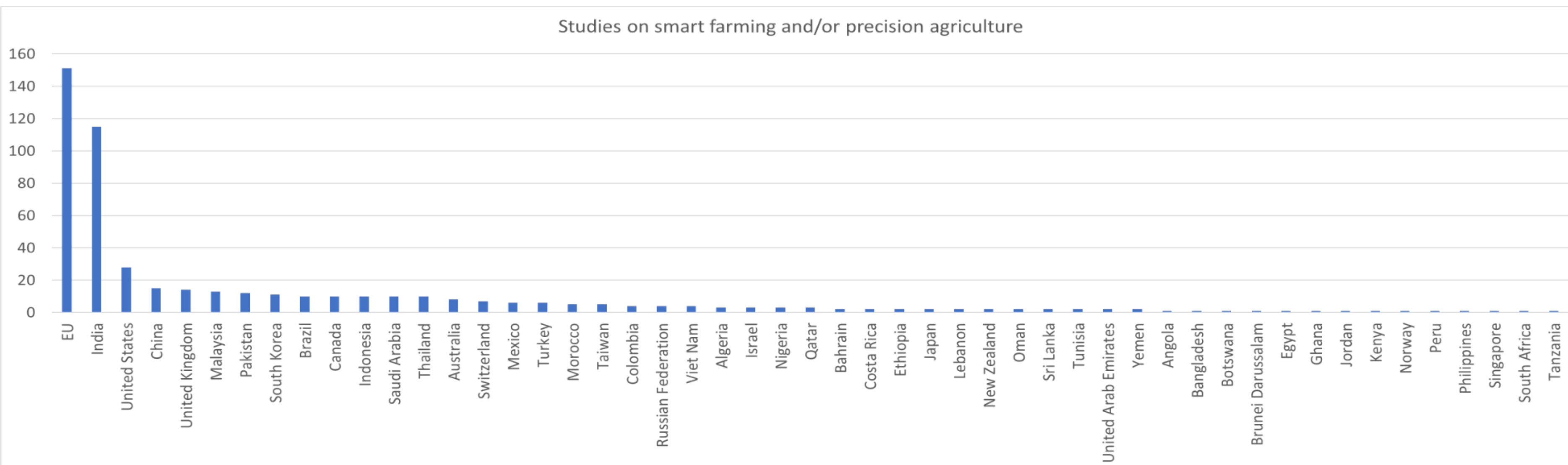


Figure 49: Studies on Smart Farming and Precision Farming (EU aggregated analysis)

A detailed analysis by country, after being mapped and extracted from the affiliations listed in the publications revealed the following distribution: 3 institutions in Africa, 7 in South America and the Middle East, 12 in North America, 19 in the Far East, 39 in South Asia and 52 in Europe. Within AgriDataValue and using the google maps tool, we have created the following interactive map, which can be accessed at [161]:

Figure 50: AgriDataValue Interactive map with detailed publications on smart farming. Link

As can be seen, except for Morocco and Madagascar, Africa relatively lacks any smart farming activities or publications. This disparity in smart farming publications may be related to differences in technology levels, access to data and technology, and a general knowledge of the topic. While an evolving topic, geographical gradients reveal a heterogenous distribution, hence underlining the need for more cross-collaborations and cross-geographical efforts.

Table 10 provides an indicative list of projects funded by the European Commission in smart farming presenting also the smart farming technologies, such as UAVs, UGVs, WSN, image processing, cloud computing and machine learning that have been utilised. A more detailed list of more than 520 past projects in smart farming are available at the following Link.

Table 10: An indicative list of projects targeting Smart Farming

Project	Start/ End	Involved Technologies	Crop	Field Operations	Program	Coord	Webpage
4D4F (Data Driven Dairy Decisions 4 Farmers)	1-Mar-16/ 28-Feb-19				H2020-EU.3.2. - Food security, sustainable agriculture and forestry, marine, maritime and inland water research, and the bioeconomy	INNOVATION FOR AGRICULTURE, UK	Link
BRIGHTANIMAL (Multidisciplinary Approach to Practical and Acceptable Precision Livestock Farming for SMEs in Europe and world-wide)	1-May-09/ 30-Apr-11				FP7-KBBE - Specific Programme "Cooperation": Food, Agriculture and Biotechnology	FOODREG TECHNOLOGY SL, Spain	Link
CATTLECHAIN 4.0 Enhancing farm productivity and guaranteeing CATTLE traceability and welfare with blockCHAIN	1-Apr-19/ 31-Mar-22				H2020-EU2.1. - Industrial leadership - Leadership in enablig and industrial technologies	MANAGEMENT, CONSTRUCTION AND TRADE, INNOVATIVE SOLUTIONS INTERNATIONAL SL, Spain	Link
DRAGON Data Driven Precision Agriculture Services and Skill Acquisition	1-Oct-18/ 31-Jan-22				H2020-EU.4.b. - Twinning of research institutions	BIOSENSE, Serbia	Link
ECHORD Plus Plus (European Clearing House for Open Robotics Development Plus Plus)	1-Oct-13/ 30-Sep-18	Cloud Computing Image Processing Machine Learning UAV UGV	Asparagus Corn Cucumber Eggplant Melons Peppers Sugar Beet Tomatoes Vineyard	Crop Monitoring Grafting Harvesting Pruning Seeding Spraying Weed Management	FP7-ENVIRONMENT	Technische Universität München, Germany	Link

Project	Start/ End	Involved Technologies	Crop	Field Operations	Program	Coord	Webpage
			Watermelons				
ENORASIS (ENvironmental Optimization of IRrigAtion anagement with the Combined uSe and Integration of High PrecisIon Satellite Data)	01-Jan-12/ 31-Dec-14	WSN	Apple Trees Cherry Trees Corn Cotton Grapefruit Maize Potatoes Raspberry	Water Management	FP7-ENVIRONMENT	Draxis Environmental S.A., Greece	Link
ERMES (An Earth obseRvation Model based RicE information Service),	5-Sept-13/ 28-Feb-17	Big Data Cloud Computing UAV WSN	Rice	Crop Monitoring	FP7-SPACE	CNR – IREA, Italy	Link
FIGARO (Flexible and PrecIse IrriGation PlAtform to Improve FaRm Scale Water PrOductivity),	1-Oct-12/ 30-Sept-16	WSN	–	Water Management	FP7- KBBE.2012.1.1-03 - Precision technologies to improve irrigation management and increase water productivity in major water-demanding crops in Europe	NETAFIM LTD, Israel	Link
FLEXIGROBOTS (Flexible robots for intelligent automation of precision agriculture operations)	1-Jan-21/ 31-Dec-23	Big Data Cloud Computing Image Processing AI/ML UAV UGV	Blueberry Vineyards Rumex Weed	Crop Monitoring Spraying Weed Management Harvesting Disease Detection	H2020-EU.2.1.1. - Leadership in enabling and industrial technologies - ICT	ATOS IT SOLUTIONS AND SERVICES IBERIA SL, Spain	Link
Flourish (Aerial Data Collection and Analysis, and Automated Ground Intervention for Precision Farming)	1-Mar-15/ 31-Aug-18	Image Processing UAV UGV	Sugar Beet Sunflower	Crop Monitoring Spraying	H2020-EU.2.1.1.5. - Advanced interfaces and robots: Robotics and smart spaces	EIDGENOESSISCHE TECHNISCHE HOCHSCHULE ZUERICH, Switzerland	Link

Project	Start/ End	Involved Technologies	Crop	Field Operations	Program	Coord	Webpage
FRACTALS (Future Internet Enabled Agricultural Applications)	1-Dec-14/ 31-Aug-16	WSN Future Internet	Olive Trees	Crop Monitoring Disease Detection Fertilization	FP7-FI- ICT-2013.1.8 - Expansion of Use Cases	RAZVOJNI FOND AUTONOMNE POKRAJINE VOJVODINE D.O.O., Serbia	Link
GATES (Applying GAming TEchnologies for training professionals in Smart Farming)	1-Jan-17/ 30-Jun-19	Machine Learning	–	Educational	H2020-EU.2.1.1. - - Leadership in enabling and industrial technologies	GEOPONIKO PANEPISTIMION ATHINON, Greece	Link
Healthy Livestock Tackling Antimicrobial Resistance through improved livestock Health and Welfare	1-Sep-18/ 28-Feb-23	Machine Learning			H2020-EU.3.2.1.1. - Increasing production efficiency and coping with climate change, while ensuring sustainability and resilience	STICHTING WAGENINGEN RESEARCH, Netherlands	Link
LANDSUPPORT (Development of Integrated Web-Based Land Decision Support System Aiming Towards the Implementation of Policies for Agriculture and Environment)	1-May-18/ 30-Apr-22	Cloud Computing			H2020-EU.3.2.1.3. - Empowerment of rural areas, support to policies and rural innovation	UNIVERSITA DEGLI STUDI DI NAPOLI FEDERICO II, Italy	Link
MISTRALE (Monitoring of SoIl moiSture and wateR-flooded Areas for agricuLture and Environment)	01-Jan-15/ 31-Dec-17	Image Processing UAV	Potatoes Vineyard	Crop Monitoring Water Management	H2020- EU2.1.6- Leadership in enabling and industrial technologies – Space	M3 SYSTEMS. Belgium	Link
PANTHEON Precision Farming of Hazelnut Orchards	1-Nov-17/ 31-Oct-21	Big Data UAV, UGV WSN	Hazelnuts	Crop Monitoring Water Management	H2020-EU.2.1.1. Leadership in enabling and industrial technologies - ICT	UNIVERSITA DEGLI STUDI ROMA TRE, Italy	Link

Project	Start/ End	Involved Technologies	Crop	Field Operations	Program	Coord	Webpage
ROMI RObotics for MIcrofarms	1-Nov-17/ 31-Jul-22	UAV UGV	–	Crop Monitoring Weed Management	H2020-EU.2.1.1. - Leadership in enabling and industrial technologies - ICT	INSTITUT D'ARQUITECTURA AVANCADA DE CATALUNYA, Spain	Link
SmartAgriFood2 (Smart Food and Agribusiness: Future Internet for Safe and Healthy Food from Farm to Fork)	1-Jun-14/ 30-Sep-16	WSN Future Internet	Various	KMS	FP7-ICT ICT-2013.1.8 - Expansion of Use Cases	STICHTING WAGENINGEN RESEARCH. Netherlands	Link
Smart-AKIS (European Agricultural Knowledge and Innovation Systems towards innovation-driven research in Smart Farming Technology)	1-Mar-16/ 31-Aug-18	Cloud Computing		KMS	H2020-EU.3.2. - SOCIETAL CHALLENGES - Food security, sustainable agriculture and forestry, marine, maritime and inland water research, and the bioeconomy	GEOPONIKO PANEPISTIMION ATHINON, Greece	Link
SMARTER SMAll RuminanTs breeding for Efficiency and Resilience	1-Nov-18/ 31-Oct-22	Cloud Computing			H2020-EU.3.2.1.1. - Increasing production efficiency and coping with climate change, while ensuring sustainability and resilience	INRAE, France	Link
SWEEPER (Sweet Pepper Harvesting Robot)	1-Feb-15/ 31-Oct-18	Image Processing UGV	Peppers	Harvesting	H2020-EU.2.1.1.5. - Advanced interfaces and robots: Robotics and smart spaces	STICHTING WAGENINGEN RESEARCH, Netherlands	Link
TEKNOAX 2.0 (Bringing Intelligence onto Axles of	1-Jan-17/ 31-Dec-18	WSN Cloud Computing		Farm Management	H2020-EU.2. - PRIORITY 'Industrial leadership'	A.D.R. S.P.A., Italy	Link

Project	Start/ End	Involved Technologies	Crop	Field Operations	Program	Coord	Webpage
Third Millennium Farming Trailers)							
ULTRAFINEWINE (Novel method for assisting and accelerating the aging process of wine)	1-Dec-10/ 30-Nov-12	WSN	Vineyard	Crop Monitoring Harvesting	FP7-SME	IRIS TECHNOLOGY SOLUTIONS, Spain	Link
VINBOT (Autonomous Cloud-Computing Vineyard Robot to Optimize Yield Management and Wine Quality)	01-Feb-14/ 31-Jan-17	Could Computing	Vineyard	Crop Monitoring Yield Prediction	FP7-SME	ROBOTNIK AUTOMATION SL, Spain	Link
VINEROBOT (VINEyard ROBOT. A wheeled robot to monitor grape growth)	1-Dec-13/ 31-May-17	Image Processing Machine Learning UGV	Vineyard	Crop Monitoring Disease Detection Water Management	FP7-ICT	UNIVERSIDAD DE LA RIOJA, Spain	Link
WATER-BEE (Low cost, easy to use Intelligent Irrigation Scheduling System)	1-Oct-08/ 30-Sep-10	WSN	–	Water Management	FP7-SME - Specific Programme "Capacities": Research for the benefit of SMEs	OSV SRL, Italy	Link

5.5.1 Research Efforts on smart farming in Europe

This sub-section presents the research efforts European countries conducted on smart farming. Figure 51 shows the different European countries involved in smart farming research effort between 2008-2020. Spain and Italy are leading these efforts, in numbers of scientific articles published on smart farming, followed by Germany and Greece. Figure 52 illustrates that, in Europe, most scientific publications about smart farming focus on crop monitoring, followed by water and weed management. Figure 53 indicates that image processing and UAV are the most research technologies in Europe when it comes to smart farming.

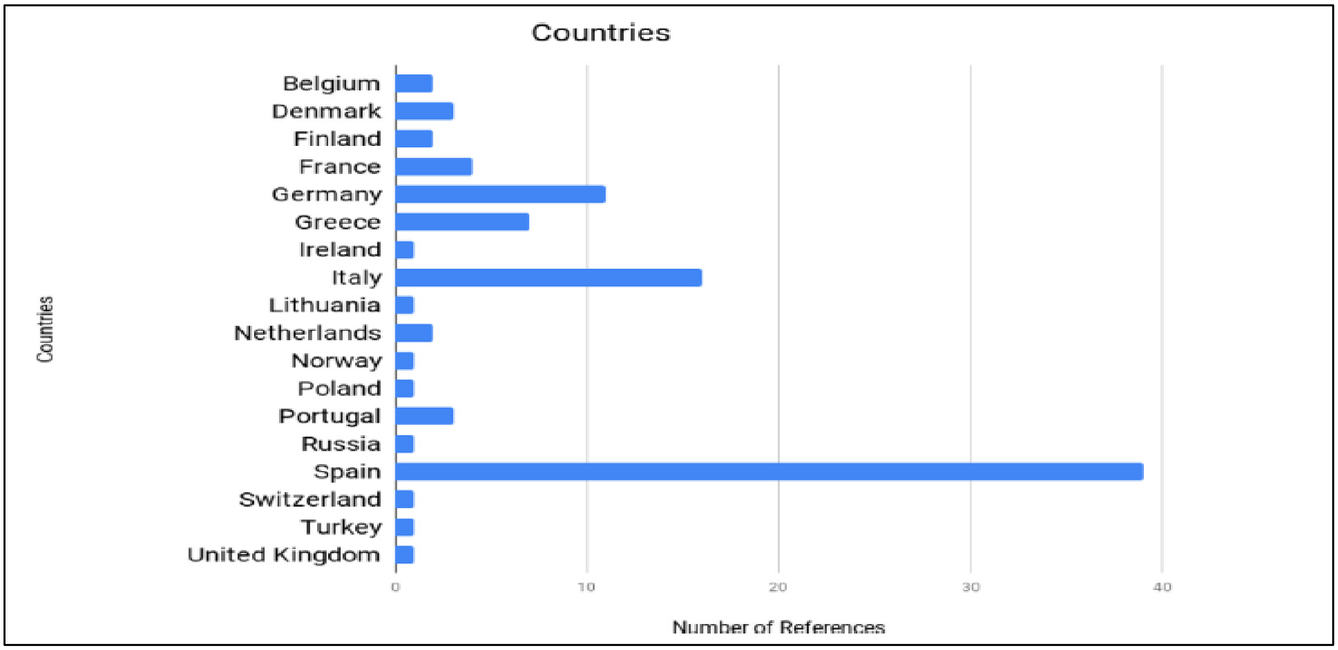


Figure 51. Research efforts conducted by European countries [113]

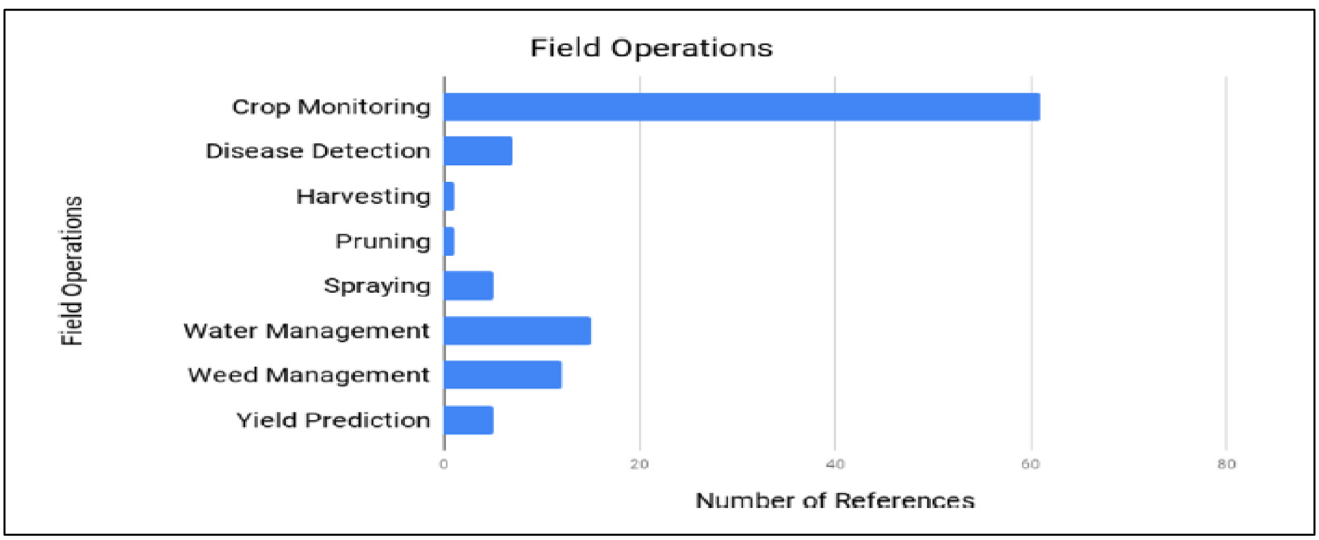


Figure 52. Number of scientific publications across different types of field operations

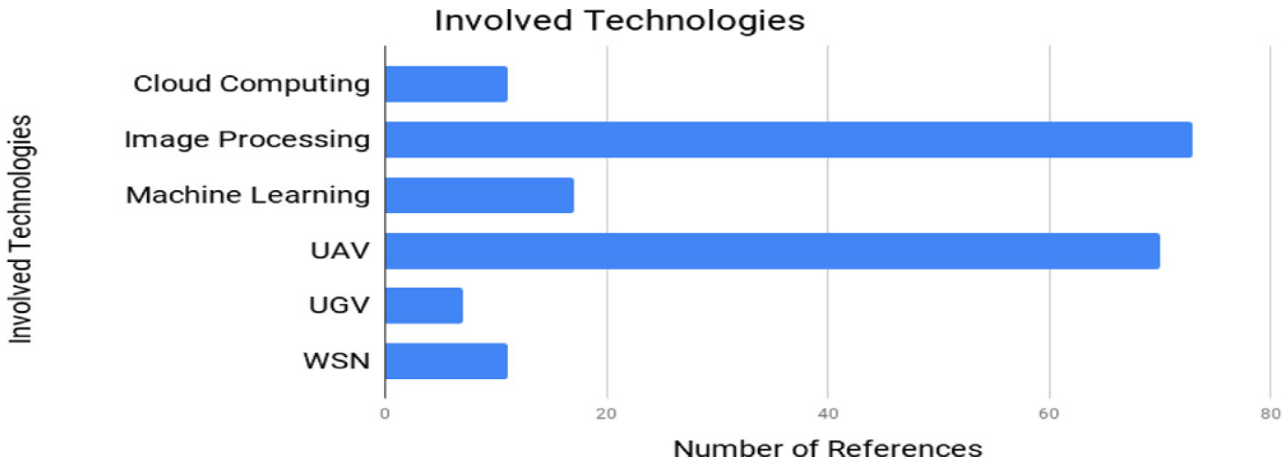


Figure 53. Number of scientific publications across involved technologies in European research efforts

The tables below offer references of scientific publications related to smart farming in Europe. More specifically, Table 34 offers the references for involved technologies in European research efforts, Table 35 lists the references of scientific publication across European countries (where the research took place), Table 36 gives references of scientific publications across the types of crops used in European research efforts, and Table 37 offers references for scientific publications across the different field of operations in European research efforts.

5.6 Analysis of existing methods

Currently different types of methodologies and techniques exist to monitor impacts of climate change on crops and livestock, provide accurate information in real time to growers. These methods have been used to improve the farms operation, by turning on early warning system or adopting the more adequate measures to protect their crops and livestock. The adoption of robotic techniques, such as the Internet of Things, Big Data analysis, artificial intelligence, cloud computing and remote sensing are part of the recent agricultural era, the smart farming. In this section, some of these techniques to evaluate, adapt and monitor impacts of climate (and climate change) on crops and livestock will be exposed.

5.6.1 Earth Observation Services

Information of vegetation or soil conditions can be collected from satellites, aircrafts, and other aerial vehicles like drones. According to the UK Space Agency [162], earth observation (EO) is the gathering of information about the physical, chemical, and biological systems of the planet via remote-sensing technologies, supplemented by Earth-surveying techniques, which encompasses the collection, analysis, and presentation of data. EO data is widely used to map agricultural patterns or monitor land use and land cover, identify when crops were planted and how they are developing, estimate crop irrigation, soil properties, crop–livestock systems, etc. [163]. Moreover, the impact of climate change on agriculture can be predicted, by the identification of seasonal variation of precipitation, droughts, harvests, and potential crop damage such as the arrival of swarms of locusts [164]. This is very useful to adopt solutions that ensuring sustainable agricultural practices. Data related to climate (and climate change) from EO technologies are of big interest for farmers in areas, where ground information are not available or limited.

5.6.1.1 Sentinel Hub

Sentinel Hub provides unprecedented access to earth observation data, focused on Copernicus satellites but also supporting other sources such as Landsat, Modis, and others. It uses cloud infrastructure and innovative methods to efficiently process and distribute data in a matter of seconds. It can be integrated into any mapping application for web application allowing for an easy-to-use and cost-effective way to exploit the data. It removes the major hassle of downloading, archiving, and processing petabytes of data and simply makes the full and global archive easily available immediately via web services. Application developers can focus on added value services and end-user applications rather than having to deal with the complexity of remote sensing data. Sentinel Hub technology is designed to work with original EO data, avoiding the need for computing intensive pre-processing and additional storage for processed tiles.

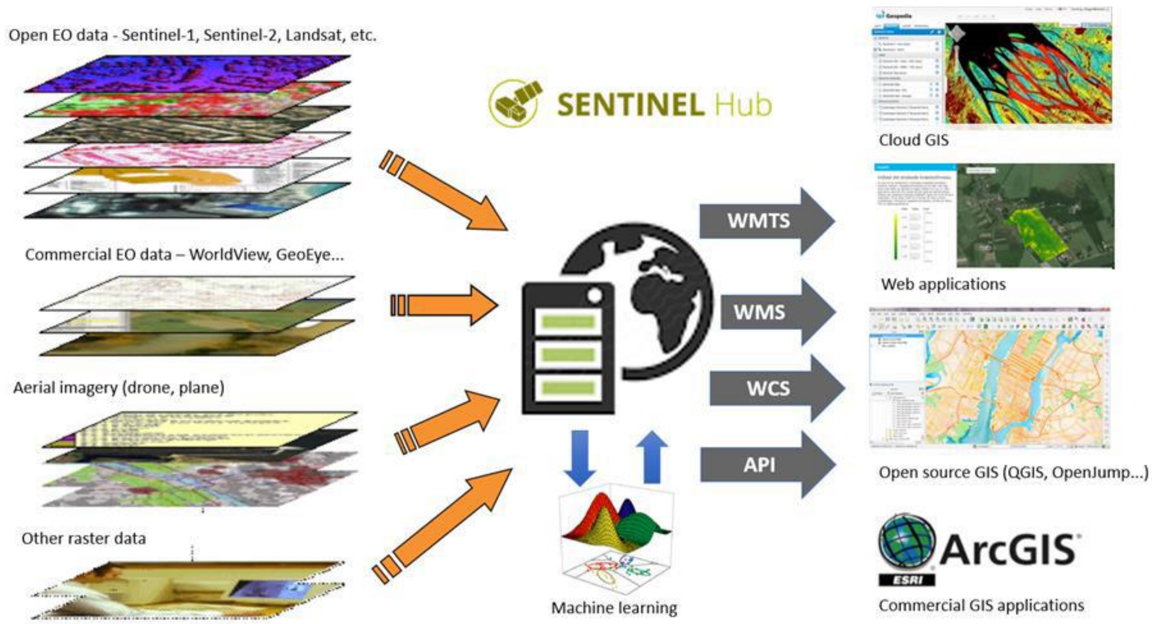


Figure 54: Concept diagram of Sentinel Hub services

The Sentinel Hub Open Geospatial Consortium (OGC) API supports:

- Web Map Service (WMS) for seamless integration in GIS applications
- Web Map Tile Service (WMTS) provides access to Sentinel-2's 13 unprocessed bands and other processed data
- Web Coverage Service (WCS) for provision of exact EO data, best used when integrated in application developers' post-processing workflows; giving developers an ability to specify exactly, what kind of data they require (resolution, reflectance, etc.);
- Web Feature Services (WFS) for meta-data provision (Catalogue access)

Standard OGC service interfaces are extended to support additional EO parameters, such as maximum cloud coverage, mosaicking order, composites, etc.

5.6.1.2 Real-time processing of EO data.

Sentinel Hub OGC API is optimized for on-demand on-the-fly processing of raw (unchanged) EO data. The following steps are typically performed within a standard request:

1. Query Catalogue for chosen AOI, time range, cloud coverage, mission, etc.
2. Download necessary data from on-line storage
3. Decompress data
4. Application of pre-mosaic filters (e.g. DOS-1, statistical atmospheric correction, etc.)
5. Creation of mosaic based on priority (e.g. most recent data on top), cloud replacement, etc.

6. Compositing relevant bands to chosen EO product (true color, false color, NDVI, etc.) using chosen style (greyscale, RGB, red temperature, etc.)
7. Application of post-mosaic filters (color balance, HDR, midtone, gamma correction)
8. Re-projection to chosen CRS (e.g. Popular Web Mercator, WGS 84, national CRS systems).
9. Output creation in chosen file type (JPG, PNG, JP2, JPX, GeoTiff, etc.)
10. Compression of the output for faster download, based user settings

5.6.1.3 Configuration utility

Every registered user can add as many unique-named instances as he/she chooses. An instance acts as a separate WMS/WMTS/WFS/WCS service and each can be configured to provide a certain set of layers with different settings. It is therefore possible to create multiple instances each with a different set of layers fulfilling various needs. Instances may contain an arbitrary number of layers. Each layer is associated with either one of the raw sensor bands or the products (such as TRUE_COLOR) and product styles. Layers are also additionally configurable using the settings defined above, such as MAXCC, TIME, the max area limitation, etc. The instance itself also has some global settings for default values on all layers, like image quality.

5.6.1.4 EO data

Characteristics of Earth observation data from various satellites are categorized in the following table.

Table 11: Earth observation data categorization

Data collection	Availability - Spatial	Availability - Temporal	Revisit
Sentinel-2 L1C	Whole world	November 2015 →	5 days
Sentinel-2 L2A	Whole world	January 2017 →	3-5 days
Sentinel -1	Whole world	For eo-cloud: October 2014 → For services: January 2017 →	6-12 days
Sentinel-3 OLCI L1B	Land and coastal areas where solar zenith angle <80 degrees	April 2016 →	< 2 days
Sentinel-3 SLSTR L1B	Land and coastal areas where solar zenith angle <80 degrees	May 2016 →	< 0.9 days
Sentinel 5P L2	Whole world	April 2018 →	daily
Landsat 1-5 MSS Collection 2 Level 1 Data	Global land	LS1: July 1972 → January 1978 LS2: January 1975 →February 1982 LS3: March 1978 → March 1983 LS4: July 1982 → December 1993 LS 5: 1984 → October 1992, and from June 2012 → January 2013 July 1972 → October 1992, June 2012 → January 2013	various (16 – 18 days)

Landsat 4-5 TM Collection 2 Level 1 Data	Global land	LS4: July 1982 → December 1993 LS5: March 1984 → May 2012	16 days
Landsat 4-5 TM Collection 2 Level 2 Data	Global land	LS4: July 1982 → December 1993 LS5: March 1984 → May 2012	16 days
Landsat 7 ETM+ Collection 2 Level 1 Data	Global land	April 1999 →	16 days
Landsat 7 ETM+ Collection 2 Level 2 Data	Global land	April 1999 →	16 days
Landsat 8-9 OLI-TIRS Collection 2 Level 1 Data	Land	February 2013 →	16 days
Landsat 8-9 OLI-TIRS Collection 2 Level 2 Data	Land	February 2013 →	16 days
Envisat Meris	Whole world	from June 2002 to April 2012	3 days
Digital Elevation Model (DEM)	Whole world	Static	/
Copernicus DEM 90	Whole world	Static	/
Copernicus DEM 30	Whole world	Static	/
MODIS	Whole world	24 February 2000 →	daily
Commercial Data – PlanetScope	Whole world	2009 →	daily
Commercial Data – Pleiades	Whole world	December 2011 →	on-demand acquisitions
Commercial Data – Spot	Whole world	September 2012 →	on-demand acquisitions
Commercial Data – WorldView (+GeoEye)	Whole world	2009 →	on-demand acquisitions, archive

All above EO data is accessible through Sentinel-Hub services. There are several options to get the data:

- EO Browser [165] for quick and fast checks what data is available where.
- Sentinelhub-py [166] and EO-learn [167] for programmatic access with Python.
- Other approaches (integrations with different applications) as documented on Sentinel-Hub [168].

Examples and documentation for access with Python libraries are available on sentinelhub-py documentation [169] and eo-learn documentation [170].

5.6.1.5 Copernicus Sentinel-1

Copernicus Sentinel-1 [171] imagery is provided by two polar-orbiting satellites, operating day and night performing C-band synthetic aperture radar imaging, enabling them to acquire imagery regardless of the weather. Main applications are for monitoring sea ice, oil spills, marine winds, waves and currents, land-use change, land deformation among others, and to respond to emergencies such as floods and earthquakes.

Table 12: Copernicus Sentinel-1 Endpoints Locations

Service	Notes
services.sentinel-hub.com/api/	Global since January 2017
eocloud.sentinel-hub.com/v1/	Global since October 2014
shservices.mundiwebservices.com/api/	Rolling policy: 48 months for Europe, 12 months for World

5.6.1.6 Copernicus Sentinel-2

Copernicus Sentinel-2 [172] is a European wide-swath, high-resolution, multi-spectral imaging mission. Its high-resolution optical images have many applications, including land monitoring, emergency response and security services assistance. The satellite's multispectral imager provides a versatile set of 13 spectral bands spanning from the visible and near infrared to the shortwave infrared.

Table 13: Copernicus Sentinel-2 Basic facts – Sentinel-2L1C

Property	Info
Spatial resolution	10 m, 20 m, and 60 m depending on the wavelength
Sensor	MultiSpectral Instrument (MSI), 13 bands: 4 visible bands, 6 Near-Infrared bands, and 3 Short-Wave Infrared bands
Revisit time	5 days with two satellites
Spatial coverage	Land and coastal areas between latitudes 56°S and 83°N
Data availability	Since November 2015
Measurement	Top of the atmosphere (TOA) reflectance
Common usage/purpose	Land-cover maps, land-change detection maps, vegetation monitoring, monitoring of burned areas
Common usage/purpose	Land-cover maps, land-change detection maps, vegetation monitoring, monitoring of burned areas

Level 2A [173] is processed using Sen2Cor as provided by ESA. To access the data, you need to send a POST request to the process API. The requested data will be returned as the response to your request. Each POST request can be tailored to get exactly the data required. This requires setting various parameters which depend on the data source being queried. For an overview of all API parameters see the API Reference [174]. Additional information, descriptions on available bands, search functionalities, filtering, mosaicking, examples and other capabilities can be found at [175] [176].

Table 14: Copernicus Sentinel-2 Endpoint Locations Sentinel-2 Data

Type	Services Endpoint	Notes
L1C	services.sentinel-hub.com/api/	Global since November 2015
	eocloud.sentinel-hub.com/v1/	Global since November 2015
	creodias.sentinel-hub.com/api/	Global since November 2015
	code-de.sentinel-hub.com/api/	Germany since July 2015
	shservices.mundiwebservices.com/api/	Europe coverage since July 2015 Rolling policy of 12 months for World
L2A	services.sentinel-hub.com/	Europe since November 2016 Global since January 2017
	shservices.mundiwebservices.com/	Europe since July 2016

5.6.1.7 Copernicus Sentinel-3

Copernicus Sentinel-3 [177] is a European wide-swath, medium-resolution, multi-spectral imaging mission designed to monitor ocean surface topography as well as land and sea surface temperature. The satellite hosts 4 instruments: the Sea and Land Surface Temperature Radiometer (SLSTR), the Ocean and Land Colour Instrument (OLCI), a Sar Radar Altimeter (SRAL) and a Microwave Radiometer (MWR). Sentinel-3A was launched on 16 February 2016 and its twin Sentinel-3B on 25 April 2018. Sentinel Hub currently provides access to OLCI and SLSTR data collections.

Table 15: Copernicus Sentinel-3 Basic facts for Sentinel-3 OLCI

Property	Info
Spatial resolution	~300 m
Sensor	Ocean and Land Colour Instrument (OLCI), 21 bands: 16 visible bands, 5 Near-Infrared bands
Units	Radiance (mW.m-2.sr-1.nm-1). Note that Sentinel Hub returns reflectance.
Revisit time	< 2 days with 2 satellites
Spatial coverage	Land and coastal areas where the solar zenith angle < 80º
Data availability	Since April 2016
Measurement	Top of the atmosphere (TOA) radiance
Common usage/purpose	Maritime, land, atmospheric and climate change monitoring

Table 16: Copernicus Sentinel-3 Basic facts for Sentinel-3 SLSTR

Property	Info
Spatial resolution	~500 m or 1km
Sensor	Sea and Land Surface Temperature Radiometer (SLSTR), 11 bands: 3 VNIR bands, 3 SWIR bands, 5 thermal IR bands.
Units	Radiance: $mW.m^{-2}.sr^{-1}.nm^{-1}$ (Note that Sentinel Hub returns reflectance) Brightness temperature: K.
Revisit time	< 0.9 days with 2 satellites
Spatial coverage	Land and coastal areas where the solar zenith angle < 80º
Data availability	Since May 2016
Measurement	Top of the atmosphere (TOA) radiance
Common usage/purpose	Climate change monitoring, vegetation monitoring, active fire detection, land and sea surface temperature monitoring.

5.6.1.8 Copernicus Sentinel 5P

Sentinel Hub supports Sentinel-5P [178] level 2 (L2) data products as provided by ESA. Raw bands (Level 1 products) are not available in Sentinel Hub. The Sentinel-5P (P for precursor) mission aims at providing information and services on air quality and climate between 2017 and at least 2023. With the TROPOMI sensor on board it makes daily global observations of key atmospheric constituents, including ozone, nitrogen dioxide, sulphur dioxide, carbon monoxide, methane, formaldehyde as well as cloud and aerosol properties. The mission aims at ensuring data continuity between the retirement of the Envisat satellite and NASA's Aura mission and the launch of Sentinel-5 [179]

Table 17: Basic facts Sentinel 5P

Property	**Info**
Spatial resolution	Up to 5.5 km x 3.5 km [180]
Sensor	Tropospheric Monitoring Instrument (TROPOMI), a spectrometer measuring ultraviolet and visible (270–495 nm), near infrared (675–775 nm) and shortwave infrared (2305–2385 nm) light.
Revisit time	Less than one day.
Spatial coverage	Global coverage.
Data availability	Since April 2018.
Common usage/purpose	To provide global information on a multitude of atmospheric trace gases, aerosols and cloud distributions affecting air quality and climate.

5.6.1.9 Landsat 1-5 MSS L1

The Landsat Multispectral Scanner System (MSS) sensors were carried onboard Landsats 1 to 5. It provides 4 spectral bands.

Table 18: Basic facts Landsat 1-5 MSS L1

Property	**Info**
Spatial resolution	68 m x 83 m (commonly resampled to 57 m, or 60 m)
Sensor	Multispectral Scanner System (MSS) with 4 spectral bands
Revisit time	18 days for Landsats 1-3 and 16 days for Landsat 4-5
Spatial coverage	Whole globe
Data availability	Landsat 1: July 1972 → January 1978 Landsat 2: January 1975 →February 1982 Landsat 3: March 1978 → March 1983 Landsat 4: July 1982 → December 1993 Landsat 5: 1984 → October 1992, and from June 2012 → January 2013
Common usage/purpose	Vegetation monitoring, land use, land cover maps and monitoring of changes.

5.6.1.10 Landsat 4-5 TM

The Landsat Thematic Mapper (TM) sensor was carried onboard Landsats 4 and 5. It provides 6 spectral bands and 1 thermal infrared band. Both Level 1 and Level 2 data are available.

Table 19: Basic facts Landsat 4-5 TM

Property	**Info**
Spatial resolution	30 m (the thermal band is re-sampled from 120 m)
Sensor	Thematic Mapper (TM) with 6 spectral bands and 1 thermal infrared band
Revisit time	16 days
Spatial coverage	Whole globe
Data availability	Landsat 4 from July 1982 to December 1993 Landsat 5 from March 1984 to May 2012
Common usage/purpose	Vegetation monitoring, land use, land cover maps and monitoring of changes.

5.6.1.11 Landsat 7 ETM+

The Landsat 7 Enhanced Thematic Mapper (ETM+) sensor is carried onboard Landsat 7. It provides 7 spectral bands and 1 thermal band.

Table 20: Basic facts Landsat 7 EMT+

Property	Info
Spatial resolution	15 m for the panchromatic band and 30 m for the rest (the thermal band is re-sampled from 60 m)
Sensor	Enhanced Thematic Mapper (ETM+) with 8 spectral bands and 1 thermal band
Revisit time	16 days
Spatial coverage	Whole globe
Data availability	Since April 1999
Spatial resolution	15 m for the panchromatic band and 30 m for the rest (the thermal band is re-sampled from 60 m)

5.6.1.12 Landsat 8-9

Landsat 8-9 Level 2 collection includes both Landsat 8 and the most recently launched Landsat 9 satellites (provided by NASA/USGS), both carrying the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS), providing seasonal coverage of the global landmass. Landsat 8-9 Level 2 provides global surface reflectance and surface temperature science products. Level 2 science products are generated from Collection 2 Level-1 inputs that meet the <76 degrees Solar Zenith Angle constraint and include the required auxiliary data inputs to generate a scientifically viable product. Both Level 1 [181]and Level 2 [182] data are available. Please note that Level 2 data does not include the panchromatic band.

Table 21: Basic facts Landsat 8-9

Property	Info
Spatial resolution	15 m for the panchromatic band and 30 m for the rest (the thermal bands is re-sampled from 100 m)
Sensor	Operational Land Imager (OLI) with 9 spectral bands and Thermal Infrared Sensor (TIRS) with 2 thermal bands
Revisit time	16 days
Spatial coverage	Whole globe
Data availability	Landsat 8: since February 2013 Landsat 9: since February 2022
Common usage/purpose	Vegetation monitoring, land use, land cover maps and monitoring of changes.

5.6.1.13 Envisat MERIS

The purpose of the Medium Resolution Imaging Spectrometer (MERIS) is primarily, to aid in Ocean Colour Observations, and secondary, to aid in the understanding of the atmospheric parameters associated with clouds, water vapour and aerosols. Additionally, it is useful for land surface parameters, particularly for vegetation processes. It monitors changes of oceans (phytoplankton, yellow substance, suspended matter), atmosphere (water vapour, CO_2, clouds, aerosols), and land (vegetation index, global coverage, moisture etc.). MERIS has a high spectral and radiometric resolution and a dual spatial resolution. It acquires 15 spectral bands, which can be programmed in their width and position. The data is available from June 2002 to April 2012. It has 3 days revisit time. Spatial Resolution: Full 260 m resolution across track and 290 m along track. Reduced resolution of 1040 m across track and 1160 m along track [183].

5.6.1.14 Digital Elevation Model

A Digital Elevation Model (DEM) is a digital model or 3D representation of a terrain's surface. DEM allows analysing heights within an area of interest and integrate the data in 3D applications. The data can also be used for the orthorectification of satellite imagery (e.g., Sentinel 1). Sentinel Hub supports Mapzen's DEM, available through Amazon Web Services (AWS) [184] through EU-Central-1 and US-West-2 regions, and Copernicus DEM, available through AWS EU-Central-1 region.

Copernicus DEM is based on World DEM that is infilled on a local basis with the following DEMs: ASTER, SRTM90, SRTM30, SRTM30plus, GMTED2010, TerraSAR-X Radar grammetric DEM, ALOS World 3D-30m. We provide two instances named COPERNICUS_30 and COPERNICUS_90, with worldwide coverage. COPERNICUS_90 uses COP-DEM GLO-90, which has 90 meters resolution. COPERNICUS_30 uses COP-DEM GLO-30 Public, which has 30 meters resolution, where it's available, and for the rest is uses GLO-90. Tiles that are missing from GLO-30 Public are not yet released to the public by Copernicus Programme. Both instances are static and do not depend on the date. It returns a homogeneous DEM with zeros in regions where there are no source tiles (e.g., in ocean areas). More information about the various elevation models on Sentinel Hub is available here [185, 186]

5.6.1.15 MODIS

MODIS (Moderate Resolution Imaging Spectroradiometer) is a sensor aboard two satellites, Aqua and Terra. It images the earth in 36 different bands at 3 different resolutions (250 m for bands 1-2, 500 meters for bands 3-7 and 1 km for bands 8-36). The MCD43A4 V006 is a product used by Sentinel Hub, with daily global coverage, offering bands 1-7 in 500-meter resolution.

The MCD43A4 V006 is a Version 6 Nadir Bidirectional Reflectance Distribution Function (BRDF) - Adjusted Reflectance (NBAR) dataset. As an NBAR product [187], it provides estimations of the surface spectral reflectance as it would be measured at ground level in absence of atmospheric scattering and absorption. Each pixel contains the best possible information available in a 16-day period as selected based on high observation coverage, low view angle, the absence of clouds or cloud shadow, and aerosol loading. The following information holds for the MODIS MCD43A4.006 data product in Sentinel Hub, and not for MODIS in general.

Table 22: Basic facts MODIS

Property	Info
Spatial resolution	500 m
Sensor	MODIS - Moderate Resolution Imaging Spectroradiometer
Units	Reflectance and DN
Revisit time	Daily
Spatial coverage	Global
Data availability	Since February 24, 2000
Measurement	Surface reflectance
Common usage/purpose	Monitoring of large-scale land, ocean and atmosphere changes, such as vegetation monitoring or flood, hurricane and wildfire detection.

