ICAERUS

D2.1: ICAERUS Drone Data Analytics Library
Version A

WP2: Drone Data Analytics Library

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Executive Summary

The ICAERUS project proposes an "application-oriented" approach through the selection of five (5) specific drone applications to explore the multi-purpose application potential of drones in agricultural production, forestry and rural communities. The selected drone applications represent the main sectoral and societal uses of drones in Europe and cover multiple applications that are interconnected within Europe's complex rural landscape. The vision of ICAERUS is to explore opportunities and provide a more comprehensive and interconnected representation of the potential and impact of drones as multi-purpose vehicles in agriculture, forestry and rural areas of the European Union (EU). The aim is to demonstrate and support the effective, efficient and safe use of drones through their application and to identify the risks and added values associated with their use. "Taking off" from the current state of the art in the drone ecosystem, ICAERUS will "rise up" by further developing existing software technology, platform components and knowledge related to drones to harness the potential of drones and strengthen capacities to reduce their risks, achieve better informed decision-making and improve sustainability performance and competitiveness in agriculture, forestry and rural areas. This will be done in two ways: a) basic 'eye in the sky' applications using the drone as a positioning system for visual observation and recording, and b) a "hand in the sky' application for spraying and delivery of goods. ICAERUS plans to create an efficient, trusted and safe environment for the EU drone services market through research, technology optimisation, demonstration and education on drones to achieve the EU's decarbonisation, digitalisation and resilience goals. ICAERUS consists of a balanced, cross-sectoral and experienced consortium including research institutions, SMEs (small and medium-sized enterprises), technology providers, associations and non-profit organisations.

Deliverable "D2.1 ICAERUS Drone Data Analytics Library" is intended to provide a general overview of the activities to be undertaken as part of Task 2.1, which is to identify existing drone data analytics models. This task includes the review, identification and evaluation of established and emerging models and algorithms for drone data analytics based on the needs identified (T1.1) and the five use cases (WP3). The resulting information will be used to create the ICAERUS Drone Data Analytics Library, which will be a repository of existing drone data analytics models. The Library will be regularly updated with new research and the results of the Open Call Trials (WP5). A step-by-step guide will be created explaining how to use the selected models and this guide will be used for WP4 training.

The ICAERUS Drone Data Analytics Library will be an open-access repository of the most significant existing and emerging drone data analytics models and algorithms that meet end-user requirements. The models and algorithms will be identified and evaluated based on stakeholder needs as indicated in the Drone Market Landscape analysis. The information collected is used to create the ICAERUS Drone Data Analytics Library, which is continuously updated based on new research and the results of the ICAERUS UC and OCTs (PUSH /PULL). The Library will be developed and maintained by WU with support from NMN. It will consist of various models including photogrammetry techniques with 3D digital elevation models, statistical models, machine learning and data mining algorithms, vegetation index calculation, autonomous routing and fleet management optimisation algorithms such as the Travelling Salesman Problem (TSP) for last mile delivery.

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1. Introduction

1.1 Purpose

WP2 “Drone Data Analytics Library” is responsible for the identification, optimisation of existing data analytics models for drones and selection of application-oriented models to build the Drone Data Analytics Library. The objectives are the following:

1) Identify and asses well-established and emerging drone data analytics models
2) Optimise the most significant models and algorithm to analyse and visualise drone data
3) Create an open-access, free and public Drona Data Analytics Library
4) Expand the Drone Data Analytics Library content and scale-up its usability through the open calls

Task T2.1 “Identify Existing Drone Data Analytics Models” has an objective to review, identify and assess existing drone data analytics models and algorithms according to the recorded needs (T1.1) with the help of the five Use Cases (WP3). This information will lead to the creation of the ICAERUS Drone Data Analytics Library, a GitHub repository of the existing drone data analytics models. The library will be constantly updated from continued research and the Open Call Trials (WP5). A step-by-step user guide on how to use the selected models will be created, and will feed WP4 for training.

The models used in the Library have been sourced from scientific literature to ensure accuracy and reliability. We have chosen to use literature as our primary source because it provides a more comprehensive and validated set of data than a simple online search. By utilising scientific literature, we can access research that has undergone rigorous peer-review processes, ensuring the reliability and accuracy of the data. Furthermore, scientific literature provides a standardised set of methods and results that we can use to compare our findings to the original results.

This document is structured in four sections, Section 2 provides and in-depth explanation of the methodology used to search for the models. This section outlines the search process and selection criteria that were used to ensure that the most relevant and reliable models were chosen for our analysis.

In Section 3, an overview of the GitHub repository created for this task is provided. The section includes a detailed explanation of the structure of the repository, as well as the data and models that it contains. Specifically, it is described the organisation of the repository, including the main directories and files.

Finally, Section 4, an evaluation of the selected models is presented using the methodology implemented in this task. The evaluation includes a set of questions that guide the UC members in recognising the limitations of the models and identifying areas for improvement in future steps. By undertaking this evaluation, a clear and comprehensive picture of the performance of the models is provided, and the UC members are enabled to make informed decisions about how to refine and optimise them for their intended use.

Thus, the purpose of this document is to report the activities that take place in Task T2.1 to identify, review and assess existing drone data analytics models and algorithms, in order to create the ICAERUS Drone Data Analytics Library. This Library will be a comprehensive collection of existing drone data analytics models, which will be constantly updated with new research and Open Call Trials, and will serve as a valuable resource for the ICAERUS project and the wider research community.

2. Identifying Existing Drone Data Analytics Models

For this task a methodology has been developed for assessing and identifying drone data analytics models. *This methodology is structured around six steps: 1. selecting appropriate research questions, 2. searching databases, 3. selecting studies, 4. assessing the quality of the studies, 5. extracting data and recording the information on a shared spreadsheet. The goal of this methodology is to identify analytics models and algorithms used for all the Use Cases of ICAERUS and present different techniques for all Use Case scenario*s.

The methodology consists of six steps that are structured in a specific order to ensure a thorough and comprehensive analysis, following the guidelines of the article "Guidelines for performing Systematic Literature Reviews in Software Engineering" (Kitchenham & Charters, 2007).

- The first step is to select appropriate research questions that will guide the analysis. These research questions should be relevant to the topic being studied, and should help to identify the key areas that need to be examined.
- The second step involves searching databases to identify relevant studies that have been conducted on drone data analytics models. This step ensures that the analysis is based on a broad range of literature and that all relevant studies are included.
- The third step is to select studies that meet specific inclusion criteria. These criteria may include factors such as the date of publication, the quality of the study, and the relevance to the research questions being examined.
- The fourth step assesses the quality of the studies that have been selected. This may involve using specific tools or criteria to evaluate the methodological rigour and validity of the studies.
- The fifth step focuses on extracting data from the selected studies. This may include information on the types of models and algorithms used, the data sources used, and the results of the analysis. The information is recorded on a shared spreadsheet. This spreadsheet is used to collect and organise the data that has been extracted from the different UC.

The overall goal of this methodology is to identify analytics models and algorithms used for all the Use Cases of ICAERUS and present a taxonomy of techniques for all Use Case scenarios. By following this methodology, researchers can ensure that their analysis is comprehensive and rigorous, and that they are able to identify the most effective and efficient drone data analytics models for their specific Use Cases.

2.1 Methodological steps

The steps for assessing and identify drone data analytics models are explained in this section and their purpose was to guide the Use Case partners to identify valuable analytics models and algorithms.

2.1.1 Step 1: Research questions

The questions developed correspond to the goal of the review which is to identify techniques (software and models), and to find how to improve these techniques. The specific questions used are the following:

Q1: What is the accessibility of the dataset?

This question focuses on the availability of data that can be used for monitoring. It is important to determine whether the data is accessible and available for use by researchers, or if there are any restrictions on its uses that may impact the reproducibility of the study.

Q2: What is the applicability?

This question seeks to identify the suitability of the techniques for the different Use Case scenarios. It is important to determine whether the techniques are appropriate for each use case and whether they can produce accurate and reliable results in different scenarios.

Q3: Which algorithms are used and how are they implemented?

This question aims to identify the specific algorithms that are being used in the study, and how they are implemented. This information can be used to determine the effectiveness of the algorithms, and to identify any potential areas for improvement or optimisation.

Q4: Are the algorithms scalable? Do they support large variances?
This question focuses on the scalability or flexibility to adapt to new cases of the study. It is interesting to understand if the algorithm can be applied to large datasets or different scenario conditions.

Q5: Which sensors and UAVs are used in the study?
This question aims to determine the sensors that are being used in the different studies. This information is very useful and important for understanding the data extraction process as well as to understand which sensors will perform better and give higher accuracies on the study.

Overall, these questions help to identify the strengths and weaknesses of existing techniques and to develop strategies for improving these techniques.

2.1.2 Step 2: Search in databases

The step aims to give tips on the correct use of the different databases to find relevant papers. To fulfil this objective there are different steps that should be followed:

1. Use specific search terms: Use specific keywords and phrases that are related to the research. This will narrow down the search results and find more relevant papers.
2. Use Boolean operators: Using boolean operators such as “AND”, “OR” and “NOT” for more precise results.
3. Use advanced search options: Most search databases have advanced search options that allow you to refine your search using specific criteria, such as date of publication, author, or publication type.

Following these tips the researcher can find relevant papers on the search databases and do a SoTA analysis.

2.1.3 Step 3: Study selection

To narrow down the selection of articles and get the most important ones for the use case there are several filters that can be applied.

- The first filter is to read all the abstracts and do a check to see if the content of the articles is relevant to your case. After reading all the abstracts the researcher has an idea of the content of all articles and can make an informed decision on which of them are more relevant for their specific case.
- The second filter can be the publication date since often the most relevant studies will be the ones that are up to date with new emerging technologies.
- The third filter and the most important one, is to read all the articles to assure that the selection made is appropriate to the case. When reading the full article, the researcher will understand all the specific details of the study and will be able to determine the real relevance of that study for their case.

2.1.4 Step 4: Quality assessment

The quality assessment is the process that helps to ensure that the selected articles are of sufficient quality to provide valuable insights into the research question or topic being studied. In this methodology the quality assessment process consists of answering a set of questions and assigning a score to this answer to be able to filter the articles once all of them are evaluated.

The quality assessment questions are the following:

- Are the limitations of the study discussed?
- Are the research processes (methods) on the paper applicable to the specific UC?
- Is the data collection procedure clearly defined?
- Are the Machine Learning (ML) models described and evaluated?

The possible answers to the questions are:

Question 1: Y (Yes), the limitations are explicitly in the paper; P (Partly) the limitations are implicit; N (No) the limitations are not defined.
Question 2: Y (Yes), the author gives technical details about the methods and are directly applicable to our UC; P (Partly) the methods are explained and they are useful but not directly applicable; N (No) the methods are not defined.
Question 3: Y (Yes), the data collection procedure is explicitly in the paper and with technical details (number of images and number of flights); P (Partly) the data collection procedure is explicit but missing some details; N (No) the data collection procedure is not defined or it is not using UAV.
Question 4: Y (Yes), the ML models are explicitly in the paper and give details about the training and the models evaluation; P (Partly) the ML models are mentioned but missing some details; N (No) the ML models are not defined or used.

By using this methodology, the quality assessment process can be more objective, consistent, and efficient in evaluating the selected articles' quality. The articles with higher scores represent the articles that should have more weight on the study.

