Development of an Integrated System of Solution for Decision Support of Crop Health Diagnosis: Case of a Machine Learning Enabled Unmanned Aerial Vehicle

by

Rachel Elizabeth Olivier

(u17055696)

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Executive Summary

The agricultural sector developed a need to utilise technology to make informed decisions about crops. Remote sensing technologies, which typically utilises satellite, airborne, or ground-based sensors, has been increasingly used in precision agriculture lately. However, Unmanned Aerial Vehicles (UAVs) or drones have become a more cost-effective and versatile solution, providing higher-resolution imagery and greater flexibility in flight time, frequency, and crop visibility.

The project opportunity stems from the growing usage of UAVs in agriculture. The problem statement addresses the need for a comprehensive framework for selecting, designing, and implementing a crop monitoring UAV system, which has not yet been identified. This project developed an integrated system of solution for a machine learning enabled drone that combines different attributes into a unique solution.

The literature review highlighted several aspects to consider for a drone remote sensing system and illustrated how such a system fits into precision agriculture applications. Required equipment and technologies identified for a system include a machine learning enabled UAV, control systems, sensors, and data processing tools. A case study research approach is deemed appropriate as it allows for the review of literature and available solution options before designing a solution.

Attributes were identified and modelled to create a unique decision support framework for a crop monitoring solution system following their relevance and combinatorial characteristics. The integrated system is divided into three solution paths, each with critical user decisions and recommended selection processes. Possible solutions are categorised by farm and aircraft specifications to facilitate simpler selection. The research objectives were addressed through the identification of these attributes and through designing the main decision systems along with the categorisation of potential solution options.

A case study research approach is deployed throughout the project to allow for the integration of literature and available solution options to the holistic system and each smaller decision sub-system. The methodology was iterated within each main decision path to define and analyse a unique case for each decision system and create a solution based on the information available for the specific decision system.

Despite this research being skewed towards qualitative investigations, some quantifications from the research findings include that from the 31 UAV models considered for analysis, they can be categorised into six categories relating to UAVs characteristics and two categories related to the farm characteristics. The categories are designed to group together those aircrafts with similar characteristics or specifications, to allow for an easy reference and selection by the user.

The presented solution addresses the complexity of the system and identified literature gaps through an encompassing and integrated system of solution. Future work includes creating a comprehensive database that includes all possible solution options and developing a functioning decision support system based on the developed solution system.

Certification

I, Rachel Elizabeth Olivier, here by certify that this dissertation is a presentation of my original work. The contributions of others have been clearly acknowledged through citations and referencing. This dissertation has been submitted in fulfilment of the requirements for the degree of Magister Engineering, Industrial Engineering.

Rachel Elizabeth Olivier

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List of Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Networks
ASL	Air Service License
ATO	Approved Training Organisation
CAR	Civil Aviation Regulations
CAS	Clustering Algorithm System
CATS	Civil Aviation Technical Standards
CNN	Convolutional Neural Networks
C of R	Certificate of Registration
COTS	Commercial off the Shelf
DEM	Digital Elevation Models
DCS	Drone Control System
DSF	Decision Support Framework
DSS	Decision Support System
ENDVI	Enhanced Normalised Difference Vegetation Index
ExG	Excess Greenness
GCS	Ground Control System
GIS	Geographic Information Systems
GNDVI	Green Normalised Difference Vegetation Index
HD	High-Definition
IoT	Internet of Things
LiDAR	Light Detection and Ranging
MAV	Micro Aerial Vehicle
MTOM	Maximum take-off Mass
NDI	Normalised Difference Index
NDVI	Normalised Difference Vegetation Index
NIR	Near Infrared
NDRE	Normalised Difference Red Edge Index
OBIA	Object Based Image Analysis
PA	Precision Agriculture
RE	Red Edge
RGB	Visibly Light Sensors
RLOS	Radio Line-of-Sight
ROC	RPAS Operator Certificate

RPA	Remote Pilot License
RPAS	Remotely Piloted Aircraft System
RVI	Ration Vegetation Index
SACAA	South African Civil Aviation Authority
SAVI	Soil Adjusted Vegetation Index
SE	Systems Engineering
SWIR	Shortwave Infrared
TGM	Technical Guidance Material
UCAVS	Unmanned Combat Aerial Vehicles
UAS	Unmanned Aerial System
UAV	Unmanned Aerial Vehicle
VARI	Visible Atmospherically Resistant Index
VI	Vegetation Index
VIS	Visible Light
VRA	Variable-rate Application
3PSP	Third-Party Service Provider

Definition of Terms

The definition of the most important and most frequently used terms are presented in this section. All of the terms used within the project are largely explored within the literature review in Chapter 2: Literature Review. Terms are defined and introduced before assigning an acronym to them. Thereafter, the terms are referred to by only their acronym in some cases. The commonly used terms are defined below:

Drone or Unmanned Aerial Vehicle (UAV): Any aircraft that operates without a human on-board the aircraft but rather by way of remote control from the ground or pre-programmed autonomous flight controls. The term *drone* and *UAV* are used interchangeably throughout the entire document.

Crops: This is a generalised term used when referring to all plants grown and harvested on a large scale for profit generation or personal subsistence. The term crops are used when referring to crops in general throughout the document, in rare cases specific crop types or crop groups are mentioned.

Machine Learning Enabled UAVs: This includes aircrafts that are in some manner controlled using machine learning methods, or the control system is designed using machine learning methodologies. An assumption can be made that all UAVs included in this analysis are machine learning controlled, unless otherwise specified.

Non-Machine Learning Controlled UAVs: This includes aircrafts that does not incorporate machine learning methods in the design of the navigational system or integrate the learning ability within any part of the aircraft control mechanisms.

Precision Agriculture (PA): This is defined as the science of improving crop yields. It aids with agricultural decision making based on high technology sensors and analysis tools (Singh et al., 2020).

Remote Sensing: This is a way of monitoring and detecting physical characteristics of a geographic area based on the reflected radiation measured from either a satellite or aircraft.

Payload: This is a sensor or camera (or combination thereof) attached to the UAV that captures the data used for crop monitoring purposes.

Holistic: This refers to the system or object as a whole, rather than parts of it.

Integrated System: This is a combination of different components and sub-systems into a single functional system.

System User: This consists of the farmer, farm manager or individual that will utilise and operate the crop monitoring system on the respective farm. The system user is referred to using male pronouns, throughout the document as a method of generalisation.

Decision Support System (DSS): A responsive system designed and developed to promote the decision making process of ill-structured decision-making problems or scenarios.

Decision Support Framework (DSF): An integrated framework created to incorporate all factors and considerations imperative to the design of a functioning decision support framework.

Chapter 1: Introduction

1.1 Background Information

By 2050, the world population is estimated to increase by two billion people while the percentage of land used for cultivation will only increase by a meagre 4%, according to the United Nations' Food and Agriculture Organisation (FAO) (Dharmaraj & Vijayanand, 2018). Statistics South Africa estimates 20% of the country's population suffers from food insecurity, and with the estimated global population increase, food security will only become an increasingly urgent matter (Statistics South Africa, 2019). Agriculture plays a vital role in the economy and livelihood of any country. Commercial farms as well as smallholder farms are important to ensure food security for a single household, community or country. In addition, farming activities generate large revenue for both individual households and larger farming businesses, which in turn supports the local and global economies. Encouraging sustainable agricultural practices along with rural development is crucial to eliminate extreme poverty in both South Africa and the rest of the African continent (Aguera et al., 2020).

The use of advanced technologies adapted for agricultural applications has the potential to transform this sector under the correct enabling conditions. These technologies include machine learning, computer vision, artificial intelligence (AI), Internet of Things (IoT), remote sensing and Unmanned Aerial Vehicles (UAVs) (Aguera et al., 2020). Applied in the agricultural sector the above mentioned technological implementations, form part of a much larger and broader global digital transformation. For the technologies to be applied, digitalisation of agriculture should be conducted. Aguera et al. (2020) define the digitalisation of agriculture as changing measured agricultural inputs and outputs into digital data to be used for advanced decision making based on additional information and the automation of systems.

Improved technologies allow for larger and increasing amounts of data to be captured on farms and analysed. A new form of agriculture, namely 'precision- or smart farming' emerged as a result of the increasing datafication of the sector. The entire step towards digitalising the agricultural sector can lead to opportunities that could aid South Africa and the entire African continent to tackle food insecurity while creating the possibility for additional job creation. The South African agricultural sector has started to indicate the use of some of these advanced technologies and digitalisation. The technologies mentioned above including additional satellite systems, robotics, data management and analytics tools are all incorporated to develop services geared towards cost reduction, resource conservation, input optimisation and output maximisation (Aguera et al., 2020).

Mulla (2013) predicted that in the near future, there would be a need for massive data collection and analysis of crop characteristics to identify and manage various factors that can affect overall crop health. This information is to be obtained by sensors from satellites, aeroplanes, remotely piloted aircrafts and other robots or machines. The data will assist in identifying weeds, pests and diseases at an early stage, as well as the crop health, water stress and nutritional deficit, for the precise and selected application of fertilisers and pesticides.

1.2 History and Overview of UAVs

A drone or an Unmanned Aerial Vehicle (UAV) is a pilotless aircraft, that is either operated using remote control or by way of a pre-programmed flight route (Krishna, 2018). The term drone is typically used as a collective term for an aircraft without an on-board pilot. These aircrafts can either be operated from the ground with a remote-control system or fly autonomously (Custers, 2016). Different terms exist when referring to a drone, but none of these terms has the same scope or meaning to the different stakeholders. A *drone* is the term adapted by the media and thus the term most widely known by the public (Custers, 2016). The first association for the term drone was within the military, however, the term is now used for unmanned aeroplanes and helicopters, usually equipped with a camera which can be controlled remotely using a smartphone.

The terms UAV or Unmanned Aerial System (UAS) refer to the same type of aircraft as a drone, however, these terms are more commonly used in official documents or legislation. In practice, a UAV refers to the flying platform, whereas a UAS refer to both the platform and the control system in place at the ground station (Custers, 2016). A *Remotely Piloted Aircraft System (RPAS)* refers to a UAS that is remotely controlled by a pilot. An RPAS, therefore, differs from a UAV and UAS as a pilot is necessary to operate the system, whereas a UAV or UAS can be operated by any individual or is autonomously operated. Custers (2016) stipulates that all RPASs are UAVs, but not all UAVs are RPASs. Other terms used to describe specific subsets of drones include Unmanned Combat Aerial Vehicles (UCAVs), Micro Aerial

Vehicle (MAV) or micro copters. Drones used for recreational purposes such as model aeroplanes or radio-controlled aircrafts indicate another subset of drones.

Drones were first developed during the First World War as an unmanned, radio controlled airplane used in remote warzones for enemy surveillance (Stehr, 2015). Drones used in the military sector range from aerial torpedoes or fling bombs to enemy scouting UAVs. Since then, drones have been developed and sold commercially while adopting various other roles in different fields including journalism, photography, entertainment, mining, agriculture, healthcare, parcel delivery or e-commerce, emergency response systems, and wildlife conservation, to name a few. UAVs within the field of agriculture have been gaining more popularity, especially within the South African market. Drones within agriculture are being used for several purposes, including, crop monitoring and evaluating purposes, livestock monitoring, safety and security as well as pesticide spraying.

Over the recent years, significant development within drone technology has led to drones being sold commercially for various uses including but not limited to: photography, surveillance, package delivery, entertainment and recreational use. Puri, Nayyar, and Raja (2017) indicated that drones offer many advantages above anything else of the same nature such as ease of use, availability and monitoring of areas that are hard to reach by man, observation of forest fires, tracing of illegal activities and crop yields surveillance. Consumers can purchase drones at an affordable price for personal or recreational use as the user does not require a license to operate the drone.

Modern drone technologies have advanced considerably in the last 10-15 years (Puri et al., 2017). Most drones are equipped with a GPS and camera which the pilot can use to track and fly the drones over longer distances while making use of smartphones with built-in GPS systems. Drones can integrate with High-Definition (HD) cameras by way of Wi-Fi technology and provide a real-time video or First Person View of the flight over a smartphone or tablet.

Drones are mostly categorised into two categories, fixed-wing aeroplanes and rotary motor helicopters as mentioned above. A fixed-wing drone looks like an aeroplane and uses lift and drag to fly, similar to a normal aircraft (Miller & Adkins, 2018). These drones usually have a longer battery life and can fly at greater speeds, thus covering a larger surface in the same amount of time. A fixed-wing drone does however require a 'landing strip' or space to take off and land. A rotary motor helicopter or rotary drone is distinguished based on the number of propellers, similar to a helicopter, attached to the drone. The number of propellers typically ranges from 4 to 8 propellers. These propellers allow the drone to take-off and land vertically, even in a small confined space and hover over a specific area (Miller & Adkins, 2018). Rotary drones have a shorter battery life compared to fixed-wing drones but are easier to operate and manoeuvre.

Most commercially available drones are fitted with their own cameras, typically used for photography or scouting. Drones with a specialised purpose may be fitted with a camera or sensor specifically for that purpose. Some drones allow the user to attach a camera of choice, whereas other cameras are fitted to a drone permanently. South African drone company, Aerobotics, designed and developed two cameras in-house, which can only be fitted onto the specific drone that they use for their operations (Reinecke & Prinsloo, 2017).

1.3 Problem Statement

Current methods of crop monitoring and evaluation are extremely time and labour consuming, as you need people are needed to physically walk through the fields and evaluate the health of the crops. Depending on the type of crop or plant, the human inspectors might need to inspect each tree, bush or plant. For crops such as wheat, maize, sugar cane, etc. only a small sample of the field will be evaluated. This could lead to incorrect conclusions on the overall health of the crop field, which in turn can lead to the farmer spending more time and resources to perform maintenance on the incorrectly diagnosed fields.

Currently, aerial images of a field can be obtained through satellite images or aeroplanes. These options however provide low-resolution images at a higher cost (Stehr, 2015). In addition, these options are weather permitting as clouds or bad weather can obstruct the view of the field. Satellite images usually have a delay of a week or two before the images can be retrieved and then analysed by the farmer.

Drones provide farmers with a low-cost, high-resolution, highly efficient, flexible alternative to manual crop and satellite-based monitoring and evaluation. UAVs provide aerial maps of the entire crop field and if fitted with the correct camera and equipment, the drones can determine the health of crops by measuring the temperature, chlorophyll levels and near infrared light emitted by the plants. These factors, including others, can ultimately determine and monitor the health of a single plant, as well as an entire field of crops. Drones can fly below the cloud level, thus the view of the field is hardly ever obstructed. In addition, drones can be flown at regular intervals or at any time, depending on the need of the specific farmer.

The need for a holistic and integrated system of solution to implement a drone system, for monitoring and evaluation of crops within the agricultural sector has been identified as a gap in the literature. This is premised on the fact that different drone designs have their respective capabilities and limitations. Hence, drones aren't universally fit for all aerial monitoring tasks. The need to guide potential crop monitoring drone users on specifics concerning the selection and assemblage of a customised drone system is quite significant. As part of the integrated system of solution, a holistic perspective is considered to evaluate all relevant aspects and elements obtained from the literature. The system of solution as developed in this research is quite robust and capable of aiding the user to make an easy and more informed decision regarding the design and/or selection of a crop monitoring system to be implemented as part of the user's farming business. The solution should take into consideration all of the relevant elements that can influence the system, or the decisions made in the system to deliver an accurate and more suitable solution to address the specific needs of a customer.

1.4 Research Questions

The following research questions have been identified:

1. What benefits does a remote sensing drone system present to the agricultural sector?
2. How can drones be used to monitor or evaluate crop health to ultimately improve crop yield?
3. What factors or measurements need to be considered or measured to determine or model the health of crops?
4. What attributes or variables need to be considered when designing an integrated system of solution for the implementation of an agricultural drone system?
5. How do the identified variables influence the main decisions to be made in the system?

1.5 Project Aim and Research Objectives

This section of the report defines the project aim and specific research objectives.

1.5.1 Project Aim

The aim of this research is to develop an integrated system of solution based on a decision support framework for the selection and design of a drone system for agricultural crop monitoring. The framework makes provision for different inputs and preferences to aid in the design and selection of a suitable agricultural crop monitoring system. The goal of the solution system is to assist any user with the selection and integration design of a system suited to the users' specific goals.

1.5.2 Research Objectives

The research objectives (RO) correspond to the project aim as well as the research questions specified above. The following under listed are the objectives addressed in this research:

1. Holistically identify attributes of drones that are relevant to the monitoring of crop health diagnostics.
2. Conduct of analysis on identified attributes for different crop farming systems.
3. Design and development of an integrated system of solution capable of being deployed for the purpose of decision support and evaluation of crops in semi-commercial or commercial farms.

1.5 Project Rationale

The use of drones to monitor crops offers multiple possibilities to obtain data from crop fields in an easy, fast and cost-effective manner, compared to previous methods of crop monitoring. Drones can fly at a constant speed while taking high-resolution aerial images of the area to which the camera is pointed. Along with these features, drones can be operated using either a remote control or a pre-programmed flight system. These features along with proficient image analysis software and advantages such as ease of use, flexibility and accuracy enable drones to be used within precision agriculture as a remote sensing method.

Not only does a drone system save the user time and money, but more informed farming decisions can be made based on the data and images captured by the system and analysed by the accompanying software or algorithms. The high flexibility of a drone system allows the user to capture high-resolution images as often as required.

A standardised configuration encompassing all of the different variables and inputs, providing a unique output or system design option has not yet been identified within relevant research. Due to this factor, many users employ ad-hoc procedures or continue to utilise traditional and alternative crop monitoring methods. Due to the current high cost of implementing a complete agricultural drone system, this crop monitoring method has not yet been commercialised and is only employed by large commercial farmers or businesses.

Creating an integrated system of solution considering all of the variables and the different arrangements of these said variables would allow the system designer to develop and design a crop monitoring system for any customer, based solely on the specified needs and stated inputs of the user. The decision support solution system is designed in such a manner that the system user can also utilise the system to make informed and substantiated decisions regarding such a system.

1.6 Motivation

In recent years, airborne and satellite remote sensing systems are gradually being replaced by UAVs. Stehr (2015) indicates that the resolution of the cameras attached to drones is 40 000 times better than the commonly available satellite data and 44 times better than the best commercial satellite images. C. Anderson (2014) indicates that drones are much cheaper and offer a higher resolution compared to satellite imagery. This is mostly since drones can fly below the clouds and thus offer an unobstructed view of the agricultural fields. Compared to a manned aircraft, a drone can be purchased for almost the same price one would pay to have a manned aircraft run for an hour.

Drones can provide farmers with a different view of the crops, which in turn presents the farmers with valuable information regarding the health and growth of crops. For instance, an aerial view of a field can reveal patterns to the farmer that is not apparent at eye level or from the ground. Multispectral sensors and cameras can collect data from the infrared and visible light spectrum. This information can assist the farmer in differentiating between healthy and stressed plants, long before the plant shows physical signs of distress. Lastly, drones can conduct crop surveys as frequently as required by the end user, which is much more frequent than provided by satellite or manned aircrafts.

The fundamental motivation for this research project is the lack of an integrated system of solution for an agricultural crop monitoring system. Various systems exist, designed for a specific scenario or farm, but no generalised system has yet been identified that encompasses all of the necessary factors and variables for the effective implementation of such a system

1.7 Scope of the Research

The scope of the research is to design and develop a holistic decision support system of solution to implement an agricultural drone monitoring system on any farm, given that information and data for the specific crop type cultivated on the farm are readily available. The project is limited to PA products and services provided or readily available within South Africa. The scope of the project does not include the AI aspect, thus designing or developing image recognition or specific data analysis software to determine the health of the crops or predict the yield. This component of the project is to be fulfilled using available off-the shelf solutions.

1.8 Limitation of the Research

The project is limited by the literature available within this area of study. The project is also limited to the current commercially available software, equipment and technology used for remote sensing drone applications. All software and hardware components identified within this study are those models available up to and including August 2022. Any new hardware components, equipment or updated software systems identified after the end of August are not considered for research purposes. No additional software or equipment will be designed during this project. Currently, no prospects of testing such a system exist, thus no data will be collected, and the project will solely be based on available literature and information provided freely by UAV manufacturing companies.

1.9 Delimitation of the Project

All AI-related aspects will not be included in this project, but rather consulted within the available literature. Already existing software applications or packages will be identified, and evaluated and a suitable software package will be selected to be implemented as part of the solution.

The used of drones, especially those designed for agricultural purposes need to adhere to set out regulations and some legislation. These regulations and legislation apply more to the drone operator and the areas in which the drone(s) can be flown and not. For this project, these rules, regulations and legislation will be briefly mentioned, as part of the design phase of the project, but not evaluated critically. These regulations only need to be considered if the system is to be tested or implemented on a real farm.

The inputs identified for the solution system, during analysis, will be limited to those critically discussed within available literature. If no reputable literature is found regarding a specific aspect, topic or variable, the variable will be excluded from the study. If this variable, topic or aspect is crucial to the success of the project, a grey literature review will be conducted to obtain the necessary information.

1.10 Project Organization

Chapter one of this project document contains the background to the problem. The project opportunity is identified within the project statement subsection. Based on the identified need, applicable research questions and objectives are identified along with the project aim. Further, the project motivation, rational and scope of the research are presented in this Chapter. The appropriate limitations and delimitations are established along with the definitions of the terms mostly used throughout the document.

The second Chapter addresses the relevant literature consulted to obtain an in-depth understanding of the research domain. Alternative solutions are identified and evaluated. The preferred solution alternative is selected and introduced in this Chapter.

Chapter three contains the research methodology or research approach alternatives. The conceptual and theoretical frameworks are defined within this Chapter as an accurate outline of the project.

Chapter four contains the design of the final system of solution and the accompanying information and discussions. The chapter is divided into the three main solution paths and their accompanying sub-decisions. Finally, a conclusion and recommendations for the project along with the anticipated future work are discussed in Chapter five.

Chapter 2: Literature Review

2.1 Introduction

This chapter contains a literature review including the basic concepts pertaining to the implementation of an agricultural drone system. Research was conducted to gain a thorough understanding of concepts such as precision agriculture, remote sensing, drones and UAVs and crop monitoring techniques and methods.

2.2 Precision Agriculture

Zachariah (2019) defines precision agriculture (PA) as a farm management methodology that utilises IT technology to ensure that crops reach ideal health and efficiency. Pierce (1999) describes PA as the utilisation of technology to manage variabilities, spatial and temporal, related to agricultural production, to improve the performance of crops as well as environmental quality. PA focuses on the protection of the environment while ensuring profitability and sustainability. C. Yang (2018) indicates the main idea of PA is to identify and monitor variability within the fields and to manage the variability accordingly. PA utilises specialised equipment, IT services, and software to continuously gather information regarding various factors such as the condition or health of crops, soil, and ambient air, among other relevant information. According to Santos, Barbosa, and Andrade (2019), PA is designed to improve the long-term, site-specific or production efficiency of the entire farm, as well as the profitability and productivity of production. Zachariah (2019) indicates that PA is the combination of IT and production experience, utilised to: optimise quality and production efficiency; and minimise risk and environmental impact.