5.6.1.16 Commercial Data – Planet Scope

Planet Scope [188] satellite constellation consists of more than 130 small satellites called Doves. Each Dove satellite is a CubeSat made of three cubic units and thus measures only 10 cm x 10 cm x 30 cm. The satellites are launched in groups, which constantly improves mission's characteristics such as revisit times, spatial and spectral resolutions. The constellation is constantly "on" and does not require an acquisition planning. PlanetScope data is an excellent source for vegetation monitoring. It complements Sentinel-2 data with better spatial resolution and better temporal coverage, which is especially important in cloudy areas as it increases the chance of acquiring a cloudless image.

Table 23: Basic facts PlanetScope

Property	Info
Spatial resolution	3 m (resampled)
Sensor	Four-band frame Imager: Blue, Red, Green and Near-Infrared band
Revisit time	1 day
Spatial coverage	global
Data availability	Since 2009
Measurment	Top of the atmosphere (TOA) reflectance
Common usage/purpose	Land-cover maps, land-change detection maps, vegetation monitoring

5.6.1.17 Commercial Data – Pleiades

Pléiades [189] is composed of two twin satellites orbiting the Earth 180° apart. The satellites deliver 0.5 m optical imagery and offer a daily revisit capability to any point on the globe. A data acquisition must be tasked and various collection scenarios are available: Target, Strip Mapping, Tri-Stereo, Corridor and Persistent Surveillance. Pleiades' satellites share the orbit with SPOT satellites, which makes it possible to combine the data form both sources.

The Pléiades data with its high spatial resolution is suitable for a range of remote sensing applications such as vegetation monitoring, precise mapping, risk and disaster management.

Table 24: Basic facts Pléiades

Property	Info
Spatial resolution	0.5 m for panchromatic band and 2 m for all other bands
Sensor	Multispectral Imager, 5 bands: panchromatic, Blue, Red, Green and Near-Infrared band
Revisit time	Up to a daily revisit of any point on the globe. A data acquisition must be tasked; data is not acquired systematically.
Spatial coverage	global
Data availability	Since December 2011
Measurment	Top of the atmosphere (TOA) reflectance
Common usage/purpose	vegetation monitoring, risk and disaster management, urban and mapping applications, civil engineering

5.6.1.18 Commercial Data – SPOT

SPOT 6/7 [190] constellation is composed of two twin satellites orbiting the Earth 180° apart. The satellites deliver 1.5 m optical imagery and offer a daily revisit capability to any point on the globe. SPOT 6/7 data with its high spatial resolution is suitable for a range of remote sensing applications such as vegetation monitoring, precise mapping, risk, and disaster management.

Table 25: Basic facts SPOT

Property	Info
Spatial resolution	1.5 m for panchromatic band and 6 m for all other bands
Sensor	Multispectral Imager, 5 bands: panchromatic, Blue, Red, Green, and Near-Infrared band
Revisit time	Up to a daily revisit of any point on the globe. A data acquisition must be tasked; data is not acquired systematically.
Spatial coverage	global
Data availability	Since September 2012
Measurment	Top of the atmosphere (TOA) reflectance
Common usage/purpose	vegetation monitoring, risk and disaster management, urban and mapping applications, civil engineering

More information: https://www.intelligence-airbusds.com/en/8577-spot-67-user-guide-download.

5.6.1.19 Commercial Data – WorldView (+GeoEye)

WorldView provides high resolution optical imagery and is owned by Maxar [191]. It is now possible to purchase, order and access WorldView data using Sentinel Hub. Sentinel Hub orders WorldView data through European Space Imaging. The WorldView constellations consists of four active satellites: WorldView-1 (data not available in SH), GeoEye-1 (GE01), WorldView-2 (WV02), and WorldView-3 (WV03). The WorldView-4 (WV04) satellite was operational from November 2016 to January 2019 and the data it acquired is available in Sentinel Hub.

Table 26: Basic facts WorldView

Property	Info
Spatial resolution	Varies from 0.3m to approx. 2m. SH supports 0.5 m for panchromatic band and 2 m for multispectral bands.
Sensor	Multispectral Imagery, 5 bands are supported in SH: panchromatic, Blue, Red, Green and Near-Infrared band.
Revisit time	From approx. 1 day to 3 days depending on the satellite. Note that the data is in general **not** acquired systematically. Archive data is available sporadically over an area of interest. In case you need systematic monitoring of a specific area, contact us to order tasking (different pricing conditions apply).
Spatial coverage	Global
Data availability	Since 2009
Measurement	Top of the atmosphere (TOA) reflectance
Common usage/purpose	Land-cover maps, land-change detection maps, vegetation monitoring, defence, traffic, marine monitoring

5.6.2 Other data sources

5.6.2.1 EO-derived data

Sentinel Hub, with its Bring your own Data functionality allows sharing any raster-based data. Such datasets can be used as a source of "ground truth", as validation datasets, filters (e.g., remove pixels that belong to water in Global Surface Water data collection) etc. The possibilities of having access to such wide array of data are endless.

Table 27: Various EO-derived data collections, accessible through Sentinel Hub

Data collection	Availability - Spatial	Availability – Temporal	Revisit
Sentinel-2 L2A 120m Mosaic	Land surface area between 58°S and 72°N	2019, 2020	15 days
Corine Land Cover	Pan-European, French overseas regions and departments	1990, 2000, 2006, 2012, 2018	every 6 years
Corine Land Cover Accounting Layers	EEA39 region	2000, 2006, 2012, 2018	every 6 years
ESA WorldCover	Global land	2020	yearly
Global Land Cover	Global land	2020	yearly
Global Surface Water	Global coverage from longitude 170°E to 180°W and latitude 80°N to 50°S	1984 → 2019, 1984 → 2020	yearly
Global Human Settlements Layer	Global coverage with longitude from 180°W to 180°E and latitude from 72°N to 56°S	2018	static
Sea Ice Index	Longitude from 180°W to 180°E and latitude from 39.23°N to 90°N and 30.98°S to 90°S	2017 → May 2021	none (demo)
Water Bodies	Global coverage from longitude -180°E to +180°W and latitude +80°N to -60°S. Depending on the month, some high latitude areas are not available	October 2020 →	monthly
Seasonal Trajectories, 10-daily	Europe	January 2017 →	yearly
Vegetation Indices, daily	Europe	October 2016 → February 2021	daily
Vegetation Phenology and Productivity Parameters Season 1, yearly	Europe	January 2017 →	yearly

Vegetation Phenology and Productivity Parameters Season 2, yearly	Europe	January 2017 →	yearly
Theia Land Cover Map	France	2016-2020	yearly

5.6.2.2 Type of Data, Purpose and Determined use

As a rule, the data, with the exception of user-login information, should not contain any personal data. Users can obtain specific data from different services and applications. Some data, provided through eo-learn, might come from third-party services and applications. In such a case, the user is subject to the licensing, personal data collection and management therein.

The access to EO data is provided through the Sentinel-Hub services. EO data does not contain any personal information. In order to use the service, the user has to provide some personal information that is used for login (e.g. name and e-mail), as described in Privacy Policy [192].

5.6.2.3 Analysis of data management and privacy for Smart-Farming in each country and across EU

Data-driven machine learning modelling schemes promise to pave ways for the exploitation and valorisation of EO data at large spatial scale and temporal frequency. Although such techniques have shown impressive performance in the recent past, this advantage comes with the burden of increased computational costs and requires the availability of huge amounts of data. While the input data is nowadays provided through modern and numerous Earth observation technologies at high quantity and various modalities, these data repositories lack matching annotation data, needed as ground-truth reference for training machine learning models. Since such approaches are condemned to infer the physical interrelationships of the observed processes exclusively from the patterns contained in the training data, special requirements must be placed on the available reference data. Besides the high volume of data needed to optimize the huge number of parameters driving such models, the provided training data needs to show enough diversity and variability to provide meaningful learning signals. Further, it needs to be complete, in order cover all possible configurations expected to be perceived at inference time. On top, such data must show sufficient degree of reliability and trustworthiness, to avoid the extraction of bogus information which would manifest in spurious correlations extracted from the training data. Sourcing such data is an important, yet tedious, expensive, and error-prone task and, thus, prohibitively expensive. The EuroCrops project (eurocrops.tum.de) addresses these issues.

5.6.2.4 Crop-Type Reference Data

The automated identification of vegetation classes of cultivated crops instantiates one particularly relevant task in remote sensing Earth observation in general. Evidently, the contemporary satellite missions provide meaningful data at various scales and modalities that capture the phenological processes of vegetation. Previous studies have shown that modern machine learning approaches can extract relevant data representations efficiently and reliable. Nevertheless, as outlined before, they are to data limited by the availability of rich ground-truth annotations.

EuroCrops [193] is a dataset collection combining all publicly available self-declared crop reporting datasets from countries of the European Union. The project is funded by the German Space Agency at DLR on behalf of the Federal Ministry for Economic Affairs and Climate Action (BMWK). It takes advantage of already existing data sources: Under the umbrella of the EU's *common agricultural policy (CAP)*, farmers must provide self-declarations of all the crops they are cultivating on their field parcels and report this information to the local authorities. These carry out extensive quality checks, *e.g.*, *in-situ* surveys, as such information is ultimately used to distribute subsidy payments back to the farmers. As such, those data can be considered the gold-standard of information which makes it highly suitable for various machine learning training schemes.

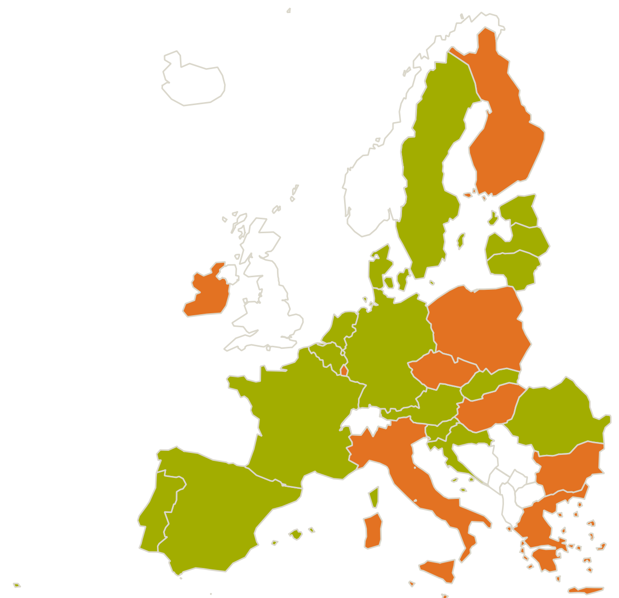


Figure 55: EuroCops Data. In green the countries already participating and orange the ones that intend to participate

Until recently, only a few EU member states had made this information publicly available, making it inaccessible and mostly invisible to the research and application domains of machine learning and remote sensing. The EuroCrops initiative has set itself the mission of getting these states to cooperate and collect such data in a unified way. At the current time, more than 15 countries (shown in Figure 55) contribute data or intend to do so over the course of the project.

5.6.2.5 Trans-National Taxonomy

Although the mere compilation of the data described earlier is already a mammoth task, it is not yet readily usable in its entirety due to the different coding schemes used by the member states. As these are usually optimized to allow the best possible processing of such data for the country in question, they are usually not readily compatible with those of other countries which may use representation regimes that cover diverging sets of classes or different granularity.

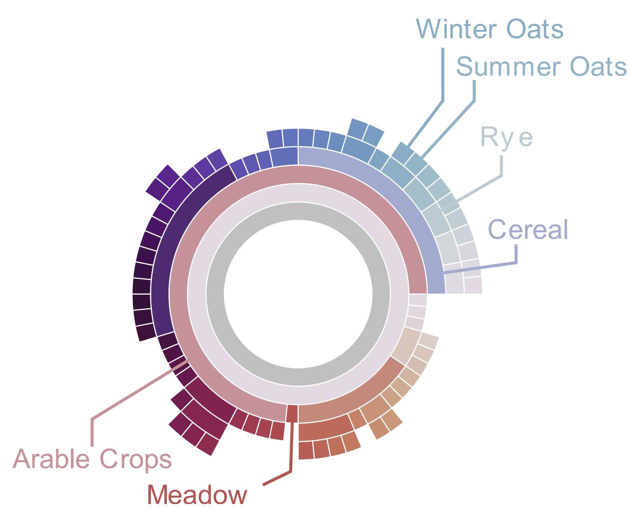


Figure 56: Illustration of hierarchical crop and agriculture taxonomy

For that reason, EuroCrops comes with an own representation scheme for cultivated crop classes, the *hierarchical crop and agriculture taxonomy (HCAT)*. As illustrated in HCAT organizes all species hierarchically with respect to their phylogenetics, phenotypes, or agricultural usage. This provides country-pair-wise bidirectional mappings and, thus, allows for Figure 56 information-preserving *conversion* between national schemes and HCAT. As each node and leaf of the nomenclature tree is precisely described by a unique identifier, cross-country *comparison* becomes possible, even when data is provided at different granularity.

5.6.2.6 Additional Information

EuroCrops contains geo-coded polygons describing all field parcels registered relevant for CAP in any contributing country. Each of these records is augmented with the reported crop class label in HCAT representation, as visualized in Figure 57. Further, EuroCrops provides translations of each crop class from their local language into English.

EuroCrops data, once harmonized and ready, will be available through GeoDB [194], a Euro DataCube service provided by Brockmann Consult. EO-learn has already been extended with tasks to facilitate the retrieval of data from GeoDB collection.

Figure 57: Map with recorded crop class labels in HCAT representation.

5.6.2.7 Advantages and applications of EO data

Some of the advantages of EO for crops and live stocks according to the UK Space Agency are:

- ***Coverage and quality*****:** Satellites have regular revisit times, as they orbit the earth and provide consistent observations of land features, making it possible to monitor agriculture and scale up as appropriate from field and farm to catchment, landscape, regional, national, and global scale in an accurate and repeatable way.
- ***Range of data*****:** Satellites collect data via several sensor types. This allows identification of crop and vegetation types and the monitoring of many different environmental conditions including moisture, temperature, soil condition and vitality of leaf vegetation.
- ***Analysis ready data*****:** Satellite data can be processed to defined industry standards and organized in a form that allows immediate value-addition and analysis, for example as inputs to models, such as those being developed in IPP. Field, farm, or regional scale measures can be derived automatically using satellite imagery and presented as simple outputs in the form of maps, dashboards, spreadsheets, and graphs compatible for use with Geographic Information Systems (GIS), farm and business management platforms. Satellite data services enable these products to be delivered directly to agricultural stakeholders.
- ***Remoteness and safety*****:** Data collection using satellites is significantly faster than on-ground data collection and is a safe and cost-effective way to obtain data in remote areas or areas affected by conflict.
- ***Speed of delivery*****:** Increasingly, analysis ready EO data is available for use soon after it is acquired, which is important for crop production monitoring or in disaster situations where a rapid response is required. Satellite data services enable stakeholders to quickly receive the EO derived information they need.

In addition, there are several EO sets of data from satellites free and open access. Regarding the aircraft systems or drones, they are fast growing but they are limited to restrictions (regulation) for their use.

5.6.3 IoT enabled agro-environmental sensing stations

Internet of Things (IoT) has become a key technology that enables continuous monitoring and control of crops, soil, and microclimate as it allows farmers to obtain (near) real time quantitative data with high spatiotemporal resolution. IoT is a system of devices connected remotely (over the Internet or other communications networks). According to Chamara et al. (2022), there is a boom in the adoption of internet connectivity solutions in agriculture in the last two decades, for improving the sustainability of the farming practices. The IoT includes different sensors that monitor crops lifecycle and animals, such as acoustic sensors, biological sensors, chemical sensors, electric sensor, mechanical sensors, optical sensors, thermal sensors, etc and retrieves information to farmers in mobile phones or devices.

Table 28: Sensor types and their applications [195]

Sensors	Applications	Working Procedure
Acoustic sensors	Pest monitoring and detection classifying seed varieties, fruit harvesting.	Measuring the variations in noise level when intermingling with other materials, i.e., soil particles.
Airflow sensors	Measuring soil air permeability, moisture, and structure in a static position or mobile mode.	Based on various soil properties, unique identifying signatures.
Eddy covariance-based sensors	Quantifying exchanges of CO_2, water vapor, methane, or other gases. Measuring surface atmosphere and trace gas fluxes in various agricultural ecosystems.	Measuring continuous flux over large areas.
Electrochemical sensors	Measuring soil nutrient levels and pH.	Nutrients in soil, salinity, and pH are measured using sensors.
Electromagnetic sensors	Recording electrical conductivity, electromagnetic responses, residual nitrates, and organic matter in soil.	Electrical circuits measure the capability of soil particles to conduct or accumulate electrical charge.
Field programmable gate array (FAAA) based sensors	Measuring real-time plant transpiration, irrigation, and humidity.	Programmable silicon chips and logic blocks are surrounded together by programmable interconnected resources of the digital circuit.
Light detection and ranging (LIDAR)	Land mapping, soil type determination, farm 3D modelling, erosion monitoring and soil loss, and yield forecasting.	Sensors emit pulsed light waves and bounce off when colliding with objects and are returned to the sensor.
Mass flow sensors	Yield monitoring based on the amount of grain flow through a combine harvester.	Sensing the mass flow of grain with modules, e.g., grain moisture sensor, data storage device, and an internal software.
Mechanical sensors	Soil compaction or mechanical resistance.	Sensors record the force assessed by strain gauges or load cells.
Optical sensors	Soil organic substances, soil moisture, colour, minerals, composition, clay content, etc. Fluorescence-based optical sensors are used to supervise fruit maturation. Integrating optical sensors with microwave scattering to characterize orchard canopies.	Sensors use light reflectance phenomena to measure changes in wave reflections.
Optoelectronic sensors	Differentiate plant types to detect weeds in wide-row crops.	Sensors differentiate based on reflection spectra.
Soft water level-based (SWLB) sensors	Used in catchments to characterize hydrological behaviours (water level and flow, time-step acquisitions).	Measuring rainfall, stream flow, and other water presence options.
Telematics sensors	Assessing location, travel routes, and machine and farm operation activities.	Telecommunication between places (especially inaccessible points).

Sensors	Applications	Working Procedure
Ultrasonic ranging sensors	Tank monitoring, spray distance measurement, uniform spray coverage, object detection, monitoring crop canopy, and weed detection.	An ultrasonic sensor uses a transducer to send and receive ultrasonic pulses that relay information about an object's proximity.
Remote sensing	Crop assessment, yield modelling, forecasting yield date, land cover and degradation mapping, forecasting, the identification of plants and pests, etc.	Satellite-based sensor systems collect, process, and disseminate environmental data from fixed and mobile platforms.

Among sensors for crop monitoring the loadcells are used in indoor farming pots to measure the plant weight. The chemical sensors are used to measure soil nutrients, oxygen, carbon dioxide, methane, pH and conductivity of irrigation water, and photosynthesis. Based on the chemical or electrical technique used chemical sensors are mainly categorized in two types: photochemical, which measure chemical reactions or chemical by their spectral signature; and electrochemical sensors, which measure the electrical properties due to chemical reactions or the presence of chemicals.

There are four fundamentals features of IoT for their application in the agriculture:

- ***Robust model:*** The distinctive features of the agriculture sector are diversity, complexity, spatio-temporal variability, and uncertainties of the right types of harvests and facilities.
- ***Scalability:*** The variation in farm size from smaller to larger; hence, the results should be scalable. The placement and testing planning should be progressively scaled up with fewer expenses.
- ***Affordability:*** Affordability is vital to farming achievement, and therefore price should be suitable with significant assistance. Standardized platforms, products, tools, and facilities could obtain a satisfactory price.
- ***Sustainability:*** The problem of sustainability is a vital issue due to strong economic pressure and intense competition worldwide.

5.6.4 Quality of the parcels' signal

The EU CAP requires the control of subsidies claimed annually for millions of agricultural parcels over all Member States. All parcels, whether small, large, elongated or rectangular, need to be monitored. Small and elongated parcels pose a challenge for the Checks by Monitoring system (as well as the future Area Monitoring System) that uses Copernicus Sentinel data as the main data source. Figure 58 shows the results addressing these challenges using Planet Scope and Planet Fusion data to monitor parcels that are too small to be monitored with Sentinel.

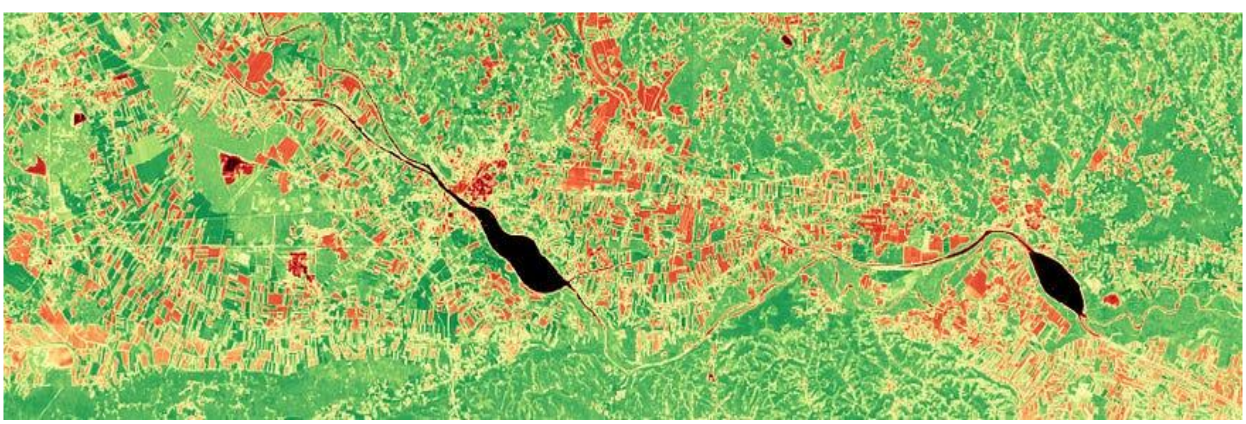


Figure 58: Planet Fusion, May 1st 2021, Ptuj, Slovenia

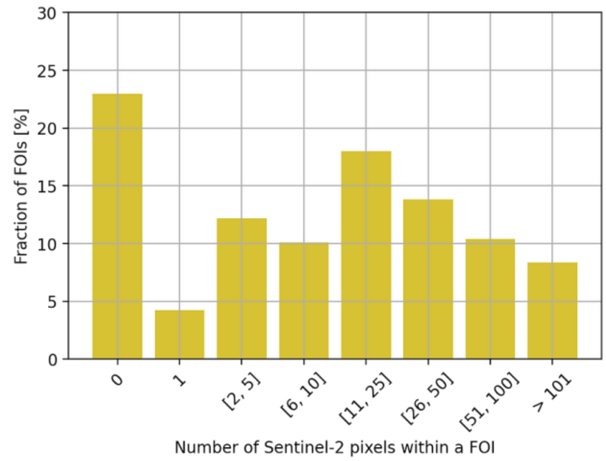


Figure 59: Number of Sentinel-2 pixels within a FOI (feature of interest)

To ensure the quality of the parcels' signal, Joint Research Centre (JRC), the research body of the European Commission, recommends a limiting criteria of at least eight full Sentinel-2 pixels inside the border of the specific Feature Of Interest (FOI) and, if possible, introduction of 5-meter (1/2 Sentinel-2 pixel) internal buffer [196]. This rule makes a lot of sense. Sentinel-2 data are not perfectly aligned (same for all other automatically processed satellite data), its multi-temporal geometrical accuracy being assessed as 0.3 pixels, which is why the spectral measurements at the border will be distorted with the signal of the neighbourhood objects (Figure 59). And taking statistics of numerous observations within the field will surely produce much better quality of the results. The reality, however, is often not too compliant with scientific best practices. In several member states, where agriculture parcels were often split during the inheritance proceedings, more than 40% of the parcels are lost by complying to this rule, even if not considering the internal buffer.

Due to this structure of the parcels, in selected EU countries, it has been decided, together with Paying Agencies, to use Sentinel for monitoring of all parcels, which contain at least one full Sentinel-2 pixel. Even then, there are parcels that do not contain even a single full Sentinel-2 pixel. One might argue that even though there are indeed a large number of "problematic" parcels, these represent only a small percentage of the total area (and thus distributed funds), 3% to be precise, so this is not really a problem. However, the current set of Check by Monitoring and Area Monitoring System (AMS) rules in many EU countries require all parcels to be monitored and this makes sense to ensure fair and non-discriminatory handling of all farm holders.

5.6.4.1 Addressing the challenge of small parcels

With Sentinel data being out of the picture for monitoring of small parcels, there are a handful of options remaining. The most mentioned one is using Geotagged photo application, where the Paying Agency asks the farmer to take several pictures of the field using their mobile phones. This sounds simple, but introduces a new administrative burden for the farmer, the hated red tape, and might represent a significant technological obstacle for the older generation. It is also time consuming, both for the farmer as well as for the Paying Agency, whose staff then has to go through hundreds of thousands of good-or-bad photos. On the other side of the spectrum is the rapid field visit option, Paying Agency taking most of the burden, but this makes the overall process extremely expensive. Using Earth observation data seems to be the most feasible way to perform wall-to-wall monitoring. And so far the only feasible option we've found, aside from Sentinel, is Planet's PlanetScope monitoring product, which provides systematic, near-daily imaging of the entire Earth's landmass. The alternative very high-resolution satellite providers require tasking and are not technically feasible. We have experimented with one of them and they were not able to provide consistent weekly products even for an area 10x10km due to competitive tasks in the area. But if they were, this option would probably be way too expensive. Even in the foreseeable future this will probably not change. Several startups have announced plans for (sub)meter-level resolution and daily cadence, but it will take several years for them to get there. If they actually do manage. And then costs will probably remain problematic. Sentinel-2 Next Generation will presumably do the job, but this is at least five to ten years away.

5.6.5 Planet Fusion Solution for CAP

We decided to test Planet Fusion within our area monitoring activities. We got Planet Fusion for eight 24x24 km² large tiles that together cover around one-quarter of all parcels in Slovenia. We were excited to be able to test this capability that promises cleaner data for our modelling through radiometric harmonization and the removal of clouds, cloud shadows, and other kinds of noise and provides gap-filled surface reflectance values daily.The plot below shows Planet Fusion NDVI time series for the same parcel as shown above. As you can see the time series is smooth, which is to some extent by design.

The number of parcels with detected mowing events using PlanetScope is thus lower by almost a factor a two when compared to Planet Fusion. Since the number of meadows (including small ones) is large in Slovenia this leads to a significant reduction of the number of inconclusive parcels and consequently large efforts the Slovenian National Paying Agency would have to invest to resolve them. This fact alone justifies the usage of Planet Fusion over PlanetScope. On the other hand, there are only around 4 thousand parcels where the algorithm finds an event with Sentinel-2 but not with Planet Fusion

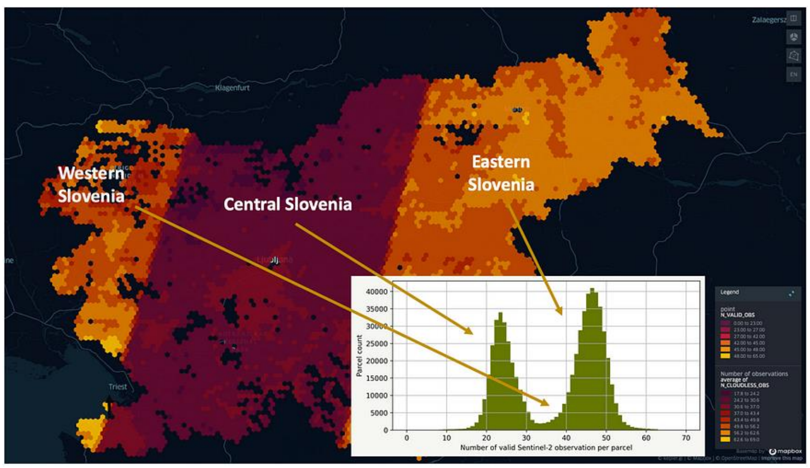


Figure 60: Map of the average number of valid Sentinel-2 observations per parcel

Studies showed that Planet Fusion is an excellent data source for monitoring small and elongated parcels. Beyond resolution, the value is also showcased in mowing markers, where consistency of individual observations in a time series is of paramount importance. In addition to small parcels, Planet Fusion has also been used to get a second opinion about parcels where mowing events were expected, but not detected with Sentinel-2 data.

6 Data models and systems

This chapter focuses on the core aspects of data interoperability within the AgriDataValue project. In this chapter, we work on mapping the essential components and frameworks that enable the seamless exchange, integration, and utilization of agricultural data.

Effective data models and systems are critical for achieving the project's objectives. These components provide a foundation for organizing, structuring, and representing agricultural data in a consistent and standardized manner. By establishing robust data models and systems, we can ensure the seamless exchange of data between different stakeholders, systems, and technologies involved in the AgriDataValue project.

Through the exploration of data models and systems, this chapter aims to provide valuable insights and guidelines for enabling effective data interoperability, integration, and utilization within the AgriDataValue project, ultimately contributing to the advancement of smart farming and sustainable agricultural practices. In this document, that will evolve, we will try to address not only the challenges of intra dataspace interoperability (which involves data integration and exchange within the AgriDataValue project's own ecosystem) but also the critical aspect of inter dataspace interoperability. This broader perspective encompasses the seamless exchange and harmonization of data with external dataspaces from agriculture and/or other industries.

6.1 Review of existing data model frameworks

In this section, we conduct a review of existing data model frameworks that are relevant to the AgriDataValue project. We explore a range of frameworks with a focus on their applicability to the agricultural domain and their potential to support data interoperability. Two prominent frameworks that warrant special attention in this review are GAIA-X and IDSA, which offer standards and guidelines for data exchange and interoperability.

The GAIA-X Trust Framework provides a robust and reliable foundation for data sharing and collaboration in the digital ecosystem. It establishes a set of principles, rules, and standards to ensure trust, security, and sovereignty of data. The AgriDataValue project can greatly benefit from the GAIA-X Trust Framework as it aims to strengthen the capacities for smart farming and enhance the environmental and economic performance of the agricultural sector. By adhering to the principles and guidelines of the GAIA-X Trust Framework, AgriDataValue can ensure secure and transparent data exchange among diverse stakeholders within the agricultural domain. The framework's focus on data sovereignty and control allows AgriDataValue to maintain ownership and governance over its data assets while promoting interoperability and collaboration with other projects and initiatives.

The International Data Spaces Association (IDSA) offers a framework for secure and trusted data exchange. IDSA promotes a decentralized approach to data sharing and interoperability by providing specifications, protocols, and architectures. The IDSA framework emphasizes concepts such as data sovereignty, semantic interoperability, and data usage control. By leveraging the IDSA framework, the AgriDataValue project can enhance its data interoperability capabilities while ensuring compliance with security and privacy requirements.

There is a notable trend among data sharing initiatives such as IDSA, GAIA-X, BDVA, and FIWARE to align their technical approaches and architectures, facilitated by the collaborative efforts of the Data Spaces Business Alliance (DSBA) [197]. The AgriDataValue project consortium recognizes the significance of this alignment and commits to staying updated on DSBA's publications to ensure compliance with these initiatives and their frameworks. Specifically, the DSBA publishes valuable insights and guidelines for technical convergence in the form of a technical convergence document [198], which serves as a reference for the AgriDataValue project's interoperability efforts.

Beyond GAIA-X and IDSA, several other data model frameworks merit consideration for their potential applicability to the AgriDataValue project. Some examples include:

- **Open Geospatial Consortium (OGC):** The OGC offers standards and specifications for geospatial data interoperability. This framework can support the integration of spatial data, such as soil types, weather patterns, and satellite imagery, into the AgriDataValue project.
- **Sensor Observation Service (SOS):** The SOS is an OGC standard for exchanging sensor data. It provides a standardized interface for accessing and sharing real-time data from agricultural sensors, facilitating interoperability among different sensor networks and platforms.
- **Agricultural Linked Data (AgLD):** AgLD is an initiative that promotes the use of Linked Data principles to enhance the integration and exchange of agricultural data. By leveraging semantic web technologies, AgLD facilitates interoperability by linking and enriching diverse agricultural datasets.
- **AgGateway ADAPT:** ADAPT is an interoperability framework developed by AgGateway, a consortium focused on agricultural data exchange. It provides guidelines and tools for seamless data integration across different agricultural systems, improving efficiency and collaboration within the sector.
- **Agriculture Information Model (AIM)**: As already explained, AIM is an information model for data interoperability developed by DMETER project. The AIM model adopts widespread standardized solutions such as NGSI-LD, Saref4Agri and ADAPT, to enable interoperability of heterogeneous data handling approaches. For this conversion to be feasible, each AKIS needs to provide the specifications of the utilized data model and semantics, or it should parse returning content in the AIM format. The AIM is not built ab initio but incorporates and extends existing ontologies and vocabularies already available for this domain.

The review of existing data model frameworks has highlighted the importance of leveraging established frameworks such as GAIA-X and IDSA to enhance data interoperability within the AgriDataValue project. These frameworks, along with others like OGC, SOS, AgLD, ADAPT and AIM, offer valuable guidelines, standards, and specifications that can inform the development of robust and effective data models specific to the agricultural domain. By adopting these frameworks, the AgriDataValue project can ensure compatibility, secure data exchange, and facilitate collaboration with external stakeholders and data providers.

6.2 Data Model Exchange and Semantic Interoperability

Effective data model exchange plays a vital role in enabling semantic interoperability among diverse agricultural systems and stakeholders. By facilitating the seamless sharing and understanding of data models, it becomes possible to align data structures, semantics, and relationships across different platforms and domains. This, in turn, promotes efficient data integration, collaboration, and meaningful insights for smart farming, environmental enhancement, and economic performance improvement. To do so, we identified the categories below as the main drivers to ensure the semantic interoperability within AgriDataValue project:

- **Standardized Data Model Formats**: Adopting standardized data model formats, such as XML, JSON, or RDF, facilitates easy exchange and interpretation of data models between different systems and stakeholders. These formats provide a common syntax and structure that enable seamless data model integration and interoperability.

- **Data Model Mapping and Transformation:** Data model mapping and transformation mechanisms allow for the conversion of data models from one format or structure to another. By employing appropriate mapping techniques and transformation tools, different data models can be aligned and harmonized, ensuring compatibility and seamless data exchange.
- **Metadata and Vocabulary Alignment:** Metadata and vocabulary alignment techniques play a crucial role in data model interoperability. By aligning metadata definitions, data element names, and controlled vocabularies across systems, data models can be effectively integrated and understood, promoting consistency and shared understanding among stakeholders.
- **Ontology-based Interoperability:** Leveraging ontologies and semantic web technologies can enhance data model interoperability by capturing domain-specific knowledge and establishing semantic relationships between data elements. Ontologies provide a common vocabulary and enable reasoning capabilities, allowing for advanced data integration and inference across diverse data models.

Semantic data model exchange is essential for achieving meaningful data integration and collaboration across diverse agricultural systems. By leveraging semantic interoperability, the AgriDataValue project can ensure that data models are understood and interpreted accurately, fostering a shared understanding of agricultural data and enabling efficient data exchange, integration, and analysis.

6.2.1 Semantic Interoperability Mechanisms

In this section we highlight the main semantic technologies for interoperability. As semantic technologies and standards evolve, it is essential for the AgriDataValue project to stay in alignment with emerging frameworks, and best practices in semantic interoperability in agriculture.

6.2.1.1 FIWARE NGSI and FIWARE AgriFood Data Model

FIWARE NGSI provides a standard API for data management and exchange, while the FIWARE AgriFood Data Model offers a comprehensive data model specifically designed for the agriculture domain. Leveraging these mechanisms, AgriDataValue can achieve semantic interoperability by exchanging and harmonizing data using FIWARE standards.

6.2.1.2 GS1 Standards and Data Model

GS1 standards, widely used in supply chain management, facilitate semantic interoperability by providing a common framework for data exchange and identification of agricultural products. By incorporating GS1 standards and data models, AgriDataValue can enhance interoperability across the supply chain, from farm to consumer.

6.2.1.3 Saref4Agri

Saref4Agri is an ontology that enables semantic interoperability in the agricultural domain. It provides a shared vocabulary for describing and integrating agricultural data, facilitating data exchange and integration across different systems and stakeholders.

6.2.1.4 IDS Information Model

The International Data Spaces (IDS) Information Model provides a domain-agnostic reference model, that acts as a top-level ontology for secure and sovereign data exchange across industries, that can also be used for agriculture domain. By adhering to the IDS Information Model, AgriDataValue can achieve semantic interoperability while ensuring data sovereignty and security.

The IDS Information Model serves as the underlying framework for describing and publishing Data Assets and Data Apps within the Industrial Data Space. These resources are fundamental components of the IDS and are published in a structured, semantically annotated format to ensure that only relevant resources are provided to meet the specific needs of Data Consumers. This approach enables automated resource discovery and consumption through service interfaces and protocol bindings that are defined using semantic definitions.

In addition to its core resources, the Information Model also encompasses other critical elements of the IDS, including participants, infrastructure components, and processes. However, it's important to note that the Information Model itself is not domain-specific and delegates domain modeling to shared vocabularies and data schemata provided by specific communities within the Industrial Data Space. Furthermore, the Information Model does not include a meta-model for defining custom structured datatypes, unlike other standards such as OData or OPC-UA. While the Information Model provides a generic framework for describing digital assets and facilitating their interchange, it does not address the side effects of data exchange on the Data Consumer's side, such as real-time machine control scenarios. Additionally, the Information Model does not cover the remote procedure call (RPC) semantics of data messages. It is essential to understand that the Information Model focuses on standardized resource description and publication within the Industrial Data Space, with certain considerations and aspects falling outside its scope.

6.2.1.5 INSPIRE Data Model for Agricultural and Aquaculture Facilities

The INSPIRE data model provides a harmonized framework for the exchange and integration of geospatial data related to agricultural and aquaculture facilities. By utilizing the INSPIRE data model, AgriDataValue can facilitate semantic interoperability of geospatial information in the agricultural sector.

6.2.1.6 OGC SensorThings API

The OGC SensorThings API is a standard for IoT sensor data exchange and interoperability. It provides a unified interface for querying and accessing sensor data, enabling semantic interoperability across diverse sensor networks and platforms in the agricultural domain.

6.2.1.7 Semantic Web Rule Language

SWRL is a rule language for the Semantic Web that combines OWL ontologies with rules expressed in the form of logical axioms. By leveraging SWRL, AgriDataValue can enhance semantic interoperability by defining rules that facilitate automated reasoning and inference over agricultural data.

6.2.1.8 AgGateway ADAPT

AgGateway's ADAPT framework offers a comprehensive set of tools and specifications for seamless data integration and interoperability in the agricultural domain. ADAPT enables the mapping and transformation of data models, facilitating semantic interoperability across various agricultural systems and applications.

6.2.1.9 Other Semantic Interoperability Mechanisms

Additional mechanisms that contribute to semantic interoperability in the AgriDataValue project include the rmAgro model, Semantic Sensor Network (SSN) ontology, AGROVOC, FOODIE ontology, FOODON ontology, Weather Data Models, ADAPT (Agricultural Data Application Programming Toolkit), DCAT, W3C Data Quality Vocabulary, PROV-O, and DUV. These mechanisms offer standardized vocabularies, ontologies, and frameworks for improved semantic interoperability and data integration.

The AgriDataValue project consortium commits to compliance with established semantic frameworks and initiatives, such as the ones mentioned above, to ensure semantic interoperability. By aligning with these frameworks, AgriDataValue can enhance collaboration and data exchange with external stakeholders, enabling effective semantic data model exchange and interoperability.

6.3 Data transfer, processing, privacy, storage requirements

The International Data Spaces Association (IDSA) has established a comprehensive set of standards that serve as the foundation for data exchange and data sovereignty, aligning with European principles of trust and data usage self-determination. The IDS Reference Architecture (IDS-RAM) [199] operates at a higher level of abstraction compared to typical architecture models for specific software solutions. It offers a holistic perspective complemented by specialized architecture specifications that provide detailed insights into the specific components of the International Data Spaces, such as Connector, Broker, and App Store.

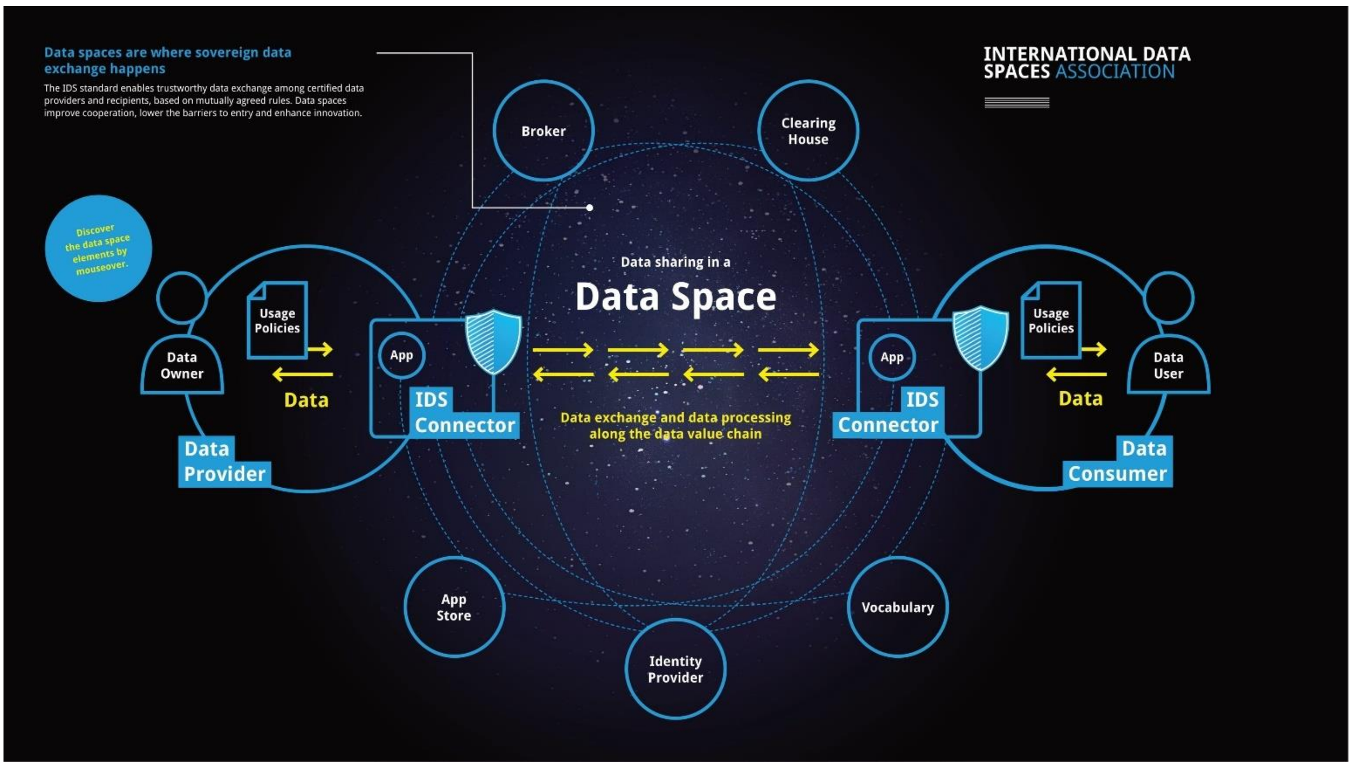


Figure 61: Infographic depicting IDS-compliant dataspace

The infographic above illustrates the process of data exchange within an IDS-compliant data space, highlighting the roles described in the IDS-RAM. Primarily, data exchange occurs between data providers and data consumers, with data providers having the ability to define usage policies for their data, specifying rules on how the provided data should be consumed. According to the IDS approach, the participants in a dataspace can either be a data provider or a data consumer and all the participants should access the dataspace via an IDS connector. IDS approach focuses on data exchange and explains how it should happen. According to the IDS approach, data storage is an external process, which is not positioned inside the dataspace.

