Innovation and Capacity building

in Agricultural Environmental and Rural UAV Services

ICAERUS

D3.6: Report on Socio-economic and Environmental Impact

Version B

WP3: Use Cases and Demonstration Activities

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Executive Summary

The introduction and adoption of new technologies has always been a challenging process: individual and organisational aspects jointly influence the decision to use a technology in a complex pattern of relationships. The process of adoption has been widely studied in literature with the development of several approaches stemming from organisation behaviour and management of information systems literatures (Carli et al., 2017). Besides the decision to use, the United Nations Sustainable Development Goals and the attention to sustainability have considerably increased the attention to lifecycle costs of new technologies and their impact on the environment.

The main objective of ICAERUS Task 3.3 is to develop a Socio-economic and Environmental Impact Assessment of the innovations developed in the five ICAERUS Use Cases (UCs). This twofold objective is achieved by combining two parallel research studies—a Life Cycle Assessment (LCA) and Life Cycle Costing (LCC) and a Technology Adoption study. These two studies adopt different methodologies but share the aim of developing not just an assessment of socio-economic and environmental aspects, but also to inform policy development at regional, national and EU levels.

This first deliverable related to Task 3.3 outlines the methodology to be used in both the research studies. It presents the methodological choices and the approaches to be taken in terms of data collection.

This deliverable is organised in two Chapters:

- Chapter 1 presents the methodology to be applied to develop the Life Cycle Assessment (LCA) and Life Cycle Costing (LCC);
- Chapter 2 presents the methodology to be applied to develop the Technology Adoption study.

Each chapter includes an overview of the expected results.

Update from Deliverable 3.5

Chapter 1: Since the last submission (Del. 3.5) where the LCA and LCC Goal and Scope definition and the questionnaires for each Use Case were presented, the main focus for year 2024 has been data collection. Given the characteristics of each Use Case, this data collection process has adapted to the needs, challenges, and limitations of each Use Case. In order to update on the state of these data collection processes, a section is devoted to each Use Case describing the current status, missing data aspects, the main challenges encountered, a clear timeline for conclusion (when relevant) and the next steps to be followed. An additional section covering these 5 points has been included for the relevant data collection on UAVs assembly, operation, and maintenance.

Chapter 2: Since the last submission (Del. 3.5), the methodology has been enhanced to consider the results of the first pilot study conducted during the demonstration event of Use Case 2 in Greece (31/10/2024). The demonstration event suggested simplifying the survey and considering the risk of lower attendance at demonstrations. The survey was then refined as reported in Paragraphs 2.3.2 and 2.3.3. The data collection approach now follows a combined strategy that includes collection at demo events and online, as detailed in Paragraph 2.4.2. Initial descriptive analyses of the pilot data are presented in Paragraph 2.5.2.

Table of Contents

List of Figures

List of Tables

1. Environmental and economic impact analysis

This chapter focuses on how two of the pillars of sustainability, namely the environmental and economic dimensions, are going to be analysed within the ICAERUS project. Despite being two very different aspects, in this chapter describing the methodologies to be followed for our sustainability analysis we are presenting them together due to both assessments following the same methodological approach and the fact that both studies will be undertaken in parallel within the same software.

1.1 Lifecycle thinking

To properly analyse the environmental and economic impacts of the UAVs solutions proposed by the ICAERUS project, a life cycle thinking has been selected. The main idea behind this approach is taking into consideration all the different stages or phases in the life of a product or service, from the 'cradle to the grave' (Finkbeiner et al, 2010) when estimating their impacts, thus avoiding the displacement of 'impacts from one part of the life cycle to another or from one type of impact to another (burden shifting)' (Roy et al. 2009), thanks to which it has been recognized as a key tool in the pursuing of a sustainability transition (Sala et al., 2017; Chloé et al., 2020; Notarnicola et al., 2017).

This way of proceeding allows for the factoring in of impacts linked not only to the mere use of any given product or service but also to all previous and posterior stages, from the extraction and processing of the raw materials needed to produce it in the first place, their actual production process in factories, all the transport requirements along the life of the product/service to, later on if needed, any end-of-life steps, whether reuse, disposal or recycling (Sica et al, 2022). In this way, it is possible to acquire a more comprehensive understanding of all the life-long environmental and economic consequences derived from that product or service under study instead of just getting a limited understanding of them.

In the case of the ICAERUS project, 5 very different uses of UAVs in agricultural and rural settings are being put into practice. For instance, in UC2 UAVs are being used for spraying plant protection products in a Greek vineyard producing grapes. Following the Life Cycle thinking mentioned above, in order to analyse the environmental and economic impacts of the use of this technological innovation in grape production, an effort is going to be made to gather relevant data regarding not only the vineyard production system where UAVs will be used but also from previous stages associated with the origin, extraction and processing of raw materials, production of all material inputs, as well as the transport requirements for all those inputs needed to finally produce the grapes.

As a result, by the end of the ICAERUS project, we aim to be able to provide a detailed overview of how the products and services systems introducing the use of UAVs affect the environment and what economic consequences they have all along their different life cycles, as compared to the conventional systems currently used. Dealing as we are doing with 2 very different dimensions, however, these results are going to be obtained through different Life Cycle thinking methodologies: the environmental impacts assessment will be obtained through the Life Cycle Assessment (LCA), while the economic ones will be ascertained through the so-called Life Cycle Costing (LCC).

With the goal of further explaining in detail what these 2 dimensions of sustainability mean, why they are so relevant for this project, and which are the specific Life Cycle methodologies to be applied to each, we proceed now to focus our attention first on the environmental impacts assessment and second on the economic one.

1.1.1 Environmental Impact Assessment

Environmental impacts refer to the effects that human activities and natural processes have on the natural environment by producing changes in it that often have adverse effects on the air, land, water, wildlife and population of our ecosystems. These impacts can be both positive and negative, but more attention is increasingly given to the latter given their potential to result in harm or degradation of ecosystems, biodiversity, and natural resources (Abdallah, 2017).

The consequences on the environment deriving specially from human actions can have short-term or long-term ramifications, with most adverse environmental impacts also having a direct connection to public health and quality of life issues (Abdallah, 2017).

Understanding and mitigating these environmental impacts, therefore, has become crucial to protect ecosystems, preserve natural resources and ensure the well-being of the planet and its inhabitants. To this end, efforts are being made at local, national, and international levels to address and minimise these impacts through conservation, sustainable practices, and environmental regulations (Speight, 2017). These mitigation strategies, however, require first a proper analysis and identification of all the potential impacts on the environment and how they relate to the different human activities.

Among the wide range of human activities having a significant impact upon the environment, agriculture activities play a significant role, with this economic sector in particular being responsible for between 13-21% of global GHG (Greenhouse Gas) emissions (Nabuurs et al, 2022) associated with climate change. Beyond impacts affecting only climate change, however, food production activities in Europe are said to also account for between 20-30% of all other anthropogenic effects on the environment (Notarnicola et al., 2017).

Some of the most relevant environmental impacts derived from agricultural activities include deforestation, soil erosion, water pollution, water scarcity, greenhouse gas emissions, loss of biodiversity, plant protection products' resistance, land degradation or waste generation (van der Werf et al., 2014; McMichael et al, 2015; Notarnicola et al., 2017).

Addressing these environmental impacts in agriculture often involves adopting new sustainable solutions to farming, such as organic farming, crop rotation, reduced pesticide and fertiliser use, responsible water management, and reforestation efforts, always with the essential aim to minimise negative environmental impacts while promoting long-term food security in a difficult context of climate change, growing world population and increasing urbanisation (Arthur et al, 2021).

In these circumstances, digital technologies and its application in agriculture and rural settings have emerged as a potential solution to the big challenges food production systems are facing worldwide, by contributing to achieve better performance while reducing negative environmental impacts (Sacco et al, 2021; Solimene et al., 2023). Among the technological solutions contributing to this 'digital agricultural revolution' (Arthur et al, 2021) UAVs are being recognised as a useful tool with a wide range of possible applications (Moradi et al, 2022).

It is important to consider, however, that although digital technologies like UAVs are often seen for their potential to enable a more sustainable agriculture, the transformation they entail is not 'inherently good' (Sacco et al, 2021) due to its implications at many levels (e.g., economic, environmental, social, technological, institutional) and their relationships. A proper understanding of its actual sustainability potential requires, therefore, further research, analysis and quantification of its specific implications at all those different levels, including at the environmental level (Arthur et al, 2021) where many different impact categories are involved.

Within the ICAERUS project, where 5 different applications of UAVs in agriculture and rural settings are being implemented in 5 different European countries, a considerable effort is being done to ensure a proper analysis of the actual environmental impacts derived from the use of this technology.

In practice, however, there are several different ways in which this assessment can be performed (Finkbeiner et al, 2010), with existing quantitative and qualitative methods, as well as mono or multi criteria methods (Rousseaux et al., 2017). Among all these options, within the ICAERUS project the method selected is a well-established, recognised and internationally standardised (ISO 14040, 2006) method known as Life Cycle Assessment (LCA), for being this one of the more reliable tools to 'characterise and assess multiple environmental impacts of products and services's (Chloé et al., 2020).

LCA has been defined as an 'objective process to evaluate the environmental burdens associated with a product, process, or activity by identifying energy and materials used and waste released to the environment' (SETAC, 1990) through its entire life cycle.

The idea behind LCA, therefore, was to make available a standard tool capable of taking into consideration not only the most obvious and direct materials, resources and emissions required to make a product but also all those necessary but less obvious inputs and outputs in former and later stages of the production chain, the places where all those elements in turn come from, how they were extracted, treated, transported and eventually used to create the final product.

Accordingly, the application of LCA requires far more information that it is apparent at first sight. In order to know what is the environmental load of, let's say, 1 kg of grapes, it is necessary to consider each and every one of the steps followed to make them possible: from the extraction of natural resources and energy needed to produce the materials and equipment used for farming, to all the resources and energy used in each task of the farming process (including for the tilling of the soil, the growing, training and pruning of the vineyards, the monitoring and protection of their health or for the irrigation and harvesting of the fruit), to how all those components are transported from one place to the other, to what happens to them after they've left the farm and have been used and disposed of. Each of those elements in every one of the steps generate its own number of emissions to air, land and water that have to be added up to the total environmental load of the final product.

Other characteristic that distinguishes LCA from other environmental assessment tools is its 'cross-media environmental approach' (Finkbeiner et al, 2010), by which not just a few environmental impact categories are considered but a wide range of them, providing as a result a deep understanding of the effects that producing 1 kg of grapes (to continue with our example) has on the environment. Then, by creating this comprehensive map of the whole life cycle of 1 kg of grapes and its impacts, it is possible to find the critical points along the chain on which to intervene to effect significant reductions on different impact categories.

As we can see, LCA thus becomes a very data intensive process in which a great deal of effort should be put into carefully defining the system under study, understanding its components and gathering data to build a detailed inventory of all the inputs and outputs associated with it. Upon the accessibility and quality of these data (Bhinge et al. 2015) depends in good measure the reliability and robustness of the whole method, since the lack of essential information leads to making assumptions that takes us away from the real picture (Sica et al, 2022). In this respect, it has been noted (Hospido et al. 2010) how the collection of data related to new technological products, processes, and services (like the ones performed by UAVs in the ICAERUS project) present a particularly challenging issue for LCA practitioners, precisely for the additional difficulties to access relevant data.

1.1.2 Economic Impact Assessment

Moving now onto the economic dimension, the impacts here refer to effects that new sustainability initiatives or solutions have on the economic performance of institutions, industries, communities or businesses applying them. These impacts can be both positive and negative and can manifest in various ways. From a change on the cost of key materials and energy, to the most efficient functioning of equipment and machinery or from a reduction in labour costs to the improvement of productivity, these impacts can determine the financial viability or lack thereof of any given enterprise (Spicka et al, 2019).

And since this economic viability is crucial for the long-term survival of any organisation, efforts to adequately assess economic impacts of new solutions become of the utmost importance to quantify, analyse and understand the costs, benefits, risks and opportunities derived from any changes aimed at improving the sustainability of any organisation or company (Arslan et al, 2017).

In the case of agriculture and agrifood businesses, facing as they are the conundrum of having to increase their production capacity to feed a record level of worldwide population while reducing their environmental footprint, coping with climate change, the depopulation of rural areas or the volatility of global prices, this economic dimension becomes of vital importance. More so, when one of the main solutions being promoted to this challenging situation is the transition towards agricultural practices based on the use of digital technologies and smart infrastructures, which can have very significant effects (both positive and negative) on the overall structure of costs and benefits, risks and opportunities underpinning their economic feasibility. As it has been pointed out, often the driving factor leading to the investment and adoption of digital technologies by companies is more linked to the enhancement of efficiency and cost reduction rather than environmental considerations (Sica et al, 2022), which emphasises the influence of this dimension on any sustainability push.

For all these reasons, the sustainability assessment of the UAVs solutions proposed by the ICAERUS project requires an adequate consideration and understanding of their economic implications to gauge their actual potential to expand into the real economy.

Once more, there are different ways of undertaking this task (Finkbeiner et al, 2010), whether a more traditional cost-benefit analysis, an input-output economic analysis or studies based on the development of key economic indicators.

Within the ICAERUS project, the economic impacts of the 5 uses given to UAVs devices in agriculture and local settings are going to be analysed following the Life Cycle thinking approach mentioned above, through a specific method known as Life Cycle Costing (LCC). According to Woodward (1997), the LCC of ‘an item is the sum of all funds expended in support of the item from its conception and fabrication through its operation to the end of its useful life’. While this definition can be applied to a broader analysis scope that can include a wider range of performance parameters, a narrower conception has also emerged (Hunkeler, 2008; Rödger et al, 2018) that calls for an environmental version of Life Cycle Costing that focuses on: the total cost of ownership from the producer or user point of view (Finkbeiner et al, 2010); an individual product/service as a reference object of all costs; the structuring of all those costs in accordance to life cycle stages; and establishing money flows in and out of the system under study in the same fashion as LCA does with material and energy flows (Finkbeiner et al, 2010).

In contrast to the more conventional LCC, this environmental LCC follows the ISO standards 14040 and 14044 on LCA and is conceived as a supporting tool for LCA that covers the economic dimension while helping to identify cost related hotspots (Rödger et al, 2018). On top of that, the environmental LCC allows for the consideration of all actors involved in the different stages of the product/service’s life cycle and for the potential inclusion of external costs (Rödger et al, 2018).

Therefore, making use again of our previous example of 1 kg of grapes, applying LCC means taking into consideration all the costs and revenues along the whole life cycle of the product, from the origin and extraction of natural resources, their processing and transport to the farm, the equipment, materials and energy used in each stage of the farming process, as well as all fix and variable costs of the farm. With all this information, it will be possible to establish the flows of money in and out of the product system, obtaining an economic performance overview of the system producing our grapes in which it is easy to identify hotspots in terms of costs or make comparisons with alternatives equipment or practices.

In the specific case of the ICAERUS project and its Use Cases, the main goal is to compare the economic performance overview of producing grapes in a conventional way with the economic performance overview of producing them using UAVs whether for spraying or monitoring the vines' health. By obtaining these two results, it will be possible to determine and compare the economic impacts of each production system and assess to which extent the alternative UAV-based production system implemented in the project is financially viable.

1.2 Life Cycle Assessment and Life Cycle Costing Methodology

Having presented the general concept of Life Cycle Thinking, the relevance of environmental and economic impacts in sustainability analysis and some of the tools available, this section is going to focus on the specific methodological features of the two techniques selected in the ICAERUS project: LCA and LCC.

1.2.1 Life Cycle Assessment (LCA)

As mentioned above, LCA is an internationally recognised and standardised methodology (Chloé et al., 2020). In order to understand the structure and application of this tool it is necessary to follow the premises established by ISO 14040 and ISO 14044.

According to these standards, a Life Cycle Assessment (LCA) is defined as the systematic analysis of the potential environmental impacts of products or services during their entire life cycle (“cradle-to-grave” analysis). The application of LCA allows to:

- Evaluate the environmental burdens associated with a product, process, or activity by identifying and quantifying energy and materials used and wastes released into the environment.
- Assess the impact of the energy and materials used and released into the environment.
- Identify and evaluate opportunities to affect environmental improvements.

The LCA methodology consists of 4 main steps (Figure 1):

Step 1- Goal and scope of the analysis: define the product or service to be assessed, choose a functional basis for comparison and define the required level of detail. Then, set a main goal for the study and determine its scope, including objective, application and audience.

Step 2- Inventory analysis: data compilation and an inventory analysis of all inputs and outputs associated with the life cycle of your product or service.

Step 3- Impact assessment: classify resource use and emissions generated according to their potential impacts and quantify them for a specific number of impact categories.

Step 4- Interpretation: Discuss the results in terms of contributions, relevance, robustness, data quality and limitations, and systematically evaluate any opportunities for reducing the negative effects of the product or service on the environment.

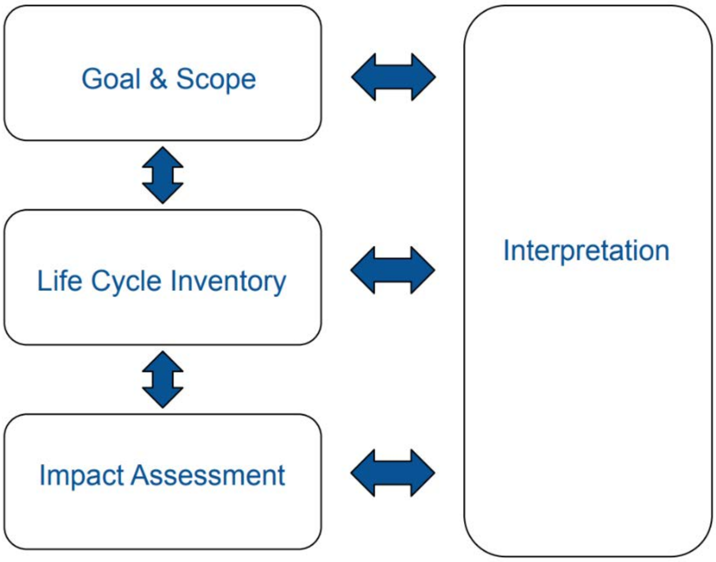

Figure 1 Graphic Representation of the different stages of LCA and their interactions

It is important to take into consideration that despite this distinction between 4 different stages, the LCA methodology is conceived as an interactive process in which feedback loops exist between those stages. This continued feedback, in turn, allows for a continued adaptation and refining of the different stages through the LCA study (Housechild, 2018).