2.1.5 Step 5: Data extraction process

From the included articles, additional details are extracted, for giving an overview and more insight into the various models used in literature. These are extracted by reading the document, and finding the relevant variables, and writing them down in a spreadsheet. These variables are categorised as follows:

- Basic article information contains specific information regarding the article such as the year of publication, name of the article and the weight of the punctuation assessment questions.
- Data Extraction Details, contains specific information regarding the data used on the paper. This includes the number of images used, the location, the extraction date, weather conditions, percentage of image overlap, flight altitude and speed.
- Software Extraction, includes detailed analysis of the methods employed like the model classification type, model accuracy. Additionally it contains some available resources provided by the Authors (e.g. github repositories and datasets). Methods used include computer vision, in very few cases there is no use of Artificial Neural Networks (ANN) or model on the research paper, in these cases they include the main task or process developed by computer vision.
- Hardware Extraction provides information on the UAV model, UAV classification, specific use, payload name and payload type.

Additional variables were extracted, the most important ones are listed above.

Finally, by categorising the extracted data in this manner it is ensured that the information is structured and easy to analyse, thereby allowing deeper insights and the identification of patterns.

The following figure shows the flowchart of the methodology implemented for the Use Case of Crop Monitoring.

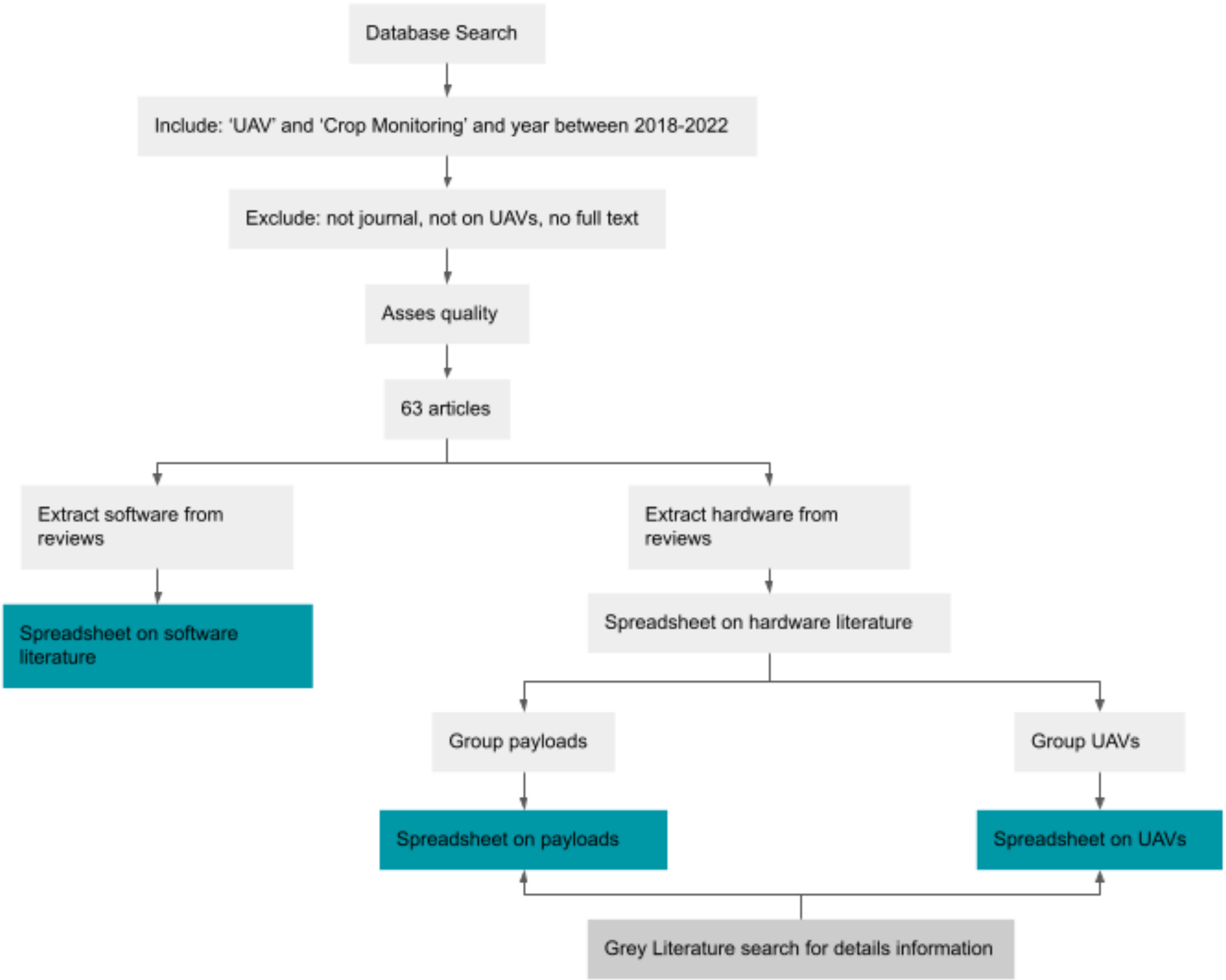

Figure 1:Methodlogy flowchart

2.2 Methodology Implementation by the ICAERUS UC

Each UC was provided with a document explaining the steps to perform the Systematic Literature Review as well as a workshop organised by NMN, AUA and WU members. Each UC (WP3) delivered a spreadsheet containing around 50 articles and the corresponding information for their specific case.

2.2.1 Use Case 1: Crop Monitoring

To conduct a literature review, UC1 Crop Monitoring followed a series of steps. Firstly, we used the predefined research questions to establish the objectives of our search. Next, we utilised the Google Scholar database and filtered our search using the keywords "crop monitoring" and "UAV." Additionally, we incorporated the term "vine disease" to ensure a more accurate search. We also applied a filter to only show results from 2018 onwards, allowing us to focus on the latest technologies and advancements in the field.

We reviewed the abstracts of the resulting articles and identified 61 of the most relevant papers. To assess the quality of the selected papers, we used a set of predetermined assessment questions and recorded the information in an Excel file.

Based on our literature review, we found a significant gap in information regarding the datasets used and the conditions under which they were obtained. Additionally, we found it challenging to find open-source codes and algorithms for crop monitoring. These conclusions emphasise the need for more open-source data and codes to overcome these challenges and advance the field of crop monitoring.

2.2.2 Use Case 2: Drone Spraying

To conduct the literature review for Task 2.1, AUA conducted an online study on the academic search engine “Google Scholar” that collected relevant all recently published manuscripts and studies on the field of Drone Spraying. To this end, the search query {"UAV" OR "UAS" AND "SPRAYING"} was used, while the year of each study was selected to be no older than 6 years, thus setting the temporal filter to the year “2018” as a starting point (including the year 2018). This methodology yielded a total of approximately 50 papers that were identified as relevant to the experimental operations of UC2 based on their Abstracts, which were then further shortened down to a total of 38 papers after examining each manuscript individually.

The information from each paper was then converted to tabular form, using the Excel template provided by the partners of WP2 responsible for this task. Based on the findings of the literature review, a significant variability across all papers was identified, for both the methodological protocols followed, as well as the spatial distribution of the studies, with the majority of experiments taking place in Asia. Therefore, it becomes apparent that a number of robust studies conducted within the EU and the crops of interest to the EU population are required to provide evidence on the efficiency and potentially help facilitate a regulatory update regarding spraying drones by the EASA.

2.2.3 Use case 3: Livestock Monitoring

To conduct a literature review, UC3 Livestock Monitoring followed a series of steps. Firstly, we used the predefined research questions to establish the objectives of our search. Next, we utilised the Google Scholar and Science Direct databases and filtered our search using the requests:

- (« UAV » OR « drone ») AND (“livestock” OR “sheep” OR “ewes” OR “cow” OR "cattle") AND ("monitoring" OR "management")
- (« UAV » OR « drone ») AND (“livestock” OR “sheep” OR “ewes” OR “cow” OR "cattle") AND ("counting" OR "detection")

We also applied a filter to only show results from 2015 onwards, allowing us to focus on the latest technologies and advancements in the field. We excluded the papers which focused on grass management. We added papers that were not the result of our requests but cited by them. We reviewed the abstracts of the resulting articles and identified 37 of the most relevant papers. To assess the quality of the selected papers, we used a set of predetermined assessment questions and recorded the information in an Excel file.

Based on our literature review, an important variability across all papers was defined, for methodology used and the environment where the data sets were recorded. However, it seems that the task of detecting animals and counting them is possible by drones even if the extremely good accuracy of some models (>98 %) seems not enough for the needs of the farmers. Indeed, in a flock of 1000 sheep, an error of 2% results in an error of 20 sheep. Some authors described semi-automatic detection and counting strategies based on the very good performance of some models to largely simplify the task for farmers. We found it challenging to find open-source codes and algorithms for livestock monitoring. The challenge is the same for finding open-source datasets. However, models used, and methodology are very well defined by some authors allowing us to reproduce it and to train new models to detect and count animals. These conclusions emphasise the need for more open-source data and codes, and to open more largely to similar work to detect mammals in ecology studies, to overcome these challenges and advance the field of livestock monitoring supported by drones.

2.2.4 Use Case 4: Forestry and Biodiversity

The literature review for the UC4 Forestry and Biodiversity was performed following the predefined procedure. We used Google Scholar, a free academic search engine, to find and filter drone data analytics models that are relative to our use case. Because the Forestry and Biodiversity use case involves three use case scenarios, including forest tree health monitoring, forest wildfire monitoring, and wild boar monitoring, we divided our search into three queries to cover all three scenarios. The following queries were used: 1) “UAV” AND “forest health”; 2) “UAV” AND “forest fire”; 3) “UAV” AND “wild animals” AND “monitoring”. To focus on the most recent advancements, we filtered search results by date so that only the papers published since 2018 would be displayed. We reviewed the titles and abstracts of the filtered papers and selected 11–21 papers that were the most relevant for each use case scenario. In total, 45 articles were selected.

We assessed the quality of 45 selected articles based on predefined quality assessment questions related to the data collection procedure, methods that were used, or model evaluation. Finally, all the information was recorded into an Excel template file.

After examining the selected articles, we observed that most of the forest monitoring studies either focus on developing and optimising architectures of artificial intelligence models or apply the most common machine learning techniques to various forest monitoring use cases. However, there is a lack of studies that are based on forestry applications in real-world conditions and use state-of-the-art artificial intelligence models. The possibility of such studies is limited by the fact that most of the studies included in the literature review did not publish their datasets or models in open-source repositories. Limited availability of open models and datasets creates a lack of data to develop reliable models applicable to forest monitoring and a lack of openly available models that could be used in real-world forest applications.

2.2.5 Use Case 5: Rural Logistics

A literature review for the UC5 (Rural logistics) for the ICAERUS Project was conducted following a series of steps. Firstly, we used the predefined research questions to establish the objectives of our research. Next, we utilised the Google Scholar database and filtered our search using the keywords “logistics” and “UAV”. Additionally, we incorporated the terms “Photogrammetry” and “BVLOS” to ensure a more accurate search. Moreover, we applied a filter to only show results from 2018 onwards, allowing us to focus on the latest technologies and advancements in the particular field.

We reviewed the abstracts of the resulting articles and identified 43 of the most relevant papers. To access the quality of the selected papers, we used a set of predetermined assessment questions and recorded the information in a Microsoft Excel (Spreadsheet) file.

According to our literature review, we found relative explanatory information for the implementation of photogrammetry methods in a variety of environments, whereas in some cases the data provided from the research papers were described in detail. On the contrary, the retrieved information regarding the drone logistics, as well as the “Beyond the Visual Line Of Sight” (BVLOS) flights of drones in rural or remote areas, were rather limited. These conclusions emphasise the necessity of more applications and testing in the field of drone logistics and BVLOS flights in inaccessible areas, incorporating the development of appropriate algorithms for fleet deployment.