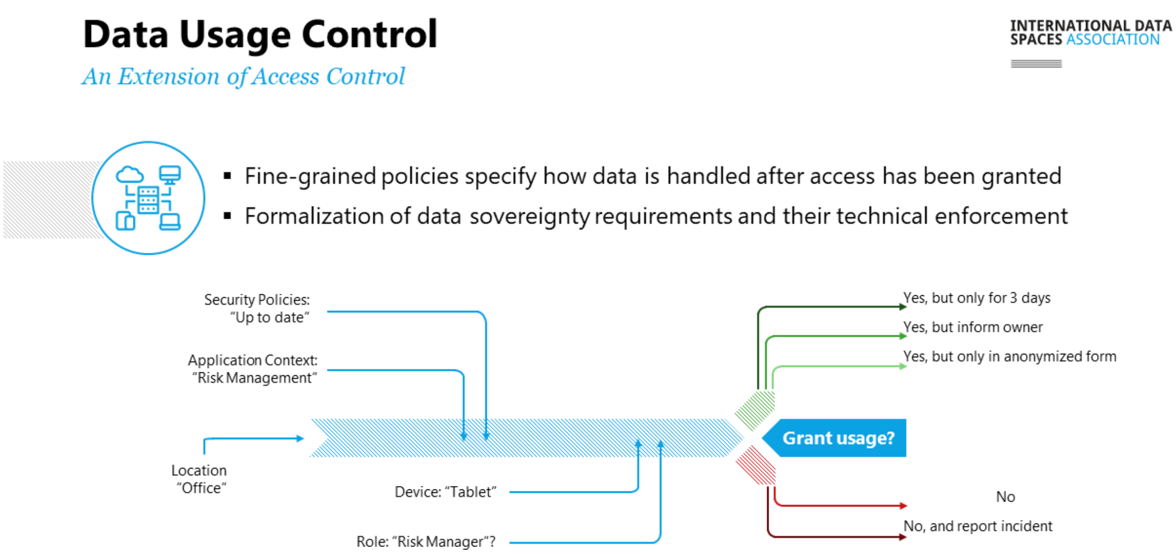
At the heart of data exchange lies the IDS connector, a central component that grants participants entry into a trusted ecosystem and ensures a high level of trust during peer-to-peer data exchange between data providers and consumers. This trust is established through the implementation of connectors based on the IDS Reference Architecture Model and their independent evaluation, conducted by approved evaluation facilities and the IDSA certification body. This evaluation process, known as IDS certification [200], assesses 156 security criteria (as of 2023), covering core components and operational environments.

Apart from IDS-RAM (v4.0), the IDSA provides several complementary assets accessible through their GitHub page [201]. These assets include the IDS Rulebook, IDS Testbed, minimum viable data space, component specifications, IDS Information Model [202], and open-source components and frameworks that can be leveraged for secure and sovereign data exchange.

6.3.1 Usage Control in IDS

The concept of Usage Control within the IDS framework is extensively discussed in the position paper titled "Usage Control in the International Data Spaces" [203]. In contrast to access control, which focuses on restricting access to specific resources, such as services or files, the IDS architecture introduces an additional layer of data-centric usage control. This approach aims to enforce usage restrictions for data even after access has been granted. By associating policies with exchanged data, the IDS architecture enables continuous control over how messages are processed, aggregated, or forwarded to other endpoints. This data-centric approach empowers users to exert ongoing control over data flows rather than merely restricting access to services. During configuration, these policies assist developers and administrators in establishing appropriate data flows.

During runtime, usage control enforcement ensures that IDS connectors do not handle data in unintended ways, such as forwarding personal data to public endpoints. This mechanism provides system integrators with a tool to ensure compliance with security requirements while also offering an audit trail that demonstrates compliant data usage. Overall, the data-centric perspective and usage control mechanisms inherent in the IDS architecture facilitate secure and sovereign data sharing while granting users greater control over their data flows.



As depicted in the simplified diagram above, usage control within an IDS-compliant dataspace entails the implementation of fine-grained policies that dictate how data is handled once access has been granted to data consumers. Essentially, the data provider retains the authority to establish rules and policies governing the consumption of their data.

6.4 Communication protocols in agriculture

The ability of different systems to seamlessly communicate and exchange data is crucial for achieving effective interoperability. This is where communication protocols play a vital role. Communication protocols serve as the language and framework that enable systems to understand and interact with one another, regardless of their underlying technologies, platforms, or programming languages. By establishing a standardized set of rules and formats for data exchange, these protocols ensure smooth and reliable communication between disparate systems.

In the realm of system interoperability, several communication protocols have gained wide acceptance due to their effectiveness in facilitating seamless data exchange and integration The most widely used ones are summarized in the following sections:

6.4.1 REST (Representational State Transfer)

REST is an architectural style that uses standard HTTP methods for communication between client and server systems. It leverages the familiar request-response model to exchange data in a platform-independent manner. RESTful APIs have become ubiquitous, enabling interoperability between different systems and applications across various domains.

6.4.2 SOAP (Simple Object Access Protocol)

SOAP is a messaging protocol that allows programs running on different operating systems to communicate with each other. It uses XML (eXtensible Markup Language) for message format and relies on various transport protocols such as HTTP, SMTP, or TCP. SOAP provides a standardized approach to accessing web services and is widely used in enterprise-level integrations.

6.4.3 MQTT (Message Queuing Telemetry Transport)

MQTT is a lightweight publish-subscribe messaging protocol designed for resource-constrained devices and unreliable networks. It is commonly used in IoT scenarios where efficient and reliable data transmission is essential. MQTT facilitates real-time data exchange between devices, sensors, and backend systems, making it suitable for applications such as home automation, industrial monitoring, and agriculture.

6.4.4 AMQP (Advanced Message Queuing Protocol)

AMQP is an open standard protocol designed for reliable and scalable message-oriented communication. It provides a flexible framework for asynchronous messaging, allowing different systems to exchange messages in a decoupled manner. AMQP is widely adopted in enterprise messaging systems, IoT deployments, and distributed systems that require high-throughput and interoperability.

6.4.5 OPC-UA (OPC Unified Architecture)

OPC-UA is a widely used industrial communication protocol that enables interoperability between different automation and control systems. It provides a platform-independent and secure means of exchanging data between devices, sensors, and applications in industrial settings. OPC-UA supports both real-time and historical data access, making it suitable for various industrial applications. These communication protocols form the foundation of interoperability between diverse systems, allowing for seamless data exchange, integration, and collaboration across different domains and technologies. By adhering to these standards, organizations can unlock the potential of their systems, achieve interoperability, and foster innovation in an increasingly connected world.

6.5 Intra- and Inter-Dataspace Interoperability

Intra-data space interoperability focuses on the seamless integration and harmonization of data within a single data space or ecosystem. It entails establishing standardized protocols, data formats, and communication mechanisms that enable different components and entities within the data space to effectively exchange, share, and utilize data. This level of interoperability ensures that data can flow smoothly and be meaningfully interpreted and processed by various systems and applications within the same data space. By promoting intra-data space interoperability, organizations can optimize their internal data operations, enhance data collaboration, and leverage the full potential of the data assets within their own ecosystem.

Inter-data space interoperability extends beyond the boundaries of a single data space and focuses on establishing connections and harmonizing data exchange mechanisms between multiple data spaces or ecosystems. It involves defining common standards, protocols, and frameworks that facilitate seamless data exchange, integration, and collaboration across different data space instances. The approach taken by every data space initiative should include a clear positioning on how it will seamlessly work with other data space instances. This ensures that data spaces can effectively communicate, share data, and collaborate, even if they are governed by different organizations, operate under different technical architectures, or cater to specific industry requirements. By embracing inter-data space interoperability, data spaces can break down barriers, foster collaboration between diverse stakeholders, and create a network of interconnected data ecosystems that collectively drive innovation and deliver value on a broader scale.

In conclusion, inter-data space interoperability plays a pivotal role in the AgriDataValue project by enabling seamless collaboration, data exchange, and innovation across multiple agricultural data spaces. The project's objectives of strengthening the capacities for smart farming, enhancing environmental and economic performance, and supporting climate monitoring align closely with the need for inter-data space interoperability. By embracing this approach (which is more detailed in [204]), the AgriDataValue project consortium can leverage the collective knowledge, resources, and data from diverse data spaces, ultimately leading to more comprehensive insights, improved decision-making, and sustainable agricultural practices. Inter-data space interoperability ensures that AgriDataValue remains adaptable, scalable, and future-proof, as it can seamlessly integrate with other dataspaces both from agriculture and other relevant industries. The technical work being carried out under IDSA umbrella (which is called as Communication Protocol) can be seen on IDSA’s Github, under Communication Guide repository [201].

7 User and System Requirements

7.1 User Requirements

User requirements are generated with the aim of addressing the specific needs and challenges of farmers.

7.1.1 Crop-based farming

Table 29: User requirements about crop – based farming

ID	Requirement Description
REQ.US.01.01	**Crop Selection**: Users need information and guidance on selecting suitable crops based on factors such as climate, soil conditions, market demand, and personal or local preferences
REQ.US.01.02	**Crop Selection**: They may require access to data on crop varieties, their adaptability to local conditions, yield potential, and resistance to pests and diseases
REQ.US.01.03	**Soil Management**: Users require knowledge and tools for assessing and managing soil health and fertility
REQ.US.01.04	**Soil Management**: They need information on soil testing, nutrient management, organic matter improvement, pH adjustment, and soil erosion control practices
REQ.US.01.05	**Soil Management:** Guidance on crop rotation, cover cropping, and soil conservation techniques may also be required.
REQ.US.01.06	**Irrigation and Water Management**: Users need guidance on irrigation methods, scheduling, and water management practices to optimize water use efficiency.
REQ.US.01.07	**Irrigation and Water Management**: They may require information on the water requirements of different crops, soil moisture monitoring techniques, and access to weather data for irrigation decision-making.
REQ.US.01.08	**Pest and Disease Management**: Users require information on integrated pest and disease management practices.
REQ.US.01.09	**Pest and Disease Management**: They need guidance on pest and disease identification, prevention strategies, biological control methods, and appropriate use of pesticides, considering environmental and health considerations
REQ.US.01.10	**Fertilizer and Nutrient Management**: Users need recommendations and guidance on appropriate fertilizer application rates, timing, and nutrient management practices.
REQ.US.01.11	**Fertilizer and Nutrient Management**: They may require information on the nutrient requirements of different crops, soil testing, nutrient deficiencies, and the use of organic and synthetic fertilizers.
REQ.US.01.12	**Crop Monitoring and Yield Optimization**: Users require tools and techniques for monitoring crop growth, health, and yield.

REQ.US.01.13	**Crop Monitoring and Yield Optimization**: They may need guidance on crop scouting, disease and pest monitoring, nutrient deficiencies identification, and crop-specific management practices to optimize yield potential.
REQ.US.01.14	**Market Analysis and Planning**: Users may require access to market information, pricing trends, and demand-supply dynamics to make informed decisions about crop selection, production volumes, and marketing strategies.
REQ.US.01.15	**Market Analysis and Planning**: They may need assistance in developing business plans, understanding market requirements, and identifying potential marketing channels.
REQ.US.01.16	**Sustainable and Environmental Considerations**: Users may prioritize sustainable and environmentally friendly farming practices.
REQ.US.01.17	**Sustainable and Environmental Considerations**: They may require guidance on conservation agriculture, agroecology, organic farming methods, biodiversity conservation, and reducing the environmental impact of agricultural activities.
REQ.US.01.18	**Access to Resources and Support**: Users may need access to extension services, agricultural experts, training programs, and resources such as research findings, best practices, and technological innovations
REQ.US.01.19	**Access to Resources and Support**: They may require support in terms of financial planning, access to credit, and government assistance programs.

7.1.2 Livestock farming

Table 30: User requirements about livestock farming

ID	Requirement Description
REQ.US.02.01	The user wants to be informed about how to add, update and delete information regarding their farm data.
REQ.US.02.02	The user wants to be informed about how to make data-driven decisions about reducing greenhouse gas emissions.
REQ.US.02.03	The user wants to be informed about how to make data-driven decisions about reducing nitrogen deposition.
REQ.US.02.04	The user wants to be informed about how to make data-driven decisions about animal health and welfare.
REQ.US.02.05	The user wants to be informed about how to make data-driven decisions about calving monitoring.
REQ.US.02.06	The user wants to be informed on how livestock policies will further incorporate even greater demands with respect to the environment and animal/livestock welfare.
REQ.US.02.07	The user wants to be informed on the proper animal management, proper feed and feeding management.

REQ.US.02.08	The user wants to be informed on real-time monitoring of livestock and environmental conditions, allowing farmers to make data-driven decisions about production parameters and disease control
REQ.US.02.09	The user wants to be informed on the weather forecast for heat waves and drought periods as an early warning mechanism
REQ.US.02.10	The user wants to be informed immediately in case an outbreak occurs that impacts his farm through an alarm mechanism
REQ.US.02.11	The platform should provide a user-friendly interface that is accessible and easy to use for farmers with varying levels of technical expertise.
REQ.US.02.12	The user wants to be informed about new technologies, such as precision agriculture, and digital tools, that can help optimize farm management and enhance productivity.
REQ.US.02.13	The farmer needs to learn good agricultural practices in the face of reducing greenhouse gas emissions, nitrogen deposition, animal health and welfare.

7.2 Technical Requirements

This section provides a detailed description of the technical requirements for each use case. This includes crop-based farming, livestock farming, and aquaculture farming, and covers IoT devices, satellite imagery specifications, equipment requirements etc. Moreover, functional and non – functional requirements are extracted for the AgriDataValue platform.

7.2.1 Weather/Micro-clima related system requirements

ID	Requirement Name	Requirement Description
REQ.FN.01.01	Weather monitoring	Weather conditions must be monitored.
REQ.FN.01.02	Weather Parameters	The AgriDataValue platform must store (near)real-time or historical data of: a) Air temperature b) Air Humidity c) Wind Direction d) Wind Speed e) Leaf Wetness f) Rain Volume
REQ.FN.01.03	Additional Parameters	The AgriDataValue platform may store (near)real-time or historical data of: a) Solar irradiance b) Relative humidity c) Barometric pressure
REQ.FN.01.04	Calculated Parameters	The AgriDataValue platform may store (near)real-time or historical data of: a) Degree Days b) Monthly/Annual Precipitation
REQ.FN.01.05	Weather impact assessment	The platform must provide weather impact assessment on agriculture.
REQ.FN.01.06		

7.2.2 Soil related system requirements

ID	Requirement Name	Requirement Description
REQ.FN.02.01	Location	• The system should support geolocation services to accurately identify and record the location of soil samples or observations. • It should provide mapping capabilities to visualize soil data and associated location information. • The system should allow users to search and select specific locations or areas of interest for analysis or management purposes. • The system should provide tools for conducting location-based analysis, allowing users to analyze soil data within specific geographic boundaries or regions.
REQ.FN.02.02	Soil parameters	The system should facilitate the analysis of various soil parameters such as pH, nutrient content, organic matter, texture, and moisture content.
REQ.FN.02.03	Data Management	• The system should have a database to store and manage soil-related data. • It should support efficient data entry, retrieval, and updating of soil analysis results. • The system should be capable of storing historical data for trend analysis and comparison.
REQ.FN.02.04	Reporting and Visualization	• The system should generate comprehensive reports summarizing soil analysis results. • It should provide graphical representations and visualizations of soil data. • The system should allow users to customize and export reports in various formats.
REQ.FN.02.05	Decision Support	• The system should provide recommendations or suggestions based on the soil analysis results. • It should offer insights on suitable crops, fertilizers, or soil amendments based on the specific soil conditions. • The system should support integration with external resources such as soil databases or research findings.
REQ.FN.02.06	Support for advice	Based on soil parameters, various agricultural advice can be given to optimize crop productivity and soil health. Here are some examples: Nutrient Management, pH Adjustment, Irrigation Management, Crop Selection, Disease and Pest Management. The system should be able to

7.2.3 Greenhouse Air Quality related system requirements

ID	Requirement Name	Requirement Description
REQ.FN.03.01	Air Quality Parameters	AgriDataValue platform must store real-time or historical data of: a) Temperature b) Humidity c) CO_2
REQ.FN.03.02	Additional parameters of interest to be measured inside the greenhouse	The AgriDataValue platform may store (near)real-time or historical data of inside greenhouse: a) Solar radiation b) PAR radiation c) NVDI

7.2.4 Farm Air Quality related system requirements

ID	Requirement Name	Requirement Description
REQ.FN.04.01	Air Quality Parameters	The AgriDataValue platform must store (near)real-time or historical data of: a) Temperature b) Humidity c) CO2 d) CH4 e) Particulate Matter (PM1.0, PM2.5, PM4, PM10) Flow rate in mechanically ventilated barns/ compartments
REQ.FN.04.02	Additional Parameters	The AgriDataValue platform may store (near)real-time or historical data of: a) N2O b) O2

7.2.5 Livestock wellbeing related system requirements

ID	Requirement Name	Requirement Description
REQ.FN.05.01	Air Quality Parameters	The AgriDataValue platform must store (near)real-time or historical data of: a) Temperature b) Humidity c) CO2 d) CH4 e) Particulate Matter (PM1.0, PM2.5, PM4, PM10) f) Flow rate in mechanically ventilated barns/ compartments
REQ.FN.05.02	Feed Quality	The AgriDataValue platform must store (near)real-time or historical data of: a) quantity b) concentrate c) roughage
REQ.FN.05.03	Feed intake	Dry Matter intake
REQ.FN.05.04	Bedding material	Refresh rate
REQ.FN.05.05	Milk production parameters	The AgriDataValue platform must store (near)real-time or historical data of:

		a) Quantity b) Fat content c) Protein content d) Urea e) somatic cell count
REQ.FN.05.06	Weight	Weight gain
REQ.FN.05.07	Moving behavior	Data activity tracker
REQ.FN.05.07	RFID tag	Data individual recognition
REQ.FN.05.08	Camera's	Identify specific behaviour

7.2.6 Terrestrial Geotagged-Photos' Capturing system requirements

ID	Requirement Name	Requirement Description
REQ.FN.06.01	Image quality	The AgriDataValue project should implement toolkit to enhance the quality of the image that is being captured by the mobile sensors. The toolkit will remove image blur and compensate for any external factors (such as motion from hand shake) to improve the quality of the image.
REQ.FN.06.02	Image pre-processing	The image pre-processing toolkit could enable segmentation and re-orientation of the image to be suitable for performing classification process.
REQ.FN.06.03	Image analytics	The image analytics must enable the implementation of automated classification of the image for detecting the health of the trees, farm crop, and plants.
REQ.FN.06.04	Knowledge extraction	The knowledge extraction component must enable the representation of the plant health through a structured knowledge base, that is aggregated from the community of experienced users.

7.2.7 CAP related actions system requirements

ID	Requirement Name	Requirement Description
REQ.FN.07.01	CAP supervisory services	AgriDataValue could provide models for input for the land cover, vegetation growing, grassland mowing and land cover change
REQ.FN.07.02	Weather and livestock data	AgriDataValue could provide models for weather and livestock data to determine the optimal composition of feeding habitants and brood stock, increasing the farming efficiency
REQ.FN.07.03	Economic risk assessment	AgriDataValue could develop economic risk assessment models for predicting the yield quality.
REQ.FN.07.04	Comparative evaluation and monitoring of ecological schemes	AgriDataValue could provide comparative and eco-scheme monitoring tools to support the new CAP towards fair income, land use protection and environmental care
REQ.FN.07.05	Food security in the face of climate change and biodiversity loss	AgriDataValue could provide tools which will support farmers in their day by day activities in crop/ livestock production and getting informed decisions
REQ.FN.07.06	Global transition towards competitive sustainability from farm to fork	AgriDataValue could provide tool for food traceability and innovative business models that turn farmers from data consumers to data and knowledge prosumers

7.2.8 Satellite Earth Observation Capturing requirements

ID	Requirement Name	Requirement Description
REQ.FN.08.01	EO imagery catalogue	The platform (via Sentinel Hub) should provide a catalogue of the available EO satellite imagery and EO derived datasets
REQ.FN.08.02	EO imagery access	The platform should provide access to EO satellite imagery and EO derived datasets, listed in the catalogue
REQ.FN.08.03	Ingestion of and access to other datasets	The platform (via Sentinel Hub) should allow ingestion of other (raster) imagery and datasets, to be accessible via the same API as EO satellite imagery and EO derived datasets
REQ.FN.08.04	EO data processing	The platform (via Sentinel Hub) should allow for efficient processing (e.g., on the cloud) of EO data, using JavaScript code to define how the satellite data shall be processed by Sentinel Hub and what values the service shall return
REQ.FN.08.05	EO Large Scale (raster) processing	The platform (via Sentinel Hub) should allow for efficient large-scale processing and creation of analysis ready data-cubes
REQ.FN.08.06	EO Large Scale (object-based) processing	The platform (via Sentinel Hub) should allow for efficient large-scale data aggregation to compute statistics over objects (e.g., agricultural fields) without having to download images, thus obtaining time-series data

7.2.9 Data Sovereignty related requirements

ID	Requirement Name	Requirement Description
REQ.FN.09.01	Data Federation	The AgriDataValue platform should support data storage in a decentralized way. Taking into account data heterogeneity we need to offer a platform that offers federation, rather than integration of data silos.
REQ.FN.09.02	Data Openness	Data should be associated with self-descriptions or meta-descriptions so that it is straight forward to identify the actual data context
REQ.FN.09.03	Blockchain & NFTs	There should be a way to trace data sharing and data origin. As such a blockchain or NFT like technology is needed for offering data via a marketplace and smart contracts.
REQ.FN.09.04	Usage Policies & enforcement	Each participant should be able to define data usage policies and attach them to outbound data. Policies might include restrictions, such as disallowing persistence of data, or disallowing transfer of data to other parties, for example.
REQ.FN.09.05	Data discoverability & observability	Data should be able to be discovered, accessed and observed via the appropriate policies.

7.2.10 Data Interoperability related requirements

ID	Requirement Name	Requirement Description
REQ.FN.10.01	Data Standardization	Ensuring that data exchanged within the project follows standardized formats, structures, and definitions to facilitate seamless integration, interpretation, and analysis across different systems and stakeholders.

REQ.FN.10.02	Data Mapping and Transformation	Implementing mechanisms to map and transform data from various sources and formats into a common data model or schema, allowing for effective data integration and interoperability.
REQ.FN.10.03	Data Quality Assurance	Establishing protocols and/or mechanisms to ensure the accuracy, consistency, completeness of the exchanged data between parties, promoting reliable and trustworthy information for decision-making and analysis.
REQ.FN.10.04	Data Governance and Metadata Management	Implementing governance frameworks and metadata management practices to provide clear guidelines, policies, and documentation for data sharing, usage control, privacy, security, and provenance
REQ.FN.10.05	Data Exchange Protocols and APIs	Utilizing standardized data exchange protocols and application programming interfaces (APIs) to enable seamless and efficient data sharing, integration, and interoperability among different data space participants that will consume/provide data.

7.2.11 Federated ML related requirements

ID	Requirement Name	Requirement Description
REQ.FN.11.01	Agent identification	Provide a mechanism to identify the different agents (or clients) involved in the federated learning protocol.
REQ.FN.11.02	Global parameters communication	Establish a secure channel and all the related mechanisms needed for communicating the global parameters from the server to the agents to ensure client privacy
REQ.FN.11.03	Local training	Clients (e.g., IoT nodes) should have enough power computation to perform their local training on the data they own, so no critical information is sent to the server
REQ.FN.11.04	Aggregated model	The server must receive all the local models and aggregate them
REQ.FN.11.05	Anomaly detection	Before aggregating the model, the server must check if the local models coming from the clients could have suffered attacks, and act accordingly
REQ.FN.11.06	Data preprocessing	Ensure that all data involved in the Federated Learning approach is pre-processed homogeneously

7.2.12 System level Requirements

ID	Requirement Name	Requirement Description
REQ.FN.12.01	Authentication/ Authorization	The system shall support a mechanism to authenticate/authorize users.
REQ.FN.12.02	IoT data collection	Data should be collected from the farming fields from various IoT devices and sensors (agro-meteorological stations, soil sensors, animals' wearable devices, smartphones, etc).
REQ.FN.12.03	IoT data transmission	IoT data should be transmitted to the centralized AgriDataValue platform utilizing the best available communications infrastructure or a dedicated communication system provided by AgriDataValue.
REQ.FN.12.04	IoT sensors/devices management	The platform could provide options to manage/view sensors/devices.
REQ.FN.12.05	IoT device connectivity	The devices must support connectivity.
REQ.FN.12.06	Historical data processing	The platform should process historical data.

REQ.FN.12.07	Data access	The platform should provide access to IoT measurements.
REQ.FN.12.08	IoT data storage	The platform must support storage of precision agriculture and weather IoT data in any agreed format.
REQ.FN.12.09	Processed data storage	The platform shall support the storage of data processed by internal AgriDataValue Backend modules.
REQ.FN.12.10	Satellite image processing	The platform should be able to process Sentinel-1 and Sentinel-2 images using the ESA SNAP software.
REQ.FN.12.11	Satellite image exposure API	The platform should be able to expose the processed data using a standard Open Geospatial Consortium (OGC) compliant API.
REQ.FN.12.12	Standard APIs	Standard APIs should be used to interface with external platform services.
REQ.FN.12.13	Receiving control commands	The IoT devices could receive control commands from the AgriDataValue platform. To support this requirement, AgriDataValue communications must enable bi-directional communications.
REQ.FN.12.14	Data reports	The platform could provide the ability to export reports in a range of formats (e.g., pdf, image, office) of measurements, model outcomes etc.
REQ.FN.12.15	Data geo-visualization	The platform could provide geo-visualization of data.
REQ.FN.12.16	Monitoring	The platform should have the ability to run supervised and unsupervised algorithms and models for monitoring purposes.

7.2.13 UC related requirements

ID	Requirement Name	Requirement Description
REQ.FN.13.01		
REQ.FN.13.02	Field status	The platform could provide options to view the farming field status.
REQ.FN.13.03	Pest infestation identification	The platform should utilize Deep Learning algorithms to identify pest infestation.
REQ.FN.13.04	Disease outbreaks module	Platform should contain models which proactively predict the onset of disease outbreak.
REQ.FN.13.05	Disease outbreaks alert	Dashboard should alert users about disease outbreaks.

7.2.14- Non - Functional Requirements

The Non-Functional requirements of the AgriDataValue project are listed in Table 31, giving a unique identifier, a name and a description.

Table 31: Non – functional requirements of the AgriDataValue platform

ID	Requirement Name	Requirement Description
REQ.NFN.01	Low latency	The required amount of time to transmit data to the AgriDataValue platform should be minimized. If communications infrastructure in a given location is available, the data transmission should be in real time. If communication infrastructure is not available (temporarily or permanently due to rural location) the measured data should be stored

		locally and be transmitted once communications is restored or from the location where communication is available.
REQ.NFN.02	Availability	The platform should support high availability.
REQ.NFN.03	Scalability	The platform should be able to integrate additional components, such as additional data sources. In addition, the platform should support hierarchical architecture.
REQ.NFN.04	Usability	The platform should be developed to be simple, intuitive and efficient for the end users and easy to understand.
REQ.NFN.05	Security & Privacy	The platform should be secure and prevent unauthorized access to private information.
REQ.NFN.06	Reliability	The platform should indicate potential malfunctions.
REQ.NFN.07	Power efficient & Hybrid electrically powered devices	The platform devices should factor in usage in remote areas with limited access to electric power supply and be designed for power efficiency. As much as possible, the devices should be designed for hybrid power supply options including solar, battery and mains power supply.
REQ.NFN.08	Accuracy	New devices should be designed to meet minimum requirements of accuracy and functionality provided by existing alternative systems
REQ.NFN.09	Rapid testing	Test devices should be capable of rapid, non-destructive measurement, typically within a few seconds
REQ.NFN.10	Durability and ruggedness	Installed IoT devices should be designed to withstand harsh conditions and usage that is typical of farm equipment and devices.

8 Meta-Architecture Considerations

AgriDataValue considers a multilevel architecture, exploiting key properties of data sovereignty, locality and traceability to deliver a secure and trustworthy platform that relies on federation and decentralized processing. To achieve its ambitious goals and realize the described use cases, AgriDataValue project will develop an **efficient, massively distributed, open-source, privacy-preserving, federated AI-based platform, aiming at capturing and managing agri-environment data, from a variety of heterogeneous data sources, enabling trustworthy secure and GDPR compliant interoperability and data sharing across end-users, industries and organizations.**

As it has been already analysed in section 3 (Figure 3), we consider the AgriDataValue platform (also called, **Agri-Environmental Big Data Space, ADS)** is logically split in two main components: a) the **ADS Core** (ADS-C) where all data is stored and processed. And b) the **ADS Marketplace** (ADS-M) that enables the realization of innovative business models and turns end-users (e.g., farmers) to data/ML models prosumers.

Following a bottom-up approach, AgriDataValue platform utilizes 5 building blocks:

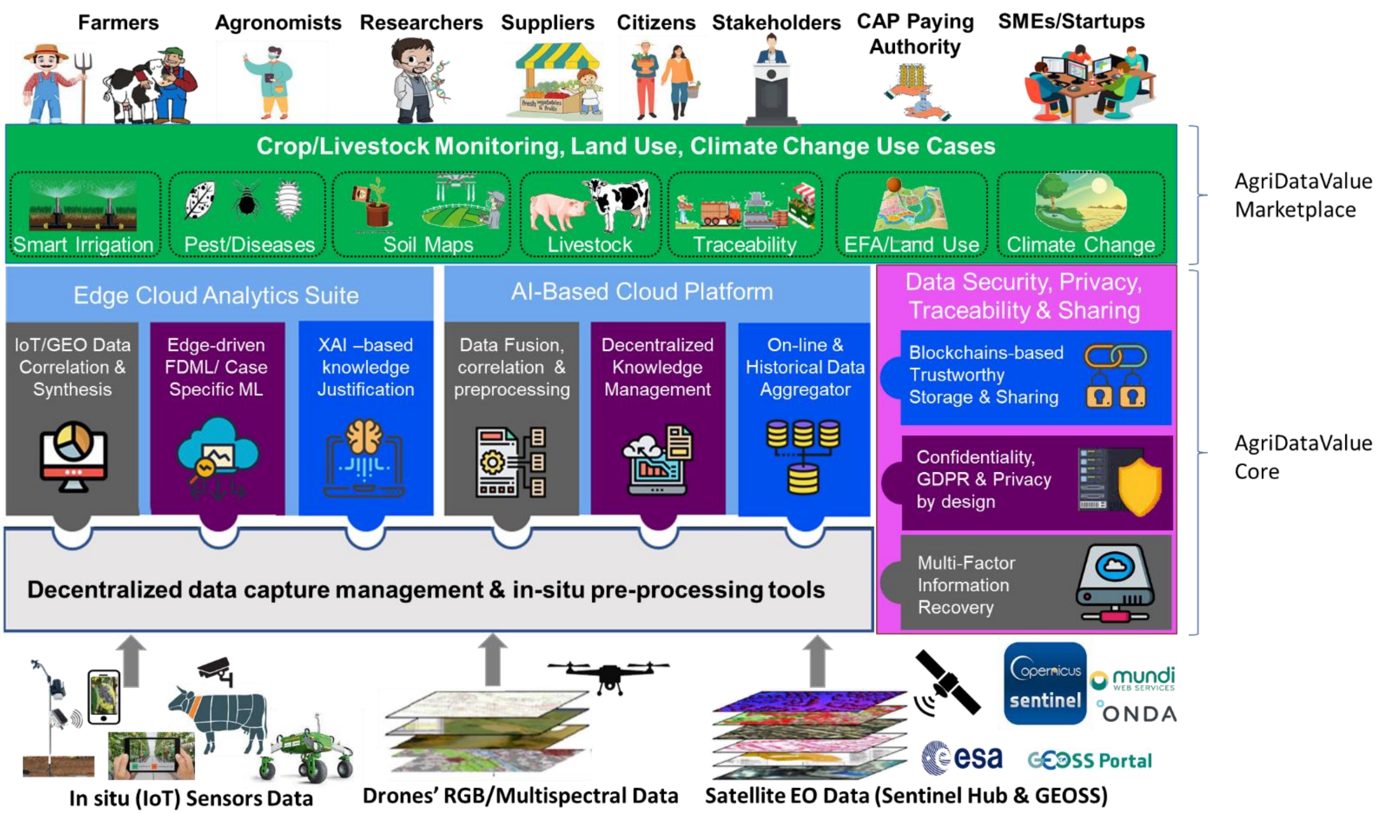


Figure 62: AgriDataValue platform high level architecture

a) <u>Decentralized data capture management & in-situ processing tools</u> offer capturing and close-to-the-sources processing of data, by exploiting the IoT advancements in communications and computational power and storage (varying from IoT sensors and smart phones to GPS-enabled agri-robots) as well as (5G) edge computing. Since IoT agri-environment data is typically captured at the edge, AgriDataValue will push processing near to the sources following the in-situ processing paradigm, thus distributing the processing load, and reducing the amount of transferred data. Moreover, via ***SINER's award winning Sentinel DIAS*** (Data and Information Access Services) [205] hub and ***Copernicus Open Access Hubs (ONDA*** [206] and ***CREODIAS*** [207]), AgriDataValue will gain direct access to >44 PB of EO data (EODATA/EODATA+) from Copernicus Sentinels, Landsat and Envisat (well over the normal free data samples) available with instant and local access. By means of in-situ processing, AgriDataValue increases the efficiency of processing by online aggregation and by eliminating redundant data, while enhancing privacy, since the identity of moving objects can be stored locally and only (pseudo) anonymized location information can be transmitted to the Cloud for global, data-intensive analysis operations.

b) Edge cloud analytics suite. AgriDataValue will realise efficient methods and techniques towards low-latency communications and processing of IoT and spatiotemporal data for real-time analytics, as well as high throughput processing for batch analysis tasks. This includes advanced partitioning techniques, which comprise a key factor for efficient distributed processing and edge-driven FDML based data fusion methods for data upscaling, along with techniques that address the shortcoming of existing (5G) edge cloud caching algorithms, which are predominantly preoccupied with identifying which data to keep locally and which to remove from the cache. AI-based caching will enable the prediction of the future use of data by identifying patterns in the read requests and use that to determine, which data will be accessed, where and when, before the actual read requests, thus facilitating the performance requirements of large-scale analytics. Thus, AgriDataValue will deliver novel algorithms for proactive data loading, prefetching, fusion and aggregation based on AI-based predictions and forecasts. In parallel, AgriDataValue will apply IoT/GEO Data correlation, analysis and synthesis and XAI predictive modelling to improve the end-user experience and increase their trust to the platform advice and recommendations.

c) AI-Based Cloud Platform. AgriDataValue platform will provide federation of multiple IoT and spatiotemporal data sources along with decentralized data and knowledge management solutions, enhanced FDML models training and high throughput processing for batch data analysis tasks. AgriDataValue platform needs to bridge the gap between, on the one hand, applications processing requests and, on the other hand, access to the underlying data to be processed. It will combine a highly efficient and decentralized data ingestion mechanism to handle semantic interoperability and heterogeneity, pre-processing of data, as well as online and historical data aggregation techniques. For the batch data analysis scenarios that require scalability, AgriDataValue platform will apply specialized analytics algorithms coupled with advanced indexing techniques tailored for spatiotemporal data and trajectories. The platform will be based on knowhow from ***IDSA which is becoming the "de facto" data spaces architecture.***

d) Data Security, Privacy, Traceability & Sharing. AgriDataValue platform offers a vertical "pillar" to cover the research and development activities related to data security/ privacy and data sharing. Instead of a "monolithic" and custom-made solution, the platform will allow flexible design of processing pipelines, across all layers (from edge devices to data centres), moving as little data as possible away from its origin, protecting sensitive data and providing a central access point to data insights and visualizations. Data security will be achieved through cyber-security defence mechanisms, blockchain/DLT policy-based access traceability and identity management techniques, while data provenance will be applied in the complete data lifecycle, from data acquisition to delivery. With regards to privacy, besides compliance to regulations such as GDPR, AgriDataValue platform will apply appropriate anonymization that prevent attackers from disclosing the identity of the data owner, while preserving the ability to perform data analysis and extract useful knowledge (e.g. shape and trajectory clustering). To enable seamless exchange of data, AgriDataValue platform will support standardized representation formats (e.g. ETSI NGSI-LD, OGC for geospatial data). To enhance interoperability even further, programming interfaces will be provided to facilitate not only data transformation, but also the exchange of ML models and sharing personalized visualizations, including tables, maps, and charts.

e) Crop/Livestock Monitoring, Land Use, Climate Change Use Cases will include the use case specific apps to validate AgriDataValue platform efficiency, along with specialized FDML models to be shared to interested end-users.

8.1 In-Situ Data Collection/Processing Tools

AgriDataValue platform will utilize (IoT) data collection, processing and analysis devices to monitor production and agri-environment conditions. During the project lifetime, these tools will be adapted and enhanced, their volume will be increased or even modified following the use cases feedback and most recent development and innovations in the fields of sensors. However, the tools that the consortium will bring, develop or utilize in the initial project phase are:

8.1.1 Open-Field Crops' IoT Sensors Data Capturing Toolbox

Beyond already installed or off-the-self sensing devices, additional IoT in-situ data capturing devices will be installed in AgriDataValue platform' pilots. One of the main capturing devices will be SynField [205]. SynField™ is Synelixis' (project coordinator) flexible sensing and actuating precision agriculture solution.

Figure 63: Selected SynField IoT sensor options

It is expected to give a significant head start in AgriDataValue platform, as it already supports more than 50 different types of sensors to remotely monitor in real-time climate/weather, radiation, soil and leaf conditions, ranging from air temperature and barometric pressure to soil moisture/ salinity, irrigation pipes network pressure/flow and drilling pressure/ flow/ operational efficiency, while additional meta-sensing indices (e.g. evapotranspiration, thermo-hours, dew point) and data analytics are calculated in-situ using edge cloud computational resources. SynField also controls irrigation networks, public/private sharing drilling facilities, fertilization and anti-frost policies, using AI models and rules, either fully or partially automated. SynField features a GPS sensor to enable geotagged information (and as anti-theft protection) and communicates with the cloud using 3G/4G/NB-IoT cellular technology. A Bluetooth interface is available for system set-up and management and a LoRA interface may coordinate an ad-hoc network of peripherals, covering even locations where the cellular network is weak or not available, while reducing the communications' cost. SynField™ is already deployed in 8 countries (i.e. Greece, Italy, Spain, Denmark, Serbia, Germany, Finland and India). Additional nodes will be installed during AgriDataValue platform lifetime, while additional wireless interfaces (e.g. WiFi, sigfox, zigbee) and additional sensors will be integrated following the most recent development and innovations in the fields of communications and sensors.

8.1.2 Greenhouse/Farm Air Quality IoT devices

AgriDataValue' will go beyond crop monitoring to utilize already available data, while collecting and upgrading new data from greenhouses' crop and livestock farms production. GHG, such as carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) from crop and livestock enteric fermentation are of paramount importance. Synelixis SynAir™ [206] is a versatile sensor platform that can accommodate a multitude of Air Quality sensors, including CO, CO_2, CH_4, N_2O, NO_2, NH_3, O_2, O_3, Alcohol detection, Volatile Organic compounds (VOC) and Particulate Matter ($PM_{1.0}$, $PM_{2.5}$, PM_4, PM_{10}). Synelixis SynAir [206] will be installed in selected pilots, while additional sensors will be integrated during the project lifetime (Figure 64).

One of the key benefits of air quality sensors is that they can provide real-time data on air quality conditions. This allows farmers to identify areas of the operation that are generating high levels of pollution and take corrective action.

Figure 64:SynAir indoor (Greenhouse) and outdoor Installation

8.1.3 Animals' Wearable IoT Data Capturing Toolbox

The Federation of Veterinarians in Europe advises [207] all involved in animal farming to use animal-based indicators for assessing the welfare conditions of farmed animals on a routine basis. The regular monitoring of animal welfare allows the early identification of animal health and welfare issues at farm level and timely implementation of corrective measures. The adoption of suitable tools/protocols for the implementation of routine checks at adequate frequency is fundamental to improve responsiveness allowing the prevention and/or early identification of animal health and welfare issues. Technological tools to support data collection and analysis exist and are in constant development. However, not all of these devices are suitable or applicable for AgriDataValue defined scenarios. During the project, we will analyse existing solutions and select the most appropriate wearable devices for AgriDataValue applications. The most obvious candidates are:

- GPS animal collars tracking animals and showing their location in real time
- Ear tag sensors for measuring behavioural indicators like posture, gait, vocalization, and external temperature which can help in evaluating the health and welfare of animals.
- Remote animal health monitoring systems
- ECG systems which are used on racing horses, etc.

Typical example of a GPS animal collar is shown in Figure 65. AgriDataValue' will also utilize off-the-shelf smart neck collars and ear tags for cows/pigs, including 3 axis accelerometers and GPS trackers, along with cameras to get insights of the health/welfare, activity, and livestock calving status. All these measurements will be combined with the temperature/humidity data and outdoor wind sensors to calculate the emissions concentration.

Figure 65: Typical example of a GPS animal smart Collar

8.1.4 GreenFeeds and multi-gas analyzers

There are many different measurement methods available to measure greenhouse gases. ILVO also has 6 GreenFeed (C-lock) feeders, which are special concentrate feeders that measure the emissions of the cow on a relative scale during feeding. The dairy cows in the ILVO free stall barn can voluntarily visit these GreenFeeds throughout the day. This allows methane emissions from larger groups of cows to be measured under practical conditions. Recently, ILVO also has some mobile GreenFeeds available for methane measurements on the pasture. Manure emissions are measured with multi-gas analysers.

8.1.5 Terrestrial Geotagged-Photos' Data Capturing Toolbox

The AgriDataValue Terrestrial Geotagged-Photos' Data Capturing Toolbox will enable farmers, agronomists and stakeholders to capture and upload geotagged photos from their crop or livestock and receive automated, AI-based feedback and technical recommendations on the health of the parcels and potential bugs, diseases, pests, weeds, fungi, fungal-like organisms, bacteria, phytoplasmas, viruses, viroids, nematodes and parasitic, along with guidance on how they could deal with them. The sensing and data collection process will be supported by a mobile application implemented in both Android and iOS framework that will allow end users to review related content about their parcels and receive notifications and recommendation in a user-friendly Augmented Reality (AR) framework.

Figure 66: Geotagged Photos App

Moreover, based on XAI technology, the app will provide explanation of the recommendations and relevant cases, to increase farer trust and confidence on the recommendation. The complete process will be implemented utilizing a smart mobile as capturing device, the (5G) edge cloud as processing node offloading computational heady processes and AgriDataValue platform ML model/data. Based on advanced security and multifaceted anonymization, validation, reliability and traceability technology, the user will have the option to either make the captured photos public or enable just the dissemination of the AI result as a warning, recommendation or inceptive-based knowledge sharing.

8.2 Regional/Global Data Collection/Processing Tools

In-site (IoT) sensor data collection/processing tools will be combined and upscaled with regional and global tools:

8.2.1 Aerial Geotagged-Photos' Data Capturing Toolbox

The Aerial Geotagged-Photos' Data Capturing Toolbox will be based on SLG drone's precise plant-level data platform and SINER technology. The toolbox represents a combination of tools that are employed towards the conduction of drone flights in targeted areas of interest (i.e. fields of small, narrow or elongated land parcels and/or areas with significant cloud cover). In parallel to drone's GNSS supported/automated flight control, the drone will be equipped with both a visual and a multispectral camera, to capture Blue (450 nm ± 16 nm), Green (560 nm ± 16 nm), Red (650 nm ± 16 nm), Red edge (730 nm ± 16 nm) and Near-infrared (840 nm ± 26 nm) images. Drone's cameras will go through a rigorous calibration process where radial and tangential lens distortions will be measured, so that the distortion parameters gathered to be saved into each image's metadata, letting post-processing software adjust uniquely for every user.