Precision agriculture commenced in the late 1980s with research and development of grid soil sampling and sensors, yield monitors, positioning systems and variable rate technology. Significant growth in PA technologies has occurred since the GPS systems and Geographic Information Systems (GIS), sensor technology and finally remote sensing technology were introduced and improved on. C. Yang (2018) proposes that PA is changing the way in which farmers are managing their fields as a whole. While the general adoption rate of precision agriculture is still low, some of the developed technologies have become standard practices within production agriculture. In the USA automatic guidance systems and yield monitors are the most popular PA technologies used (C. Yang, 2018). Other PA technologies include real-time crop and soil sensors, soil sampling using GPS technologies, variable rate technology and remote sensing. These applications or technologies are mostly used by customers or consultants to enable site-specific water, fertiliser and pesticide application. PA can be divided into three components, namely: data capturing; data analysis and interpretation; and the implementation of a timely management response (Zachariah, 2019).

2.2.1 Remote Sensing

Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring the reflected and emitted radiation at a distance (typically from a satellite or aircraft). Special cameras collect remotely sensed images, which help researchers "sense" things about the Earth.

Remote sensing technologies supplement many PA activities as farmers are able to alter inputs according to specific conditions determined by spatial information technology (C. Yang, 2018). Z Chen, Zhou, and Tang (2004) indicate that the inherent characteristics of agriculture allow remote sensing to be a suitable method of monitoring and management of crops and agricultural fields. These characteristics include:

- Traditional methods of field monitoring or survey are time-consuming and costly, as agricultural activities are usually performed in large spatial regions.
- The economic output from agriculture is not so substantial, compared to other sectors.
- Different crops have different phenological or biological rhythms as growth and development happen at different times of the year.
- As humans monitor and manage agricultural activities, they require accurate and timely information regarding all aspects of agriculture.

Remote sensing technology in the agricultural sector has been utilised for a long period of time, due to the technology meeting these inherent characteristics mentioned above. Zhongxin Chen et al. (2008) specify that remote sensing meets these requirements by way of its own characteristics, including: accuracy, timing, economy, rapidness, and repetitive and dynamic monitoring abilities.

Remote sensing systems provide users with accurate information used for production and management in agriculture, in a timely manner. The main applications of remote sensing within this field include the monitoring of crop growth, yield estimation or prediction, identification of crops, mapping of croplands, precision farming, etc.

Wójtowicz, Wójtowicz, and Piekarczyk (2016) divide remote sensing into three categories: satellite, ground-based and airborne remote sensing. Each of these categories is evaluated based on their spatial and spectral resolutions. Spectral resolution specifies the spectral band width that can be detected with the sensor, whereas the spatial resolution indicates the pixel size or number of pixels used for satellite or airborne pictures. The three categories of remote sensing technology used for agricultural applications are described below.

2.2.1.1 Satellite Remote Sensing

The first satellite sensors to be used for agricultural applications, the Landsat and SPOT were introduced in the 1970s (C. Yang, 2018). Since then, high-resolution satellite sensors were developed providing users with high spatial resolution, and high revisit time.

Nguyen et al. (2020) propose satellite imagery as an alternative method to generate field maps, or specifically paddy maps. Satellite images offer a wide spatial range over a large geographic area. These images can sometimes be accessed free of charge and cover a high temporal resolution, the number of times the same area or location is revisited to acquire data. Differentiation between crop areas and non-crop areas is done using different image indices, based on the multi-spectral nature of satellite images. These image indices usually require comprehensive knowledge to analyse and might be subject to contradicting conditions.

Some challenges experienced by satellite imagery as a remote sensing mechanism include cloud coverage or solar radiation influencing the images taken (Nguyen et al., 2020). In addition, older generation sensors have very low spatial resolution. The spatial resolution of a digital image indicates the number of pixels used to construct or form the image. Low-resolution images increase the probability of confusion between crops and natural vegetation (Zhongxin Chen et al., 2008). This confusion is however not limited to low-resolution images, as areas with complicated planting patterns and seasons can also lead to such confusion. The satellites used to gather the images are usually polar-orbiting satellites, which contain a relatively low sampling rate. Another challenge experienced by satellite imagery is the empirical nature of the current spectral indices used to identify areas or vegetation, thus requiring additional domain-specific calibration and validation of the data.

Significant improvements were made since high-resolution satellite sensors were first developed. The improved image sensors now offer a higher spatial resolution as well as a high revisit frequency. Along with the large area coverage and improved turnaround time for data, these high-resolution sensors can be used for many applications within the agricultural sector (C. Yang, 2018). These improved high-resolution satellite sensors have significantly closed the gap between satellite imagery and airborne imagery used for precision agricultural purposes. The most recent high-resolution satellites provide the user with multispectral imagery, and resolutions ranging between 1.24m to 4m.

Various applications for high-resolution satellite sensors exist within agriculture. The IKONOS satellite sensor delivered multispectral images which were used to map the leaf area index for vineyard canopy management; improve field map accuracy; estimate variability in soil properties; and created soil organic matter maps (C. Yang, 2018). The QuickBird satellite sensor was utilised for cotton yield mapping, crop type identification, mapping yield patterns for grain sorghum, disease detection in wheat and oil palms, estimating nitrogen concentration in irrigated maize as well as classifying weed patches in winter for site-specific control. The Spot-5 satellite sensor was evaluated by C. Yang, Everitt, and Murden (2011) for crop type identification and crop yield estimation purposes. Other satellite sensors were evaluated against ground-based sensors for the calculation of site-specific nitrogen fertilisation, nitrogen uptake in wheat and predicting the yield for different crops and plants.

Despite the recent improvement in satellite sensors, some challenges are still experienced. Some customers or farmers are ill-informed or not up to date with the technology, and are therefore uncertain about which images to select or how to order new or even archived images (C. Yang, 2018). Acquiring and delivering images in a timely manner is a challenge to most companies. The actual image acquisition can vary greatly from the specified revisit time of the satellite sensors. This is due to weather conditions and possible competition between customers in a similar geographic area. Assorted publications of image processing exist, however, there are no standard methods or software available to convert images into vegetation index maps, classification maps or prescription maps. Customers often face challenges when selecting the correct or appropriate software, due to the different capabilities, prices and complexities of these software (C. Yang, 2018).

2.2.1.2 Ground-Based Remote Sensing

Hand-held remote sensing devices are effective for smaller-scale field monitoring (Wójtowicz et al., 2016). These sensors offer greater spectral, temporal and spatial resolutions compared to airborne or satellite remote sensing mechanisms. The main limitation of these hand-held sensors is the efficiency and reduced time when evaluating small areas, compared to the larger areas monitored by aircraft or satellite sensors at a time. Ground-based remote sensing is usually performed using field spectrometers, to measure and monitor nutritional requirements or plants, water demands, weed control, detecting damage pertaining to pests, and forecasting yields (Wójtowicz et al., 2016).

2.2.1.3 Airborne Remote Sensing

Airborne remote sensing and imaging systems have been used within the field of precision agriculture since the 1990s (C. Yang, 2018). Up until recently, airborne remote sensing was conducted with piloted aircrafts but is now replaced by sensors attached to drones. Aeroplanes also offer a relatively cost-effective option for remote sensing uses as the systems are designed to capture high-resolution images at a low altitude, and slowly enough to allow a thorough analysis of these images (Zachariah, 2019). The uses for airborne remote sensing are similar to that of satellite sensors, as they include weed detection, estimating yield, plant population count, evaluating the salinity of soil and measuring the chlorophyll content in plants. Tsouros, Bibi, and Sarigiannidis (2019) indicate that manned aircrafts often need to perform multiple flights to obtain sufficient images of crops and can therefore result in a higher cost.

2.3 Drones and UAVs

In recent years, airborne remote sensing systems are gradually being replaced by UAVs. Limited research was found regarding manned aircraft remote sensing systems due to the influx of research on UAVs and their application within remote sensing and precision agriculture. The following section of the literature review will therefore focus on using drones within precision agriculture and for remote sensing applications. The term drone or UAV has already been defined as an aircraft that operates through the use of remote controls or by a pre-programmed flight route.

2.3.1 Drone Licensing and Legislation

The South African Civil Aviation Authority (SACAA) specifies certain regulations to be followed when flying drones within South Africa. The flying or operating of drones is legal in SA, subject to strict regulations. The most important rules pertain to the premise under which drones are flown as Part 101 of the Civil Aviation Regulations (CAR) applies to all RPAS, operated for the following purposes: ("Civil Aviation Act No 13 of 2009, Civil Aviation Regulations Part 101 of 2011,")

- Commercial operations
- Corporate operations
- Private operations
- Non-profit operations.

Excluded from the regulations specified in Part 101, is the following type of aircrafts:

- Unmanned free balloons
- Autonomous unmanned aircrafts
- Model and Toy aircrafts
- Aircrafts operated in terms of Part 94.

RPAS classified as either class 1 or 2 aircrafts as well as individuals who act as owners, pilots, operators, observers and persons performing maintenance fall within the regulations of Part 101 of the Civil Aviation Regulations. Drones or RPAS are classified according to four parameters: the mass of the aircraft, referred to as the Maximum Take Off Mass (MTOM); the height above ground level it can fly; impact energy of the RPA (converted from the impact velocity of the RPA) and; the flight rules. The rules of flight correspond to the Radio line-of-sight (RLOS) between the operator and the aircraft. Various classification options exist for RLOS. The available classifications for RLOS aircrafts and operations are described in Table 1.

Table 1 RLOS Aircraft Classifications and Operations

Line of Sight	**Explanation**
RLOS: Radio Line-of-sight	Direct contact linking the transmitter and receiver through electronic point-to-point contact.
VLOS: Visual Line-of-sight	An unobstructed view of the UAV from the person who operates the aircraft. The operator must be able to see the UAV with natural vision, or vision corrected with glasses or contact

Line of Sight	Explanation
	lenses. The UAV operates within 120m above the ground level where the operator is situated and does not exceed a distance of 500m from the operator.
R-VLOS: Restricted Visual Line-of-sight	UAV operates within 500m of the operator and below the height of the highest obstacle within a 300m radius of the aircraft. The operator is required to maintain direct, unaided visual contact with the aircraft.
E-VLOS: Extended Visual Line-of-sight	Aircraft operates within 120m above the surface, where an observer maintains direct visual contact with the UAV, within a radius of 1000m from the pilot.
B-VLOS: Beyond Visual Line-of-sight	Operations where the operator cannot uphold a direct visual line of sight with the aircraft and thus manage the flight visually.

Determination of the impact energy of an RPA is described in the Technical Guidance Material (TGM) appendix in Part 101 of the CAR. The TGM for RPAS is currently under review, thus not information could be obtained from this material to calculate the impact energy of an RPA. The classification of RPAS as specified by the SACAA and the CAR is outlined in Table 2 ("Civil Aviation Act No 13 of 2009, Civil Aviation Regulations Part 101 of 2011,").

Table 2 RPAS Aircraft Classification

Class	Line-of-sight	Energy (kJ)	Height (ft)	MTOM (kg)
Class 1A	R-VLOS/VLOS	$E < 15$	$h < 400$	$m < 1.5$
Class 1B	R-VLOS/VLOS/E-VLOS	$E < 15$	$h < 400$	$m < 7$
Class 1C	VLOS/E-VLOS	$E < 34$	$h < 400$	$m < 20$
Class 2A	VLOS/E-VLOS	$E < 34$	$h < 400$	$m < 20$
Class 2B	Experimental/Research			
Class 3A	B-VLOS	$E < 34$	$h < 400$	$m < 150$
Class 3B	VLOS/E-VLOS	Any	$h < 400$	$m < 150$
Class 4A	B-VLOS	Any	$h < 400$	$m < 150$
Class 4B	Any	Any	Any	$m < 150$
Class 5	Reserved	Reserved	Reserved	Reserved

The term 'Reserved' refers to information that will be defined in the future, whereas the 'h' refers to the height above the surface.

In addition to the different classifications of the aircrafts, different approvals and/or licenses are required to fly a drone for a specific use. Table 3 indicates each licence and/or approval required to operate RPAS for commercial, corporate, non-profit and private operations. According to subpart 101.01.2 of the CAR, *private operations,* refer to the use of a UAV for private or individual purposes with non-commercial outcome, gain or interest. Provisions and regulations not applicable to RPAS for private use are provided in the subpart dealing with private operations of drones. *Commercial operations* refer to all drone operations performed for business purposes, performed for remuneration or hire, such as: anti-poaching, security surveillance, mapping, animal counting, aerial applications, etc. *Corporate operations* describe all non-commercial drone operations, where UAVs are used by any entity to assist in the conduct of their business.

Table 3 Required Licence and Approval to Operate RPAS for Different Operations

Type of Operation	**Commercial**	**Corporate**	**Non-Profit**	**Private**
Required Approval				
ASL: Air Service Licence	Yes	N/A	N/A	N/A
ROC: RPAS Operator Certificate	Yes	Yes	Yes	N/A
RLA: RPAS Letter of Approval	Yes	Yes	Yes	N/A
RPL: Remote Pilot Licence	Yes	Yes	Yes	N/A
C of R: Certificate of Registration	Yes	Yes	Yes	N/A

The Air Service License (ASL) referred to in Table 3 is awarded to applicants should they adhere to the stipulations mentioned in the Air Service Licencing Act ("Air services Licensing Act No.115," 1990). The ASL issued by the council is in accordance with the prescribed class of air service. *Air Service* refers to any service performed by an aircraft for a reward. The general requirements for an RPAS Operator Certificate (ROC) are specified in Part 101 of the CAR. The Regulation specifies that no individual shall operate any RPAS in terms of Part 101 or the CAR unless the person is the holder of: a) in the case of commercial, corporate and non-profit operations, a valid ROC including the operations specifications attached thereto; and b) in the case of commercial operations, an ASL issued in terms of the Air Service Licensing Act, 1990 (Act No.115 of 1990). The RPAS Letter of Approval

(RLA) refers to a letter of approval granted to the applicant by the Director. According to Part 101 of the CAR, no RPAS shall be operated within the Republic, unless such RPAS has been issued with a letter of approval by the Director. Thus, no aircraft can be operated without a valid RLA.

A Remote Pilot License (RPL) allows the holder of an RPAS to operate the system for financial gain. The license is issued by the SACAA upon completion of the course that contains a combination or theoretical and practical training. For an individual to obtain an RPL several compulsory requirements should be adhered to. These include:

1. The applicant must be 18 years and older
2. The applicant must hold current medical assessments
3. An Approved Training Organisation (ATO) for training purposes must be identified
4. Foreign theoretical training will be approved and validated
5. Successful completion will only be accepted
6. The applicant must pass the practical assessment for an RPL
7. The applicant must pass the Radiotelephony Examination
8. The applicant must achieve English Language Proficiency (ELP) level 4 or higher
9. All RPL applications must be submitted to the SACAA.

Part 101 of the CAR along with the Civil Aviation Technical Standards (CATS) provides an extensive list of requirements for RPL. All RPAs to be operated in the Republic of South Africa, require a Certificate of Registration (C of R) issued by the Director in accordance with Part 101 of the Civil Aviation Regulations of 2011.

In general, it is acceptable to use RPAS for *private use*, given that a) the aircraft is used for the individual's personal and private purposes, with no commercial outcome, gain or interest; b) All statutory requirements relating to privacy, liability and other laws should be adhered to by the pilot. For *all other uses* of an RPAS, the aircraft must be registered and when operated, must adhere to the terms stated in Part 101 of the South African Civil Aviation Regulations. The regulations specify that no RPA should be flown/operated within 50m from any person of group of persons, or on any property without the property owners' permission.

RPA’s are not permitted to fly in the following cases unless it has been approved by the SACAA:

- Close to a manned aircraft
- In a controlled airspace
- 10km or closer to an aerodrome, such as an airport, airfield or helipad.
- In restricted airspace
- In prohibited airspace
- If the aircraft weighs more than 7kg.

Other more detailed regulations regarding more specific instances are discussed the Part 101 of the CAR that is not as important to this specific project.

2.3.2 Machine Learning Enabled Drone Control System

Traditional and most used methods to control UAVs are through a remote control system operated by a RPAS pilot. This method of control is usually referred to as a manual mode of control. Spinka, Kroupa, and Hanzálek (2007) identified a growing demand for other drone control systems. Many projects in both commercial and academic institutions are aiming to design a UAV autopilot system, to allow for a fully autonomous UAV system. Since then, Choi and Cha (2019) have identified the challenges faced by autonomous flight systems. These challenges were identified as control strategies that include parameter tuning, recognition of objects in specific environments, and real-time path planning.

Different approaches were used to attempt to solve these challenges, such as a heuristic approach, a graph theory approach and a negotiation approach (Bortoff, 2000; Gan & Sukkarieh, 2011; Sabo, Kingston, & Cohen, 2014). However, the above-mentioned approaches still had issues with system dynamics, sensors, etc. Machine learning has evolved into a more appealing approach for autonomous drone flights and also overcame the above challenges (Choi & Cha, 2019). Through utilising machine learning methodologies, UAVs are enabled to recognise patterns and make predictions from data without the need for designed programming for an autonomous flight. The study conducted by Choi and Cha (2019) identifies previous studies conducted where machine learning principles are applied to drones for autonomous flights. The two main contributions discussed are contributions to control strategies, and object recognition. The key to autonomous flight of UAVs is the control strategy adopted or improved by machine learning. Three categories are identified for control strategies where machine learning is applied, namely:

Parameter tuning, navigation and real-time path planning. Another challenge faced by autonomously controlled UAVs is that of object recognition, where the aircraft is required to identify or recognise objects in real-time to avoid collisions. In addition to collision avoidance, drones might require object recognition for altitude monitoring or checking for suitable landing areas. Although autonomous flight mechanisms still contain a number of challenges and issues, extensive research is being conducted to solve or address these challenges through the use of machine learning methods.

Due to the increased amount of available data and the development of high-performance processors and graphics processing units, the development of UAVs have benefitted immensely (Hashesh et al., 2022). Machine learning especially are known to provide machines with increased intelligence and enable the machines to perform some tasks more efficiently than human beings are capable of. As mentioned earlier, UAVs are traditionally designed to be controlled and operated by humans, but with the immense improvement and growth in popularity or machine learning and its applications, smart UAVs have become more fashionable (Hashesh et al., 2022).

Data collected by the drone sensors can be used as inputs to perform distinct AI tasks. Machine learning solutions can aid UAVs through improving the energy efficiency of the aircrafts by way of efficient resource management and interference mitigation. In addition, machine learning can be used to aid in trajectory planning, to enable UAVs to be equipped with the correct battery capacity to be able to avoid obstacles and plan autonomous routes, while prolonging battery life.

Moreover, essential UAV applications including landing site recognition, traffic control and surveillance could be intelligently enhance through the application of AI and machine learning algorithms (Hashesh et al., 2022). Another prospectively promising direction is to utilise existing machine learning computer vision algorithms for picture enhancements for UAV applications. Thus, using various machine learning techniques to automate more complex UAV tasks and thus improve the overall system efficiency.

Mozaffari, Saad, Bennis, Nam, and Debbah (2019) states that machine learning can potentially be utilised to design and more importantly optimise UAV-based wireless communication systems. This is achieved through the basis that machine learning allows systems to better performance from learning from past experiences and their environments. Some machine learning algorithms that can be used to assist a drone in adjusting flight positions, directions and motion control dynamically is reinforcement learning algorithms. UAVs are thus able to adapt to these dynamic environments and autonomously optimise their flight trajectory. Machine learning tools can further be used to predict user behaviour and effectively operate the aircrafts from these predictions.

A. I. Khan and Al-Mulla (2019) states that the combination of machine learning and UAVs lead to increased precision, accuracy and higher efficiency in image classification and object detection. In general, the research pertaining to UAVs and machine learning combinations have increased over time, with the research within the agricultural sector maintaining a constant growth pattern.

2.3.3 Drones in Agriculture

The Association for Unmanned Aerial Vehicle Systems International (AUVSI) forecasts a high increase in the commercial use of drones over the next 12-15 years, with agricultural drone use amounting to 80% of commercial drone usage (Karst, 2013). After military use, the AUVSI predicts that agricultural drone use will be the leading user.

Drones within the agricultural sector have a range of different uses. Among the wide range of uses, Veroustraete (2015) specifies that a drone can be used for mid-season crop monitoring, cattle or animal herd monitoring, mid-field weed identification, monitoring of irrigation equipment and determining soil fertility based on variable-rate application. Puri et al. (2017) indicate the following practical applications for drones within agriculture: farm analysis by way of 3D mapping, air monitoring of a field, Geographic Information System (GIS) mapping integration and determining crop health status through imaging. The implementation of drones for crop monitoring and pesticide spraying is presented by Mogili and Deepak (2018).

According to Veroustraete (2015) crop health monitoring is thus far the leading use for drones in the agricultural sector. Drones have the ability to fly above crops while capturing images and other data that cannot be seen by a human, like near infrared emitted by the plants or the Normalised Difference Vegetative Index (NDVI). Determining crop health by way of drone imaging allows the farmer to monitor the crop health, transpiration and sunlight absorption rates, using multispectral sensors and near infrared and NDVI data (Puri et al., 2017). Drones can conduct an inspection of the farm as well as a soil and/or field analysis can also be performed using a drone and 3D mapping. These inspections provide valuable information that leads to better crop growth (Puri et al., 2017). Using the same data and images used to determine crop health, a weed map can be created to differentiate between areas with high-intensity weed growth and areas with healthy crop growth (Veroustraete, 2015).

Another use for drones within agriculture is to assist the farmer with specific application of fertilisers to crops. The nutrient uptake is determined based on a drone-generated variable-rate application (VRA) map, based on NDVI values. This VRA map allows the farmer to adjust the amount of fertiliser to be applied to different areas of the field, depending on the nutrient uptake in that specific area. Less fertiliser is applied to healthy areas and more to struggling areas, in essence decreasing fertiliser costs (Veroustraete, 2015). The reasoning behind the precise application of fertiliser can also be applied to the application of pesticides and water, which would increase the yield for a piece of agricultural land (Puri et al., 2017). Drones integrated with GIS mapping can assist farmers to outline field borders and determine an accurate flight pattern.

Tracking and monitoring of herds of animals are simplified by utilising drones to monitor herds from the sky. Some drones contain heat sensors or cameras allowing the monitoring of herds during the night. This can be used as a method to curb livestock theft, by continuously monitoring herd quantity and activity. Drones are also used to monitor irrigation equipment, over a large surface area and especially when crops reach certain heights (Puri et al., 2017).

2.3.4 Drones in Precision Agriculture

In comparison to images obtained by satellites, drones have a higher temporal and spatial resolution, which allows the availability of high-resolution images to be examined within PA (Zhang & Kovacs, 2012). Drones offer a practical, yet inexpensive substitute for obtaining imagery through satellite or aircraft applications. Zhang and Kovacs (2012) estimate that the UAS industry could potentially exceed the demand for the traditional manned aircraft industry, due to the flexible acquisition time as well as the reduced cost of image extraction.

2.3.4.1 Remote Sensing

Drones can fly at a low altitude and therefore provide images with an ultra-high spatial resolution, thus improving the overall performance of the images exceptionally (Tsouros et al., 2019). Drones provide the user with high flexibility as they can be flown at any time and as frequently as the user requires and thus provides a high temporal resolution. In comparison with a manned aircraft, a drone is much cheaper and easier to use. With regards to ground-based sensors, a drone is more efficient as it can cover a larger area in a shorter amount of time and collect imagery in a non-destructive way.