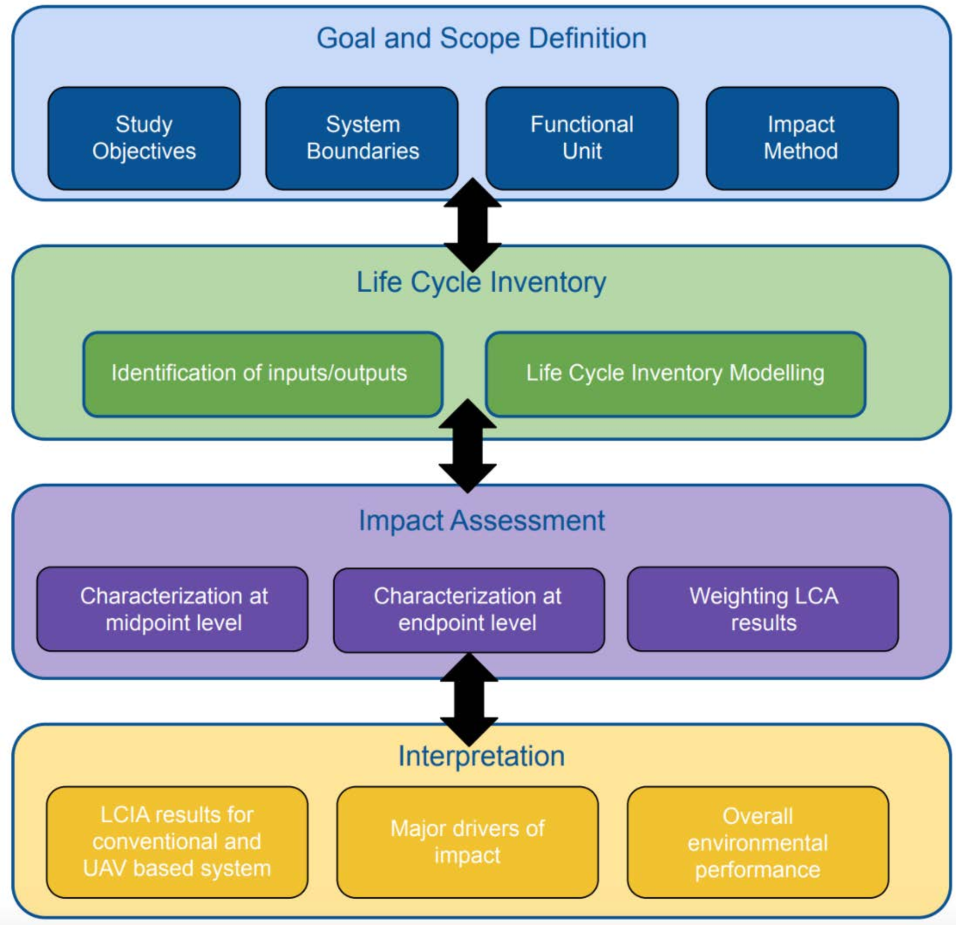

Figure 2 Breakdown Representation of each of the 4 stages of LCA

Step 1. Goal and scope of the analysis

The goal and scope are defined at the outset of the study. It is a very important phase of LCA methodology because this is where the exact approach to be followed is determined. However, the goal, as well as the scope, can be modified during the work as data are collected and new information is revealed, e.g., it may be discovered that not enough data is available to assemble a full life cycle inventory, or that the production system under study presents particularities that require a refining of the stated goal, etc.

The definition of the study's goal should include intended application, reasons for carrying out the study, intended audience and whether the results are intended to be used in comparative assertions intended to be disclosed to the public.

The scope definition, in turn, needs to determine items like the following ones: the product system to be studied, the functions of the product system or -in the case of comparative studies- the systems, the functional unit, the system boundary, allocation procedures (if any), impact categories selected and methodology of impact assessment, and subsequent interpretation to be used, data requirements, assumptions, limitations, initial data quality requirements, type of critical review, if any and type and format of the report required for the study.

Defining the system boundaries: This is a description of the activities within the product's life cycle phases that are included and excluded from consideration.

A whole life cycle of a product/service encompasses a number of stages:

- material extraction
- production
- packaging and distribution
- use

- end of use
- waste treatment or recovery

An LCA analysis considering all these stages follow a system boundary known as cradle-to-grave (from extraction of raw materials to disposal of our product). Not all LCA, however, consider all stages of the product/service life. According to the needs and goals of the study, a LCA can also account for other more narrow system boundary models of life cycles, such as cradle-to-gate (up to the second stage: production) or well-to-wheel (for analysis of energy costs of fuel extraction).

Functional Unit: it quantifies a product system's performance serving as a reference unit and is the reference variable to which the input and output data from the inventory analysis are normalised (in a mathematical sense). The study will carry out all assessments based on this unit. It is therefore important that this parameter is clearly defined and measurable because all impacts are allocated to the FU. Examples: 1kg of harvested grapes, 1 litre of milk, etc.

Step 2. Inventory analysis

When a LCA is performed, metrics will be set to quantify the different inputs (e.g., energy, water, resources, land) and outputs (e.g., emissions, wastes, products) that occur throughout the life cycle of an industrial process, technology, or commodity. This allows for the mapping of the flows of energy, resources, and materials in and out of the system under study (Figure 2). These are objective measurements, tracking distinct quantities like volume, mass, or weight. They are collected as part of the life cycle inventory (LCI).

The kind and quality of the data used to compile this inventory will determine the robustness of the results obtained. In this sense, it is important to distinguish between: a) foreground data (collected or determined specifically in or for the study) and b) background data (representative, adequate and up-to-date data, although not created exclusively for the circumstances of the individual study, accessible through public databases). Obtention of as much foreground data as possible is essential to increase the credibility and reliability of the study. In this context, the use of background data should be understood as an appropriate way of filling in the information gaps from foreground data.

The life cycle inventory data is interpreted later in the study, during the life cycle inventory assessment (LCIA), to represent actual impacts on the environment or human health. For example, a certain volume of diesel may be used to power machinery used to produce grapes in a vineyard. This should be duly recorded in the LCI. In the LCIA, this measurement is used to calculate how much the use of this specific fossil fuel contributes to a specific environmental impact category like climate change.

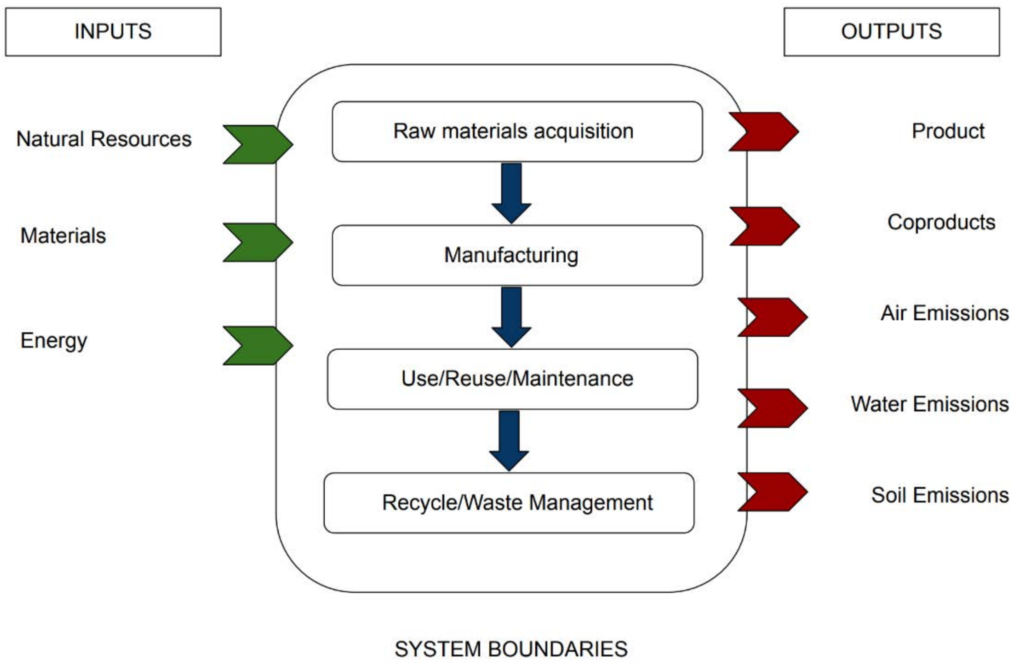

Figure 3 Graphic Representation of flows in and out of the system

Step 3. Impact Assessment

The impact assessment consists of three mandatory stages:

- Selection and identification of impact categories: relevant environmental impacts (e.g., climate change, acidification, terrestrial toxicity, etc.) are identified.
- Classification: sort and combine the LCI results into classes or impact categories according to the corresponding impact on the environment, human health, and resource use.
- Characterisation: LCI findings are multiplied by characterisation factors to convert and combine into representative impact indicators that emphasise their relationship to the different impact categories. The result is presented as an impact assessment in a unit that is common to all inputs within the impact category.

Additionally, this impact assessment stage allows for further analytical steps through three additional and optional steps:

- Normalisation: compares the quantified impacts of a defined flow with a reference value, e.g. in a global or regional sum.
- Grouping: in which impact categories are assigned in groups to facilitate the interpretation of the results in certain problem areas.
- Weighting: in this step, the results of the category indicators are grouped and weighted to include the social preferences of the different impact categories.

The impact assessment can be performed using various methodologies. Each methodology has in common that the environmental impacts are classified and characterised using two main approaches. These are the problem-oriented approach (midpoint) and the damage-oriented approach (endpoint). The first converts impact in environmental issues such as climate change, acidification, human toxicity, etc., while the second translates or groups those environmental impacts into issues of concern like human health, natural environment, and natural resources.

Step 4. Interpretation

Interpretation is the part of the study where results of the LCIA step are discussed and interpreted. The results of the LCI or LCIA phases shall be interpreted according to the goal and scope of the study. The life cycle interpretation of an LCA comprises three main elements: identification of the significant issues based on the results of the LCI and LCIA phases of the LCA study, evaluation of results, including completeness, sensitivity, and consistency checks. Results from uncertainty analysis and data quality analysis are considered as well. Finally, the interpretation concludes and gives recommendations mentioning the limitations of the study.

1.2.2 Life Cycle Costing (LCC)

The LCC method to be used in the ICAERUS project is aligned with LCA as regards the definition of its most relevant aspects like the functional unit or system boundaries while also following a very similar methodological structure or steps (Rödger et al, 2018). In general terms, LCC covers three basic steps:

Step 1- Goal and scope of the analysis: define the product or service to be assessed, choose a functional basis for comparison and define the required level of detail. Then, set a goal which determines the scope, including objective, application and audience.

Step 2- Inventory compilation: data collection and an inventory analysis of all costs/revenue associated with the life cycle of your product or service.

Step 3- Interpretation: discussion of obtained results in terms of contributions, relevance, robustness, data quality and limitations.

Despite significant structural similarities between LCC and LCA, some differences can also be observed, especially as regard the absence in LCC of an impact assessment step. While in LCA it is necessary to classify different kind of inputs and outputs and to link them to a number of environmental impact categories, in LCC the ‘aggregated cost data provides a direct measure of the financial aspect and can be aggregated without further processing’ (Rödger et al, 2018).

Step 1. Goal and scope of the analysis

This first step in LCC should be similar to the definition of the Goal and Scope of the LCA study. Therefore, this is an important phase of the methodology to be undertaken at the beginning of the study where the intended application, reasons for carrying out the study, objective and extent of the study and intended audience are determined. Again, despite this early definition, the iterative approach followed in life cycle thinking allows for a revision later on the study of these basic premises in order to adjust to the kind of data available (Rödger et al, 2018).

LCC can be given different uses, whether as a tool for planification, as an accounting tool or for reporting purposes. At the same time, it is often used as a ‘change-oriented assessment’ (Rödger et al, 2018) for the evaluation and comparison of alternatives and their cost impacts along the life cycle stages of a product/service.

The scope definition, in turn, shall determine the following items: the product system to be studied, the functions of the product system or -in the case of comparative studies- the systems, the functional unit, the system boundary and subsequent interpretation to be used, data requirements, assumptions and limitations.

Regarding the system boundaries, these must also be clearly defined and, especially when LCC is conducted in parallel to an LCA study, the boundaries shall be equivalent. It is important to remark, however, than in LCC it will not always be necessary to ‘break down all stages and collect all upstream processes’ (Rödger et al, 2018) like in LCA, while LCC also allows for the potential inclusion of external costs when those are anticipated to be internalised in the near future (Rödger et al, 2018).

As for the Functional Unit, when LCC is intended to be conducted in parallel to an LCA (like in our case), both functional units' definitions have to be identical (Rödger et al, 2018).

Step 2. Inventory compilation

LCC requires the collection of all relevant costs and revenues of the system under study. Both costs and revenues should be quantified in the same currency and, ideally, based on the same year. When an LCC takes into consideration products or costs in different periods, an effort must be made to match those prices to the actual value of the currency in their respective times.

When dealing with costs in LCC it has been noted how (Rödger et al, 2018) adding the costs of all actors in each of the life cycle stages of a product or service does not provide a particularly meaningful result by itself, since it may end up aggregating costs multiple times along the life cycle. For this reason, in LCC more focus should be given to the added value at each stage of the life cycle (Rödger et al, 2018).

The obtention of specific and reliable economic data is essential to conduct a LCC. The nature of this kind of data, however, makes it a challenge sometimes to obtain it due to reticence by producers and sellers to provide detailed information about their cost and revenue structures. This circumstance makes this step in the LCC methodology time consuming and dependent on the close collaboration and good will of companies/organisations. Given the fact that the quality of this data is of the utmost importance for the completion of a LCC analysis, different data collection strategies should be contemplated, from direct company-based information to direct but independent data sources (i.e. public databases) to indirectly derived data through surveys, experts opinions or cost estimation techniques (Rödger et al, 2018).

Once data is collected and compiled in a cost/revenue inventory, this can be classified in categories on different levels (i.e. manufacturing, use, end-of-life phases) and cost categories (i.e. fixed and variable costs). It is recommended (Rödger et al, 2018) to distinguish between the manufacturer and user perspectives beforehand, since this difference affects the kind of data required: while the former requires higher level of detail on every one of the manufacturing processes and costs, the latter requires more emphasis on costs associated with the use and maintenance of the product or service.

Step 3. Interpretation

Interpretation is the part of the study where results obtained are discussed and interpreted. These results shall be interpreted according to the goal and scope of the study.

It is important to take into consideration, however, that unlike environmental impacts and emissions, prices are more volatile due to market dynamics and more sensitive to cyclical effects. For that reason, in LCC 'the timing of costs is very important and costs with high price variability such as fuel costs should be subject to sensitivity checks' (Rödger et al, 2018).

1.2.3 Specific Application to ICAERUS' Use Cases

During the first year of the ICAERUS project, a considerable amount of thought has been given to the analysing and understanding of the Use Cases under study, in order to properly define the main characteristics of each of them for our assessments. Following the methodological structure of Life Cycle studies described above, the focus of the work so far has been on the first of the 4 stages, i.e. Goal and Scope definition.

With the intention of fulfilling this first stage, special attention has been given to the following aspects for each UC:

- Definition of the goals and intentions of each study, including specific objectives, intended application, reasons for carrying out the study, intended audience, whether the results are intended to be used in comparative assertions intended to be disclosed to the public.
- Establishing the scope of the studies, including aspects like the description of the product or service systems to be compared (namely the conventional and drone-based systems for each UC), the selected impact method for the impact assessment phase with its categories of impact, data requirements, assumptions, limitations, initial data quality requirements, type of critical review, if any, and type and format of the report required for the study.
- Determining the boundaries of each of the systems under study through a careful description of the activities included in each of the life cycle phases considered in our study.
- Selecting the appropriate functional unit, understood this as the reference unit that will allow us to quantify the performance of the product/service systems under study.

Let it be remembered, however, how the LCA methodology has been conceived as an iterative process, by which each phase provides feedback that can, in turn, contribute to an adaptation and refining of the others (Housechild, 2018). The information presented below, therefore, while serving as the starting point for our studies, will be subjected to this continued feedback process and may, eventually, experience some necessary modifications.

1.2.4 Goal and Scope definition of each of ICAERUS' 5 Use Cases

In this section we present, therefore, the Goal and Scope definition of each of the 5 ICAERUS' Use Cases. Each section starts with a brief description of the Use Case before dealing with the objectives and scope of the LCA and LCC studies.

1.2.4.1 Goal and Scope definition UC1 – Health Crop Monitoring

Use Case Description

Use Case 1 aims to create a set of transversal solutions to manage, monitor, and interact within grapevines of vineyard crops with the objective of increasing productivity and efficiency, reducing the use of chemical pesticides, encouraging and introducing bio solutions, and incrementing the quality of crops. Robotics will be implemented to identify causes and provide treatments at individual plant levels, minimising the effort to keep crops in good health and hence, maximise crop production and revenues. In order to accomplish these objectives, the solutions will be based on the adoption of unmanned aerial vehicle (UAV) for image analytics process, and a crop management dashboard to monitor and assess field data and operational field strategies.

The UAV platform will be equipped with multispectral cameras and sensors to monitor plant growth, canopy health, detect diseases and introduce the concept of spot-spraying. On the other side, a crop management dashboard will be implemented for mapping, monitoring plant health, disease detection, and pesticide applications.

Goal Definition

In the context of the ICAERUS project, the use of LCA and LCC is born from the need to obtain a clear and detailed understanding of the environmental and economic impacts associated with the introduction of new digital technologies like AUV's for agricultural practices.

More specifically, the study of UC1 - Health Crop Monitoring, intends to analyse the environmental and economic impacts of introducing drones for performing the health monitoring activities of a vineyard crop. Therefore, it has two main objectives. Firstly, to analyse the environmental profile and economic impact of viticulture practices followed in a specific vineyard before and after the introduction of UAVs solutions. Secondly, to assess the weight that, on those environmental and economic impacts, health monitoring practices have before and after UAVs solutions' implementation. In order to undertake this comparative analysis, the life cycle model will be implemented at 2 levels: i) at the crop production system (considering all agriculture activities within the vineyard); ii) at the health monitoring level (focusing on the specific tasks related to detection of diseases).

The outcomes will mainly concern agricultural researchers and agri-food companies as well as farmers/associations across the EU. They will also be useful for governmental institutions, forest protection specialists, academia, nature scientists, monitoring service providers and drone and imaging device manufacturers.

The LCA and LCC results will be shared with the respective stakeholders and will also be part of WP3 of the EU funded project ICAERUS.

Scope Definition

Product/service: The main outcome of the system under study is grapes harvested from the vineyard in Catalonia (Spain) where UC1 is being implemented, with a special focus on the health monitoring service provided within the vineyard system by UAVs.

Product system: The assessment of UC1 will be a product-based study, in which the system under consideration is the vineyard where our reference product (i.e., grapes) is being produced. Since the introduction and use of drones will affect a specific part of the production tasks within the system, that is the health monitoring tasks, beyond looking at the entire production system as whole, a further analysis step is going to be taken as well in order to look more in detailed into the monitoring tasks alone, comparing both the conventional practices and the drone-based ones.

In this product system all the upstream and downstream processes are also included. Specifically, raw materials, energy (fuel, electricity, etc.), natural resources will be included as inputs to the system and wastes as well as emissions to air soil and water will be classified as outputs.

Impact assessment method: Among the impact methods available within the SimaPro software, the recently adapted Environmental Footprint 3.1. has been selected. This is an impact assessment method developed by the European Commission to be used in the Context of the Footprint (EF) initiative. This method allows an analysis mid-point with up to 16 impact categories within the former and 3 within the latter. The mid-point categories considered include: Climate change, Ozone depletion, Human toxicity-cancer, Human toxicity-non cancer, Particulate matter, Ionising radiation-human health, Photochemical ozone formation-human health, Acidification, Terrestrial eutrophication, Freshwater eutrophication, Marine eutrophication, Land use, Freshwater ecotoxicity, Water use, Resource depletion - fossils, Resource depletion - minerals and metals.

Functional Unit: The reference product of our study is going to be 1 kg of harvested grapes.

System Boundaries: UC1 system boundaries will be from ‘cradle to farm gate’.