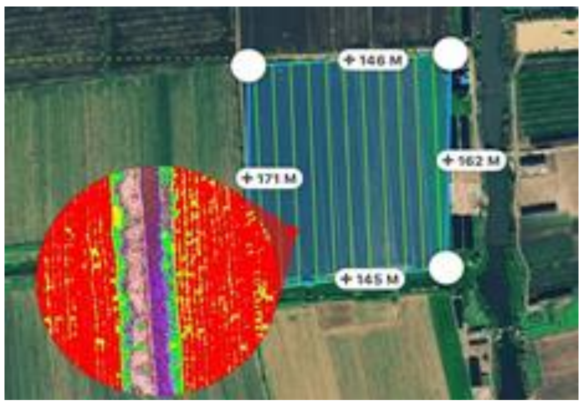


Figure 67: Aerial Geotagged Toolbox

The toolbox will play a significant role in calculating accurate Vegetation Indexes such as NDRE and NDVI, enabling farmers to make timely and informed decisions on crop treatment, lowering costs, saving resources, and maximizing yields. In combination with satellite EO data, the toolbox via routine inspections will support accurate monitoring such as land usage, riparian vegetation, forest health and biomass.

8.2.2 Satellite Earth Observation Data Capturing Toolbox

AgriDataValue platform will capitalize on recent results of ESA's SEN4CAP and H2020 EO4AGRI and DIONE projects and upscale data captured by IoT in-situ and obtained by drones' tools with EODATA. The toolbox will be based on Sentinel-1 and Sentinel-2 (A and B) Copernicus Contributing Missions (CCM), with a high revisit time of 2-3 days at mid-latitudes, enabling the observation of significant changes in canopy growth (e.g. new phenological stage or biotic and abiotic stresses). Sentinel-2 features 13 different spectral bands, 10 of which being particularly interesting for the computation of vegetation indices. In parallel, Sentinel-5 will be considered complimenting Sentinel-1 on climate change, as Sentinel -1 is observing among others the forest, water and soil management, while Sentinel-5 is focused on air quality and composition-climate interaction with the main data products being O_3, NO_2, SO_2 and aerosols. Sentinel-5 will also deliver quality parameters for CO, CH_4, and stratospheric O_3 with daily global coverage for climate, air quality, and ozone/surface UV applications. The toolbox will exploit DIAS (Data and Information Access Services) in its fullness, through ***Sentinel DIAS Hub*** and ***Copernicus Open Access Hubs (ONDA**, **CREODIAS** and **MUNDI**)* to gain access not only to more than 44 PB of EODATA/ EODATA+ from Copernicus Sentinels, Landsat and Envisat available with instant and local access, but also their services, i.e. the data catalogue and Copernicus Land (CLMS) and Atmosphere (CAMS) Monitoring Services.

Figure 68: Evia, Greece 2021 Wildfire (Copernicus Sentinel-2)

Moreover, by exploiting existing ***GEOSS*** datasets, metadata and semantic search tools based on AI, and build upon prior knowledge, AgriDataValue platform will enable added-value services on Climate Change adaptation and mitigation with minimal new data collection activities.

8.2.3 Upscaling in-situ/regional/global datasets

AgriDataValue platform will combine and upscale in-site, regional and global IoT and geospatial datasets to provide more accurate results and images with better resolution. As an example, with respect to Sentinel-2, though it provides images of high resolution, still it is not impossible to obtaining pure pixels of a crop. Indeed, images are made up of mixed pixels (crop/soil or crop/cover crop when the inter-row is grassed). Moreover, depending on the location under study, cloudy weather conditions can be of great concern as they limit the number of usable images. It should also be stressed that to our knowledge, beyond SEN4CAP tools, the end-to-end chain (a.k.a. to process and correct) Sentinel-2 images considering new services for dynamic crops and climate change monitoring has not yet been sufficiently tested.

Figure 69: Upscaling Sentinel-2 Images

AgriDataValue platform will introduce novel image processing techniques, ML-based pre-/post-processing and fusion of LPIS/GSAA datasets, GEOSS/Copernicus DIAS-sourced data with VHR (Very High Resolution) EO and drone-obtained optical and SAR multispectral data to improve the resolution below 0.5m. This will enable the provision of valuable tools for new services. As examples, AgriDataValue platform tools will

- enhance resolution maps of permanent pastures, crop-types, non-productive EFA (Ecological Focus Areas) types (i.e. fallow land, buffer strips, hedges) and farmers' activities (e.g. grassland mowing/ploughing),
- calculate quite important vegetation indexes, such as FAPAR, GNDVI/NDVI, EVI,
- support the assessment of bio-geophysical parameters such as Leaf Area Index (LAI), chlorophyll vegetation index (CVI), Leaf Chlorophyll Content (LCC) and Leaf Cover (LC),
- calculate soil related parameters, such as Soli-Adjusted Vegetation Index (SAVI) and Soil-related Indicators
- analyse Disaster Resilience and climate change effects.

Moreover, we will significantly ***contribute to CAP supervision services*** by providing input for land cover, vegetation growing, grassland mowing and land cover change. AgriDataValue platform will also combine and upscale ***weather and livestock data***, related to animal's habits, birth, health and welfare, to determine the optimal composition of feeding habitants and brood stock, while increasing the farming efficiency, measured in milk, meat and manure to be used in electricity generation as biogas and finally as compost/fertilizers.

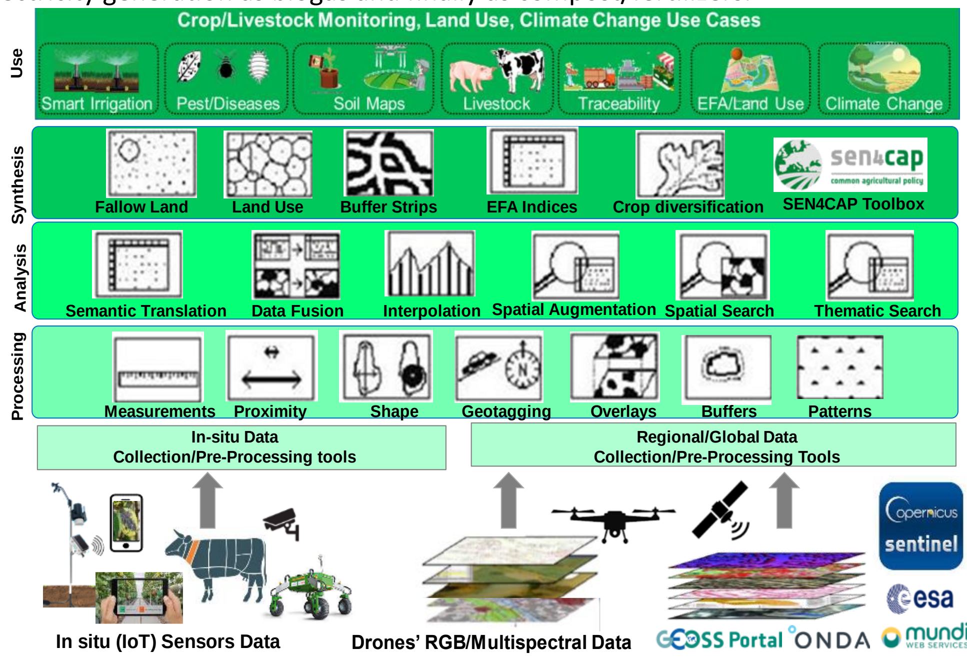


Figure 70:Upscaling in-situ/regional/global datasets Tools

AgriDataValue platform will offer a complete toolset (Figure 70) for correlation of IoT and geospatial data, covering processing, analysis, synthesis and use of data, ranging from generic spatial, EO satellite data geotagging up to calculation of specific parameters such as buffer strips, EFA indices, and crop diversification, while integrating SEN4CAP and EO4AGRI toolbox.

It is important to note that ***AgriDataValue platform will focus on (real-time) on-demand data upscaling, based on specific application requirements***. In this way, end-users will be able to utilize the most recent in-situ/ regional/ global data, based on their instant needs, and not generic historical data. To face data interoperability, we plan to utilize **Federated Deep ML (FDML)** thus: a) initially ML models will be pre-train in a fully distributed manner, while avoiding data transferring or translation wherever possible, b) the pre-trained ML models will be aggregated to create enhanced FDML models, c) FDML models will be utilized at the edge cloud with minimal processing requirements. This will be achieved by offloading, wherever possible, processing intensive tasks, such as FDML aggregation on the edge cloud, while utilizing semi-trained ML models and on-device intelligence. In case data translation can't be avoided, an **ontology-based semantic data model** will be adopted and extended using existing vocabularies (i.e. agroRDF, GACS, EPCIS**)**, along with real-time translation hosted at the edge, engaging standardised solutions such as OMA Next Generation Sensors Initiative (NGSI) and ETSI NGSI-LD.

8.3 Federated Deep ML (FDML)

Federated Deep Machine Learning (FDML) is a distributed approach to Machine Learning (ML) that has gained momentum in recent years since it allows training and serving Artificial Intelligence (AI) models on decentralized data sources. As can be seen in the image below, an FDML approach consists of two components:

- **Server:** receives local model updates (weights or gradients) from the clients and aggregates them to generate a global model. This global model is then sent back to the clients to perform on-device inference.

- **Clients:** entities or devices with computation capabilities that possess sensitive data. These clients train AI models with their local data and send their model updates to the server. Finally, they update their local model with the aggregated model generated by the server.

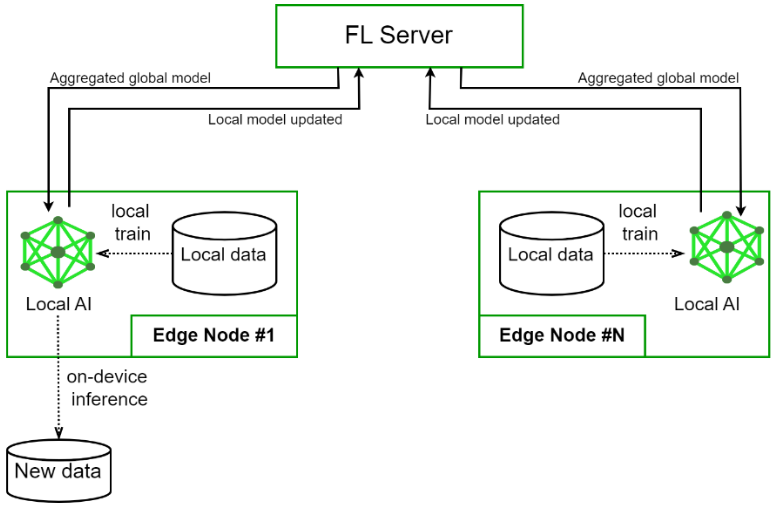


Figure 69: Federated Machine Learning architecture

The deployment of an FDML scheme has several advantages over traditional centralized machine learning ones. On the one hand, FDML clients do not have to share any private or sensitive data for training the global model. This not only involves an enhancement in terms of privacy and security but also encourages interoperability between entities reluctant to share their data. On the other hand, FDML assumes that the training and inference processes are performed locally on each device. This implies the parallelization of both procedures and increments the scalability of the ML solution. These advantages are the reason why FML has gained momentum, especially in scenarios where i) data privacy is a critical requirement, and/or ii) multiple sources of data coexist. Agri-environmental and agri-food supply chain applications are clear examples of scenarios where the adoption of FML approaches has become an essential object of research [208] [209, 210, 211, 212], since it is a domain that can extremely benefit from the two main advantages stated before. First, the agriculture domain is especially vulnerable to data silos: oftentimes, the data generated to test aspects such as food quality is kept private and isolated by the institutions gathering them. Secondly, because of this isolation, any data sharing becomes impossible, which in turn removes any possibility of scaling the insights extracted from the data under study to a macroscopic level [208].

However, the application of FDML schemes in the agriculture sector has created new potential risks, namely adversarial attacks, where an attacker can cheat the server by impersonating a client, which in the end can result in data leakage or poisoning attacks [211, 212]. As a result of this, in recent years there has been a lot of research towards i) avoiding private data leakage at any stage of the machine learning pipeline, including model training, data sharing, and model serving, through Privacy-Preserving Federated Machine Learning (PPML) [212]; and ii) minimizing poisoning attacks by using generative methods, such as Generative Adversarial Networks or Normalizing Flows [213].

In this context, AgriDataValue will provide an AI-enabled Decision Support System (DSS) adjusted to end-users' constraints and specific requirements of the project UCs, where FDML, PPML, and state-of-the-art generative methods will be combined to enhance privacy and security in the federated network, exploring differential privacy-based algorithms such as Private Aggregation of Teacher Ensembles (PATE) [214]. In this way, AgriDataValue will leverage secure edge computing techniques and aggregation primitives to privately and securely combine local training to update a global model.

8.4 Blockchain Technology

Based on initial research, there are many efforts, mainly RTD and some commercial ones, of introducing Blockchain in the food supply chain. The main objectives of such efforts have been:

- the introduction of transparency and traceability in the production line,
- the trustworthy monitoring, immutable cataloguing and control of vital parameters through the whole product life span,
- comforting the consumer concerns about the origin, certification and production process details.

In fact, the integration of Blockchain ledger offers a replacement of a central database system and expunge its subsequent single point of failure vulnerability. It also promotes trust among supply chain parties since data falsification is close to impossible, due to Blockchain data immutability and makes the traceability retrieval process more trustworthy.

Although it is a relatively new technology, approximately one of three food traceability frameworks utilize blockchain technology [209] [210] [211]. On the other hand, the application of Blockchain still faces challenges related to: a) performance and scalability issues, since most of the major public Blockchain networks implementations are not designed towards commercial efficiency; b) data privacy concerns, especially in the case of public ledgers, where corporate data are available to all participants; c) lack of central authority that can enforce global policies; d) concerns regarding energy-efficient operation. [212] [213] [214] [215] [216]

9 Conclusion

AgriDataValue presents a comprehensive and innovative approach to revolutionize the agricultural sector by leveraging advanced technologies and data-driven solutions. Throughout the project, significant advancements will be made in several key areas, including data integration and interoperability, DSSs, precision agriculture, remote sensing, IoT, and blockchain technology.

The project recognizes the immense potential of data in agriculture and emphasizes the need for efficient data collection, processing, and analysis. By integrating heterogeneous data sources from various stakeholders, such as farmers, researchers, and agri-food supply chain actors, AgriDataValue aims to create a unified data ecosystem that enables seamless data sharing, collaboration, and knowledge exchange. The project's emphasis on data interoperability and standardisation ensures that diverse datasets can be effectively integrated, leading to more comprehensive and valuable insights for all stakeholders involved.

One of the key outcomes of AgriDataValue is the development of advanced DSSs that empower farmers and other actors in the agricultural value chain to make informed decisions. By utilizing ML, predictive analytics, and optimization techniques, these systems provide real-time and personalized recommendations on crop management, resource allocation, and risk mitigation. The integration of historical and real-time data, combined with sophisticated models, enables the generation of accurate and actionable insights, leading to improved productivity, resource efficiency, and sustainability in agriculture.

Precision agriculture is a crucial aspect of AgriDataValue. By harnessing the power of IoT sensors, satellite imagery, and drone technology, the project aims to enable precise and site-specific agricultural practices. From soil monitoring and crop health assessment to irrigation management and yield prediction, precision agriculture techniques contribute to optimized resource usage, reduced environmental impact, and increased profitability for farmers. The integration of regional and global data collection and processing tools, such as aerial geotagged photos and satellite earth observation, further enhances the accuracy and scope of the generated insights

The AgriDataValue project places a strong emphasis on remote sensing and Earth observation (EO) technologies as invaluable tools for agricultural monitoring and analysis. By leveraging the capabilities of satellite-based EO platforms like Sentinel, MODIS, and Landsat, the project enables frequent and comprehensive monitoring of vegetation growth, land usage, forest health, climate change, and air quality. The fusion of EO data with in-situ and drone-obtained data enhances the resolution and accuracy of the generated information, supporting diverse applications such as land cover mapping, vegetation index calculation, assessment of bio-geophysical parameters, and disaster resilience analysis.

Furthermore, the project recognizes the potential of blockchain technology in enhancing transparency, traceability, and trust in the food supply chain. By leveraging blockchain's distributed ledger system, AgriDataValue aims to overcome the limitations of centralized databases and enable secure and immutable tracking of vital parameters throughout the product lifecycle. Blockchain technology ensures data integrity, reduces the risk of data falsification, and fosters trust among supply chain actors and consumers. However, challenges related to performance, scalability, data privacy, and the absence of a central authority remain to be addressed in the implementation of blockchain solutions in the agriculture sector.

The AgriDataValue project has not only made significant progress in the integration of various technologies but has also recognized the importance of collaboration, knowledge sharing, and stakeholder engagement. By actively involving farmers, researchers, industry experts, and policymakers, the project promotes a holistic and inclusive approach to agriculture, fostering innovation and sustainability. The project's emphasis on real-time, on-demand data upscaling and federated deep machine learning ensures that end-users can access the most recent and relevant data, tailored to their specific needs, while preserving privacy and security.

Overall, the AgriDataValue project signifies a transformative shift in the agricultural sector, where data-driven approaches, advanced technologies, and collaborative frameworks converge to address the challenges and unlock the opportunities in modern agriculture. By integrating diverse datasets, developing advanced decision support systems, promoting precision agriculture and remote sensing, and exploring blockchain technology, the project paves the way for a more sustainable, efficient, and resilient agricultural ecosystem. The outcomes of the project have the potential to drive innovation, optimize resource utilization, mitigate risks, and ultimately contribute to global food security and environmental stewardship.

While the AgriDataValue project has achieved significant milestones, it also highlights areas for future research and development. Further exploration of emerging technologies like artificial intelligence, robotics, and the Internet of Things can enhance automation and efficiency in agricultural operations. Continued efforts in data standardization, interoperability, and privacy protection will enable seamless data exchange and collaboration across different platforms and stakeholders. Moreover, the integration of socio-economic factors, market dynamics, and policy frameworks can facilitate the adoption and scalability of data-driven solutions in the agricultural sector.

In conclusion, the AgriDataValue project serves as a catalyst for the transformation of agriculture into a data-powered, knowledge-intensive domain. By embracing the potential of data integration, advanced analytics, and emerging technologies, the project aims to address the pressing challenges faced by the agricultural sector and unlock new avenues for sustainable development. Through collaboration, innovation, and stakeholder engagement, the project contributes to a future where agriculture is not only productive and profitable but also environmentally conscious, socially inclusive, and resilient to global changes. The AgriDataValue project sets the stage for a data-driven revolution in agriculture, where information becomes the most valuable crop, and data-driven insights sow the seeds of prosperity and sustainability for generations to come.

10 References

[1] United Nations, “Global Sustainable Development Report (GSDR) 2023,” March 2023. [Online]. Available: https://sdgs.un.org/gsdr/gsdr2023.

[2] “DataBio - Responsibility & Sustainability,” [Online]. Available: https://www.databio.eu/.

[3] “IoF2020 - Internet of Food and Farm 2020,” [Online]. Available: https://www.iof2020.eu/.

[4] “A FarCloud - Aggregate Farming in the Cloud,” [Online]. Available: https://www.kdt-ju.europa.eu/projects/afarcloud.

[5] “DEMETER - Building an Interoperable, Data-Driven, Innovative and Sustainable European Agri-Food Sector,” [Online]. Available: https://h2020-demeter.eu/.

[6] “Personas,” [Online]. Available: https://www.usability.gov/how-to-and-tools/methods/personas.html.

[7] A. Bernth and M. McCord, “Terminology Extraction for Global Content Management,” IBM, Oct. 2002. [Online]. Available: https://dominoweb.draco.res.ibm.com/reports/Rc22615.pdf.

[8] Z. Zhu, “Requirements Determination and Requirements Structuring,” University of Missouri-ST. Luis, [Online]. Available: http://www.umsl.edu/~sauterv/analysis/6840_f03_papers/zhu/. [Accessed 2023].

[9] “EIP-AGRI Network,” [Online]. Available: https://ec.europa.eu/eip/agriculture/en/.

[10] ISO/IEC 19501:2005, “Unified Modeling Language (UML) Version 1.4.3,” ISO, 2005.

[11] “Soil Moisture and Irrigation,” SoiSensor.com, [Online]. Available: https://soilsensor.com/soil/soil-moisture-and-irrigation/.

[12] “Orchard Irrigation: Soil Water Content,” Utah State University, Intermount Tree Fruit Production Guide, [Online]. Available: https://intermountainfruit.org/orchard-irrigation/swc. [Accessed 2023].

[13] ISO/TC 23/SC 18 Irrigation and drainage equipment and systems, “ISO 21622-2 Irrigation techniques - Remote monitoring and control for irrigation- Part 2: Tests,” https://www.iso.org/standard/76900.html.

[14] ISO/TC 23/SC 18 Irrigation and drainage equipment and systems, “ISO/FDIS 21622-3 Irrigation techniques- Remote monitoring and control for irrigation- Part 3: Interoperability,” https://www.iso.org/standard/76901.html.

[15] VLM, “Fiche plantenvoeding,” 15 12 2020. [Online]. Available: https://www.vlm.be/nl/SiteCollectionDocuments/Bedrijfsadvies/Fiches%20BA/10%2020151210_BAS_FICHE_Plantenvoeding.pdf. [Accessed 11 05 2023].

[16] T. S. Varanasi, “History of soil fertility and plant nutrition,” *Just Agriculture,* p. 14, 7 2021.

[17] Y. Sun, M. Wang, L. Mur, Q. Shen and S. Guo, “Unravelling the Roles of Nitrogen Nutrition in Plant Disease Defences,” *Int J Mol Sci,* p. 572, 16 Jan 2020.

[18] EAA, “European environment agency,” 11 Dec 2019. [Online]. Available: https://www.eea.europa.eu/publications/nutrient-enrichment-and-eutrophication-in. [Accessed 11 05 2023].

[19] International Fertilizer Industry Association (IFA), International Water Management Institute (IWMI), International Plant Nutrition Institute (IPNI), International Potash Institute (IPI), Managing Water and Fertilizer for Sustainable Agricultural Intensification, Paris, 2015.

[20] N. Macnack, K. C. Bee, A. Bayer and B. Arnall, "Oklahoma State university extension," Apr 2017. [Online]. Available: https://extension.okstate.edu/fact-sheets/print-publications/pss/fertilization-based-on-sufficiency-build-up-and-maintenance-concept-pss-2266.pdf. [Accessed 11 Apr 2023].

[21] M. Almaraz, M. Y. Wong, E. K. Geoghegan and B. Z. Houlton, "A review of carbon farming impacts on nitrogen cycling, retention, and loss," *Annals of the New York Academy of Sciences,* pp. 102-117, Dec 2021.

[22] JRS, MARS, P. J. Zarco-Tejada, N. Hubbard and P. Loudjan, "European parliament," Jun 2014. [Online]. Available: https://www.europarl.europa.eu/RegData/etudes/note/join/2014/529049/IPOL-AGRI_NT%282014%29529049_EN.pdf. [Accessed 11 May 2023].

[23] J. Van Loon, A. B. Speratti, L. Gabarra and B. Govaerts, "Precision for Smallholder Farmers: A Small-Scale-Tailored Variable Rate Fertilizer Application Kit," *Agriculture,* p. 48, 24 03 2018.

[24] SBB, VITO, ULG, FZJ, AU, WUR field crops, ILVO and Fasterholt, "Variable rate irrigation and nitrogen fertilization in potato," 1 2020. [Online]. Available: https://www.bdb.be/files/rap202001.pdf. [Accessed 11 05 2023].

[25] A. Guerrero and A. M. Mouazen, "AgEng2021," in *Simulation for variable-rate nitrogen fertilization with different application schemes*, Évora, 2021.

[26] Wikipedia, "Leaf Sheath," [Online]. Available: https://en.wikipedia.org/wiki/Leaf_sheath.

[27] Wikipedia, "Raceme - Spike," [Online]. Available: https://en.wikipedia.org/wiki/Raceme#Spike.

[28] VESELS AUGS, "Wheat diseases," [Online]. Available: https://www.veselsaugs.lv/diseases/all.

[29] Eurostat, 07 2021. [Online]. Available: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=The_EU_potato_sector_-_statistics_on_production,_prices_and_trade#Potato_production_in_the_EU_is_highly_concentrated. [Accessed 11 05 2023].

[30] Copernicus, 01 03 2023. [Online]. Available: https://www.copernicus.eu/en/news/news/observer-farming-future-supporting-food-security-and-europes-potato-industry-space. [Accessed 11 05 2022].

[31] Z. Toth and M. W. Nasir, "Effect of Drought Stress on Potato Production: A Review," *Agronomy,* p. 635, 04 03 2022.

[32] S. S. Jayanty, "Colorado state university extension," 06 2019. [Online]. Available: https://extension.colostate.edu/docs/pubs/crops/05621.pdf. [Accessed 16 05 2023].

[33] B. Park, R. Lu and eds, Hyperspectral imaging technology in food and agriculture, Berlin, Germany: Springer, 2015.

[34] M. Zhu, D. Huang, X.-J. Hu, W.-H. Tong, B.-L. Han, J.-P. Tian and H.-B. Luo, "Application of hyperspectral technology in detection of agricultural products and food: A Review," *Food Science & Nutrition,* vol. 8, no. 10, pp. 5206-5214, 2020.

[35] A. Lopez-Maestresalas, J. C. Keresztes, M. Goodarzi, S. Arazuri, C. Jaren and W. Saeys, “Non-destructive detection of blackspot in potatoes by Vis-NIR and SWIR hyperspectral imaging,” *Food Control,* pp. 229-241, 2016.

[36] K. D'Haene, J. Salomez, S. De Neve, J. De Waele and G. Hofman, “Environmental performance of nitrogen fertiliser limits imposed by the EU nitrates directive,” *Agriculture, Ecosystems & Environment,* pp. 67-74, 2014.

[37] S. M. Hirsh and R. R. Weil, “Deep soil cores reveal large end-of-season residual mineral nitrogen Pool,” *Agricultural & Environmental Letters,* p. 180055, 2019.

[38] H. F. Ten Berge, S. L. Burgers, H. G. Van der Meer, J. J. Schröder, J. R. Van der schoot and W. Van Dijk, “Residual inorganic soil nitrogen in grass and maize on sandy soil,” *Environmental pollution,* vol. 145, no. 1, pp. 22-30, 2007.

[39] H. P. Lorenz, J. Schlaghecken, G. Engl, A. Maync and J. Ziegler, “Ordnungsgemabe Stickstoffdungung im Freiland-Gemusebau nach dem ‘Kulturbegleitenden Nmin Sollwerte (KNS)-System,” *Ministerium für Landwirtschaft, Weinbau und Forsten,* 1989.

[40] M. Fink and H. C. Scharpf, “N-expert-A decision support system for vegetable fertilization in the field,” *Workshop on Ecological Aspects of vegetable fertilization in integrated crop production in the field,* pp. 67-74, 1992.

[41] J. Wehrmann and H. C. Scharpf, “The Nmin-method–an aid to integrating various objectives of nitrogen fertilization,” *Zeitschrift für Pflanzenernährung und Bodenkunde,* vol. 4, pp. 428-440, 1986.

[42] P. M. Nkebiwe, M. Weinmann, A. Bar-Tal and T. Müller, “Fertilizer placement to improve crop nutrient acquisition and yield: A review and meta-analysis,” *Field crops research,* vol. 196, pp. 389-401, 2016.

[43] J. Haumont, J. Diels, E. Schrevens, S. Cool, P. Lootens and W. Saeys, “Assessment of fertilization strategies and policy measures for vegetables by simulation of a long-term cauliflower leek rotation (under revision)”.*European Journal of Agronomy.*

[44] I. Chuine, I. d. Cortazar-Atauri, K. Kramer and H. Hänninen, “Plant development models,” *Springer Phenology: an integrative environmental science,* pp. 275-293, 2013.

[45] D. Basler, “Evaluating phenological models for the prediction of leaf-out dates in six temperate tree species across central Europe,” *Agricultural and Forest Meteorology. ,* vol. 10, no. 21, p. 217, 2016.

[46] I. Chuine and J. Régnière, “ “Process-based models of phenology for plants and animals,” *Annual Review of Ecology, Evolution, and Systematics,* vol. 48, pp. 159-182, 2017.

[47] A. Weisheimer and T. Palmer, “On the reliability of seasonal climate forecasts,” *Interface, The Journal of Royal Society,* vol. 11, 2014.

[48] M. Zhao, C. Peng, W. Xiang, X. Deng and X. Zhou, “Plant phenological modeling and its application in global climate change research: overview and future challenges,” *Environmental Reviews,* vol. 21, no. 1, pp. 1-14, 2013.

[49] S. Taylor and E. White, “Automated data-intensive forecasting of plant phenology throughout the United States,” *Ecological Applications,* pp. 20-25, 2020.

[50] V. R. Galiano, M. S. Castillo, J. Dash, P. Atkinson and J. O. Zújar, “Modelling interannual variation in the spring and autumn land surface phenology of the European forest,” *Biogeosciences,* vol. 13, pp. 3305-3317, 2016.

[51] “Mediterranean fruit fly,” University of Florida, [Online]. Available: https://entnemdept.ufl.edu/creatures/fruit/mediterranean_fruit_fly.htm.

[52] Government of Western Australia, “Mediterranean fruit fly life cycle & biology,” June 2018. [Online]. Available: https://www.agric.wa.gov.au/medfly/mediterranean-fruit-fly-life-cycle-biology.

[53] “Forest Pests,” University of Georgia’s Center for Invasive Species and Ecosystem Health, [Online]. Available: https://www.forestryimages.org/. [Accessed 2023].

[54] Y. Diller, A. Shamsian and e. al., “A real-time remote surveillance system for fruit flies of economic importance: sensitivity and image analysis,” *Journal of Pest Science,* vol. 96, p. 611–622, 2023.

[55] I. Potamitis, I. Rigakis, N. Vidakis, M. Petousis and M. Weber, “Affordable Bimodal Optical Sensors to Spread the Use of Automated Insect Monitoring,” *Hindawi Journal of Sensors,* p. 25, 2018.

[56] US Department of Agriculture, “Mediterranean Fruit Fly Action Plan,” 2003. [Online]. Available: https://www.aphis.usda.gov/import_export/plants/manuals/emergency/downloads/medfly_action_plan.pdf.

[57] M. Ricalde, D. Nava, A. Loeck and M. Donatti, “Temperature-Dependent Development and Survival of Brazilian Populations of the Mediterranean Fruit Fly, Ceratitis capitata, from Tropical, Subtropical and Temperate Regions,” *Journal of Insect Science,* vol. 12, no. 33, 2012.

[58] A. Diamantidis, N. Papadopoulos and J. Carey, “Medfly populations differ in diel and age patterns of sexual signalling,” *Wiley Entomologia Experimetalis Applicata,* 2008.

[59] R. Thornhill and J. Alcock, The Evolution of Insect Mating Systems., Harvard University Press, 2013.

[60] “Olive fruit fly,” Wikipedia, [Online]. Available: https://en.wikipedia.org/wiki/Olive_fruit_fly.

[61] “Bactrocera oleae,” University of Florida, 2019. [Online]. Available: https://entnemdept.ufl.edu/creatures/fruit/tropical/olive_fruit_fly.htm.

[62] “Olive Fruit Fly,” Univerity of California Agricultural & Natural Resources, 2009. [Online].

[63] M. Crociati, L. Sylla, A. De Vincenzi, G. Stradaioli and M. Monaci, “How to Predict Parturition in Cattle? A Literature Review of Automatic Devices and Technologies for Remote Monitoring and Calving Prediction,” *Animals,* vol. 12, p. 405, 2022.

[64] “MEDRIA,” [Online]. Available: https://www.medria.fr/en/services/calving.html.

[65] “Agriculture Cooperative Agrinion Union,” [Online]. Available: https://www.e-ea.gr/.

[66] J. Pagés-Díaz, J. Westman, M. Taherzadeh, I. Pereda-Reyes, Horváth and I. Sárvári, “Semi-continuous co-digestion of solid cattle slaughterhouse wastes with other waste streams: Interactions within the mixtures and methanogenic community structure,” *Elsevier Chemical Engineering Journal,* vol. 273, pp. 28-36, 2015.

[67] IEA, “World Energy Outlook 2022,” 2022.

[68] B. Afotey and G. Sarpong, "Estimation of biogas production potential and greenhouse gas emissions reduction for sustainable energy management using intelligent computing technique," *Elsevier Measurement: Sensors,* vol. 25, 2023.

[69] European Parliament and Council, "Regulation 2017/625, Enforcing EU rules for the agri-food chain," *Official Journal of the European Union,* 2017.

[70] FAO/FAOLEX, "Regulation 2017/625 - Official controls and other official activities performed to ensure the application of food and feed law, rules on animal health and welfare, plant health and plant protection products," [Online]. Available: https://leap.unep.org/countries/eu/national-legislation/regulation-eu-2017625-european-parliament-and-council-official.

[71] FAO, "Status of digital agriculture in 18 countries of europe and central asia," ITU, 2020.

[72] A. Gabriel and G. Markus, "Adoption of digital technologies in agriculture—an inventory in a european small-scale farming region," *Precision Agriculture,* vol. 24, no. 1, pp. 68-91, 2023.

[73] A. Barnes, I. Soto, V. Eory, B. Beck, A. Balafoutis, B. Sanchez, J. Vangeyte, S. Fountas, T. Van der Wal and M. Gomez-Barbero, "Exploring the adoption of precision agricultural technologies: a cross regional study of," *Land use policy,* vol. 80, pp. 163-174, 2019.

[74] S. A. Osinga, D. Paudel, S. A. Mouzakitis and I. N. Athanasiadis, "Big data in agriculture: Between oppurtunity and solution," *Agricultural Systems,* vol. 195, p. 103298, 01 2022.

[75] S. Barral and C. Detang-Dessendre, "Reforming the Common Agricultural Policy (2023–2027): multidisciplinary views," *Review of Agricultural, Food and Environmental Studies volume,* vol. 104, pp. 47-50, 2023.

[76] European Commission, "Common Agricultural Poicy for 2023-2027 at a glance," Agricultural and Rural Development Unit, [Online]. Available: https://agriculture.ec.europa.eu/system/files/2022-12/csp-at-a-glance-eu-countries_en.pdf.

[77] F. v. Evert and P. Leffelaar, "Modelling nutrient dynamics in precision agriculture: Implications for closed nutrient management systems," *European Journal of Agronomy,* vol. 43, pp. 142-153, 2012.

[78] X. Cai and M. Rosegrant, ". Modeling water resources management at the basin level: Review and future directions," *Water Resources Research,* vol. 38, no. 12, p. 1301, 2002.

[79] e. a. A. Garrett, "Climate change effects on plant disease: genomes to ecosystems," *Annual Review of Phytopathology,* vol. 44, pp. 489-509, 2006.

[80] e. a. K. Panda, " Crop planning under climate change using a climatic suitability tool for rice in India," *Current Science,* vol. 101, no. 3, pp. 345-356, 2011.

[81] G. Zobel and A. Elgersma, "Effects of shade and cows lying close to each other on the behavior and milk production of grazing dairy cows in hot weather.," *Journal of Dairy Science,* vol. 93, no. 5, pp. 1707-1712, 2010.

[82] A. Schimidt, H. Boizard and M. Morandi, "Soil health and climate change: Evaluation of the impact of different land uses on the organic matter stability in soils.," *Revista Brasileira de Ciência do Solo,* p. 40, 2016.

[83] S. Hafner, E. Rembiałkowska and A. Fliessbach, “Crop rotations including ley and manure can promote ecosystem services in conventional farming systems,” *Sustainability,* vol. 10, no. 2, p. 486, 2018.

[84] F. Sinclair and R. Jamnadass, “The contribution of agroforestry to reducing risks to livelihoods in mixed agricultural landscapes: Experiences from Machakos, Kenya.,” *World Agroforestry Centre (ICRAF),* 2014.

[85] S. Hemming and P. van Weel, “Climate control in greenhouse horticulture,” *Acta Horticulturae,* vol. 1003, pp. 33-40, 2013.

[86] N. McMeniman and C. Clifton, “Climate adaptation strategies for beef cattle production systems in Western Australia,” 2013.

[87] T. J. Suhrhoff, G. Blom and L. M. Sunde, “Climate-induced changes in the growth of brown trout: implications for fish farming and fisheries management in Norway,” *Regional Environmental Change,* vol. 19, no. 1, pp. 73-83, 2019.

[88] M. A. Boudreau and K. E. Sackett, “ Implications of climate change for managing spotted wing drosophila in berry crops.,” *Journal of Pest Science,* vol. 86 , no. 4, pp. 687-697, 2013.

[89] T. Hertel, H. Lee and S. K. Rose, “ How do commodity prices affect food security?,” *Agricultural Economics, ,* vol. 41, no. 1, pp. 45-60, 2010.

[90] “GAIA-X Initiative,” no. https://gaia-x.eu/.

[91] “Aligning Reference Architectures, Open Platforms and Large-Scale Pilots in Digitising European Industry,” [Online]. Available: https://www.opendei.eu/.

[92] OpenDEI, “D2.1 Reference Architecture for Cross-Domain Digital Transformation,” [Online]. Available: https://www.opendei.eu/case-studies/d2-1-reference-architecture-for-cross-domain-digital-transformation/.

[93] GoFAIR Initiative, “FAIR Guiding Principles for scientific data management and stewardship’,” 2016. [Online]. Available: https://www.go-fair.org/fair-principles/.

[94] European Commission, “Germany: Industrie 4.0,” January 2017. [Online]. Available: https://ati.ec.europa.eu/sites/default/files/2020-06/DTM_Industrie%204.0_DE.pdf.

[95] [Online]. Available: http://www.industrialdataspace.org/ .

[96] ETSI SmartM2M, “Extension to SAREF; Part 6: Smart Agriculture and Food Chain Domain.,” [Online]. Available: https://www.etsi.org/deliver/etsi_ts/103400_103499/10341006/01.01.01_60/ts_10341006v010101p.pdf .

[97] “ADAPT - Agricultural Data Application Programming Toolkit,” [Online]. Available: https://adaptframework.org/.

[98] “DjustConnect,” [Online]. Available: https://www.djustconnect.be/en/ConnectShop.

[99] L. Hannah, P. Roehrdanz and e. al., “ Climate change, wine, and conservation,” *National Academy of Sciences,* vol. 110, no. 17, pp. 6907-6912, 2013.

[100] E. Duchêne, F. Huard, J. Dury and A. Marquier, "Modelling the impacts of climate change on grapevine growth for Bordeaux vineyards: potential yields, phenology, and canopy density.," *International Journal of Biometeorology,* vol. 62, no. 11, pp. 2021-2033, 2018.

[101] I. G. De Cortazar-Atauri, N. Brisson, J. P. Gaudillère and J. M. Moisselin, "Climate change impacts on viticulture: a review.," *Agronomy for Sustainable Development,* vol. 30, no. 3, pp. 577-589, 2010.

[102] M. Signorini, A. Bikindou, C. Belloc, D. Durand, I. Veissier and R. Guatteo, "Association between heat stress and dairy cattle welfare, udder health, and production: A systematic literature review.," *Animal,* vol. 11, no. 8, pp. 1379-1388, 2017.

[103] C. Vallet-Coulomb, F. Baudin, J. F. David and G. M. Saulnier, "Vulnerability of French agricultural areas to climate change: Water stress, drought and adaptation options.," *Science of the Total Environment,* vol. 740, p. 139977, 2020.

[104] D. Ruelland, S. Ardoin-Bardin and W. Ludwig, "Assessing the impact of climate change on agricultural water resources in the French Mediterranean region using indicators.," *Hydrology and Earth System Sciences,* vol. 24, no. 8, pp. 4173-4194, 2020.

[105] F. Huard and P. Balandier, "Impact of climate change on the phenology of fruit trees in France from the fruit producer's perspective.," *2018,* vol. 252, pp. 132-145., Agriculture, Ecosystems & Environment.

[106] V. Lebourgeois, J. Dury and F. Huard, "Impact of climate change on wheat phenology in France over the 21st century.," *Agricultural and Forest Meteorology,* vol. 239, pp. 37-48, 2017.

[107] M. F. Destain, A. Hervieu and A. Gobin, "Vulnerability and adaptation of European summer crops to climate change in observational and crop model ensemble simulations.," *Agricultural and Forest Meteorology,* vol. 248, pp. 278-291, 2018.

[108] Colomina and M. P., "Unmanned aerial systems for photogrammetry and remote sensing: A review," *ISPRS J. Photogramm. Remote Sens.,* vol. 92, p. 79–97, 2014.

[109] R. Zarco-Tejada and V. A. P. Diaz-Varela, "Tree height quantification using very high resolution imagery acquired from an unmanned aerial vehicle (UAV) and automatic 3D photo-reconstruction methods," *Eur. J. Agron. ,* vol. 55, p. 89–99, 2014.

[110] J. Bendig, K. Yu, H. Aasen, A. Bolten, S. Bennertz, J. Broscheit, M. L. Gnyp and G. Bareth, "Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley," *International Journal of Applied Earth Observation and Geoinformation,* no. 39, p. 79–87, 2015.

[111] M. Chao, A. Baumann, Y. Jensen, Y. Chen and W. Cao, "Bandreconfigurable multi-UAV-based cooperative remote sensing for real-time water management and distributed irrigation control," *IFAC Proc.,* vol. 41, no. 2, p. 11744–11749, 2008.

[112] F. F. et.al., "The use of unmanned aerial vehicles and wireless sensor networks for spraying pesticides," *J. Syst. Archit. ,* vol. 60, no. 4, p. 393–404, 2014.

[113] V. Moysiadis, S. P., V. Vitsas and K. A., "Smart farming in Europe," *Elsevier Computer Science Review,* vol. 39, p. 100345, 2021.

[114] J. Albetis, S. Duthoit, F. Guttler, A. Jacquin, M. Goulard, H. Poilvé, J. B. Féret and G. Dedieu, "Detection of Flavescence dorée grapevine disease using Unmanned Aerial Vehicle (UAV) multispectral imagery," *Remote Sensing,* no. 9 (4) , p. 308, 2017.

[115] F. Kurtulmuş and I. Kavdir, "Detecting corn tassels using computer vision and support vector machines," *Expert Systems with Applications,* no. 41, p. 7390–7397, 2014.

[116] S. Kontogiannis, G. Kokkonis and S. Ellinidou, "Proposed fuzzynn algorithm with loracommunication protocol for clustered irrigation systems,," *Future Internet,* 2017.

[117] N. Sales, O. Remédios and A. Arsenio, "Wireless sensor and actuator system for smart irrigation on the cloud," in *IEEE 2nd World Forum on Internet of Things*, 2015.

[118] G. Louargant, R. Jones, J.-N. Faroux, T. Maillot and C. Gée, "Unsupervised classification algorithm for early weed detection in rowcrops by combining spatial and spectral information," *Remote Sens. ,* vol. 10, no. 5, p. 761, 2018.

[119] [Online]. Available: https://www.easa.europa.eu/document-library/easy-access-rules/easy-access-rules-unmanned-aircraft-systems-regulation-eu.

[120] M. V., S. P., V. V. and K. A., " Smart Farming in Europe.," *Computer Science Review,* vol. 39, p. 100345, 2021.

[121] M. Vu, V. Raković and A. Delic, "Trends in development of UAV cooperation approaches in precision agriculture," *Spinger International Conference on Interactive Collaborative Robotics,* p. 213–221, 2018.