2.4 Crop Monitoring

Traditional methods of crop monitoring are labour-intensive as it requires observational field work, usually conducted by several individuals walking into the fields and assessing the plants. Some farmers conduct the monitoring process by themselves, which becomes more timely and inefficient as the size of the farm increases. Methods like sectioning and numbering different parts of the fields are also utilised during manual crop inspection procedures. Alternative methods to conduct crop monitoring correspond to the different types of remote sensing techniques, such as ground-based, airborne and satellite remote sensing. However, most farmers (more specifically smaller-scale farmers) do not utilise these remote sensing methods due to the increased cost of these methods. They rather utilise their already employed labour force to conduct inspections of the crops and agricultural fields

2.4.1 Crop Monitoring Using Drones

The simplest form of a drone system contains the drone and attached to it a basic camera, usually a GoPro or Canon digital camera, which only takes still images (Stehr, 2015). Once the customer has decided what features are needed, other types or cameras or sensors can be attached to the drone. A wide range of measurements is typically taken when conducting crop monitoring or crop scouting with the aid of a drone.

A UAS typically includes the drone used as well as the control systems and additional sensors, when used within PA. Tsouros et al. (2019) specify the key elements or equipment needed when utilising a UAS for PA. The necessary components usually include the following:

- *One or multiple drones (UAVs):* A drone suitable for use within agriculture is required, which can either operate autonomously or remotely.

- *Sensors:* The sensors typically include the cameras used to capture necessary images and the different sensors. The most common sensors used for agricultural applications are discussed later in this section.
- *Drone control system (DCS):* This system is used to control the drone(s). Drone flights are typically either controlled by a built-in computer, with a built-in GPS or a remote control system. Recreational drones typically contain a built-in GPS and are controlled via a remote control application on a smart device (smartphone or tablet). This system allows for the proper operation of the drone by communicating in two directions with the flight control system or autopilot system. The DCS receives data and in turn processes it to ensure the drone operates as it should. The control system also has the ability to receive information from the sensors attached or included on the drone, perform correcting actions and in turn, communicate this to the ground control system in real-time. These sensors monitor flight properties, such as air force, altitude, etc.
- *Ground Control Station (GCS):* The GCS is usually a computer that can communicate to either the DCS or directly to the drone. This system monitors the drone flight information. The GCS provides the user with flight data along with data measured by supporting on-board sensors. The software required to process and analyse data obtained by the drone is included in the GCS. The software allows the user to extract the necessary information used for crop monitoring.

The list above indicates the necessary components or elements required to utilise drones within PA. Additional information pertaining to each element is provided in the paragraphs to follow.

2.4.1.1 Drones

Various categories of *drones*, as mentioned above, and different models and makes of drones within the same classification exist. Puri et al. (2017) identified different drones available for agricultural use along with their technical specifications. Due to the fast-changing nature of technology, and especially with regard to improved models of agricultural drones, more information on the available drones and their specifications will be provided at a later stage in this project.

2.4.1.2 Sensors

Sensors are included in a UAS to capture high spatial and temporal resolution images to facilitate the monitoring of various vegetation characteristics. G. Yang et al. (2017) specify that a large variety of sensors are available for drone usage in PA, dependent on the variety of crop parameters to be monitored. Sensors attached to drones need to adhere to certain requirements, for instance: they must be small in size; have a low weight; and low energy consumption. Limitations such as a low payload capacity as well as the application of small platforms limit the selection of drones. The most important requirement a drone needs to adhere to is its ability to capture high-resolution images that can be analysed after the flight has been performed.

The latest on-board sensors used within PA can be divided into four types according to (Tsouros et al., 2019), namely:

- Multispectral sensors
- Hyperspectral sensors
- Visible light sensors (RGB)
- Thermal sensors

Other sensors available for use include laser scanners or light detection and ranging (LiDAR), however, these sensors are mostly used for environmental purposes such as terrestrial scanning. The sensor types mentioned above can monitor separate characteristics pertaining to vegetation. They can monitor the colour and texture of the vegetation, as well as the geometric outline of crops. Other sensors measure the radiation, only particular wavelengths emitted from the plants. Important crop characteristics throughout the different growth stages can be determined through further processing of data obtained by these sensors. The characteristics monitored include soil moisture, plant biomass and vegetation health (Tsouros et al., 2019).

Airborne imaging sensors are classified as multispectral and hyperspectral according to the number of spectral bands and band widths measured by the sensor (C. Yang, 2018). A multispectral image sensor measures emitted or reflected energy in 3–12 different spectral bands, whereas a hyperspectral sensor measures the radiation across the electromagnetic spectrum in tens to hundreds of narrow spectral bands. In short, these sensors gather information regarding the spectral absorption and reflection of vegetation on several bands (Tsouros et al., 2019).

According to C. Yang (2018), hyperspectral sensors deliver images with a higher spectral detail than that multispectral sensors.

For most PA applications, multispectral imagery with the four standard spectral bands (green, blue, red and Near Infrared (NIR)) are sufficient. Additionally, one can add bands in red edge, Shortwave Infrared (SWIR) and thermal wavelengths can be used for other specific applications. Hyperspectral sensors on the other hand can detect spectrally identical plant species or symptoms. The spectral information obtained from these sensors can assess various biological and physical characteristics of crops. Tsouros et al. (2019) specify that the unhealthy plants or part of the plants can be distinguished with an image. This is possible due to the chlorophyll in the plant absorbing the visible radiation in the red band or channel, but strongly reflecting the NIR. The information obtained by the NIR channel is sufficient even if it is not yet visible in the red channel. Calculations of multiple vegetation indices are based on the spectral information obtained by the sensors. Vegetation indices are discussed in more detail at a later stage in this section.

Despite the high cost of multispectral and hyperspectral sensors, these sensors are frequently used within PA. Between the two sensors, multispectral sensors are used more frequently due to their slightly lower cost (Tsouros et al., 2019). The only drawback identified concerning these sensors is the need for complex post-processing techniques required to extract information from the images.

Visible light sensors (RGB) are used most frequently for PA applications containing a drone or UAV. Compared to other sensors, these sensors are cheaper, while still offering high-resolution images. The sensors are easy to operate, they are lightweight and the processing of information is relatively simple (Tsouros et al., 2019). RGB sensors can capture images in both sunny and cloudy weather conditions, but require a specific time frame (depending on the weather conditions), to limit under- or overexposure of images. These sensors are used in conjunction with other sensors, as they are incapable of analysing various vegetation parameters that require spectral information outside of the visible spectrum.

Another type of sensor used in PA is *thermal infrared sensors.* These sensors measure the temperature of plants or objects. A thermal image is created which is then analysed, instead of studying the visual properties of the images. Infrared energy is obtained through an infrared sensor as well as an optical lens. Objects containing a temperature above absolute zero (-273ºC), emit infrared radiation at specific long-wave infrared (LWIR) and medium-wave infrared (MWIR) bands, proportional to their internal temperature (Tsouros et al., 2019). A grayscale image indicating the heat representation of an area is developed based on the radiation within these wavelengths detected by the thermal camera. Some sensors or thermal cameras can also create a coloured image indicating the warmer objects as yellow or red and the cold objects as blue. Infrared sensors are less often used for crop monitoring purposes, but have other specific applications within PA.

2.4.2 UAV Data Processing Methods

Various data processing techniques exist to analyse the imagery obtained during drone flights. Tsouros et al. (2019) discuss the diverse methods to study the different vegetation features from the information obtained from sensors or cameras attached to drones. The most common crop features that can be monitored by a remote sensing drone system are shown in Table 4.

Table 4 Crop Features to be monitored by Drone System

The entity to be measured	**Crop features**
Vegetation	Vegetation indices Nitrogen status Biomass Temperature Spatial position of object(s) Vegetation colour Moisture content Shape and size of different elements and plants Spectral behaviour of chlorophyll
Soil	Temperature Moisture content Electrical conductivity

Tsouros et al. (2019) identified three of the most commonly used analysis techniques to process and analyse imagery obtained from drones for PA applications. These techniques include the following:

- Vegetation indices calculation
- Machine learning methods
- Photogrammetry techniques.

These three techniques will be discussed in further detail in the subsections to follow.

2.4.2.1 Vegetation Indices

The most popular method to analyse data for remote sensing applications within PA is Vegetation Indices (VIs). VIs are defined as unit less radiometric measures, which characterises the biophysical features of plants (Wójtowicz et al., 2016). VIs are calculated as ratios or the difference between two or more bands within the Visible Light (VIS), NIR and SWIR wavelengths. VIs utilise different mathematical combinations of two or more spectral bands within the electromagnetic spectrum. These indices are designed to minimise external confounding factors while maximising vegetation characteristics' contributions (Tsouros et al., 2019). A VI is deemed useful based on the low sensitivity to factors limiting the remote sensing data interpretation as well as their high correspondence to the actual biophysical parameters of plants. VIs are effective when monitoring the health and growth of crops, based on the absorption of electromagnetic radiation from the vegetation (Tsouros et al., 2019). VIs are deemed to be an effective method to measure and monitor the health of crops qualitatively and quantitatively.

Different VIs have been developed, as each environment consists of its unique characteristics, which need to be taken into account when using a VI. Each VI, therefore, has a unique combination of the reflectance of different spectral bands, to be able to detect vegetation (Tsouros et al., 2019). The calculations can be done premised on the information pertaining to an individual photograph as well as an orthophoto or orthomosaic of the entire crop. An orthophoto is a geometrically corrected aerial photograph, whereas an orthomosaic is an aerial image created by combining many smaller images (usually orthophotos) into one large image.

VIs share a relation with different parameters of vegetation, and therefore a full understanding of spectral behaviour is required to analyse various features of vegetation. VIs are typically calculated based on the light or radiation reflected from the vegetation compared to the soil. Two categories of VIs exist. The first uses multispectral and hyperspectral data, whereas the second uses information from the visible spectrum. More information regarding specific VIs is discussed in the theoretical framework of this report.

2.4.2.2 Machine Learning

The second data or image processing method identified by Tsouros et al. (2019) is that of machine learning. Mitchell (1997) defines machine learning as "the field of study that gives a computer the ability to learn without being explicitly programmed." According to Carbonell, Michalski, and Mitchell (1983), machine learning can be divided into three main areas of focus, namely:

- *Task-oriented studies:* This approach is also known as the engineering approach and consists of the analysis and development of learning systems to improve the performance of a set of predetermined tasks.
- *Cognitive simulation:* This entails the simulation and investigation of human learning processes.
- *Theoretical analysis:* An independent theoretical analysis of possible learning methods and algorithms within an application domain.

In addition to the categories of machine learning, the three main types of machine learning are specified, namely: supervised learning; unsupervised learning; and reinforcement learning (Das, 2017). *Supervised learning* occurs if the relationship between the input and output is already known. Thus, the user knows what the correct output is based on the given data set. Supervised learning can in turn be classified into classification and regression problems. A classification problem aims to predict or map input variables into a discrete category of outputs. A regression problem on the other hand aims to map input variables to a continuous output. During *unsupervised learning,* problems or instances are approached to which results are unknown to the researcher. Structure is derived through a method of clustering data with regard to the relationships identified between variables. The only drawback of unsupervised learning is the lack of feedback from the predicted results. Finally, *reinforcement learning* is a field of machine learning that studies how agents should behave in an environment to maximise their cumulative reward. Different types of machine learning techniques used most commonly include: function approximation and nonlinear regression; Pattern recognition and classification; clustering and; time series and dynamic systems. Each of the mentioned machine learning techniques is discussed in the sub-parts to follow.

i) Function Approximation and Nonlinear Regression

Another way used to describe supervised learning within machine learning is through the use of function approximation (Brownlee, 2020b). Function approximation is a methodology used to estimate an unknown, underlying function using historical or available observations from a domain. Thus, an unknown underlying function is assumed within a dataset that continuously maps inputs to outputs within a target domain and therefore results in a complete dataset. Supervised learning, more specifically neural networks can be used to approximate the unknown function represented by the dataset. Other approaches to function approximation include least squares linear approximation and other complex methods like approximation with splines (Andras, 2013). The approximation is done by minimising the calculated error between predicted and expected outputs.

A popular method used to predict an output variable based on a set of given inputs or predictor variables is that of regression (Saeed, 2021). An unknown function maps the input variables to the output variables within regression analysis, where one can assume that a linear or nonlinear regression model can be used to approximate this function. Nonlinear regression can be distinguished through the relation between the prediction equation and one of more of the unknown parameters. This relation is defined as a nonlinear relation (Smyth, 2002). Linear regression on the other hand is most often used to create an empirical model, whereas nonlinear regression is utilised when physical evidence exists that the relationship between the predictors and response follows a specific functional form. Rhinehart (2016) specifies the objective of regression is to alter and adjust model coefficients to match the output data obtained by the model in accordance with the fixed input values. Once the model coefficients is found that minimise the sum of the squared distances/difference between the actual data point and the model curve, one can assume that the best model is identified.

ii) Pattern Recognition and Classification

The process of describing, grouping and classifying patterns is known as *pattern recognition* (K. Chen, Kvasnicka, Kanen, & Haykin, 2001). Pattern recognition utilises computer or machine learning algorithms to recognise or identify patterns and regularities within data (Waweru, 2021). Patter recognition can be divided into either supervised or unsupervised schemes, based on the availability of information. Supervised schemes recognise unknown patterns as part of a predefined class. Whereas, input patterns are classified into clusters or classes in unsupervised schemes (K. Chen et al., 2001). These pattern recognition algorithms classify data on either statistical information or the understanding obtained by patterns and corresponding representation. Pattern recognition is classified as a type of machine learning that aims to match new data with the existing information in the database. The aim of pattern recognition is to automatically discover patterns within different forms of data, including visual data. To achieve pattern recognition the given dataset is divided into two separate datasets, the training data and the testing data. The goal for the training data is to train or build the model, through the utilisation of the learning concept. Rules used for training provide output decision criteria. The algorithms are trained to match the provided input data to each corresponding output decision (Waweru, 2021). Once a training algorithm is successfully created, the testing dataset is used to validate the accuracy of the system, by evaluating the accuracy of the outputs attained by the trained system. Once an algorithm is successfully created and trained, the process of pattern recognition can be divided into two main parts, namely an explorative and descriptive part. The explorative part of the algorithm searches for patterns in general, whereas the descriptive part categorizes the patterns found in the data.

Classification forms part of supervised machine learning and utilises algorithms to assign class labels to examples within the dataset (Al-Omary & Jamil, 2006). Classification predictive modelling predicts a class label for a given example of input data (Brownlee, 2020a). Similar to pattern recognition, a training dataset is required with numerous inputs and outputs, from which the model can learn. The created model will use the training data to calculate the best way to map the examples of input data to their specific labels. Several algorithms exist for classification problems, however, it is advised that controlled experiments should be used to identify the algorithm or configuration of algorithms that return the best performance for the classification task at hand. The success of a classification algorithm is assessed on the results obtained from modelling.

Classification can be sub-divided into four main classification tasks, including: Binary, Multi-Class, Multi-Label and Imbalanced classification (Brownlee, 2020a). Binary classification entails classification problems, where one of two class labels are assigned to the input. The two class labels used within this type of classification are usually the normal and abnormal states, denoted by the values 1 and 0 respectively. These two states are described through more fitting terms, relating to the problem, for instance 'spam' and 'not spam' for classifying emails. *Multi-Class classification* allows for the classification tasks with more than two class labels. This classification method allows examples to be categorised to a class within a known range of classes and not to either normal or abnormal states as done with binary classification. *Multi-label classification* allows for an example to be assigned to one or more class labels from the two or more available class labels. This method of classification is used to predict multiple outputs, whereas both binary and multi-class classification predicts a sole class label for each example. The classification task where the amount of examples included in each class is unevenly distributed is known as *imbalanced classification* tasks. These classification tasks are usually of binary nature, where most of the examples included in the training dataset are categorised in the normal class, with the minority in the abnormal class (Brownlee, 2020a).

iii) Clustering

According to Madhulatha (2012), clustering can be deemed as the most important unsupervised learning problem. The goal of clustering is to find natural patterns or structures within the feature space. A cluster is defined as a group of data objects with a similarity between them and a dissimilarity to the data objects categorised in the other clusters. The goal of clustering is to determine and decide which examples within the dataset should be grouped together into a cluster (Al-Omary & Jamil, 2006). Clustering algorithms can be divided into hierarchical or partitional algorithms. Hierarchical algorithms identify sequential clusters based on previously identified clusters. Partitional clustering algorithms are used to determine all of the clusters at the same time. Many different clustering algorithms exist with no single best algorithm for all cases, therefore it is recommended to investigate different algorithms and algorithm configurations for each problem (Madhulatha, 2012). An example of a machine learning algorithm, based on clustering mechanisms is the Clustering Algorithm System (CAS) (Al-Omary & Jamil, 2006). The CAS combines two separate machine learning approaches, to utilise the advantages of the approaches. The first approach learns from examples, whereas the second approach learns through observation.

iv) Time Series and Dynamic Systems

Bontempi, Ben Taieb, and Borgne (2012) define a time series as a string of observations ordered in time. A time series dataset, therefore, refers to a dataset with a known time dimension, or a series of data points ordered in time (Peixeiro, 2019). Time series analysis deals with understanding the data, whereas time series forecasting makes predictions based on historical data. When plotting the time series data, different patterns, including trends, cycles, level shifts and unusual observations are uncovered. The most common approach used to model, analyse and forecast time series data is through basis statistical methodologies, including visual displays and numerical analyses. Analysis and/or forecasting of time series data is usually initiated by a graphical display of the data, known as a time series plot (Box, Jenkins, Reinsel, & Ljung, 2015). Numerical time series modelling methods include the moving average and exponential smoothing models.

Traditional time series models are categorised as either univariate of multivariate models. Univariate models include two variables, one being the time and the other the field or output to be forecasted. Multivariate models include multiple variables, with one variable fixed as time. Within machine learning, unique models are utilised to analyse, interpret and create theories or assumptions from the time series data (Tyagi, 2020). Through the use of machine learning, time series analysis and forecasting are done much faster, more precisely and more efficiently than traditional methods as machine learning algorithms allow for faster processing of larger amounts of data.

2.4.2.3 Machine Learning in Agriculture

Machine learning methods are largely used within the field of PA to analyse data obtained by drone(s) (Tsouros et al., 2019). Machine learning can be used to extract different vegetation parameters from the data collected from an agricultural field. Due to the large amount of data collected from such a field, machine learning can be applied to ultimately improve the performance of an agricultural drone system within PA. For instance, machine learning methods can assess and calculate parameters such as the growth rate of crops, detect diseases and identify objects within images. Machine learning can therefore be used for various purposes and in many different cases pertaining to agriculture (Tsouros et al., 2019).

Within an agricultural domain, both supervised and unsupervised machine learning techniques can be utilised, through regression, clustering and classification methods. *Regression* methods are frequently used in PA, specifically for drone or UAV applications. Regression methods have been applied to calculate vegetation indices based on spectral data obtained from RGB images (Z. Khan, Rahimi-Eichi, Haefele, Garnett, & Miklavcic, 2018). Other studies identified by Tsouros et al. (2019) investigated the relationship between VIs and other vegetation features. For these types of analyses, both linear and nonlinear regression methods are utilised. Information obtained by RGB, thermal sensors and multispectral sensors, investigated by way of regression methods can predict the crop water status (Romero, Luo, Su, & Fuentes, 2018).

For weed mapping and disease identification purposes, classification methods are utilised. Algorithms, including the Artificial Neural Networks (ANNs) group, are among the most commonly used classification techniques. These algorithms utilise visible light (obtained from RGB), light intensity and spectral information from the imagery captured by the drones. In addition to this data, classification techniques can utilise VIs to improve the accuracy of the analysis. Different techniques or algorithms deliver different levels of accuracy, for different crops. Convolutional Neural Networks (CNNs), a form of deep learning algorithm is one of the most popular algorithms and is deemed very effective in object detection within a large set of data (Romero et al., 2018).

A recent, yet promising machine learning technique used in PA is that of deep learning. Deep learning has become increasingly popular and can widen the typical machine learning use through added complexity within derived models (Tsouros et al., 2019). This technique uses different functions to convert data to allow a hierarchical representation of the data. Object Based Image Analysis (OBIA) is another common application of machine learning methods within PA. OBIA is used to distinguish objects within aerial images captured by a drone. The high spatial resolution of drone captured images allows for a more accurate grouping of pixels into vector objects. A typical object-oriented classification method divides the image pixels into homogenous groups, and then further classifies these groups or segments into classes according to other characteristics. OBIA is typically used to detect weeds and distinguish between different plant species in an agricultural field.

i) Photogrammetric Techniques

The final data processing technique proposed by Tsouros et al. (2019), is that of photogrammetry techniques. These techniques consider creating an accurate reconstruction of an object or scene from multiple pictures that overlap one another. 2D data is processed and a geometric relationship is determined between the images to create a 3D model of the object or area. This technique is mostly used to create or extract digital 3D surface or terrain models and/or orthophotos. Due to a drone's ability to fly at a low altitude and capture images with a higher spatial resolution, data collection for the construction of 3D models are much simpler.

In order to create orthophotos or Digital Elevation Models (DEMs) of crops or a field, a large number of overlapping pictures are required. Once a 3D model or orthophoto is created, information regarding the three-dimensional characteristics of plants or crops can be evaluated. According to research done by Tsouros et al. (2019), photogrammetric techniques are popular in all types of PA applications, since these techniques are used to create VIs maps.

2.5 Systems Engineering and Systems Thinking

Kossiakoff, Sweet, Seymour, and Biemer define the main focus of *Systems Engineering (SE)* is to "guide the engineering of complex systems." Incose and Wiley (2015) define SE as "an interdisciplinary approach and means to enable the realisation of successful systems." SE is a multidisciplinary process or profession that considers the system as a whole. The *system* is defined as a group of "interrelated components that work together to achieve a common objective" (Kossiakoff et al.). Incose and Wiley (2015) define a system through different definitions regarded as the characteristics of a system. A system is therefore defined as:

- "Man-made, created and utilised to provide products or services in defined environments for the benefit of users and other stakeholders" (ISO/IEC/IEEE15288, 2015).
- A set of elements, subsystems, assemblies or parts that are integrated to achieve a stated objective (Incose & Wiley, 2015).
- The functioning of a complex whole that is dependent on the parts and how the parts interact.
- A group of interacting elements arranged to achieve a stated purpose or purposes (ISO/IEC/IEEE15288, 2015).

A system is therefore regarded more as a whole than the combination of its individual parts. In the same sense, SE focuses on the system as a whole and its complete operation (Kossiakoff et al.). SE evaluates the system from an outsider's point of view, thus evaluates the systems' interactions with the environment and other systems as well as the interactions within the system. SE not only focuses on the design of the system, but takes into account the external factors that can affect the system design. These factors include the system operation environment, customer needs, interfacing or interacting systems, personnel capabilities and many other factors that should be incorporated into the system design. The role of systems engineers within SE is to not only guide but to lead the concept development stage of a new system development. The concept development stage concludes with the functional design of the system, aimed at meeting the user needs. Essential decisions to be made at this stage of the system design process rely on the qualitative judgements of the SE, through the exploitation of experience in different disciplines (Kossiakoff et al.). The SE process over a life cycle includes the following generic stages: concept, development, production, utilisation, support, and retirement. Through the life cycle stages, technical processes are invoked. The technical processes are applied to define the requirements for a system and then use the requirements to develop a product (Incose & Wiley, 2015). The 14 technical processes included in the ISO/IEC/IEEE15288 (2015) standards are identified and discussed in Table 5.