System Representation is given in Figure 4:

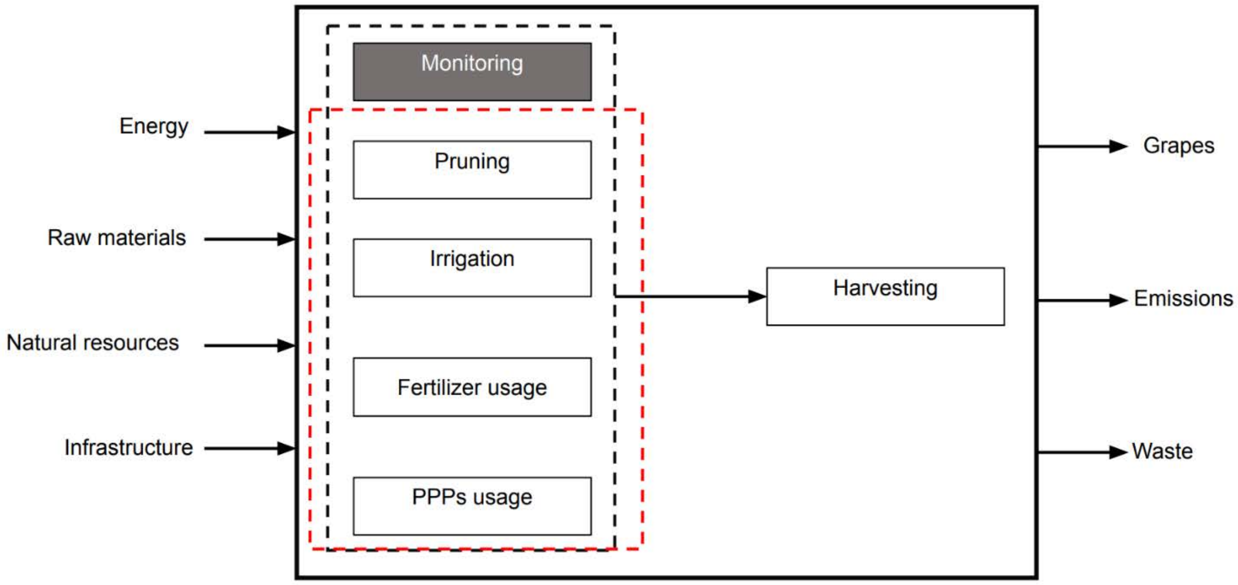

Figure 4 UC1 System Representation

1.2.4.2 Goal and Scope definition UC2 - Spraying

Use Case Description

Plant protection products (PPPs) are used in farming to protect crops against pests, weeds and diseases, and help ensure European agriculture remains productive, profitable and sustainable. Plant protection applications, and more specifically spraying, is a core aspect of the agricultural production of all open-field crops, including vegetables, orchards and vineyards, and arable crops. Spraying drone refers to any UAV, operated manually or automatically, that is capable of applying agrochemicals at a desired rate close to the canopy (commonly <5m). The scope of the Use Case 2 is to test and assess spraying configurations for optimal drone spraying applications in field conditions. To this end, the experimental design focuses on both the evaluation of spraying quality (i.e. deposition, canopy penetration and spray drift) achieved through various operational configurations (i.e. spraying altitude, speed, nozzle flow and liquid deposition rates) for spraying drones, as well as their comparison with existing conventional spraying machinery, such as conventional terrestrial boom and mist sprayers. Finally, the UC aims to identify inherent risks of drone spraying and address them through the development of novel mitigation strategies, enabling safe and eco-friendly drone-based plant protection applications.

Goal Definition

Regarding the impact assessment of UC2 - Spraying, it aims at analysing the environmental and economic impacts of introducing drones for performing the spraying of plant protection products on a vineyard in Greece. The study will, therefore, have two main objectives: on the one hand, to analyse the environmental profile and economic impact of viticulture practices followed in a specific vineyard before and after the introduction of UAVs solutions; on the other one, to assess the weight that spraying practices have on the environment and economically before and after UAVs solutions have been implemented. In order to undertake this comparative analysis, the life cycle model will be implemented at 2 levels: i) at the crop production system (considering all agriculture activities within the vineyard); ii) at spraying level (focusing on the specific tasks related to spraying of plant protection products).

The outcomes will mainly concern agricultural researchers and agri-food companies as well as farmers/associations across the EU. They will also be useful for governmental institutions, forest protection specialists, academia, farmers advisors, nature scientists, monitoring service providers and drone and imaging device manufacturers.

The LCA and LCC results will be applied to the respective stakeholders and will also be part of WP3 of the EU funded project ICAERUS.

Scope Definition

Product/service: The main outcome of the system under study is grapes harvested from the vineyard in Greece where UC1 is being implemented, with a special focus on the spraying service provided within the vineyard system by UAVs.

Product system: The assessment of UC2 will be a product-based study, in which the system under consideration is the vineyard where our reference product (i.e. grapes) is being produced. Since the introduction and use of drones will affect a specific part of the production within the system, that is the spraying of plant protection products, beyond looking at the entire production system as whole, a further analysis step is going to be taken as well in order to look more in detailed into the spraying practices, comparing both the conventional practices and the drone-based ones.

In this product system all the upstream and downstream processes are also included. Specifically, raw materials, energy (fuel, electricity, etc.), natural resources will be included as inputs to the system and wastes as well as emissions to air soil and water will be classified as outputs.

Impact assessment method: Among the impact methods available within the SimaPro software, the recently adapted Environmental Footprint 3.1. has been selected. This is an impact assessment method developed by the European Commission to be used in the Context of the Footprint (EF) initiative. This method allows an analysis mid-point with up to 16 impact categories within the former and 3 within the latter. The mid-point categories considered include: Climate change, Ozone depletion, Human toxicity-cancer, Human toxicity-non cancer, Particulate matter, Ionising radiation-human health, Photochemical ozone formation-human health, Acidification, Terrestrial eutrophication, Freshwater eutrophication, Marine eutrophication, Land use, Freshwater ecotoxicity, Water use, Resource depletion - fossils, Resource depletion - minerals and metals.

Functional Unit: The reference product of our study is going to be 1 kg of harvested grapes.

System Boundaries: UC2 system boundaries will be from ‘cradle to farm gate’.

System Representation is given in Figure 5:

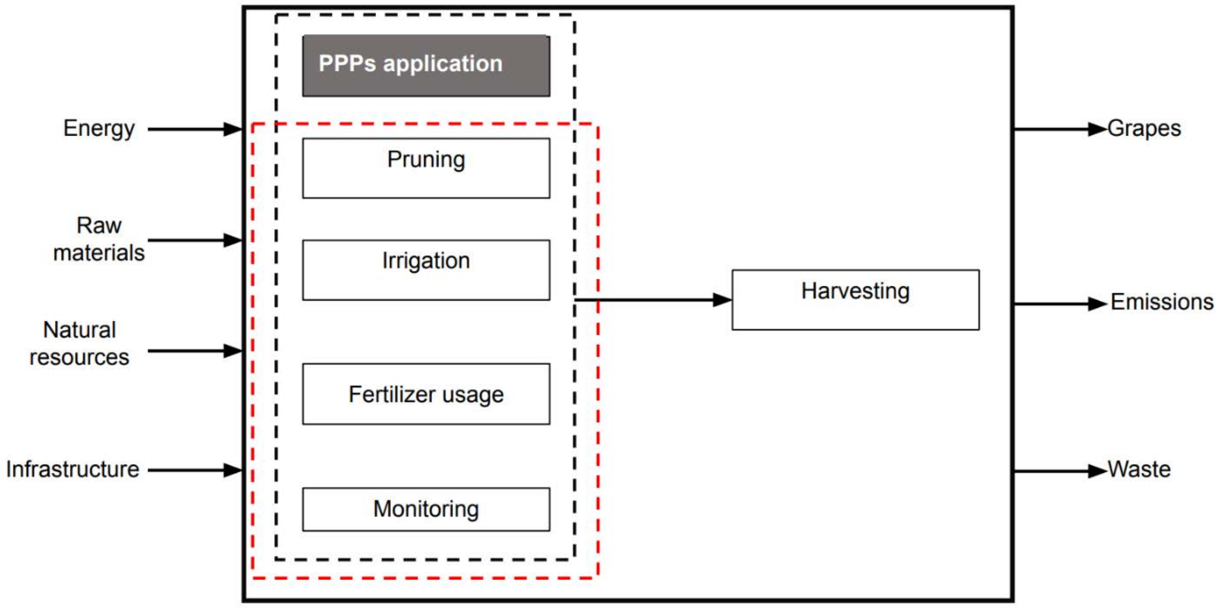

Figure 5 UC2 System Representation

1.2.4.3 Goal and Scope definition UC3 – Livestock Monitoring

Use Case Description

The scope of the UC is to evaluate the risks and the interests to use drones for monitoring cattle and sheep in grassland-based systems facilitating the monitoring work and improving the quality of life of farmers. Building on existing and “off-the-shelves” drones technologies, the UAVs will be evaluated in 2 complementary pilot farms representing 2 species and 3 types of grasslands: the first farm with a beef cattle herd in pastures low-lands, the second farm with a sheep flock in a pastoral system based on 3 types of grasslands (low-lands pastures, woody rangelands, summer mountain rangeland). Drones will be used as an “eye-in-the-sky” supporting farmers and sheepherders with visual information. Indeed, from the drones’ images, livestock farmers can collect a lot of information that they are currently obtaining through a close visual check of the herd (number of animals, position of the animals, access to water, health and welfare levels) when they are visiting them or shepherding them. The idea is not to replace farmers but to evaluate if a part of the farmers' visits can be facilitated by drones.

Goal Definition

The goal of this LCA and LCC study is to assess the environmental and economic impacts of introducing drones for livestock monitoring, which will be deployed in two different pilot areas of France, including two species (cattle and sheep) and three types of grasslands (low-land pastures, woody rangelands, summer mountain rangelands), as compared to the impacts associated to the conventional monitoring system (by farmers in-person monitoring).

The outcomes will mainly concern livestock farmers with grassland-based systems, wetlands and rangelands, focusing on Europe. They will also concern private sector companies that wish to enter or expand their business in drone-based monitoring services, drone manufacturers and academia.

The LCA and LCC results will be applied to the respective stakeholders and will be also part of WP3 of the EU funded project ICAERUS.

Scope Definition

Product/service: The service under study is ‘livestock monitoring’. The scenarios examined will be:

- Monitoring of beef cattle in “bocage” grasslands (low-land pastures).
- Monitoring of sheep flocks in a pastoral system (low-land pastures, woody rangelands, summer mountain rangelands).

Product System: The monitoring service will be conducted either by a drone and cameras system, or conventionally by farmers and more specifically regarding the former:

- a drone (MAVIC 3 Enterprise from DJI) equipped with RGP camera (x56 zoom), approved by national authority for flying BVLOS into a 1 km radius.
- a drone (MAVIC 3 Thermal from DJI) equipped with both RGB and thermal cameras (x56 zoom), approved by national authority for BVLOS into a 1 km radius.
- Speakers that will be tested as an additional payload on the drones, in order to assess their implementation for relocating the animals using specific sounds.

In the product (service) system all the upstream and downstream processes are also included. Specifically, raw materials, energy (fuel, electricity, etc), natural resources will be included as inputs to the system and wastes as well as emissions to air soil and water will be classified as outputs.

Impact assessment method: Among the impact methods available within the SimaPro software, the recently adapted Environmental Footprint 3.1. has been selected. This is an impact assessment method developed by the European Commission to be used in the Context of the Footprint (EF) initiative. This method allows an analysis mid-point with up to 16 impact categories within the former and 3 within the latter. The mid-point categories considered include: Climate change, Ozone depletion, Human toxicity-cancer, Human toxicity-non cancer, Particulate matter, Ionising radiation-human health, Photochemical ozone formation-human health, Acidification, Terrestrial eutrophication, Freshwater eutrophication, Marine eutrophication, Land use, Freshwater ecotoxicity, Water use, Resource depletion - fossils, Resource depletion - minerals and metals.

Functional Unit (FU): Monitoring (counting, identification, health analysis and availability of grass and water) of cattle/sheep's heads per hectare of grasslands per hour and working day for 1 year.

System Boundaries: UC3 system boundaries will be from 'cradle to service gate'. Therefore, this assessment will take into consideration all upstream processes from raw materials extraction, processing, materials and equipment production and transport to the 'gate' representing here the performance of the service (in this case, livestock monitoring).

System Representation is given in Figure 6:

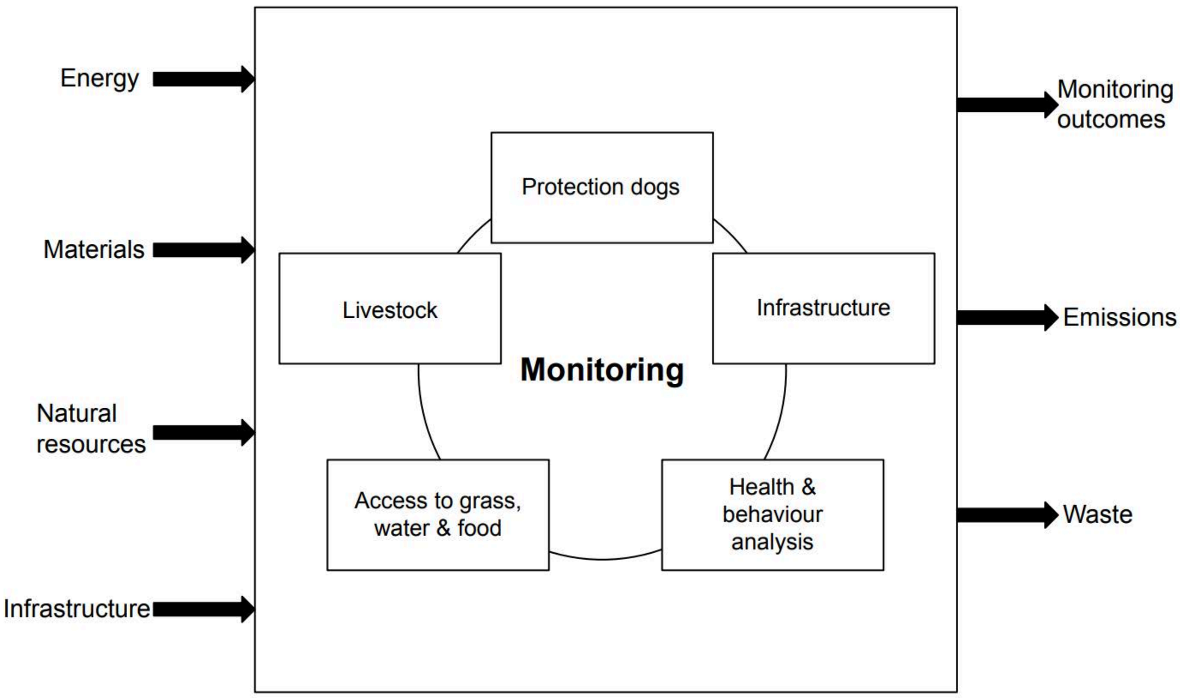

Figure 6 UC2 System Representation

1.2.4.4 Goal and Scope definition UC4 – Forest Monitoring

Use Case Description

Forestry and forest maintenance can be a tedious and tiring process that, in some sense, requires a lot of manpower, skills and relevant resources. The maintenance of forest lands is carried out to prevent dangers that pose a greater risk to nature - forest fires, illegal logging, etc. However, surveillance and monitoring of the forest status is the main current and future challenge of forestry due to their vast surface and lack of experienced personnel (forest managers, engineers and workers) based onsite, making it very difficult to spot risks at early stages. Given the importance of early risk detection, UAVs could play a significant role in forest monitoring.

In this Use Case the combination of different types of UAVs and imaging cameras will be used to create optimised solutions for 3 specific scenarios: for tree health monitoring; fire risk monitoring; and for wildlife monitoring.

Satellite imaging data will be used to detect possible tree stress, meanwhile multi-rotor drones will be used for detailed (high-resolution) monitoring of specific forest areas (including tree health and fire risks), while fixed-wing drones are becoming an efficient tool in forestry research and will be used for wildlife monitoring due to their capacity to cover vast areas and provide fast monitoring data.

Goal Definition

The goal of this LCA and LCC study is to assess the environmental impact of different types of UAVs and cameras in creating solutions for specific scenarios, such as forestry monitoring, including forest tree health assessment and fire risk assessment, and wildlife monitoring estimating the size and geographical distribution of the wild boar population. The analysis approach will be based on calculating the environmental and economic impacts of using drones for 3 different forest monitoring activities and comparing them with the impacts derived from current conventional monitoring systems.

The outcomes will mainly concern agricultural researchers and agri-food companies as well as farmers/associations across the EU. They will also be useful for governmental institutions, forest protection specialists, academia, nature scientists, monitoring service providers and drone and imaging device manufacturers.

The LCA and LCC results will be applied to the respective stakeholders and will also be part of WP3 of the EU funded project ICAERUS.

Scope Definition

Product: The service under study is the monitoring of forestry and wildlife in Lithuanian forest areas. The scenarios examined will be:

- Forest Tree Health monitoring: Identifying possibly unhealthy forest areas and determining the symptoms of forest health deterioration.
- Wildfire Risk Monitoring: Identifying Forest fire fuel types, their availability and condition.
- Wild Boars Monitoring: Detecting and counting wild boars.

Product System: The monitoring service will be conducted either by different types of UAVs and cameras, or by a conventional-based system and more specifically regarding the former:

- a multispectral satellite imagery (Sentinel-2 MSI), a multi-rotor drone and VNIR-range hyperspectral camera and a flight mission planning software.
- a multi-rotor drone, VNIR-range hyperspectral camera and a flight mission planning software.
- a fixed-wing UAV, a long-range infrared thermal imaging camera and a flight planning and execution software.

In this service system all the upstream and downstream processes are also included. Specifically, raw materials, energy (fuel, electricity, etc.), natural resources will be included as inputs to the system and waste as well as emissions to air soil and water will be classified as outputs.

Impact assessment method: Among the impact methods available within the SimaPro software, the recently adapted Environmental Footprint 3.1. has been selected. This is an impact assessment method developed by the European Commission to be used in the Context of the Footprint (EF) initiative. This method allows an analysis mid-point with up to 16 impact categories within the former and 3 within the latter. The mid-point categories considered include: Climate change, Ozone depletion, Human toxicity-cancer, Human toxicity-non cancer, Particulate matter, Ionising radiation-human health, Photochemical ozone formation-human health, Acidification, Terrestrial eutrophication, Freshwater eutrophication, Marine eutrophication, Land use, Freshwater ecotoxicity, Water use, Resource depletion - fossils, Resource depletion - minerals and metals.

Function: There will be three different functions and functional units for the three different scenarios concerning forestry and wildlife monitoring.

- Functional Unit 1 (FU1): Pathogenic area (ha) x monitored hectare of forest x working day for 1 year
- Functional Unit 2 (FU2): Forest fire fuel detected x monitored hectare of forest x working day for 1 year
- Functional Unit 3 (FU3): Monitoring (counting, geographical distribution) wild boars in a specific area (ha) x working day for 1 year

System Boundaries: UC4 system boundaries will be from ‘cradle to service gate’. Therefore, this assessment will take into consideration all upstream processes from raw materials extraction, processing, materials and equipment production and transport to the ‘gate’ representing here the performance of the service (in this case, 3 different kind of forest monitoring).