[122] M. Kernecker, A. Knierim and A. Wurbs, "Experience versus expectation: farmers' perceptions of smart farming technologies for cropping systems across Europe.," *Precision Agric ,* vol. 21, pp. 34-50, 2020.

[123] R. S. and D. Rizzo, "Training in agricultural technologies: a new prerequisite for smart farming.," in *3rd Rendez-Vous Techniques. AXEMA*, Villepinte, France, 2019.

[124] G. Hanitravelo, " Impacts des technologies numériques sur les exploitations agricoles en France. Economies et finances.," *Agrocampus Ouest,* 2020.

[125] T. Griffin, J. Shockley and T. Mark, "Economics of Precision Farming.," *Precision Agriculture Basics acsess,* p. 221–230, 2018.

[126] H. Bai and G. Zhou, "Traceability technologies for farm animals and their products in China.," *Food Control,* vol. 79, pp. 35-43, 2017.

[127] [Online]. Available: https://fruitionsciences.com/en/home.

[128] [Online]. Available: https://www.agricolus.com/en/.

[129] [Online]. Available: https://www.naio-technologies.com.

[130] [Online]. Available: http://www.promete.fr/.

[131] [Online]. Available: https://www.agroptima.com/en/.

[132] [Online]. Available: https://www.agroptimize.com/.

[133] [Online]. Available: https://www.agro.basf.fr/fr/.

[134] [Online]. Available: https://www.medria.fr/solutions/pilotage-global.html.

[135] [Online]. Available: https://www.climatefieldview.fr/.

[136] [Online]. Available: https://corhize.com/.

[137] [Online]. Available: https://sencrop.com/fr/oad/.

[138] [Online]. Available: https://ekylibre.com/eng/home/.

[139] [Online]. Available: https://info.farmx.ch/home-fr/.

[140] [Online]. Available: https://www.vantage-am.fr/gps-agriculture-trimble-farmworks.

[141] [Online]. Available: https://www.flexio.fr/notre-cto-a-teste-la-serre-connectee-avec-le-boitier-multi-capteurs-flexio/.

[142] [Online]. Available: https://www.arvalis.fr/outils-et-services/outils-et-fiches/irre-lis.

[143] [Online]. Available: https://www.itbfr.org/outils/irribet/.

[144] [Online]. Available: https://www.arvalis.fr/.

[145] [Online]. Available: https://www.move-connect.com/.

[146] [Online]. Available: https://sencrop.com/fr/oad/.

[147] [Online]. Available: https://www.myeasyfarm.com/en/solutions/myeasyfarm/.

[148] [Online]. Available: https://www.nextfarming.fr/agriculteur/a-propos-de-nous/entreprise.

[149] [Online]. Available: https://tcsd.fr/en/rimpro/.

[150] [Online]. Available: https://www.syngenta.fr/servicespro/services-distributeurs/scan-bean-risque-sclerotinia-haricot.

[151] [Online]. Available: https://sencrop.com/fr/meteo-agricole/.

[152] [Online]. Available: https://sensing-labs.com/.

[153] [Online]. Available: https://www.spacesense.ai/industries/agriculture.

[154] [Online]. Available: https://www.synfield.gr/.

[155] [Online]. Available: http://www.carah.be/.

[156] [Online]. Available: https://vitimeteo.de/vitimeteo/default/index.

[157] "Pilotage de l'irrigation - Découvrez Wago - TerraNIS," [Online]. Available: https://www.terranis.fr/agriculture-wago-irrigation/.

[158] [Online]. Available: https://weenat.com/en/.

[159] [Online]. Available: https://www.xarvio.com/fr/fr/products/field-manager.html.

[160] [Online]. Available: https://www.yara.fr/fertilisation/outils-et-services/yara-checkit/.

[161] [Online]. Available: https://www.google.com/maps/d/u/1/edit?mid=1mEWoQCuoiGY65_ZbwQolq00dJ08mi9E&usp=sharing.

[162] UK Space Agency, “Space for Agriculture in Developing countries,” June 2018. [Online]. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/736211/6.4502_UKSA_SPACEUK_Solutions_for_Agriculture_220818_CMYK_web.pdf .

[163] ESA, “EARTH OBSERVATION SUPPORT FOR THE INTERNATIONAL FUND FOR AGRICULTURAL DEVELOPMENT,” Aug 2014. [Online]. Available: https://eo4society.esa.int/wp-content/uploads/2021/11/ESA_EOsupport-for-IFAD-Aug2014.pdf.

[164] ESA, “Agriculture,” [Online]. Available: https://www.esa.int/Applications/Observing_the_Earth/Agriculture.

[165] “EO Browser,” [Online]. Available: https://apps.sentinel-hub.com/eo-browser/.

[166] “Sentinel Hub py,” [Online]. Available: https://github.com/sentinel-hub/sentinelhub-py.

[167] “EO Learn,” [Online]. Available: https://github.com/sentinel-hub/eo-learn.

[168] [Online]. Available: https://www.sentinel-hub.com/develop/.

[169] “Sentinel Hub-py Examples,” [Online]. Available: https://sentinelhub-py.readthedocs.io/en/latest/examples.html.

[170] “EO Learn IO examples,” [Online]. Available: https://eo-learn.readthedocs.io/en/latest/examples.html#io-examples.

[171] “Compernicus Sentinel 1,” [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/sentinel-1-grd/#endpoint-locations.

[172] “Copernicus Sentinel-2,” [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/sentinel-2-l1c/.

[173] [Online]. Available: https://sentinel.esa.int/web/sentinel/missions/sentinel-2.

[174] [Online]. Available: https://docs.sentinel-hub.com/api/latest/reference/.

[175] [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/sentinel-2-l1c/examples/.

[176] [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/sentinel-2-l2a/examples.

[177] “Copernicus Sentinel-3,” [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/sentinel-3-olci-l1b/.

[178] “Copertnicus Sentinel 5P,” [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/sentinel-5p-l2/.

[179] [Online]. Available: https://earth.esa.int/web/guest/missions/esa-eo-missions/sentinel-5p.

[180] [Online]. Available: https://sentinel.esa.int/web/sentinel/news/-/article/copernicus-sentinel-5-p-increased-spatial-resolution-change-now-operational.

[181] [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/landsat-8/.

[182] [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/landsat-8-l2/.

[183] [Online]. Available: https://www.sentinel-hub.com/explore/data/.

[184] [Online]. Available: https://registry.opendata.aws/terrain-tiles/.

[185] [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/dem/.

[186] [Online]. Available: https://collections.sentinel-hub.com/copernicus-dem/.

[187] [Online]. Available: http://www.ga.gov.au/scientific-topics/earth-obs/accessing-satellite-imagery/technical-information/modis-online-nadir-brdf-adjusted-reflectance-nbar-products.

[188] [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/planet-scope/ .

[189] "Pleiades," [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/airbus/pleiades/.

[190] [Online]. Available: https://docs.sentinel-hub.com/api/latest/data/airbus/spot/.

[191] [Online]. Available: https://www.maxar.com/.

[192] [Online]. Available: https://www.sentinel-hub.com/tos/#privacy.

[193] [Online]. Available: https://github.com/maja601/EuroCrops.

[194] [Online]. Available: https://eurodatacube.com/marketplace/services/edc_geodb.

[195] M. Dhanaraju, P. Chenniappan, K. Ramalingam, S. Pazhanivelan and R. Kaliaperumal, "Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture," *MDPI Agriculture,* vol. 12, no. 10, p. 1745, 2022.

[196] V. B., F. D., W. C., L. S. and D. W, "Assessing Spatial Limits of Sentinel-2 Data on Arable Crops in the Context of Checks by Monitoring," *MDPI Remote Sensing,* vol. 12, p. 2195, 2020.

[197] "Data Spaces Business Alliance," [Online]. Available: https://data-spaces-business-alliance.eu/.

[198] Data Space Business Alliance, "Unleasing the Data Economy," 21 April 2023. [Online]. Available: https://data-spaces-business-alliance.eu/wp-content/uploads/dlm_uploads/Data-Spaces-Business-Alliance-Technical-Convergence-V2.pdf.

[199] IDSA, "IDS Reference Architecture," [Online]. Available: https://docs.internationaldataspaces.org/ids-ram-4/.

[200] IDSA, "Certification: the basis of trust," [Online]. Available: https://internationaldataspaces.org/offers/certification/.

[201] IDSA, "IDSA Github," [Online]. Available: https://github.com/International-Data-Spaces-Association.

[202] IDSA, "Information Model," [Online]. Available: https://international-data-spaces-association.github.io/InformationModel/docs/index.html.

[203] IDSA, "Usage Control in the International Data Spaces," March 2021. [Online]. Available: https://internationaldataspaces.org/wp-content/uploads/dlm_uploads/IDSA-Position-Paper-Usage-Control-in-the-IDS-V3..pdf.

[204] IDSA, "Governance for Data Space Instances," Agust 2021. [Online]. Available: https://internationaldataspaces.org/wp-content/uploads/IDSA-Position-Paper-Governance-for-Data-Space-Instances-Aspects-and-Roles-for-IDS-Stakeholders-1.pdf.

[205] "SynField: Precision Agriculture Solution," [Online]. Available: https://www.synfield.gr/.

[206] "SynAir: Professional Air Quality monitorying system," Synelixis, [Online]. Available: https://www.synfield.gr/about-synair/.

[207] “Monitoring of farm animal welfare using animal indicators,” FEDERATION OF VETERINARIANS OF EUROPE, [Online]. Available: https://fve.org/cms/wp-content/uploads/058_AWIndicatorsPaper_finaldraft18sept2018_GA_adopted.pdf.

[208] Y. Jiaojiao, Y. Chen, Z. Wang, J. Liu and B. Huang., “Food Risk Entropy Model Based on Federated Learning.,” *Applied Sciences ,* vol. 12, no. 10, p. 5174, 2022.

[209] K. Prabhat, G. Gupta and R. Tripathi, “PEFL: Deep privacy-encoding-based federated learning framework for smart agriculture.,” *IEEE Micro,* vol. 42, no. 1, pp. 33-40, 2021.

[210] O. Friha, M. A. Ferrag, L. Shu, L. Maglaras, K.-K. Choo and M. Nafaa, “FELIDS: Federated learning-based intrusion detection system for agricultural Internet of Things.,” *Journal of Parallel and Distributed Computing,* vol. 165, pp. 17-31, 2022.

[211] T. Manoj, K. Makkithaya and V. G. Narendra, “A Federated Learning-Based Crop Yield Prediction for Agricultural Production Risk Management.,” *IEEE Delhi Section Conference (DELCON),* pp. 1-7, 2022.

[212] M. A. P. Chamikara, P. Bertok, I. Khalil, D. Liu and S. Camtepe., “Privacy preserving distributed machine learning with federated learning.,” *Computer Communications ,* p. 171, 2011.

[213] I. Kobyzev, S. J. Prince and M. A. Brubaker, “Normalizing flows: An introduction and review of current methods.,” *IEEE transactions on pattern analysis and machine intelligence,* vol. 43, no. 11, pp. 3964-3979, 2020.

[214] N. Papernot, S. Song, I. Mironov, A. Raghunathan, K. Talwar and Ú. Erlingsson, “Scalable private learning with pate,” 2018. [Online]. Available: arXiv preprint arXiv:1802.08908.

[215] M. M. M. L. A. C. Maria Elena Latino, “Voluntary traceability in food supply chain: a framework leading its implementation in Agriculture 4.0,” *Technological Forecasting and Social Change,* 2022.

[216] Q. Lin, H. Wang, X. Pei and J. Wang, “Food safety traceability system based on blockchain and EPCIS.,” *IEEE Access,* 2019.

[217] S. Figorilli, F. Antonucci, C. Costa, F. Pallottino, L. Raso, M. Castiglione, E. Pinci, D. Del Vecchio and G. Colle, “A blockchain implementation prototype for the electronic open source traceability of wood,” *Sensors,* 2018.

[218] P. Lucena, A. Binotto, F. Momo and H. Kim, “A Case Study for Grain Quality Assurance Tracking based,” in *Symposium on Foundations and Applications*, Los Angeles, 2018.

[219] A. Shahid, A. Almogren, N. Javaid, F. Al-Zahrani, M. Zuair and M. Alam, “Blockchain-based agri-food supply chain: A complete solution.,” *IEEE Access,* 2020.

[220] Q. Yao and H. Zhang, “Improving Agricultural Product Traceability Using Blockchain,” *Sensors,* 2022.

[221] Z. Hao, D. Mao and B. Zhang, “A Novel Visual Analysis Method of Food Safety Risk Traceability Based on Blockchain,” *International Journal of Environmental Research and Public Health,* 2020.

[222] K. X. Yuxin Liao, “Traceability System of Agricultural Product Based on Block-chain and Application in Tea Quality Safety Management,” *J. Phys.: Conf. Ser. 1288,* 2019.

[223] S. Wolfert, L. Ge, C. Verdouw and M.-J. Bogaardt, “Big data in smart-farming- A review,” *Agricultural systems,* vol. 153, pp. 69-80, 2017.

[224] M. A. Zamora-Izquierdo, J. Santa, J. A. Martínez, V. Martínez and A. F. Skarmeta, “Smart farming IoT platform based on edge and cloud computing,” *Biosystems Engineering,* no. 177, pp. 4-17, 2019.

[225] P. Psirofonia, V. Samaritakis, P. Eliopoulos and I. Potamitis, “Use of unmanned aerial vehicles for agricultural applications with emphasis on crop protection: Three novel case-studies,” *International Journal of Agricultural Technology,* no. 5 (1), pp. 30-39, 2017.

[226] A. C. Cruz, A. Luvisi, L. D. Bellis and Y. Ampatzidis, “X-FIDO: An effective application for detecting olive quick decline syndrome with deep learning and data fusion,” *Frontiers in Plant Science,* no. 8, p. 1741, 2017.

[227] A. Somov, D. Shadrin, I. Fastovets, A. Nikitin, S. Matveev, I. Seledets and O. Hrinchuk, “Pervasive agriculture: IoT-enabled greenhouse for plant growth control,” *IEEE Pervasive Computing,* no. 17 (4), pp. 65-75, 2018.

[228] F. J. Ferrández-Pastor, J. M. García-Chamizo, M. Nieto-Hidalgo, J. Mora-Pascual and J. Mora-Martínez, “Developing ubiquitous sensor network platform using internet of things: Application in precision agriculture,” *Sensors ,* no. 16 (7) , p. 1141, 2016.

[229] M. Pérez-Ortiz, J. M. Peña, P. A. Gutiérrez, J. Torres-Sánchez, C. H.-. Martínez and F. López-Granados, “Selecting patterns and features for betweenand within-crop-row weed mapping using UAV-imagery,” *Expert Systems with Applications,* no. 47, p. 85–94, 2016.

[230] N. Wilke, B. Siegmann, L. Klingbeil, A. Burkart, T. Kraska, O. Muller, A. v. Doorn, S. Heinemann and U. Rascher, “Quantifying lodging percentage and lodging severity using a UAV-based canopy height model combined with an objective threshold approach,” *Remote Sensing,* no. 11 (5), p. 515, 2019.

[231] A. Matese and S. F. D. Gennaro, “Practical applications of a multisensor uav platform based on multispectral, thermal and rgb high resolution images in precision viticulture,” *Agriculture,* no. 8 (7), p. 116, 2018.

[232] L. Quebrajo, M. Perez-Ruiz, L. Pérez-Urrestarazu, G. Martínez and G. Egea, “Linking thermal imaging and soil remote sensing to enhance irrigation management of sugar beet,” *Biosystems Engineering,* no. 165 , p. 77–87, 2018.

[233] G. Mozgeris, D. Jonikavičius, D. Jovarauskas, R. Zinkevičius, S. Petkevičius and D. Steponavičius, “Imaging from manned ultra-light and unmanned aerial vehicles for estimating properties of spring wheat,” *Precision Agriculture,* no. 19 (5), p. 876–894, 2018.

[234] A. Michez, S. Bauwens, Y. Brostaux, M. P. Hiel, S. Garré, P. Lejeune and B. Dumont, “How far can consumer-grade UAV RGB imagery describe crop production? A 3D and multitemporal modeling approach applied to zea mays,” *Remote Sensing,* no. 10 (11), p. 1798, 2018.

[235] R. A. Díaz-Varela, R. D. l. Rosa, L. León and P. J. Zarco-Tejada, “High-resolution airborne UAV imagery to assess olive tree crown parameters using 3D photo reconstruction: application in breeding trials,” *Remote Sens,* no. 7 (4), p. 4213–4232, 2015.

[236] C. Potena, R. Khanna, J. Nieto, R. Siegwart, D. Nardi and A. Pretto, “AgriColMap: Aerial-ground collaborative 3D mapping for precision farming,” *IEEE Robotics and Automation Letters,* no. 4 (2), p. 1085–1092, 2019.

[237] J. Campos, J. Llop, M. Gallart, F. García-Ruiz, A. Gras, R. Salcedo and E. Gil, "Development of canopy vigour maps using UAV for site-specific management during vineyard spraying process," *Precision Agriculture,* no. 20 (6) , p. 1136–1156, 2019.

[238] P. Katsigiannis, L. Misopolinos, V. Liakopoulos, T. Alexandridis and G. Zalidis, "An autonomous multi-sensor UAV system for reduced-input precision agriculture applications," in *MED 2016 - 24th Mediterranean Conference on Control and Automation*, 2016.

[239] I. Navrozidis, T. K. Alexandridis, A. Dimitrakos, A. L. Lagopodi, D. Moshou and G. Zalidis, "Identification of purple spot disease on asparagus crops across spatial and spectral scales," *Computers and Electronics in Agriculture,* no. 148, p. 322–329, 2018.

[240] K. Kuželka and P. Surovy, "Automatic detection and quantification of wild game crop damage using an unmanned aerial vehicle (UAV) equipped with an optical sensor payload: a case study in wheat," *Remote Sensing,* no. 51 (1), p. 241–250., 2018.

[241] H. Hoffmann, H. Nieto, R. Jensen, R. Guzinski, P. Zarco-Tejada and T. Friborg, "Estimating evaporation with thermal UAV data and two-source energy balance models," *Hydrology and Earth System Sciences,* no. 20 (2) , p. 697–713, 2016.

[242] S. Marino and A. Alvino, "Detection of homogeneous wheat areas using multitemporal UAS images and ground truth data analyzed by cluster analysis," *Remote Sensing,* no. 51 (1), p. 266–275., 2018.

[243] L. Santesteban, S. D. Gennaro, A. Herrero-Langreo, C. Miranda, J. Royo and A. Matese, "High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard," *Agricultural Water Management,* no. 183, pp. 49-59, 2017.

[244] M. P. Christiansen, M. S. Laursen, R. N. Jørgensen, S. Skovsen and R. Gislum, "Designing and testing a UAV mapping system for agricultural field surveying," *Sensors,* no. 17 (12) , p. 2703, 2017.

[245] D. Gómez-Candón, N. Virlet, S. Labbé, A. Jolivot and J. L. Regnard, "Field phenotyping of water stress at tree scale by UAV-sensed imagery: new insights for thermal acquisition and calibration," *Precision Agriculture,* no. 17 (6), p. 786–800, 2016.

[246] P. G.-d. Santos, A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez-Granados, M. Brandstoetter, S. Tomic, S. Pedrazzi, A. Peruzzi, G. Pajares and G. Kaplanis, "Fleets of robots for environmentally-safe pest control in agriculture," *Precision Agriculture,* no. 18 (4), p. 574–614, 2017.

[247] H. Hoffmann, R. Jensen, A. Thomsen, H. Nieto, J. Rasmussen and T. Friborg, "Crop water stress maps for an entire growing season from visible and thermal UAV imagery)," *Biogeosciences,* no. 13 (24), p. 6545–6563, 2016.

[248] X. E. Pantazi, D. Moshou, T. Alexandridis, R. L. Whetton and A. M. Mouazen, "Wheat yield prediction using machine learning and advanced sensing techniques," *Computers and Electronics in Agriculture,* no. 121, p. 57–65, 2016.

[249] A. Tewes and J. Schellberg, "Towards remote estimation of radiation use efficiency in maize using uav-based low-cost camera imagery," *Agronomy,* no. 8 (2), p. 16, 2018.

[250] K. Espinoza, D. L. Valera, J. A. Torres, A. López and F. D. Molina-Aiz, "Combination of image processing and artificial neural networks as a novel approach for the identification of bemisia tabaci and frankliniella occidentalis on sticky traps in greenhouse agriculture," *Computers and Electronics in Agriculture,* no. 127,

p. Combination of image processing and artificial neural networks as a novel approach for the identification of bemisia tabaci and frankliniella occidentalis on sticky traps in greenhouse agriculture, 2016.

[251] I. Burud, G. Lange, M. Lillemo, E. Bleken, L. Grimstad and P. J. From, "Exploring robots and UAVs as phenotyping tools in plant breeding," *IFAC-PapersOnLine,* no. 50 (1), p. 11479–11484, 2017.

[252] M. Schirrmann, A. Hamdorf, A. Giebel, F. Gleiniger, M. Pflanz and K. H. Dammer, "Regression kriging for improving crop height models fusing ultra-sonic sensing with UAV imagery," *Remote Sensing,* no. 9 (7), p. 665, 2017.

[253] F. López-Granados, J. Torres-Sánchez, A. Serrano-Pérez, A. I. d. Castro, F. Mesas-Carrascosa and J. Pena, "Early season weed mapping in sunflower using UAV technology: variability of herbicide treatment maps against weed thresholds," *Precision Agriculture,* no. 17 (2), p. 183–199, 2016.

[254] K. Ivushkin, H. Bartholomeus, A. K. Bregt, A. Pulatov, M. H. Franceschini, H. Kramer, E. N. v. Loo, V. J. Roman and R. Finkers, "UAV based soil salinity assessment of cropland," *Geoderma,* no. 338, p. 502–512, 2019.

[255] B. Rey, N. Aleixos, S. Cubero and J. Blasco, "XF-ROVIM. A field robot to detect olive trees infected by xylella fastidiosa using proximal sensing," *Remote Sensing,* no. 11 (3) , p. 221, 2019.

[256] M. Louargant, G. Jones, R. Faroux, J. N. Paoli, T. Maillot, C. Gée and S. Villette, "Unsupervised classification algorithm for early weed detection in rowcrops by combining spatial and spectral information," *Remote Sensing,* no. 10 (5), p. 761, 2018.

[257] A. Burkart, V. Hecht, T. Kraska and U. Rascher, "Phenological analysis of unmanned aerial vehicle based time series of barley imagery with high temporal resolution," *Precision Agriculture,* no. 19 (1), p. 134–146, 2018.

[258] F. López-Granados, J. Torres-Sánchez, A. I. D. Castro, A. Serrano-Pérez, F. J. Mesas-Carrascosa and J. M. Peña, "Object-based early monitoring of a grass weed in a grass crop using high resolution UAV imagery," *Agronomy for Sustainable Development,* no. 36 (4), p. 67, 2016.

[259] A. C. Kyratzis, D. P. Skarlatos, G. C. Menexes, V. F. Vamvakousis and A. Katsiotis, "Assessment of vegetation indices derived by UAV imagery for durum wheat phenotyping under a water limited and heat stressed mediterranean environment," *Frontiers in Plant Science,* no. 8, p. 1114, 2017.

[260] Á. Maresma, M. Ariza, E. Martínez, J. Lloveras and J. A. Martínez-Casasnovas, "Analysis of vegetation indices to determine nitrogen application and yield prediction in maize (Zea mays L.) from a standard UAV service," *Remote Sensing,* no. 8 (12), p. 973, 2016.

[261] ETSI, "Context Information Management (CIM); NGSI-LD API," [Online]. Available: https://www.etsi.org/deliver/etsi_gs/CIM/001_099/009/01.01.01_60/gs_CIM009v010101p.pdf .

11 Annex: Literature Analysis

11.1 Adoption of smart farming technology, benefits, and barriers

Table 32 offers a summary of using smart farming technology, and the barriers to increasing the adoption rate. The review identified that the use of digital technologies in farming allows a decrease in energy consumption, water and pesticide use. The idea is that digital technologies allow farmers to optimize input use and thus emit fewer pollutants that have negative impacts on the environment. Although digital technologies seem to have a positive impact on the environment, there is a gap in research on impacts on the entire agricultural sector, notably towards whether digital tools in agriculture improve knowledge about environmental practices [124].

Table 32. Summary of studies that discussed environmental benefits of digital technologies on the farm

Reference	Technology	Country or Region	Results
Ahmad, L., Mahdi, S.S. (Eds.), Satellite Farming: An Information and Technology Based Agriculture. Springer International Publishing, Cham, pp. 129–138.	all digital technologies	World	
Anisi, M.H., Abdul-Salaam, G., Abdullah, A.H., 2015. A survey of wireless sensor network approaches and their energy consumption for monitoring farm fields in precision agriculture. Precis. Agric. 16, 216– 238. https://doi.org/10.1007/s11119-014-9371-8	all digital technologies	Malaysia	less energy consumption
Bauckhage, C., Kersting, K., 2013. Data Mining and Pattern Recognition in Agriculture. KI - Künstl. Intell. 27, 313–324. https://doi.org/10.1007/s13218-013-0273-0	data meaning	Germany	
Bill, R., Nash, E., Grenzdörffer, G., 2012. GIS in Agriculture, in: Kresse, W., Danko, D.M. (Eds.), Springer Handbook of Geographic Information, Springer Handbooks. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 461–476. https://doi.org/10.1007/978-3-540-72680-7_24	all digital technologies		
Burgos-Artizzu, X.P., Ribeiro, A., Tellaeche, A., Pajares, G., Fernández-Quintanilla, C., 2009. Improving weed pressure assessment using digital images from an experience-based reasoning approach. Comput. Electron. Agric. 65, 176–185. https://doi.org/10.1016/j.compag.2008.09.001	image	Spain	
Casa, A. de la, Ovando, G., Bressanini, L., Martínez, J., Díaz, G., Miranda, C., 2018. Soybean crop coverage estimation from NDVI images with different spatial resolution to evaluate yield variability in a plot. ISPRS Journal of Photogrammetry and Remote Sensing 146,	image	Argentina	less water used

531–547. https://doi.org/10.1016/j.isprsjprs.2018.10.018			
Dehnen-Schmutz, K., Foster, G.L., Owen, L., Persello, S., 2016. Exploring the role of smartphone technology for citizen science in agriculture. Agron. Sustain. Dev. 36, 25. https://doi.org/10.1007/s13593-016-0359-9	application/ software	UK, France	Apps and smartphones improve environmental practices
Edan, Y., Han, S., Kondo, N., 2009. Automation in Agriculture, in: Nof, S.Y. (Ed.), Springer Handbook of Automation, Springer Handbooks. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 1095–1128. https://doi.org/10.1007/978-3-540-78831-7_63	all digital technologies	OCDE countries	
Ge, Y., Thomasson, J.A., Sui, R., 2011. Remote sensing of soil properties in precision agriculture: A review. Front. Earth Sci. 5, 229–238. https://doi.org/10.1007/s11707-011-0175-0	RS	world	
Gonzalez-de-Soto, M., Emmi, L., Benavides, C., Garcia, I., Gonzalez-de-Santos, P., 2016. Reducing air pollution with hybrid-powered robotic tractors for precision agriculture. Biosyst. Eng. 143, 79	robotic	Spain	Robotic tractors use less fuel and thus emit less carbon
Grilli, G., Borgonovo, F., Tullo, E., Fontana, I., Guarino, M., Ferrante, V., 2018. A pilot study to detect coccidiosis in poultry farms at early stage from air analysis. Biosyst. Eng., Advances in the Engineering of Sensor-based Monitoring and Management Systems for Precision Livestock Farming 173, 64–70	application/ software	Italy	
Gutiérrez, P.A., López-Granados, F., Peña-Barragán, J.M., Jurado-Expósito, M., Hervás-Martínez, C., 2008. Logistic regression product-unit neural networks for mapping Ridolfia segetum infestations in sunflower crop using multitemporal remote sensed data. Comput. Electron. Agric. 64, 293–306. https://doi.org/10.1016/j.compag.2008.06.001	application data analysis	Spain	less herbicide used
Hajjaj, S.S.H., Sahari, K.S.M., 2014. Review of Research in the Area of Agriculture Mobile Robots, in: Mat Sakim, H.A., Mustaffa, M.T. (Eds.), The 8th International Conference on Robotic, Vision, Signal Processing & Power Applications, Lecture Notes in Electrical Engineering. Springer Singapore, pp. 107–117.	robotic	world	
Jain, L., Kumar, H., Singla, R.K., 2014. Localization of Information Dissemination in Agriculture Using Mobile Networks, in: Satapathy, S.C., Avadhani, P.S., Udgata, S.K., Lakshminarayana, S. (Eds.), ICT and Critical Infrastructure: Proceedings of the 48th Annual			

Convention of Computer Society of India- Vol I, Advances in Intelligent Systems and Computing. Springer International Publishing, pp. 409–415.			
Kamilaris, A., Kartakoullis, A., Prenafeta-Boldú, F.X., 2017. A review on the practice of Big Data analysis in agriculture. Comput. Electron. Agric. 143, 23–37. https://doi.org/10.1016/j.compag.2017.09.037 Karner, E., 2017. The Future of Agriculture is Digital: Showcasting e-Estonia. Front. Vet. Sci. 4, 151. https://doi.org/10.3389/fvets.2017.00151	Big Data	world	
Khanal, S., Fulton, J., Shearer, S., 2017. An overview of current and potential applications of thermal remote sensing in precision agriculture. Comput. Electron. Agric. 139, 22–32. https://doi.org/10.1016/j.compag.2017.05.001	RS	world	
Langner, H.-R., Böttger, H., Schmidt, H., 2006. A Special Vegetation Index for the Weed Detection in Sensor Based Precision Agriculture. Environ. Monit. Assess. 117, 505–518. https://doi.org/10.1007/s10661-006-0768-3	image	Germany	
Lokers, R., Knapen, R., Janssen, S., Randen, Y. van, Jansen, J., 2016. Analysis of Big Data technologies for use in agro-environmental science. Environ. Model. Softw. 84, 494–504. https://doi.org/10.1016/j.envsoft.2016.07.017	data	EU	
Lovato, G.D., Vale, M.M. do, Oliveira, V. de, Klein, D.R., Branco, T., Lovato, G.D., Vale, M.M. do, Oliveira, V. de, Klein, D.R., Branco, T., 2017. Application of a precision nutrition tool for growing and finishing pigs. Rev. Bras. Zootec. 46, 755–759. https://doi.org/10.1590/s1806-92902017000900007	data learning	Brazil	
Mesas-Carrascosa, F.J., Verdú Santano, D., Meroño, J.E., Sánchez de la Orden, M., García-Ferrer, A., 2015. Open source hardware to monitor environmental parameters in precision agriculture. Biosyst. Eng. 137, 73–83. https://doi.org/10.1016/j.biosystemseng.2015.07.005	DSS	Spain	
Nie, P.C., Wu, D., Zhang, W., Yang, Y., He, Y., 2010. Hybrid Combination of GIS,GPS,WSN and GPRS Technology in Modern Digital Agriculture Application [WWW Document]. Adv. Mater. Res. https://doi.org/10.4028/www.scientific.net/AMR.108-111.1158	all digital technologies		
O'Shaughnessy, S.A., Rush, C., 2014. Precision Agriculture: Irrigation, in: Van Alfen, N.K. (Ed.), Encyclopedia of Agriculture and Food Systems. Academic	all digital technologies	USA	less water used

Press, Oxford, pp. 521–535. https://doi.org/10.1016/B978-0-444-52512-3.00235-7			
Okayasu, T., Nugroho, A.P., Arita, D., Yoshinaga, T., Hashimoto, Y., Tachiguchi, R., 2017. Sensing and Visualization in Agriculture with Affordable Smart Devices, 2017	all digital technologies		better environmental performance
Palaniswami, C., Gopalasundaram, P., Bhaskaran, A., 2011. Application of GPS and GIS in Sugarcane Agriculture. Sugar Tech 13, 360–365. https://doi.org/10.1007/s12355-011-0098-9	GIS	India	
Santos, V.B. dos, Silva, E.K.N. da, Oliveira, L.M.A. de, Suarez, W.T., 2019. Low cost in situ digital image method, based on spot testing and smartphone images, for determination of ascorbic acid in Brazilian Amazon native and exotic fruits. Food Chem. 285, 340–346. https://doi.org/10.1016/j.foodchem.2019.01.167	image	Brazil	
Shrivastava, S., Singh, S.K., Hooda, D.S., 2017. Soybean plant foliar disease detection using image retrieval approaches. Multimed. Tools Appl. 76, 26647–26674. https://doi.org/10.1007/s11042-016- 4191-7	application data analysis	India	
Todde, G., Caria, M., Gambella, F., Pazzona, A., 2017. Energy and Carbon Impact of Precision Livestock Farming Technologies Implementation in the Milk Chain: From Dairy Farm to Cheese Factory. Agriculture 7, 1–11.	all precision technologies	Italy	Real-time milk analysis decrease energy use by 44% on the farm and by 69% in the entire production chain
Vranken, E., Berckmans, D., 2017. Precision livestock farming for pigs. Anim. Front. 7, 32–37. https://doi.org/10.2527/af.2017.0106	application/ software	Belgium	better practices
Wright, D., Hammond, N., Thomas, G., MacLeod, B., Abbott, L.K., 2018. The provision of pest and disease information using Information Communication Tools (ICT); an Australian example. Crop Prot. 103, 20–29. ttps://doi.org/10.1016/j.cropro.2017.08.023	network/media	Australia	better knowledge

11.2 Indicative References to Economic Benefits of Smart Farming Digital Technologies

The following Table 33 offers a summary of studies of economic benefits of smart farming and the key insights on economic benefits from digital technologies used in agriculture. Contrary to the studies on the environment where there was a certain consensus on the positive impact of smart technologies, there is a lack of studies illustrating the profitability of digital technologies in agriculture [124].

Table 33. Summary of the studies discussing economic benefits of digital technologies

Reference	Technology	Country or Region	Results
Anabel, N.J., Mohan, P., Rajkumar, R., 2018. Role of hub and spoke model for ICTs in agriculture. CSI Trans. ICT 6, 231–243. https://doi.org/10.1007/s40012-018-0207-y			more knowledge spillover
Bai, Hongwu Zhou, Guanghong Hu, Yinong Sun, Aidong Xu, Xinglian Liu, Xianjin Lu, Changhua, 2017	RFID	China	The reading capacity of RFID has the highest cost in the traceability chain
Barnes, A.P., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., Vangeyte, J., Fountas, S., van der Wal, T., Gómez-Barbero, M., 2019. Exploring the adoption of precision agricultural technologies: A cross regional study of EU farmers. Land Use Policy 80, 163–174. https://doi.org/10.1016/j.landusepol.2018.10.004	all precision technologies	EU	Economic cost is a barrier to adoption; optimism for the technology
Colaço, A.F., Bramley, R.G.V., 2018. Do crop sensors promote improved nitrogen management in grain crops? Field Crops Res. 218, 126–140. https://doi.org/10.1016/j.fcr.2018.01.007	image	world	A lack of consistent evidence of economic benefits limits farmers' adoption.
DeStefano, T., Kneller, R., Timmis, J., 2018. Broadband infrastructure, ICT use and firm performance: Evidence for UK firms. J. Econ. Behav. Organ. 155, 110–139. https://doi.org/10.1016/j.jebo.2018.08.020	network/ media	UK	ICT causally affects farm size (identified via sales or employment), but not productivity.
Drach, U., Halachmi, I., Pnini, T., Izhaki, I., Degani, A., 2017. Automatic herding reduces labour and increases milking frequency in robotic milking. Biosyst. Eng. 155, 134–141. https://doi.org/10.1016/j.biosystemseng.2016.12.010	robotic	Israel	Empirical studies: due to robot milking, farm labour decreases by 80%
Edan, Y., Han, S., Kondo, N., 2009. Automation in Agriculture, in: Nof, S.Y. (Ed.), Springer Handbook of Automation, Springer Handbooks. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 1095–1128. https://doi.org/10.1007/978-3-540-78831-7_63		OCDE countries	
Feng, Jianying Fu, Zetian Wang, Zaiqiong Xu, Mark Zhang, Xiaoshuan, 2013	RFID	China	The reading capacity of RFID has the highest cost in the traceability chain
Ferreira, J.J.M., Fernandes, C.I., Ferreira, F.A.F., 2018. To be or not to be digital, that is the question: Firm innovation and performance. J. Bus. Res. https://doi.org/10.1016/j.jbusres.2018.11.013	network/media	Portugal	competition between farms
Gutiérrez, P. A. López-Granados, F. Peña-Barragán, J. M. Jurado-Expósito, M. Hervás-Martínez, C., 2008	Application data analysis	Spain	

Hay, R., Pearce, P., 2014. Technology adoption by rural women in Queensland, Australia: Women driving technology from the homestead for the paddock. J. Rural Stud. 36, 318–327. https://doi.org/10.1016/j.jrurstud.2014.10.002	All new communication technologies	Australia	
Isaksson, A.J., Harjunkoski, I., Sand, G., 2018. The impact of digitalization on the future of control and operations.	DSS	world	competition between farms
Jakku, E., Taylor, B., Fleming, A., Mason, C., Fielke, S., Sounness, C., Thorburn, P., 2018. “If they don’t tell us what they do with it, why would we trust them?” Trust, transparency and benefit- sharing in Smart Farming. NJAS - Wageningen Journal of Life Sciences. https://doi.org/10.1016/j.njas.2018.11.002	all precision technologies		trust issues about the data holder
Lio, M., Liu, M.-C., 2006. ICT and agricultural productivity: evidence from cross-country data. Agric. Econ. 34, 221–228. https://doi.org/10.1111/j.1574-0864.2006.00120.x	ICT sector		ICT sector improves agricultural productivity
Lovato, 2017	data learning	Brazil	more profitability
Luvisi, A., 2016. Electronic identification technology for agriculture, plant, and food. A review. Agron. Sustain. Dev. 36, 13. https://doi.org/10.1007/s13593-016-0352-3	Identification technologies	world	lack of economic studies
Marcelino, R., Casagrande, L.C., Cunha, R., Crotti, Y., Gruber, V., 2018. Internet of Things Applied to Precision Agriculture, in: Auer, M.E., Zutin, D.G. (Eds.), Online Engineering & Internet of Things, Lecture Notes in Networks and Systems. Springer International Publishing, pp. 499–509.	image	Spain	lack of economic studies
Mesas-Carrascosa, F. J. Verdú Santano, D. Meroño, J. E. Sánchez de la Orden, M. García-Ferrer, A., 2015	DSS	Spain	
O’Shaughnessy, S. A. Rush, C., 2014	all precision technologies	USA	potential to use sensors to manage irrigation
Ojeda-Bustamante, Waldo González-Camacho, Juan Manuel Sifuentes-Ibarra, Ernesto Isidro, Esteban Rendón-Pimentel, Luis, 2007	application/software	Mexico	mapping technologies improve irrigation efficiency
Pavón-Pulido, N. López-Riquelme, J. A. Torres, R. Morais, R. Pastor, J. A., 2017	cloud	Spain	cloud computing improves economic performance for farmers
Pham, X., Stack, M., 2018. How data analytics is transforming agriculture. Business Horizons 61, 125– 133. https://doi.org/10.1016/j.bushor.2017.09.011	DSS	USA	competition between farms
Raymond Hunt Jr, E., Daughtry, C.S.T., 2018. What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture? Int. J. Remote Sens. 39,	RS	USA	higher costs

5345–5376. https://doi.org/10.1080/01431161.2017.1410300			
Regan, Á., 2019. 'Smart farming' in Ireland: A risk perception study with key governance actors. NJAS - Wagening. J. Life Sci. https://doi.org/10.1016/j.njas.2019.02.003	all precision technologies	Ireland	lower costs
Ruß, G., Kruse, R., Schneider, M., Wagner, P., 2009. Visualization of Agriculture Data Using Self- Organizing Maps, in: Allen, T., Ellis, R., Petridis, M. (Eds.), Applications and Innovations in Intelligent Systems XVI. Springer London, pp. 47–60.	data	USA	
Shepherd, Mark Turner, James A. Small, Bruce Wheeler, David, 2018	all precision technologies	USA	
Steinfield, C., Scupola, A., López-Nicolás, C., 2010. Social capital, ICT use and company performance: Findings from the Medicon Valley Biotech Cluster. Technol. Forecast. Soc. Change 77, 1156–1166. https://doi.org/10.1016/j.techfore.2010.03.004	network/ media		competition changed
Symeonaki, E.G., Arvanitis, K.G., Piromalis, D.D., 2019. Cloud Computing for IoT Applications in Climate- Smart Agriculture: A Review on the Trends and Challenges Toward Sustainability, in: Theodoridis, A., Ragkos, A., Salampasis, M. (Eds.), Innovative Approaches and Applications for Sustainable Rural Development, Springer Earth System Sciences. Springer International Publishing, pp. 147–167.	all precision technologies		
Torres-Sánchez, J. Peña, J. M. Castro, A. I. de López-Granados, F., 2014	UAV	Spain	
Vranken, E. Berckmans, D., 2017	software	Belgium	
White, R.R., Capper, J.L., 2014. Precision diet formulation to improve performance and profitability across various climates: Modeling the implications of increasing the formulation frequency of dairy cattle diets. J. Dairy Sci. 97, 1563–1577. https://doi.org/10.3168/jds.2013-6859	data learning	Spain	Formulating diets weekly rather than seasonally could increase returns over variable costs by US$25,000 per year for moderate- sized (300-cow) operations
Wolfert, S., Ge, L., Verdouw, C., Bogaardt, M.-J., 2017. Big Data in Smart Farming – A review. Agricultural Systems 153, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023	all precision technologies	World	
Yang, H., Wang, X., Zhuang, W., 2010. Case Analysis of Farm Agriculture Machinery Informatization Management Network System, in: Li, D., Zhao, C. (Eds.), Computer and Computing Technologies in Agriculture III, IFIP Advances in	all precision technologies	China	Difficulty in quantifying benefits due to complex agricultural techniques ad farm managements

Information and Communication Technology. Springer Berlin Heidelberg, pp. 65–76.			
Yong, L., Xiushan, L., Degui, Z., Fu, L., 2002. The main content, technical support and enforcement strategy of digital agriculture. Geo-Spat. Inf. Sci. 5, 68–73. https://doi.org/10.1007/BF02863497 Young, S.L., Meyer, G.E., Woldt, W.E., 2014. Future Directions for Automated Weed Management in Precision Agriculture, in: Young, S.L., Pierce, F.J. (Eds.), Automation: The Future of Weed Control in Cropping Systems. Springer Netherlands, Dordrecht, pp. 249–259. https://doi.org/10.1007/978-94-007-7512-1_15	all precision technologies	China	higher costs and more trust in digital technologies
Zhou, L., Song, L., Xie, C., Zhang, J., 2013. Applications of Internet of Things in the Facility Agriculture, in: Li, D., Chen, Y. (Eds.), Computer and Computing Technologies in Agriculture VI, IFIP Advances in Information and Communication Technology. Springer Berlin Heidelberg, pp. 297–303.	all precision technologies	China	

PA: Precision Agriculture, ICT: Information Communication Technologies, RS: Remote Sensing, UAV: Unmanned Aerial Vehicle, RFID: Radio Frequency Identification

11.3 Indicative Publications to Smart Farming Digital Technologies

The tables below offer references of scientific publications related to smart farming in Europe. More specifically, Table 34 offers the references for involved technologies in European research efforts, followed by a list of the references of scientific publication across European countries (where the research took place), references of scientific publications across the types of crops used in European research efforts, and references for scientific publications across the different field of operations in European research efforts.