3. GitHub repository

3.1 Overview and purpose

GitHub is an online platform for sharing software and version management. It is also often used as a medium to share information like a webpage, through readme.md files. Additionally, documentation on code, processes and wiki pages can be created as part of a repository (repo). This makes GitHub an ideal candidate for continuous development of the drone data analytics library throughout the ICAERUS project, as information on the analytical models can be shared, data can be linked, and pipelines developed as an open-access Github repository.

As a starting point for this online version of the library are the excel sheets and their models as identified using the methodology from the previous section (Section 2). Only models and datasets that have online access, or the original authors who provide access are included in the GitHub. These models have been organised into their respective Use Case numbers (1-5) they are linked and additional details are given in a "readme" file, which is shown on the web page by default.

The link to the repository: *https://github.com/icaerus-eu/ddal.*

3.2 Methodology and structure definition

The organisation of the repository is currently made through a folder structure and markdown (.md) files which contain hyperlinks and text about specific models and details. These are adapted from the AgML github repository on agricultural machine learning. The current structure of the repo is as follows:

Template structure for every UC (1-5):

- UCx/
    - dataset/
        - dataset1.md
        - dataset2.md
    - models/
        - model_a.md
        - model_b.md
        - deeplearning/
            - weights.pt
    - readme.md

Additional files:

- readme.md

readme.md

This initial file is opened when opening the repository; it, explains the structure of the repository and presents host to get started using the repository and data analytics in general. Getting started with analytics can require a lot of set-ups of programming environments, so a start is given with premade environments through python environment.yaml files and docker containers. These will be expanded and upgraded throughout the duration of the project.

UCx/readme.md

Every UC has their own subfolder, UCx serves as an example. The readme file in this folder links to the original article, and shows if it contains a dataset and/or a model. For every dataset or model, the title for the article, dataset, subject of the data and URL to original files is given. The title is clickable, which will open that respective dataset or model details as another markdown file.

UCx/dataset/dataset.md

Opened when clicking on it from the readme file, this contains a summary of the dataset, and metadata, such as which UAV acquired the data, how many images in the dataset, etc.

UCx/model/model.md

Opened when clicking on it from the readme file, this contains a summary of the model, and metadata, such as task/function, architecture and accuracy.

The long-term plan for the repository is to transfer the contents of these files to wiki pages in the repo, develop working examples of using the models and explain how other users could add to the library. These are in addition to the continuation of work in WP2: optimising the identified models, and expanding this library as part of the ICAERUS project.

3.3 Machine Learning Models and datasets

This section will provide an overview of the information that can be found on the GitHub repository, it will be updated in coming months with more data and models for the different UCs.

For each UC folder there is a general .md file that provides a general overview of the content available for the specific UC. And three folders, datasets, models and jupyter notebooks. In the case of the models and datasets the folder contains a .md file with the specific and technique information.

The general .md file is organised as follows. First there is an initial table containing the titles of the articles with open-source data as well as the specification of the data that can be found (either the model or the dataset). After the introductory part there are two subsections, datasets and models, for each of them a table of content with clickable links provided, one for the original content and the other for the technical information provided in the folder of models or datasets of the same GitHub repo. An example of this file is shown in Figure 2.

README.md

Use Case 4: Forestry and biodiveristy monitoring

This folder contains datasets and models subfolders. Which respectively contain datasets relating to the use-case, as found in the data-extraction task for ICAERUS WP1/T.2. The data-extraction task identified the following papers and respective models and datasets:

Title	Model in this repo	Dataset in this repo
Predicting Tree Mortality Using Spectral Indices Derived from Multispectral UAV Imagery	x	x
Individual Sick Fir Tree (Abies mariesii) Identification in Insect Infested Forests by Means of UAV Images and Deep Learning		x
A Forest Fire Recognition Method Using UAV Images Based on Transfer Learning		x
Performance of unmanned aerial vehicle with thermal imaging, camera trap, and transect survey for monitoring of wildlife		x
Antler detection from the sky: deer sex ratio monitoring using drone-mounted thermal infrared sensors		x

Datasets

Under the datasets folder, the following datasets are included:

Article title	Dataset title	Dataset subject	Original dataset link
Predicting Tree Mortality Using Spectral Indices Derived from Multispectral UAV Imagery	dataset_tree_mortality_prediction	Tree mortality prediction	Tree mortality dataset link
Individual Sick Fir Tree (Abies mariesii) Identification in Insect Infested Forests by Means of UAV Images and Deep Learning	dataset_sick_fir_tree	Classifying tree health and species class from RGB images	Sick Fir Tree dataset
Performance of unmanned aerial vehicle with thermal imaging, camera trap, and transect survey for monitoring of wildlife	dataset_animal_movement	Animal movement samples	Animal movement dataset
Antler detection from the sky: deer sex ratio monitoring using drone-mounted thermal infrared sensors	dataset_deer_detection	Deer monitoring dataset	Deer monitoring

Models

Under the models folder, the following models are included:

Article title	Model title	Model Classification	Original model link
Predicting Tree Mortality Using Spectral Indices Derived from Multispectral UAV Imagery	rf_predicting_tree_mortality	Machine Learning: Random Forest	Random Forest link

Figure 2:General .md example for the case of UC5: Forestry and biodiversity monitoring

Inside the folders datasets, .md files with a table filled with the technical details of each dataset can be found. The technical details that can be found are the following:

1. UC Task
2. Machine Learning task
3. Location
4. Location (lat/lon)
5. Sensor type
6. UAV Platform
7. Flight path
8. Weather conditions

9. Input data format
10. Annotation format
11. Number of images
12. Size on disk
13. Classes

The table is filled with the data recorded on the spreadsheet created for the methodology. An example of the technical .md file for one dataset can be found on Figure 3. There are empty spaces in the table since most of the articles do not provide this type of information.

dataset_deer_detection.md

Dataset metadata

Metadata item	Value
UC Task:	Wildlife monitoring
Machine Learning task	Wild animal recognition and counting in thermal images
Location	Tottori Sand Dunes, Japan
Location lat/lon	
Sensor type	Thermal
UAV Platform	DJI Inspire 1 V2
Flight path/GPS available?	
Weather conditions	Night with no rain, snowfall or strong wind
Input data format	.XLSX
Annotation format	
Number of images	
Size on disk	0.5 MB
Documentation	
Classes	

Figure 3: Technical .md example for the case of UC5: Forestry and biodiversity monitoring showing the .md file for the dataset of deer detection.

The third folder, models, contains separate .md files specific for each model of each UC. The file contains a table with the technical information of the models. The data that can be found is the following:

1. UC Task
2. Machine Learning task
3. Model architecture
4. Reported accuracy on train
5. Reported accuracy in test
6. Pretrained weights link

Additionally, it is shown and exampled in Figure 4.

Random Forest for predicting tree mortality

Model metadata

Metadata item	Value
UC Task:	Predicting tree mortality and classifying tree species in multispectral images
Machine Learning task	Tree mortality prediction
Model architecture	Random Forest
Reported accuracy on train	
Reported accuracy on test	83.3%
Pretrained weights link	

Architecture example

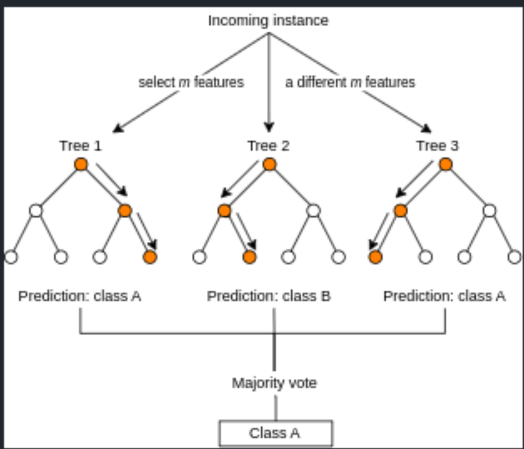

Figure 4:Technical .md example for the case of UC5: Forestry and biodiversity monitoring showing the .md file for the model for the case of predicting tree mortality.

3.4 Importance and connection to the ICAERUS Platform

The GitHub repository plays a vital role in the ICAERUS Platform as it is used to host the drone data analytics models and algorithms that are identified and assessed by ICAERUS. The ICAERUS Drone Data Analytics Library will be developed and maintained using information from ongoing research, as well as the ICAERUS Use Cases and Operation Concept Templates (OCTs). By linking the GitHub repository to the ICAERUS Platform, which will serve as a central hub for information dissemination, communication, and collaboration, users will be able to access the Drone Data Analytics Library through the platform, making it an integral part of the ICAERUS Platform.

Furthermore, the publicly accessible nature of the drone data analytics models and algorithms in the GitHub repository can foster collaboration and knowledge sharing between researchers, industry experts, and other stakeholders. This collaborative environment can lead to the development of more advanced and effective drone technology and the creation of new applications and uses for drones. As a result, the ICAERUS Platform's goals of increasing the use of drones for sectoral and societal purposes will be more readily achieved through open innovation and collaboration.

4. Evaluating Drone Data Analytics Models

4.1 Template

This template has been created as part of Task 2.1, which involves identifying existing Drone Data Analytics Models. The goal is to **gather information, perform an analysis, and evaluation** on the **Drone Data Analytics Models** identified by UC partners.

Each UC partner is required to select the most suitable Drone Data Analytics Model for their use case and complete this template, answering the following five (5) criteria/questions covering Model Description, Data Sources, Model Performance, Limitations, and Recommendations for Improvement.

By understanding a model's **capabilities, limitations, and potential**, ICAERUS partners can gain a better understanding of how the model can be used and what its strengths and weaknesses are. This can help UC partners make more informed decisions about whether to deploy the model in their use case and how to optimise its performance. Moreover, by identifying potential areas for improvement and challenges in advance, WP2 and UC partners can proactively address these issues and minimise risks associated with deploying the model.

This template will serve as the basis for Task 2.2: Optimising Drone Data Analytics Models. The models identified in Task 2.1 will be further developed, optimised, and adapted to better address end-user needs (as identified in Task 1.1) and to advance the state-of-the-art in drone-based data modelling.

Criteria/questions:

- **Model Description:** What is the purpose of the drone data analytics model? Can you provide examples of how the drone data analytics model has been applied in specific use cases? How does the model work, and what are its main components? Are there any use cases where the model is not well-suited? What types of insights can the model provide?
- **Data Sources:** What types of data were used to train the model? How was the data collected, and what methods were used to ensure data quality? Were any data preprocessing techniques used, such as normalisation or feature scaling? What is the size of the dataset? Were any data augmentation techniques used to increase the size of the training dataset? Were the sample sizes or populations used in the study large enough to draw reliable conclusions?
- **Model Performance:** How well does the identified drone data analytics model perform? What performance metrics were used to evaluate the model? Which section of the data has been used for testing, validation and training? How does the model's performance compare to other similar models? Which techniques are implemented to avoid overfitting?
- **Limitations:** Are there any limitations to the data used to train the model, such as biases or gaps in the data? Are there any limitations to the model itself, such as accuracy or interpretability issues? What are the potential risks of relying on the model's outputs? Can the results be applied to other populations, settings, or contexts, or are they specific to the study sample or location?
- **Recommendations for Improvement:** Are there any areas where the model's performance (speed, size, accuracy, scalability) could be improved? What steps could be taken to enhance the usefulness of the model? Are there any new data sources or technologies that could be integrated into the model?

4.2 Individual Use Case Input on Evaluating One Drone Data Analytics Model

This section presents the different inputs received by each UC member.

4.2.1 Use Case 1: Crop Monitoring

Paper: Vine disease detection in UAV multispectral images using optimised image registration and deep learning segmentation approach (Kerkech et al., n.d.)