System Representation is given in Figure 7:

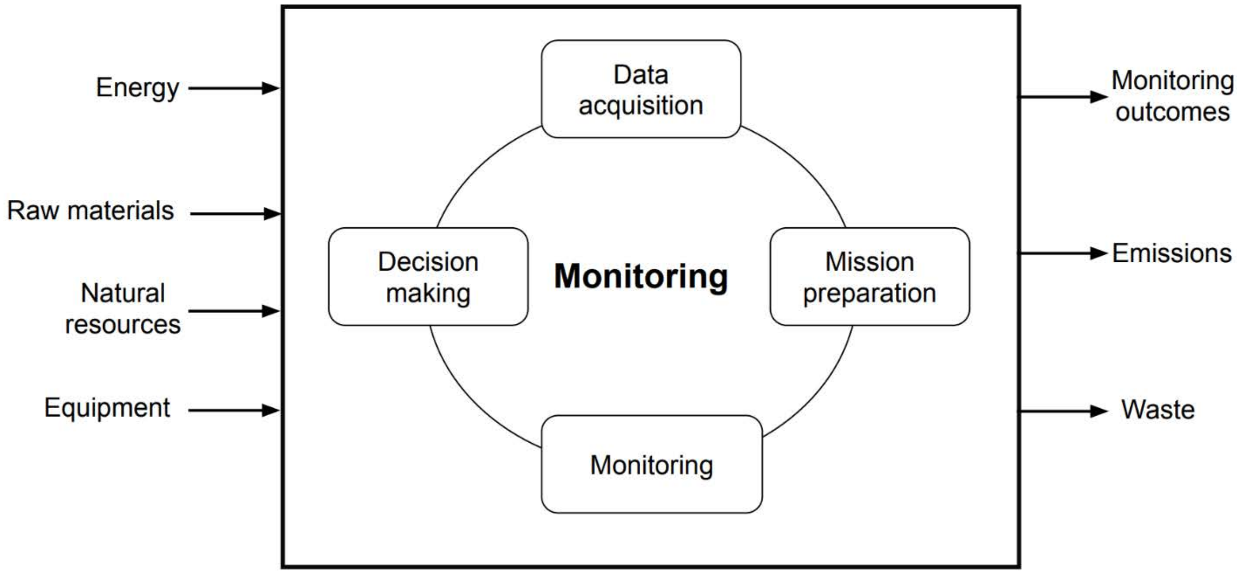

Figure 7 UC2 System Representation

1.2.4.5 Goal and Scope definition UC5 – Rural Logistics

Use Case Description

The goal of the UC5 is to design, develop and deploy an innovative drone-delivery fleet management system that will act as an alternative fast response system for delivering small parcels of importance (e.g. medical supplies, documentation, etc.) in remote areas of European rural areas. Such a system in case of expansion across Europe would serve these areas and optimise people’s lives providing security of important supplies provision on time.

The proposed system will consist of both software and hardware. From the software side there will be a cloud-based management system accepting requests for delivery services. The software will:

  - Accept and sort requests depending on various criteria
- Decide on the service availability and the service time slots
- Book suitable drones and time slots to cover the demand for service
- Assign tasks and monitor the drones enroute
- Keep a record of all actions

From the hardware side, different drone systems will be deployed serving different size/weight cargo and traveling distance. Drones will follow predefined routes taking in consideration the local regulations, the airspace restrictions, the terrain elevation, and the obstacles in the pathway. As with the practices followed in civilian aviation, each route will have different flight levels so even more than one drone can utilise it without risking collusion.

Goal Definition

The goal of this LCA and LCC study is to assess the environmental impacts of an innovative drone-delivery fleet management system that will act as an alternative fast response system for delivering small parcels of importance in remote rural areas of North Macedonia. The analysis approach will include the comparison of the LCA and LCC data with the respective data regarding the incumbent conventional delivery system.

The outcomes will mainly concern private sector companies that wish to enter or expand their business in drone logistics, already operational courier service providers, administrative authorities, drone manufacturers, academia, citizens in remote areas and public health authorities.

The LCA and LCC results will be applied to the respective stakeholders and will be also part of WP3 of the EU funded project ICAERUS.

Scope Definition

Product: The service under study is the delivery of a cargo mass between 0,1 to 7 kg, on a traveling distance up to 45 km. The scenarios examined will be:

  - Items such as mail, medicine, documents and blood samples are to be delivered to remote and isolated settlements connected with a big service centre, Ohrid.
- Items such as seeds, pesticides and liquid chemicals are to be delivered to 3 agricultural settlements connected with a big service centre, Kuklish.

Product System: The delivery service will be conducted either by a drone-delivery fleet management system, or a conventional delivery system and more specifically regarding the former:

  - a 4-rotor multirotor drone based on Pixhawk autopilot technology being able to carry small mass cargo, up to 2kg and a maximum distance up to 5km
- a 6-rotor or 8-rotor system drone based on Pixhawk autopilot technology. This drone will be able to carry big mass cargo up to a maximum of 8kg. Depending on the number of rotors and the payload mass maximum distance will be no more than 3km. (exact architecture will be available after simulations)
- a hybrid VTOL (Vertical Take Off and Landing) fixed wing drone based on Pixhawk autopilot technology. This drone will be able to carry a cargo mass up to 3kg for a maximum distance of 60km.
- a software, such as a cloud-based management system accepting requests for delivery services,

while for the latter the equipment used will consider delivery vans or trucks.

In this service system all the upstream and downstream processes are also included. Specifically, raw materials, energy (fuel, electricity, etc.), natural resources will be included as inputs to the system and wastes as well as emissions to air soil and water will be classified as outputs.

Impact assessment method: Among the impact methods available within the SimaPro software, the recently adapted Environmental Footprint 3.1. has been selected. This is an impact assessment method developed by the European Commission to be used in the Context of the Footprint (EF) initiative. This method allows an analysis mid- point with up to 16 impact categories within the former and 3 within the latter. The mid-point categories considered include: Climate change, Ozone depletion, Human toxicity-cancer, Human toxicity-non cancer, Particulate matter, Ionising radiation-human health, Photochemical ozone formation-human health, Acidification, Terrestrial eutrophication, Freshwater eutrophication, Marine eutrophication, Land use, Freshwater ecotoxicity, Water use, Resource depletion - fossils, Resource depletion - minerals and metals.

Function: Delivery of small cargos of importance to remote rural settlements.

Functional Unit (FU): delivery of 1kg of payload per km per day.

System Boundaries: UC5 system boundaries will be from 'cradle to service gate'. Therefore, this assessment will take into consideration all upstream processes from raw materials extraction, processing, materials and equipment production and transport to the 'gate' representing here the performance of the service (in this case, delivery of small cargos to remote rural settlements).

System Representation is given in Figure 8:

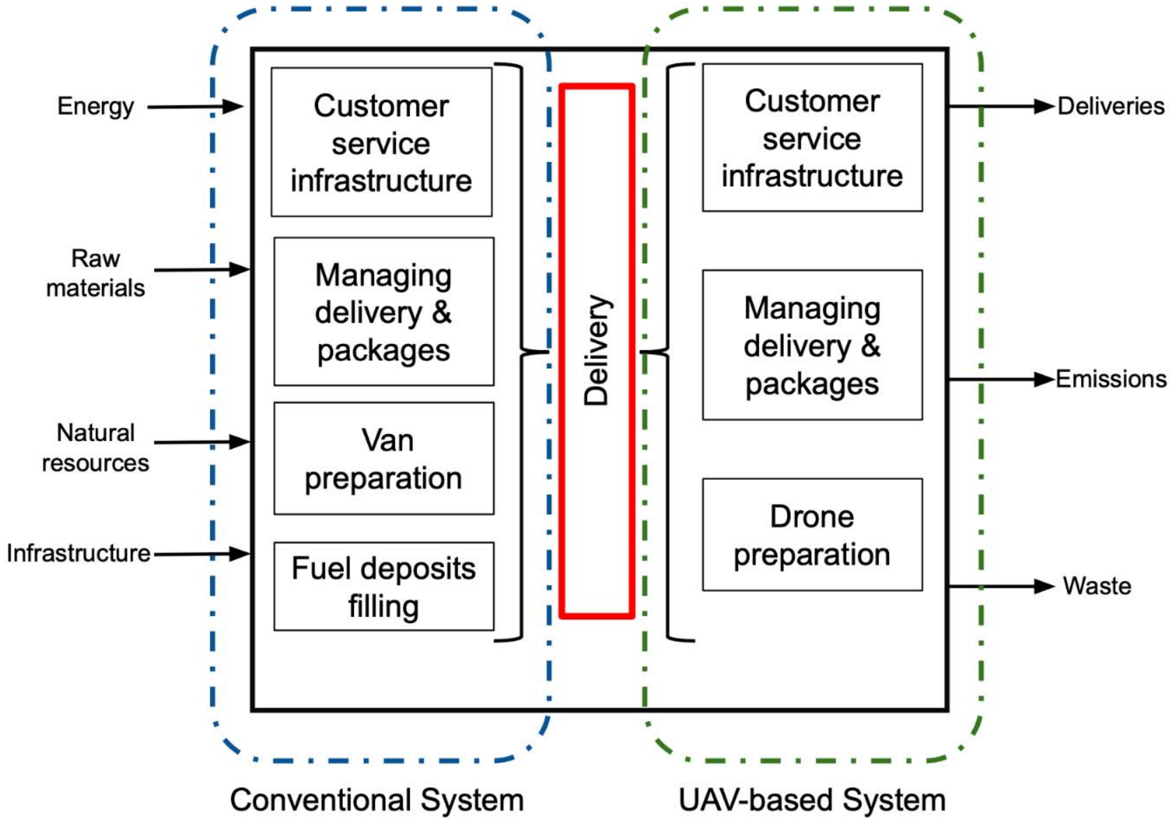

Figure 8 UC2 System Representation

1.2.5 State of data collection and next steps

The Critical Role of Data Collection in LCA

Data collection is a cornerstone of any Life Cycle Assessment (LCA), serving as the foundation for evaluating the environmental impacts of a product, process, or system. As explained earlier on, the goal of an LCA is to provide reliable, evidence-based insights to guide sustainable decision-making. And achieving this requires a comprehensive and meticulous approach to data collection, which, while time-intensive, ensures the accuracy and credibility of the assessment.

An LCA covers multiple phases of a product's lifecycle—raw material extraction, production, transportation, use, and end-of-life. Each phase involves numerous processes, inputs, outputs, and interactions. Missing or incomplete data at any stage can compromise the results, leading to misrepresentation of environmental impacts and potentially flawed recommendations. For example, underestimating energy use during production could result in an inaccurate carbon footprint, ultimately misleading sustainability strategies.

Data accuracy is critical for producing valid results. Collecting precise details on resource consumption, energy inputs, emissions, and waste streams enables the LCA to capture the full environmental scope. This requires time and collaboration, often involving coordination across diverse stakeholders, from suppliers and manufacturers to transporters and end-users. Additionally, seasonal or operational variability in factors like energy use or emissions necessitates extended data monitoring to ensure representativeness.

Detailed data collection also provides insights into key environmental hotspots, allowing stakeholders to identify opportunities for improvement and innovation. For instance, knowing the exact amount of water used or emissions generated during a specific phase can guide efforts to reduce impacts, enhance resource efficiency, or develop more sustainable alternatives.

Despite its challenges, the time and effort invested in thorough data collection are essential. High-quality data not only ensures the credibility of the LCA but also supports informed decision-making, fosters compliance with standards like ISO 14040/14044, and enables meaningful comparisons between alternatives. In essence, the more detailed the data, the more powerful the LCA becomes as a tool for advancing sustainability.

To better understand the point in which the data collection process stands at, we will look now at each use case specifically.

1.2.5.1 Data collection process UC1 - CROP HEALTH MONITORING

Current Status

At this point within the project, a comprehensive collection and recording of the key components and resource requirements for both traditional and drone-assisted crop health monitoring methods in the vineyard has been undertaken. This data collection effort and the analysis that will ensue aims to identify the differences in processes, inputs, and outcomes, providing a clear understanding of their respective impacts on labour, materials, energy, and costs. Since the Goal and Scope of this study looks at the whole vineyard operation and considers 1 kg of grapes as its functional unit, although particular attention is given to the health monitoring activities, all relevant farming practices are considered and data on them have been gathered.

On the one hand, for each monitoring approach, specific tasks involved have been mapped, from initial preparation to data collection and subsequent analysis. Traditional crop health monitoring primarily relies on manual and visual inspections, requiring field workers to physically assess and gather data from the vineyard while performing other tasks. In contrast, drone-based monitoring involves tasks such as planning flight paths, operating the drones, processing and interpreting the collected data.

Data on the materials and equipment used in each method has also been collected. For conventional monitoring, no specific tools or equipment has been reported, indicating the less formal and less resource intensive nature of this activity. For drone-assisted monitoring, on the other hand, we are analysing the use of drone hardware, batteries, and data processing software, along with associated maintenance needs. Differences in the types and frequency of consumables required specially for the second system are also being assessed to provide a detailed comparison of resource use.

To capture the labour dynamics, which are of great importance specially for the economic impact assessment, the total hours spent on preparation, execution, and analysis for both methods have been recorded. For traditional monitoring, this involves time spent on physical inspections on the field, while drone monitoring includes technical tasks such as equipment setup, drone operation, and data processing.

Missing Aspects

Most of the relevant data has already been collected through the respective questionnaire. The main data aspects that haven't yet been fully collected relate to:

- Costs associated with plant protection products for the year 2024
- Costs associated with some energy sources for the year 2024
- Energy requirements for the images processing
- A final recount of total monitored area and, if possible, trees

Further enquiries to the farmer are being made to find information regarding the two former points. Alternatively, costs indexes for Spain for the year 2024 will be duly consulted.
As for the latter points, an additional effort will be made in close collaboration with the UC leader in order to find the most appropriate estimate value.

Challenges

First, obtaining accurate and consistent data across both systems (conventional and drone-based systems) has presented some complexities due to variations in tasks, equipment, and labour requirements. Conventional monitoring relies heavily on manual inputs, such as field inspections, which can be difficult to precisely quantify. Drone-based systems, on the other hand, involve advanced technology and specialised equipment, making it challenging to gather enough detailed information on energy use, maintenance, and operational costs. The latter data gaps, however, are being covered with efforts to collect direct specific data on drones' assembly, operation, energy requirements and maintenance.
Another significant challenge lies in properly aligning data quality and granularity between the two monitoring approaches, which is critical to ensure a fair comparison. Overcoming these challenges has required undertaking a systematic and well-documented data collection strategy, supported by stakeholder collaboration to fill data gaps.

Timeline for Completion

The main bulk of data collection has been completed by December 2024 as expected.

Next steps

First, all the data collected and contained in the relevant questionnaire will start to be processed in order to compose the basic inputs and outputs inventory for the 2 systems compared (conventional and drone-based systems).
At the same time, based on the data gaps already identified and additional missing aspects that could be detected during the inventory configuration, supplementary data will be collected either directly through the UC leader and farmer or through relevant background data available in databases. The coming demonstration during the first months of 2025 (most probably around March) will contribute considerably to this task of filling data gaps.
Finally, upon completion of the final inventory during the first 3 months of 2025, the modelling process within the SimaPro software will be undertaken before proceeding with the actual environmental and economic impact assessment and interpretation of results, with the aim of having preliminary results for this UC by the end of 2025.

1.2.5.2 Data collection process UC2 - SPRAYING

Current Status

Similar to the previous UC, in UC2 a detailed analysis of the key components and resource requirements for both traditional and drone-based plant protection product spraying methods in the vineyard has been conducted. This study aims to highlight the differences in processes, inputs, and outcomes, providing a clear understanding of their respective impacts on labour, materials, energy, and costs. With a Goal and

Scope that encompasses the entire vineyard operation and using 1 kg of grapes as its functional unit, particular focus is placed on the spraying activities, while data from all relevant farming practices are incorporated.

For each spraying method, the specific tasks involved have been identified, from preparation to application and post-application analysis. Traditional spraying relies on manual operations, involving field workers using handheld or tractor-mounted sprayers to apply products directly to the vineyard. In contrast, drone-assisted spraying involves tasks such as flight path planning, operating drones equipped with sprayer systems, and monitoring spray coverage and precision.

Data on the materials and equipment used in each method has been carefully collected. For conventional spraying, this includes air-blast sprayers, and diesel to power them, reflecting a more established yet resource-intensive approach. For drone spraying, we are analysing inputs such as drone hardware, spray nozzles, and batteries, as well as maintenance requirements.

Labor dynamics, which are particularly important for the economic assessment, have also been thoroughly examined. The total hours required for preparation, execution, and follow-up have been recorded for both methods. Traditional spraying involves significant manual labour for equipment operation and field coverage. Meanwhile, drone spraying demands specialised technical labour for equipment setup, operation, and software use.

Missing Aspects

Most of the necessary data has already been gathered through the corresponding questionnaire. However, there are still a few key data points that require further collection, including:

- More detailed information regarding yields and waste amounts
- Other farm overhead costs for 2024 (related to insurances, taxes, …)
- More detailed information of tasks, frequency and labour requirements for relevant farm practices other than spraying

To address these three points, additional inquiries are being made with the farmer to fill the data gap.

Challenges

Collecting data for an LCA and LCC analysis comparing conventional and drone-based plant protection product (PPP) spraying in a vineyard presents several challenges. After one year of data collection and the recording of most relevant aspects, the main difficulty of this UC lies in the fact that current regulations in the EU prohibit the use of drones for spraying real chemical products, making it impossible to directly measure the comparative yield from each system within the studied vineyard. As a result, the study would have to rely on secondary data from other vineyards where drone spraying may have been authorised and tested. This requires identifying credible sources that report on yield variations and productivity impacts associated with drone spraying. Additionally, aligning this external data with local conditions, such as soil, climate, and grape variety, is critical for ensuring relevance and accuracy. The impossibility of obtaining this kind of data with this level of granularity may entail a reframing of the Goal and Scope of the current study for this UC, in order to focus it more in the actual spraying practices as a distinct service within the vineyard and their impacts (both environmental and economic) instead of the whole vineyard with all its farming practices and yields.

Timeline for Completion

Although the main bulk of data collection has been completed by December 2024 as expected, there are several key aspects that need to be confirmed, especially when it comes to the potential yield difference obtained between the two studied spraying systems. This key aspect will need to be addressed in the next two months to decide whether a Goal and Scope redefinition is needed.

Next steps

Based on the decision on whether a new Goal and Scope definition is required and on all the other relevant data already obtained, the input/output inventories for each system will be produced from March 2025. The modelling of the inventories within the SimaPro software will follow, with the aim at having first preliminary results by the end of 2025.

1.2.5.3 Data collection process UC3 - Livestock Monitoring

Current Status

Data collection efforts for this study have primarily been conducted on the beef cattle farm. Over the course of three distinct monitoring periods—Fall 2023, Spring 2024, and Fall 2024—comprehensive data has been gathered on the seasonal and paddock-specific distribution of traditional monitoring methods versus drone-based monitoring. This includes the equipment usage patterns both within and between animal paddocks.

To date, the aggregated dataset covers approximately 60 days of monitoring, capturing the average resource consumption for both conventional and drone-based equipment. This data will serve as the foundation for a year-round distribution model of resource usage. However, there is a noted gap in the dataset regarding specific equipment details, such as the brand, manufacturing location, and import methods. While most of this information has been collected by the UC leader in close collaboration with the farmers, it is in the process of being recorded in the final questionnaire.