Table 34. Involved Technologies in European Research Efforts (Adapted from [113])

Involved technologies	References			
Cloud Computing	M.A. Zamora-Izquierdo, J. Santa, J.A. Martínez, V. Martínez, A.F. Skarmeta, Smart farming IoT platform based on edge and cloud computing, Biosyst. Eng. 177 (2019) 4–17.	J. López-Riquelme, N. Pavón-Pulido, H. Navarro-Hellín, F. Soto-Valles, R. Torres-Sánchez, A software architecture based on FIWARE cloud for precision agriculture, Agric. Water Manag. 183 (2017) 123–135.	P. Psirofonia, V. Samaritakis, P. Eliopoulos, "Use of unmanned aerial vehicles for agricultural applications with emphasis on crop protection: Three novel case-studies," Int. J. Agric. Sci. Technol. 5 (1) (2017) 30–39.	A.C. Cruz, A. Luvisi, L. De Bellis, Y. Ampatzidis, X-FIDO: An effective application for detecting olive quick decline syndrome with deep learning and data fusion, Front. Plant Sci. 8 (2017) 1741.
	F.F. Montesano, M.W. Van Iersel, F. Boari, V. Cantore, G. D'Amato, A. Parente, Sensor-based irrigation management of soilless basil using a new smart irrigation system: Effects of set-point on plant physiological responses and crop performance, Agric. Water Man. 203 (2018) 20–29	E. Salamí, A. Gallardo, G. Skorobogatov, C. Barrado, On-the-fly olive tree counting using a UAS and cloud services, Remote Sens. 11 (3) (2019) 316.	R. Morais, N. Silva, J. Mendes, T. Adão, L. Pádua, J. López-Riquelme, N. Pavón-Pulido, J.J. Sousa, E. Peres, Mysense: A comprehensive data management environment to improve precision agriculture practices, Comput. Electron. Agric. 162 (2019) 882–894.	A. Somov, D. Shadrin, I. Fastovets, A. Nikitin, S. Matveev, O. Hrinchuk, et al., Pervasive agriculture: IoT-enabled greenhouse for plant growth control, IEEE Pervasive Comput. 17 (4) (2018) 65–75.
	F.J. Ferrández-Pastor, J.M. García-Chamizo, M. Nieto-Hidalgo, J. Mora- Pascual, J. Mora-Martínez, Developing ubiquitous sensor network platform using internet of things: Application in precision agriculture, Sensors 16 (7) (2016) 1141.	L. Busetto, S. Casteleyn, C. Granell, M. Pepe, M. Barbieri, M. Campos-Taberner, R. Casa, F. Collivignarelli, et al., Downstream services for rice crop monitoring in europe: From regional to local scale, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 10 (12) (2017) 5423–5441.	N. Pavón-Pulido, J. López-Riquelme, R. Torres, R. Morais, J. Pastor, New trends in precision agriculture: a novel cloud-based system for enabling data storage and agricultural task planning and automation, Precis. Agric. 18 (6) (2017) 1038–1068.	
Image Processing	J. Primicerio, S.F. Di Gennaro, E. Fiorillo, L. Genesio, E. Lugato, A. Matese, F.P. Vaccari, A flexible unmanned aerial vehicle for precision	F. Kurtulmuş, I. Kavdir, Detecting corn tassels using computer vision and support vector machines, Expert Syst.	F. Castaldi, F. Pelosi, S. Pascucci, R. Casa, Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide	J. Albetis, S. Duthoit, F. Guttler, A. Jacquin, M. Goulard, H. Poilvé, J.-B. Féret, G. Dedieu, Detection of Flavescence dorée grapevine disease using

	agriculture, Precis. Agric. 13 (4) (2012) 517–523.	Appl. 41 (16) (2014) 7390–7397.	patch spraying in maize, Precis. Agric. 18 (1) (2017) 76–94.	Unmanned Aerial Vehicle (UAV) multispectral imagery, Remote Sens. 9 (4) (2017) 308.
	M. Pérez-Ortiz, J.M. Peña, P.A. Gutiérrez, J. Torres-Sánchez, C. Hervás- Martínez, F. López-Granados, Selecting patterns and features for betweenand within-crop-row weed mapping using UAV-imagery, Expert Syst. Appl. 47 (2016) 85–94.	N. Wilke, B. Siegmann, L. Klingbeil, A. Burkart, T. Kraska, O. Muller, Quantifying lodging percentage and lodging severity using a UAV-based canopy height model combined with an objective threshold approach, Remote Sens. 11 (5) (2019) 515.	J.M. Peña, J. Torres-Sánchez, A. Serrano-Pérez, A.I. De Castro, F. López- Granados, Quantifying efficacy and limits of unmanned aerial vehicle (UAV) technology for weed seedling detection as affected by sensor resolution, Sensors 15 (3) (2015) 5609–5626.	A. Matese, S.F. Di Gennaro, Practical applications of a multisensor uav platform based on multispectral, thermal and rgb high resolution images in precision viticulture, Agriculture 8 (7) (2018) 116.
	L. Quebrajo, M. Perez-Ruiz, L. Pérez-Urrestarazu, G. Martínez, G. Egea, Linking thermal imaging and soil remote sensing to enhance irrigation management of sugar beet, Biosyst. Eng. 165 (2018) 77–87.	G. Mozgeris, D. Jonikavičius, D. Jovarauskas, R. Zinkevičius, S. Petkevičius, D. Steponavičius, Imaging from manned ultra-light and unmanned aerial vehicles for estimating properties of spring wheat, Precis. Agric. 19 (5) (2018) 876–894.	A. Michez, S. Bauwens, Y. Brostaux, M.-P. Hiel, S. Garré, P. Lejeune, B. Dumont, How far can consumer-grade UAV RGB imagery describe crop production? A 3D and multitemporal modeling approach applied to zea mays, Remote Sens. 10 (11) (2018).	R.A. Díaz-Varela, R. De la Rosa, L. León, P.J. Zarco-Tejada, High-resolution airborne UAV imagery to assess olive tree crown parameters using 3D photo reconstruction: application in breeding trials, Remote Sens. 7 (4) (2015) 4213–4232.
	C. Potena, R. Khanna, J. Nieto, R. Siegwart, D. Nardi, A. Pretto, AgriColMap: Aerial-ground collaborative 3D mapping for precision farming, IEEE Robot. Autom. Lett. 4 (2) (2019) 1085–1092.	L. Busetto, S. Casteleyn, C. Granell, M. Pepe, M. Barbieri, M. Campos-Taberner, R. Casa, F. Collivignarelli, et al., Downstream services for rice crop monitoring in europe: From regional to local scale, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 10 (12) (2017) 5423–5441	J. Kaivosoja, L. Pesonen, J. Kleemola, I. Pölönen, H. Salo, E. Honkavaara, A case study of a precision fertilizer application task generation for wheat based on classified hyperspectral data from UAV combined with farm history data, in: Remote Sensing for Agriculture, Ecosystems, and Hydrology XV, vol. 8887, International Society for Optics and Photonics, 2013, p. 8870H.	F.-J. Mesas-Carrascosa, J. Torres-Sánchez, I. Clavero-Rumbao, A. García-Ferrer, J.-M. Peña, I. Borra-Serrano, F. López-Granados, Assessing optimal flight parameters for generating accurate multispectral orthomosaicks by UAV to support site-specific crop management, Remote Sens. 7 (10) (2015) 12793–12814.

	J. Torres-Sánchez, J.M. Pena, A.I. de Castro, F. López-Granados, Multitemporal mapping of the vegetation fraction in early-season wheat fields using images from UAV, Comput. Electron. Agric. 103 (2014) 104–113.	V. Gonzalez-Dugo, P. Zarco-Tejada, E. Nicolás, P.A. Nortes, J. Alarcón, D.S. Intrigliolo, E. Fereres, Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard, Precis. Agric. 14 (6) (2013) 660–678.	T.T. Nguyen, K. Vandevoorde, E. Kayacan, J. De Baerdemaeker, W. Saeys, Apple detection algorithm for robotic harvesting using a RGB-D camera, in: International Conference of Agricultural Engineering, Zurich, Switzerland, 2014.	D. Stroppiana, M. Migliazzi, V. Chiarabini, A. Crema, M. Musanti, C. Franchino, P. Villa, Rice yield estimation using multispectral data from UAV: A preliminary experiment in northern Italy, in: 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), IEEE, 2015, pp. 4664–4667.
	J. Campos, J. Llop, M. Gallart, F. García-Ruiz, A. Gras, R. Salcedo, E. Gil, Development of canopy vigour maps using UAV for site-specific management during vineyard spraying process, Precis. Agric. 20 (6) (2019) 1136–1156.	X. Jin, S. Liu, F. Baret, M. Hemerlé, A. Comar, Estimates of plant density of wheat crops at emergence from very low altitude UAV imagery, Remote Sens. Environ. 198 (2017) 105–114.	P. Katsigiannis, L. Misopolinos, V. Liakopoulos, T.K. Alexandridis, G. Zalidis, An autonomous multi-sensor UAV system for reduced-input precision agriculture applications, in: 2016 24th Mediterranean Conference on Control and Automation (MED), IEEE, 2016, pp. 60–64.	G. Caruso, L. Tozzini, G. Rallo, J. Primicerio, M. Moriondo, G. Palai, R. Gucci, Estimating biophysical and geometrical parameters of grapevine canopies ('sangiovese') by an unmanned aerial vehicle (UAV) and VIS-NIR cameras, Vitis 56 (2) (2017) 63–70.
	F.A. Vega, F.C. Ramirez, M.P. Saiz, F.O. Rosua, Multi-temporal imaging using an unmanned aerial vehicle for monitoring a sunflower crop, Biosyst. Eng. 132 (2015) 19–27.	L. Pádua, P. Marques, J. Hruška, T. Adão, E. Peres, R. Morais, J.J. Sousa, Multi-temporal vineyard monitoring through UAV-based RGB imagery, Remote Sens. 10 (12) (2018) 1907.	I. Navrozidis, T.K. Alexandridis, A. Dimitrakos, A.L. Lagopodi, D. Moshou, G. Zalidis, Identification of purple spot disease on asparagus crops across spatial and spectral scales, Comput. Electron. Agric. 148 (2018) 322–329.	K. Kuželka, P. Surovy`, Automatic detection and quantification of wild game crop damage using an unmanned aerial vehicle (UAV) equipped with an optical sensor payload: a case study in wheat, Eur. J. Remote Sens. 51 (1) (2018) 241–250.
	P.J. Zarco-Tejada, V. González-Dugo, J.A. Berni, Fluorescence, temperature and narrow-band indices acquired from a UAV	H. Hoffmann, H. Nieto, R. Jensen, R. Guzinski, P. Zarco-Tejada, T. Friborg, Estimating evaporation with thermal UAV	C. Romero-Trigueros, P.A. Nortes, J.J. Alarcón, J.E. Hunink, M. Parra, S. Contreras, P. Droogers, E.	S. Marino, A. Alvino, Detection of homogeneous wheat areas using multitemporal UAS images and ground truth data

	platform for water stress detection using a micro-hyperspectral imager and a thermal camera, Remote Sens. Environ. 117 (2012) 322–337.	data and two-source energy balance models, Hydrol. Earth Syst. Sci. 20 (2) (2016) 697–713.	Nicolás, Effects of saline reclaimed waters and deficit irrigation on citrus physiology assessed by UAV remote sensing, Agric. Water Manag. 183 (2017) 60–69.	analyzed by cluster analysis, Eur. J. Remote Sens. 51 (1) (2018) 266–275.
	P.J. Zarco-Tejada, R. Diaz-Varela, V. Angileri, P. Loudjani, Tree height quantification using very high resolution imagery acquired from an unmanned aerial vehicle (UAV) and automatic 3D photo-reconstruction methods, Eur. J. Agron. 55 (2014) 89–99	D. Gómez-Candón, A. De Castro, F. López-Granados, Assessing the accuracy of mosaics from unmanned aerial vehicle (UAV) imagery for precision agriculture purposes in wheat, Precis. Agric. 15 (1) (2014) 44–56.	L. Santesteban, S. Di Gennaro, A. Herrero-Langreo, C. Miranda, J. Royo, A. Matese, High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard, Agric. Water Manag. 183 (2017) 49–59.	J. Bendig, A. Bolten, G. Bareth, UAV-based imaging for multi-temporal, very high Resolution Crop Surface Models to monitor Crop Growth Variability Monitoring des Pflanzenwachstums mit Hilfe multitemporaler und hoch auflösender Oberflächenmodelle von Getreidebeständen auf Basis von Bildern aus UAV-Befliegungen, Photogramme.-Fernerkundung-Geoinf. 2013 (6) (2013) 551–562.
	S. Candiago, F. Remondino, M. De Giglio, M. Dubbini, M. Gattelli, Evaluating multispectral images and vegetation indices for precision farming applications from UAV images, Remote Sens. 7 (4) (2015) 4026–4047.	M.P. Christiansen, M.S. Laursen, R.N. Jørgensen, S. Skovsen, R. Gislum, Designing and testing a UAV mapping system for agricultural field surveying, Sensors 17 (12) (2017) 2703	D. Gómez-Candón, N. Virlet, S. Labbé, A. Jolivot, J.-L. Regnard, Field phenotyping of water stress at tree scale by UAV-sensed imagery: new insights for thermal acquisition and calibration, Precis. Agric. 17 (6) (2016) 786–800.	P. Gonzalez-de Santos, A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez-Granados, M. Brandstoetter, S. Tomic, S. Pedrazzi, A. Peruzzi, G. Pajares, G. Kaplanis, et al., Fleets of robots for environmentally-safe pest control in agriculture, Precis. Agric. 18 (4) (2017) 574–614.

	H. Hoffmann, R. Jensen, A. Thomsen, H. Nieto, J. Rasmussen, T. Friborg, Crop water stress maps for an entire growing season from visible and thermal UAV imagery, Biogeosciences 13 (24) (2016) 6545–6563	X.E. Pantazi, D. Moshou, T. Alexandridis, R.L. Whetton, A.M. Mouazen, Wheat yield prediction using machine learning and advanced sensing techniques, Comput. Electron. Agric. 121 (2016) 57–65.	A. Tewes, J. Schellberg, Towards remote estimation of radiation use efficiency in maize using uav-based low-cost camera imagery, Agronomy 8 (2) (2018) 16.	J.M. Mendes, F.N. dos Santos, N.A. Ferraz, P.M. do Couto, R.M. dos Santos, Localization based on natural features detector for steep slope vineyards, J. Intell. Robot. Syst. 93 (3–4) (2019) 433–446.
	R. Calderón, M. Montes-Borrego, B. Landa, J. Navas-Cortés, P. Zarco-Tejada, Detection of downy mildew of opium poppy using high-resolution multispectral and thermal imagery acquired with an unmanned aerial vehicle, Precis. Agric. 15 (6) (2014) 639–661.	M. Fawakherji, A. Youssef, D. Bloisi, A. Pretto, D. Nardi, Crop and weeds classification for precision agriculture using context-independent pixelwise segmentation, in: 2019 Third IEEE International Conference on Robotic Computing (IRC), IEEE, 2019, pp. 146–152.	S.C. Kefauver, R. Vicente, O. Vergara-Díaz, J.A. Fernandez-Gallego, S. Kerfal, A. Lopez, J.P. Melichar, M.D. Serret Molins, J.L. Araus, Comparative UAV and field phenotyping to assess yield and nitrogen use efficiency in hybrid and conventional barley, Front. Plant Sci. 8 (2017) 1733.	K. Espinoza, D.L. Valera, J.A. Torres, A. López, F.D. Molina-Aiz, Combination of image processing and artificial neural networks as a novel approach for the identification of bemisia tabaci and frankliniella occidentalis on sticky traps in greenhouse agriculture, Comput. Electron. Agric. 127 (2016) 495–505.
	J. Bendig, K. Yu, H. Aasen, A. Bolten, S. Bennertz, J. Broscheit, M.L. Gnyp, G. Bareth, Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley, Int. J. Appl. Earth Obs. Geoinf. 39 (2015) 79–87.	H. Aasen, A. Burkart, A. Bolten, G. Bareth, Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: From camera calibration to quality assurance, ISPRS J. Photogramm. Remote Sens. 108 (2015) 245–259.	J. Geipel, J. Link, W. Claupein, Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system, Remote Sens. 6 (11) (2014) 10335–10355.	M. Schirrmann, A. Giebel, F. Gleiniger, M. Pflanz, J. Lentschke, K.-H. Dammer, Monitoring agronomic parameters of winter wheat crops with low-cost UAV imagery, Remote Sens. 8 (9) (2016) 706.
	E. Honkavaara, H. Saari, J. Kaivosoja, I. Pölönen, T. Hakala, P. Litkey, J. Mäkynen, L. Pesonen, Processing and assessment of spectrometric,	I. Burud, G. Lange, M. Lillemo, E. Bleken, L. Grimstad, P.J. From, Exploring robots and UAVs as phenotyping tools in plant breeding, IFAC-	J. Martinez-Guanter, P. Agüera, J. Agüera, M. Pérez-Ruiz, Spray and economics assessment of a UAV-based ultra-low-volume application in	M. Schirrmann, A. Hamdorf, A. Giebel, F. Gleiniger, M. Pflanz, K.-H. Dammer, Regression kriging for improving crop height models fusing ultra-

	stereoscopic imagery collected using a lightweight UAV spectral camera for precision agriculture, Remote Sens. 5 (10) (2013) 5006–5039.	PapersOnLine 50 (1) (2017) 11479–11484.	olive and citrus orchards, Precis. Agric. 21 (1) (2020) 226–243.	sonic sensing with UAV imagery, Remote Sens. 9 (7) (2017) 665.
	J.M. Peña, J. Torres-Sánchez, A.I. de Castro, M. Kelly, F. López-Granados, Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images, PLoS One 8 (10) (2013).	J. Torres-Sánchez, F. López-Granados, A.I. De Castro, J.M. Peña-Barragán, Configuration and specifications of an unmanned aerial vehicle (UAV) for early site specific weed management, PLoS One 8 (3) (2013).	F. López-Granados, J. Torres-Sánchez, A. Serrano-Pérez, A.I. de Castro, F.-J. Mesas-Carrascosa, J.-M. Pena, Early season weed mapping in sunflower using UAV technology: variability of herbicide treatment maps against weed thresholds, Precis. Agric. 17 (2) (2016) 183–199.]	J. Bendig, A. Bolten, S. Bennertz, J. Broscheit, S. Eichfuss, G. Bareth, Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging, Remote Sens. 6 (11) (2014) 10395–10412.
	K. Ivushkin, H. Bartholomeus, A.K. Bregt, A. Pulatov, M.H. Franceschini, H. Kramer, E.N. van Loo, V.J. Roman, R. Finkers, UAV based soil salinity assessment of cropland, Geoderma 338 (2019) 502–512.	B. Rey, N. Aleixos, S. Cubero, J. Blasco, XF-ROVIM. A field robot to detect olive trees infected by xylella fastidiosa using proximal sensing, Remote Sens. 11 (3) (2019) 221.	N. Sales, O. Remédios, A. Arsenio, Wireless sensor and actuator system for smart irrigation on the cloud, in: 2015 IEEE 2nd World Forum on Internet of Things (WF-IoT), IEEE, 2015, pp. 693–698.	M. Louargant, G. Jones, R. Faroux, J.-N. Paoli, T. Maillot, C. Gée, S. Villette, Unsupervised classification algorithm for early weed detection in rowcrops by combining spatial and spectral information, Remote Sens. 10 (5) (2018) 761.
	J.I. Córcoles, J.F. Ortega, D. Hernández, M.A. Moreno, Estimation of leaf area index in onion (Allium cepa L.) using an unmanned aerial vehicle, Biosyst. Eng. 115 (1) (2013) 31–42.	A. Burkart, V. Hecht, T. Kraska, U. Rascher, Phenological analysis of unmanned aerial vehicle based time series of barley imagery with high temporal resolution, Precis. Agric. 19 (1) (2018) 134–146.	F. López-Granados, J. Torres-Sánchez, A.-I. De Castro, A. Serrano-Pérez, F.- J. Mesas-Carrascosa, J.-M. Peña, Object-based early monitoring of a grass weed in a grass crop using high resolution UAV imagery, Agron. Sustain. Dev. 36 (4) (2016) 67.	L. Comba, P. Gay, J. Primicerio, D.R. Aimonino, Vineyard detection from unmanned aerial systems images, Comput. Electron. Agric. 114 (2015) 78–87.

	J. Baluja, M.P. Diago, P. Balda, R. Zorer, F. Meggio, F. Morales, J. Tardaguila, Assessment of vineyard water status variability by thermal and multispectral imagery using an unmanned aerial vehicle (UAV), Irrigat. Sci. 30 (6) (2012) 511–522.	A.C. Kyratzis, D.P. Skarlatos, G.C. Menexes, V.F. Vamvakousis, A. Katsiotis, Assessment of vegetation indices derived by UAV imagery for durum wheat phenotyping under a water limited and heat stressed mediterranean environment, Front. Plant Sci. 8 (2017) 1114	Á. Maresma, M. Ariza, E. Martínez, J. Lloveras, J.A. Martínez-Casasnovas, Analysis of vegetation indices to determine nitrogen application and yield prediction in maize (Zea mays L.) from a standard UAV service, Remote Sens. 8 (12) (2016) 973.	K. Ribeiro-Gomes, D. Hernández-López, J.F. Ortega, R. Ballesteros, T. Poblete, M.A. Moreno, Uncooled thermal camera calibration and optimization of the photogrammetry process for UAV applications in agriculture, Sensors 17 (10) (2017) 2173.
Machine Learning	F. Kurtulmuş, I. Kavdir, Detecting corn tassels using computer vision and support vector machines, Expert Syst. Appl. 41 (16) (2014) 7390–7397.	E. Honkavaara, H. Saari, J. Kaivosoja, I. Pölönen, T. Hakala, P. Litkey, J. Mäkynen, L. Pesonen, Processing and assessment of spectrometric, stereoscopic imagery collected using a lightweight UAV spectral camera for precision agriculture, Remote Sens. 5 (10) (2013) 5006–5039.	N. Sales, O. Remédios, A. Arsenio, Wireless sensor and actuator system for smart irrigation on the cloud, in: 2015 IEEE 2nd World Forum on Internet of Things (WF-IoT), IEEE, 2015, pp. 693–698.	M. Louargant, G. Jones, R. Faroux, J.-N. Paoli, T. Maillot, C. Gée, S. Villette, Unsupervised classification algorithm for early weed detection in rowcrops by combining spatial and spectral information, Remote Sens. 10 (5) (2018) 761.
	M. Pérez-Ortiz, J.M. Peña, P.A. Gutiérrez, J. Torres-Sánchez, C. Hervás- Martínez, F. López-Granados, Selecting patterns and features for betweenand within-crop-row weed mapping using UAV-imagery, Expert Syst. Appl. 47 (2016) 85–94.	D. Gómez, P. Salvador, J. Sanz, J.L. Casanova, Potato yield prediction using machine learning techniques and sentinel 2 data, Remote Sens. 11 (15) (2019) 1745.	E. Salamí, A. Gallardo, G. Skorobogatov, C. Barrado, On-the-fly olive tree counting using a UAS and cloud services, Remote Sens. 11 (3) (2019) 316.	X.E. Pantazi, D. Moshou, T. Alexandridis, R.L. Whetton, A.M. Mouazen, Wheat yield prediction using machine learning and advanced sensing techniques, Comput. Electron. Agric. 121 (2016) 57–65.
	J.I. Córcoles, J.F. Ortega, D. Hernández, M.A. Moreno, Estimation of leaf area index in onion (Allium cepa L.) using an unmanned aerial vehicle,	M. Fawakherji, A. Youssef, D. Bloisi, A. Pretto, D. Nardi, Crop and weeds classification for precision agriculture using context-independent pixelwise	B. Siegmann, T. Jarmer, Comparison of different regression models and validation techniques for the assessment of wheat leaf area index from hyperspectral data,	K. Espinoza, D.L. Valera, J.A. Torres, A. López, Combination of image processing and artificial neural networks as a novel approach for the identification of bemisia tabaci

	Biosyst. Eng. 115 (1) (2013) 31–42.	segmentation, in: 2019 Third IEEE International Conference on Robotic Computing (IRC), IEEE, 2019, pp. 146–152.	Int. J. Remote Sens. 36 (18) (2015) 4519–4534.	and frankliniella occidentalis on sticky traps in greenhouse agriculture, Comput. Electron. Agric. 127 (2016) 495–505.
	A. Somov, D. Shadrin, I. Fastovets, A. Nikitin, S. Matveev, O. Hrinchuk, et al., Pervasive agriculture: IoT-enabled greenhouse for plant growth control, IEEE Pervasive Comput. 17 (4) (2018) 65–75.	S. Kontogiannis, G. Kokkonis, S. Ellinidou, S. Valsamidis, Proposed fuzzynn algorithm with loracommunication protocol for clustered irrigation systems, Future Internet 9 (4) (2017) 78.	E.I. Papageorgiou, A.T. Markinos, T.A. Gemtos, Fuzzy cognitive map based approach for predicting yield in cotton crop production as a basis for decision support system in precision agriculture application, Appl. Soft Comput. 11 (4) (2011) 3643–3657	S. Marino, A. Alvino, Detection of homogeneous wheat areas using multitemporal UAS images and ground truth data analyzed by cluster analysis, Eur. J. Remote Sens. 51 (1) (2018) 266–275.
UAV	J. Primicerio, S.F. Di Gennaro, E. Fiorillo, L. Genesio, E. Lugato, A. Matese, F.P. Vaccari, A flexible unmanned aerial vehicle for precision agriculture, Precis. Agric. 13 (4) (2012) 517–523.	F. Castaldi, F. Pelosi, S. Pascucci, R. Casa, Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize, Precis. Agric. 18 (1) (2017) 76–94.	J. Albetis, S. Duthoit, F. Guttler, A. Jacquin, M. Goulard, H. Poilvé, J.-B. Féret, G. Dedieu, Detection of Flavescence dorée grapevine disease using Unmanned Aerial Vehicle (UAV) multispectral imagery, Remote Sens. 9 (4) (2017) 308.	J. Campos, J. Llop, M. Gallart, F. García-Ruiz, A. Gras, R. Salcedo, E. Gil, Development of canopy vigour maps using UAV for site-specific management during vineyard spraying process, Precis. Agric. 20 (6) (2019) 1136–1156.
	L. Pádua, P. Marques, J. Hruška, T. Adão, E. Peres, R. Morais, J.J. Sousa, Multi-temporal vineyard monitoring through UAV-based RGB imagery, Remote Sens. 10 (12) (2018) 1907.	K. Kuželka, P. Surovy` , Automatic detection and quantification of wild game crop damage using an unmanned aerial vehicle (UAV) equipped with an optical sensor payload: a case study in wheat, Eur. J. Remote Sens. 51 (1) (2018) 241–250.	H. Hoffmann, R. Jensen, A. Thomsen, H. Nieto, J. Rasmussen, T. Friborg, Crop water stress maps for an entire growing season from visible and thermal UAV imagery, Biogeosciences 13 (24) (2016) 6545–6563	A. Tewes, J. Schellberg, Towards remote estimation of radiation use efficiency in maize using uav-based low-cost camera imagery, Agronomy 8 (2) (2018) 16.
	S. Marino, A. Alvino, Detection of homogeneous wheat areas using multitemporal UAS images and ground truth data analyzed by cluster analysis,	R. Calderón, M. Montes-Borrego, B. Landa, J. Navas-Cortés, P. Zarco-Tejada, Detection of downy mildew of opium poppy using high-	S.C. Kefauver, R. Vicente, O. Vergara-Díaz, J.A. Fernandez-Gallego, S. Kerfal, A. Lopez, J.P. Melichar, M.D. Serret Molins, J.L. Araus,	J. Baluja, M.P. Diago, P. Balda, R. Zorer, F. Meggio, F. Morales, J. Tardaguila, Assessment of vineyard water status variability by thermal and

	Eur. J. Remote Sens. 51 (1) (2018) 266–275.	resolution multispectral and thermal imagery acquired with an unmanned aerial vehicle, Precis. Agric. 15 (6) (2014) 639–661.	Comparative UAV and field phenotyping to assess yield and nitrogen use efficiency in hybrid and conventional barley, Front. Plant Sci. 8 (2017) 1733.	multispectral imagery using an unmanned aerial vehicle (UAV), Irrigat. Sci. 30 (6) (2012) 511–522.
	J. Bendig, K. Yu, H. Aasen, A. Bolten, S. Bennertz, J. Broscheit, M.L. Gnyp, G. Bareth, Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley, Int. J. Appl. Earth Obs. Geoinf. 39 (2015) 79–87.	H. Aasen, A. Burkart, A. Bolten, G. Bareth, Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: From camera calibration to quality assurance, ISPRS J. Photogramm. Remote Sens. 108 (2015) 245–259.	J. Geipel, J. Link, W. Claupein, Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system, Remote Sens. 6 (11) (2014) 10335–10355.	M. Schirrmann, A. Giebel, F. Gleiniger, M. Pflanz, J. Lentschke, K.-H. Dammer, Monitoring agronomic parameters of winter wheat crops with low-cost UAV imagery, Remote Sens. 8 (9) (2016) 706.
	X. Jin, S. Liu, F. Baret, M. Hemerlé, A. Comar, Estimates of plant density of wheat crops at emergence from very low altitude UAV imagery, Remote Sens. Environ. 198 (2017) 105–114.	P. Katsigiannis, L. Misopolinos, V. Liakopoulos, T.K. Alexandridis, An autonomous multi-sensor UAV system for reduced-input precision agriculture applications, in: 2016 24th Mediterranean Conference on Control and Automation (MED), IEEE, 2016, pp. 60–64.	G. Caruso, L. Tozzini, G. Rallo, J. Primicerio, M. Moriondo, G. Palai, R. Gucci, Estimating biophysical and geometrical parameters of grapevine canopies (‘sangiovese’) by an unmanned aerial vehicle (UAV) and VIS-NIR cameras, Vitis 56 (2) (2017) 63–70.	D. Gómez-Candón, N. Virlet, S. Labbé, A. Jolivot, J.-L. Regnard, Field phenotyping of water stress at tree scale by UAV-sensed imagery: new insights for thermal acquisition and calibration, Precis. Agric. 17 (6) (2016) 786–800.
	J.M. Peña, J. Torres-Sánchez, A. Serrano-Pérez, A.I. De Castro, F. López- Granados, Quantifying efficacy and limits of unmanned aerial vehicle (UAV) technology for weed seedling detection as affected by sensor resolution, Sensors 15 (3) (2015) 5609–5626.	A. Matese, S.F. Di Gennaro, Practical applications of a multisensor uav platform based on multispectral, thermal and rgb high resolution images in precision viticulture, Agriculture 8 (7) (2018) 116.	E. Salamí, A. Gallardo, G. Skorobogatov, C. Barrado, On-the-fly olive tree counting using a UAS and cloud services, Remote Sens. 11 (3) (2019) 316.	F.A. Vega, F.C. Ramirez, M.P. Saiz, F.O. Rosua, Multi-temporal imaging using an unmanned aerial vehicle for monitoring a sunflower crop, Biosyst. Eng. 132 (2015) 19–27.

	R.A. Díaz-Varela, R. De la Rosa, L. León, P.J. Zarco-Tejada, High-resolution airborne UAV imagery to assess olive tree crown parameters using 3D photo reconstruction: application in breeding trials, Remote Sens. 7 (4) (2015) 4213–4232.	P.J. Zarco-Tejada, V. González-Dugo, J.A. Berni, Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera, Remote Sens. Environ. 117 (2012) 322–337.	H. Hoffmann, H. Nieto, R. Jensen, R. Guzinski, P. Zarco-Tejada, T. Friborg, Estimating evaporation with thermal UAV data and two-source energy balance models, Hydrol. Earth Syst. Sci. 20 (2) (2016) 697–713.	C. Romero-Trigueros, P.A. Nortes, J.J. Alarcón, J.E. Hunink, M. Parra, S. Contreras, P. Droogers, E. Nicolás, Effects of saline reclaimed waters and deficit irrigation on citrus physiology assessed by UAV remote sensing, Agric. Water Manag. 183 (2017) 60–69.
	P.J. Zarco-Tejada, R. Diaz-Varela, V. Angileri, P. Loudjani, Tree height quantification using very high resolution imagery acquired from an unmanned aerial vehicle (UAV) and automatic 3D photo-reconstruction methods, Eur. J. Agron. 55 (2014) 89–99	D. Gómez-Candón, A. De Castro, F. López-Granados, Assessing the accuracy of mosaics from unmanned aerial vehicle (UAV) imagery for precision agriculture purposes in wheat, Precis. Agric. 15 (1) (2014) 44–56.	L. Santesteban, S. Di Gennaro, A. Herrero-Langreo, C. Miranda, J. Royo, A. Matese, High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard, Agric. Water Manag. 183 (2017) 49–59.	J. Bendig, A. Bolten, G. Bareth, UAV-based imaging for multi-temporal, very high Resolution Crop Surface Models to monitor Crop Growth 2013 (6) (2013) 551–562.
	D. Stroppiana, M. Migliazzi, V. Chiarabini, A. Crema, M. Musanti, C. Franchino, P. Villa, Rice yield estimation using multispectral data from UAV: A preliminary experiment in northern Italy, in: 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), IEEE, 2015, pp. 4664–4667.	S. Candiago, F. Remondino, M. De Giglio, M. Dubbini, M. Gattelli, Evaluating multispectral images and vegetation indices for precision farming applications from UAV images, Remote Sens. 7 (4) (2015) 4026–4047.	M.P. Christiansen, M.S. Laursen, R.N. Jørgensen, S. Skovsen, R. Gislum, Designing and testing a UAV mapping system for agricultural field surveying, Sensors 17 (12) (2017) 2703	J.I. Córcoles, J.F. Ortega, D. Hernández, M.A. Moreno, Estimation of leaf area index in onion (Allium cepa L.) using an unmanned aerial vehicle, Biosyst. Eng. 115 (1) (2013) 31–42.
	P. Gonzalez-de Santos, A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez-Granados, M. Brandstoetter, S. Tomic, S. Pedrazzi, A. Peruzzi, G. Pajares,	E. Honkavaara, H. Saari, J. Kaivosoja, I. Pölönen, T. Hakala, P. Litkey, J. Mäkynen, L. Pesonen, Processing and assessment of spectrometric, stereoscopic imagery collected	I. Burud, G. Lange, M. Lillemo, E. Bleken, L. Grimstad, P.J. From, Exploring robots and UAVs as phenotyping tools in plant breeding, IFAC-	J. Martinez-Guanter, P. Agüera, J. Agüera, M. Pérez-Ruiz, Spray and economics assessment of a UAV-based ultra-low-volume application in olive and citrus orchards,

	G. Kaplanis, et al., Fleets of robots for environmentally-safe pest control in agriculture, Precis. Agric. 18 (4) (2017) 574–614.	using a lightweight UAV spectral camera for precision agriculture, Remote Sens. 5 (10) (2013) 5006–5039.	PapersOnLine 50 (1) (2017) 11479–11484.	Precis. Agric. 21 (1) (2020) 226–243.
	A. Burkart, V. Hecht, T. Kraska, U. Rascher, Phenological analysis of unmanned aerial vehicle based time series of barley imagery with high temporal resolution, Precis. Agric. 19 (1) (2018) 134–146.	F. López-Granados, J. Torres-Sánchez, A.-I. De Castro, A. Serrano-Pérez, F.- J. Mesas-Carrascosa, J.-M. Peña, Object-based early monitoring of a grass weed in a grass crop using high resolution UAV imagery, Agron. Sustain. Dev. 36 (4) (2016) 67.	L. Comba, P. Gay, J. Primicerio, D.R. Aimonino, Vineyard detection from unmanned aerial systems images, Comput. Electron. Agric. 114 (2015) 78–87.	A. Matese, P. Toscano, S.F. Di Gennaro, L. Genesio, F.P. Vaccari, J. Primicerio, C. Belli, A. Zaldei, R. Bianconi, B. Gioli, Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture, Remote Sens. 7 (3) (2015) 2971–2990.
	Á. Maresma, M. Ariza, E. Martínez, J. Lloveras, J.A. Martínez-Casasnovas, Analysis of vegetation indices to determine nitrogen application and yield prediction in maize from a standard UAV service, Remote Sens. 8 (12) (2016)	C. Potena, R. Khanna, J. Nieto, R. Siegwart, D. Nardi, A. Pretto, AgriColMap: Aerial-ground collaborative 3D mapping for precision farming, IEEE Robot. Autom. Lett. 4 (2) (2019) 1085–1092.	J. Martínez, G. Egea, J. Agüera, M. Pérez-Ruiz, A cost-effective canopy temperature measurement system for precision agriculture: a case study on sugar beet, Precis. Agric. 18 (1) (2017) 95–110.	J. Valente, R. Almeida, L. Kooistra, A comprehensive study of the potential application of flying ethylene-sensitive sensors for ripeness detection in apple orchards, Sensors 19 (2) (2019) 372.
	J. Torres-Sánchez, F. López-Granados, A.I. De Castro, J.M. Peña-Barragán, Configuration and specifications of an unmanned aerial vehicle (UAV) for early site specific weed management, PLoS One 8 (3) (2013).	F. López-Granados, J. Torres-Sánchez, A. Serrano-Pérez, A.I. de Castro, F.-J. Mesas-Carrascosa, J.-M. Pena, Early season weed mapping in sunflower using UAV technology: variability of herbicide treatment maps against weed thresholds, Precis. Agric. 17 (2) (2016) 183–199.	J. Bendig, A. Bolten, S. Bennertz, J. Broscheit, S. Eichfuss, G. Bareth, Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging, Remote Sens. 6 (11) (2014) 10395–10412.	J. Torres-Sánchez, J.M. Pena, A.I. de Castro, F. López-Granados, Multitemporal mapping of the vegetation fraction in early-season wheat fields using images from UAV, Comput. Electron. Agric. 103 (2014) 104–113.

	M. Schirrmann, A. Hamdorf, A. Giebel, F. Gleiniger, M. Pflanz, K.-H. Dammer, Regression kriging for improving crop height models fusing ultra-sonic sensing with UAV imagery, Remote Sens. 9 (7) (2017) 665.	P. Psirofonia, V. Samaritakis, P. Eliopoulos, I. Potamitis, Use of unmanned aerial vehicles for agricultural applications with emphasis on crop protection: Three novel case-studies, Int. J. Agric. Sci. Technol. 5 (1) (2017) 30–39.	K. Ivushkin, H. Bartholomeus, A.K. Bregt, A. Pulatov, M.H. Franceschini, H. Kramer, E.N. van Loo, V.J. Roman, R. Finkers, UAV based soil salinity assessment of cropland, Geoderma 338 (2019) 502–512.	R. Pudelko, T. Stuczynski, M. Borzecka-Walker, et al., The suitability of an unmanned aerial vehicle (UAV) for the evaluation of experimental fields and crops, Agriculture 99 (4) (2012) 431–436.
	K. Ribeiro-Gomes, D. Hernández-López, J.F. Ortega, R. Ballesteros, T. Poblete, M.A. Moreno, Uncooled thermal camera calibration and optimization of the photogrammetry process for UAV applications in agriculture, Sensors 17 (10) (2017) 2173.	M. Pérez-Ortiz, J.M. Peña, P.A. Gutiérrez, J. Torres-Sánchez, C. Hervás- Martínez, F. López-Granados, Selecting patterns and features for betweenand within-crop-row weed mapping using UAV-imagery, Expert Syst. Appl. 47 (2016) 85–94.	N N. Wilke, B. Siegmann, L. Klingbeil, A. Burkart, T. Kraska, O. Muller, A. van Doorn, S. Heinemann, U. Rascher, Quantifying lodging percentage and lodging severity using a UAV-based canopy height model combined with an objective threshold approach, Remote Sens. 11 (5) (2019) 515.	J.M. Peña, J. Torres-Sánchez, A.I. de Castro, M. Kelly, F. López-Granados, Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images, PLoS One 8 (10) (2013).
	M.L. Guillén-Climent, P.J. Zarco-Tejada, J.A. Berni, P.R. North, F.J. Villalobos, Mapping radiation interception in row-structured orchards using 3D simulation and high-resolution airborne imagery acquired from a UAV, Precis. Agric. 13 (4) (2012) 473–500.	L. Quebrajo, M. Perez-Ruiz, L. Pérez-Urrestarazu, G. Martínez, G. Egea, Linking thermal imaging and soil remote sensing to enhance irrigation management of sugar beet, Biosyst. Eng. 165 (2018) 77–87.	G. Mozgeris, D. Jonikavičius, D. Jovarauskas, R. Zinkevičius, S. Petkevičius, D. Steponavičius, Imaging from manned ultra-light and unmanned aerial vehicles for estimating properties of spring wheat, Precis. Agric. 19 (5) (2018) 876–894.	A. Michez, S. Bauwens, Y. Brostaux, M.-P. Hiel, S. Garré, P. Lejeune, B. Dumont, How far can consumer-grade UAV RGB imagery describe crop production? A 3D and multitemporal modeling approach applied to zea mays, Remote Sens. 10 (11) (2018) 1798.
	J. Kaivosoja, L. Pesonen, J. Kleemola, I. Pölönen, H. Salo, E. Honkavaara, A case study of a precision fertilizer application task generation for wheat based on classified	F.-J. Mesas-Carrascosa, J. Torres-Sánchez, I. Clavero-Rumbao, A. García-Ferrer, J.-M. Peña, I. Borra-Serrano, F. López-Granados, Assessing optimal flight parameters for	A.C. Kyratzis, D.P. Skarlatos, G.C. Menexes, V.F. Vamvakousis, A. Katsiotis, Assessment of vegetation indices derived by UAV imagery for	N. Pavón-Pulido, J. López-Riquelme, R. Torres, R. Morais, J. Pastor, New trends in precision agriculture: a novel cloud-based system for enabling data storage and

	hyperspectral data from UAV combined with farm history data, in: Remote Sensing for Agriculture, Ecosystems, and Hydrology XV, vol. 8887, International Society for Optics and Photonics, 2013, p. 8870H.	generating accurate multispectral orthomosaicks by UAV to support site-specific crop management, Remote Sens. 7 (10) (2015) 12793–12814.	durum wheat phenotyping under a water limited and heat stressed mediterranean environment, Front. Plant Sci. 8 (2017) 1114	agricultural task planning and automation, Precis. Agric. 18 (6) (2017) 1038–1068.
	V. Gonzalez-Dugo, P. Zarco-Tejada, E. Nicolás, P.A. Nortes, J. Alarcón, D.S. Intrigliolo, E. Fereres, Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard, Precis. Agric. 14 (6) (2013) 660–678.	J. Torres-Sánchez, A.I. de Castro, J.M. Pena, F.M. Jiménez-Brenes, O. Arquero, M. Lovera, F. López-Granados, Mapping the 3D structure of almond trees using UAV acquired photogrammetric point clouds and object-based image analysis, Biosyst. Eng. 176 (2018) 172–184		
UGV	P. Gonzalez-de Santos, A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez-Granados, M. Brandstoetter, S. Tomic, S. Pedrazzi, et al., Fleets of robots for environmentally-safe pest control in agriculture, Precis. Agric. 18 (4) (2017) 574–614	I. Burud, G. Lange, M. Lillemo, E. Bleken, L. Grimstad, P.J. From, Exploring robots and UAVs as phenotyping tools in plant breeding, IFAC-PapersOnLine 50 (1) (2017) 11479–11484.	L. Cantelli, F. Bonaccorso, D. Longo, C.D. Melita, G. Schillaci, G. Muscato, A small versatile electrical robot for autonomous spraying in agriculture, AgriEngineering 1 (3) (2019) 391–402.	J.M. Mendes, F.N. dos Santos, N.A. Ferraz, P.M. do Couto, R.M. dos Santos, Localization based on natural features detector for steep slope vineyards, J. Intell. Robot. Syst. 93 (3–4) (2019) 433–446.
	M. Fawakherji, A. Youssef, D. Bloisi, A. Pretto, D. Nardi, Crop and weeds classification for precision agriculture using context-independent pixelwise segmentation, in: 2019 Third IEEE International Conference on Robotic Computing (IRC), IEEE, 2019, pp. 146–152.	C. Potena, R. Khanna, J. Nieto, R. Siegwart, D. Nardi, A. Pretto, AgriColMap: Aerial-ground collaborative 3D mapping for precision farming, IEEE Robot. Autom. Lett. 4 (2) (2019) 1085–1092.	T.T. Nguyen, K. Vandevoorde, E. Kayacan, J. De Baerdemaeker, W. Saeys, Apple detection algorithm for robotic harvesting using a RGB-D camera, in: International Conference of Agricultural Engineering, Zurich, Switzerland, 2014.	