Table 5 Technical Processes

Technical Process	**Definition**
Business or mission analysis	Definition of the problem and its domain, identification of main stakeholders, describe the solution space and establish probable solutions.
Stakeholder needs and requirements definition process	Identification of stakeholder needs and transforming the needs into formal stakeholder requirements.
System requirements definition process	Transformation of stakeholder needs into system requirements.
Architecture definition process	Evaluate alternative architectures designs for the system, select the most suitable option
Design definition process	Define system elements in more detail to allow consistent implementation, in accordance with the chosen system architecture.
System analysis process	Other analysis techniques such as simulation, modelling or mathematical analysis support decision-making activities.
Implementation process	Allows for the development of the system and each of its elements in accordance with the requirements specified.
Integration process	System elements are combined into a complete system that adheres to the system requirements, architecture and design.
Verification process	Aims to prove that the system and/or elements satisfy the requirements.
Transition process	The designed system is installed into the operational environment.
Validation process	Provide evidence that the system operates as intended in the correct operational environment and meets all the defined operational requirements.
Operation process	The system is used as intended.
Maintenance process	The system is maintained to ensure it functions as intended.
Disposal process	System reaches the end of its existence. Parts or elements or the whole system are disposed of in responsible ways.

Smith and Terry Bahill (2010) refine the basic SE process to the following steps:

1. Customer needs definition
2. Document requirements
3. System design
4. System implementation
5. Verification and validation of the system
6. System deployment, use and disposal

This process is illustrated in Figure 1. Smith and Terry Bahill (2010) deem attributes as highly important as it is essential in satisfying the needs of customers. The authors Smith and Terry Bahill (2010) conducted a study on attribute substitution within SE and the SE process life cycle. Thus, attributes are included in the SE process illustrated in Figure 1.

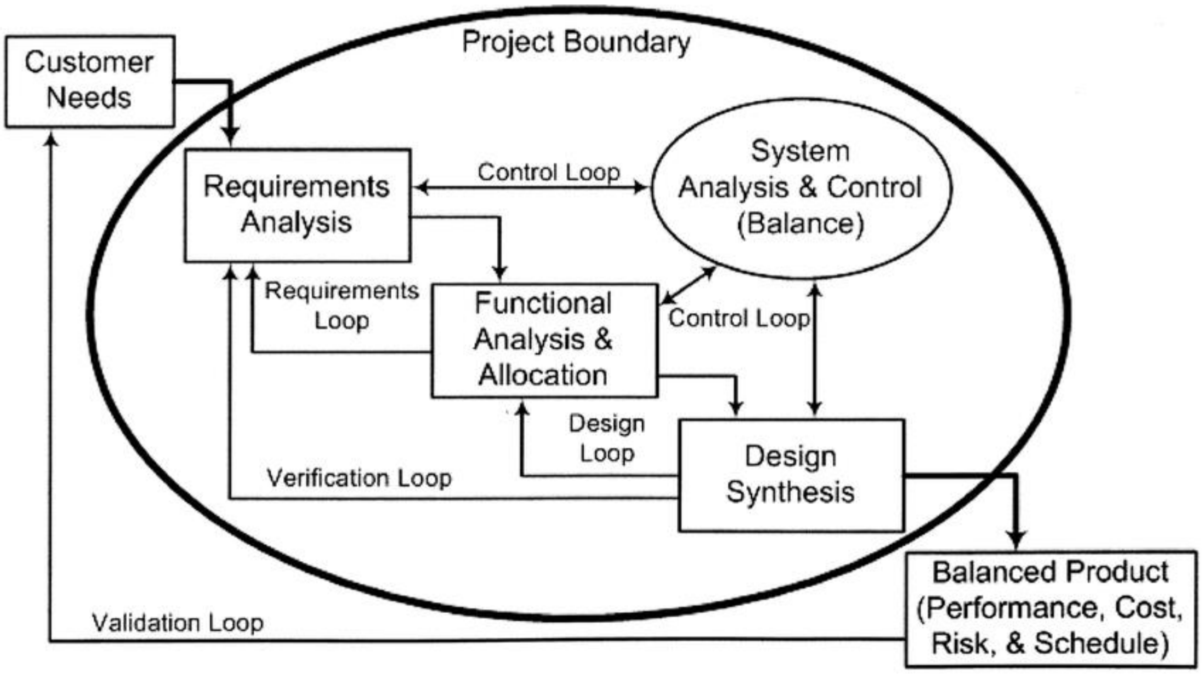

Figure 1 Systems Engineering Process (Smith & Terry Bahill, 2010)

Attributes are defined as characteristics that are intangible and complex, which makes it difficult to specify. Regardless, attributes play a vital role in SE activities according to Smith and Terry Bahill (2010). Attributes become tangible when they are realised as requirements. The customer needs that serve as the main input to the requirements analysis phase typically fall outside of the project boundary and are usually defined in the project statement. Included as part of the customer needs are the goals or capabilities of the project, the project scope, stakeholders, and list of deliverables, key decisions and the preferred alternatives. The rest of the SE process follows the generic process as described above, however, some processes are condensed and combined into one larger process. Once the customer needs have been defined, the needs are transformed into requirements and analysed in the requirements analysis phase. The defined requirements are then translated into system functions. The functions are analysed and allocated in the functional analysis and allocation process. Requirements and functions are evaluated and verified through the requirements loop. In the design synthesis, the defined functions are utilised to design the system according to the defined functions. The design loop is used to review and evaluate the functional analysis and design synthesis processes against one another. Each of the three processes mentioned is evaluated and validated through control loops connecting each process with the system analysis and control process. The output from the design synthesis phase is typically a balanced product, which should be validated through comparison with the originally defined customer needs.

2.5.1 Complex Systems

Systems engineers require sufficient knowledge of the different interacting disciplines included in complex system development (Kossiakoff, Sweet, Seymour, & Biemer). A *complex system* is typically defined as a system consisting of complicated, interrelated parts. Complex systems are known for their hierarchical structure containing various important elements that interact. These elements are known as *subsystems*, which are broken down into components, subcomponents and parts. Ottino (2003) defines a complex system as a system with many communicating elements that interact with each other and the external environment. A common quality of complex systems is how they exhibit organisation without anything organising the elements. Another way to identify a complex system is the systems' tendency for many interactions, including non-linear interactions. Interactions occur between immediate elements as well as distant elements. Complex systems are difficult to understand or predict its behaviour in different scenarios or environments. Many complex systems cannot be broken down into independent elements for analysis, design and development. Knowledge of the elementary parts of a complex system does not necessarily define the behaviour of the larger system (Ottino, 2003).

2.5.2 Systems Thinking

The term *systems thinking* has been defined and redefined numerous times, with no single best definition. Through the use of different definitions of systems thinking, the concept is explained. Systems thinking can be described as the identification of assorted individual elements that relate with one another towards a common purpose, the function of the unit (Munro, Ramu, & Zrymiak). It utilises tools and methodologies to comprehend the activities conducted at a specific operation and how that activity might affect other activities or be affected by other activities. Systems thinking can be used to understand a process and identify the changes that might occur within the rest of the process when a single factor is influenced or changed in a certain way. Senge (2006) defines systems thinking as "a discipline for seeing wholes and a framework for seeing interrelationships rather than things." V. Anderson and Johnson (1997) describes systems thinking as a set of tools, as well as a framework to review problems or issues as systemic wholes. V. Anderson and Johnson (1997) categorised systems thinking into foundational principles that aid in the definition of systems thinking. These principles are: think of the 'big picture; recognise the nature of systems to be dynamic, complex and interdependent; measurable as well as non-measurable factors should be taken into account; balance both short and long-term perspectives and; keep in mind that everybody forms part of those systems in which they function and influence those systems in a similar way that the systems influence the individuals. Sweeney and Sterman (2000) defines systems thinking as the capability to illustrate and analyse the dynamic complexity of a system, either through textual or graphical displays of both. From this definition of systems thinking, a list of systems thinking skills are listed, which include:

- Understand the dynamic complexity of a system, thus how its behaviour emerges from interacting agents over time.
- Identify and illustrate feedback processes that portray system behaviour patterns.
- Be able to identify stock and flow models.
- Recognise a delay within the system and how it can impact the system.
- Be able to identify nonlinearities.
- Identify the boundaries of mental and formal models and how these boundaries can be challenged.

This definition focuses on the dynamic complexity of systems, and not on the elements that interact with each other.

2.6 Decision Support Systems and Frameworks

A decision support system (DSS) is formally defined as an interactive system designed to assist the decision-making process of unstructured or ill-structured decision-making problems (Sprague Jr, 1980). These systems are typically computer-based and rely on using data and models to solve problems. Generally, a DSS can be subdivided into three subsystems, the user-system interface, the data subsystem, and the model subsystem (Kim-keung Ho & Sculli, 1994). The user-system interface is the link between the decision-maker and the system. The data subsystem, known as the database management system, is where all data is stored, managed and can be retrieved from to be analysed and displayed. The third subsystem, formally known as the model base management system, incorporates the model(s) or groups of models, used for analytical purposes and solving user queries. Sprague Jr (1980) specifies that a DSS should possess the essential features, listed below:

- The aim of a DSS is to support or assist in the decision-making process, not replace it.
- A DSS should focus on unstructured or poorly structured decision-making tasks.
- All models and data included in the DSS should be arranged around the potential decision.
- A DSS should be easy to use and understand and is typically delivered as a software package.

Along with the above-mentioned essential features, some nonessential, yet desirable features for a DSS are identified. These features include:

- The decision-makers should have complete control over the DSS, if possible.
- An immediate response should be enabled through interactive processing.
- The designed DSS should be comprehensive while providing support throughout the entire decision-making process.

Boza, Ortiz, Vicens, and Poler (2009) identifies three constructs that play a vital role in information systems and decision technologies, especially in how they interact. These constructs include: data modelling; decision modelling and; model analysis. Decision modelling is the most relevant construct and develops a model(s) that grasps the structure and decisions regarding a given problem. The models are further used to evaluate all feasible decisions or actions that can be made within the given problem area, and the potential outcomes of the selected actions or decisions. The data modelling construct provides the necessary information about the decision problem to the decision-maker. The construct refers to how recorded facts are represented internally and presented externally. The third construct, model analysis and investigation, allows for the creation of model instances with data and the evaluation of the parameters and results of the model. This is all done to gain insight and build confidence into the model.

2.6.1 A Framework for Decision Support System in Hierarchical Extended Enterprise Decision Making

Boza et al. (2009) developed a framework for DSS in hierarchical extended enterprise decision-making, which is deconstructed into four parts, namely: components, relationships between components, main roles and a DSS platform. The first part or step of the framework is to define the *components* for each of the constructs (data modelling, decision modelling and model analysis). The data modelling components are defined to generate a structure for the representation of the data used in the system. The datasets are structured into entities, relations and attributes. Decision modelling components are used to determine the structured visualisation of hierarchical decision models. The last construct, model analysis and investigation, allows for the creation of instances of the model with the data. The data modelling construct is further defined into its entities, relations, attributes and models. The decision modelling construct relates to the structure of the decision models. Components defined within this construct defines the hierarchy of the decision models. The first component, *hierarchy,* identifies the hierarchy of the decision problems of a complex problem. The *hierarchy level* identifies the level of the hierarchy, as each level corresponds to a decision sub-problem. A *decision model* presents the mathematical representation of the problem, to find the most optimal solution. The decision model correlates to the data model. A *level model* is where the decision model and data model connect to a hierarchy level. Each level model is regarded as abstract to a certain level, and the *aggregation or disaggregation processes* allow for the link between the lower and higher levels of the hierarchy.

The second part of the framework defines and explains the *relationships* between the components of the framework defined in the previous step (Boza et al., 2009).

Relationships exist on different levels within the framework. Within the data modelling construct, relationships and interactions exist between entities and their attributes, as well as between different entities and other attributes should new relationships arise. Within the decision modelling construct relationships usually exist between different hierarchical levels defined within this construct. Components within the model analysis and investigation construct are resolved using the level resolution process within the extended enterprise decision data model.

Thirdly, the main *roles* required to model and operate the DSS are identified and defined. These roles are defined as the: decision maker; decision model designer and; information system designer. The decision maker is the individual(s) who are responsible for deciding on a particular hierarchical level of the system. The decision model designer designs and constructs the decision models for every level of the decision problem hierarchy. Finally, the information system designer is the individual responsible for constructing the final information system. The final part of the framework is the *DSS platform*, usually a software tool, to be used within the correct context (Boza et al., 2009). The platform to be built must include all three constructs mentioned above. The DSS platform must include all necessary information included in the structural components of the hierarchy.

2.6.2 A Multi-Perspective Systems-based Framework for Decision Support System Design

Ho and Sculli (1994) proposed a system-based framework for DSS design that allows for the integration of different systems concepts into DSS design and analysis. The framework proposed by Ho and Sculli (1994) combines systems thinking concepts with DSS studies by making use of exploratory questions. As a response to the increasing complexity of DSS studies, the author proposed this framework, to allow researchers and system users to view DSSs from a wider perspective. The framework is suggested to be a comprehensive framework, based on concepts of multiperspectivity, with a critical and creative approach. The building blocks of the framework originate from systems thinking methods, including synthesis, expansionism and producer-product relationships. Synthesis allows for the explanation of the system in which the to-be-explained event is located, the explanation of the behaviour of the domain that contains the event, and the explanation of the role(s) of the event within the containing domain. Expansionism explains how expanding the domain of the area under study, can increase the understanding of the phenomenon. The producer-product relationship supports the concept of influencing factors or producers, which is required, but not sufficient to explain the results or products.

2.8 Alternative Solutions

By conducting a thorough review of the literature within the PA and remote sensing environments, specifically with regard to crop monitoring through the use of drones or UAVs, different techniques were identified to implement such a system on a farm. In addition, different techniques with regard to data analysis processes were also identified. As a result of the above-mentioned review, alternative solutions were identified to address the stated need. Of these alternatives, one alternative will be selected as the preferred solution. The alternative solutions were evaluated against one another based on various criteria.

The identified alternative solutions are discussed in the paragraphs to follow.

2.8.1 Alternative Solution 1: Holistic Framework for Traditional Crop Monitoring Methods

The most basic method of crop monitoring is manual crop or field inspection. This is usually conducted by a number of workers walking a section of the fields or the entire field and evaluating and inspecting a sample or all of the plants or crops. An alternative method utilised by many farmers is the evaluation of aerial images obtained through satellite remote sensing methods. Other farmers utilise traditional manned aircrafts to capture aerial footage, however, this methodology is not as widely used as satellite imagery.

An alternative to meet the defined project need and opportunity is to create a holistic framework for the monitoring of crops, by processing and analysing satellite obtained images. This method does not require any aeroplanes, cameras or sensors as the images are obtained from an existing satellite. These images are usually ordered from an organisation providing these types of footage and then analysed either in-house or by a service provider specialising in data extraction and analysis of aerial footage.

The framework to be designed should encompass various inputs and variables, and present the user with sufficient and accurate data to make informed decisions regarding their crops. The inputs to this framework are relatively straightforward as one only needs to decide on the data to be collected from the aerial images and the data processing methodologies to be followed. Since the images are captured from orbiting satellites, one cannot determine the altitude of the satellite or the frequency of when the images are captured. These variables are specified by the company providing the service. The only aspects to be determined by this framework is the type of data and the information gathered from the data. The cost of such a system varies depending on the spatial, and temporal resolution required.

2.8.2 Alternative Solution 2: Integrated System of Solution for Crop Monitoring using UAVs

This solution alternative aims to design and develop an integrated system of solution for decision support for the implementation of a remote sensing crop monitoring system, using drones, related sensors, equipment and data processing techniques and software. As determined throughout the literature study, such systems were specifically designed or evaluated on a single farm or study area. Due to the ever-improving technology and development of new software tools, many studies only evaluate the effectiveness of drones or UAVs for remote sensing or PA applications. Other studies evaluate the accuracy of data processing methods such as machine learning and image processing software. Some studies focus solely on the sensors or equipment used and how to process and interpret the data obtained by these sensors. Little to no literature was found defining a complete holistic framework or solution system to be used to implement a remote sensing system, utilising drones on any farm.

Hosseiny, Rastiveis, and Homayouni (2020) proposed a framework for detecting plant species in agricultural lands using drone images, based on image processing and deep learning methodologies. This framework operates completely automated and unsupervised and is designed to generate unlimited amounts of simulated training data from captured drone images. Another study, conducted by Gao, Sun, Hu, and Zhang (2020), attempted to design a framework for the monitoring of agricultural diseases and pests based on drones and Internet-of-Things (IoT). The goal of this work was to design a framework to provide useful insights into the specific relationships between different weather parameters and the existence of pests or diseases on crops. Rakhade, Patil, Pardeshi, and Mhasde (2021) develop a hierarchical framework that selects the most optimal crop spraying drone using multiple attribute decision-making (MADM) strategies. This study aims to find the most optimal UAV for a certain scenario of crop monitoring purposes.

This solution will encompass different inputs to the system, and based on these inputs, one would be able to generate outputs regarding the various aspects of the system. These aspects to be considered include: the types of drones, the level of automation of the system, the sensor types, camera type, data to be collected, data analysis methods, the frequency of drone flights, and the altitude at which drones should fly. This list will continue to grow as the design and development of the system proceeds.

2.8.3 Evaluating Alternatives

The alternatives above are evaluated against certain criteria to determine the preferred solution to effectively address the identified project need and aim. The main criterion to be met by the selected alternative solution is its ability to create a usable product that recommends a solution to the end user, with regard to the design of an agricultural drone system. Additional criteria used to evaluate the identified alternatives are indicated in Table 6.

Table 6 Evaluation of Alternative Solutions

Criteria	**Alternative Solution 1**	**Alternative Solution 2**
Does the alternative address the stated project need/opportunity to meet the project aim?	Yes	Yes
Does the alternative address all of the research questions?	No	Yes
Does the alternative address/meet all of the research objectives?	No	Yes
Is the supporting literature relevant and supporting the effectiveness of the solution space?	No	No
Does the alternative address the opportunity and created a solution from a holistic point of view?	Yes	Yes
Does a gap exist in the literature, giving way to a newly designed solution alternative?	No	Yes
Does the alternative provide an effective end-product, suggesting a solution specific to the stated inputs?	Yes	Yes

When comparing the alternative solutions, solution 2 should be selected as the preferred solution, as the solution meets more of the stated criteria and especially the most important criteria. The preferred alternative solution is discussed in the following section.

2.9 Preferred Solution

Ultimately this project aims to address the identified research questions as well as meet the research objectives. The selected solution alternative is intended to address the research questions and objectives defined in Chapter 1. The research questions and objectives are defined in such a manner that the overall project aim is reached, and the identified opportunity is addressed.

The solution approach is divided into two large phases. The first is conducting a thorough literature review to obtain the necessary information required to construct the solution. The second part is the designing and developing of the integrated system of solution based on the relevant literature. These two phases or sections, along with the steps and objectives of each are summarised in Table 7. The research objective addressed by each proposed step is also identified below.

1. Holistically identify attributes of drones that are relevant to the monitoring of crop health diagnostics.
2. Conduct of analysis on identified attributes spanning across their optimum combinatorial integration for different crop farming systems.
3. Design and development of an integrated system of solution capable of being deployed for the purpose of decision support and evaluation of crops in semi-commercial or commercial farms.

Table 7 Solution Steps

Phase	**Aim**	**Steps**
Review literature	The main goal of this step is to thoroughly review literature regarding the entire project scope.	Determine the feasibility of designing such a solution within PA applications. (RO 1) Identify all of the various aspects to be considered when designing a holistic framework. (RO 1) Define different input variables and obtain sufficient information regarding each input. (RO 1 & 2) Evaluate different input alternatives, such as methodologies and

Phase	Aim	Steps
		technologies. (RO 1 & 2) Investigate the relationship of each input with the selected output, based on literature. (RO 3)
Design solution	The goal for this phase of the project is to design and develop the final solution framework	Evaluate the accuracy of the relationships between the identified inputs and relevant outputs. (RO 2 & 3) Design a system of solution taking into account all of the different combinations of inputs and what outputs each present. (RO 3) Evaluate the accuracy and effectiveness of the solution system. (RO 2 & 3)

Note that the table above is only a suggestion of the steps and phases to be followed throughout this project to meet the desired solution and address the project's aim. In addition to these steps, the selected research methodology (discussed in Chapter 3), should be followed in conjunction with these steps. This solution approach is designed to allow the researcher to obtain a comprehensive understanding of the research field before designing the system of solution. Due to the high reliability on the latest technologies available, the researcher will have to continuously update the information on the technologies such as the drone(s), sensors and data analysis methods or software, up until a certain date within the project timeline.

2.10 Chapter Summary

Discussed within this Chapter are the relevant areas of literature consulted to gain a better understanding of the project. The area of PA is discussed, along with a detailed explanation of remote sensing applications within PA. Three different methods of remote sensing are identified, namely: Satellite remote sensing; airborne remote sensing; and ground-based remote sensing.

UAVs are defined along with the different terms used to refer to a drone system. A brief history of drones as well as their multiple applications within the agricultural sector is explained with reference to drones within PA specifically. The legislation applicable to UAV and RPAS is investigated, especially the requirements for commercial or corporate applications. Various drone control mechanisms have been identified and evaluated. Crop monitoring methods are specifically explored, starting with a brief mention of the traditional methods of crop monitoring and then describing how crop monitoring can be done using drones. All of the identified equipment and technology required is included within this subsection. The equipment includes drone(s), ground control systems, sensors, and drone control systems. Various alternative data processing systems frequently used within PA are consulted and discussed. Machine learning is introduced and different techniques within this domain are further investigated. In addition, the specific applications of machine learning methodologies within the PA and agricultural field are discussed.

An introduction and basic explanation of systems engineering and specifically systems thinking practices are provided. The focus is placed on complex systems within the systems engineering practices and how these systems differ from other systems. Decision support systems (DSS) and accompanying frameworks are elaborated on and discussed in depth to provide a thorough understanding of these methodologies. Two previous studies conducted on how a DSS and framework interact are reviewed within this subsection.

Finally, two alternative solutions to the project opportunity were identified and discussed briefly. These alternatives were evaluated against one another and additional criteria to determine the preferred solution. Once the preferred solution was determined, a brief explanation including the planned or proposed steps to reach the desired solution system was addressed.

Chapter 3: Research Approach

3.1 Introduction

This section introduces two alternative research approaches, considered for this project. In addition, the conceptual and theoretical framework for the project is specified within this Chapter.