Missing Aspects

Despite significant progress, some critical components of the analysis remain unresolved. Specifically, some raw data still needs to be processed to estimate daily resource use for both systems and extrapolate this data to represent a full year of monitoring. The unique resource demands for each system are as follows:

1. Conventional System:
    - Estimation of diesel consumption for the pickup vehicle used during monitoring.
2. Drone System:
    - Estimation of electricity consumption for drone operation.
    - Estimation of diesel consumption for the vehicle supporting drone logistics.

These calculations are essential to fully differentiate the resource impacts between the two systems and ensure a robust environmental and economic impact comparison.

Challenges

A significant challenge lies in extrapolating the 60 days of monitoring data to accurately represent the resource use over an entire year. Seasonal variations, paddock-specific differences, and equipment usage patterns complicate this process, necessitating careful adjustments to ensure reliability.

Another challenge relates to the ongoing discussions about updating the UC plan for the sheep scenario. Initially, the plan included a comprehensive environmental impact assessment similar to the beef cattle scenario. However, emerging priorities, such as an increased emphasis on innovation through AI development, suggest a potential shift in focus. A simplified scenario for the sheep context is under consideration, which would reduce the scope of impact assessments. Alternatively, we could concentrate exclusively on the beef cattle scenario to streamline efforts. Discussion on this matter are underway to find the most adequate and feasible solution while aligning with the project’s goals.

Timeline for Completion

Currently, an in-depth analysis of working conditions is underway, leveraging the same dataset. Following this, the environmental impact analysis for the initial dataset is expected to be completed between

December 2024 and February 2025. This analysis will include the fulfilment of the outstanding questionnaire, scheduled to begin in December and conclude by mid-February.
The final data collection period is planned for Spring 2025. Given the limited time for full analysis within this phase, it is proposed to use this period primarily for validation purposes rather than a comprehensive reassessment. This approach will allow us to refine and confirm findings from earlier data while maintaining a realistic timeline for project deliverables.

Next Steps
The environmental impact monitoring has made substantial progress, with 60 days of data providing a solid foundation for analysis. However, critical tasks remain, including the processing of resource-use data, addressing equipment-specific gaps, and resolving the scope of the sheep scenario. Decisions on the latter will directly impact the allocation of resources and the overall focus of the study. Completing the environmental analysis by February 2025 will ensure timely validation of findings during the final data collection period in Spring 2025. Collaboration and feedback will be vital to navigate the outlined challenges and finalise the next steps effectively.

1.2.5.4 Data collection process UC4 - WILDLIFE MONITORING

UC4 presents the peculiarity of consisting of three very distinctive scenarios that don't allow for an easy common assessment. As a result, the economic and environmental assessment of this UC has been approached as three distinct LCA and LCC studies, one for each scenario, that is: a) conventional forest health monitoring vs a drone-based system; b) conventional wild-fire risk monitoring vs a drone-based monitoring system; c) conventional wild-life monitoring vs a drone-based system. In order to properly update on the progress made so far in this UC, therefore, it will be necessary to look at each of the scenarios separately.

Current Status
a) Regarding the first scenario, considerable progress has been made during 2024 to gather data for both the conventional and drone-based systems for forest health monitoring. Gaining a detailed understanding of the tasks, resources, and outputs associated with each approach has been the main focus in order to ensure a robust comparison of their performance and sustainability.
The main aspects covered in this data gathering process have been tasks and activities involved in each system, equipment and material inputs used, energy consumption, outputs obtained and costs. When it comes to the conventional system, obtaining data has been dependent on the accessibility and openness of forest engineers working on the field, which has limited the level of detailed data obtained. In contrast, for the drone-based system, data has been collected during this year regarding the more technologically intensive tasks it involves, including pre-flight preparations, flight path planning, drone operation, and post-flight data processing, such as analysing images to assess tree health. At the same time, relevant information regarding the equipment and material inputs for the drone-based system has been collected, including drones, sensors (e.g., multispectral cameras), GPS tools, and image processing software.

b) A similar situation arises for the second scenario. Progress has been achieved in 2024 in gathering data for both conventional and drone-based systems for wild-fire monitoring in forests. The primary objective has been to develop a comprehensive understanding of the tasks, resources, and outputs associated with each approach, ensuring a thorough and reliable comparison of their performance and efficiency.
The data collection process has focused on several key aspects, including the specific activities and workflows involved, the equipment and materials required, energy consumption, outputs produced, and associated costs. For the conventional wildfire monitoring system, data acquisition has relied heavily on

input from field-based forest engineers. However, the level of detail has, once more, been somewhat limited due to accessibility challenges and varying degrees of information availability.
In contrast, data collection for the drone-based wildfire monitoring system has been more straightforward, with particular attention given to the system’s advanced technological components. Information has been gathered on critical tasks such as pre-flight setup, flight path planning, drone operation, and the post-flight analysis of collected data, including the interpretation of aerial imagery to detect potential fire risks. Additionally, detailed data regarding equipment and material inputs for the drone system have been collected, including drones, thermal and multispectral sensors, GPS tools, and image processing software.

c) When it comes to the third scenario on wild-life monitoring, however, the data gathering process has met important obstacles mainly due to weather constraints and the difficulty of spotting the wild-boar herds, all of which have made the obtention of enough data so far insufficient.

Missing Aspects
a) Regarding the first scenario, additional data must be gathered on drone battery usage, energy for charging equipment, and maintenance needs, such as battery replacements or repairs. These inputs are crucial for understanding resource use and the environmental and economic impact associated with each system's operation. Further information is also needed regarding performance, output data and timings, in order to fully understand and evaluate the precision, reliability, and scope of health monitoring in the two compared systems.
At the same time, more detailed information regarding the full list of costs associated with each system will be necessary, including not only the purchase of tools, vehicles, and drones, as well as ongoing costs such as fuel, batteries, labour, and equipment maintenance, but also any indirect costs which may differ from the general labour costs associated with conventional methods.

b) For the wildfire monitoring scenario, further data collection is required to accurately quantify drone energy consumption, including battery usage, charging requirements, and maintenance demands such as battery replacements or system repairs. Additionally, more information is needed regarding system performance, including the accuracy, response times, and overall reliability of fire detection capabilities, to comprehensively compare the effectiveness and scope of the two methods.
Moreover, a detailed breakdown of costs for both systems is crucial to ensure a robust evaluation. This includes not only direct costs, such as the purchase of drones, sensors, tools, and vehicles, but also operational expenses like fuel, battery replacements, labour, and routine maintenance. Equally important are the indirect costs, such as specialised training for drone operators and maintenance personnel, which differ significantly from the general labour typically required for conventional wildfire monitoring systems. Collecting and recording this information will provide a clear understanding of the economic implications of both approaches, supporting a well-rounded comparison.

c) As mentioned above, the whole data gathering process for the third scenario has faced considerable hurdles due mainly to weather conditions and wild-boar herds behaviour patterns, which has prevented most of the relevant data to be collected so far. On top of that, there seems to be very limited information regarding conventional ways of performing the kind of wild-life monitoring the drone-based system intends to perform, rendering the comparative approach less insightful.

Challenges
For the three scenarios contemplated a number of challenges have arisen, mainly linked to the difficulty to access enough detailed data regarding the conventional systems and the limitations imposed by weather conditions.

Particularly, acquiring sufficient LCA and LCC data from forest engineers performing the tasks implemented by the ICAERUS project and who are not directly involved in the project can be challenging due to several factors. First, these professionals often have demanding workloads, leaving limited time or motivation to respond to external data requests. Additionally, since they have no direct stake or incentive to participate, they may view sharing detailed information as an unnecessary burden. Concerns over data confidentiality and competition may also arise, particularly when it comes to information relating to operational costs, practices, or performance outcomes. This lack of alignment between their priorities and the project's goals can significantly limit the accessibility and completeness of the required data.

On the other hand, adverse weather conditions have significantly hindered LCA and LCC data collection, especially for the drone-based wild-life monitoring system. Drones rely on stable weather for safe and efficient operation, as strong winds, heavy rain, fog, or low visibility can disrupt flights, reduce data quality, or even damage the equipment. These interruptions have delayed and/or prevented fieldwork. Moreover, unpredictable weather patterns can complicate scheduling and require contingency plans, ultimately impacting the consistency and reliability of the data gathered for analysis.

Concerning scenario 3 on wild-life monitoring, the success of wild boar data collection relies also heavily on the location of the wild boars during field operations. Finding wild boars can be particularly challenging due to their elusive behaviour, wide-ranging habitats, and movement patterns, which may vary depending on the time of day, season, and external disturbances.

Timeline for Completion

Regarding the 2 first scenarios, the recording in the relevant questionnaire of all the data collected so far collected and finding of as much of the missing aspects identified as possible, will need to be covered in the next 2 to 3 months.

When it comes to the third scenario on wild-life monitoring, further efforts are scheduled for the coming winter, when the wild-boars behaviour patterns and their identification potential is at its peak. Based on the results of this coming data collection campaign, a new timeline for the completion of this scenario's analysis will be established.

Next Steps

For scenarios 1 and 2, the main next step is the completion of the questionnaires and finding as many of the missing data aspects as possible within the next 2 to 3 months (by the end of March 2025 at the latest) in order to provide enough time afterwards for the analysis of the gathered data, the recognition of data gaps, the bridging of those gaps with adequate background data and the compilation of the respective inputs/outputs inventories, prior to the actual impact assessment through the SimaPro software.

For scenario 3, as mentioned above, the next step is to try and collect as much data as possible regarding both conventional and drone based wild-life monitoring systems during the coming winter. Any further steps in the analysis of this scenario will depend entirely on the possibility of acquiring enough quality and detailed data in the coming months.

1.2.5.5 Data collection process UC5 - RURAL LOGISTICS

Current Status

The data collection process for the LCA and LCC studies of UC5, which aims to compare the environmental and economic impacts of drone-based and conventional delivery systems in rural areas, is currently ongoing. At this stage, data has been successfully gathered for the conventional delivery system, providing a solid foundation for analysis. Specifically, detailed records have been obtained on several key parameters critical for assessing its environmental and economic performance.

Firstly, comprehensive data on fuel consumption has been collected, focusing on diesel usage by delivery vehicles, which serves as a primary input for evaluating energy use and emissions. Additionally, information regarding the operational parameters of the delivery system has been recorded, including the total distance travelled, the load capacity of the vehicles, and the frequency of deliveries—all of which are essential for understanding the scale and efficiency of conventional operations. Lastly, emissions data has been derived based on vehicle usage and routine maintenance activities, offering insights into the environmental footprint associated with both direct emissions and the upkeep of delivery fleets.

The collected data will serve as a benchmark against which the drone-based delivery system will be evaluated, allowing for a robust comparison of the two approaches in terms of energy efficiency, emissions, and overall environmental impacts.

Unfortunately, due to administrative delays and restrictions that have hindered the implementation of drone flights, no data has yet been collected for the drone delivery system. These challenges have temporarily stalled progress in acquiring the necessary information for the drone system's operational, economic and environmental impacts.

Missing Aspects

The primary data gaps pertain to the drone delivery system, where the key aspects to be identified include:

- Electricity consumption during drone operation.
- Energy requirements for battery charging infrastructure.
- Logistics data, such as average delivery distances, payloads, and operational frequencies.

Regarding the conventional delivery system, some additional information is needed, especially when it comes to overhead costs and fleet management system details.

These missing data points are critical for accurately assessing and comparing the environmental and economic impacts of the drone delivery system against the conventional alternative.

Challenges

The primary challenges encountered during the data collection process are administrative in nature:

- Flight Authorisation Delays: Regulatory restrictions have delayed the approval process for conducting drone flights in the planned regions and limit them to the demonstration activities. During these demonstrations (to be held before the summer of 2025), specific data will have to be gathered regarding the timings for each step/action required during the drone delivery system, human resources needed, flying times and battery needs for kg and km of parcel transported. Based on this information, an extrapolation model will be developed to cover the needs of a full year of operations.
- Logistical and Operational Barriers: Coordinating test flights and securing necessary permissions has proven more complex than anticipated, particularly in cross-border locations such as Thessaloniki (Greece) and North Macedonia.
- Data Availability: Without operational drone data, we are currently unable to gather primary inputs for the drone system, limiting the comprehensiveness of the study at this stage.

Despite these obstacles, efforts are ongoing to overcome these hurdles and ensure that the necessary drone demonstrations can proceed in 2025 and to make sure that all the relevant data about the drone system is duly collected.

Timeline for Completion

To address the current gaps and complete the data collection phase, the following timeline has been established:

- Spring 2025: Conduct drone delivery demonstrations in Thessaloniki (Greece) and North Macedonia. During these demonstrations, collect data on:
    - Electricity consumption.
    - Operational logistics (e.g., flight distances, delivery times, and payloads).
    - Maintenance and infrastructure requirements.
- Summer 2025: Process and extrapolate and compose the corresponding input/output inventories for both systems, which will afterwards be modelled within the SimaPro software.
- Autumn of 2025: the environmental and economic impact assessments will be performed within the SimaPro software with the aim of having preliminary results by the end of 2025.

The conventional delivery system data has already been processed and will serve as a baseline for comparison once the drone data becomes available.

Next Steps
The LCA and LCC studies remain a work in progress, with significant strides made in gathering data for the conventional delivery system. However, the drone system data is currently pending due to administrative challenges. Demonstrations scheduled for 2025 in Thessaloniki and North Macedonia will be pivotal in filling the existing data gaps and enabling a robust comparative analysis. Efforts are underway to resolve these challenges and ensure the successful completion of the data collection process within the revised timeline.

1.2.5.6 Data collection - DRONES

Performing an LCA and LCC for drones and their applications presents unique challenges that stem largely from the scarcity of reliable data. Current environmental impact databases often lack comprehensive background information on the materials, components, and specially manufacturing processes specific to drones. As a result, practitioners frequently face gaps in key inventory data, leading to uncertainties and approximations in their assessments.

Compounding this issue is the limited access to direct data due to the proprietary nature of drone production. Manufacturers are often reluctant to disclose detailed information about their technologies, citing intellectual property concerns and competitive advantages. This restricts transparency and makes it difficult to accurately model the environmental and economic impacts associated with drone production, operation, and disposal.

Efforts to develop more precise and robust inventories for various drone models can significantly enhance the quality of these kinds of studies. By systematically collecting data on drone materials, energy requirements, operational lifespans and maintenance needs, researchers can fill critical knowledge gaps. More accurate inventories not only improve the reliability of impact assessments but also enable better comparisons across different drone applications, such as agriculture, logistics, or environmental monitoring.

Ultimately, advancing the accuracy of LCA and LCC methodologies for drones is crucial for guiding their sustainable integration into diverse industries, including agriculture. Comprehensive assessments will provide stakeholders with actionable insights to reduce environmental footprints, optimise resource use, and foster innovation toward greener drone technologies.

As a result, within the ICAERUS project a considerable effort has been made so far to seize on the knowledge and skills of the consortium to try and gather as much foreground data as possible regarding key aspects of drone assembling, operation, maintenance and energy requirements. In this context, data on 4 main models of drones has been collected to create as accurate as possible input and outputs models. We present below an update of these specific data collection processes for the 4 considered drone models:

VELOS
Current Status

Following the structured data collection approach outlined in the first deliverable, significant progress has been achieved in gathering detailed information about the UAV systems used for different applications in Greece. The first deliverable marked the distribution of a specific questionnaire to one of the consortium partners and UC leader (GeoSense), which focused on obtaining preliminary data about the drone's components, logistics, and operational requirements. The results from this process now form the basis for further refinement and expansion of the dataset.

Key details have been collected on:

1. Drone Components: Information on the frame, batteries, motors, ESCs, flight controller, and transmission belts, including weights, costs, and basic specifications.

2. Transport and Logistics: Data on transportation modes, distances, and fuel types for a few components. However additional data is needed for the rest of the components.

Missing Aspects and Data Gaps

While significant progress has been made in collecting data for the VELOS drone, several gaps remain that are critical for developing an accurate Life Cycle Inventory (LCI).

Firstly, there are missing details about the drone's subassemblies, such as the exact quantities of aluminium 7075 and carbon fibre used in the frame, as well as the manufacturing processes for these materials. Similarly, the composition and material specifications for transmission belts, remote controller and GNSS Unit are incomplete. These inputs are essential for accurately modelling the resource demands of these components. Additionally, key details regarding the country of origin and transportation of certain subassemblies remain missing.

Another critical gap relates to the batteries. The operating voltage of the LiPo (100Ah) and Li-ion (4Ah) batteries is not provided, making it difficult to calculate their total stored energy in watt-hours (Wh). Furthermore, there is no data on the drone's energy consumption during operation, including the power drawn during flight and variations based on task load. This data is essential for understanding the energy efficiency and environmental impact of the system.

Finally, it is essential to incorporate maintenance data alongside operational information. The maintenance tasks, such as lubrication, blade replacements, and motor replacements, are tied to the drone's operational hours. According to the questionnaire, blades and motors are replaced every 200 hours, while lubrication occurs every 2 hours of use. To properly allocate these activities and their environmental impacts to the functional unit, it is crucial to know the total operational hours or cycles of the drone. This information allows us to calculate the frequency of maintenance tasks, the material and energy inputs required, and the waste generated per functional unit.

These data gaps will be filled by further engaging the expertise of the consortium and by using direct data provided by the UC in their respective questionnaires.

Next Steps

To address these gaps, a second round of questions will be developed and sent to Use Case leaders and relevant stakeholders. This will focus on:

1. Gathering missing technical and material data for subassemblies, including aluminium, carbon fibre, transmission belts, and electronic components like the BEC and remote controller.

2. Requesting precise voltage information and operational energy consumption metrics for the batteries and drone system.

3. Collecting detailed operational and maintenance needs on the field by each relevant UC.

GEO690, 4 rotor light weight drone

Current Status

Following the structured data collection process initiated in the first deliverable, significant progress has been made in gathering detailed information about the GEO690, 4 rotor light weight drone. The initial questionnaire responses provided insights into the drones' components, logistics, and maintenance requirements, laying a solid foundation for further refinement and expansion of the dataset.
Key details have been collected on:

a) Drone Components: Information on the frame, propellers, motors, ESCs, flight controller, GNSS unit and remote controller, including weights, costs, and specifications. Although, like the UC2, there are gaps in the detailed quantities and material composition of certain components.

b) Transport and Logistics: Data on transportation modes, distances, and fuel types for all the components. In this case, we already have the country of origin and transport methods, so additional data on their origin is not required.

Missing Aspects and Data Gaps

Also, for this UAV there are missing details about the drone's subassemblies. The composition and material specifications for transmission belts, remote controller and GNSS Unit are incomplete.
Additionally, drone's operational energy consumption during logistics tasks, including power draw and variations under different payloads, is not yet available.
While maintenance frequencies for components such as motors and batteries are documented, we need also to know the operational hours or number of cycles the drone performs. This information is crucial to calculate the environmental and economic impact of needs and wastes during the maintenance phase.

Next Steps

To address the identified gaps, the next steps involve gathering the missing details about the drone's subassemblies, including the composition and material specifications for components and transportation models. Additionally, precise data on the drone's operational energy consumption during logistics tasks, such as power draw and variations under different payloads, must be collected. It is also essential to determine the annual operational hours or number of cycles the drones perform to accurately calculate replacement needs, maintenance impacts, and waste generation. These gaps will be addressed through follow-up questions and direct communication with relevant partners to ensure the completeness and accuracy of the dataset, enabling robust environmental and economic assessments in subsequent analyses.