Model Description

The objective of this paper is to detect Mildew disease using deep learning segmentation with visible and infrared image captured by UAV. The method implemented for this model consists of the following steps; first the image registration that enables pixel-wise superposition between the two types of images allowing segmentation fusion, secondly, the segmentation of the plot using visible and infrared images with SegNet algorithm, lastly, the merge of both images to create the disease map. This model is very specific to disease detection and how to merge to different set of images that have to be taken under the same characteristics and ideally in the same flight. This method could be applied to multiple types of plants that present visible diseases that can be captured with UAVs.

Data Sources

The models were trained using data obtained from a quadcopter equipped with RGB and NIR sensors. The images were captured under ideal weather and lighting conditions. To ensure the quality of the data, the study was conducted in two vineyards. In the first vineyard, half of the terrain was treated with phytopharmaceutical products to protect the vines from diseases, while the other half remained untreated. The second vineyard was completely treated against diseases and remained healthy throughout the study. This vineyard was used as a control. The vineyards had different types of soil (silty sand and sandy loam soil) and sun exposure (one facing North-South and the other Northwest-Southeast), but both had similar weather conditions, with temperatures ranging from 1 to 26ºC.

Although the size of the dataset is not specified, the researchers only flew the UAV for one day and extracted all the data from that. However, there was a lack of symptomatic samples, so data augmentation techniques such as horizontal shifting, rotation, and scaling were applied.

The data pre-processing technique used in this study involved pixel-wise superposition of the two types of images, allowing segmentation fusion. It should be noted that this study was conducted under specific conditions, and only disease was detected in one of the vineyards. The sample sizes were not large enough to draw reliable conclusions, but the method shows promising results.

Model Performance

The segmentation performance of the models is measured using two methods. The first method involves leaf-level (pixel-wise) computation of various metrics, including Recall, Precision, F1-score, Dice coefficient, and Accuracy, for each class (shadow, ground, healthy, and symptomatic). The second evaluation method uses the same metrics but at the grapevine-level. This method achieves better results overall, with scores of around 90%, while the first method scores around 85% for all metrics.

The 85% of the data was used for training and the remaining 15% was used for validation. The images contained in both sets were randomly selected from the union of the original data and the data obtained applying data augmentation.

The model achieves good performances but there are no techniques to avoid overfitting[2].

Limitations

There are several limitations in this model. The first one and most relevant is that they mention that they have only a few samples of diseased plants, which will make very difficult the learning since there is an unbalanced dataset. To try to solve the problem they perform data augmentation to all the data causing this another problem since it is not clear if they are only using the augmented data in the training. For the other part the accuracy is pretty high which in this case can be an indicator of overfitting since the data that they are using was only extracted one day from one vineyard, meaning that is not a varied dataset. The methodology that they implement looks promising but taking into account the limitations, it is not safe to say that it will work in a different environment.

Recommendations for Improvement

The current model could be improved by increasing the size of the datasets, particularly for cases of diseased plants. It would also be beneficial to extract data with higher resolution, as the low resolution currently difficulties the process of disease detection.

To enhance the model's usefulness, it would be useful to apply it to detect other diseases and various types of plants. Additionally, to improve the accuracy of disease detection, additional markers could be added to the terrain to ensure a better match between the data extracted from RGB sensors and thermal imaging, or the use of more precise geolocalisators like RTK.

Overall, by expanding the dataset size, improving the resolution, and optimising the matching process, the model's disease detection capabilities could be significantly improved and extended to other plant species and diseases.

4.2.2 Use Case 2: Drone Spraying

Paper: Effect of Unmanned Aerial Vehicle Flight Height on Droplet Distribution, Drift and Control of Cotton Aphids and Spider Mites (Lou et al., 2018)

Model description

In this study, various operational configurations were tested through numerous flying configurations and spraying parameters such as droplet uniformity, coverage rate, deposition, and drifting ability were evaluated in cotton for their respective efficiency in the control of cotton aphids and spider mites. Finally, the results of the drone spraying were compared to a conventional terrestrial boom sprayer.

Data Sources

The data collection methodology followed is similar to a simplified version of the UC2 strategy. Initially, water sensitive kromekote cards were used to assess qualitative parameters such as coverage and deposition in three different canopy heights, similarly to UC2 with the use of water sensitive papers (WSPs). Moreover, droplet displacement in the form of droplet drift was measured with filter paper targets outside the spraying area, similarly to UC2, although without following a specific standardised methodology. The image analysis of the kromekote cards was conducted with the popular ImageJ

[2] Overfitting is a phenomenon that occurs when a machine learning model is trained too well on a particular dataset, to the extent that it begins to fit the noise or random fluctuations in the data instead of learning the underlying patterns. As a result, the model becomes highly specialised to the training data and performs poorly on new, unseen data.

software, while the retrieval of the active substances in the filter papers was done through laboratory retrieval, in similar methodologies used in UC2.

Model Performance

This section is not applicable to UC2 as there are no model performance metrics. The spraying efficiency is the only metric that can be referenced for the UAV activity performance. In this study, the boom sprayer performed better for the control of both cotton aphids (90.0% vs 64%) and spider mites (68.0% vs 61.3%). An interesting find is that, similar to the trials of UC2, this study also found that the UAV performed better in higher layers of canopy, while its efficiency decreased in lower, more difficult to penetrate layers.

Limitations

The main limitation of the study is the low number of iterations for each configuration, with only a single repetition for each flight treatment, whereas in UC2 all iterations are conducted a total of three (3) times, all under valid environmental conditions. Moreover, the study does not follow a standardised method for the deployment of drift measurement, while the overall reference in weather conditions is minimal, a parameter with major importance based on the findings of UC2 as well as multiple spraying papers.

Recommendations for Improvement

As mentioned in the "Limitations" section, UC2 will aim to both follow more standardised procedures for the measurement of spraying drift, while more metrics for spraying quality (e.g. Volume Median Diameter or VMD at different thresholds) will be used in our trials. Similarly, a larger number of spraying configurations (8 in total, each repeated 3 times) will be tested in UC2, compared to the 2 UAV flights of this study

4.2.3 Use Case 3: Livestock Monitoring

Paper: A Study on the Detection of Cattle in UAV Images Using Deep Learning

Model Description:

This paper focused on the detection of cattle in large extensive pastures in drone images using deep learning. The objectives of this paper were to determine:

- The highest possible accuracy of detection of cows (local Brazilian breed: canchim) from images taken by drones,
- The ideal ground sample distance for animal detection
- The most accurate CNN architecture for this objective

The authors tested many 15 different CNN architectures. Then they applied these 15 CNN architectures on 3 spatial resolutions, 2 datasets and 10-fold cross validation resulting of 900 models. The models provide the number of animals and their position. Models were trained to detect Canchim cows that have uniform white coats. Thus, the lack of diversity of cattle colours in the dataset might result in low performance for detecting cattle of other colours and the inability to use those models to detect other breeds of cattle. However, the methodology can be reproduced with more variability in the cattle and also on small ruminants (sheep and goats).

Data Sources:

The authors made sure to capture drone images in a wide variety of conditions: sunny/overcast (different weather), Day/night (levels of light), time of the year (soil condition and color). Then they used 2 methods to create square images.

- A first approach consisted in carefully and manually selecting a box of size 224x224 around each animal in each image (first data set).
- A second approach consisted in dividing each drone image in a grid-like mesh with grid cells of 224x224 pixels (second data set).

To train the models, authors labelled square images as “cattle” when 50% of the cow was contained in the image, and as “non-cattle” if not. The authors divided their 2 datasets into a training dataset (80% of the sample) and a validation dataset (20% of the sample) resulting of 13.806 images for training and 3452 images for testing in the first dataset and 23.182 images for training and 5796 images for testing in the second dataset. Regarding the models, they applied down sampling or up sampling to balance the sample classes “cattle” and “non-cattle”. To simulate different GSD (ground surface distance), authors down sampled the original image blocks to 112x112 pixels and 56x56 pixels. The dataset used and the methodology seem appropriate to draw reliable conclusions on the detection of white cattle into a variety of conditions.

Model Performance:

Many CNN architectures are robust enough to reliably detect animals in aerial images even under far from ideal conditions, indicating the viability of using UAVs for cattle monitoring. Four performance metrics were considered: Accuracy, Precision, Recall, and F1-Score. They depend on the algorithm used, but the best algorithm tested (NASNet Large) reached:

- For the first approach (carefully selected squares), with only 224x224 squares:
  - 0.992 Accuracy, 0.993 Precision, 0.993 Recall and 0.995 F1-Score.
- For the second approach (images split into a grid):
  - 0.958 Accuracy, 0.963 Precision, 0.960 Recall and 0.958 F1-Score. (224x224)
  - 0.962 Accuracy, 0.963 Precision, 0.963 Recall and 0.963 F1-Score. (112x112)
  - 0.964 Accuracy, 0.965 Precision, 0.965 Recall and 0.965 F1-Score. (56x56)

For the detection part, these scores are robust and similar to the result of other studies in our review. However, counting performances can be improved by using algorithm to decrease the number of duplicate animals as suggested by (Soares, 2021). No effort is described to avoid overfitting.

Limitations:

The study seems to be generalised to a lot of conditions, weather, soil and environment, lighting and also to different image qualities (presence of blurry image) but generalisation to other cattle is yet to be determined. Indeed, the main limit is that the dataset is based on only white animals and might struggle to detect animals of other colours or spotted. In the same way, it is not determined if the models can be reproduced with an appropriate training set on other grassing species such as sheep and goats that are smaller and with different colours.

Another limit is that the positions of the animals in a new image to be analysed by the model will not be known a priori, so image blocks cannot be properly generated to perfectly encompass the animals to be detected (similarly to the grid approach, animals may very well be split into multiple squares). A possible solution to this is a sliding square that runs over the whole image to give a heatmap of object detection probability.

Recommendations for Improvement:

After animal detection, algorithms and methods can be used to decrease the number of duplicate animals as suggested by Soares et al. (2021). However, cattle movement will always be a problem in large areas when a unique drone image cannot provide sufficient resolution and capture the wholeness of the herd. It is why guidelines have to be done to select the best areas and time of the day where the flight should occur to ensure the best performances. These guidelines should be based on a better knowledge of animals behaviours regarding their environment. However, even under the best conditions, performances of animal detection and counting might not be satisfactory for the needs of farmers or sheepherders. Indeed, in a flock of 1000 sheep, an error of 2% results in an error of 20 sheep. Models and their optimisation should be considered in a semi-automatic process where operators can improve the performance of animal counting through a minimal operation. Such as using a model optimised on its recall, and just having an operator manually examine the objects detected with the bigger incertitude to decrease the number of false positives and then manually increase the precision.

4.2.4 Use Case 4: Forestry and Biodiversity

Paper: Assessment of defoilation during the *Dendrolimus tabulaeformis Tsai et Lui* disaster outbreak using UAV-based hyperspectral images (Zhang et al., 2018, #)

Model Description

The purpose of the model proposed in the paper is to quantify the degree of damage of individual Chinese pine trees affected by the pine caterpillar, Dendrolimus tabulaeformis Tsai et Liu, using UAV hyperspectral imaging data. The damage assessment framework suggested in the paper includes the selection of optimal wavebands, the determination of the domain, and the construction of the piecewise function model. Four different methods were tested for the determination of the wavelengths sensitive to different pine defoliation rates and piecewise modelling: instability index between classes (ISIC), principal component analysis (PCA), successive projection algorithm (SPA), and the combined ISIC-SPA method. For piecewise model fitting, each band selection method was combined with partial least squares regression (PLSR). Finally, the ISIC-SPA-PLSR model was suggested. It can be employed to reduce the dimensionality of hyperspectral data and predict tree defoliation rate using the reflectance in specific narrow wavebands. The suggested framework is suitable for monitoring changes in the coniferous tree crowns caused by forest insects. However, it is better suited to evaluate moderate and severe forest insect damage than to detect early stages of tree health deterioration and distinguish healthy trees from stressed ones.