3.2 Case Study Research

Saunders, Lewis, and Thornhill (2016) defined a *case study* as a detailed investigation into a specific topic within its real-life setting. A *case* can refer to anything or anybody including, but not limited to, a person, a group of people, an organisation or association, an event or a change process. Another definition as presented by Gerring (2017), specifies a case as a "spatially and temporally delimited phenomenon of theoretical significance." In addition to the different cases mentioned above, a case can also refer to a state or state-like entity (such as nations, municipalities, etc.) and social groups (referring to ethnicity, gender, race, age, etc.). A case study can therefore be defined in many different ways, where the main principle is the need to explore an event or phenomenon, within its natural context (Crowe et al., 2011). Due to this reason, case study research can be referred to as a naturalistic design instead of the traditional experimental design.

Stake (1995) distinguished between three main types of case studies, namely: intrinsic; instrumental and collective. When investigating and learning about a unique phenomenon, an intrinsic case study is usually conducted, where the researcher specifically defines the uniqueness of the phenomenon. An instrumental case study evaluates a specific case to understand and appreciate the specific issue or phenomenon. When studying multiple cases either simultaneously or sequentially to generate and even broader understanding or appreciation of an issue, a collective case study is utilised (Crowe et al., 2011; Stake, 1995). One should be aware that the identified types of case study research are not mutually exclusive and can be combined.

According to Gerring (2017), a case study is a study of a single case, or a small number of cases, based on observational data, that promises to provide insight into a larger population of cases. The goal of case study research is to understand the dynamics of the topic being studied (Saunders et al., 2016).

A large amount of time is spent by researchers analysing a single case due to it being an extremely focused methodology. Therefore, when presenting the selected case(s) it can be viewed as the researcher providing substantial evidence for the argument. According to Gerring (2017), the time and attention devoted to a single case decrease as the number of cases included in the study increases. A small-C constitutes of a study of one or several cases. When the focus shifts from an individual case to that of a sample of cases, the study is defined as a large-C. In essence, this means that fewer cases are studied more intensively, while fewer cases are studied more superficially. The causal factor within case study research is observational, thus it is not intentionally manipulated by the researcher. An assumption can be made that a range of styles regarding observational evidence is applied, granting a holistic view of the case study. Evidence regarding the case study is usually generated through multilevel inference, by utilising different levels of analysis.

The goal of case study research is to analyse and explain the case(s) under investigation as well as to provide insight into a population or larger class of cases. One must be able to put the study into a larger context for it to qualify as case study research, even if it is not the goal of the author (Gerring, 2017). Case study research allows the researcher to gather information regarding the 'how,' 'what,' and 'why' aspects of the case study (Crowe et al., 2011).

3.2.1 How is Case Study Research Conducted

Crowe et al. (2011) specify the main phases of case study research:

1. Case definition
2. Case(s) selection
3. Data collection
4. Data analysis and interpretation
5. Reporting the findings

The first step in case study research is to define the case. To define a case briefly, yet appropriately one should consider the research questions, and existing literature along with a prior appreciation of the theoretical issues and setting(s) (Crowe et al., 2011). A theory-driven approach to defining a case can produce potentially transferable data. Essentially, each case should consist of a predetermined boundary, clarifying the nature of the case study and the potential time period of the case. In addition, the group of interest (social group or organisation), or geographical area of interest, the data collection and analysis priorities and the evidence types to be collected should be predefined (Crowe et al., 2011). The case definition step is preceded by the definition of the research question(s), regarding the specific direction of the research. The research questions should however correlate with the definition of the case.

The second step included in the case study research approach is selecting the case(s). When selecting a case for an intrinsic case study, the case is selected due to its uniqueness and interest to the researcher(s). Within an experimental case study, Gerring (2017) defines generic features regarding case selection, which include: case independence; intrinsic importance; within-case evidence; representativeness; and logistics.

Case independence specifies that selected cases should be independent from one another and of the other cases in the population if the study is designed to investigate a causal question.

Intrinsic importance relates to the fact that some cases are influenced by the perceived importance of a case, since some cases matter more than others, or matter more to a specific group of people.

When the purpose of a case is to provide knowledge regarding a specific subject, evidence should be extracted from that specific case, given the evidence is not available or not in a precise and reliable form. The new evidence is typically found at a lower level of analysis, referred to as *within-case evidence.*

The selected case should be *representative* of the larger population pertaining to the larger argument, in any relevant way. Within a descriptive argument, representativeness relates to features highlighted by the theory.

When identifying within-case evidence as referred to above, the availability of this type of evidence is partly due to the case itself, and partly due to the personal attributes of the researcher. An assumption is made that in any case selection process, these *logistical* features are taken into account both implicitly and explicitly.

The third step in case study research as defined by Crowe et al. (2011) is collecting the necessary data regarding the case(s). To thoroughly understand the case, multiple sources of evidence are usually gathered using a range of both quantitative and qualitative techniques. Data triangulation is suggested as a method to increase the internal validity of a case study, thus the degree to which the method appropriately answers the research question (Stake, 1995). Within multiple case study analyses, the data analysis technique should be flexible enough to allow the researcher to develop a detailed description of each individual case, before analysing the differences and similarities of the cases altogether.

Data analysis and interpretation, the fourth step of case study research, overlaps with the third step, data collection. Crowe et al. (2011) suggest the analysis of data regarding the individual component of each case should be done first, before comparing the findings against other cases. A method of organising and coding data along with key issues from the literature and dataset is proposed to allow for easy retrieval at a later stage in the process. An approach suggested for analysing large datasets in a limited time is the Framework approach. This approach consists of five stages, namely: familiarisation; identify a thematic framework; indexing; charting; mapping; and finally interpretation. Integrating the different data sources and reviewing emerging themes, is aided by theoretical frameworks (Crowe et al., 2011).

The final step in case study research is to report the findings, thus providing the reader with sufficient contextual information to understand the processes followed and the conclusions reached (Crowe et al., 2011). Many researchers choose to present individual case findings separately before combining findings across cases in a collective case study. Gerring (2017) defines this last step in case study research as the validation part of the process, where both internal and external validity is assessed. Internal validity refers to the inferences regarding the causal effects, thus the relationship of two instances with regard to one another. The external validity attempts to generalise the selected case(s) to a larger population of cases or to the natural context of the case.

3.2.2 Advantages of using Case Study Research

Krusenvik (2016) analysed the advantages of using case studies as a research methodology and presents various statements and evidence from other sources of literature. The main advantage of case study research is its ability to understand and change interwoven complexities of interpersonal processes emerging in a wider social context. Case study research is applicable to both qualitative and quantitative research methodologies. Some advantages of the case study research approach include:

Flyvbjerg (2006) states the most important advantage of case study research is that it can focus on a single real-life situation and test different views directly concerning the phenomena as it unfolds in a real-life context, and thus provides a detailed analysis of a single case. The internal validity of case studies is high due to the study methods gaining relevant and detailed data, which is not taken out of context (Jacobsen & Sandin, 2002). Case studies allow the researcher to get as close as possible to the area of interest under investigation, by observing the phenomenon within its natural environment or context. Other advantages include the ability of the case study research method to perform an intensive study into an event, phenomena or topic. It allows the researcher to continuously analyse the situation and provides the opportunity to compare different facts about the topic under investigation. Case study research is one of the best ways to stimulate new research or studies within a specific field or research topic.

3.2.3 Disadvantages of Case Study Research

Most critics demonstrate that the very status of case study research as a scientific method is being questioned, thus its theory, reliability and validity are the main issues (Flyvbjerg, 2006). Krusenvik (2016) expresses the five most commonly discussed disadvantages of case study research, as mentioned by Flyvbjerg (2006). These disadvantages include:

- One cannot accurately generalise a topic, event or phenomenon from a single case.
- Case studies are effective in generating hypotheses, whereas other methods are more suitable for testing hypotheses.
- Theoretical knowledge is more valuable than practical knowledge.
- One often struggles to summarise specific case studies.
- Some case studies contain a bias towards verification.

According to Yin (2009), the greatest concern of case study research is its lack of rigour. It is common that the researcher or investigator has too much freedom when investigating a case and therefore does not follow systematic procedures.

3.3 Inductive Research Approach

Inductive and deductive approaches are referred to as broad methods of reasoning (Trochim & Donnelly, 2007). Induction is defined as moving from the specific to the general while, deduction starts at the general and ends at the specific. According to Trochim and Donnelly (2007), any argument or topic based on observation or experience is communicated effectively through induction, while arguments based solely on laws, rules or other principles are best communicated deductively. Streefkerk (2019) specifies the aim of inductive reasoning is to develop a theory, while deductive reasoning aims to test an existing theory. According to Goddard and Melville (2004), an inductive approach (or reasoning) starts with the observation of cases, thus collecting sufficient data, and proposing theories towards the end of the research process. According to Thomas (2003), the inductive approach is a structured approach to analyse qualitative data, guided by specific objectives. Bernard (2011) indicates that inductive reasoning allows the researcher to search for patterns from observation, and only then develop explanations or theories for those identified patterns. The goal of an inductive approach is to allow research-based findings to emerge from raw data without the restraints posed by structured methodologies (Thomas, 2003).

Using an inductive approach does not suggest theories be disregarded when formulating objectives and research questions and therefore does not prevent the researcher to use or consult existing theories when defining research questions (Dudovskiy, 2018). The process of inductive reasoning starts with an in-depth observation of the world, a topic, phenomenon, case or idea. After thorough observation, the aim is to determine patterns or relationships within the observed case. The type and nature of the research findings and the final hypotheses are only determined once the study is completed. An inductive approach is typically associated with qualitative data collection and analysis methods (Dudovskiy, 2018).

Some underlying assumptions are identified by Thomas (2003) for the use of the general inductive approach. These assumptions include the following:

- The findings from the analysis are determined by both the outlined research objectives (a deductive approach), as well as the findings and interpretations obtained from the data analysis (an inductive approach).
- The fundamental method of analysis aims to develop categories obtained from the data into a model or framework. This model or framework should capture the key themes and/or processes deemed significant by the researcher.
- The findings obtained from the research are shaped by the researchers' assumptions and experiences while conducting the data analysis. The researcher, therefore, needs to decide on the importance of the findings within the research.

- As each researcher uses discretion, the findings presented will not be identical or contain overlapping components.
- Techniques exist to evaluate the trustworthiness of the findings. These techniques include independent replication of the research; comparison of findings to that of previous research; participant feedback; triangulation of data and conclusions; and feedback from the users of the research findings.

Keeping the assumptions in mind, the following procedure is defined to conduct an inductive analysis of qualitative data (Thomas, 2003):

1. *Prepare raw data files*: Format all of the raw data files into the same format and make a backup of each data file.
2. *Read text closely*: The researcher is required to read the data files closely in order to become familiar with the content while gaining a thorough understanding of the possible themes and details.
3. *Create categories:* The researcher identifies important or recurring categories or themes. The general categories are most likely to be derived from the research objectives and aims, whereas the specific categories will be obtained from reading the raw data multiple times. Text coding methods are utilised during this step of the approach.
4. *Overlapping coding and un-coded text:* Qualitative coding contains two distinct rules compared to quantitative coding, namely: a segment of text may be coded into multiple categories; a large amount of text may not be allocated to a category, as a large part of that text is not relevant.
5. *Continuous revision and refinement of category system:* Revise each category and identify sub-topics, contradicting points and new insights. Identify suitable quotes from the text that convey the main points or theme of each category. Categories with similar meanings can be linked or combined under a single subordinate category.

Thomas (2003) specifies that the ideal number of categories to be created is between three and eight, which should capture the core themes prevalent in the data. These categories are to be assessed against the research objectives.

3.4 Conceptual Framework

Figure 2 specifies the conceptual framework for the project, based on the selected research approach.

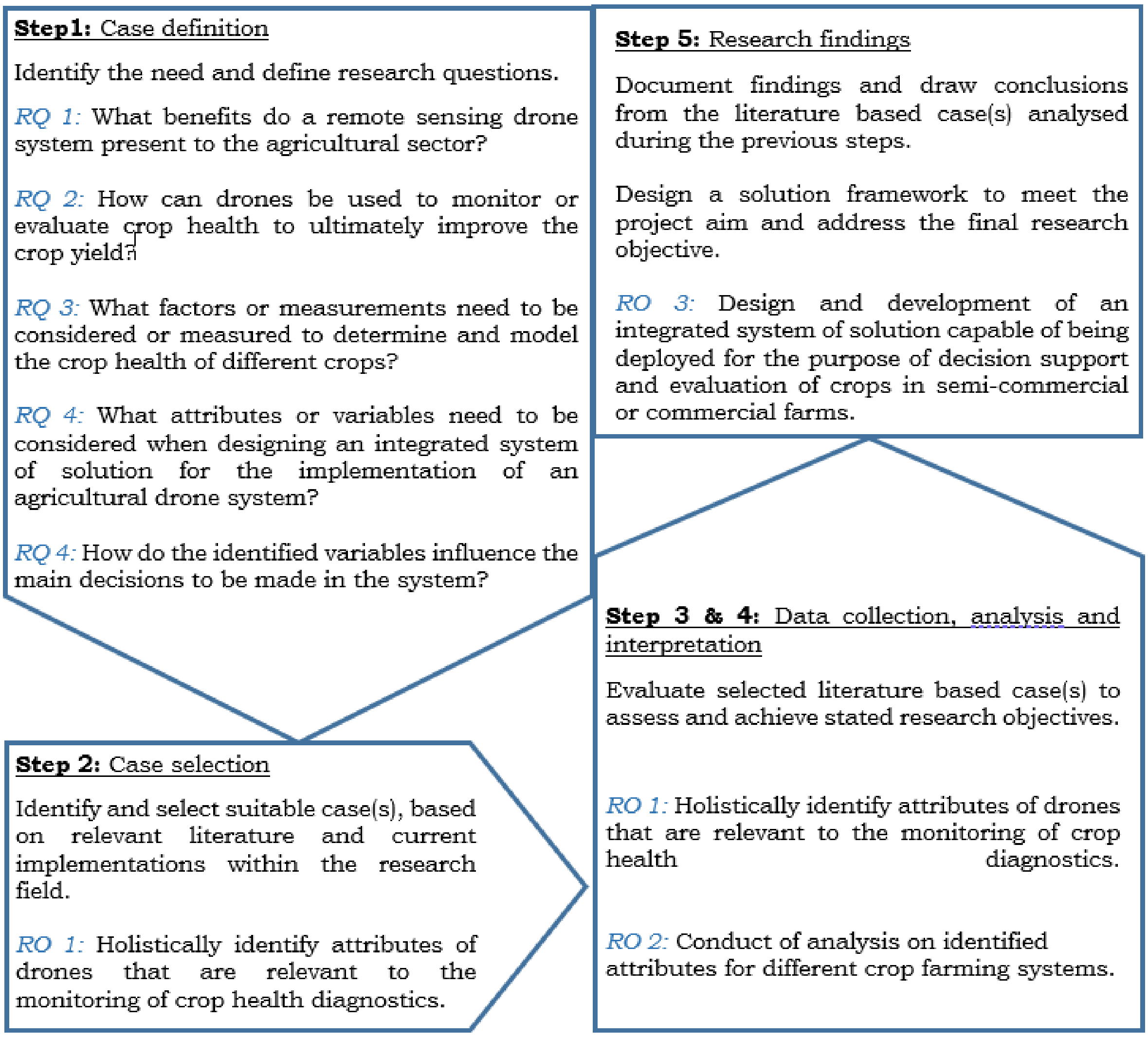

Figure 2 Conceptual Framework

3.4.1 Research Methodology

A case study research approach is followed throughout the project. The conceptual framework illustrated in Figure 2 depicts how the research approach is linked to the defined research objectives and questions. This methodology corresponds to the solution steps presented in Table 7 as part of the preferred solution outline. Along with the objectives and questions, each step of the methodology is explained briefly. This sub-section aims to expand on these steps performed in accordance with the selected research approach to form the methodology followed to reach the end results.

The first step defines the case, through the evaluation of the research questions and existing literature. This step is mainly performed in Chapter 1: Introduction where the research questions and objectives are defined. Further, the case is defined in more detail through the information provided in the literature review presented in Chapter 2: Literature Review.

The second step, case selection, aims to identify and select appropriate case(s) based on the literature and current implementations within the research field. This step of the methodology is mainly addressed within the literature review in Chapter 2: Literature Review. From the relevant literature a basic crop monitoring system is defined, including all the basic components required for such a system. The crop monitoring system with the main components required for successful operation is defined and discussed in Section 4.1 Crop Monitoring System. Hereon the basic form for the integrated system of solution is created stemming from the first decision: "What solution does the user require?" and incorporating the factors that possibly influences this decision.

The data collection, analysis and interpretation steps of the methodology are combined into a single step, which is addressed in Section 4.2 Integrated System of Solution. This step allows for information and data obtained through literature review to be included in the design and development of the solution system and each of the main decision paths stemming from the first decision to be made. Including the identification of all factors and variables that can possibly affect each decision as well as possible solution options unique to each decision system. Each individual decision path thus re-iterates the basic case study research approach in a simpler manner to deliver the individual decision systems and accompanying solution selection processes produced as the outcomes.

The final step of the methodology relates to the reporting of the findings from the previous steps. The main findings presented from this research is of qualitative nature and presented as the decision systems and selection processes. Quantitative findings are incorporated into the project by means of classifying possible solution options based on common (and available) denominators between the relevant solution options. This categorisation is represented in Section 4.3 Solution Categorisation, where solution options are categorised according to output selections based on the various categories created relating to the solution type, farm characteristics and UAV characteristics.

3.5 Theoretical Framework

The theoretical framework specifies the methods and equations required to process the data obtained from UAV flights. These methods are used during the post-flight processing stage when performing crop health diagnostics. These equations and methods are not used within the project, but rather included to ensure a thorough understanding of the methods exist. The most popular data processing technique within remote sensing and PA is that of Vegetation Indices (VIs) as discussed in the literature review. The specific application and equations of the most frequently used VIs are presented in the paragraphs to follow.

In an attempt to model the biophysical parameters of vegetation, separate VIs was created. These VIs are divided into two categories. The first category contains all of the VIs based on multispectral and/or hyperspectral data. These VIs combine several bands obtained from the multispectral or hyperspectral information. The second category calculates VIs from information from the visible spectrum. Different VIs have been created to utilise the visible spectrum as an alternative to multispectral and hyperspectral information due to the high cost of these sensors.

The most popular VI is the Normalised Difference Vegetation Index (NDVI). The NDVI is calculated as a quotient of the difference and the sum of the NIR and red region reflectance (Wójtowicz et al., 2016). Healthy plants typically reflect green and infrared (NIR) wavelengths of light, while a stressed plant typically reflects a different type of light. This is due to the green parts of the plant reflecting in the NIR range due to the scattering of the leaf mesophyll, and chlorophyll absorption of red and blue light (Stehr, 2015). Unhealthy plants reflect more visible light than infrared light. Vegetation can thus be distinguished from the soil due to the fact that red visible radiation is absorbed and NIR is reflected (Tsouros et al., 2019). These changes in the reflected light can be picked up by cameras or near infrared sensors (Stehr, 2015). These measurements are then used to calculate the NDVI. The formula to calculate the ration of NIR to VIS, known as the NDVI is indicated below in equation 1. Some formulas calculate the NDVI as the ratio between the NIR and Red visible light. This deviation of the formula is indicated in Table 8.

$$NDVI = \frac{NIR-VIS}{NIR+VIS} \tag{1}$$

The NDVI is the most commonly used VI to determine the condition, biomass and developmental stages of cultivated plants and in turn forecast their yield. Various other VIs are defined.

In order to understand and correctly interpret the equations of the VIs, a list of abbreviations identifying the light reflection in the respective colour and/or spectrum, along with their wave length is listed below:

- G: Green (500 – 560 nm)
- R: Red (620 – 670 nm)
- B: Blue (430 – 500 nm)
- NIR: Near Infrared (720 – 1500 nm)
- RE: Red Edge (670 – 720 nm)

One of the earliest and most well-known indices is the Ration Vegetation Index (RVI). This index is used to distinguish between vegetation and soil by enhancing the contrast between them. The RVI is however very sensitive to the optical properties of soil (Tsouros et al., 2019). From the popular NDVI, other VIs have been developed utilising the same method. For instance, the Normalised Difference Red Edge Index (NDRE) uses the NDVI method to normalise NIR radiation with Red Edge (RE) radiation. Similarly, NIR radiation is normalised using green bands, to form the Green Normalised Difference Vegetation Index (GNDVI). A summary of the frequently used VIs, as specified by Tsouros et al. (2019), and identified through additional research, is indicated in Table 8.

Table 8 Most Common Vegetation Indices

Abbreviation	**Vegetation Index (VI)**	**Formula**
Multispectral information		
NDVI	Normalised Difference Vegetation Index	$\frac{NIR - R}{NIR + R}$
RVI	Ratio Vegetation Index	$\frac{NIR}{R}$
NDRE	Normalised Difference Red Edge Index	$\frac{NIR - RE}{NIR + RE}$
GNDVI	Green Normalised Difference Vegetation Index	$\frac{NIR - G}{NIR + G}$
ENDVI	Enhanced Normalised Difference Vegetation Index	$\frac{(NIR + G) - (2 * B)}{(NIR + G) + (2 * B)}$
SAVI	Soil Adjusted Vegetation Index	$\frac{(NIR - R)}{(NIR + R + L)(1 + L)}$ L = amount of green

Abbreviation	Vegetation Index (VI)	Formula
		vegetation cover
Visible light (RGB)		
ExG	Excess Greenness Index	$2 * G - R - B$
NDI	Normalised Difference Index	$\frac{G - R}{G + R}$
VARI	Visible Atmospherically Resistant Index	$\frac{G - R}{G + R - B}$

The ENDVI mentioned above utilises three spectral bands (NIR, B and G) to allow for an improved perception of the index, when compared to the original NDVI (Strong, Burnside, & Llewellyn, 2017). The chlorophyll reflection values are inflated by adding the NIR and green reflectance. The blue light reflection also inflates the chlorophyll absorption values due to the higher amplitude of blue wavelength energy absorption. The green reflection illustrates a higher sensitivity to the concentration of chlorophyll when compared to the red reflection. The GNDVI is thus developed to provide a more accurate measurement of pigment concentrations (Strong et al., 2017). The SAVI is an enhancement to the existing NDVI, where the soil variations are normalised so that it does not influence vegetation canopy measurements (Huete, 1988). This index is usually used where the vegetation cover is low. The VARI index identifies and highlights the vegetation within the visible light section of the spectrum. This index is mainly used as a correction to some atmospheric effects (Gitelson, Kaufman, Stark, & Rundquist, 2002).

VIs utilise visible light obtained from RGB sensors, such as the ExG and NDI indices mentioned above is mostly based on the fact that plants display great levels of green visible light. For instance, the ExG index is based solely on the assumption that vegetation or crops show a clear high level of greenness compared to soil, which is only seen as an element in the background. The ExG is calculated by multiplying the radiation measured in the green channel with a factor of 2 and then subtracting the radiation from the red and blue channels. The NDI only use the measured radiation from the red and green bands to distinguish between plants, soil and background images.

Chapter 4: Solution and Discussion

4.1 Crop Monitoring System

Remote sensing systems aimed at monitoring the health of crops utilise different types of sensors to capture data. This data is used as an input to a range of software tools or algorithms to calculate various vegetation indices, soil water quantities and the overall health of the crops. In this case, airborne sensors, more specifically UAVs are utilised to capture the required data, and a range of components that make up such a system are identified. The basic system comprises of an Unmanned Aerial System (UAS), a drone operator or pilot, the system user and the farm to be monitored, as illustrated in Figure 3. In addition to the monitoring system, a software tool is utilised to analyse and evaluate the information captured by the system, to produce a final result. In the subsections to follow, each of the identified components is explained and discussed with relevance to a crop monitoring system. The component pertaining to the farm itself, describes the various physical characteristics of the farm and how these characteristics could influence the crop monitoring system. Similarly, the component relating to the system user identifies different needs and requirements that can be specified by the user and how these user defined specifications can affect the system as a whole.