GEO920, 4 rotor medium weight drone

Current Status - Missing Aspects and Data Gaps

A second drone model, similar to UAV 2 but designed for medium-weight logistics tasks, has been documented with the same level of detail as the previous UAV. The current status for this drone mirrors that of UAV 2, with detailed information available on components, transport, and maintenance frequencies, but with gaps in all of them. To proceed, the same actions outlined for UAV 2 are required.

VTOL

Current Status

Following the approach used for previous drones, data on the VTOL drone system has been collected through questionnaires. While this provides a strong foundation, additional details are still required to complete the dataset.
Key information has been collected on:

1. Drone's Components: Information on the frame, tail and VTOL propellers, including weights, costs, and specifications.

2. Transport and Logistics: Data on the country of origin for all components has been collected. However, additional information on the transport mode, distances, and type of fuel used is still required to complete the dataset

Missing Aspects and Data Gaps

Firstly, also in this case the exact quantities of aluminium 7075 and carbon fibre used in the frame, as well as the manufacturing processes for these materials are unknown. While the frame material has been defined as fiberglass and aluminium 7075, the compositions of other essential components such as the servo motors, motors with ESCs, flight controller, GNSS unit, BEC, cables, bolts, screws, and the remote controller are not fully defined yet.

While data on the LiPo battery's capacity, charging efficiency, and lifespan has been provided, additional details are needed to fully assess its environmental and economic impact. Specifically, we need to determine how many times the battery needs to be charged per use or per operational task and how these scales over the course of a year. This includes understanding the total number of flights or tasks performed annually and how many charging cycles are required to support this activity. These details are critical for estimating the annual energy demand, the frequency of battery replacements, and the associated environmental impacts of charging and end-of-life management.

Furthermore, detailed data on maintenance tasks, including their frequency, time requirements, and associated waste generation, has been provided, this information is currently based on operational hours. To accurately model the environmental impact, we need to scale this data to reflect the actual maintenance activities over one year of drone operation according to the UC experience. This requires knowing the total annual operational hours or flight cycles to estimate the number of maintenance tasks (e.g., propeller replacements, motor replacements, and visual inspections) performed in a year

Next steps

Also in this case, to address the identified gaps, the next steps involve gathering missing details about the drone's subassemblies, such as material specifications and transportation data, including modes, distances, and fuel types. Additionally, precise data on operational energy consumption, including power draw, is needed. Determining the annual operational hours or cycles is also crucial to accurately calculate maintenance impacts, replacement needs, and waste generation. These gaps will be addressed through follow-up questions and direct communication with stakeholders

1.3 Expected results

Although it is still early at this stage of the LCA and LCC assessments to determine what the results are going to be, we can venture a few general expectations as for what kind of information the study of each Use Case may bring:

Use Case 1: Through the integration of advanced technologies such as UAVs, sensors, monitoring dashboards, and ML algorithms, a superior monitoring insight for crops and farms will be offered. This will enable stakeholders to make well-informed decisions regarding the environment and economy, resulting in a healthier plant population and an improved quality and yield ratio per plant. Moreover, this analysis will facilitate efficient fertiliser usage and resource administration management, thereby reducing the necessity for harmful chemical PPPs. On the economic side, it is expected that this reduction in the amount of key inputs (like PPPs) and increase of the quality and yield ratio per plant could contribute to an improved financial performance of farms.

Use Case 2: Our analysis of using UAVs for spraying purposes leads us to believe that they offer significant benefits over traditional methods. By reducing the amount of agrochemicals applied, we anticipate a decrease in groundwater and soil contamination while preventing biodiversity loss and soil compaction. Additionally, the use of electric-powered drones will result in a reduced carbon footprint and lower fuel consumption. Ultimately, we expect that the efficiency of utilising UAVs for pest control will lead to reduced operational and input costs.

Use Case 3: The utilisation of UAVs for livestock monitoring is intended to ease the burden on farmers while enhancing the effectiveness of current monitoring techniques. This approach minimises the carbon footprint of the task, emitting low levels of CO2 and producing minimal noise, reducing pollution and disturbance to the environment. Moreover, the implementation of drones can help in the preservation and advancement of agriculture. An economic assessment of this innovative monitoring approach will determine its benefits and drawbacks compared to the conventional methods used by farmers.

Use Case 4: UAVs can monitor forestry, assess wildfire risk, and track wildlife, which has several advantages over traditional methods. Using UAVs, forests can be kept healthy, drought can be detected before it becomes fuel for fires, and biodiversity loss and soil health issues can be prevented. Moreover, UAVs can help achieve the EU's goal of reducing greenhouse gas emissions by 2030 through carbon sequestration, such as planting new forests, restoring degraded ones, improving forestry management, and supplying biomass for bio-based products. The economic analysis is expected to indicate the financial losses regarding the suspension of exports of pigs and pork due to the contagious ASF disease affecting these populations.

Use Case 5: The utilisation of UAVs for delivering cargo to remote regions is anticipated to yield favourable environmental outcomes owing to their minimal emissions and noise levels. This translates into reduced ecological impacts, with lesser pollution and disturbance to flora and fauna. Nevertheless, the cost-effectiveness of this approach remains uncertain as there is a lack of enough data so far that our study intends to contribute to mitigate.

2. Technology Adoption Study

In this second chapter, we present the methodology to be applied to the study of adoption of the five Use Case drone technologies. This chapter is organised by introducing the different models that can be considered and then, concentrating on the model selected by ICAERUS, the Technology Acceptance Model. After these introductory sections, the methodological development is introduced with the extensive literature review conducted to create the survey instrument. The selected constructs and items for the survey are presented with reference to previous published studies. The final sections of this chapter present the approach to be used to select participants, collect their responses, and analyse the data.

2.1 Technology Adoption models

There are numerous technology adoption models in the literature to discuss factors and processes that may influence people's acceptance of new technologies. For instance,

- *Diffusion of Innovation Theory (DIT)* (Roger, 1995): explains how an innovation spreads and eventually adopts in a specific population or social system.
- *Theory of Reasoned Action (TRA)* (Fishbein & Ajzen, 1975): suggests an individual's behaviour (e.g., applying a new technology) would be influenced by the person's intention to perform the behaviour (e.g., the intention to use the new technology); attitudes (e.g., beliefs about the new technology) and subjective norms (e.g., beliefs about others' attitudes toward the new technology) are predictors of behavioural intention.
- *Theory of Planned Behaviour (TBP)* (Ajzen, 1991): is an extension of TRA, which added a variable named 'perceived behaviour control' in the TRA model to predict one's behaviour intentions. Perceived behaviour control refers to individuals' perception of their ability to perform a behaviour (e.g., to use a new technology).
- *The Model of PC Utilisation* (Thompson et al., 1991): was adopted from Triandis' theory (1980) and discussed the factors influencing computer utilisation. Triandis (1980) proposed human behaviour is determined by what they like to do, what they think they should do and what they usually do as well as the expected consequences of their behaviour. Based on this foundation, the following factors were included in the model to explain the use of computers, they are social factors, affect, three cognitive factors of perceived consequences (complexity, job fit and long-term consequences) and facilitating conditions.
- *The Motivation Model* (Davis et al., 1992): discusses the influential relationships of usefulness (extrinsic motivation) and enjoyment (intrinsic motivation) on intention to use and usage of computers in the workplace.
- *Unified Theory of Acceptance and Use of Technology* (UTAUT) (Venkatesh et al., 2003): summarises historical technology adoption theories and extracts a unified model to discuss influential factors on behaviour intention and, in turn, on use behaviour.
- *Technology Acceptance Model* (Davis, 1989; Davis et al., 1989) and the extended TAMs (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008): focuses on two key factors, ease of use and usefulness of a new technology and their determinants. Those factors would affect users' attitude and intention, and in turn the actual usage of the new technology. As to the popularity and effectiveness of the theory, more details will be discussed in the next section.

2.2 Technology Acceptance Model

The Technology Acceptance Model (TAM) initially proposed by Davis (1989) is an effective and widely applied model to predict and explain individuals' adoption of new technologies. It has been empirically supported in various research studies in different subjects (Turner et al., 2010). For these reasons it was been selected for application in Task 3.3 of ICAERUS. TAM suggests individuals' attitudes toward using a new technology are linked to the actual usage of the technology (Davis et al.,1989). Later, behavioural intention to use (BI) was included in the model (Davis & Venkatesh,1996). Attitude toward using a

technology is influenced by two key factors, perceived usefulness (PU) and perceived ease of use (PEOU). Attitude toward using is defined as the degree of evaluative affect that individuals have by using a new technology in their roles. Perceived usefulness refers to the degree to which individuals believe using a new technology would improve their job performance; perceived ease of use refers to the degree to which individuals believe using a new technology would be free of effort (Davis,1989).
With the development of TAM, many modifications and extensions of the model have been flourished (Marangunić & Granić, 2015). For instance, incorporating additional factors into the original TAM to explain the predictors of PU and PEOU, TAM 2 (Venkatesh & Davis, 2000) and TAM 3 (Venkatesh & Bala, 2008) have been introduced. Integrating other external factors with original TAM could enhance the model's explanatory power (Taheri et al., 2022). Modification and application of TAM have never stopped, usually researchers tend to include external predictors to understand more of the determinants of TAM's core variables, such as computer self-efficacy; or they combine factors from other theories to increase predictive validity, such as trust and risk (Marangunić & Granić, 2015). In this research, we moved in the line of previous studies and considered the necessity to adapt TAM and TAM3 models to the specificity of the object of study by selecting appropriate construct to be evaluated.

2.3 Method: approach used to design the study

The method followed to design this study is articulated in the steps shown in Figure 9.

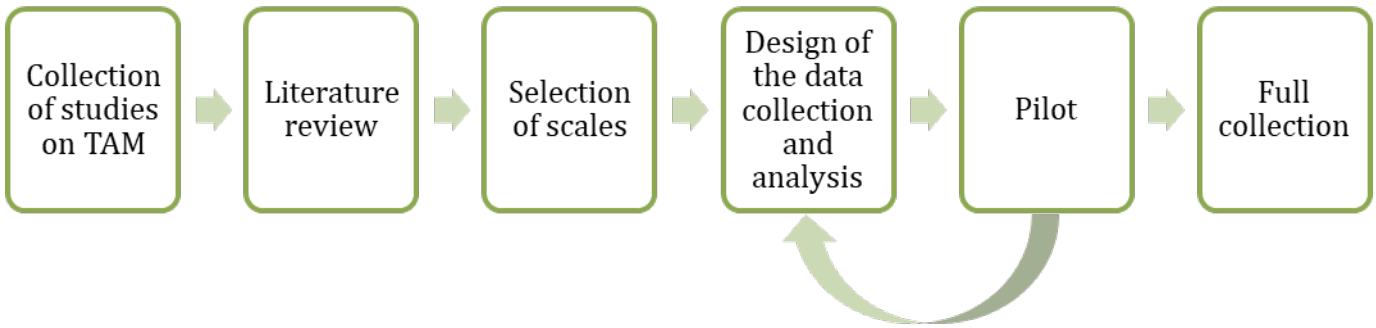

Figure 9 Method applied to design the study

First, we developed a structured and organised collection of relevant empirical studies that adopt TAM models in order to study the adoption of agricultural-related technologies. Second, we mapped the relevant studies to evaluate which dimensions were considered in the study of adoption. Third, we met twice to define the relevant scales to be used. Fourth, the first pilot was conducted in a demonstration event in Greece (31/10/2024). This led to the revision of the scale and a second pilot that will be conducted in February 2025 in Greece, which will lead to the final collection.

2.3.1 Collection of studies and literature review

To collect the literature related to technology adoption, we resorted to the Scopus database, which is considered a reliable source for assessing research productivity (Baruffaldi et al., 2016; Chavarro et al., 2017). In Scopus we ran three queries, as shown in Table 1, which returned a total number of 163 studies collected. The three queries share the words "technology acceptance" with the addition of three different words: "agriculture", "forestry", and "drone". We selected publications between 2008 to 2023 considering that 2008 is the year the TAM3 model was presented in the foundational publication of Venkatesh and Bala (2008).

Table 1 Queries performed on Scopus

Query #	**Keywords**	**Studies collected**
1	"technology acceptance", "agriculture"	123
2	"technology acceptance", "forestry"	29
3	"technology acceptance", "drone".	11

A first screening of the studies filtered the manuscripts that did not present a TAM, totalling **66** studies as listed in Table 4 in the Annexes. These selected studies were analysed to evaluate which dimensions were measured to assess agricultural-related technologies. For each study, all the dimensions (*latent constructs*) measured were listed. The resulting table allowed for a cross-study comparison. Latent constructs are real phenomena that are better measured through one or more *indicators* (Hair et al., 2018, p. 605). The combination of the indicators or *items* can offer a good measure of the latent construct when good psychometric properties are present.

Our analysis showed that there are constructs that are common to the large majority of studies. The first three are present in more than 70% of studies because they are the core TAM constructs: perceived usefulness (80.5%), perceived ease of use (73.2%), and behavioural intention to use (70.7%). Only one other recurrent dimension of TAMs scored more than 50%: it is attitude (50.0%). Attitude relates to judgments towards an object of some individual (Barki & Hartwick, 1994) and can be affective or evaluative.

What emerged from the analysis of the constructs is that only a few independent constructs are present in the modelling of acceptance, and the choice is often related to the contexts of their application. This is considered in the next phase of this study.

2.3.2 Selection of scales

To select appropriate scales, the list of all constructs was studied by the authors of this section and discussed in two meetings. The two meetings were dedicated to selecting which scales were the most applicable to the drone technologies portrayed in the five ICAERUS Use Cases. The resulting list of dimensions and constructs show what we plan to use in the survey (see Table 2).

The survey was revised after the first pilot, as discussed in Par. 2.4.2. Participants in the pilot found the Neuroticism scale difficult to answer and somewhat invasive of their privacy. Since the scale is only meant to measure the Common Method Bias, which is also be assessed through the Social Desirability scale, we decided to remove it. Table 2 shows this change by striking out the Neuroticism scale.

Table 2 Selected scales

Item ID	**Item text from the original study**
	Perceived usefulness (PU) (Venkatesh & Bala, 2008)
PU1	Using the system (drones) improves my performance in my job. (.88)
PU2	Using the system (drones) in my job increases my productivity. (.89)
PU3	Using the system (drones) enhances my effectiveness in my job. (.90)
PU4	I find the system (drones) to be useful in my job. (.92)
	Perceived Ease of Use (PEOU) (Venkatesh & Bala, 2008)
PEOU1	My interaction with the system (drones) is clear and understandable. (.90)

Item ID	Item text from the original study
PEOU2	Interacting with the system (drones) does not require a lot of my mental effort. (.91)
PEOU3	I find the system (drones) to be easy to use. (.91)
PEOU4	I find it easy to get the system (drones) to do what I want it to do. (.93)
Behavioural Intention (BI) (Venkatesh & Bala, 2008)	
BI1	Assuming I had access to the system (drones), I intend to use it. (.82)
BI2	Given that I had access to the system (drones), I predict that I would use it. (.92)
BI3	I plan to use the system in the next <n> months. (.87)
Attitudes (Xiang&Guo,2023) adopted from (Abadi, 2018) Cronbach's Alpha .905	
AT1	Adopting GCT (drones) can result in economic benefits.
AT2	Adopting GCT (drones) can reduce environmental pollution.
AT3	Adopting GCT (drones) can promote the sustainable development of agriculture (/forestry/rural logistics)
Computer Self-Efficacy (CSE) (Venkatesh & Bala, 2008) 10-point Guttman scale	
I could complete the job using a new technology (drones)…	
CSE1	I could complete the job using the new technology (drones)
CSE2	If there was no one around to tell me what to do as I go. (.80)
CSE3	If I had just the bult-in help facility for assistance. (.74)
CSE4	If someone showed me how to do it first. (.72)
CSE5	If I had used similar packages before this one to do the same job. (.72)
Subjective Knowledge (Jürkenbeck et al., 2019) Cronbach's Alpha .531, .539, .627 three groups	
SK1	I know this technology (*drones*).
SK2	I have already dealt with this technology (*drones*) (yes/no/I don't know)
SK3	I am interested in agricultural (*drone*) topics.
Social Influence (Venkatesh, 2003) ICR .91, .92, .92 (3 times)	
SI1	People who influence my behaviour think that I should use technological innovations (drones).
SI2	People who are important to me think that I should use technological innovations (drones).
SI3	The senior management of this business has been helpful in the use of technological innovations (drones) in the past.
SI4	In general, my company has supported the use of technological innovations (drones).
Facilitating Conditions (Venkatesh, 2003) ICR .85, .88, .88 (3 times)	

Item ID	Item text from the original study
FC1	I have the resources necessary to use this technology (drones).
FC2	I have the knowledge necessary to use this technology (drones).
FC3	This technology (drones) is compatible with other systems I use.
FC4	A specific person (or group) is available for assistance with difficulties with this technology (drones).
Performance expectancy (Ronaghi & Forouharfar, 2020) Cronbach's Alpha .864	
PE1	I found the technologies (drones) useful in doing my farm activities.
PE2	Using the technologies (drones) help me to accomplish my tasks more quickly than before in the farm.
PE3	Using the technologies (drones) will increase my chances of achieving higher crop productivity.
PE4	If I use the technologies (drones), I will increase my chances of increasing my income.
Trialability (Aubert et al., 2012) Cronbach's Alpha .86	
Think about the possibility to try the technology (drones) before deciding to adopt it. How much do you agree with the following statements?	
TR1	I would be able to use it on a trial basis.
TR2	I would be permitted to use them long enough to see what they can do.
TR3	I would be able to try it out properly.
Quality of support (Aubert et al., 2012) Cronbach's Alpha .79	
Think about the quality of support you could get about this new software. How much do you agree with the following statements?	
QS1	It is easy to get support for the farm management software (drones).
QS2	The people providing support for the farm management software (drones) have the required knowledge to answer my questions.
QS3	I feel that the people providing support for the farm management software (drones)work in my best interest.
Perceived Risk (Vimalkumar et al., 2021) Cronbach's Alpha .888	
PR1	PDA (drone) data may be sold to third parties.
PR2	Personal data in PDA (drones) may be misused.
PR3	PDA (drone) data could be given to unidentified persons or companies without my consent.
PR4	PDA (drone) data could be made available to government agencies.
Perceived Privacy Concerns (Vimalkumar et al., 2021) Cronbach's Alpha .935	

Item ID	Item text from the original study
PC1	I am concerned that the information I submit to PDA (drones) could be misused.
PC2	I am concerned that a person can find private information about me through PDA (drones).
PC3	I am concerned about submitting information to PDA (drones), because what others might do with it.
PC4	I am concerned about submitting information to PDA (drones), because it could be used in a way I did not foresee.
Perceived resources (Aubert et al. 2012) Cronbach's Alpha .81	
RES1	I have the resources, opportunities and knowledge for using precision agriculture technologies.
RES2	I would be able to use precision agriculture technologies if I wanted to.
RES3	I have access to the resources I would need for using precision agriculture technologies.
RES4	There are no barriers to me using precision agriculture technologies.
~~**Neuroticism from the 44-item Big Five Inventory (BFI)**~~ ~~(John & Srivastava, 1999)~~	
~~I see Myself as Someone Who…~~	
~~NE1~~	~~Is depressed, blue.~~
~~NE2~~	~~Is relaxed, handles stress well. (R)~~
~~NE3~~	~~Can be tense.~~
~~NE4~~	~~Worries a lot.~~
~~NE5~~	~~Is emotionally stable, not easily upset. (R)~~
~~NE6~~	~~Can be moody.~~
~~NE7~~	~~Remains calm in tense situations. (R)~~
~~NE8~~	~~Gets nervous easily.~~
Social Desirability–Gamma Short Scale (Nießen et al., 2019)	
The following statements may apply more or less to you personally. Please indicate to what extent they apply to you.	
SO1	In an argument, I always remain objective and stick to the facts.
SO2	Even if I am feeling stressed, I am always friendly and polite to others.
SO3	When talking to someone, I always listen carefully to what the other person says.
SO4	It has happened that I have taken advantage of someone in the past.
SO5	I have occasionally thrown litter away in the countryside or on to the road.