Data Sources

The model was trained using the ground truth and the remote sensing datasets. The ground-truth data were collected for 213 sample trees by evaluating the defoliation percentage for standard branches of each tree. The ground-truth dataset was divided into healthy, mildly damaged, moderately damaged, and severely damaged groups, but healthy samples were removed from the analysis because of the small sample size. Also, several mutated samples were identified and eliminated to ensure data quality.

The remote sensing dataset was obtained with an octocopter equipped with VNIR hyperspectral and digital cameras. UAV flights were performed on a single day under sunny and windless conditions. Before each flight, spectral on and a standard whiteboard were used, as well as ground spectrum was measured for image calibration. In total, over 14,000 images were collected. To ensure the geopositional and radiometric accuracy of images, geometric and radiometric corrections were applied to hyperspectral images. Before the analysis, hyperspectral cubes were resampled. No augmentation techniques were used to increase the size of the training dataset.

The sampling dataset used in the study is large enough to evaluate the potential of the model to predict the degree of damage caused by a pine insect pest. The authors implemented the required procedures and collected high-quality ground-truth and UAV-based hyperspectral datasets, but the dataset represents a single date in a very local area and is relatively small for further model applications. For the model to be applicable, a larger dataset comprising the data collected on multiple dates under different conditions and in multiple locations should be considered.

Model Performance

The performance of the models that were used to predict pine defoliation percentage was evaluated using several metrics: the correlation coefficient (R), root-mean-square error (RMSE), and the coefficient of determination (R2). The performance of the models to predict mild, moderate, and severe pine damage classes was assessed using the confusion matrix. The dataset, comprising 226 samples, was randomly divided into a training/cross-validation dataset with 152 samples and a testing dataset with 74 samples.

In general, models performed well (R2=0.89–0.95) with the ISIC model showing the best accuracy. However, the moderate-to-severe damage levels were predicted with higher accuracy than the mild damage level by all models except the ISIC model, which was superior to other models in predicting mild damage. In addition, the SPA algorithm was observed to be useful in increasing the efficiency of the optimal waveband selection. Therefore, the final ISIC-SPA-PLSR piecewise model that predicts the defoliation percentage with 95.2% accuracy was proposed.

Although the final model demonstrates good prediction accuracy, no techniques were implemented to avoid overfitting.

Limitations

The data used in the study included only the samples representing different pine damage levels, but due to the small sample size, healthy tree samples were excluded from the modelling, limiting the model's capabilities to differentiate between healthy and damaged trees. Also, sample groups of moderately and severely damaged pines were significantly larger than the mildly damaged group, which might be one of the reasons why models performed poorly in predicting mild pine damage. These results suggest that the model is better suited to evaluating the degree of damage at later stages of an insect outbreak with considerable tree damage than at early infestation stages.

The suggested model could be applied to other coniferous forests to assess the damage caused by forest insect pests. However, the model should be used with caution or additionally tested before such applications because it was not tested in different locations and with different tree species. Therefore, in such cases, the model’s accuracy would be unknown.

Also, the methodological framework suggested in the study could be used to develop tree damage assessment models of different locations or tree species using additional UAV-based hyperspectral datasets.

Recommendations for Improvement

The dataset used to train the model should be supplemented with more samples, and a better sample size balance between the different pine damage classes should be established, to improve the accuracy of mild damage predictions. Furthermore, a healthy sample group could be included in the model's development. Then, the model would be able to discriminate between healthy and infected trees in addition to evaluating the degree of damage in already affected trees.

The proposed model could be tested with other UAV hyperspectral datasets collected over coniferous forests with insect infections to evaluate its performance and possible usability in other use cases: different locations, insects, or tree species.

Additional UAV-based hyperspectral and ground-truth datasets could be collected in different locations with different coniferous tree species on multiple dates or even with different hyperspectral cameras to retrain the model and increase its versatility and applicability in other cases.

The capabilities of the proposed model could be tested using identified optimal wavelengths and multispectral UAV imagery to determine if more expensive hyperspectral technologies are necessary for the assessment. Also, model performance could be tested with multispectral satellite data to evaluate its possible applicability with spaceborne remote sensing data.

4.2.5 Use Case 5: Rural Logistics

Paper: A quickly deployed and UAS-based logistics network for delivery of critical medical goods during healthcare system stress periods: A real use case in Valencia (Spain) (Quintanilla et al., 2021)

Model Description

This paper aims to leverage the flexibility of UAVs as complementary support for healthcare logistic systems when under high-stress conditions, via quick development of an air delivery network.

For this reason, a logistics network model was defined and flight tests was performed for three scenarios, including urban areas and controlled airspace.

Generally, the flights were successful, being able to deliver medical goods without requiring any dedicated infrastructure.

However, a moderate number of contingencies occurred, mainly related to the control link quality and Air Traffic Management (ATM) integration.

This study suggests that the use of UAVs as part of logistic networks is feasible and able to support existing structures, especially in situations in dire need. Furthermore, it serves as an experimental use case which shall feed the development of U-Space/UTM services, certification standards, and regulatory procedures that will enable large-scale deployment of UAV operations.

Data Sources

The data used by the logistics network model were the European Union (EU) definitions for populated areas in order to design the flight paths of the UAVs, which could include blocks, parks, streets and urban roads, whilst excluding fields and service roads. Considering these restrictions, the overall route length across the two points of interest was slightly increased for all the considered scenarios.

To monitor the possible deviations of the drones from the flight route, several control points were set with the presence of pilots, contributing to the visual inspection of the deployed equipment.

No pre-processing techniques were used to define the flight routes.

The dataset size is not specified, although it mainly consists of log files recording various parameters, such as the above ground level (AGL) height, the cruise speed, occurred events (e.g., signal loss), etc., which can be easily stored and manipulated.

The defined scenarios in this study cover different environmental and topographic conditions, as well as transportation needs. Thus, the results of the test flights are adequate to extract reliable conclusions about the performance of the models.

Model Performance

The logistic network model proposed in this study performed successfully, being able to transport lightweight medical goods and protective personal equipment (< 2Kg) from a selected departure to an arrival point.

For the evaluation of the model the event record was exploited. In particular, areas with a significant interference to the control link signal (i.e., due to electromagnetic radiation, metallic structures, etc., practically unavoidable in urban environments) were identified and used to refine the flight route.

All available and acquired data from this study have been used for testing.

Limitations

The main limitations of the flight routes for the implementation of a logistic network model are the restrictions imposed by the EU and local authorities. On the other hand, the drone logistics service has not reached the required level of maturity, at least for large-scale deployment.

The potential risks of drone deployment for logistics services are the communication issues that arise in urban environments, as well as the weather conditions, which in some cases can be unpredictable. These facts could possibly lead to a failure of the drone operation, compromising the safety of the population.

The results of this study can be applied to any environment for drone logistics networks implementation.

Recommendations for Improvement

For the drone logistics networks several advancements still need to be achieved, especially regarding the support for BVLOS operations and integration within a populated airspace.

The required steps to enhance the usefulness of the logistics network model are mainly the optimization of the BVLOS flight operation, as well as the real-time mapping of the drone surroundings and environment.

Relatively recent and new technologies that could be integrated into the logistics network model mainly concerns the utilisation of 4G/5G cellular networks, especially in cases where the control signal is lost, the exploitation of detect and avoid (DAA) techniques and the development of fleet management algorithms in order to deploy a swarm of drones for fast and multiple deliveries to various points of interest.

5. Summary

The objectives of WP2 are to identify and assess existing drone data analytics models, optimise significant models and algorithms, create an open-access, free, and public Drone Data Analytics Library, and expand the library's content and usability through open calls. Task T2.1 aimed to review, identify, and assess existing drone data analytics models and algorithms based on the recorded needs and five Use Cases provided by WP3. The Drone Data Analytics Library has been created on GitHub with an initial set of models and datasets, and this platform will be continuously updated. Additionally, a step-by-step guide on how to use the selected models will be included.

The first step of the task, "Identify and assess existing drone data analytics models," was successfully achieved with the methodology created. All Use Cases followed the provided guidelines to perform the Systematic Literature Review, which led them to similar findings. These findings show that there is very little data available for all Use Cases and a lack of open-source data and models, for these reasons the implementation of the GiHub repository will be very relevant in the project.

The second achievement is the creation of the functional GitHub repository, which has all the structure created. Currently, the repository contains around 20 models and datasets and will be continuously updated throughout the project. The repository will be accessible through the ICAERUS Platform to enable better access and dissemination of information on drone technology. By providing a central repository for drone data analytics models, the platform can facilitate the development and use of drones for sectoral and societal purposes. This will ultimately help accelerate the adoption of drones and promote their use in various industries such as agriculture, forestry and logistics, leading to improved efficiency, cost savings and reduced environmental impact.

The general recommendations and future steps for the GitHub repository are the following

- Create a wiki for how to access the data and how to perform commits and forks
- Transfer all the current documentation to wikis
- Create “Getting started” notebooks that will serve as guides to use the models
- Implement some of the models
- Upload more datasets and models

Lastly, after performing the Systematic Literature Review following the methodology developed in this task, each Use Case was able to identify the limitations and recommendations of the selected models. These findings will serve as the basis for the implementation of T2.2.

Below is a bulleted list of the limitations and recommendations for each Use Case.

Use Case 1: Crop Monitoring

- Limitations:
  - Small datasets
  - Class imbalance
  - Low image resolution
  - No actions to prevent overfitting of the models
  - All the data tested was obtained under the same conditions
- Recommendations:
  - Increase dataset size
  - Increase image resolution
  - Use more precise geolocalisators

Use Case 2: Drone Spraying

- Limitations:
  - Low number of iterations

    - Does not follow a standardised method for the deployment of drift measurement
    - No mention of weather conditions
- Recommendations:
    - Increase number of iterations
    - Use more standardised procedures for the deployment of drift measurement

Use Case 3: Livestock monitoring

- Limitations
    - Only using white animals
    - Position of the animals known a priori
    - Not mentioning weather conditions
- Recommendations:
    - Study to understand animal behaviour
    - Take into account weather conditions
    - Models and their optimisation should be considered in a semi-automatic process where operators can improve the performance of animal counting through a minimal operation.

Use Case 4: Forestry and Biodiversity

- Limitations
    - Small dataset
    - Class imbalance
    - All data tested was obtained under the same conditions
- Recommendations:
    - Increase dataset size
    - Balance classes
    - Use data with different conditions (location, light)
    - Use multispectral images

Use Case 5: Rural logistics

- Limitations:
    - Flight routes for the implementation of a logistic network model are have restrictions imposed by the EU and local authorities.
    - The drone logistics service has not reached the required level of maturity, at least for large-scale deployment.
    - Communication issues in urban environments
    - Weather conditions
- Recommendations
    - Optimisation of the BVLOS flight operation
    - Real-time mapping of the drone surroundings and environment

Finally, T2.1 serves as a basis for T2.2 which will have two main objectives. The first objective is to optimise, further develop and adapt to better address the end user needs (T1.1) and advance the state-of-the-art in drone-based data modelling. The second objective is to ensure that the optimised models are engineered to become more transparent and more effective for non-expert users, this will be ensured with the use of the GitHub repository that will be open-source and it will contain all the necessary documentation so all the code is understandable and applicable.

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Annexes

The images below show the different spreadsheet created by the different UC.