Figure 3 Basic System Components

4.1.1 Unmanned Aerial System

As mentioned in Chapter 2, a UAS used for crop monitoring purposes require basic elements to operate effectively. These elements include the drone or UAV(s), the camera and/or sensor attached to the drone, the drone control system (DCS) and the ground control system (GCS). In general, these elements are imperative to the successful operation of the system, however, the specific details or specifications regarding each element are interchangeable depending on each unique system and the specific needs and requirements of that system. In some systems the GCS include the post-flight processing software, however, for this system, the post-flight processing software is regarded as independent from the GCS. The GCS as part of the monitoring UAS is used to communicate to the DCS or the drone directly to obtain flight information. The four elements of the UAS monitoring system are dependent on one another as the selection of one element, may affect the selection of the other three elements. Almost all commercially available drones are developed alongside their own DCS and/or GCS. These systems are often not distinguished from one another, especially if the drone is equipped with autonomous flight abilities. A traditional drone that requires a drone operator, contains a DCS used to navigate and control the drone during take-off, flight, data capturing and landing operations. The GCS in such a system will obtain flight information through communication with the drone itself or the DCS. Typically, with a fully autonomous system, the DCS and GCS are combined into a single control system. This control system is used to plan the flight, initiate the flight, and monitor the flight progress. Thus, selecting a drone manufacturer or a specific drone model affects the DCS and GCS included in the system as the UAV and control systems are developed synchronously.

The other important elements to the crop monitoring UAS are the aircraft itself and the sensors/cameras to be attached to the drone for data capturing. The specific drone selected affects the sensors/cameras available to use, as not all drones are compatible with all cameras or all sensors. Specific drone models are compatible to be used in conjunction with specified sensors or cameras. Some monitoring drone manufacturers developed a range of sensors and cameras or combinations thereof in-house to be used along with their drone model(s). These drones are known to contain a swappable payload feature, where the payload attached to the drone can be changed depending on the data to be captured. In the instance of a monitoring drone, the payload refers to the camera or sensor or combination thereof attached to the drone. Other drone manufacturers designed their drones in such a way that it is compatible with commercially available cameras or sensors. For instance, the WingtraOne GEN II drone is compatible with a range of Sony cameras ("WingtraOne GEN II drone Technical Specifications," 2022). The users' final choice of a specified drone model consequently affects the availability of sensors and cameras to choose from. This dependency between the drone and the cameras or sensors can be described as a bi-directional dependency. This is because the selection of a specific camera or sensor, will automatically limit the drone options or drone manufacturer options to select from. Figure 4 indicates the UAS with the basic elements and how these elements affect and interact within the system.

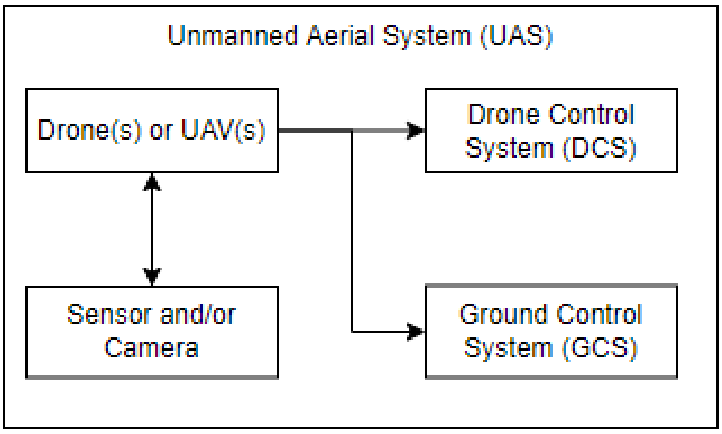

Figure 4 Unmanned Aerial System (UAS) and the Required Components

A range of service providers offers users a full-stack solution, containing all the necessary hardware, equipment and software required to suit their specific needs. This Commercial off the Shelf (COTS) solutions are presented to the client with all the required hardware (drones, cameras, sensors) and software (DCS, GCS) included in the solution. Some of these service providing companies offer the user freedom to select a specific drone model and corresponding cameras or sensors, developed by the company, depending on the need of the client. In some cases, a full-stack solution provides the client with post-flight processing software or a list of recommended software options to choose from. Full-stack solutions typically include a warranty and maintenance plan for the hardware and a subscription to the required software.

4.1.2 Farm Characteristics

The four elements required in the drone monitoring UAS will allow the user to fly the drone and capture data. For the data captured to be of relevance, the drone should be flown over an agricultural field or pasture used to cultivate crops on a farm. One of the primary inputs to the system and its overall working is the physical characteristics of the farm or area where the monitoring system is to be operated. These characteristics include the topography of the farm, the types of crops planted, the size of the fields, etc. and are discussed later in this section.

The physical characteristics of the farm where the system is to be implemented serve as a main input to the crop monitoring UAV system. This input category deals with the *physical features* of the farm where the system is to be implemented. The term *farm* refers to any farming business cultivating and producing crops, regardless of the size of the farm or fields, location of the farm, type of farming business (commercial or non-commercial farming) or the profits generated. Here *crops* refer to all types of crops grown and harvested for profit or subsistence. The physical farm attributes can be grouped into three main categories namely the topographic characteristics of the farm or area where crops are cultivated, the types of crops planted and their respective features and the layout of the farm. These characteristics influence other attributes throughout the entire system. Further investigation into the main physical features revealed additional information or factors for consideration.

The *topographic characteristics* of a farm area and especially where the fields are located should be taken into consideration when developing an agricultural drone monitoring system. The topography of an area refers to the natural formations of an area, like the mountains, valleys, rivers, lakes and dams. Human-made features are sometimes also included in topographic maps. These features include roads, bridges, buildings etc. The topographic characteristics can affect certain decisions made within the crop monitoring system. The topography of an area can either affect the system as a whole or the component(s) within the system. Should the specific topographic characteristics of an area affect a component or feature included in the system, one can assume that it will, in turn, also have an effect on the system as a whole, maybe not directly, but secondary.

Some factors affected by the topographic characteristics of an area are discussed below. The topography of the area of interest could affect decisions regarding the type of drone, multi-rotor or fixed-wing, to be selected for the monitoring task. Multi-rotor machines are a more practical solution for mountainous areas or where fields are arranged over or between rolling hills. On the other hand, a fixed-wing type drone might be more advantageous to use on a large flat area. Another important consideration is a drone's ability to fly at a steady altitude in relation to the changing ground surface, otherwise known as terrain following. If a UAV is equipped with this feature, the machine will fly at the set altitude above the surface and as the topography changes, the drone will adjust its flight path to remain at the set altitude. This feature prevents drones from flying too close to dangerous obstructions like cliffs, boulders or trees. The topography of an area may have an effect on the take-off and landing position or circumstances. These circumstances in turn affect the choice of drone to be selected for the system.

The second category takes the *crops* planted, the type and related features, into consideration. Each type of crop planted or cultivated has a range of features or attributes related to that specific crop type. For instance, a field of corn grows completely differently compared to a field of potatoes. A cornstalk grows on average up to 2.5 meters, with the cob of corn growing above ground on the plant. A potato plant on the other hand typically stands up to 1 meter tall, with the stalk and leaves above the ground and the vegetables growing below the ground. Thus, each crop type grows to a different height, and width and can visually be distinguished from one another. These traits associated with a specific crop type affect how and possibly where the crop is planted. The 'how' refers to how close individual plants are planted next to each other, how big a field is used for that specific crop and the growing season of the crop, etc.

A UAV-based crop monitoring system acquires visual data from flying above a field where crops are planted. Thus the only characteristics of significance are the height to which the plant grows, and the colour of the plant or field as seen from above during the different life-cycle stages of the plant. Most data utilised as a part of the UAV-based monitoring system is visual data, or NIR or Visible light reflected from the plants. Each individual crop type grows to an average range of heights and widths for that specific species of crop. The actual growth trends for each crop have an effect on the flight patterns of the drones. Crops that grow to a larger height may require the drone to fly at a greater altitude, whereas shorter crops can allow the drone to fly at much lower altitudes. The flight altitude of the drone in turn affects the accuracy of the data or images obtained. However, many drones fly at a predefined cruising altitude, regardless of the height of the crops to ensure the predetermined absolute accuracy of the captured images and data is maintained. Some commercially available UAVs provide the user with the option to set the cruising altitude during the pre-flight planning phase, especially for fully-autonomous flight systems. For these systems, the height of the crops may affect the defined flight altitude, however, most drones fly at an altitude that is not affected by the crop heights.

The type of crop to be monitored can vary from one farming business to the next. A single farm can cultivate more than one crop type throughout a growing season.

Each type of crop that needs to be monitored has a different lifecycle. The lifecycle or growing cycle of the crop has an effect on the frequency of flights required to provide the user with sufficient information. Thus, the planning and scheduling of flights differ for each crop type, as it has a different lifecycle and may require monitoring at specific time intervals throughout the lifecycle of the crop. Flight planning and scheduling can further be complicated if more than one crop type with different growth cycles is planted on the same farm within the same season. The layout of different crop types in relation to one another on a farm impacts the total area to cover as well as the scheduling and planning of flights. More is elaborated on this consideration within the farm layout category.

The third category included in the physical characteristics of the farm is defined as the *farm layout*. This category includes all the information related to the size of the agricultural fields to be monitored, the layout of these fields on the farm and especially in relation to one another and the layout of individual crops within a single field. The total size of the farm should be broken down into the areas used for cultivating crops and those used for other purposes. The UAV crop monitoring system should only monitor those areas or fields where crops are planted, thus only those field sizes (usually measured in hectares or acres) are of relevance. The system should not only take the total size of cultivated fields (the sum of the sizes of all individual fields together) into consideration but also the size of each individual field and the layout of these fields in relation to one another. If the fields are located next to each other or in close relation to one another, and the same crop type is planted in these fields, one can combine them into a single monitoring area. If however, the fields are not close to one another, or different crops are planted on adjoining fields, each individual field is regarded as a single monitoring area. For this project, a monitoring area is defined as an agricultural area to be monitored by a single UAV flight. A monitoring area can either be determined by the drone model selected, as each drone has a predefined coverage area and can thus only monitor areas less than the defined coverage area, or by the requirements specified by the user. The user can define the monitoring area based on what he wishes to achieve with the monitoring system. For instance, if the user wants to monitor the entire farm with a single flight, the total size of all of the fields is defined as the monitoring area. In such a case, when the monitoring area is less than the drone coverage of the selected drone, the entire area can be monitored in a single flight. If this is not the case and the monitoring area exceeds the drone coverage area for a single drone, multiple flights or drones might be required to produce the same output. Utilising more than one drone or multiple flights with a single drone can affect flight planning and further complicate flight scheduling steps. Once a limit is determined for the maximum size of a monitoring area to be "serviced" by a single drone, multiple drones or multiple flights will be required.

The total size of the monitoring area has a direct influence on the type of drone (multi-rotor or fixed wing) to be considered as well as the specific model of the drone to be considered, as each drone has a different battery capacity and in turn a predefined flight time. The predefined flight times for available drones are determined in ideal conditions, with no additional payload added to the drone, other than the absolute essentials. Some drone models allow the option to add additional batteries or an endurance battery option, to extend the flight time for every single flight. Each drone's specified flight time reflects the total area of coverage, in hectares or acres, for that specific drone. Drone selection should be performed in conjunction with information regarding the monitoring area, the predefined flight time or area coverage of the drone and the user requirements. The layout of the farm, more specifically where fields are situated in relation to one another can also have an impact on the flight planning phase. This is due to additional distances and flight times that might need to be included in the flight map to allow the drone to map two or more monitoring areas within one flight. If a continuous flight is not possible, the drone operator might need to perform multiple flights from different locations to cover the required monitoring areas, which extends the total time required to perform monitoring. If the farm under investigation plant and produce different crops the layout of the different crop fields in relation to one another, also has an impact on the coverage area and flight planning and scheduling requirements. If fields with the same crop is located close in relation to one another, flights can be combined or performed in succession to simplify planning and scheduling.

4.1.3 System User

In addition to the physical characteristics of the farm, the other main component in the system that has an impact on the system as a whole is the users' preferences. The user in this case refers to the farmer, farm owner or farm manager who wishes to use UAVs to capture data regarding crops and in such a way monitor the crops. These preferences specified by the user, for the system should be taken into consideration before designing or selecting a suitable system or system configuration. The decisions made by the system user affects the entire operation and final goals of the system. Implementation of an agricultural crop monitoring system using UAVs is extremely user-dependent. This is due to the entire system relying on the user's personal requirements and preferences for what the system should be able to do or not do. One can assume that for a crop monitoring system the main goal of the system is to periodically capture and process crop data to assist the farmer in making more informed decisions, which in turn will possibly lead to a higher yield.

In addition to the physical characteristics of the farm, the *user-specified needs and requirements* affect the system as a whole. These needs and requirements, similarly to the farm characteristics, affect the whole system as well as individual parts or aspects of the system. Since the entire system is user dependent, the needs and requirements specified by the user should be known well in advance, before designing the system, to ensure the system operates as envisioned by the user. One of the main decision variables that have an effect on the entire system and how it operates is the user-defined *goals* for the system. These goals include the users', desires and demands for the system. As a UAV-based crop monitoring system is customised for a specific farming business, the requirements for the system differ depending on the user. Each user might have a preference as to what is expected from the system, what output is preferred and how he envisioned the entire system operating. For instance, a user might require the system to only monitor a single cultivated area, where a single crop is planted, on a monthly basis; whereas another user might require weekly monitoring of the entire farm and of all of the different crops planted on the farm. In addition to these preferences on how the system should operate, a user can define the *desired output* to be delivered by the system. The desired output is typically the type (the format) of the data presented after analysis. The data can be presented to the user in numerical format, through the use of the original orthophotos or orthomosaic or by way of adapting the orthophoto or orthomosaic to indicate the calculated vegetation indices based on the measurements obtained by the attached sensors. The most commonly used mode of measuring crop health is through the use of vegetation indices, such as the NDVI, NDI, NDRE, RVI, etc. These indices require measurements obtained from sensors (specifically multispectral sensors) attached to the drone. Once the data is captured by the sensor/camera combination, the data is processed using an available software program. If the system user wishes to utilise these inferences to evaluate the health of crops, the system should be designed to accommodate all of the factors to ensure that the desired output is reached. The decisions made regarding the desired outputs produced by the system influence how the system should operate as well as the sensors or cameras selected as part of the system and finally the image processing software programs selected to generate these outputs.

In addition to knowing the user preferences pertaining to the main goal of the project and the desired outputs produced by the system an important consideration to be prescribed by the user is the *hardware and software preferences*. This factor distinguishes between whether the user wishes to own his own hardware and software to be used in the system and whether a third-party service provider option is to be considered. A third-party service provider provides the service of flying and capturing the data and images using their own hardware components, analysing the data using their own processing software and then only presenting the final data and results to the user. The decision between these two options greatly affects the main design of the system. For the system where a third-party service provider is used, the main decision driver is the needs and requirements specified by the user, specifically the main goals for the system and the desired outputs. This decision driver will ultimately aid in the selection of a service provider. Along with the users' needs and requirements, the farm characteristics are also taken into account when designing the system, but this information is rather used by the service provider to alter the proposed solution to suit the needs of the client. If the selected service provider is unable to produce a solution based on the characteristics of the farm, another more suitable service provider must be selected.

If the system user wishes to own his own hardware and software components, the system design is much more complicated, as the entire system containing all hardware and software components should be designed to meet the needs of the system user. The needs and requirements specified by the system user (along with the other system inputs) will ultimately affect the components selected as part of the solution. The desired outputs of the system also have an effect on the components selected. This is attributable to the user requiring a specific output (data type, or format) and the hardware and software components to be altered in such a way that the desired output is met. Should the user have the desire to own the hardware and software, the user must ensure that additional human resources are available to plan, manage and operate the system. In the case of a fully autonomous system, the system user can be any person who has received training on how to operate the system. Whereas, a manual system requires a drone operator with the required training and RPAS licencing. This can lead to additional capital investment to provide training for an existing employee or the hiring of a trained and licensed drone operator. In addition to the added human resources, a large capital investment is required to initially purchase the required hardware and software. The *budgetary constraints* specified by the system owner can limit the availability of options for the system as a whole (if a COTS system is selected) or for the selection of hardware and software components.

4.1.4 Drone Pilot or Operator

The final component required for the successful operation of a crop monitoring system using a UAV is the drone operator or pilot. According to Part 101 of the Civil Aviation Regulations, for both commercial and corporate use of a RPAS, the operator or pilot requires a valid RPAS Operator Certificate (ROC) and a Remote Pilot License (RPL). These regulations are however only valid in the case where a manually operated UAV classified as either class 1 or 2, is used to monitor crops. In the case of a fully autonomous operating drone, the operator does not require a ROC or RPL licenses or certificates. However, a different set of regulations apply to an autonomous flying drone. For fully-automated systems, a system operator is still required to plan and initiate flights. In some cases, the operator might be the farmer or system user, but it can differ in some cases.

The drone operator does not directly affect the decision of the system as a whole, but the system cannot operate without a trained and licensed pilot or operator. This regulation can have an effect on the initial capital investment required for the system. The user will either have to appoint a licensed drone pilot or arrange for a current employee to undergo the required training to obtain the necessary licenses. If the user wishes to send a current employee to acquire the correct licensing, the project timeline should be adjusted to include the time necessary for the individual to attend the necessary courses. Due to the absence of a direct influence between the drone operator and the decisions to be made in the system, the operator is disregarded within the decision frameworks.

4.2 Integrated System of Solution

The aim of the integrated system of solution for an agricultural crop monitoring system using UAVs is to assist any individual in making an informed decision regarding the acquisition, or simply the use of such a system. Before designing or purchasing an entire system, a few considerations should be revised to ensure the system delivers what the user needs from the system. The first, and seemingly most important decision to be considered is what type of solution system the user wants. Does the user wish to own his own hardware and software for the crop monitoring UAS or does the user only want the end results obtained from the system? The term 'his' in this context, refers to the system user, regardless of the gender of the person. This initial decision is influenced by a number of factors such as the users' preferences for the system, budgetary constraints experienced by the user and additionally possible licencing constraints for the system. The *user's preferences* for the system are identified as the most influential variable, as the user has the power to make a decision regarding the system, regardless of any of the other variables. *Licencing constraints* can limit the user as most UAVs require a licenced drone pilot to operate and control the aircraft. In addition to a licenced pilot, the aircraft itself also requires a licence if it is used for commercial or corporate applications. The licencing requirements increase the total cost of the system and can delay the timeline of the entire project.

The *user's preferences* for the system are defined as a main variable but can contain many sub-variables or considerations that effect this variable. The sub-variables, mentioned earlier in this chapter, include the following:

- User needs and requirements
- User-defined system goals
- User desired outputs
- User hardware and software preferences
- Budgetary constraints

For the selection of a solution option, the *budgetary constraints* are defined as an individual decision variable, due to the large impact that this variable has on the solution selection. The other sub-variables are grouped as the users' preferences for the initial decision regarding the type of solution. However, in later parts of the solution system, some of these preferences are defined individually.

A potential system user needs to decide between three alternative solution options. The solutions are divided based on the user's hardware and software preferences, whether the user wishes to own his own hardware or whether he only requires the final results produced by the system. If an individual is not entirely convinced about the advantages such a system could pose to his business, the user can contact a Third-Party Service Provider (3PSP) to capture crop data and deliver the results to the user. If the user is satisfied with the results, he can decide whether to purchase his own system hardware and software or continue to make use of the services provided by a 3PSP. If the user wishes to purchase the hardware and software, one of two options can be selected. Either the user can design his own system, by selecting a specific drone model and accompanying sensor(s) or camera(s) and purchasing the selected processing software applications to generate reports. If the user does not wish to design a unique system to suit his specific needs, a Commercial off the Shelf (COTS), a full-stack solution can be purchased. These solutions include the necessary hardware, software and additional support, maintenance and information within a single solution package. Typically a COTS solution is designed to perform a specific task or function. Some COTS solutions provide the user with slight variability in the main function of the system, by offering different payloads (sensors and cameras) to select as part of the solution.

In the case where the user does not want to own his own system, but still requires the data captured by a UAV-based crop monitoring system, a third-party service provider should be used. A third-party service provider refers to any company that provides the service of collecting crop data on the users' farm and then producing a report after data analysis is completed. The user is thus not required to purchase any hardware or software, while still benefitting from the data acquired by a UAV crop monitoring system.

Figure 5 illustrates the different solution paths, described above, that can be followed by a farmer who desires to implement or reap the benefits of an agricultural crop monitoring system using UAVs.

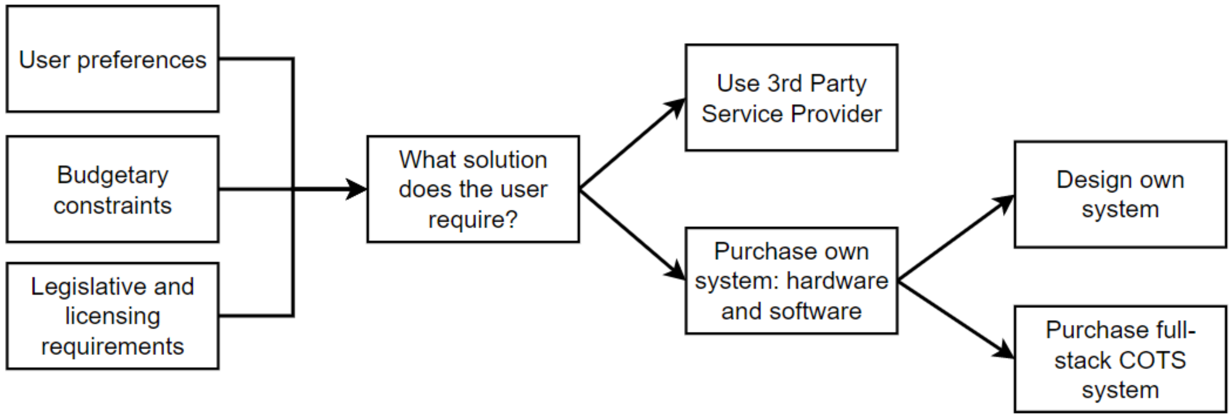

Figure 5 Visualisation of Different Solution Paths

Each solution path can be divided into the core decisions to be made as part of that main solution path. The first solution path, where the user decides to make use of a 3PSP, simply requires the user to select a 3PSP. Nevertheless, this decision is influenced by a range of factors and considerations. If the user chooses to follow the service-provider route, the 3PSP selection process should be followed, while evaluating the specific system to ensure the final decision adheres to the users' requirements. The second solution stream is where the user buys the necessary hardware and software. If the user decides to design his own system, this solution path is divided into three decision activities. The decisions to be made when designing a system are the UAV model to select, the accompanying payload and the processing software solution. Each of these sub-decisions is modelled as its own individual system, along with a corresponding selection process. It is advised that the user should follow these selection processes to select a suitable aircraft, payload and software solution, to complete the monitoring system. An integrated solution system combining the three sub-decisions when designing your own system is also developed, to illustrate the collective influence of certain variables. If the user, however, decides to purchase a COTS solution, the only two decisions to be made within this solution path are what COTS solution to purchase and what processing software to acquire. Similar to the previous decision paths, each sub-decision within the COTS selection decision, is illustrated by a system and recommended selection process, to enable the user to make a quicker and more informed decision regarding the solution selection. Figure 6 illustrates the main decision paths along with the different decisions to be made within each main solution path.