Item ID	Item text from the original study
SO6	Sometimes I only help people if I expect to get something in return.

2.3.3 Other measures

The survey will include several additional measures that are typically used to study the acceptance of technology as listed in the Table 3. They are mostly control variables.

Similar to the measurement scales, the descriptive variables were also revised after the first pilot data collection described in Paragraph 2.4.2. Participants suggested simplifying and reducing the number of variables collected which resulted in updates reported in the last column of Table 3.

Table 3 Other measures

Code	Variable name	Question	Possible responses	Update after pilot
NA	Country	--	List of EU countries	Confirmed
AG	Age	--	Insert age	Confirmed
GE	Gender	What gender do you identify as?	Male/Female/Non-binary/Trans-gender/Other/Prefer not to answer	Confirmed
EL	Education	--	Primary school; middle school; high school; bachelor's degree; master's degree; PhD	Confirmed
JB	Job	--	Farmer; technician; engineer; researcher or academic; entrepreneur; Student; other	Allow multiple answers; Updated
FO/FS	Farm ownership/Farm size	Do you work on a farm (or are you the owner of a farm)?	No/Yes. What is its size in ha? num. Ha (Less than 5 ha; from 5 to 10 ha; from 11 to 20 ha; from 21 to 30 ha; from 31 to 40 ha; from 41 to 50 ha; more than 50 ha)	Deleted
FO/FS	Farm ownership/Farm size	If you don't work on a farm, what is the core business of your company?	Specify (activity)	Deleted
EM	Employees	How many employees work in your company?	Specify (number)	Deleted

Code	Variable name	Question	Possible responses	Update after pilot
FT	Turnover.	What are the revenues per year of your company in euros?	Categorical variable based on Eurostat	Deleted
TIU1	Number of drones producers currently use	Do you currently use drones in your company or in general ?	No/Yes.	Updated
TIU2	Number of drones planned to use	Do you plan to introduce drones in your company in the next couple of years?	No/Yes.	Updated
TIU3		If yes, can you describe which drones you are planning to introduce?	Insert answer (open end question)	New

2.4 Data collection plan

In this section, plans for sampling of respondents and data collection are exposed.

2.4.1 Sampling

The administration of the survey will consider the different Use Cases, by adopting a staggered approach: the collection will be organised in five consecutive waves. The survey will be preceded by description of the specific. Respondents for each case study will be approached by different means. The specific stakeholder groups of each Use Case will be considered when approaching possible respondents. We do not plan to design a stratified sampling, but to reach good coverage of different categories of stakeholders, including farmers, technicians, and entrepreneurs.

We will concentrate on obtaining a large number of responses with a good coverage of European countries, in order to achieve a good relevance of findings for policymaking at an international level.

2.4.2 Procedure of collection

Before initiating the data collection, a full ethical review from the Open University Human Research Ethics Committee (HREC) will be obtained (see the process here). Informed consent forms have been prepared, and the survey will be translated into the relevant languages to facilitate the participation of stakeholders not fluent in English. The approach to data collection is focused on maximising the number of respondents and combines both online (Qualtrics) and in-person methods. First, a pilot launch of the survey allowed us to test the survey’s duration and the understanding of questions by a group of stakeholders. The pilot was conducted in Greece during the first demonstration event of Use Case 2 on 31 October 2024. A tailored version of the survey was developed referring to spraying drones, indicating the type of drones in both the text of each question and the text of the items. Respondents' feedback was collected during the demo event and discussed in a meeting on 4 November 2024, among Use Case 2 Leaders, the ICAERUS Project Coordinator, and Task 3.3 Leaders.

This meeting led to the revision of two critical aspects: the number of variables measured in the survey and the approach to data collection. The former highlighted the need for simplification and led to the reduction of the number of scales measured, finalised in a meeting on 13 November 2024 (see Paragraph 2.3.2), and the revision of the descriptive variables (see Paragraph 2.3.3). The latter was related to the low number of participants at the demo event, which suggested a revision of the data collection approach.

A new approach for data collection was conceived. The survey questions will be revised to indicate only the generic word 'drone' instead of the specific drone type of each use case (e.g., spraying drone). Then, the data collections during demonstration events will be focused on the specific drone technology presented in the demo event. This will produce five different datasets. At the same time, a broader data collection will be launched online through different channels (e.g., the ICAERUS Platform, LinkedIn, the online Open Learn course). This collection will benefit from the collaboration with Image Line, a company that specialises in providing digital solutions for the agricultural sector. Image Line Network hosts a thriving community of over 298,000 farmers and agricultural professionals.

We plan to conduct two waves of data collections during 2025 and analyse the data in line with the project plan.

2.5 Data analysis and expected results

This section outlines the data collection and introduces the preliminary and expected results.

2.5.1 Data analysis

The data will be analysed according to the consolidated procedures suggested by Hair et al. (2018, Chapters 9–12). Having resorted to validated scales, the Exploratory Factor Analysis is not deemed necessary. All the modelling will be developed in AMOS v.28. A two-step approach will be applied (Fornell & Yi, 1992). First, a Confirmatory Factor Analysis (CFA) will be conducted to evaluate the model's goodness of fit and measure construct reliability, convergent, and discriminant validity. Before proceeding with the next step, we will also test for Common Method Bias, which indicates that all answers can be attributed to a single underlying factor (Spector, 2006). We will perform a Harman's single-factor test as supported by recent simulation results (Fuller et al., 2016). We will also perform a second test of CMB, "controlling for the effects of a directly measured latent methods factor" (Podsakoff et al., 2003, p. 891). This approach is considered more robust by some scholars, but it still assumes that a valid measure of common method can be identified by researchers. We have included in our instrument both the scales of social desirability and neuroticism reported at the end of Table 2.

During the pilot, we will evaluate which of the two scales is more appropriate to evaluate CMB. The second step of the analysis will focus on the fitting of a Structural Equation Model. We will test hypotheses from literature on several sub-models. Tests on mediations will be conducted according to Hair et al. (2018, pp. 745–746).

To compare the Use Cases, we will perform a Multi-Group Analysis in AMOS: this technique compares the relationships between variables across groups of respondents and can be considered as a moderation applied to the entire model. This approach will allow the comparison between two groups at a time.

2.5.2 Initial results

This paragraph presents the descriptive statistics of the first 24 responses collected during the pilot study. Considering the limited number of respondents, it is not possible to conduct a CFA and to develop a SEM.

Code	Variable name	Results from initial data collection

NA	Country	24 based in Greece
AG	Age	24 to 59 (*M*=41.22, *SD*=11.66)
GE	Gender	15 men, 9 women
EL	Education	3 with bachelor's degree, 18 with master's degree 3 with PhD
JB	Job	6 Technicians 6 Researcher/academics 12 Other including: 6 Agronomists 2 Private sector employees 1 Regulatory manager 1 Agricultural supplies company 1 Employee of a competent authority 1 Agronomist trainer
TIU1	Number of drones producers currently use	18 No 5 Yes
TIU2	Number of drones planned to use	13 Yes 8 No
TIU3		2 DJI MINI 1 DJI Mapping 1 Monitoring and Spraying 1 Multi-Spectral Camera 1 Phantom, Mavic 3T, Spraying 1 Ucandrone Day 1 Don't know 1 Mainly for Monitoring, perhaps later for Spraying 1Spraying Drones

These initial data suggest the majority of respondents are technicians interested in demonstration of new technologies, but only few of them are currently using drones (25%). This suggests that the survey is targeting a range of respondents who are also potential adopters of new technologies (75%).

2.5.3 Expected results

The modelling of acceptance of the five drone technologies of the ICAERUS project will give the possibility to understand the perceptions of stakeholders in the European context. The comparisons across Use Cases will also show different patterns of factors influencing adoption, differentiating the definition of adoption strategies for each Use Case.

Besides the interest from an academic point of view, the outcomes of this study will inform each Use Case partner by highlighting what important factors affects the intention to adopt and how they are interrelated. This level of understanding will also support the development of sustainable business models by suggesting possible aspects that would need to be considered in the modelling action of the value propositions, such as an attention to trialability.

At a policy-making level, the whole picture offered by this study will be useful to inform policy makers at regional, national, and EU levels in devising policies oriented at stimulating adoption by leveraging the aspects that can positively or negatively influence it.

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References are organised in three different subsections: first, references for Chapter 1; second, references for Chapter 2, third, the list of studies selected during the literature review conducted for the Technology Adoption Study.

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Annexes

Annex 1. LCA-LCC Questionnaires for Use Cases

Questionnaire UC1 - Crop Health Monitoring

The following tables have been designed to gather all relevant information regarding inputs (natural resources, materials, infrastructure, equipment, energy, labour requirements), outputs (product, by-products, emissions, waste) and economic information for UC1.

Natural Resources & Material inputs												
Unit Process	Description	Amount/ application rate	Units	Cost	Units	Origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the aforementioned Cost of Input Materials?	Transport cost	Units
Pruning + trimming												
Tilling												
Irrigation												
PPPs usage												
Fertilizers usage												
Monitoring												
Harvesting												

Infrastucture & equipment inputs													
Unit Process	Description	Amount	Purchase Cost	Units	Year of purchase	Country of origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Units	Transport cost	Cost of maintenance & Repairs
Pruning + trimming													
Tilling													
Irrigation													
PPPs usage													
Fertilizers usage													
Monitoring													
Harvesting													

Energy inputs

Unit Process	Description	Amount	Units	Cost	Units	Link to equipment	Link to material
Pruning + trimming							
Tilling							
Irrigation							
PPPs usage							
Fertilizers usage							
Monitoring							
Harvesting							

Tasks, frequency and labour requirements

Unit Process	Description	Time needed to fullfil task	Frequency	Number of workers / shift / Unit Operation	Cost of Labour
Pruning + trimming					
Tilling					
Irrigation					
PPPs usage					
Fertilizers usage					
Monitoring/Decision making					
Harvesting					

Outputs							
Unit Process	Description	Amount	Units	Income (if any)	Link to equipment	Treatment option	Treatment cost
Products and biproducts							
Waste							
Emissions							
Monitoring							

Other costs	
	Cost
Improvements of land or buildings	
Insurance	
Taxes	
Cash and equivalents	
Inventories	
Rent payments (if applicable)	
Loan repayments (if applicable)	
Depreciation costs (if applicable)	
Subsidies (if applicable)	
Debt - commercial loans	
Debt - family/private loans	
Other overhead costs (i.e. telephone, admin costs, advisory fees, etc.)	

Questionnaire UC2 – Spraying

The following tables have been designed to gather all relevant information regarding inputs (natural resources, materials, infrastructure, equipment, energy, labour requirements), outputs (product, by-products, emissions, waste) and economic information for UC2.

Natural Resources & Material inputs											
Unit Process	Description	Amount/ application rate	Units	Cost	Origin (whether country or place of origin or orther source origin)	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price	Transport cost	Units
Pruning + trimming											
Tilling											
Irrigation											
PPPs application											
Fertilizers usage											
Monitoring											
Harvesting											

Infrastucture & equipment inputs												
Unit Process	Description	Amount	Purchase Cost	Units	Year of purchase	Country of origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Cost of maintenance & Repairs
Pruning + trimming												
Tilling												
Irrigation												
PPPs application												
Fertilizers usage												
Monitoring												
Harvesting												

Energy inputs						
Unit Process	Description	Amount	Units	Cost	Link to equipment	Link to material
Pruning + trimming						
Tilling						
Irrigation						
PPPs usage						
Fertilizers usage						
Monitoring						
Harvesting						

Tasks, frequency and labour requirements					
Unit Process	Description	Time needed to fullfil task	Frequency	Number of workers / shift / Unit Operation	Cost of Labour
Pruning + trimming					
Tilling					
Irrigation					
PPPs application					
Fertilizers usage					
Monitoring /Decision making					
Harvesting					

Outputs							
Unit Process	Description	Amount	Units	Income (if any)	Link to equipment	Treatment option	Treatment cost
Products and biproducts							
Waste							
Emissions							
PPPs application							

Other costs	
	Cost
Improvements of land or buildings	
Insurance	
Taxes	
Cash and equivalents	
Inventories	
Rent payments (if applicable)	
Loan repayments (if applicable)	
Depreciation costs (if applicable)	
Subsidies (if applicable)	
Debt - commercial loans	
Debt - family/ private loans	
Other overhead costs (i.e. telephone, admin costs, advisory fees, etc.)	

Questionnaire UC3 - Livestock Monitoring / Scenario 1

The following tables have been designed to gather all relevant information regarding inputs (natural resources, materials, infrastructure, equipment, energy, labour requirements), outputs (emissions, waste and service provided) and economic information for UC3/Scenario 1.

Natural Resources & Material inputs

Unit Process	Subcategory	Description	Amount	Units	Cost	Origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Units
Cattle reproduction												
Access to water & grass												
Health & behaviour analysis												
Infrastructure												

Infrastucture & equipment inputs													
Unit Process	Subcategory	Description	Amount	Units	Purchase Cost	Year of purchase	Country of origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Cost of maintenance & Repairs
Cattle reproduction													
Access to water & grass													
Health & behaviour analysis													
Infrastructure													

Energy inputs								
Unit Process	Subcategory	Description	Amount	Units	Cost	Units	Link to equipment	Link to material
Cattle reproduction								
Access to water & grass								
Health & behaviour analysis								
Infrastructure								

Tasks, frequency and labour requirements						
Unit Process	Subcategory	Description	Time needed to fullfil task	Frequency	Number of workers / shift / Unit Operation	Cost of Labour (i.e. in Euros per hour)
Cattle reproduction						
Access to water & grass						
Health & behaviour analysis						
Infrastructure						

Outputs							
Unit Process	Description	Amount	Units	Income (if any)	Link to equipment	Treatment option	Treatment cost
Waste							
Emissions							
Monitoring							

Other costs	
	Cost
Improvements of land or buildings	
Insurance	
Taxes	
Cash and equivalents	
Inventories	
Rent payments (if applicable)	
Loan repayments (if applicable)	
Depreciation costs (if applicable)	
Subsidies (if applicable)	
Debt - commercial loans	
Debt - family/ private loans	
Other overhead costs (i.e. telephone, admin costs, advisory fees, etc.)	

Questionnaire UC3 - Livestock Monitoring / Scenario 2

The following tables have been designed to gather all relevant information regarding inputs (natural resources, materials, infrastructure, equipment, energy, labour requirements), outputs (emissions, waste and service provided) and economic information for UC3/Scenario 2.

Natural Resources & Material inputs												
Unit Process	Subcategory	Description	Amount	Units	Cost	Origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Units
Sheep flocks												
Protection dogs												
Health & behaviour analysis												
Access to grass, water & food												
Infrastructure												

Infrastucture & equipment inputs

Unit Process	Subcategory	Description	Amount	Units	Purchase Cost	Year of purchase	Country of origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Cost of maintenance & Repairs
Sheep flocks													
Protection dogs													
Health & behaviour analysis													
Access to grass, water & food													
Infrastructure													

Energy inputs								
Unit Process	Subcategory	Description	Amount	Units	Cost	Units	Link to equipment	Link to material
Sheep flocks								
Protection dogs								
Health & behaviour analysis								
Access to grass, water & food								
Infrastructure								

Tasks, frequency and labour requirements						
Unit Process	Subcategory	Description	Time needed to fullfil task	Frequency	Number of workers / shift / Unit Operation	Cost of Labour (i.e. in Euros per hour)
Sheep flocks						
Protection dogs						
Health & behaviour analysis						
Access to grass, water & food						
Infrastructure						

Outputs							
Unit Process	Description	Amount	Units	Income (if any)	Link to equipment	Treatment option	Treatment cost
Waste							
Emissions							
Monitoring							

Other costs	
	Cost
Improvements of land or buildings	
Insurance	
Taxes	
Cash and equivalents	
Inventories	
Rent payments (if applicable)	
Loan repayments (if applicable)	
Depreciation costs (if applicable)	
Subsidies (if applicable)	
Debt - commercial loans	
Debt - family/private loans	
Other overhead costs (i.e. telephone, admin costs, advisory fees, etc.)	

Questionnaire UC4 - Forest Monitoring / Scenario 1: Forest health monitoring

The following tables have been designed to gather all relevant information regarding inputs (natural resources, materials, infrastructure, equipment, energy, labour requirements), outputs (emissions, waste and service provided) and economic information for UC4/Scenario 1.

Natural Resources & Material inputs												
Unit Process	Subcategory	Description	Amount	Units	Cost	Origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Units
Planning												
Monitoring												
Decision making												

Infrastucture & equipment inputs													
Unit Process	Subcategory	Description	Amount	Units	Purchase Cost	Year of purchase	Country of origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Cost of maintenance & Repairs
Planning													
Monitoring													
Decision making													

Energy inputs								
Unit Process	Subcategory	Description	Amount	Units	Cost	Units	Link to equipment	Link to material
Planning								
Monitoring								
Decision making								

Tasks, frequency and labour requirements						
Unit Process	Subcategory	Description	Time needed to fullfil task	Frequency	Number of workers / shift / Unit Operation	Cost of Labour (i.e. in Euros per hour)
Planning						
Monitoring						
Decision Making						

Outputs							
Unit Process	Description	Amount	Units	Income (if any)	Link to equipment	Treatment option	Treatment cost
Waste							
Emissions							
Monitoring							

Other costs	
	Cost
Improvements of land or buildings	
Insurance	
Taxes	
Cash and equivalents	
Inventories	
Rent payments (if applicable)	
Loan repayments (if applicable)	
Depreciation costs (if applicable)	
Subsidies (if applicable)	
Debt - commercial loans	
Debt - family/private loans	
Other overhead costs (i.e. telephone, admin costs, advisory fees, etc.)	

Questionnaire UC4 - Forest Monitoring / Scenario 2: Wildfire monitoring

The following tables have been designed to gather all relevant information regarding inputs (natural resources, materials, infrastructure, equipment, energy, labour requirements), outputs (emissions, waste and service provided) and economic information for UC4/Scenario 2.