Annex I: UC1: Crop Monitoring spreadsheet

ID	Secondary	Year	Journal	Paper type	Number primary s	Review topic	Q1	Q2	Q3	Q4	Q_total	les grey liter	rch year e	Category
1	Zarzour2022	2022	Springer	Journal article	NA	A survey on deep learning-based identification of plant and crop diseases from UAV-based aerial imag	1	1	0.5	1	3.5	Yes	2022	Image Pr
2	Hafiane2020	2020	Springer	Journal article	NA	Vine Disease Detection by Deep Learning Method Combined with 3D Depth Information	0	1	0.5	0	1.5	Yes	2022	Image Pr
3	Baysal-Gurel202	2021	Remote Sens	Journal article	NA	Automatic Identification and Monitoring of Plant Diseases Using Unmanned Aerial Vehicles: A Review	1	1	0.5	1	3.5	Yes	2022	Image Pr
4	Hernes2020	2020	ScienceDire	Journal article	NA	Deep learning for grape variety recognition	0.5	0.5	1	1	3	Yes	2022	Image Pr
5	Huang2020	2020	Remote Sens	Journal article	NA	Recognition of Banana Fusarium Wilt Based on UAV Remote Sensing	0	0.5	0.5	1	2	Yes	2022	Image Pr
6	Ampatzidis2020	2020	Springer	Journal article	NA	Detection of target spot and bacterial spot diseases in tomato using UAV-based and benchtop-based h	0.5	0.5	0.5	0	1.5	Yes	2022	Image Pr
7	Ampatzidis2020	2020	ScienceDire	Journal article	NA	Detecting powdery mildew disease in squash at different stages using UAV-based hyperspectral imagir	1	0.5	0.5	1	3	Yes	2022	Image Pr
8	Ballesteros2019	2019	PLOSONE	Journal article	NA	Quantifying the effect of Jacobiasca lybica pest on vineyards with UAVs by combining geometric and co	1	0.5	0.5	1	3	Yes	2022	Image Pr
9	Gonzalez2019	2019	Remote Sens	Journal article	NA	Predicting Canopy Chlorophyll Content in Sugarcane Crops Using Machine Learning Algorithms and Sp	0.5	0.5	0.5	1	2.5	Yes	2022	Image Pr
10	Hafiane2020	2020	Remote Sens	Journal article	NA	VddNet: Vine Disease Detection Network Based on Multispectral Images and Depth Map	1	1	1	1	4	Yes	2022	Image Pr
11	Mumtaz2020	2020	IEEE	Journal article	NA	A Multi-Modal Approach for Crop Health Mapping Using Low Altitude Remote Sensing, Internet of Thi	1	0.5	1	1	3.5	Yes	2022	Data Coll
12	Tufail2021	2021	PLOSONE	Journal article	NA	Real-time recognition of spraying area for UAV sprayers using a deep learning approach	0	0.5	0.5	1	2	Yes	2022	Data Coll
13	Narra2020	2020	Remote Sens	Journal article	NA	Crop Yield Prediction Using Multitemporal UAV Data and Spatio-Temporal Deep Learning Models	0.5	1	1	1	3.5	Yes	2022	Image Pr
14	Conde2022	2022	ScienceDire	Journal article	NA	Multispectral Vineyard Segmentation: A Deep Learning Comparison Study	1	1	1	1	4	Yes	2022	Image Pr
15	Mehta2022	2022	Remote Sens	Journal article	NA	A Two-Step Machine Learning Approach for Crop Disease Detection Using GAN and UAV Technology	1	0.5	0.5	0.5	2.5	Yes	2022	Image Pr
16	Bratanov2018	2018	Sensors	Journal article	NA	A Novel Methodology for Improving Plant Pest Surveillance in Vineyards and Crops Using UAV-Based H	1	0.5	1	0.5	3	Yes	2022	Data Coll
17	Inoue2018	2018	IEEE	Conference	NA	Early Rice Disease Detection and Position Mapping System using Drone and IoT Architecture	0.5	0.5	0.5	0	1.5	Yes	2022	Image Pr
18	Machado2020	2020	IEEE	Conference	NA	Automatic Recognition of Soybean Leaf Diseases Using UAV Images and Deep Convolutional Neural Ne	0.5	1	1	1	3.5	Yes	2022	Image Pr
19	Han2019	2019	Remote Sens	Journal article	NA	A Deep Learning-Based Approach for Automated Yellow Rust Disease Detection from High-Resolution	0	0.5	0.5	1	2	Yes	2022	Image Pr
20	Shi2022	2022	Remote Sens	Journal article	NA	Prediction of Field-Scale Wheat Yield Using Machine Learning Method and Multi-Spectral UAV Data	1	0.5	0.5	0.5	2.5	Yes	2022	Image Pr
21	NeverDosSantos	2020	ScienceDire	Journal article	NA	Vineyard trunk detection using deep learning – An experimental device benchmark	0.5	0.5	0	1	2	Yes	2022	Image Pr
22	Chawla2020	2020	Springer	Journal article	18	Systematic review of deep learning techniques in plant disease detection	1	1	0	1	3	Yes	2022	Image Pr
23	Starek2017	2017	Journal of A	Journal article	NA	Unmanned aircraft system-derived crop height and normalized difference vegetation index metrics for	0.5	0.5	1	0	2	Yes	2022	Image Pr
24	Gao2022	2022	Agriculture	Journal article	NA	Classification of Maize Lodging Extents Using Deep Learning Algorithms by UAV-Based RGB and Multis	1	0.5	1	0.5	3	Yes	2022	Image Pr
25	Kommers2020	2020	Journal of Int	Research artic	NA	Deep learning based intelligence cognitive vision drone for automatic plant diseases identification and	1	1	0	1	3	Yes	2022	Image Pr
26	Hafiane2020	2020	ScienceDire	Journal article	NA	Vine disease detection in UAV multispectral images using optimized image registration and deep learn	0.5	1	0.5	1	3	Yes	2022	Image Pr
27	Ma2021	2021	ScienceDire	Journal article	NA	Estimation of nitrogen nutrition index in rice from UAV RGB images coupled with machine learning alg	1	0.5	1	1	3.5	Yes	2022	Data Coll
28	Sarangi2019	2019	SemanticSch	Journal article	NA	Unsupervised Image Segmentation using Convolutional Neural Networks for Automated Crop Monitor	0.5	0.5	0	1	2	Yes	2022	Image Pr
29	Sarangi2019	2019	SemanticSch	Journal article	NA	Unsupervised Image Segmentation using Convolutional Neural Networks for Automated Crop Monitor	0	0	0	0	0	Yes	2022	Image Pr
30	Deng2018	2018	RemoteSens	Journal article	NA	A two-stage classification approach for the detection of spider mite- infested cotton using UAV multisp	0	0.5	1	1	2.5	Yes	2022	Image Pr
31	Khandelwal2019	2019	ResearchGa	Journal article	NA	Automated Monitoring Cropland Using Remote Sensing Data: Challenges and Opportunities for Machi	0.5	0.5	0.5	1	2.5	Yes	2022	Data Coll
32	Paret2019	2019	Plant Diseas	Journal article	NA	An Improved Crop Scouting Technique Incorporating Unmanned Aerial Vehicle–Assisted Multispectral	0.5	0.5	1	0	2	Yes	2022	Image Pr
33	Wenbin2020	2020	ResearchGa	Journal article	NA	UAV-BASED CROPS CLASSIFICATION WITH JOINT FEATURES FROM ORTHOIMAGE AND DSM DATA	0.5	1	0.5	0.5	2.5	Yes	2022	Image Pr
34	Yang2021	2021	Remote Sen	Journal article	NA	UAV Data as an Alternative to Field Sampling to Monitor Vineyards Using Machine Learning Based on U	0.5	0.5	0.5	0.5	2	Yes	2022	Image Pr
35	Hadjar2022	2022	Remote Sen	Journal article	NA	Potential of Ultra-High-Resolution UAV Images with Centimeter GNSS Positioning for Plant Scale Crop I	0.5	0.5	1	0	2	Yes	2022	Image Pr
36	Lack2016	2016	ResearchGa	Journal article	NA	LIGHT-WEIGHT MULTISPECTRAL UAV SENSORS AND THEIR CAPABILITIES FOR PREDICTING GRAIN YIELD	0.5	1	1	0	2.5	Yes	2022	Image Pr
37	Stewart2018	2018	Springer	Journal article	NA	Image set for deep learning: field images of maize annotated with disease symptoms	1	0	1	0	2	Yes	2022	Image Pr
38	Mercatoris2022	2022	Agriculture	Journal article	NA	Improving Wheat Yield Prediction Accuracy Using LSTM-RF Framework Based on UAV Thermal Infrared	0	1	1	1	3	Yes	2022	Image Pr
39	Zarzour2022	2022	Springer	Journal article	NA	Deep learning techniques to classify agricultural crops through UAV imagery: a review	1	0.5	0	1	2.5	Yes	2022	Image Pr

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Annex II: UC2: Drone spraying spreadsheet