	A.M. García, I.F. García, E.C. Poyato, P.M. Barrios, J.R. Díaz, Coupling irrigation scheduling with solar energy production in a smart irrigation management system, J. Clean. Prod. 175 (2018) 670–682.	M.A. Zamora-Izquierdo, J. Santa, J.A. Martínez, V. Martínez, A.F. Skarmeta, Smart farming IoT platform based on edge and cloud computing, Biosyst. Eng. 177 (2019) 4–17.	J. López-Riquelme, N. Pavón-Pulido, H. Navarro-Hellín, F. Soto-Valles, R. Torres-Sánchez, A software architecture based on FIWARE cloud for precision agriculture, Agric. Water Manag. 183 (2017) 123–135.	A.C. Cruz, A. Luvisi, L. De Bellis, Y. Ampatzidis, X-FIDO: An effective application for detecting olive quick decline syndrome with deep learning and data fusion, Front. Plant Sci. 8 (2017) 1741.
WSN	F.F. Montesano, M.W. Van Iersel, F. Boari, V. Cantore, G. D'Amato, Sensor-based irrigation management of soilless basil using a new smart irrigation system: Effects of set-point on plant physiological responses and crop performance, Agric. Water Manag. 203 (2018) 20–29	R. Morais, N. Silva, J. Mendes, T. Adão, L. Pádua, J. López-Riquelme, N. Pavón-Pulido, J.J. Sousa, E. Peres, Mysense: A comprehensive data management environment to improve precision agriculture practices, Comput. Electron. Agric. 162 (2019) 882–894.	A. Somov, D. Shadrin, I. Fastovets, A. Nikitin, S. Matveev, O. Hrinchuk, et al., Pervasive agriculture: IoT-enabled greenhouse for plant growth control, IEEE Pervasive Comput. 17 (4) (2018) 65–75.	S. Kontogiannis, G. Kokkonis, S. Ellinidou, S. Valsamidis, Proposed fuzzynn algorithm with loracommunication protocol for clustered irrigation systems, Future Internet 9 (4) (2017) 78.
	F.J. Ferrández-Pastor, J.M. García-Chamizo, M. Nieto-Hidalgo, J. Mora- Pascual, J. Mora-Martínez, Developing ubiquitous sensor network platform using internet of things: Application in precision agriculture, Sensors 16 (7) (2016) 1141.	C. Goumopoulos, B. O'Flynn, A. Kameas, Automated zone-specific irrigation with wireless sensor/actuator network and adaptable decision support, Comput. Electron. Agric. 105 (2014) 20–33.	N. Pavón-Pulido, J. López-Riquelme, R. Torres, R. Morais, J. Pastor, New trends in precision agriculture: a novel cloud-based system for enabling data storage and agricultural task planning and automation, Precis. Agric. 18 (6) (2017) 1038–1068.	

Table 35. European countries involved in research efforts ((Adapted from [113])

Country	References			
Belgium	A. Michez, S. Bauwens, Y. Brostaux, M.-P. Hiel, S. Garré, P. Lejeune, B. Dumont, How far can consumer-grade UAV RGB imagery describe crop production? A 3D and multitemporal modeling approach applied to zea mays, Remote Sens. 10 (11) (2018) 1798.		T.T. Nguyen, K. Vandevoorde, E. Kayacan, J. De Baerdemaeker, W. Saeys, Apple detection algorithm for robotic harvesting using a RGB-D camera, in: International Conference of Agricultural Engineering, Zurich, Switzerland, 2014.	
Denmark	H. Hoffmann, R. Jensen, A. Thomsen, H. Nieto, J. Rasmussen, T. Friborg, Crop water stress maps for an entire growing season from visible and thermal UAV imagery, Biogeosciences 13 (24) (2016) 6545–6563	H. Hoffmann, H. Nieto, R. Jensen, R. Guzinski, P. Zarco-Tejada, T. Friborg, Estimating evaporation with thermal UAV data and two-source energy balance models, Hydrol. Earth Syst. Sci. 20 (2) (2016) 697–713.	M.P. Christiansen, M.S. Laursen, R.N. Jørgensen, S. Skovsen, R. Gislum, Designing and testing a UAV mapping system for agricultural field surveying, Sensors 17 (12) (2017) 2703	
Finland	E. Honkavaara, H. Saari, J. Kaivosoja, I. Pölönen, T. Hakala, P. Litkey, J. Mäkynen, L. Pesonen, Processing and assessment of spectrometric, stereoscopic imagery collected using a lightweight UAV spectral camera for precision agriculture, Remote Sens. 5 (10) (2013) 5006–5039.		J. Kaivosoja, L. Pesonen, J. Kleemola, I. Pölönen, H. Salo A case study of a precision fertilizer application task generation for wheat based on classified hyperspectral data from UAV combined with farm history data, in: Remote Sensing for Agriculture, Ecosystems, and Hydrology XV, vol. 8887, International Society for Optics and Photonics, 2013,	
France	J. Albetis, S. Duthoit, F. Guttler, A. Jacquin, M. Goulard, H. Poilvé, J.-B. Féret, G. Dedieu, Detection of Flavescence dorée grapevine disease using Unmanned Aerial Vehicle (UAV) multispectral imagery, Remote Sens. 9 (4) (2017) 308.	X. Jin, S. Liu, F. Baret, M. Hemerlé, A. Comar, Estimates of plant density of wheat crops at emergence from very low altitude UAV imagery, Remote Sens. Environ. 198 (2017) 105–114.	D. Gómez-Candón, N. Virlet, S. Labbé, A. Jolivot, J.-L. Regnard, Field phenotyping of water stress at tree scale by UAV-sensed imagery: new insights for thermal acquisition and calibration, Precis. Agric. 17 (6) (2016) 786–800.	M. Louargant, G. Jones, R. Faroux, J.-N. Paoli, T. Maillot, C. Gée, S. Villette, Unsupervised classification algorithm for early weed detection in rowcrops by combining spatial and spectral information, Remote Sens. 10 (5) (2018) 761.
Germany	M. Schirrmann, A. Hamdorf, A. Giebel, F. Gleiniger, M. Pflanz, K.-H. Dammer, Regression kriging for improving crop height models	N. Wilke, B. Siegmann, L. Klingbeil, A. Burkart, T. Kraska, Quantifying lodging percentage and lodging	A. Tewes, J. Schellberg, Towards remote estimation of radiation use efficiency in maize using uav-based low-	A. Burkart, V. Hecht, T. Kraska, U. Rascher, Phenological analysis of unmanned aerial vehicle based time series of barley imagery with

	fusing ultra-sonic sensing with UAV imagery, Remote Sens. 9 (7) (2017) 665.	severity using a UAV-based canopy height model combined with an objective threshold approach, Remote Sens. 11 (5) (2019) 515.	cost camera imagery, Agronomy 8 (2) (2018) 16.	high temporal resolution, Precis. Agric. 19 (1) (2018) 134–146.
	B. Siegmann, T. Jarmer, Comparison of different regression models and validation techniques for the assessment of wheat leaf area index from hyperspectral data, Int. J. Remote Sens. 36 (18) (2015) 4519–4534.	J. Bendig, A. Bolten, G. Bareth, UAV-based imaging for multi-temporal, very high Resolution Crop Surface Models to monitor Crop Growth Variability 2013 (6) (2013) 551–562.	J. Bendig, K. Yu, H. Aasen, A. Bolten, S. Bennertz, J. Broscheit, M.L. Gnyp, G. Bareth, Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley, Int. J. Appl. Earth Obs. Geoinf. 39 (2015) 79–87.	H. Aasen, A. Burkart, A. Bolten, G. Bareth, Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: From camera calibration to quality assurance, ISPRS J. Photogramm. Remote Sens. 108 (2015) 245–259.
	J. Geipel, J. Link, W. Claupein, Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system, Remote Sens. 6 (11) (2014) 10335–10355.	M. Schirrmann, A. Giebel, F. Gleiniger, M. Pflanz, J. Lentschke, K.-H. Dammer, Monitoring agronomic parameters of winter wheat crops with low-cost UAV imagery, Remote Sens. 8 (9) (2016)	J. Bendig, A. Bolten, S. Bennertz, J. Broscheit, S. Eichfuss, G. Bareth, Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging, Remote Sens. 6 (11) (2014) 10395–10412.	
Greece	P. Katsigiannis, L. Misopolinos, V. Liakopoulos, T.K. Alexandridis, G. Zalidis, An autonomous multi-sensor UAV system for reduced-input precision agriculture applications, in: 2016 24th Mediterranean Conference on Control and Automation (MED), IEEE, 2016, pp. 60–64.	P. Psirofonia, V. Samaritakis et. Al. Use of unmanned aerial vehicles for agricultural applications with emphasis on crop protection: Three novel case-studies, Int. J. Agric. Sci. Technol. 5 (1) (2017) 30–39.	I. Navrozidis, T.K. Alexandridis, A. Dimitrakos, A.L. Lagopodi, D. Moshou, G. Zalidis, Identification of purple spot disease on asparagus crops across spatial and spectral scales, Comput. Electron. Agric. 148 (2018) 322–329.	S. Kontogiannis, G. Kokkonis, S. Ellinidou, S. Valsamidis, Proposed fuzzynn algorithm with loracommunication protocol for clustered irrigation systems, Future Internet 9 (4) (2017) 78.

	E.I. Papageorgiou, A.T. Markinos, T.A. Gemtos, Fuzzy cognitive map based approach for predicting yield in cotton crop production as a basis for decision support system in precision agriculture application, Appl. Soft Comput. 11 (4) (2011) 3643–3657	A.C. Kyratzis, D.P. Skarlatos, G.C. Menexes, V.F. Vamvakousis, A. Katsiotis, Assessment of vegetation indices derived by UAV imagery for durum wheat phenotyping under a water limited and heat stressed mediterranean environment, Front. Plant Sci. 8 (2017) 1114	L. Busetto, S. Casteleyn, C. Granell, M. Pepe, M. Barbieri, M. Campos-Taberner, R. Casa, F. Collivignarelli, et al., Downstream services for rice crop monitoring in europe: From regional to local scale, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 10 (12) (2017) 5423–5441	
Ireland	C. Goumopoulos, B. O'Flynn, A. Kameas, Automated zone-specific irrigation with wireless sensor/actuator network and adaptable decision support, Comput. Electron. Agric. 105 (2014) 20–33.			
Italy	J. Primicerio, S.F. Di Gennaro, E. Fiorillo, L. Genesio, E. Lugato, A. Matese, F.P. Vaccari, A flexible unmanned aerial vehicle for precision agriculture, Precis. Agric. 13 (4) (2012) 517–523.	F. Castaldi, F. Pelosi, S. Pascucci, R. Casa, Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize, Precis. Agric. 18 (1) (2017) 76–94.	G. Caruso, L. Tozzini, G. Rallo, J. Primicerio, M. Moriondo, G. Palai, R. Gucci, Estimating biophysical and geometrical parameters of grapevine canopies ('sangiovese') by an unmanned aerial vehicle (UAV) and VIS-NIR cameras, Vitis 56 (2) (2017) 63–70.	B. Rey, N. Aleixos, S. Cubero, J. Blasco, XF-ROVIM. A field robot to detect olive trees infected by xylella fastidiosa using proximal sensing, Remote Sens. 11 (3) (2019) 221.
	N. Sales, O. Remédios, A. Arsenio, Wireless sensor and actuator system for smart irrigation on the cloud, in: 2015 IEEE 2nd World Forum on Internet of Things (WF-IoT), IEEE, 2015, pp. 693–698.	F.F. Montesano, M.W. Van Iersel, F. Boari, V. Cantoreet. Al. Sensor-based irrigation management of soilless basil using a new smart irrigation system: Effects of set-point on plant physiological responses and crop performance, Agric. Water Manag. 203 (2018) 20–29	A. Matese, S.F. Di Gennaro, Practical applications of a multisensor uav platform based on multispectral, thermal and rgb high resolution images in precision viticulture, Agriculture 8 (7) (2018) 116.	L. Cantelli, F. Bonaccorso, D. Longo, C.D. Melita, G. Schillaci, G. Muscato, A small versatile electrical robot for autonomous spraying in agriculture, AgriEngineering 1 (3) (2019) 391–402.

	L. Comba, P. Gay, J. Primicerio, D.R. Aimonino, Vineyard detection from unmanned aerial systems images, Comput. Electron. Agric. 114 (2015) 78–87.	A. Matese, P. Toscano, S.F. Di Gennaro, L. Genesio, F.P. Vaccari, J. Primicerio, C. Belli, A. Zaldei, R. Bianconi, B. Gioli, Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture, Remote Sens. 7 (3) (2015) 2971–2990.	S. Marino, A. Alvino, Detection of homogeneous wheat areas using multitemporal UAS images and ground truth data analyzed by cluster analysis, Eur. J. Remote Sens. 51 (1) (2018) 266–275.	R. Calderón, M. Montes-Borrego, B. Landa, J. Navas-Cortés, P. Zarco-Tejada, Detection of downy mildew of opium poppy using high-resolution multispectral and thermal imagery acquired with an unmanned aerial vehicle, Precis. Agric. 15 (6) (2014) 639–661.
	M. Fawakherji, A. Youssef, D. Bloisi, A. Pretto, D. Nardi, Crop and weeds classification for precision agriculture using context-independent pixelwise segmentation, in: 2019 Third IEEE International Conference on Robotic Computing (IRC), IEEE, 2019, pp. 146–152.	L. Busetto, S. Casteleyn, C. Granell, M. Pepe, M. Barbieri, M. Campos-Taberner, et al., Downstream services for rice crop monitoring in europe: From regional to local scale, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 10 (12) (2017) 5423–5441	D. Stroppiana, M. Migliazzi, V. Chiarabini, A. Crema, M. Musanti, C. Franchino, P. Villa, Rice yield estimation using multispectral data from UAV: A preliminary experiment in northern Italy, in: 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), IEEE, 2015, pp. 4664–4667.	S. Candiago, F. Remondino, M. De Giglio, M. Dubbini, M. Gattelli, Evaluating multispectral images and vegetation indices for precision farming applications from UAV images, Remote Sens. 7 (4) (2015) 4026–4047.
Lithuania	G. Mozgeris, D. Jonikavičius, D. Jovarauskas, R. Zinkevičius, S. Petkevičius, D. Steponavičius, Imaging from manned ultra-light and unmanned aerial vehicles for estimating properties of spring wheat, Precis. Agric. 19 (5) (2018) 876–894.			
Netherlands	K. Ivushkin, H. Bartholomeus, A.K. Bregt, A. Pulatov, M.H. Franceschini, H. Kramer, E.N. van Loo, V.J. Roman, R. Finkers, UAV based soil salinity assessment of cropland, Geoderma 338 (2019) 502–512.		J. Valente, R. Almeida, L. Kooistra, A comprehensive study of the potential application of flying ethylene-sensitive sensors for ripeness detection in apple orchards, Sensors 19 (2) (2019) 372.	
Norway	I. Burud, G. Lange, M. Lillemo, E. Bleken, L. Grimstad, P.J. From, Exploring robots and UAVs as phenotyping tools in plant breeding, IFAC-PapersOnLine 50 (1) (2017) 11479–11484.			
Poland	R. Pudelko, T. Stuczynski, M. Borzecka-Walker, et al., The suitability of an unmanned aerial vehicle (UAV) for the evaluation of experimental fields and crops, Agriculture 99 (4) (2012) 431–436.			
Portugal	A.C. Cruz, A. Luvisi, L. De Bellis, Y. Ampatzidis, X-FIDO: An effective application for detecting olive quick decline syndrome with	L. Pádua, P. Marques, J. Hruška, T. Adão, E. Peres, R. Morais, J.J. Sousa, Multi-temporal vineyard	J.M. Mendes, F.N. dos Santos, N.A. Ferraz, P.M. do Couto, R.M. dos Santos, Localization based on natural features	

	deep learning and data fusion, Front. Plant Sci. 8 (2017) 1741.	monitoring through UAV-based RGB imagery, Remote Sens. 10 (12) (2018) 1907.	detector for steep slope vineyards, J. Intell. Robot. Syst. 93 (3–4) (2019) 433–446.	
Russia	A. Somov, D. Shadrin, I. Fastovets, A. Nikitin, S. Matveev, O. Hrinchuk, et al., Pervasive agriculture: IoT-enabled greenhouse for plant growth control, IEEE Pervasive Comput. 17 (4) (2018) 65–75.			
Spain	V. Gonzalez-Dugo, P. Zarco-Tejada, E. Nicolás, P.A. Nortes, J. Alarcón, D.S.Intrigliolo, E. Fereres, Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard, Precis. Agric. 14 (6) (2013) 660–678.	J. Torres-Sánchez, A.I. de Castro, J.M. Pena, F.M. Jiménez-Brenes, O. Arquero, M. Lovera, F. López-Granados, Mapping the 3D structure of almond trees using UAV acquired photogrammetric point clouds and object-based image analysis, Biosyst. Eng. 176 (2018) 172–184	N. Pavón-Pulido, J. López-Riquelme, R. Torres, R. Morais, J. Pastor, New trends in precision agriculture: a novel cloud-based system for enabling data storage and agricultural task planning and automation, Precis. Agric. 18 (6) (2017) 1038–1068.	M.A. Zamora-Izquierdo, J. Santa, J.A. Martínez, V. Martínez, A.F. Skarmeta, Smart farming IoT platform based on edge and cloud computing, Biosyst. Eng. 177 (2019) 4–17.
	J. López-Riquelme, N. Pavón-Pulido, H. Navarro-Hellín, F. Soto-Valles, R. Torres-Sánchez, A software architecture based on FIWARE cloud for precision agriculture, Agric. Water Manag. 183 (2017) 123–135.	J. Campos, J. Llop, M. Gallart, F. García-Ruiz, A. Gras, R. Salcedo, E. Gil, Development of canopy vigour maps using UAV for site-specific management during vineyard spraying process, Precis. Agric. 20 (6) (2019) 1136–1156.	P. Gonzalez-de Santos, A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez-Granados, M. Brandstoetter, S. Tomic, S. Pedrazzi, A. Peruzzi, G. Pajares, et al., Fleets of robots for environmentally-safe pest control in agriculture, Precis. Agric. 18 (4) (2017) 574–614.	J. Martinez-Guanter, P. Agüera, J. Agüera, M. Pérez-Ruiz, Spray and economics assessment of a UAV-based ultra-low-volume application in olive and citrus orchards, Precis. Agric. 21 (1) (2020) 226–243.
	K. Ribeiro-Gomes, D. Hernández-López, J.F. Ortega, R. Ballesteros, T. Poblete, M.A. Moreno, Uncooled thermal camera calibration and optimization of the photogrammetry process for	M. Pérez-Ortiz, J.M. Peña, P.A. Gutiérrez, J. Torres-Sánchez, C. Hervás-Martínez, F. López-Granados, Selecting patterns and features for betweenand within-crop-	J.M. Peña, J. Torres-Sánchez, A. Serrano-Pérez, A.I. De Castro, F. López- Granados, Quantifying efficacy and limits of unmanned aerial vehicle (UAV) technology for weed seedling detection as affected	D. Gómez, P. Salvador, J. Sanz, J.L. Casanova, Potato yield prediction using machine learning techniques and sentinel 2 data, Remote Sens. 11 (15) (2019) 1745.

	UAV applications in agriculture, Sensors 17 (10) (2017) 2173.	row weed mapping using UAV-imagery, Expert Syst. Appl. 47 (2016) 85–94.	by sensor resolution, Sensors 15 (3) (2015) 5609–5626.	
	E. Salamí, A. Gallardo, G. Skorobogatov, C. Barrado, On-the-fly olive tree counting using a UAS and cloud services, Remote Sens. 11 (3) (2019) 316.	P.J. Zarco-Tejada, V. González-Dugo, J.A. Berni, Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera, Remote Sens. Environ. 117 (2012) 322–337.	C. Romero-Trigueros, P.A. Nortes, J.J. Alarcón, J.E. Hunink, M. Parra, S. Contreras, P. Droogers, E. Nicolás, Effects of saline reclaimed waters and deficit irrigation on citrus physiology assessed by UAV remote sensing, Agric. Water Manag. 183 (2017) 60–69.	F.J. Ferrández-Pastor, J.M. García-Chamizo, M. Nieto-Hidalgo, J. Mora- Pascual, J. Mora-Martínez, Developing ubiquitous sensor network platform using internet of things: Application in precision agriculture, Sensors 16 (7) (2016) 1141.
	S.C. Kefauver, R. Vicente, O. Vergara-Díaz, J.A. Fernandez-Gallego, S. Kerfal, A. Lopez, J.P. Melichar, M.D. Serret Molins, J.L. Araus, Comparative UAV and field phenotyping to assess yield and nitrogen use efficiency in hybrid and conventional barley, Front. Plant Sci. 8 (2017) 1733.	K. Espinoza, D.L. Valera, J.A. Torres, A. López, F.D. Molina-Aiz, Combination of image processing and artificial neural networks as a novel approach for the identification of bemisia tabaci and frankliniella occidentalis on sticky traps in greenhouse agriculture, Comput. Electron. Agric. 127 (2016) 495–505.	J. Baluja, M.P. Diago, P. Balda, R. Zorer, F. Meggio, F. Morales, J. Tardaguila, Assessment of vineyard water status variability by thermal and multispectral imagery using an unmanned aerial vehicle (UAV), Irrigat. Sci. 30 (6) (2012) 511–522.	Á. Maresma, M. Ariza, E. Martínez, J. Lloveras, J.A. Martínez-Casasnovas, Analysis of vegetation indices to determine nitrogen application and yield prediction in maize (Zea mays L.) from a standard UAV service, Remote Sens. 8 (12) (2016) 973.
	J. Martínez, G. Egea, J. Agüera, M. Pérez-Ruiz, A cost-effective canopy temperature measurement system for precision agriculture: a case study on sugar beet, Precis. Agric. 18 (1) (2017) 95–110.	L. Busetto, S. Casteleyn, C. Granell, M. Pepe, M. Barbieri, M. Campos-Taberner, R. Casa, F. Collivignarelli, et al., Downstream services for rice crop monitoring in	F.-J. Mesas-Carrascosa, J. Torres-Sánchez, I. Clavero-Rumbao, A. García-Ferrer, J.-M. Peña, I. Borra-Serrano, F. López-Granados, Assessing optimal flight parameters for generating accurate	P.J. Zarco-Tejada, R. Diaz-Varela, V. Angileri, P. Loudjani, Tree height quantification using very high resolution imagery acquired from an unmanned aerial vehicle (UAV) and automatic 3D photo-

		europe: From regional to local scale, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 10 (12) (2017) 5423–5441	multispectral orthomosaicks by UAV to support site-specific crop management, Remote Sens. 7 (10) (2015) 12793–12814.	reconstruction methods, Eur. J. Agron. 55 (2014) 89–99
	L. Santesteban, S. Di Gennaro, A. Herrero-Langreo, C. Miranda, J. Royo, A. Matese, High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard, Agric. Water Manag. 183 (2017) 49–59.	J.M. Peña, J. Torres-Sánchez, A.I. de Castro, M. Kelly, F. López-Granados, Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images, PLoS One 8 (10) (2013).	J. Torres-Sánchez, F. López-Granados, A.I. De Castro, J.M. Peña-Barragán, Configuration and specifications of an unmanned aerial vehicle (UAV) for early site specific weed management, PLoS One 8 (3) (2013).	F. López-Granados, J. Torres-Sánchez, A. Serrano-Pérez, A.I. de Castro, F.-J. Mesas-Carrascosa, J.-M. Pena, Early season weed mapping in sunflower using UAV technology: variability of herbicide treatment maps against weed thresholds, Precis. Agric. 17 (2) (2016) 183–199.
	D. Gómez-Candón, A. De Castro, F. López-Granados, Assessing the accuracy of mosaics from unmanned aerial vehicle (UAV) imagery for precision agriculture purposes in wheat, Precis. Agric. 15 (1) (2014) 44–56.	J. Torres-Sánchez, J.M. Pena, A.I. de Castro, F. López-Granados, Multitemporal mapping of the vegetation fraction in early-season wheat fields using images from UAV, Comput. Electron. Agric. 103 (2014) 104–113.	R. Morais, N. Silva, J. Mendes, T. Adão, L. Pádua, J. López-Riquelme, N. Pavón-Pulido, J.J. Sousa, E. Peres, Mysense: A comprehensive data management environment to improve precision agriculture practices, Comput. Electron. Agric. 162 (2019) 882–894.	F.A. Vega, F.C. Ramirez, M.P. Saiz, F.O. Rosua, Multi-temporal imaging using an unmanned aerial vehicle for monitoring a sunflower crop, Biosyst. Eng. 132 (2015) 19–27.
	K. Kuželka, P. Surovy` , Automatic detection and quantification of wild game crop damage using an unmanned aerial vehicle (UAV) equipped with an optical sensor payload: a case study in wheat, Eur. J. Remote Sens. 51 (1) (2018) 241–250.	J.I. Córcoles, J.F. Ortega, D. Hernández, M.A. Moreno, Estimation of leaf area index in onion (Allium cepa L.) using an unmanned aerial vehicle, Biosyst. Eng. 115 (1) (2013) 31–42.	F. López-Granados, J. Torres-Sánchez, A.-I. De Castro, A. Serrano-Pérez, F.- J. Mesas-Carrascosa, J.-M. Peña, Object-based early monitoring of a grass weed in a grass crop using high resolution UAV imagery, Agron. Sustain. Dev. 36 (4) (2016) 67.	M.L. Guillén-Climent, P.J. Zarco-Tejada, J.A. Berni, P.R. North, F.J. Villalobos, Mapping radiation interception in row-structured orchards using 3D simulation and high-resolution airborne imagery acquired from a UAV, Precis. Agric. 13 (4) (2012) 473–500.

	R.A. Díaz-Varela, R. De la Rosa, L. León, P.J. Zarco-Tejada, High-resolution airborne UAV imagery to assess olive tree crown parameters using 3D photo reconstruction: application in breeding trials, Remote Sens. 7 (4) (2015) 4213–4232.	A.M. García, I.F. García, E.C. Poyato, P.M. Barrios, J.R. Díaz, Coupling irrigation scheduling with solar energy production in a smart irrigation management system, J. Clean. Prod. 175 (2018) 670–682.	L. Quebrajo, M. Perez-Ruiz, L. Pérez-Urrestarazu, G. Martínez, G. Egea, Linking thermal imaging and soil remote sensing to enhance irrigation management of sugar beet, Biosyst. Eng. 165 (2018) 77–87.	

Table 36. Crops used in European research efforts (Adapted from [113])

Crops	References		
Almond Trees	J. López-Riquelme, N. Pavón-Pulido, H. Navarro-Hellín, F. Soto-Valles, R. Torres-Sánchez, A software architecture based on FIWARE cloud for precision agriculture, Agric. Water Manag. 183 (2017) 123–135.	V. Gonzalez-Dugo, P. Zarco-Tejada, E. Nicolás, P.A. Nortes, J. Alarcón, D.S.Intrigliolo, E. Fereres, Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard, Precis. Agric. 14 (6) (2013) 660–678.	J. Torres-Sánchez, A.I. de Castro, J.M. Pena, F.M. Jiménez-Brenes, O.Arquero, M. Lovera, F. López-Granados, Mapping the 3D structure of almond trees using UAV acquired photogrammetric point clouds and object-based image analysis, Biosyst. Eng. 176 (2018) 172–184
Apple Trees	D. Gómez-Candón, N. Virlet, S. Labbé, A. Jolivot, J.-L. Regnard, Field phenotyping of water stress at tree scale by UAV-sensed imagery: new insights for thermal acquisition and calibration, Precis. Agric. 17 (6) (2016) 786–800.	J. Valente, R. Almeida, L. Kooistra, A comprehensive study of the potential application of flying ethylene-sensitive sensors for ripeness detection in apple orchards, Sensors 19 (2) (2019) 372.	T.T. Nguyen, K. Vandevoorde, E. Kayacan, J. De Baerdemaeker, W. Saeys, Apple detection algorithm for robotic harvesting using a RGB-D camera, in: International Conference of Agricultural Engineering, Zurich, Switzerland, 2014.
Apricot Trees	V. Gonzalez-Dugo, P. Zarco-Tejada, E. Nicolás, P.A. Nortes, J. Alarcón, D.S. Intrigliolo, E. Fereres, Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard, Precis. Agric. 14 (6) (2013) 660–678.		
Asparagus	I. Navrozidis, T.K. Alexandridis, A. Dimitrakos, A.L. Lagopodi, D. Moshou, G. Zalidis, Identification of purple spot disease on asparagus crops across spatial and spectral scales, Comput. Electron. Agric. 148 (2018) 322–329.		
Barley	E. Honkavaara, H. Saari, J. Kaivosoja, I. Pölönen, T. Hakala, P. Litkey, J. Mäkynen, L. Pesonen, Processing and assessment of spectrometric, stereoscopic imagery collected using a lightweight UAV spectral camera for precision agriculture, Remote Sens. 5 (10) (2013) 5006–5039.	R. Pudelko, T. Stuczynski, M. Borzecka-Walker, et al., The suitability of an unmanned aerial vehicle (UAV) for the evaluation of experimental fields and crops, Agriculture 99 (4) (2012) 431–436.	H. Hoffmann, R. Jensen, A. Thomsen, H. Nieto, J. Rasmussen, T. Friborg, Crop water stress maps for an entire growing season from visible and thermal UAV imagery, Biogeosciences 13 (24) (2016) 6545–6563
	A. Burkart, V. Hecht, T. Kraska, U. Rascher, Phenological analysis of unmanned aerial vehicle based time series of barley imagery with high temporal resolution, Precis. Agric. 19 (1) (2018) 134–146.	H. Hoffmann, H. Nieto, R. Jensen, R. Guzinski, P. Zarco-Tejada, T. Friborg, Estimating evaporation with thermal UAV data and two-source energy balance models, Hydrol. Earth Syst. Sci. 20 (2) (2016) 697–713.	S.C. Kefauver, R. Vicente, O. Vergara-Díaz, J.A. Fernandez-Gallego, S. Kerfal, A. Lopez, J.P. Melichar, M.D. Serret Molins, J.L. Araus, Comparative UAV and field phenotyping to assess yield and nitrogen use efficiency in hybrid and

			conventional barley, Front. Plant Sci. 8 (2017) 1733.
	J. Bendig, A. Bolten, G. Bareth, UAV-based imaging for multi-temporal, very high Resolution Crop Surface Models to monitor Crop Growth Variability Monitoring des Pflanzenwachstums mit Hilfe multitemporaler und hoch auflösender Oberflächenmodelle von Getreidebeständen auf Basis von Bildern aus UAV-Befliegungen, Photogramme.-Fernerkundung-Geoinf.2013 (6) (2013) 551–562.	J. Bendig, K. Yu, H. Aasen, A. Bolten, S. Bennertz, J. Broscheit, M.L. Gnyp, G. Bareth, Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley, Int. J. Appl. Earth Obs. Geoinf. 39 (2015) 79–87.	H. Aasen, A. Burkart, A. Bolten, G. Bareth, Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: From camera calibration to quality assurance, ISPRS J. Photogramm. Remote Sens. 108 (2015) 245–259.
	J. Bendig, A. Bolten, S. Bennertz, J. Broscheit, S. Eichfuss, G. Bareth, Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging, Remote Sens. 6 (11) (2014) 10395–10412.		
Basil	F.F. Montesano, M.W. Van Iersel, F. Boari, V. Cantore, G. D'Amato, A. Parente, Sensor-based irrigation management of soilless basil using a new smart irrigation system: Effects of set-point on plant physiological responses and crop performance, Agric. Water Manag. 203 (2018) 20–29		
Bean	F.J. Ferrández-Pastor, J.M. García-Chamizo, M. Nieto-Hidalgo, J. Mora- Pascual, J. Mora-Martínez, Developing ubiquitous sensor network platform using internet of things: Application in precision agriculture, Sensors 16 (7) (2016) 1141.		
Cherry Trees	N. Pavón-Pulido, J. López-Riquelme, R. Torres, R. Morais, J. Pastor, New trends in precision agriculture: a novel cloud-based system for enabling data storage and agricultural task planning and automation, Precis. Agric. 18 (6) (2017) 1038–1068.		
Clementine Trees	M.L. Guillén-Climent, P.J. Zarco-Tejada, J.A. Berni, P.R. North, F.J. Villalobos, Mapping radiation interception in row-structured orchards using 3D simulation and high-resolution airborne imagery acquired from a UAV, Precis. Agric. 13 (4) (2012) 473–500.		
Corn	J. Geipel, J. Link, W. Claupein, Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system, Remote Sens. 6 (11) (2014) 10335–10355.		
Cotton	E.I. Papageorgiou, A.T. Markinos, T.A. Gemtos, Fuzzy cognitive map based approach for predicting yield in cotton crop production as a basis for decision support system in precision agriculture application, Appl. Soft Comput. 11 (4) (2011) 3643–3657		
Grapefruit Trees	C. Romero-Trigueros, P.A. Nortes, J.J. Alarcón, J.E. Hunink, M. Parra, S. Contreras, P. Droogers, E. Nicolás, Effects of saline reclaimed waters and deficit irrigation on citrus physiology assessed by UAV remote sensing, Agric. Water Manag. 183 (2017) 60–69.		

Lemon Trees	J. López-Riquelme, N. Pavón-Pulido, H. Navarro-Hellín, F. Soto-Valles, R. Torres-Sánchez, A software architecture based on FIWARE cloud for precision agriculture, Agric. Water Manag. 183 (2017) 123–135.	V. Gonzalez-Dugo, P. Zarco-Tejada, E. Nicolás, P.A. Nortes, J. Alarcón, D.S.Intrigliolo, E. Fereres, Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard, Precis. Agric. 14 (6) (2013) 660–678.	
Maize	F. Kurtulmuş, I. Kavdir, Detecting corn tassels using computer vision and support vector machines, Expert Syst. Appl. 41 (16) (2014) 7390–7397.	F. Castaldi, F. Pelosi, S. Pascucci, R. Casa, Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize, Precis. Agric. 18 (1) (2017) 76–94.	P. Gonzalez-de Santos, A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez-Granados, M. Brandstoetter, S. Tomic, S. Pedrazzi, A. Peruzzi, G. Pajares, G. Kaplanis, et al., Fleets of robots for environmentally-safe pest control in agriculture, Precis. Agric. 18 (4) (2017) 574–614.
	R. Pudelko, T. Stuczynski, M. Borzecka-Walker, et al., The suitability of an unmanned aerial vehicle (UAV) for the evaluation of experimental fields and crops, Agriculture 99 (4) (2012) 431–436.	M. Louargant, G. Jones, R. Faroux, J.-N. Paoli, T. Maillot, C. Gée, S. Villette, Unsupervised classification algorithm for early weed detection in rowcrops by combining spatial and spectral information, Remote Sens. 10 (5) (2018) 761.	M. Pérez-Ortiz, J.M. Peña, P.A. Gutiérrez, J. Torres-Sánchez, C. Hervás- Martínez, F. López-Granados, Selecting patterns and features for betweenand within-crop-row weed mapping using UAV-imagery, Expert Syst. Appl. 47 (2016) 85–94.
	N. Wilke, B. Siegmann, L. Klingbeil, A. Burkart, T. Kraska, O. Muller, A. van Doorn, S. Heinemann, U. Rascher, Quantifying lodging percentage and lodging severity using a UAV-based canopy height model combined with an objective threshold approach, Remote Sens. 11 (5) (2019) 515.	A. Tewes, J. Schellberg, Towards remote estimation of radiation use efficiency in maize using uav-based low-cost camera imagery, Agronomy 8 (2) (2018) 16.	F. López-Granados, J. Torres-Sánchez, A.-I. De Castro, A. Serrano-Pérez, F.- J. Mesas-Carrascosa, J.-M. Peña, Object-based early monitoring of a grass weed in a grass crop using high resolution UAV imagery, Agron. Sustain. Dev. 36 (4) (2016) 67.
	A. Michez, S. Bauwens, Y. Brostaux, M.-P. Hiel, S. Garré, P. Lejeune, B. Dumont, How far can consumer-grade UAV RGB imagery describe crop production? A 3D and multitemporal modeling approach applied to zea mays, Remote Sens. 10 (11) (2018) 1798.	Á. Maresma, M. Ariza, E. Martínez, J. Lloveras, J.A. Martínez-Casasnovas, Analysis of vegetation indices to determine nitrogen application and yield prediction in maize (Zea mays L.) from a standard UAV service, Remote Sens. 8 (12) (2016) 973	J.M. Peña, J. Torres-Sánchez, A.I. de Castro, M. Kelly, F. López-Granados, Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images, PLoS One 8 (10) (2013).

Mandarin Trees	P.J. Zarco-Tejada, V. González-Dugo, J.A. Berni, Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera, Remote Sens. Environ. 117 (2012) 322–337.	C. Romero-Trigueros, P.A. Nortes, J.J. Alarcón, J.E. Hunink, M. Parra, S. Contreras, P. Droogers, E. Nicolás, Effects of saline reclaimed waters and deficit irrigation on citrus physiology assessed by UAV remote sensing, Agric. Water Manag. 183 (2017) 60–69.	
Nectarine Trees	M.L. Guillén-Climent, P.J. Zarco-Tejada, J.A. Berni, P.R. North, F.J. Villalobos, Mapping radiation interception in row-structured orchards using 3D simulation and high-resolution airborne imagery acquired from a UAV, Precis. Agric. 13 (4) (2012) 473–500.		
Olive Trees	A.M. García, I.F. García, E.C. Poyato, P.M. Barrios, J.R. Díaz, Coupling irrigation scheduling with solar energy production in a smart irrigation management system, J. Clean. Prod. 175 (2018) 670–682.	P. Gonzalez-de Santos, A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez- Granados, M. Brandstoetter, S. Tomic, S. Pedrazzi, A. Peruzzi, G. Pajares, G. Kaplanis, et al., Fleets of robots for environmentally-safe pest control in agriculture, Precis. Agric. 18 (4) (2017) 574–614.	J. Martinez-Guanter, P. Agüera, J. Agüera, M. Pérez-Ruiz, Spray and economics assessment of a UAV-based ultra-low-volume application in olive and citrus orchards, Precis. Agric. 21 (1) (2020) 226–243.
	P. Psirofonia, V. Samaritakis, P. Eliopoulos, I. Potamitis, Use of unmanned aerial vehicles for agricultural applications with emphasis on crop protection: Three novel case-studies, Int. J. Agric. Sci. Technol. 5 (1) (2017) 30–39.	N. Sales, O. Remédios, A. Arsenio, Wireless sensor and actuator system for smart irrigation on the cloud, in: 2015 IEEE 2nd World Forum on Internet of Things (WF-IoT), IEEE, 2015, pp. 693–698.	B. Rey, N. Aleixos, S. Cubero, J. Blasco, XF-ROVIM. A field robot to detect olive trees infected by xylella fastidiosa using proximal sensing, Remote Sens. 11 (3) (2019) 221.
	E. Salamí, A. Gallardo, G. Skorobogatov, C. Barrado, On-the-fly olive tree counting using a UAS and cloud services, Remote Sens. 11 (3) (2019) 316.	K. Kuželka, P. Surovy` , Automatic detection and quantification of wild game crop damage using an unmanned aerial vehicle (UAV) equipped with an optical sensor payload: a case study in wheat, Eur. J. Remote Sens. 51 (1) (2018) 241–250.	R.A. Díaz-Varela, R. De la Rosa, L. León, P.J. Zarco-Tejada, High-resolution airborne UAV imagery to assess olive tree crown parameters using 3D photo reconstruction: application in breeding trials, Remote Sens. 7 (4) (2015) 4213–4232.
	P.J. Zarco-Tejada, R. Diaz-Varela, V. Angileri, P. Loudjani, Tree height quantification using very high resolution imagery acquired from an unmanned aerial vehicle (UAV) and automatic 3D photo-reconstruction methods, Eur. J. Agron. 55 (2014) 89–99		
Opium Poppy	R. Calderón, M. Montes-Borrego, B. Landa, J. Navas-Cortés, P. Zarco-Tejada, Detection of downy mildew of opium poppy using high-resolution multispectral and thermal imagery acquired with an unmanned aerial vehicle, Precis. Agric. 15 (6) (2014) 639–661.		

Orange Trees	J. Martinez-Guanter, P. Agüera, J. Agüera, M. Pérez-Ruiz, Spray and economics assessment of a UAV-based ultra-low-volume application in olive and citrus orchards, Precis. Agric. 21 (1) (2020) 226–243.	M.L. Guillén-Climent, P.J. Zarco-Tejada, J.A. Berni, P.R. North, F.J. Villalobos, Mapping radiation interception in row-structured orchards using 3D simulation and high-resolution airborne imagery acquired from a UAV, Precis. Agric. 13 (4) (2012) 473–500.	P.J. Zarco-Tejada, V. González-Dugo, J.A. Berni, Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera, Remote Sens. Environ. 117 (2012) 322–337.
	V. Gonzalez-Dugo, P. Zarco-Tejada, E. Nicolás, P.A. Nortes, J. Alarcón, D.S. Intrigliolo, E. Fereres, Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard, Precis. Agric. 14 (6) (2013) 660–678.		
Peach Trees	A.C. Cruz, A. Luvisi, L. De Bellis, Y. Ampatzidis, X-FIDO: An effective application for detecting olive quick decline syndrome with deep learning and data fusion, Front. Plant Sci. 8 (2017) 1741.	M.L. Guillén-Climent, P.J. Zarco-Tejada, J.A. Berni, P.R. North, F.J. Villalobos, Mapping radiation interception in row-structured orchards using 3D simulation and high-resolution airborne imagery acquired from a UAV, Precis. Agric. 13 (4) (2012) 473–500.	V. Gonzalez-Dugo, P. Zarco-Tejada, E. Nicolás, P.A. Nortes, J. Alarcón, D.S. Intrigliolo, E. Fereres, Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard, Precis. Agric. 14 (6) (2013) 660–678.
Pomegranate	P. Katsigiannis, L. Misopolinos, V. Liakopoulos, T.K. Alexandridis, G. Zalidis, An autonomous multi-sensor UAV system for reduced-input precision agriculture applications, in: 2016 24th Mediterranean Conference on Control and Automation (MED), IEEE, 2016, pp. 60–64.		
Potatoes	D. Gómez, P. Salvador, J. Sanz, J.L. Casanova, Potato yield prediction using machine learning techniques and sentinel 2 data, Remote Sens. 11 (15) (2019) 1745.		
Quinoa	K. Ivushkin, H. Bartholomeus, A.K. Bregt, A. Pulatov, M.H. Franceschini, H. Kramer, E.N. van Loo, V.J. Roman, R. Finkers, UAV based soil salinity assessment of cropland, Geoderma 338 (2019) 502–512.		
Rice	L. Busetto, S. Casteleyn, C. Granell, M. Pepe, M. Barbieri, et al., Downstream services for rice crop monitoring in europe: From regional to local scale, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 10 (12) (2017) 5423–5441	D. Stroppiana, M. Migliazzi, V. Chiarabini, A. Crema, M. Musanti, C. Franchino, P. Villa, Rice yield estimation using multispectral data from UAV: A preliminary experiment in northern Italy, in: 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), IEEE, 2015, pp. 4664–4667.	
Soybean	C. Potena, R. Khanna, J. Nieto, R. Siegwart, D. Nardi, A. Pretto, AgriColMap: Aerial-ground collaborative 3D mapping for precision farming, IEEE Robot. Autom. Lett. 4 (2) (2019) 1085–1092.		
Strawberry	C. Goumopoulos, B. O'Flynn, A. Kameas, Automated zone-specific irrigation with wireless sensor/actuator network and adaptable decision support, Comput. Electron. Agric. 105 (2014) 20–33.		