Natural Resources & Material inputs												
Unit Process	Subcategory	Description	Amount	Units	Cost	Origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Units
Satellite images												
Planning												
Drone preparation												
Drone monitoring												
Decision making												

Infrastucture & equipment inputs													
Unit Process	Subcategory	Description	Amount	Units	Purchase Cost	Year of purchase	Country of origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Cost of maintenance & Repairs
Satellite images													
Planning													
Drone preparation													
Drone monitoring													
Decision making													

Energy inputs								
Unit Process	Subcategory	Description	Amount	Units	Cost	Units	Link to equipment	Link to material
Satellite images								
Planning								
Drone preparation								
Drone monitoring								
Decision making								

Tasks, frequency and labour requirements						
Unit Process	Subcategory	Description	Time needed to fullfil task	Frequency	Number of workers / shift / Unit Operation	Cost of Labour (i.e. in Euros per hour)
Satellite images						
Planning						
Drone preparation						
Drone monitoring						
Decision making						

Outputs							
Unit Process	Description	Amount	Units	Income (if any)	Link to equipment	Treatment option	Treatment cost
Waste							
Emissions							
Monitoring							

Other costs	
	Cost
Improvements of land or buildings	
Insurance	
Taxes	
Cash and equivalents	
Inventories	
Rent payments (if applicable)	
Loan repayments (if applicable)	
Depreciation costs (if applicable)	
Subsidies (if applicable)	
Debt - commercial loans	
Debt - family/private loans	
Other overhead costs (i.e. telephone, admin costs, advisory fees, etc.)	

Questionnaire UC4 - Forest Monitoring / Scenario 3: Wildlife monitoring

The following tables have been designed to gather all relevant information regarding inputs (natural resources, materials, infrastructure, equipment, energy, labour requirements), outputs (emissions, waste and service provided) and economic information for UC4/Scenario 3.

Natural Resources & Material inputs												
Unit Process	Subcategory	Description	Amount	Units	Cost	Origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Units
Mission planning												
Mission implementation												
Collected data analysis and reporting												
Decision making												

Infrastucture & equipment inputs

Unit Process	Subcategory	Description	Amount	Units	Purchase Cost	Year of purchase	Country of origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Cost of maintenance & Repairs
Mission planning													
Mission implementation													
Collected data analysis and reporting													
Decision making													

Energy inputs								
Unit Process	Subcategory	Description	Amount	Units	Cost	Units	Link to equipment	Link to material
Mission planning								
Mission implementation								
Collected data analysis and reporting								
Decision making								

Tasks, frequency and labour requirements						
Unit Process	Subcategory	Description	Time needed to fullfil task	Frequency	Number of workers / shift / Unit Operation	Cost of Labour (i.e. in Euros per hour)
Mission planning						
Mission implementation						
Collected data analysis and reporting						
Decision making						

Outputs							
Unit Process	Description	Amount	Units	Income (if any)	Link to equipment	Treatment option	Treatment cost
Waste							
Emissions							
Monitoring							

Other costs	
	Cost
Improvements of land or buildings	
Insurance	
Taxes	
Cash and equivalents	
Inventories	
Rent payments (if applicable)	
Loan repayments (if applicable)	
Depreciation costs (if applicable)	
Subsidies (if applicable)	
Debt - commercial loans	
Debt - family/private loans	
Other overhead costs (i.e. telephone, admin costs, advisory fees, etc.)	

Questionnaire UC5 - Rural Logistics

The following tables have been designed to gather all relevant information regarding inputs (natural resources, materials, infrastructure, equipment, energy, labour requirements), outputs (emissions, waste and service provided) and economic information for UC5.

Natural Resources & Material inputs

Unit Process	Description	Amount	Units	Cost	Origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Units
Customer service infrastructure											
Managing delivery & packages											
Drone preparation											
Delivery											

Infrastucture & equipment inputs												
Unit Process	Description	Amount	Units	Purchase Cost	Year of purchase	Country of origin	Type of transport	Transport Standard (related to age)	Trasport distance	Is the transportation cost included in the price?	Transport cost	Cost of maintenance & Repairs
Customer service infrastructure												
Managing delivery & packages												
Drone preparation												
Delivery												

Energy inputs							
Unit Process	Description	Amount	Units	Cost	Units	Link to equipment	Link to material
Customer service infrastructure							
Managing delivery & packages							
Drone preparation							
Delivery							

Tasks, frequency and labour requirements					
Unit Process	Description	Time needed to fullfil task	Frequency	Number of workers / shift / Unit Operation	Cost of Labour (i.e. in Euros per hour)
Customer service infrastructure					
Managing delivery & packages					
Drone preparation					
Delivery					

Outputs							
Unit Process	Description	Amount	Units	Income (if any)	Link to equipment	Treatment option	Treatment cost
Waste							
Emissions							
Deliveries							

Other costs	
	Cost
Improvements of land or buildings	
Insurance	
Taxes	
Cash and equivalents	
Inventories	
Rent payments (if applicable)	
Loan repayments (if applicable)	
Depreciation costs (if applicable)	
Subsidies (if applicable)	
Debt - commercial loans	
Debt - family/ private loans	
Other overhead costs (i.e. telephone, admin costs, advisory fees, etc.)	

Questionnaire UAVs

The following tables have been designed to gather all relevant information regarding inputs (natural resources, materials, infrastructure, equipment, energy, labour requirements), outputs (emissions, waste, product) and economic information required for the assembly, operation and maintenance of the UAVs used in the ICAERUS Use Cases.

UAV 1 components													
Equipment, components & replacements	Description	Ammount	Unit	Weight	Cost	Date of purchase	Country of orgin	Transport (how it was transported)	Transport Standard (related to age)	Transport distance	Transport cost	Links/pictures to user manual, labels or technical specifications (if available)	Comments

UAV 1 assembly steps						
Name	Description	Date	Time required	Workers involved (in n of people)	Energy/fuel requierments	Cost of energy/fuel required

UAV 1 energy requirements							
Battery type	Cost	Energy needed to fully charge it	Energy loses per charging	Battery duration (in minutes)	Cost of energy/fuel required	Battery life span	Number of batteries used per year

Annex 2. Selected studies

Table 4 Studies collected and analysed

Publication Year	Author	Venue	Title
2023	Li et al.	Renewable Energy	When my friends and relatives go solar, should I go solar too? —— Evidence from rural Sichuan province, China
2023	Korsuk Kumi et al.	Heliyon	Where is the market? Assessing the role of dryer performance and marketability of solar-dried products in acceptance of solar dryers amongst smallholder farmers
2023	Jaroenwanit et al.	Uncertain Supply Chain Management	Risk management in the adoption of smart farming technologies by rural farmers
2023	Soodan et al.	Journal of Agribusiness in Developing and Emerging Economies	Modelling the adoption of agro-advisory mobile applications: a theoretical extension and analysis using result demonstrability, trust, self-efficacy and mobile usage proficiency
2023	Hendrawan et al.	Sinergi (Indonesia)	Implementing Technology Acceptance Model to measure ICT usage by smallholder farmers
2023	Ling et al.	International Journal of Environmental Research and Public Health	Effect of Farmers' Awareness of Climate Change on Their Willingness to Adopt Low-Carbon Production: Based on the TAM-SOR Model
2023	Vasan & Yoganandan	Benchmarking	Does the belief of farmers on land as God influence the adoption of smart farming technologies?
2023	Wang et al.	Climate Risk Management	Farmers' adoption intentions of water-saving agriculture under the risks of frequent irrigation-induced landslides
2023	Purnomo et al.	Asian Journal of Agriculture and Rural Development	An empirical examination of barriers to acceptance of integrated paddy and beef cattle farming in Indonesia
2023	Xiang & Guo	Sustainability (Switzerland)	Understanding Farmers' Intentions to Adopt Pest and Disease Green Control Techniques: Comparison and Integration Based on Multiple Models

Publication Year	Author	Venue	Title
2023	Edwards et al.	Annals of Operations Research	Use of delivery drones for humanitarian operations: analysis of adoption barriers among logistics service providers from the technology acceptance model perspective
2023	Koh et al.	Technology in Society	Urban drone adoption: Addressing technological, privacy and task–technology fit concerns
2023	Leong & Koay	International Journal of Hospitality Management	Towards a unified model of consumers' intentions to use drone food delivery services
2023	Shazwan Azizu et al.	Journal of the Saudi Society of Agricultural Sciences	The use of drone for rice cultivation in Malaysia: Identification of factors influencing its farmers' acceptance
2023	Parmaksiz & Cinar	Agronomy	Technology Acceptance among Farmers: Examples of Agricultural Unmanned Aerial Vehicles
2022	McDonald et al.	Agriculture (Switzerland)	Technology Acceptance, Adoption and Workforce on Australian Cotton Farms
2022	Taheri et al.	Technological Forecasting and Social Change	The intentions of agricultural professionals towards diffusing wireless sensor networks: Application of technology acceptance model in Southwest Iran
2022	Zhao et al.	Mathematical Problems in Engineering	Research on the Impact and Utility of Rural Revitalization Big Data Service on Farmers Based on Integrated Technology Acceptance Model
2022	Yasirandi & Sitohang	Lecture Notes in Networks and Systems	Influencing User Intention of Plant-Based Sensing System Adoption in Public Vocational High Schools of Indonesia Using TAM
2022	Yerebakan et al.	Proceedings of the 2022 IEEE International Conference on Human-Machine Systems, ICHMS 2022	Factors that Affect Acceptance of Agricultural Related Robotic or Wearable Technology by Agricultural Stakeholders: A Pilot Survey
2022	Suresh et al.	Indian Journal of Agricultural Economics	Farmers' Perception on Precision Farming Technologies: A Novel Approach
2022	Prasetyowati et al.	2022 International Conference on Science and	Warehouse Receipt System using Technology Acceptance Model (TAM) for Agricultural Islamic Financing

Publication Year	Author	Venue	Title
		Technology, ICOSTECH 2022	
2022	Yoganandan et al.	8th International Conference on Advanced Computing and Communication Systems, ICACCS 2022	Adoption of Disruptive Technologies by the Farmers: Evidence from India
2022	Gargiulo et al.	Computers and Electronics in Agriculture	The AMS Integrated Management Model: A decision-support system for automatic milking systems
2022	Masimba & Zuva	Lecture Notes in Networks and System	A Model for the Adoption and Acceptance of Mobile Farming Platforms (MFPs) by Smallholder Farmers in Zimbabwe
2022	Sharef	Informatica (Slovenia)	The Usage of Internet of Things in Agriculture: The Role of Size and Perceived Value
2022	Dai & Cheng	Sustainability (Switzerland)	What Drives the Adoption of Agricultural Green Production Technologies? An Extension of TAM in Agriculture
2022	Nanyanzi et al.	2022 IST-Africa Conference, IST-Africa 2022	Intent to Use a Smartphone App as a University-Engagement Tool by Kabarole Farmers in Uganda
2022	Valencia-Arias et al.	Drones	Factors Associated with the Adoption of Drones for Product Delivery in the Context of the COVID-19 Pandemic in Medellín, Colombia
2022	Castillo-Vergara et al.	Electronics (Switzerland)	Technological Acceptance of Industry 4.0 by Students from Rural Areas
2022	Shapira& Cauchard	Frontiers in Public Health	Integrating drones in response to public health emergencies: A combined framework to explore technology acceptance
2022	Lamb et al.	Journal of Air Transport Management	Small Unmanned Aircraft Operator Perceived Risk Factors in the VMUTES model
2022	Igwe et al.	Journal of Information Technology in Construction	ACCEPTANCE OF CONTEMPORARY TECHNOLOGIES FOR COST MANAGEMENT OF CONSTRUCTION PROJECTS

Publication Year	Author	Venue	Title
2022	Waris et al.	Sustainability (Switzerland)	An Empirical Evaluation of Customers' Adoption of Drone Food Delivery Services: An Extended Technology Acceptance Model
2021	Jimenez et al.	Applied Sciences (Switzerland)	Validation of a tam extension in agriculture: Exploring the determinants of acceptance of an e-learning platform
2021	Al-Maroof et al.	International Journal of Data and Network Science	Acceptance determinants of 5G services
2021	Nugroho et al.	Proceedings - 2021 IEEE 7th Information Technology International Seminar, ITIS 2021	The Acceptance of Technology in Agriculture: case in Dalangan Village
2021	Diaz et al.	Resources, Conservation and Recycling Advances	Factors affecting farmers' willingness to adopt a mobile app in the marketing of bamboo products
2021	Hannus& Sauer	Sustainability (Switzerland)	Understanding farmers' intention to use a sustainability standard: The role of economic rewards, knowledge, and ease of use
2021	Michels et al.	Precision Agriculture	The adoption of drones in German agriculture: a structural equation model
2021	Mohr, S.; Kühl, R.	Precision Agriculture	Acceptance of artificial intelligence in German agriculture: an application of the technology acceptance model and the theory of planned behavior
2021	Matias, J.B.	International Journal of Enterprise Information Systems	Understanding Intention and Behavior Toward Online Purchase of Agriculture and Fisheries Products Using Extended Technology Acceptance Model
2021	Saengavut & Jirasatthumb	Heliyon	Smallholder decision-making process in technology adoption intention: implications for Dipterocarpus alatus in Northeastern Thailand
2021	Canavari et al.	Sustainability (Switzerland)	A path model of the intention to adopt variable rate irrigation in Northeast Italy
2021	Lim et al.	2021 International Conference on Green Energy,	The Effect of System Quality Attributes on the Intention to Use E-AgriFinance

Publication Year	Author	Venue	Title
		Computing and Sustainable Technology, GECOST 2021	
2021	Otter& Beer	Journal of Cleaner Production	Alley cropping systems as Ecological Focus Areas: A PLS-analysis of German farmers' acceptance behaviour
2021	Choe et al.	Journal of Travel and Tourism Marketing	Innovative marketing strategies for the successful construction of drone food delivery services: Merging TAM with TPB
2021	Yaprak et al.	Technological Forecasting and Social Change	Is the Covid-19 pandemic strong enough to change the online order delivery methods? Changes in the relationship between attitude and behavior towards order delivery by drone
2021	Del-Real & Díaz-Fernández	Technology in Society	Lifeguards in the sky: Examining the public acceptance of beach-rescue drones
2020	Mercurio & Hernandez	Proceedings - 2020 16th IEEE International Colloquium on Signal Processing and its Applications, CSPA 2020	Understanding User Acceptance of Information System for Sweet Potato Variety and Disease Classification: An Empirical Examination with an Extended Technology Acceptance Model
2020	Akyüz &Theuvsen	Sustainability (Switzerland)	The impact of behavioral drivers on adoption of sustainable agricultural practices: The case of organic farming in Turkey
2020	Tolentino & Hernandez	International Journal of Enterprise Information Systems	User Acceptance of Agricultural Market Information System with Analytics: Insights from the Philippines
2020	Shyr et al.	International Journal of Engineering Education	Students' acceptance of applying internet of things in a smart agriculture course
2020	Chuang et al.	International Food and Agribusiness Management Review	Implementation of internet of things depends on intention: Young farmers' willingness to accept innovative technology
2020	Sayruamyat & Nadee	Smart Innovation, Systems and Technologies	Acceptance and Readiness of Thai Farmers Toward Digital Technology

Publication Year	Author	Venue	Title
2020	Haji et al.	Journal of Agricultural Science and Technology	Analyzing iranian farmers' behavioral intention towards acceptance of drip irrigation using extended technology acceptance model
2020	Zarafshani et al.	Social Sciences and Humanities Open	Evaluating technology acceptance in agricultural education in Iran: A study of vocational agriculture teachers
2020	Caffaro et al.	Journal of Rural Studies	Drivers of farmers' intention to adopt technological innovations in Italy: The role of information sources, perceived usefulness, and perceived ease of use
2020	Li et al.	Computers and Electronics in Agriculture	A hybrid modelling approach to understanding adoption of precision agriculture technologies in Chinese cropping systems
2020	Ronaghi & Forouharfar	Technology in Society	A contextualized study of the usage of the Internet of things (IoTs) in smart farming in a typical Middle Eastern country within the context of Unified Theory of Acceptance and Use of Technology model (UTAUT)
2019	Wang et al.	Information Systems Frontiers	Farmer Cooperatives' Intention to Adopt Agricultural Information Technology—Mediating Effects of Attitude
2019	Zhang et al.	Journal of Cleaner Production	Adoption behavior of cleaner production techniques to control agricultural non-point source pollution: A case study in the Three Gorges Reservoir Area
2019	Zheng et al.	China Agricultural Economic Review	Technology adoption among farmers in Jilin Province, China: The case of aerial pesticide application
2019	Sukainah et al.	Journal of Physics: Conference Series	Application of Technology Acceptance Model to E-learning Assessment (Kelase) in Agricultural Technology Education, UniversitasNegeri Makassar
2019	Purnomo	Information Development	Barriers to acceptance of information and communication technology in agricultural extension in Indonesia
2019	Syahlani et al.	IOP Conference Series: Earth and Environmental Science	The role of education in social media adoption of small and medium livestock-based food enterprises
2019	Jürkenbeck et al.	Sustainability (Switzerland)	Sustainability matters: Consumer acceptance of different vertical farming systems

Publication Year	Author	Venue	Title
2018	Tsaur & Lin	Sustainability (Switzerland)	Exploring the consumer attitude of building-attached photovoltaic equipment using revised technology acceptance model
2018	Jayashankar et al.	Journal of Business and Industrial Marketing	IoT adoption in agriculture: the role of trust, perceived value and risk
2018	Iskandar & Rosmansyah	Proceedings - 2018 4th International Conference on Science and Technology, ICST 2018	A Persuasive Mobile Learning System for Informal Learning of Vegetable Farmers
2018	Kabbiri et al.	Technological Forecasting and Social Change	Mobile phone adoption in agri-food sector: Are farmers in Sub-Saharan Africa connected?
2018	Yoo et al.	Telematics and Informatics	Drone delivery: Factors affecting the public's attitude and intention to adopt
2018	Verma & Sinha	Technological Forecasting and Social Change	Integrating perceived economic wellbeing to technology acceptance model: The case of mobile based agricultural extension service
2017	Silva et al.	Bodenkultur Journal of Land Management, Food and Environment	A technology acceptance model of common bean growers' intention to adopt integrated production in the Brazilian Central Region
2017	Tohidyan & Rezaei-Moghaddam	Journal of the Saudi Society of Agricultural Sciences	Determinants of Iranian agricultural consultants' intentions toward precision agriculture: Integrating innovativeness to the technology acceptance model
2017	Naspetti et al.	Sustainability (Switzerland)	Determinants of the acceptance of sustainable production strategies among dairy farmers: Development and testing of a modified technology acceptance model
2014	Amin & Li	13th Wuhan International Conference on E-Business, WHICEB 2014	Applying Farmer Technology Acceptance Model to Understand Farmer's Behavior Intention to use ICT Based Microfinance Platform: A Comparative analysis between Bangladesh and China.

Publication Year	Author	Venue	Title
2012	Shahbaz et al.	Life Science Journal	Evaluating the factors responsible for slow rate of technology diffusion in Livestock Sector of South Asia and developing a framework to accelerate this process: A case study using data analysis for Pakistan's Livestock Sector
2012	Aubert et al.	Decision Support Systems	IT as enabler of sustainable farming: An empirical analysis of farmers' adoption decision of precision agriculture technology
2010	Rezaei-Moghaddam & Salehi	African Journal of Agricultural Research	Agricultural specialists' intention toward precision agriculture technologies: Integrating innovation characteristics to technology acceptance model
2010	Pouratashi & Rezvanfar	Journal of the American Society for Information Science and Technology	Analysis of factors influencing application of ICT by agricultural graduate students
2008	Folorunso & Ogunseye	Data Science Journal	Applying an enhanced technology acceptance model to knowledge management in agricultural extension services

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