ID	Year	Journal	Paper type	Number primary studies	Review topic
1	2018	Computers and electronics in agriculture	Journal Paper	N/A	Near ground platform development to simulate UAV aerial spraying and its spraying test under different conditions
2	2019	Computers and Electronics in Agriculture	Journal Paper	N/A	Droplet deposition density of organic liquid fertilizer at low altitude UAV aerial spraying in rice cultivation
3	2019	Sensors	Journal Paper	N/A	Proposal for an embedded system architecture using a GNDVI algorithm to support UAV-based agrochemical spraying
4	2020	Agronomy	Journal Paper	N/A	Effect of Droplet Size Parameters on Droplet Deposition and Drift of Aerial Spraying by Using Plant Protection UAV
5	2021	International Journal of Agricultural and Biological Engineering	Journal Paper	N/A	Effects of plant protection UAV-based spraying on the vertical distribution of droplet deposition on Japonica rice plants in Nor
6	2018	International Journal of Agricultural and Biological Engineering	Journal Paper	N/A	Testing method and distribution characteristics of spatial pesticide spraying deposition quality balance for unmanned aerial v
7	2019	International Journal of Agricultural and Biological Engineering	Journal Paper	N/A	Influence of UAV flight speed on droplet deposition characteristics with the application of infrared thermal imaging
8	2022	Agriculture	Journal Paper	N/A	Preliminary Evaluation of Spraying Quality of Multi-Unmanned Aerial Vehicle (UAV) Close Formation Spraying
9	2018	International Journal of Agricultural and Biological Engineering	Journal Paper	N/A	Drift and deposition of pesticide applied by UAV on pineapple plants under different meteorological conditions
10	2018	Agronomy	Journal Paper	N/A	Effects of dosage and spraying volume on cotton defoliants efficacy: a case study based on application of unmanned aerial ve
11	2022	Agronomy	Journal Paper	N/A	Comparison of the Effects of Chemical Topping Agent Sprayed by a UAV and a Boom Sprayer on Cotton Growth
12	2020	Asia-Pacific Journal of Chemical Engineering	Journal Paper	N/A	Meteorological and flight altitude effects on deposition, penetration, and drift in pineapple aerial spraying
13	2019	Pest management science	Journal Paper	N/A	Field evaluation of an unmanned aerial vehicle (UAV) sprayer: effect of spray volume on deposition and the control of pests a
14	2018	International Journal of Agricultural and Biological Engineering	Journal Paper	N/A	Drift potential of UAV with adjuvants in aerial applications
15	2020	International Journal of Precision Agricultural Aviation	Journal Paper	N/A	Droplet deposition characteristics of plant protection UAV spraying at night
16	2022	Agronomy	Journal Paper	N/A	Study on Spray Deposition and Drift Characteristics of UAV Agricultural Sprayer for Application of Insecticide in Redgram Crop
17	2019	2019 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor)	conference	N/A	First measurements of spray deposition obtained from UAV spray application technique
18	2020	International Journal of Precision Agricultural Aviation	Journal Paper	N/A	Aerial spraying application of multi-rotor unmanned aerial vehicle on areca trees
19	2019	Pakistan Journal of Agricultural Research	Journal Paper	N/A	Spray uniformity testing of unmanned aerial spraying system for precise agro-chemical applications
20	2020	Computers and Electronics in Agriculture	Journal Paper	N/A	Effect of operational parameters of UAV sprayer on spray deposition pattern during outer field weed control application
21	2018	International Journal of Agricultural and Biological Engineering	Journal Paper	N/A	Droplet deposition and efficiency of fungicides sprayed with small UAV against wheat powdery mildew
22	2019	International Journal of Agricultural and Biological Engineering	Journal Paper	N/A	Vision-based adaptive variable rate spraying approach for unmanned aerial vehicles
23	2020	International Journal of Precision Agricultural Aviation	Journal Paper	N/A	Exploring the operation mode of spraying cotton defoliation agent by plant protection UAV
24	2021	MDPI Agronomy	Journal Paper	N/A	Influence of the Downwash Wind Field of Plant Protection UAV on Droplet Deposition Distribution Characteristics at Different
25	2022	PeerJ	Journal Paper	N/A	UAV spraying on citrus crop: impact of tank-mix adjuvant on the contact angle and droplet distribution
26	2019	International Journal of Precision Agricultural Aviation	Journal Paper	N/A	Exploring the potential of UAV imagery for variable rate spraying in cotton defoliation application
27	2020	ASABE	Journal Paper	N/A	Quantifying Spray Deposition from a UAV Configured for Spot Spray Applications to Individual Plants
28	2022	Indian Journal of Entomology	Journal Paper	N/A	On-Farm Assessment of UAV Based Spraying Technology in Green Gram
29	2021	Asian Journal of Agriculture and Biology	Journal Paper	N/A	Comparison of the physical spray efficacy between unmanned helicopter and motorized knapsack sprayer in paddy field
30	2019	Plos One	Journal Paper	N/A	Distribution characteristics on droplet deposition of wind field vortex formed by multi-rotor UAV
31	2022	Biosystems Engineering	Journal Paper	N/A	Influence of the downwash airflow distribution characteristics of a plant protection UAV on spray deposit distribution
32	2018	10th International Micro-Air Vehicles Conference	Conference Paper	N/A	Precision Weed Spraying using a Multirotor UAV
33	2020	International Journal of Precision Agricultural Aviation	Journal Paper	N/A	Droplet distribution of Unmanned Aerial Vehicle under several spray volumes and canopy heights in the cotton canopy
34	2023	MDPI Drones	Journal Paper	N/A	Effect of Operational Parameters of UAV on Droplet Deposition in Trellised Pear Orchard
35	2021	International Conference on Robotics Automation and Intelligent	Conference Paper	N/A	Droplet Distribution of an Autonomous UAV-based Sprayer in Citrus Tree Canopy
36	2018	International Journal of Agricultural and Biological Engineering	Journal Paper	N/A	Effect of aerial spray adjuvant applying on the efficiency of small unmanned aerial vehicle for wheat aphids control
37	2020	International Journal of Agricultural and Biological Engineering	Journal Paper	N/A	Parameters optimization of crop protection UAS based on the first industry standard of China
38	2018	MDPI Agronomy	Journal Paper	N/A	Effect of Unmanned Aerial Vehicle Flight Height on Droplet Distribution, Drift and Control of Cotton Aphids and Spider Mites

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Annex III:UC3: Livestock monitoring spreadsheet

ID	Secondary	Year	Journal	Paper type	Number primary s	Review topic	Q1	Q2	Q3	Q4	Q_total
1	Goolsby2016	2016	Subtropical Agriculture and Environments	Journal article		Livestock detection and counting by UAVs.	0.5	1	0.5	0	2
2	Longmore2017	2017	Remote Sensing	Journal article		Livestock detection and counting by UAVs.	1	0.5	0.5	0.5	2.5
3	Andrew2017	2017	2017 IEEE International Conference on Computer Vision Workshops (ICCVW)	Conference paper		Livestock detection and counting by UAVs ; Livestock tracking by drones	0.5	1	1	1	3.5
4	Rivas2018	2018	Sensors	Journal article		Livestock detection and counting by UAVs.	0.5	0.5	0.5	0.5	2
5	Rahnemoonfar2019	2019	Remote Sensing	Journal article		Livestock detection and counting by UAVs.	0.5	0.5	0.5	0.5	2
6	Shao2019	2019	international journal of remote sensing	Journal article		Livestock detection and counting by UAVs.	0.5	1	1	1	3.5
7	Andrew2019	2019	2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IR	Conference paper		Livestock detection and counting by UAVs.	0.5	0.5	1	1	3
8	Barbedo2019	2019	Sensors	Journal article		Livestock detection and counting by UAVs.	0.5	1	1	1	3.5
9	han2019	2019	Computional Visual Media	Journal article		Livestock detection and counting by UAVs.	0.5	0.5	0.5	0.5	2
10	Xu2020a	2020	Cumputers and electronics in Agriculture	Journal article		Livestock detection and counting by UAVs.	0.5	1	0.5	1	3
11	Xu2020b	2020	international journal of remote sensing	Journal article		Livestock detection and counting by UAVs.	0.5	0.5	1	1	3
12	Barbedo2020a	2020	Sensors	Journal article		Livestock detection and counting by UAVs.	1	0.5	1	1	3.5
13	Al-thani2020	2020	2020 IEEE 20th Mediterranean Electrotechnical Conference (MELECON)	Conference paper		Livestock detection and counting by UAVs.	0.5	0	0.5	0.5	1.5
14	Barbedo2020b	2020	Drones	Journal article		Livestock detection and counting by UAVs.	1	0.5	1	1	3.5
15	Sarwar2021	2021	Cumputers and electronics in Agriculture	Journal article		Livestock detection and counting by UAVs.	1	1	1	1	4
16	Soares2021	2021	Cumputers and electronics in Agriculture	Journal article		Livestock detection and counting by UAVs.	1	1	1	1	4
17	Vayssade2019	2019	Cumputers and electronics in Agriculture	Journal article		Livestock tracking by drones	0.5	1	0.5	1	3
18	Andrew2021	2021	Cumputers and electronics in Agriculture	Journal article		Livestock tracking by drones	1	0.5	0.5	1	3
19	Alenazi2021	2021	Sensors	Journal article		Object tracking by drones	0.5	0.5	0	1	2
20	Jung2017	2017	International Journal of Aeronautical and Space Sciences	Conference paper		Communication exploratory agencies of UAVs while tracking livestock					0
21	Li2019	2019	6th IFAC Conference on Sensing, Control and Automation Technologies for Ag	Conference paper		Communication exploratory agencies of UAVs while tracking livestock	0.5	0.5	0	1	2
22	Behjati2021	2021	Sensors	Journal article		Communication exploratory agencies of UAVs while tracking livestock	0.5	0.5	0	1	2
23	Nyamuryekung'e2016	2016	Rangeland Ecology & Management	Journal article		cattle behavior monitoring with drones.	0.5	1	1	0	2.5
24	Mufford2019	2019	Journal of Unmanned Vehicle Systems	Journal article		cattle behavior monitoring with drones.	0.5	1	1	0	2.5
25	Mulero-Pázmány2015	2015	Ecology & Evolution	Journal article		cattle distribution estimation.	0.5	0.5	0.5	0	1.5
26	Sun2020	2020	Rangeland Ecology & Management	Journal article		cattle distribution estimation.	0.5	0.5	1	0	2
27	Aquilani2021	2021	Animal	Journal article		Review					0
28	Alenazi2022	2022	IEEE Access	Journal article		Review					0
29	Kellenberger2018	2018	Remote Sensing of Environment	Journal article		Livestock detection and counting by UAVs.	1	0.5	0.5	1	3
30	Howell2021	2021	Rangelands	Journal article		Livestock behavior monitoring with drones.	1	0.5	1	0	2.5
31	Brown2022	2022	Cumputers and electronics in Agriculture	Journal article		Livestock detection and counting by UAVs.	0.5	1	0.5	0.5	2.5
32	Merwe2020	2020	Advances in Agronomy	Book chapter		Review					0
33	Abdulai	2021	Applied Animal Behaviour Science	Journal article		cattle behavior monitoring with drones.	1	1	1	0	3
34	Rey2017	2017	Remote Sensing of Environment	Journal article		Livestock detection and counting by UAVs.	0.5	0.5	1	1	3
35	Los2022	2022	Smart Agricultural Technology	Journal article		Livestock dimensions estimation	0.5	1	1	0.5	3
36	Psiroukis2021	2021	Smart Agricultural Technology	Journal article		Livestock detection and counting by UAVs					0
37	Weber2023	2023	Remote Sensing Applications: Society and Environment	Journal article		Livestock detection and counting by UAVs.					0
38											0
39											0

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Annex IV: UC4: Forestry and biodiversity spreadsheet