Sugar beet	M. Louargant, G. Jones, R. Faroux, J.-N. Paoli, T. Maillot, C. Gée, S. Villette, Unsupervised classification algorithm for early weed detection in rowcrops by combining spatial and spectral information, Remote Sens. 10 (5) (2018) 761.	L. Quebrajo, M. Perez-Ruiz, L. Pérez-Urrestarazu, G. Martínez, G. Egea, Linking thermal imaging and soil remote sensing to enhance irrigation management of sugar beet, Biosyst. Eng. 165 (2018) 77–87.	C. Potena, R. Khanna, J. Nieto, R. Siegwart, D. Nardi, A. Pretto, AgriColMap: Aerial-ground collaborative 3D mapping for precision farming, IEEE Robot. Autom. Lett. 4 (2) (2019) 1085–1092.
	J. Martínez, G. Egea, J. Agüera, M. Pérez-Ruiz, A cost-effective canopy temperature measurement system for precision agriculture: a case study on sugar beet, Precis. Agric. 18 (1) (2017) 95–110.		
Sunflowers	M. Pérez-Ortiz, J.M. Peña, P.A. Gutiérrez, J. Torres-Sánchez, C. Hervás-Martínez, F. López-Granados, Selecting patterns and features for betweenand within-crop-row weed mapping using UAV-imagery, Expert Syst. Appl. 47 (2016) 85–94.	J.M. Peña, J. Torres-Sánchez, A. Serrano-Pérez, A.I. De Castro, F. López- Granados, Quantifying efficacy and limits of unmanned aerial vehicle (UAV) technology for weed seedling detection as affected by sensor resolution, Sensors 15 (3) (2015) 5609–5626.	F.A. Vega, F.C. Ramirez, M.P. Saiz, F.O. Rosua, Multi-temporal imaging using an unmanned aerial vehicle for monitoring a sunflower crop, Biosyst. Eng. 132 (2015) 19–27.
	M. Fawakherji, A. Youssef, D. Bloisi, A. Pretto, D. Nardi, Crop and weeds classification for precision agriculture using context-independent pixelwise segmentation, in: 2019 Third IEEE International Conference on Robotic Computing (IRC), IEEE, 2019, pp. 146–152.	J. Torres-Sánchez, F. López-Granados, A.I. De Castro, J.M. Peña-Barragán, Configuration and specifications of an unmanned aerial vehicle (UAV) for early site specific weed management, PLoS One 8 (3) (2013).	F. López-Granados, J. Torres-Sánchez, A. Serrano-Pérez, A.I. de Castro, F.-J. Mesas-Carrascosa, J.-M. Pena, Early season weed mapping in sunflower using UAV technology: variability of herbicide treatment maps against weed thresholds, Precis. Agric. 17 (2) (2016) 183–199.
Tomatoes	M.A. Zamora-Izquierdo, J. Santa, J.A. Martínez, V. Martínez, A.F. Skarmeta, Smart farming IoT platform based on edge and cloud computing, Biosyst. Eng. 177 (2019) 4–17.	L. Cantelli, F. Bonaccorso, D. Longo, C.D. Melita, G. Schillaci, G. Muscato, A small versatile electrical robot for autonomous spraying in agriculture, AgriEngineering 1 (3) (2019) 391–402.	A. Somov, D. Shadrin, I. Fastovets, A. Nikitin, S. Matveev, O. Hrinchuk, et al., Pervasive agriculture: IoT-enabled greenhouse for plant growth control, IEEE Pervasive Comput. 17 (4) (2018) 65–75.
	S. Kontogiannis, G. Kokkonis, S. Ellinidou, S. Valsamidis, Proposed fuzzynn algorithm with loracommunication protocol for clustered irrigation systems, Future Internet 9 (4) (2017) 78.	K. Espinoza, D.L. Valera, J.A. Torres, A. López, F.D. Molina-Aiz, Combination of image processing and artificial neural networks as a novel approach for the identification of bemisia tabaci and frankliniella occidentalis on	S. Candiago, F. Remondino, M. De Giglio, M. Dubbini, M. Gattelli, Evaluating multispectral images and vegetation indices for precision farming applications from UAV images, Remote Sens. 7 (4) (2015) 4026–4047.

		sticky traps in greenhouse agriculture, Comput. Electron. Agric. 127 (2016) 495–505.	
Vineyard	J. Primicerio, S.F. Di Gennaro, E. Fiorillo, L. Genesio, E. Lugato, A. Matese, F.P. Vaccari, A flexible unmanned aerial vehicle for precision agriculture, Precis. Agric. 13 (4) (2012) 517–523.	J. Albetis, S. Duthoit, F. Guttler, A. Jacquin, M. Goulard, H. Poilvé, J.-B. Féret, G. Dedieu, Detection of Flavescence dorée grapevine disease using Unmanned Aerial Vehicle (UAV) multispectral imagery, Remote Sens. 9 (4) (2017) 308.	J. Campos, J. Llop, M. Gallart, F. García-Ruiz, A. Gras, R. Salcedo, E. Gil, Development of canopy vigour maps using UAV for site-specific management during vineyard spraying process, Precis. Agric. 20 (6) (2019) 1136–1156.
	G. Caruso, L. Tozzini, G. Rallo, J. Primicerio, M. Moriondo, G. Palai, R. Gucci, Estimating biophysical and geometrical parameters of grapevine canopies ('sangiovese') by an unmanned aerial vehicle (UAV) and VIS-NIR cameras, Vitis 56 (2) (2017) 63–70.	K. Ribeiro-Gomes, D. Hernández-López, J.F. Ortega, R. Ballesteros, T. Poblete, M.A. Moreno, Uncooled thermal camera calibration and optimization of the photogrammetry process for UAV applications in agriculture, Sensors 17 (10) (2017) 2173.	A. Matese, S.F. Di Gennaro, Practical applications of a multisensor uav platform based on multispectral, thermal and rgb high resolution images in precision viticulture, Agriculture 8 (7) (2018) 116.
	L. Cantelli, F. Bonaccorso, D. Longo, C.D. Melita, G. Schillaci, G. Muscato, A small versatile electrical robot for autonomous spraying in agriculture, AgriEngineering 1 (3) (2019) 391–402.	R. Morais, N. Silva, J. Mendes, T. Adão, L. Pádua, J. López-Riquelme, N. Pavón-Pulido, J.J. Sousa, E. Peres, Mysense: A comprehensive data management environment to improve precision agriculture practices, Comput. Electron. Agric. 162 (2019) 882–894.	L. Pádua, P. Marques, J. Hruška, T. Adão, E. Peres, R. Morais, J.J. Sousa, Multi-temporal vineyard monitoring through UAV-based RGB imagery, Remote Sens. 10 (12) (2018) 1907.
	J.M. Mendes, F.N. dos Santos, N.A. Ferraz, P.M. do Couto, R.M. dos Santos, Localization based on natural features detector for steep slope vineyards, J. Intell. Robot. Syst. 93 (3–4) (2019) 433–446.	L. Comba, P. Gay, J. Primicerio, D.R. Aimonino, Vineyard detection from unmanned aerial systems images, Comput. Electron. Agric. 114 (2015) 78–87.	A. Matese, P. Toscano, S.F. Di Gennaro, L. Genesio, F.P. Vaccari, J. Primicerio, C. Belli, A. Zaldei, R. Bianconi, B. Gioli, Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture, Remote Sens. 7 (3) (2015) 2971–2990.
	J. Baluja, M.P. Diago, P. Balda, R. Zorer, F. Meggio, F. Morales, J. Tardaguila, Assessment of vineyard water status variability by thermal and multispectral imagery using an unmanned aerial	L. Santesteban, S. Di Gennaro, A. Herrero-Langreo, C. Miranda, J. Royo, A. Matese, High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a	S. Candiago, F. Remondino, M. De Giglio, M. Dubbini, M. Gattelli, Evaluating multispectral images and vegetation indices for precision farming applications

	vehicle (UAV), Irrigat. Sci. 30 (6) (2012) 511–522.	vineyard, Agric. Water Manag. 183 (2017) 49–59.	from UAV images, Remote Sens. 7 (4) (2015) 4026–4047.
Wheat	X. Jin, S. Liu, F. Baret, M. Hemerlé, A. Comar, Estimates of plant density of wheat crops at emergence from very low altitude UAV imagery, Remote Sens. Environ. 198 (2017) 105–114.	P. Gonzalez-de Santos, A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez- Granados, M. Brandstoetter, S. Tomic, S. Pedrazzi, A. Peruzzi, G. Pajares, G. Kaplanis, et al., Fleets of robots for environmentally-safe pest control in agriculture, Precis. Agric. 18 (4) (2017) 574–614.	E. Honkavaara, H. Saari, J. Kaivosoja, I. Pölönen, T. Hakala, P. Litkey, J. Mäkynen, L. Pesonen, Processing and assessment of spectrometric, stereoscopic imagery collected using a lightweight UAV spectral camera for precision agriculture, Remote Sens. 5 (10) (2013) 5006–5039.
	I. Burud, G. Lange, M. Lillemo, E. Bleken, L. Grimstad, P.J. From, Exploring robots and UAVs as phenotyping tools in plant breeding, IFAC-PapersOnLine 50 (1) (2017) 11479–11484.	M. Schirrmann, A. Hamdorf, A. Giebel, F. Gleiniger, M. Pflanz, K.-H. Dammer, Regression kriging for improving crop height models fusing ultra-sonic sensing with UAV imagery, Remote Sens. 9 (7) (2017) 665.	R. Pudelko, T. Stuczynski, M. Borzecka-Walker, et al., The suitability of an unmanned aerial vehicle (UAV) for the evaluation of experimental fields and crops, Agriculture 99 (4) (2012) 431–436.
	G. Mozgeris, D. Jonikavičius, D. Jovarauskas, R. Zinkevičius, S. Petkevičius, D. Steponavičius, Imaging from manned ultra-light and unmanned aerial vehicles for estimating properties of spring wheat, Precis. Agric. 19 (5) (2018) 876–894.	S. Marino, A. Alvino, Detection of homogeneous wheat areas using multitemporal UAS images and ground truth data analyzed by cluster analysis, Eur. J. Remote Sens. 51 (1) (2018) 266–275.	B. Siegmann, T. Jarmer, Comparison of different regression models and validation techniques for the assessment of wheat leaf area index from hyperspectral data, Int. J. Remote Sens. 36 (18) (2015) 4519–4534.
	X.E. Pantazi, D. Moshou, T. Alexandridis, R.L. Whetton, A.M. Mouazen, Wheat yield prediction using machine learning and advanced sensing techniques, Comput. Electron. Agric. 121 (2016) 57–65.	A.C. Kyratzis, D.P. Skarlatos, G.C. Menexes, V.F. Vamvakousis, A. Katsiotis, Assessment of vegetation indices derived by UAV imagery for durum wheat phenotyping under a water limited and heat stressed mediterranean environment, Front. Plant Sci. 8 (2017) 1114	C. Potena, R. Khanna, J. Nieto, R. Siegwart, D. Nardi, A. Pretto, AgriColMap: Aerial-ground collaborative 3D mapping for precision farming, IEEE Robot. Autom. Lett. 4 (2) (2019) 1085–1092.
	J. Kaivosoja, L. Pesonen, J. Kleemola, I. Pölönen, H. Salo, E. Honkavaara, A case study of a precision fertilizer application task generation for wheat based on classified hyperspectral data	F.-J. Mesas-Carrascosa, J. Torres-Sánchez, I. Clavero-Rumbao, A. García-Ferrer, J.-M. Peña, I. Borra-Serrano, F. López-Granados, Assessing optimal flight parameters for generating accurate multispectral orthomosaicks by UAV	D. Gómez-Candón, A. De Castro, F. López-Granados, Assessing the accuracy of mosaics from unmanned aerial vehicle (UAV) imagery for precision agriculture

	from UAV combined with farm history data, in: Remote Sensing for Agriculture, Ecosystems, and Hydrology XV, vol. 8887, International Society for Optics and Photonics, 2013, p. 8870H.	to support site-specific crop management, Remote Sens. 7 (10) (2015) 12793–12814.	purposes in wheat, Precis. Agric. 15 (1) (2014) 44–56.
	M. Schirrmann, A. Giebel, F. Gleiniger, M. Pflanz, J. Lentschke, K.-H. Dammer, Monitoring agronomic parameters of winter wheat crops with low-cost UAV imagery, Remote Sens. 8 (9) (2016) 706.	J. Torres-Sánchez, J.M. Pena, A.I. de Castro, F. López-Granados, Multitemporal mapping of the vegetation fraction in early-season wheat fields using images from UAV, Comput. Electron. Agric. 103 (2014) 104–113.	M.P. Christiansen, M.S. Laursen, R.N. Jørgensen, S. Skovsen, R. Gislum, Designing and testing a UAV mapping system for agricultural field surveying, Sensors 17 (12) (2017) 2703

Table 37. Field operations in European research efforts (Adapted from [113])

Field Operations	References			
Crop Monitoring	M.A. Zamora-Izquierdo, J. Santa, J.A. Martínez, V. Martínez, A.F. Skarmeta, Smart farming IoT platform based on edge and cloud computing, Biosyst. Eng. 177 (2019) 4–17.	J. López-Riquelme, N. Pavón-Pulido, H. Navarro-Hellín, F. Soto-Valles, R. Torres-Sánchez, A software architecture based on FIWARE cloud for precision agriculture, Agric. Water Manag. 183 (2017) 123–135.	J. Primicerio, S.F. Di Gennaro, E. Fiorillo, L. Genesio, E. Lugato, A. Matese, F.P. Vaccari, A flexible unmanned aerial vehicle for precision agriculture, Precis. Agric. 13 (4) (2012) 517–523.	A. Burkart, V. Hecht, T. Kraska, U. Rascher, Phenological analysis of unmanned aerial vehicle based time series of barley imagery with high temporal resolution, Precis. Agric. 19 (1) (2018) 134–146.
	H. Hoffmann, R. Jensen, A. Thomsen, H. Nieto, J. Rasmussen, T. Friborg, Crop water stress maps for an entire growing season from visible and thermal UAV imagery, Biogeosciences 13 (24) (2016) 6545–6563	J.I. Córcoles, J.F. Ortega, D. Hernández, M.A. Moreno, Estimation of leaf area index in onion (Allium cepa L.) using an unmanned aerial vehicle, Biosyst. Eng. 115 (1) (2013) 31–42.	M.L. Guillén-Climent, P.J. Zarco-Tejada, J.A. Berni, P.R. North, F.J. Villalobos, Mapping radiation interception in row-structured orchards using 3D simulation and high-resolution airborne imagery acquired from a UAV, Precis. Agric. 13 (4) (2012) 473–500.	A.C. Kyratzis, D.P. Skarlatos, G.C. Menexes, V.F. Vamvakousis, A. Katsiotis, Assessment of vegetation indices derived by UAV imagery for durum wheat phenotyping under a water limited and heat stressed Mediterranean environment, Front. Plant ci. 8 (2017) 1114
	S.C. Kefauver, R. Vicente, O. Vergara-Díaz, J.A. Fernandez-Gallego, S. Kerfal, A. Lopez, J.P. Melichar, M.D. Serret Molins, J.L. Araus, Comparative UAV and field phenotyping to assess yield and nitrogen use efficiency in hybrid and conventional barley, Front. Plant Sci. 8 (2017) 1733.	J. Baluja, M.P. Diago, P. Balda, R. Zorer, F. Meggio, F. Morales, J. Tardaguila, Assessment of vineyard water status variability by thermal and multispectral imagery using an unmanned aerial vehicle (UAV), Irrigat. Sci. 30 (6) (2012) 511–522.	L. Busetto, S. Casteleyn, C. Granell, M. Pepe, M. Barbieri, M. Campos-Taberner, R. Casa, F. Collivignarelli, et al., Downstream services for rice crop monitoring in europe: From regional to local scale, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 10 (12) (2017) 5423–5441	J. Torres-Sánchez, A.I. de Castro, J.M. Pena, F.M. Jiménez-Brenes, O. Arquero, M. Lovera, F. López-Granados, Mapping the 3D structure of almond trees using UAV acquired photogrammetric point clouds and object-based image analysis, Biosyst. Eng. 176 (2018) 172–184
	J. Bendig, A. Bolten, S. Bennertz, J. Broscheit, S.	J. Torres-Sánchez, J.M. Pena, A.I. de Castro, F. López-	M.P. Christiansen, M.S. Laursen, R.N. Jørgensen, S.	G. Caruso, L. Tozzini, G. Rallo, J. Primicerio, M. Moriondo, G.

	Eichfuss, G. Bareth, Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging, Remote Sens. 6 (11) (2014) 10395–10412.	Granados, Multitemporal mapping of the vegetation fraction in early-season wheat fields using images from UAV, Comput. Electron. Agric. 103 (2014) 104–113.	Skovsen, R. Gislum, Designing and testing a UAV mapping system for agricultural field surveying, Sensors 17 (12) (2017) 2703	Palai, R. Gucci, Estimating biophysical and geometrical parameters of grapevine canopies ('sangiovese') by an unmanned aerial vehicle (UAV) and VIS-NIR cameras, Vitis 56 (2) (2017) 63–70.
	J. Campos, J. Llop, M. Gallart, F. García-Ruiz, A. Gras, R. Salcedo, E. Gil, Development of canopy vigour maps using UAV for site-specific management during vineyard spraying process, Precis. Agric. 20 (6) (2019) 1136–1156.	X. Jin, S. Liu, F. Baret, M. Hemerlé, A. Comar, Estimates of plant density of wheat crops at emergence from very low altitude UAV imagery, Remote Sens. Environ. 198 (2017) 105–114.	P. Gonzalez-de Santos, A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez-Granados, M. Brandstoetter, S. Tomic, S. Pedrazzi, A. Peruzzi, G. Pajares, G. Kaplanis, et al., Fleets of robots for environmentally-safe pest control in agriculture, Precis. Agric. 18 (4) (2017) 574–614.	F.A. Vega, F.C. Ramirez, M.P. Saiz, F.O. Rosua, Multi-temporal imaging using an unmanned aerial vehicle for monitoring a sunflower crop, Biosyst. Eng. 132 (2015) 19–27.
	L. Comba, P. Gay, J. Primicerio, D.R. Aimonino, Vineyard detection from unmanned aerial systems images, Comput. Electron. Agric. 114 (2015) 78–87.	A. Matese, P. Toscano, S.F. Di Gennaro, L. Genesio, F.P. Vaccari, J. Primicerio, C. Belli, A. Zaldei, R. Bianconi, B. Gioli, Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture, Remote Sens. 7 (3) (2015) 2971–2990.	G. Mozgeris, D. Jonikavičius, D. Jovarauskas, R. Zinkevičius, S. Petkevičius, D. Steponavičius, Imaging from manned ultra-light and unmanned aerial vehicles for estimating properties of spring wheat, Precis. Agric. 19 (5) (2018) 876–894.	K. Kuželka, P. Surovy` , Automatic detection and quantification of wild game crop damage using an unmanned aerial vehicle (UAV) equipped with an optical sensor payload: a case study in wheat, Eur. J. Remote Sens. 51 (1) (2018) 241–250.
	C. Potena, R. Khanna, J. Nieto, R. Siegwart, D. Nardi, A. Pretto, AgriColMap: Aerial-ground collaborative 3D mapping for precision farming, IEEE Robot. Autom. Lett. 4 (2) (2019) 1085–1092.	J. Martínez, G. Egea, J. Agüera, M. Pérez-Ruiz, A cost-effective canopy temperature measurement system for precision agriculture: a case study on sugar beet, Precis. Agric. 18 (1) (2017) 95–110.	J. Kaivosoja, L. Pesonen, J. Kleemola, I. Pölönen, H. Salo, E. Honkavaara, H. Saari, J. Mäkynen, A. Rajala, A case study of a precision fertilizer application task generation for wheat based on classified hyperspectral data from UAV combined with farm history	L. Pádua, P. Marques, J. Hruška, T. Adão, E. Peres, R. Morais, J.J. Sousa, Multi-temporal vineyard monitoring through UAV-based RGB imagery, Remote Sens. 10 (12) (2018) 1907.

		data, in: Remote Sensing for Agriculture, Ecosystems, and Hydrology XV, vol. 8887, International Society for Optics and Photonics, 2013, p. 88870H.	
D. Stroppiana, M. Migliazzi, V. Chiarabini, A. Crema, M. Musanti, C. Franchino, P. Villa, Rice yield estimation using multispectral data from UAV: A preliminary experiment in northern Italy, in: 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), IEEE, 2015, pp. 4664–4667.	S. Candiago, F. Remondino, M. De Giglio, M. Dubbini, M. Gattelli, Evaluating multispectral images and vegetation indices for precision farming applications from UAV images, Remote Sens. 7 (4) (2015) 4026–4047.	R. Morais, N. Silva, J. Mendes, T. Adão, L. Pádua, J. López-Riquelme, N. Pavón-Pulido, J.J. Sousa, E. Peres, Mysense: A comprehensive data management environment to improve precision agriculture practices, Comput. Electron. Agric. 162 (2019) 882–894.	
F. Kurtulmuş, I. Kavdir, Detecting corn tassels using computer vision and support vector machines, Expert Syst. Appl. 41 (16) (2014) 7390–7397.	D. Gómez-Candón, N. Virlet, S. Labbé, A. Jolivot, J.-L. Regnard, Field phenotyping of water stress at tree scale by UAV-sensed imagery: new insights for thermal acquisition and calibration, Precis. Agric. 17 (6) (2016) 786–800.	M. Schirrmann, A. Hamdorf, A. Giebel, F. Gleiniger, M. Pflanz, K.-H. Dammer, Regression kriging for improving crop height models fusing ultra-sonic sensing with UAV imagery, Remote Sens. 9 (7) (2017) 665.	B. Siegmann, T. Jarmer, Comparison of different regression models and validation techniques for the assessment of wheat leaf area index from hyperspectral data, Int. J. Remote Sens. 36 (18) (2015) 4519–4534.
A. Somov, D. Shadrin, I. Fastovets, A. Nikitin, S. Matveev, O. Hrinchuk, et al., Pervasive agriculture: IoT-enabled greenhouse for plant growth control, IEEE Pervasive Comput. 17 (4) (2018) 65–75.	L. Quebrajo, M. Perez-Ruiz, L. Pérez-Urrestarazu, G. Martínez, G. Egea, Linking thermal imaging and soil remote sensing to enhance irrigation management of sugar beet, Biosyst. Eng. 165 (2018) 77–87.	P.J. Zarco-Tejada, V. González-Dugo, J.A. Berni, Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera, Remote Sens. Environ. 117 (2012) 322–337.	M. Schirrmann, A. Giebel, F. Gleiniger, M. Pflanz, J. Lentschke, K.-H. Dammer, Monitoring agronomic parameters of winter wheat crops with low-cost UAV imagery, Remote Sens. 8 (9) (2016) 706.
Á. Maresma, M. Ariza, E. Martínez, J. Lloveras, J.A. Martínez-Casasnovas, Analysis of vegetation indices to	J. Valente, R. Almeida, L. Kooistra, A comprehensive study of the potential application of flying ethylene-	N. Wilke, B. Siegmann, L. Klingbeil, A. Burkart, T. Kraska, O. Muller, A. van Doorn, S. Heinemann, U. Rascher,	E. Salamí, A. Gallardo, G. Skorobogatov, C. Barrado, On-the-fly olive tree counting using a UAS and cloud services,

	determine nitrogen application and yield prediction in maize (Zea mays L.) from a standard UAV service, Remote Sens. 8 (12) (2016) 973.	sensitive sensors for ripeness detection in apple orchards, Sensors 19 (2) (2019) 372.	Quantifying lodging percentage and lodging severity using a UAV-based canopy height model combined with an objective threshold approach, Remote Sens. 11 (5) (2019) 515.	Remote Sens. 11 (3) (2019) 316.
	N. Pavón-Pulido, J. López-Riquelme, R. Torres, R. Morais, J. Pastor, New trends in precision agriculture: a novel cloud-based system for enabling data storage and agricultural task planning and automation, Precis. Agric. 18 (6) (2017) 1038–1068.	D. Gómez-Candón, A. De Castro, F. López-Granados, Assessing the accuracy of mosaics from unmanned aerial vehicle (UAV) imagery for precision agriculture purposes in wheat, Precis. Agric. 15 (1) (2014) 44–56.	F.J. Ferrández-Pastor, J.M. García-Chamizo, M. Nieto-Hidalgo, J. Mora- Pascual, J. Mora-Martínez, Developing ubiquitous sensor network platform using internet of things: Application in precision agriculture, Sensors 16 (7) (2016) 1141.	S. Marino, A. Alvino, Detection of homogeneous wheat areas using multitemporal UAS images and ground truth data analyzed by cluster analysis, Eur. J. Remote Sens. 51 (1) (2018) 266–275.
	E. Honkavaara, H. Saari, J. Kaivosoja, I. Pölönen, T. Hakala, P. Litkey, J. Mäkynen, L. Pesonen, Processing and assessment of spectrometric, stereoscopic imagery collected using a lightweight UAV spectral camera for precision agriculture, Remote Sens. 5 (10) (2013) 5006–5039.	I. Burud, G. Lange, M. Lillemo, E. Bleken, L. Grimstad, P.J. From, Exploring robots and UAVs as phenotyping tools in plant breeding, IFAC-PapersOnLine 50 (1) (2017) 11479–11484.	H. Aasen, A. Burkart, A. Bolten, G. Bareth, Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: From camera calibration to quality assurance, ISPRS J. Photogramm. Remote Sens. 108 (2015) 245–259.	J. Geipel, J. Link, W. Claupein, Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system, Remote Sens. 6 (11) (2014) 10335–10355.
	A. Michez, S. Bauwens, Y. Brostaux, M.-P. Hiel, S. Garré, P. Lejeune, B. Dumont, How far can consumer-grade UAV RGB imagery describe crop production? A 3D and multitemporal modeling approach applied to zea mays,	R.A. Díaz-Varela, R. De la Rosa, L. León, P.J. Zarco-Tejada, High-resolution airborne UAV imagery to assess olive tree crown parameters using 3D photo reconstruction: application in breeding trials, Remote Sens. 7 (4) (2015) 4213–4232.	P.J. Zarco-Tejada, R. Diaz-Varela, V. Angileri, P. Loudjani, Tree height quantification using very high resolution imagery acquired from an unmanned aerial vehicle (UAV) and automatic 3D photo-reconstruction methods, Eur. J. Agron. 55 (2014) 89–99	H. Hoffmann, H. Nieto, R. Jensen, R. Guzinski, P. Zarco-Tejada, T. Friborg, Estimating evaporation with thermal UAV data and two-source energy balance models, Hydrol. Earth Syst. Sci. 20 (2) (2016) 697–713.

	Remote Sens. 10 (11) (2018) 1798.			
	F.-J. Mesas-Carrascosa, J. Torres-Sánchez, I. Clavero-Rumbao, A. García-Ferrer, J.-M. Peña, I. Borra-Serrano, F. López-Granados, Assessing optimal flight parameters for generating accurate multispectral orthomosaicks by UAV to support site-specific crop management, Remote Sens. 7 (10) (2015) 12793–12814.	J. Bendig, K. Yu, H. Aasen, A. Bolten, S. Bennertz, J. Broscheit, M.L. Gnyp, G. Bareth, Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley, Int. J. Appl. Earth Obs. Geoinf. 39 (2015) 79–87.	R. Pudelko, T. Stuczynski, M. Borzecka-Walker, et al., The suitability of an unmanned aerial vehicle (UAV) for the evaluation of experimental fields and crops, Agriculture 99 (4) (2012) 431–436.	C. Romero-Trigueros, P.A. Nortes, J.J. Alarcón, J.E. Hunink, M. Parra, S. Contreras, P. Droogers, E. Nicolás, Effects of saline reclaimed waters and deficit irrigation on citrus physiology assessed by UAV remote sensing, Agric. Water Manag. 183 (2017) 60–69.
	K. Ivushkin, H. Bartholomeus, A.K. Bregt, A. Pulatov, M.H. Franceschini, H. Kramer, E.N. van Loo, V.J. Roman, R. Finkers, UAV based soil salinity assessment of cropland, Geoderma 338 (2019) 502–512.		H. Hoffmann, H. Nieto, R. Jensen, R. Guzinski, P. Zarco-Tejada, T. Friborg, Estimating evaporation with thermal UAV data and two-source energy balance models, Hydrol. Earth Syst. Sci. 20 (2) (2016) 697–713.	
Disease Detection	J. Albetis, S. Duthoit, F. Guttler, A. Jacquin, M. Goulard, H. Poilvé, J.-B. Féret, G. Dedieu, Detection of Flavescence dorée grapevine disease using Unmanned Aerial Vehicle (UAV) multispectral imagery, Remote Sens. 9 (4) (2017) 308.	P. Psirofonia, V. Samaritakis, P. Eliopoulos, I. Potamitis, Use of unmanned aerial vehicles for agricultural applications with emphasis on crop protection: Three novel case-studies, Int. J. Agric. Sci. Technol. 5 (1) (2017) 30–39.	B. Rey, N. Aleixos, S. Cubero, J. Blasco, XF-ROVIM. A field robot to detect olive trees infected by xylella fastidiosa using proximal sensing, Remote Sens. 11 (3) (2019) 221.	N. Sales, O. Remédios, A. Arsenio, Wireless sensor and actuator system for smart irrigation on the cloud, in: 2015 IEEE 2nd World Forum on Internet of Things (WF-IoT), IEEE, 2015, pp. 693–698.
	I. Navrozidis, T.K. Alexandridis, A. Dimitrakos, A.L. Lagopodi, D. Moshou, G. Zalidis, Identification of purple spot disease on asparagus crops across spatial and spectral scales, Comput. Electron. Agric. 148 (2018) 322–329.	R. Calderón, M. Montes-Borrego, B. Landa, J. Navas-Cortés, P. Zarco-Tejada, Detection of downy mildew of opium poppy using high-resolution multispectral and thermal imagery acquired with an unmanned aerial vehicle, Precis. Agric. 15 (6) (2014) 639–661.	K. Espinoza, D.L. Valera, J.A. Torres, A. López, F.D. Molina-Aiz, Combination of image processing and artificial neural networks as a novel approach for the identification of bemisia tabaci and frankliniella occidentalis on sticky traps in greenhouse agriculture, Comput.	

				Electron. Agric. 127 (2016) 495–505.
Harvesting	T.T. Nguyen, K. Vandevoorde, E. Kayacan, J. De Baerdemaeker, W. Saeys, Apple detection algorithm for robotic harvesting using a RGB-D camera, in: International Conference of Agricultural Engineering, Zurich, Switzerland, 2014.			
Pruning	J.M. Mendes, F.N. dos Santos, N.A. Ferraz, P.M. do Couto, R.M. dos Santos, Localization based on natural features detector for steep slope vineyards, J. Intell. Robot. Syst. 93 (3–4) (2019) 433–446.			
Spraying	A.M. García, I.F. García, E.C. Poyato, P.M. Barrios, J.R. Díaz, Coupling irrigation scheduling with solar energy production in a smart irrigation management system, J. Clean. Prod. 175 (2018) 670–682.	M.A. Zamora-Izquierdo, J. Santa, J.A. Martínez, V. Martínez, A.F. Skarmeta, Smart farming IoT platform based on edge and cloud computing, Biosyst. Eng. 177 (2019) 4–17.	J. López-Riquelme, N. Pavón-Pulido, H. Navarro-Hellín, F. Soto-Valles, R. Torres-Sánchez, A software architecture based on FIWARE cloud for precision agriculture, Agric. Water Manag. 183 (2017) 123–135.	S. Kontogiannis, G. Kokkonis, S. Ellinidou, S. Valsamidis, Proposed fuzzynn algorithm with loracommunication protocol for clustered irrigation systems, Future Internet 9 (4) (2017) 78.
	P. Katsigiannis, L. Misopolinos, V. Liakopoulos, T.K. Alexandridis, G. Zalidis, An autonomous multi-sensor UAV system for reduced-input precision agriculture applications, in: 2016 24th Mediterranean Conference on Control and Automation (MED), IEEE, 2016, pp. 60–64.	A.C. Cruz, A. Luvisi, L. De Bellis, Y. Ampatzidis, X-FIDO: An effective application for detecting olive quick decline syndrome with deep learning and data fusion, Front. Plant Sci. 8 (2017) 1741.	K. Ribeiro-Gomes, D. Hernández-López, J.F. Ortega, R. Ballesteros, T. Poblete, M.A. Moreno, Uncooled thermal camera calibration and optimization of the photogrammetry process for UAV applications in agriculture, Sensors 17 (10) (2017) 2173.	F.F. Montesano, M.W. Van Iersel, F. Boari, V. Cantore, G. D'Amato, A. Parente, Sensor-based irrigation management of soilless basil using a new smart irrigation system: Effects of set-point on plant physiological responses and crop performance, Agric.Water Manag. 203 (2018) 20–29
	L. Quebrajo, M. Perez-Ruiz, L. Pérez-Urrestarazu, G. Martínez, G. Egea, Linking thermal imaging and soil remote sensing to enhance irrigation management of sugar beet, Biosyst. Eng. 165 (2018) 77–87.	H. Hoffmann, H. Nieto, R. Jensen, R. Guzinski, P. Zarco-Tejada, T. Friborg, Estimating evaporation with thermal UAV data and two-source energy balance models, Hydrol. Earth Syst. Sci. 20 (2) (2016) 697–713.	F.J. Ferrández-Pastor, J.M. García-Chamizo, M. Nieto-Hidalgo, J. Mora- Pascual, J. Mora-Martínez, Developing ubiquitous sensor network platform using internet of things: Application in precision agriculture, Sensors 16 (7) (2016) 1141.	C. Goumopoulos, B. O'Flynn, A. Kameas, Automated zone-specific irrigation with wireless sensor/actuator network and adaptable decision support, Comput. Electron. Agric. 105 (2014) 20–33.

	L. Santesteban, S. Di Gennaro, A. Herrero-Langreo, C. Miranda, J. Royo, A. Matese, High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard, Agric. Water Manag. 183 (2017) 49–59.	V. Gonzalez-Dugo, P. Zarco-Tejada, E. Nicolás, P.A. Nortes, J. Alarcón, D.S. Intrigliolo, E. Fereres, Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard, Precis. Agric. 14 (6) (2013) 660–678.]	N. Pavón-Pulido, J. López-Riquelme, R. Torres, R. Morais, J. Pastor, New trends in precision agriculture: a novel cloud-based system for enabling data storage and agricultural task planning and automation, Precis. Agric. 18 (6) (2017) 1038–1068.	
	A.M. García, I.F. García, E.C. Poyato, P.M. Barrios, J.R. Díaz, Coupling irrigation scheduling with solar energy production in a smart irrigation management system, J. Clean. Prod. 175 (2018) 670–682.	M.A. Zamora-Izquierdo, J. Santa, J.A. Martínez, V. Martínez, A.F. Skarmeta, Smart farming IoT platform based on edge and cloud computing, Biosyst. Eng. 177 (2019) 4–17.	J. López-Riquelme, N. Pavón-Pulido, H. Navarro-Hellín, F. Soto-Valles, R. Torres-Sánchez, A software architecture based on FIWARE cloud for precision agriculture, Agric. Water Manag. 183 (2017) 123–135.	P. Katsigiannis, L. Misopolinos, V. Liakopoulos, T.K. Alexandridis, G. Zalidis, An autonomous multi-sensor UAV system for reduced-input precision agriculture applications, in: 2016 24th Mediterranean Conference on Control and Automation (MED), IEEE, 2016, pp. 60–64.
Water Management	A.C. Cruz, A. Luvisi, L. De Bellis, Y. Ampatzidis, X-FIDO: An effective application for detecting olive quick decline syndrome with deep learning and data fusion, Front. Plant Sci. 8 (2017) 1741.	K. Ribeiro-Gomes, D. Hernández-López, J.F. Ortega, R. Ballesteros, T. Poblete, M.A. Moreno, Uncooled thermal camera calibration and optimization of the photogrammetry process for UAV applications in agriculture, Sensors 17 (10) (2017) 2173.	F.F. Montesano, M.W. Van Iersel, F. Boari, V. Cantore, G. D'Amato, A. Parente, Sensor-based irrigation management of soilless basil using a new smart irrigation system: Effects of set-point on plant physiological responses and crop performance, Agric. Water Manag. 203 (2018) 20–29	L. Quebrajo, M. Perez-Ruiz, L. Pérez-Urrestarazu, G. Martínez, G. Egea, Linking thermal imaging and soil remote sensing to enhance irrigation management of sugar beet, Biosyst. Eng. 165 (2018) 77–87.
	H. Hoffmann, H. Nieto, R. Jensen, R. Guzinski, P. Zarco-Tejada, T. Friborg, Estimating evaporation with thermal UAV data and two-source energy balance models, Hydrol. Earth	F.J. Ferrández-Pastor, J.M. García-Chamizo, M. Nieto-Hidalgo, J. Mora- Pascual, J. Mora-Martínez, Developing ubiquitous sensor network platform using internet of	C. Goumopoulos, B. O'Flynn, A. Kameas, Automated zone-specific irrigation with wireless sensor/actuator network and adaptable decision support,	L. Santesteban, S. Di Gennaro, A. Herrero-Langreo, C. Miranda, J. Royo, A. Matese, High-resolution UAV-based thermal imaging to estimate the instantaneous and

	Syst. Sci. 20 (2) (2016) 697–713.	things: Application in precision agriculture, Sensors 16 (7) (2016) 1141.	Comput. Electron. Agric. 105 (2014) 20–33.	seasonal variability of plant water status within a vineyard, Agric. Water Manag. 183 (2017) 49–59.
	V. Gonzalez-Dugo, P. Zarco-Tejada, E. Nicolás, P.A. Nortes, J. Alarcón, D.S. Intrigliolo, E. Fereres, Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard, Precis. Agric. 14 (6) (2013) 660–678.	N. Pavón-Pulido, J. López-Riquelme, R. Torres, R. Morais, J. Pastor, New trends in precision agriculture: a novel cloud-based system for enabling data storage and agricultural task planning and automation, Precis. Agric. 18 (6) (2017) 1038–1068.	S. Kontogiannis, G. Kokkonis, S. Ellinidou, S. Valsamidis, Proposed fuzzynn algorithm with loracommunication protocol for clustered irrigation systems, Future Internet 9 (4) (2017) 78.	
Weed Management	F. Castaldi, F. Pelosi, S. Pascucci, R. Casa, Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize, Precis. Agric. 18 (1) (2017) 76–94.	P. Gonzalez-de Santos, A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez-Granados, M. Brandstoetter, S. Tomic, S. Pedrazzi, A. Peruzzi, G. Pajares, G. Kaplanis, et al., Fleets of robots for environmentally-safe pest control in agriculture, Precis. Agric. 18 (4) (2017) 574–614.	M. Louargant, G. Jones, R. Faroux, J.-N. Paoli, T. Maillot, C. Gée, S. Villette, Unsupervised classification algorithm for early weed detection in rowcrops by combining spatial and spectral information, Remote Sens. 10 (5) (2018) 761.	M. Pérez-Ortiz, J.M. Peña, P.A. Gutiérrez, J. Torres-Sánchez, C. Hervás- Martínez, F. López-Granados, Selecting patterns and features for betweenand within-crop-row weed mapping using UAV-imagery, Expert Syst. Appl. 47 (2016) 85–94.
	F. López-Granados, J. Torres-Sánchez, A.-I. De Castro, A. Serrano-Pérez, F.- J. Mesas-Carrascosa, J.-M. Peña, Object-based early monitoring of a grass weed in a grass crop using high resolution UAV imagery, Agron. Sustain. Dev. 36 (4) (2016) 67.	M. Fawakherji, A. Youssef, D. Bloisi, A. Pretto, D. Nardi, Crop and weeds classification for precision agriculture using context-independent pixelwise segmentation, in: 2019 Third IEEE International Conference on	F.-J. Mesas-Carrascosa, J. Torres-Sánchez, I. Clavero-Rumbao, A. García-Ferrer, J.-M. Peña, I. Borra-Serrano, F. López-Granados, Assessing optimal flight parameters for generating accurate multispectral orthomosaicks by UAV to support site-specific crop	J.M. Peña, J. Torres-Sánchez, A.I. de Castro, M. Kelly, F. López-Granados, Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images, PLoS One 8 (10) (2013).

		Robotic Computing (IRC), IEEE, 2019, pp. 146–152.	management, Remote Sens. 7 (10) (2015) 12793–12814.	
	J. Torres-Sánchez, F. López-Granados, A.I. De Castro, J.M. Peña-Barragán, Configuration and specifications of an unmanned aerial vehicle (UAV) for early site specific weed management, PLoS One 8 (3) (2013).	F. López-Granados, J. Torres-Sánchez, A. Serrano-Pérez, A.I. de Castro, F.-J. Mesas-Carrascosa, J.-M. Pena, Early season weed mapping in sunflower using UAV technology: variability of herbicide treatment maps against weed thresholds, Precis. Agric. 17 (2) (2016) 183–199.	J. Torres-Sánchez, J.M. Pena, A.I. de Castro, F. López-Granados, Multitemporal mapping of the vegetation fraction in early-season wheat fields using images from UAV, Comput. Electron. Agric. 103 (2014) 104–113.	J.M. Peña, J. Torres-Sánchez, A. Serrano-Pérez, A.I. De Castro, F. López- Granados, Quantifying efficacy and limits of unmanned aerial vehicle (UAV) technology for weed seedling detection as affected by sensor resolution, Sensors 15 (3) (2015) 5609–5626.
Yield Prediction	D. Gómez, P. Salvador, J. Sanz, J.L. Casanova, Potato yield prediction using machine learning techniques and sentinel 2 data, Remote Sens. 11 (15) (2019) 1745.	X.E. Pantazi, D. Moshou, T. Alexandridis, R.L. Whetton, A.M. Mouazen, Wheat yield prediction using machine learning and advanced sensing techniques, Comput. Electron. Agric. 121 (2016) 57–65.	A. Tewes, J. Schellberg, Towards remote estimation of radiation use efficiency in maize using uav-based low-cost camera imagery, Agronomy 8 (2) (2018) 16.	E.I. Papageorgiou, A.T. Markinos, T.A. Gemtos, Fuzzy cognitive map based approach for predicting yield in cotton crop production as a basis for decision support system in precision agriculture application, Appl. Soft Comput. 11 (4) (2011) 3643–3657
	Á. Maresma, M. Ariza, E. Martínez, J. Lloveras, J.A. Martínez-Casasnovas, Analysis of vegetation indices to determine nitrogen application and yield prediction in maize (Zea mays L.) from a standard UAV service, Remote Sens. 8 (12) (2016) 973.			