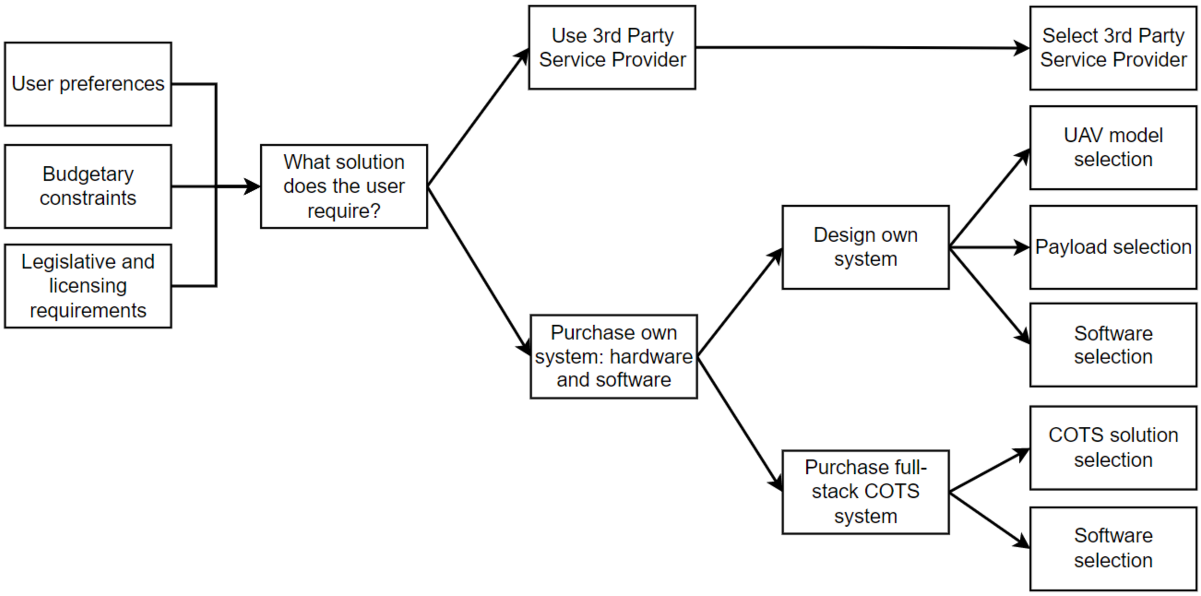

Figure 6 Main Decision Paths

The sections to follow will provide more information concerning the three main solution paths available, designing your own system, purchasing a COTS system or using a third-party service provider and their corresponding sub-decisions.

4.2.1 Third-Party Service Provider

Selecting a third-party service provider seems like a relatively simple solution in comparison to purchasing the different hardware and software components required for a crop monitoring system. In practice, this decision is however affected by a number of different factors. These factors include but is not limited to: the user needs and requirements; the desired outputs required from the system; the physical farm characteristics; budgetary limitations; services offered; and the availability of service provider. The factors all affect the decision made by the user when selecting a service provider to suit his business. As mentioned above, following this solution path allows the user to gain the benefits of continuously monitoring crops, without having to purchase hardware and/or software licences. Once a 3PSP is selected, the company captures the necessary data and delivers the agreed-upon final report to the farmer or farm owner. An assumption is made that if a farmer requires recurring flights performed by the 3PSP, a contract will be undertaken between the client and the service provider, to provide the service multiple times over an agreed-upon time period. Figure 7 illustrates how these above-mentioned factors influence the selection of a 3PSP. The factors on the left refer to the factors specified by the system user, whereas the factors on the right are the factors that are determined by the service provider.

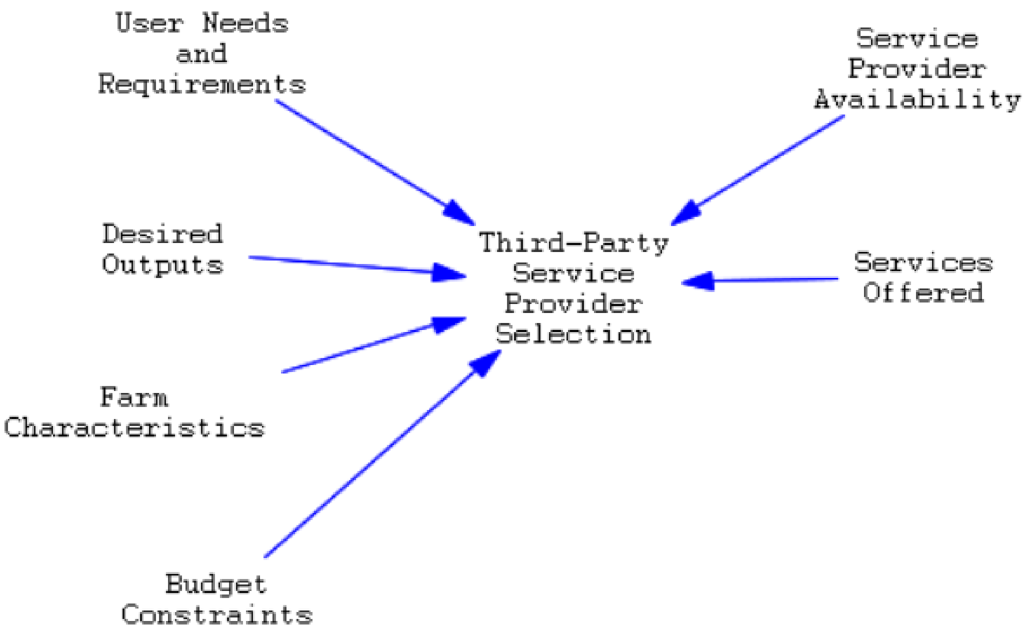

Figure 7 Factors that Influence Third-Party Service Provider Selection

Each of these factors and how they affect the 3PSP-selection decision is discussed in the paragraphs to follow. The factors are divided into elements relating to the user and features relating to the 3PSP.

The entire system is user dependent, especially when making use of a service provided by an external company, the system user is allowed to select a solution that suits his *needs and requirements*. The user will therefore not select a solution should it not provide him with the *desired outputs* from the system. If the user, for instance, only requires aerial images in the form of an orthomosaic of his crop fields, he will surely select a 3PSP that can provide him with that service. Similarly, if the user requires further analyses of different vegetation indices calculated for his crops, he will not select a 3PSP that cannot provide that solution output. In another instance, the user might require a certain frequency of flights, and thus will only select the service provider that can meet the user's needs. The *services offered* by the available 3PSPs should be noted in the selection process, as this factor should be evaluated in correspondence with the user's needs and requirements and the desired outputs to be obtained when selecting a suitable service provider. In the case where the 3PSP offers a tailored solution to the client based on the client's needs, the user can specify exactly what he requires from the solution. The users' preferences thus affect the outputs delivered by the system.

In addition to the requirements and preferences stated by the user, *budgetary limitations* can have an effect on the selection of a specific 3PSP. The farmer purchases the service of data capturing (using UAVs), data analysis and conclusions and recommendations from the service-providing company. An assumption can be made that the cost for the desired service will differ from company to company. This is due to the fact that every company has a different business model or calculates the cost of the service differently. Similarly, the cost of different jobs performed by the same company will also differ from job to job. Therefore, the financial means allocated for crop monitoring purposes by the farmer in question can possibly limit the selection of 3PSPs. Due to the fact that service providers only calculate job quotes once the farmer has requested for a quote, this factor affects the final decision when selecting a service provider.

Another group of factors for consideration is the *physical characteristics* of the farm or farming area itself. These characteristics can, in some cases, limit the selection of service providers. For instance, if the farming business produces citrus fruits, a 3PSP that is not familiar with citrus orchards will most probably not be selected, compared to a service provider that specialises in citrus farm monitoring. Along with the types of crops monitored, the size of the crop fields to be monitored and the layout of the fields may play a role in the selection of a suitable service provider.

The final factor for consideration is the *availability* of service providers within the geographical region of the farm. The influence of this factor on the selection of 3PSPs is premised on the fact that each individual service provider is located in a specific region of the country. The service provider thus only provides services within the surrounding areas of its base location. If this is not the case, 3PSPs most probably specify their regions of service. If a farm falls outside of a selected service provider's region of service, that 3PSP will be disregarded. The selection of a suitable 3PSP thus relies on the availability of the service provider within the same geographical region, where the farm is located. Conversely, service providers may not necessarily choose to limit their clients based on geographical locations. In such a case where services are provided regardless of the location of the farm, the 3PSP will remain part of the list of suitable service providers the user can select from. In this case, however, the service provider may increase the cost of the service due to additional or increased travelling costs to the farm location.

The typical process followed to select the most suitable 3PSP starts with the user (farmer) evaluating each of the above-mentioned factors, paying special attention to the needs and requirements and desired results specified by the user. Once each factor has been evaluated, the list of available service providers is assessed and through elimination, unsuitable candidates are removed from the list. Once the list of available 3PSPs is refined, based on the preferences concerning each factor, the service providers are contacted to obtain a quote for the desired service. Hereafter the user evaluates the suitability of a specific service provider to perform the required task, based on the budgetary constraints set by the user. If none of the service providers falls within the set limits, one of the previously determined factors specified by the user might need to be adjusted or changed slightly. If this is the case, the entire process will be repeated until the most fitting service provider is selected. This process is visually illustrated in Figure 8.

Figure 8 is designed to be used in collaboration with Table 9 to assist the user in selecting the most appropriate service provider. Included in the Table are 11 3PSPs identified within South Africa ("Aerobotics," 2022; "Agri-Sense International," 2022; "The Awareness Company," 2022; "DC Geomatics Drone Technology," 2022; "Epic Air," 2022; "Integrated Aerial Systems (IAS)," 2022; "RocketFarm," 2022; "Southern Mapping," 2022; "Specialised Agricultural Services," 2022; "UAV Industries (FlyUAVI)," 2022; "UVSSA," 2022). The service providers are selected through research and the elimination of unsuitable service providers. Examples of unsuitable service providers include companies that provide crop-spraying solutions or provide farming insights based solely on satellite imagery or imagery obtained through a manned flight. Other examples excluded are precision agricultural practices utilising ground-based sensors. Some of the identified service providers also operate outside of South Africa, however, these companies are primarily based in South Africa. Service providers based outside of SA are disregarded from the summary table. In addition, data included the table pertaining to each service provider is limited to information obtained through the company website. Thus, the only information used is that which is provided by the company on their respective websites.

The information is grouped and presented in an easier-to-use and reference to format to aid the user in making an informed decision. The information presented for each 3PSP includes the following: services offered; output type; crop types; location; and legal status and licencing. The information included in the *Services*

Offered column, includes the service(s) provided or marketed by each individual company. Only the services pertaining to crop health diagnostics and the use of UAVs are included. The various output(s) produced by the company is mentioned in the second column. Included as an output is the type of images captured or the data captured by different sensors. A common output provided to users is the calculation of various growth indices based on the sensor data captured. These indices can be visually illustrated in an adapted orthomosaic of the area captured. The third column provides information regarding the crop types serviced by each respective company. An assumption can be made that in the case where no individual crop types are listed, the service provider does not limit their services to specific crop types. The geographic region where each service provider is based, as well as the areas or countries in which the respective service provider can operate is indicated in the fourth column. The official licences and legal status, if mentioned on the company website, are presented in the final column. An assumption can be made that all of the companies adhere to the relevant legislation and that all aircrafts and drone operators have the correct licensing.

Information is only included in the table if it could easily be obtained through the company website. If no information could be found for a specific grouping of information or data for that particular service provider, no information is provided. If the user specifically requires that information, it can be requested from the 3PSP at a later stage. The summary table aims to provide the user with a 'one-stop' reference document with the necessary information for each respective service provider. The Table should be used in the manner, corresponding to the decision-making process illustrated and discussed above.

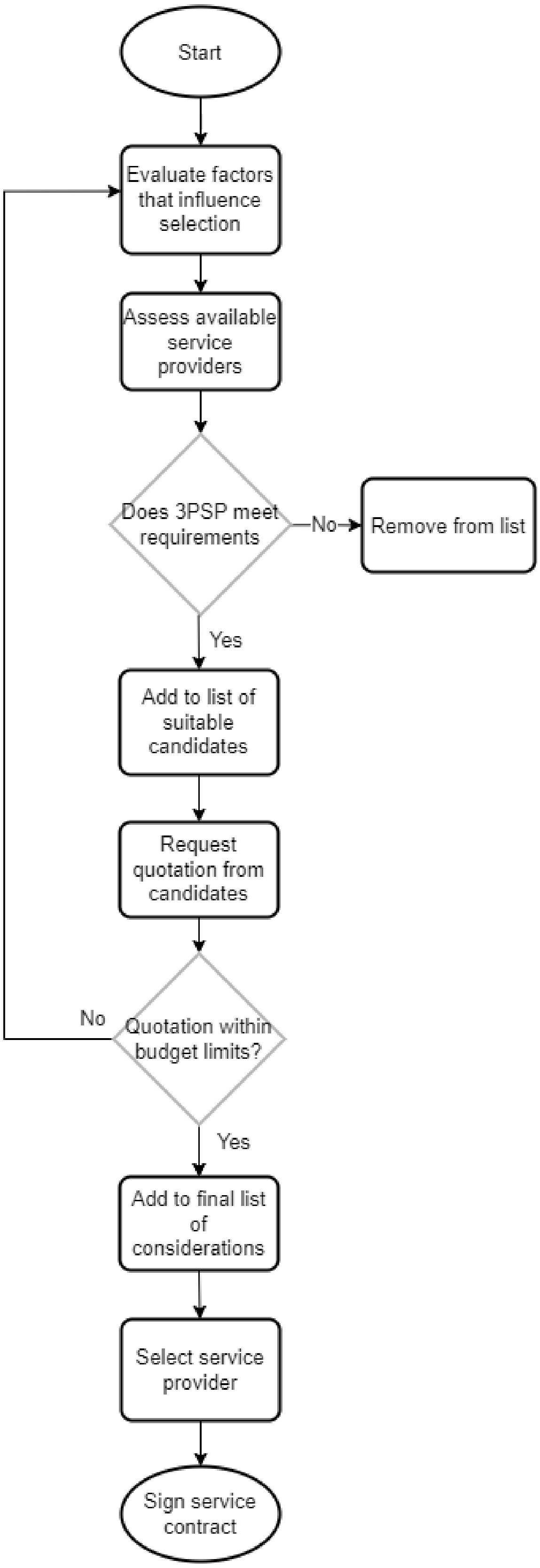

Figure 8 Process Followed to Select Most Suitable Third-Party Service Provider

Table 9 Third-Party Service Providers in South Africa

<table>
<tr><th>Services Offered</th><th>Output Type</th><th>Crop types</th><th>Location</th><th>Legal Status/ Licences</th></tr>
<tr><td colspan="5">Aerobotics</td></tr>
<tr><td>Insights for precision growing and crop insurance.

Plant performance:
ID nutrient deficiencies, pest infestations, and disease or irrigation issues. Track practices over time.

Irrigation:
Monitor irrigation, manage hardware maintenance.

Plant Count:
Tree counting, manage and maximise plant inventory.

Yield:
Continuous crop monitoring and yield prediction.

Pest and Disease:
Digital pest and disease monitoring solution.</td><td>Multispectral and thermal imagery obtained by drone flights.</td><td>Citrus
Nuts
Apples
Avocados
Berries
Pome
Stone
Grapes
Subtropical fruit
Olives
Pomegranates</td><td>Based: Cape Town

Service: 18+ Countries (Africa, Americas, Europe, Australasia)</td><td></td></tr>
<tr><td colspan="5">Integrated Aerial Systems (IAS)</td></tr>
<tr><td>Crop insights with intelligent drone data.
Goal: Reduce costs, increase yields.

Individual Tree stats:
Tree counts, height, canopy size, canopy volume and health.

Field Insights:
Detect problem areas and variations. Develop field contours and digital elevation models for crop and irrigation management.

Actionable Data:
Increase yield and reduce crop loss with rapid intervention.

In Field Scouting:
Share maps easily across different devices.

Analysis Over Time:
Monitor crop and plant health throughout the season with data captured from multiple surveys.</td><td>Flights conducted within 48 hours after request. Data processed within 24 hours after flight.

Data analysis: Advanced data analysis, detailed maps and customisable reports.

Multispectral and RGB images technology.

Field insights:
Orthomosaic, NDVI, VARI and other algorithms designed for plant health.

Critical near real-time data.</td><td></td><td>Based: Cape Town

Service: South Africa and Africa.</td><td>Fully Licensed and Insured.

CAA Certified Operator

ROC Certificate from SACAA.

Class III General ASL</td></tr>
<tr><td colspan="5">DC Geomatics</td></tr>
<tr><td>ROC partnership solution.

Crop management:

Crop monitoring
Crop protection</td><td></td><td>Crops
Orchards</td><td>Based: Umhlanga

Service: South Africa</td><td>Fully licensed and insured.

SACAA Approved.

CUAASA Diamond Member.</td></tr>
</table>

Services Offered	**Output Type**	**Crop types**	**Location**	**Legal Status/ Licences**
Epic Air				
Measure, observe and act on changes in crops. Crop scout sections of farmland. Measure plant health instantaneously. Detect crop and soil problems with NDVI and VARI. Take field action and monitor reports over time.	NDVI and VARI index maps. 2D or orthomosaic maps and 3D models within hours. Digital elevation maps. Thermal index maps. Plant counting. Real-time HD video footage streamed to multiple devices on the ground.		Based: Cape Town.	Fully Licensed and Insured. Fully licensed RPAS Operator. ROC certificate from SACAA.
Rocketfarm (division of Rocketmine)				
Precision crop monitoring solutions. Provides precise, geo-referenced, spatially dense plant population data. Analyses delivered within 48 hours after flight. *Primary services:* - Crop health trends reporting - Monitor weather damage - Crop stress analysis and plant scouting - Plant counting (entire field or specific area) - Forecast Yield - Monitor plant growth and health Specific solutions: *Waterlogging Analysis* *Nitrogen status in Crops* *Weed Analysis* *Stand Count Report* *Plant Population* *Canopy Analysis* *Drought Analysis* *Flowering Estimator* *Plant Stress Analysis* *Yield Estimates* *Plant Disease Analysis* *Pest Analysis*	NDVI index maps. High accuracy, 10 cm Ground Sampling Distance (GSD). *Additional crop analyses available on request	*Summer Crops:* Cotton Tomatoes Maize Sorghum Soybeans Dry Beans Sunflower *Winter Crops:* Potatoes Tomatoes Onions Wheat Barley *Perennial Crops:* Sugarcane Macadamias Pecans Citrus Lychees Mangos Apples Grapes Bananas Avocados Olives	Based (Rocketmine): Johannesburg Service: South Africa, Namibia, Zambia, Australia, Ghana, Cote d'Ivoire, France, Israel.	Fully licensed by the CAA. Licenced Commercial Drone Operator.
UVSSA				
Monitoring and Evaluation Services: Crop inspection. Crop health and failure detection Track progress of Crops Forecast Harvest	Customised solutions		Based: Johannesburg Service: South Africa	

Services Offered	Output Type	Crop types	Location	Legal Status/ Licences
FlyUAVI				
Drone training, Drone operations, Drone ROC for rent. *Aerial mapping and Surveys:* Raw video footage Geo-referenced Orthomosaics 3D modelling Photogrammetry *Industrial Inspections:* Orthomosaics RGB, thermal and multispectral sensors	Visual (RGB) imagery. RGB, Thermal and Multispectral Sensors.		Based: Pretoria	SACAA Certified Drone operator.
Specialised Agricultural Services				
Drone Aerial Surveys: Contour Mapping Irrigation and drainage design Tree and Crop height calculation Accurate field and area measurements 3d Modelling and volumetric calculation Plant stress detection Crop assessments Crop and orchard analysis	Accurate 3D maps. NIR cameras NDVI and other reflectance maps		Based: Dolphin Coast	
The Awareness Company				
HYDRA Holistic Agriculture *Farm Awareness:* Track livestock weight and health. Log genecology information. Harvesting or planting analysis. Pest detection and quality checks. *Agri Insights:* Enables more insights and value from data.	Drone captures data that serves as inputs to HYDRA Holistic Agriculture.		Based: Pretoria Service: South Africa	
Southern Mapping				
Support soil classification, farm design and agri business and vegetation mapping and monitoring. *Agri Monitoring:* Crop performance monitoring Monitor moisture in crops Irrigation and drainage monitoring Yield monitoring and management of factors that affect yield *Agri Farm Design:* Drainage and irrigation planning Soil management Soil survey or field sampling	NDVI and NDWI Index maps		Based: Johannesburg Service: South Africa, more than 48 countries.	

Services Offered	Output Type	Crop types	Location	Legal Status/ Licences
Agri Sense International				
Crop monitoring Services: Monitor crop performance Identify poor growth within crop Capture drone imagery on your behalf.	RGB, NIR and Thermal Imagery. Aerial imagery. Statistical Analysis. HD Geo-rectified Maps Vegetation and Crop assessment Maps (Calibrated NIR and Standardised NDVI) *Vegetation Indices:* CIG G-NDVI NDVI SR		Based: Hilton, KZN. Service: South Africa Nigeria Tanzania Ghana Angola Mozambique Rwanda DRC Malawi	

4.2.2 Purchase Own System

As mentioned in Figure 6, if the user wishes to purchase his own system, he can either design the entire system by selecting each component to make up a whole system or purchase a full-stack solution (otherwise known as a COTS solution) from a company specialising in the development of agricultural drone systems. Similarly, to selecting a 3PSP, both these solution paths are influenced by several factors and considerations.

4.2.2.1 Design of Own System

In the case where the system user decides to purchase each of the separate elements to create a crop monitoring system, each element of the UAS should be selected individually, but also taking into consideration the other elements to make up the whole system. As mentioned previously, UAVs are developed to be compatible with a specific DCS software tool, developed by the same company that developed the aircraft. Thus, if you purchase a drone, in essence, you purchase the DCS software tool along with the drone. Alternatively, not all drone developing companies provide an in-house post-flight processing software tool. An assumption is made that the user should purchase the software tool or a license to the software program to be used for post-flight processing of the captured data, separately. Many drone companies, however, make recommendations for post-flight processing software that is most compatible with the data or information obtained by their aircraft. Similarly, the user is also responsible for selecting a UAV and accompanying payload (sensor or camera) to complete the crop monitoring UAS. Aircrafts are designed either with a fixed, permanent payload or a swappable payload feature. However, if an aircraft has a swappable payload feature, it does not mean that any payload could be attached to the drone. Only payloads compatible with the drone and drones compatible with the payload can be attached. Thus, the selection of a specific drone model might limit the available payload options to select from. Similarly, selecting a payload model limits the available UAV models to select from.