ID	Primary	Year	Journal	Paper type	Number primary studies	Use case scenario	Review topic	Q1	Q2	Q3	Q4	Q_total
1	Zhang2018	2018	Remote Sensing of Environment	Journal article	NA	Forest tree health monitor	Assessment of defoliation during the Dendrolimus tabulaeformis Tsai et	0.5	0.5	1	1	3
2	Yu2021a	2021	International Journal of Applied	Journal article	NA	Forest tree health monitor	A machine learning algorithm to detect pine wilt disease using UAV-base	0	0.5	0.5	1	2
3	Nasi2018	2018	Urban Forestry & Urban Greenir	Journal article	NA	Forest tree health monitor	Remote sensing of bark beetle damage in urban forests at individual tre	1	0.5	0.5	1	3
4	Kampen2019	2019	-	Conference pap	NA	Forest tree health monitor	UAV-Based Multispectral Data for Tree Species Classification and Tree Vi	1	0.5	0.5	0.5	2.5
5	Safonova2021	2021	Drones	Journal article	NA	Forest tree health monitor	Individual Tree Crown Delineation for the Species Classification and Asse	0	1	0.5	1	2.5
6	Liu2020	2020	Forests	Journal article	NA	Forest tree health monitor	Discriminant Analysis of the Damage Degree Caused by Pine Shoot Beet	0.5	0.5	1	1	3
7	Cessna2021	2021	Forests	Journal article	NA	Forest tree health monitor	Mapping Boreal Forest Spruce Beetle Health Status at the Individual Cro	1	0.5	0.5	1	3
8	Asenova2018	2018	-	Conference pap	NA	Forest tree health monitor	GIS-based Analysis of the Tree Health Problems Using UAV Images and S	0	0.5	0.5	0	1
9	Dash2018	2018	Remote Sensing	Journal article	NA	Forest tree health monitor	UAV Multispectral Imagery Can Complement Satellite Data for Monitori	1	1	0.5	0.5	3
10	Gallardo-Salazar2020	2020	Remote Sensing	Journal article	NA	Forest tree health monitor	Detecting Individual Tree Attributes and Multispectral Indices Using Unn	0.5	1	0.5	1	3
11	Nguyen2021	2021	Remote Sensing	Journal article	NA	Forest tree health monitor	Individual Sick Fir Tree (Abies mariesii) Identification in Insect Infested F	1	0.5	0.5	1	3
12	Kopackova-Strnadova202	2021	Remote Sensing	Journal article	NA	Forest tree health monitor	Canopy Top, Height and Photosynthetic Pigment Estimation Using Parro	0.5	0.5	0.5	1	2.5
13	Fraser2021	2021	Remote Sensing	Journal article	NA	Forest tree health monitor	Monitoring Fine-Scale Forest Health Using Unmanned Aerial Systems (U	1	0.5	0.5	1	3
14	Dalponte2022	2022	Remote Sensing	Journal article	NA	Forest tree health monitor	Wood Decay Detection in Norway Spruce Forests Based on Airborne Hy	1	0.5	0.5	1	3
15	Baders2022	2022	Remote Sensing	Journal article	NA	Forest tree health monitor	An Integration of Linear Model and 'Random Forest' Techniques for Pred	1	1	0.5	1	3.5
16	Bergmuller2022	2022	Remote Sensing	Journal article	NA	Forest tree health monitor	Predicting Tree Mortality Using Spectral Indices Derived from Multispect	1	1	0.5	1	3.5
17	Yu2021b	2021	Forest Ecosystems	Journal article	NA	Forest tree health monitor	Early detection of pine wilt disease in Pinus tabuliformis in North China	1	0.5	0.5	1	3
18	Sandino2018	2018	Sensors	Journal article	NA	Forest tree health monitor	Aerial Mapping of Forests Affected by Pathogens Using UAVs, Hyperspec	0.5	0.5	0.5	1	2.5
19	Brovkina2018	2018	Geo-Spatial Information Science	Journal article	NA	Forest tree health monitor	Unmanned aerial vehicles (UAV) for assessment of qualitative classificat	0	1	0.5	1	2.5
20	RomeroRamirez2018	2018	International Journal of Applied	Journal article	NA	Wildfire monitoring	Determination of forest fuels characteristics in mortality-affected Pinus	0.5	0.5	0.5	1	2.5
21	Jiao2019	2019	2019 1st International Conferen	Conference pap	NA	Wildfire monitoring	A Deep Learning Based Forest Fire Detection Approach Using UAV and Y	1	0	0.5	0.5	2
22	Chen2018	2018	Proceedings of the 37th Chinese	Conference pap	NA	Wildfire monitoring	A UAV-based Forest Fire Detection Algorithm Using Convolutional Neura	0.5	0	0.5	0.5	1.5
23	Krukowski2020	2020	International Journal of Biologic	Journal article	NA	Wildfire monitoring	Application of UAS in Forest Firefighting for Detecting Ignitions and 3D F	0.5	0	0.5	0.5	1.5
24	Zhang2021	2021	IEEE Access	Journal article	NA	Wildfire monitoring	Data Collection Task Planning of a Fixed-Wing Unmanned Aerial Vehicle	0.5	0	0	1	1.5
25	Shin2019	2019	Forests	Journal article	NA	Wildfire monitoring	Using UAV Multispectral Images for Classification of Forest Burn Severity	0.5	0.5	0.5	1	2.5
26	Zhang2022	2022	Forests	Journal article	NA	Wildfire monitoring	A Forest Fire Recognition Method Using UAV Images Based on Transfer L	0.5	0	0.5	1	2
27	Bennett2022	2022	International Journal of Remote	Journal article	NA	Wildfire monitoring	Image to attribute model for trees (ITAM-T): individual tree detection ar	1	0.5	0.5	1	3
28	Shin2018	2018	Remote Sensing	Journal article	NA	Wildfire monitoring	Evaluating Unmanned Aerial Vehicle Images for Estimating Forest Canop	1	0.5	1	1	3.5
29	Domingo2020	2020	Remote Sensing	Journal article	NA	Wildfire monitoring	Fuel Type Classification Using Airborne Laser Scanning and Sentinel 2 Da	0.5	0.5	0.5	1	2.5
30	Psiroukis2021	2021	Smart Agricultural Technology	Journal article	NA	Wild boar monitoring	Monitoring of free-range rabbits using aerial thermal imaging	1	1	1	1	4
31	Witczuk2018	2018	International Journal of Remote	Journal article	NA	Wild boar monitoring	Exploring the feasibility of unmanned aerial vehicles and thermal imagir	1	1	1	0.5	3.5
32	Iwamoto2022	2022	Methods in Ecology and Evolutic	Journal article	NA	Wild boar monitoring	Unmanned aerial vehicles as a useful tool for investigating animal move	1	0.5	1	0.5	3
33	Rahman2021	2021	IOP Conference Series: Earth anc	Conference pap	NA	Wild boar monitoring	Performance of unmanned aerial vehicle with thermal imaging, camera	1	1	0.5	0.5	3
34	Lee2021	2021	Remote Sensing	Journal article	NA	Wild boar monitoring	Feasibility Analyses of Real-Time Detection of Wildlife Using UAV-Derive	1	1	0.5	1	3.5
35	Kim2021	2021	Remote Sensing	Journal article	NA	Wild boar monitoring	A Manual for Monitoring Wild Boars (Sus scrofa) Using Thermal Infrared	1	0.5	0	0.5	2
36	Barbedo2019	2019	Sensors	Journal article	NA	Wild boar monitoring	A Study on the Detection of Cattle in UAV Images Using Deep Learning	1	1	0.5	1	3.5
37	Ito2022	2022	Wildlife Biology	Journal article	NA	Wild boar monitoring	Antler detection from the sky: deer sex ratio monitoring using drone-mc	0.5	0.5	0.5	0.5	2
38	Kellenberger2018	2018	Remote Sensing of Environment	Journal article	NA	Wild boar monitoring	Detecting mammals in UAV images: Best practices to address a substant	0.5	1	1	1	3.5
39	Kellenberger2019	2019	IEEE Transactions on Geoscience	Journal article	NA	Wild boar monitoring	Half a Percent of Labels is Enough: Efficient Animal Detection in UAV Ima	0.5	0.5	0.5	1	2.5

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Annex V: UC5: Rural Logistics spreadsheet

ID	Secondary	Year	Journal	Paper type	Number primary studies	Review topic	Q1	Q2	Q3	Q4	Q_total
1	Agüera-Vega et al.	2018	Measurement	Journal Article	NA	Reconstruction of extreme topography from UAV structure	1	1	1	0	3
2	AlMuhaideb et al.	2021	Applied Sciences	Journal Article	NA	Optimization of Truck-Drone parcel delivery using metaheu	0.5	1	1	0	2.5
3	Besada et al.	2019	UNAGI	Conference	NA	Drones-as-a-service: A management architecture to provide	1	1	1	0	3
4	Burdziakowski	2020	Remote Sensing	Journal Article	NA	Increasing the geometrical and interpretation quality of Un	0.5	1	1	0	2.5
5	Carvajal-Ramírez et al.	2019	Measurement	Journal Article	NA	Virtual reconstruction of damaged archaeological sites base	0.5	0.5	1	0	2
6	Colica et al.	2021	Environmental Earth Sciences	Journal Article	NA	Using Unmanned Aerial Vehicle photogrammetry for digital	1	0.5	1	0	2.5
7	Dabski et al.	2020	Remote Sensing	Journal Article	NA	Mapping glacier forelands based on UAV BVLOS operation i	0.5	1	1	0	2.5
8	Davies et al.	2018	ICEPDS	Conference	NA	Review of Unmanned Aircraft System technologies to enabl	0.5	1	1	0	2.5
9	Deaconu et al.	2021	Sensors	Journal Article	NA	Algorithms for delivery of data by drones in an isolated are	0.5	1	1	0	2.5
10	Dering et al.	2019	Journal of Volcanology & Geo	Journal Article	NA	Review of drones, photogrammetry and emerging sensor te	1	1	1	0	3
11	Fang et al.	2018	Drones	Journal Article	NA	Development of small UAS Beyond-Visual-Line-of-Sight (BV	1	1	1	0	3
12	Guenzi et al.	2019	IEEE	Conference	NA	Open source, low-cost and modular fixed-wing UAV with BV	0.5	1	1	0	2.5
13	Hartley et al.	2022	Drones	Journal Article	NA	BVLOS Unmanned Aircraft operations in forest environmen	1	1	1	0	3
14	Hoon Jo & Hong	2019	International Journal of Geo-I	Journal Article	NA	Three-Dimensional digital documentation of cultural herita	0.5	0.5	1	0	2
15	Iglhaut et al.	2019	Current Forestry Reports	Journal Article	NA	Structure from motion photogrammetry in forestry: A revie	1	0.5	1	0	2.5
16	Jana & Mandal	2022	ACM	Conference	NA	Approximation algorithms for drone delivery packing proble	0.5	1	1	0	2.5
17	Jeong et al.	2020	Measurement	Journal Article	NA	Applying Unmanned Aerial Vehicle photogrammetry for me	0.5	0.5	1	0	2
18	Jiménez-Jiménez et al.	2021	International Journal of Geo-I	Journal Article	NA	Digital terrain models generated with low-cost UAV photog	1	1	1	0	3
19	Kwong & Fung	2020	International Journal of Remo	Journal Article	NA	Tree height mapping and crown delineation using LiDAR, la	1	1	1	0	3
20	Lamsters et al.	2020	Journal of Maps	Journal Article	NA	High-resolution orthophoto map and digital surface models	1	1	1	0	3
21	Liu	2018	Optimization Methods in Engi	Journal Article	NA	Optimization of drone-assisted delivery system	0.5	1	1	0	2.5
22	Loffi et al.	2022	International Journal of Aviati	Journal Article	NA	Evaluation of onboard detect-and-avoid system for sUAS BV	1	1	1	0	3
23	Nikolakopoulos et al.	2017	Journal of Archaeological Scie	Journal Article	NA	UAV vs classical aerial photogrammetry for archaeological s	0.5	0.5	1	0	2
24	Park et al.	2019	Environmental Pollution	Journal Article	NA	Sustainable monitoring coverage of Unmanned Aerial Vehic	1	1	1	0	3
25	Patrik et al.	2019	Journal of Big Data	Journal Article	NA	GNSS-based navigation systems of autonomous drone for d	0.5	1	1	0	2.5
26	Politi et al.	2022	IEEE	Conference	NA	The future of safe BVLOS drone operations with respect to	1	1	1	0	3
27	Ralitera et al.	2022	HiPEAC	Conference	NA	On using blockchains for Beyond Visual Line of Sight (BVLOS	0.5	1	1	0	2.5
28	Schellenberg et al.	2020	AIAAJ	Journal Article	NA	BVLOS operations of Fixed-Wing UAVs for the collection of	0.5	1	1	0	2.5
29	Scott & Scott	2017	HICSS	Conference	NA	Drone delivery models for Healthcare	0.5	1	1	0	2.5
30	Sorbelli et al.	2022	ICDCN	Conference	NA	Greedy algorithms for scheduling package delivery with mu	0.5	1	1	0	2.5
31	Terkildsen et al.	2021	ICUAS	Conference	NA	Safely flying BVLOS in the EU with an unreliable UAS	0.5	1	1	0	2.5
32	Villarreal et al.	2022	Journal of Industrial Informati	Journal Article	NA	Workflow for capturing information and characterizing diffi	0.5	0.5	1	0	2
33	Wang et al.	2019	Environmental Earth Sciences	Journal Article	NA	Multistep rocky slope stability analysis based on Unmanned	0.5	0.5	1	0	2
34	Wood et al.	2020	Frontiers in Robotics and AI	Journal Article	NA	BVLOS UAS operations in highly-turbulent volcanic plumes	1	0.5	1	0	2.5
35	Yang et al.	2021	Computers and Electrical Engi	Journal Article	NA	Approaches for exploration of improving multi-slice mappin	0.5	0.5	1	0	2
36	Yang et al.	2022	Computers and Electrical Engi	Journal Article	NA	A novel approach of efficient 3D reconstruction for real sce	0.5	0.5	1	0	2
37	Yingst & Marojevic	2021	IEEE	Conference	NA	Tethered UAV with high gain antenna for BVLOS CNPC: A pr	0.5	0.5	1	0	2

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