The components of a crop monitoring system identified earlier in this Chapter influence the decisions concerning the selection of each individual element of the UAS. Figure 9 demonstrates how these components (in general) affect the selection of the specific elements of the system.

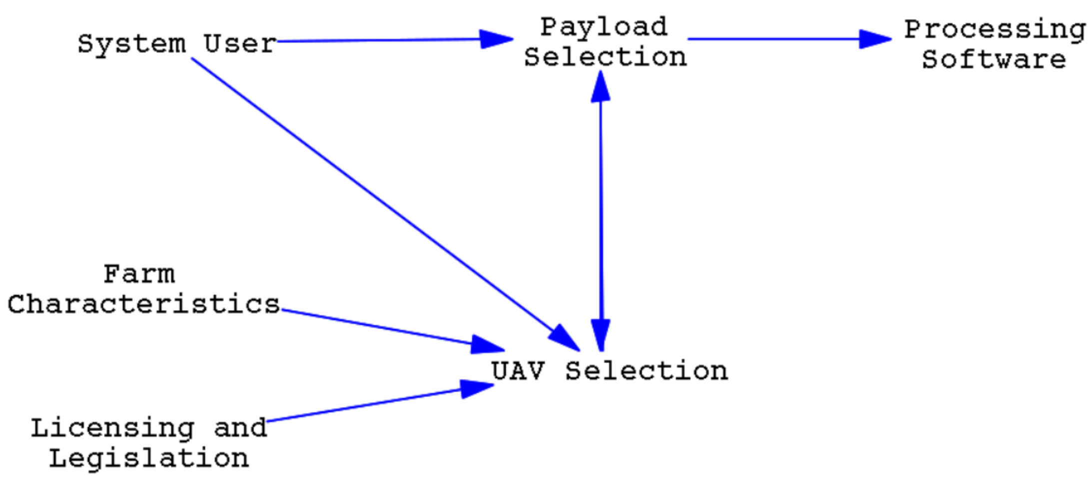

Figure 9 System Component and UAS Element Interactions

The system user directly influences the selection of the payload and the selected payload influences the selection of the post-flight processing software tool. The payload is selected based primarily on the users' desired outputs from the system and in turn, the data outputs produced by the payload affects the selection of the software tool. Different types of cameras or sensors deliver different file outputs and not all software tools can process the different file types. In a similar manner, the system user, along with the farm characteristics and the licensing and legislative requirements, affect the selection of a UAV model. And selecting a UAV affects the payload selection and vice versa.

The design of the UAS comprises of selecting a specific model or version of each of the three identified components; the UAV; payload (camera/sensor); and software. Each of these elements follows a separate selection process that will be discussed in the sub-sections to follow.

i) UAV Selection

A number of characteristics of a drone exist, that affect the selection of a specific drone model to be included in the users' crop monitoring UAV system. These characteristics do not all possess the same level of influence on the drone selection decision. To develop an integrated framework, each characteristic is considered a variable influencing the final decision of what drone model to select. These drone characteristics are regarded as key variables that influence the UAV selection decision.

The factors were selected based on the information freely provided by drone manufacturing companies combined with expert opinion. The characteristics selected are those that are most often measured, or information provided for, by drone manufacturing companies. The UAV characteristics were selected by obtaining the technical specifications of popular agricultural drone models, and drone models specifically used for crop monitoring purposes. After analysis of the information provided in the technical specifications document, the most common characteristics and features of the drone models were identified. These factors are in turn used to model the effect each characteristic has on the selection of a UAV model. The aircrafts selected as part of the analysis are those specific models mentioned in previous research articles, relevant to the current study. Due to the fast-changing nature and improvements to drone technology, many aircraft models have since been replaced with improved or updated models. The latest model of each drone is considered for the analysis unless otherwise stated. The aircrafts included in the analysis are those aircrafts that are commercially available before July 2022. Any new or improved aircrafts or aircraft models released after the end of July 2022 are not included in the analysis. The UAV models mentioned in the identified research articles were regarded as a starting point for further research into UAV models used for agricultural purposes. A basic search for commercially available drones was conducted. In some instances, the aircrafts mentioned in previous research correspond to those found through basic research. Only drones or aircrafts used specifically for *crop monitoring or mapping, precision agricultural or other, similar purposes* are considered throughout this analysis.

The following subsection identifies various drone models mentioned in previous literature sources that are considered for the analysis.

- UAV Models Mentioned in Previous Research Works

The literature consulted for this part of the analysis to identify relevant UAV/drone models are listed in

Table 10. The previously conducted research works reviewed for this part of the analysis correspond, in some cases, with the literature studied for the literature review in Chapter 2: Literature Review. The literature sources are listed in

Table 10 to allow for an increased specificity of the analysis. Each article is further analysed and the specific drone models have been identified in the paragraphs to follow.

Table 10 Literature Consulted for UAV Model Identification

Author(s)	**Title**
(Puri et al., 2017)	Agriculture drones: A modern breakthrough in precision agriculture.
(Dileep, Navaneeth, Ullagaddi, & Danti, 2020)	A study and analysis on various types of agricultural drones and its applications.
(Petkovics, Simon, Petkovics, & Čović, 2017)	Selection of unmanned aerial vehicle for precision agriculture with multi-criteria decision-making algorithm.
(G. Yang et al., 2017)	Unmanned aerial vehicle remote sensing for field-based crop phenotyping: current status and perspectives.
(Maddikunta et al., 2021)	Unmanned aerial vehicles in smart agriculture: Applications, requirements, and challenges
(Rakhade et al., 2021)	Optimal Choice of Agricultural Drone using MADM Methods

Puri et al. (2017) listed a variety of fixed-wing and multi-rotor drones within their study, highlighting how drones have gained importance within the agricultural field. Included in the analysis are a number of drones available in the market for agricultural applications. Information pertaining to these drones is mentioned in Table 11.

Table 11 UAV Models Mentioned by Puri et al. (2017)

Drone Model	**Drone Type**	**Commercially Available**
Honeycomb AgDrone System	Fixed-wing	Company temporarily closed
DJI Matrice 100	Multi-rotor (Quadcopter)	Discontinued, Matrice 300 RTK
DJI T600 Inspire 1	Multi-rotor (Quadcopter)	Discontinued, Matrice 300 RTK
Sensefly eBee SQ	Fixed-wing	Discontinued
Precision Hawk Lancaster 5	Fixed-wing	Discontinued
DSOLO AGCO Edition	Multi-rotor (Quadcopter)	Little to no information available

Dileep et al. (2020) conducted an analysis focused on the types of drones available and compared these different types of drones, and the applications these aircrafts have within the agricultural field. Table 12 lists the drone manufacturing companies mentioned in Dileep et al. (2020)'s study. Further research was conducted to identify the different drone models currently available from each company. Aircrafts specifically designed for precision agricultural purposes are included in Table 12. Sentera offers one of three full-stack solutions, namely the Research, Broad Acre and Scouting packages ("Sentera," 2022). Each of these solutions comprises of a UAV and the necessary sensor. Listed in the Table below are the three drone models included in these solutions. The DJI Matrice 300 that forms part of the Research Package by Sentera is the same aircraft as the Matrice 300 RTK model advertised by DJI. The DJI Phantom 4 Pro model which is used as part of Sentera's scouting package, has since been replaced by the DJI Phantom 4 Pro V2.0. Both of these drone models have been included in the analysis. Precision Hawk advertises two DJI drone models along with their own UAV, the BFD 1400-SE8 model ("Precision Hawk," 2022). Although the DJI Matrice 200 V2 is available if acquired through Precision Hawk and thus will be included in the analysis. The DJI Phantom series listed by Precision Hawk does not specify an exact Phantom series, thus the latest series, the Phantom 4 Pro series, will be evaluated. Similarly, the DJI Mavic series is not specified, therefore the latest Mavic model, the Mavic 3 is included.

Table 12 UAV Models Mentioned by Dileep et al. (2020)

Manufacturer	**Drone Model**	**Drone Type**
American Robotics	Scout drone	Multi-rotor (Quadcopter)
DJI: (Da-Jiang Innovations)	P4 Multispectral Phantom 4 RTK Matrice 30 Series Matrice 300 RTK	Multi-rotor (Quadcopter) Multi-rotor (Quadcopter) Multi-rotor (Quadcopter) Multi-rotor (Quadcopter)
Precision Hawk	BFD 1400-SE8 DJI Matrice 200 V2 DJI Phantom Series	Multi-rotor Multi-rotor (Quadcopter) Multi-rotor (Quadcopter)
Sensefly	eBee X eBee AG	Fixed-wing Fixed-wing
Sentera	DJI Matrice 300 Sentera PHX DJI Phantom 4 Pro DJI Mavic 3	Multi-rotor (Quadcopter) Fixed-Wing Multi-rotor (Quadcopter) Multi-rotor (Quadcopter)

Through analysis and selection of UAVs for precision agricultural purposes, Petkovics et al. (2017) identified the five most prominent drone manufacturers, namely: PrecisionHawk, AgEagle, SenseFly, Honeycomb and Delair-Tech. In addition to identifying these manufacturers, multiple drone models were identified and classified into weight categories, to distinguish performance between different drone sizes. The various drone models, along with their most common uses (as indicated by the individual drone companies) are indicated in Table 13. Many of the drones identified by Petkovics et al. (2017) are not commercially available anymore, and information about these aircrafts is difficult to come by. In the cases where information could be found on a specific drone model, the model was included in the analysis, whereas, if no information could be found, the drone model is disregarded for the analysis.

Table 13 Drone Manufacturers and Drone Models identified by Petkovics et al. (2017)

Drone Model	**Drone Type**	**Specified use**	**Commercially Available**
Sensefly eBee X	Fixed-wing		
Sensefly eBee Ag	Fixed-wing		
Sensefly eBee RTK	Fixed-wing	Survey, mapping	Discontinued
AscTec Hummingbird	Multi-rotor	Inspection	Discontinued
Novadem U130	Multi-rotor	Close inspection, Field mapping	
Blade 360X3	Multi-rotor	Aerial photography & videography	Discontinued
Ghost Aerial	Multi-rotor	Aerial photography & videography	Discontinued
FlyBi Drone	Multi-rotor (VR goggles)	Aerial photography & videography	Pilot project discontinued
Pocketflyer	Multi-rotor	Aerial photography & videography	Discontinued
Sensefly Swinglet Cam	Fixed-wing	Monitoring, Aerial Imagery	Discontinued
Trimble UX5	Fixed-wing	Mapping & Surveying	
Delair DT18 range	Fixed-wing	Mapping and Surveying	
Bramor gEO	Fixed-wing	Surveying and Remote Sensing	Discontinued Bramor ppX Bramor aGX Bramor C4EYE Atlas AS90X
Atmos 6 CATUAV	Fixed-wing	Utility drone	Discontinued Atmos 8
RAPID AgEagle	Fixed-wing		Discontinued
MINEOS CATUAV	Fixed-wing	Initially developed for landmine detection, other applications available.	Discontinued
Hexo+	Multi-rotor	Aerial Footage and videography	
ATLAS	Fixed-wing	First responders & special	Discontinued

Drone Model	Drone Type	Specified use	Commercially Available
		operations forces	ATLAS AS90X
F50 AEE UAVs	Multi-Rotor	First responders, fire detection	Discontinued
Penguin B	Fixed-wing	Surveillance & inspection	
Penguin CE	Fixed-wing	Surveillance & inspection	
Penguin BE	Fixed-wing	Surveillance & inspection (electric version of the Penguin B model)	
Serenity by ING Robotic Aviation	Fixed-wing	Inspections, mapping, monitoring.	Discontinued
Delair DT26-X	Fixed-wing	Survey, monitoring and inspection.	
CAT UAV Argos	Fixed-wing	Aerial Photography	
CAT UAV Argos Electric	Fixed-wing	Aerial Photography	
AT-100			Discontinued
Responder	Helicopter		Discontinued

The ATLAS AS90X drone, the successor of the ATLAS drone, is developed for use by first responders and special operations forces. Thus, the drone model is disregarded as part of this analysis. Similarly, both the Bramor aGX and C4EYE models are disregarded for the analysis as their specified uses do not include crop monitoring, surveying or remote sensing applications ("C-Astral Aerospace," 2022). In the study conducted by G. Yang et al. (2017), UAV-based remote sensing for field-based crop phenotyping was investigated. The study compared the current status of crop phenotyping using UAVs and the current perspectives. Included in the study are the typical UAV types used for remote sensing, but specifically for field-based crop phenotyping applications. The types of aircrafts include: multi-rotor, helicopter, fixed-wing, flying wing and blimps. Due to the limitations of the current study, only the multi-rotor and fixed-wing drone model types are included. These two drone models are included in Table 14.

Table 14 Multi-Rotor and Fixed-Wing Drones Mentioned by G. Yang et al. (2017)

Drone Model	Drone Type	Commercially Available
DJI S1000+	Multi-rotor	Discontinued
Bat-3	Fixed-wing	Could not find any information

Maddikunta et al. (2021) evaluated the uses, requirements and difficulties prevalent when utilising UAV technology in smart farming. The study explored types of UAVs and accompanying agricultural sensors used in smart farming while highlighting the different features and applications of each type. The UAVs reviewed within this study are listed in Table 15.

Table 15 UAV Models Identified by Maddikunta et al. (2021)

Drone Model	Drone Type	Commercially Available
eBee SQ	Fixed-Wing	Discontinued
Sentera PHX	Fixed-Wing	
Lancaster 5	Fixed-Wing	
HoneyComb	Fixed-Wing	Company temporarily closed
AgEagle RX-60	Fixed-Wing	
DJI Matrice 600 Pro	Multi-Rotor	Discontinued, Matrice 30 series
DJI Matrice 210	Multi-Rotor	Discontinued, DJI Matrice 300 RTK
Sentera NDVI	Multi-Rotor	
AgBot	Multi-Rotor	

- UAVs Identified through Market Research

The UAV models identified above are not an exclusive list of all of the drone models available for agricultural purposes, but rather a list of the aircrafts that have been mentioned in previous literature. While researching and analysing the technical specifications of the above-mentioned aircrafts, a range of newer models from the same companies and new models from other companies, were identified (Atmos UAV, 2021; "C-Astral Aerospace," 2022; "Delair," 2022; "Wingtra," 2022). The UAV models identified through market research are included in the analysis. The aircrafts are listed in Table 16.

Table 16 UAV Models Identified Through Market Research

Drone Model	Drone Type	Specified Use
WingtraOne GEN II	Fixed-wing	Monitor plant health, plant counts, optimise plant ROI.
Delair UX11 Ag	Fixed-wing	Mapping
Delair UX5-HP	Fixed-wing	Survey, monitor & inspect
Delair DT26E LiDAR	Fixed-wing	Laser mapping, Survey, Monitor & inspect
Delair DT26E Surveillance	Fixed-wing	Surveillance
Delair DT26E Tactical	Fixed-wing	Sensitive missions

Delair DT26E Open Payload	Fixed-wing	Monitoring, depending on the selected payload
Bramor ppX	Fixed-wing	Surveying, Remote sensing
Marlyn	Fixed-wing	Precision Agriculture

Note, that the UAV models listed are not an extensive list of all UAVs with agricultural applications, as the drone model options are endless. In addition, the technologies associated with UAVs and especially as part of the agricultural remote sensing sector, are quick-changing. Therefore, the UAV models listed in this document might be obsolete or be discontinued by the producing company in a short span of time. The UAV models selected as part of the analysis are indicated in Table 17 ("AgBot for Precision Agriculture," ; AgEagle, 2018; "American Robotics," 2022; Atmos UAV, 2021; C-Astral Aerospace, 2022; Delair; Delair; Delair, 2017, 2018, 2020; DJI, 2020a, 2020b, 2021a, 2021b, 2022a, 2022b, 2022c; Factory, 2022; "Novadem," 2022; "Precision Hawk," 2022; SenseFly, 2021a, 2021b; Sentera; Trimble, 2015; Wingtra).

Table 17 UAV Models Considered for Analysis

UAV Model	**UAV Model**
1. DJI: 1.1 Matrice 300RTK 1.2 P4 Multispectral 1.3 P4 RTK 1.4 Phantom 4 Pro 1.5 Phantom 4 Pro V2 1.6 Matrice 30 Series	6. Novadem U130 7. Trimble UX5 8. Bramor ppX 9. Atmos 8 10. Penguin B 11. Penguin BE
2. American Robotics: Scout drone	15. WingtraOne GEN II
3. PrecisionHawk: 3.1 BFD 1400-SE8 3.2 DJI Matrice 200 V2 3.3 Lancaster 5	16. Atmos Marlyn 17. AgEagle RX-60 18. AgBot
4. Sensefly: 4.1 eBee X 4.2 eBee AG **5. Sentera:** 5.1 Sentera PHX 5.2 DJI Phantom 4 Pro 5.3 DJI Mavic 3	**19. Delair** 19.1 UX11 Ag 19.2 UX5-HP 19.3 DT 26E LiDAR 19.4 DT 26E Open Payload 19.5 DT18 HD 19.6 DT18 AG

- UAV Characteristic Identification

The identification of the UAV characteristics that will be considered as the key variables influencing decision-making were identified by reviewing the technical specifications of each drone model mentioned above. Only the technical specifications that could easily be obtained or that are provided freely by the UAV manufacturing company were used. Each drone developer or manufacturer differs; thus the naming of factors might differ even though it refers to the same specification. Each of the technical specifications documents was analysed and the characteristics pertaining to the aircraft operation and output were identified. The characteristics were grouped into two main categories, namely: Technical Input and Functional Output. The technical input category includes characteristics and information regarding the technical and physical aspects of the aircraft, such as the weight of the aircraft, the battery size or capacity, connection method, etc. The technical input characteristics identified are discussed in Table 18.

Table 18 Technical Input Characteristics of UAVs

Technical Input Characteristic	**Description**
Battery information	Information pertaining to the battery included in the aircraft, such as the size, capacity, voltage, etc.
Type of UAV	UAVs are categorised into different categories, based on the propulsion method utilised by the aircraft. For the purpose of this study, two types of aircrafts are considered: fixed-wing and multi-rotor aircrafts.
Aircraft weight Maximum take-off weight Payload capacity	The weight of the body of the aircraft, excluding the payload and additional elements. The maximum weight of the aircraft at take-off, including the aircraft and the payload weight. The payload weight capacity of the aircraft.
Control system information Control system type Radio/data link Global Positioning System (GPS) Operating frequency Global Navigation Software System	Information pertaining to the control system of the aircraft. Control type of the specific aircraft: manual, semi-automatic or autonomous. Information relating to the radio frequency transmission used to receive and transmit information to and from the drone. Information regarding the GPS module included in the aircraft, if such a module is included. The frequency bands utilised by the drone for communication. GNSS data is similar to that of GPS, as the data is used to control autonomous drones, to maintain position,

Technical Input Characteristic	Description
(GNSS)	follow pre-set waypoints and return to the specified home point.
Take-off and landing information	The take-off and landing system of the specific aircraft.
Aircraft safety mechanisms and features	Safety mechanisms or features embedded in the aircraft control mechanisms that automatically react in the case of an emergency or unsafe instant.
Aircraft size	Size dimensions of the aircraft. The specified dimensions differ between different aircraft manufacturers.
Wingspan	The length (usually in mm) of the aircraft measured from wing (blade) tip to wing (blade) tip. Note the wingspan is only applicable for fixed wing drones.
Wifi connection	A connection mechanism between the drone and the users' control device, usually a cell phone.
Bluetooth connection	A method to connect the drone with the GCS and control the drone wirelessly.
Aircraft material	The material that the aircraft is made of, such as carbon fibre, aluminium, etc.
Motor type	The type of motor used in the aircraft. Typically drones contain either brushed or brushless motors.
Motor size or power capacity	The size and/or capacity of the motor used in the aircraft. This information is typically provided through the kilovolts, watts and/or lipo voltage of the motor.
Real-time kinematic (RTK)	RTK geotags images and records the GPS information throughout the drone flight, to allow each image or video captured to include its precise GPS location.
Connection/control range	The range that the aircraft can fly, in a radius, from the location of the controller or GCS.
Landing space/accuracy	The area (usually in $m^{2)}$ required for an aircraft to land, in the case where the aircrafts lands autonomously based on a predefined home point. The landing accuracy is how close the aircraft lands in range from the predefined home or landing point specified.
Take-off run	The length of open space required for the drone to take-off. This is only applicable to larger fixed-wing models.
Fuel tank size	The size of the fuel tank attached to the drone (typically in litres). This is only applicable to drones that are fuel powered and contain small combustion engines.

The characteristics classified as functional outputs include characteristics related to the performance of the aircraft. In essence, the technical characteristics of a UAV influence the performance of the drone, thus differences in the technical inputs influence the functional output of the aircraft. The functional output characteristics included in the analysis are listed and described in Table 19.

Table 19 Functional Output Characteristics of UAVs

Functional Output Characteristic	**Description**
Flight time	The average flight time of a single flight, measured in optimal conditions, usually measured in minutes.
Flight coverage	The average area (m^2) covered by the drone in a single flight.
Flight speed	The average speeds at which the aircraft flies. Different speeds are measured for different flight actions, such as take-off, hovering or cruising speeds, etc.
Wind resistance	The maximum wind speeds that the aircraft can sustain while in flight (measured in m/s or km/h or mph).
Operating temperature	Temperature range within which the drone can operate.
Ingress Protection (IP) rating	The drones' resistance to unwanted penetration of water of moisture. Typically the IP rating consists of three parts, but in this case the IP rating refer to the level of water resistance the drone has.
Service altitude Flight/cruising height	The maximum altitude at which the drone can fly, usually the service altitude is measured as the height above sea level. The flight or cruising height is the typical height or altitude above the ground that the aircraft flies at.
Ground Control Points (GCPs)	Used in conjunction with RTK and GPS information, GCPs are points set on the map to assist an autonomously controlled drone to collect information of the area being surveyed.
Hovering accuracy	The accuracy of the images and information obtained from the drone compared to the exact locations of the images.
Angular velocity	The velocity at which the propellers of the drone rotate or revolve along each of their axes.
Ground Sampling Distance (GSD)	The distance on the ground measured between two successive pixel centres. A lower GSD relates to a lower spatial resolution of the image, thus less clear images.
Rate of data collection	The rate or speed at which the drone collects information and data while in flight.
Mapping accuracy	Divided into relative and absolute accuracy. The relative accuracy is measured through comparing features from the captured image or map to other features in the same map. Absolute accuracy reviews the difference between the location of features or elements in the map and their exact position in reality. A high absolute accuracy means the map closely depicts reality.

In addition to the technical input and functional output characteristics, other characteristics are identified that cannot be categorised into any of the categories. These characteristics are the specifications relating to the built-in camera or sensor, and the payload compatibility of the specific aircraft. In the case where the drone is equipped with a camera or sensor that cannot easily be exchanged for a camera or sensor of choice, the specifications for the payload should be reviewed. Other drones allow the user to insert any camera/sensor from a range of available payloads designed specifically for that aircraft. Such drones contain a swappable payload feature. In some cases, the drones are designed in such a way that commercially available drone cameras/sensors can be attached to the aircraft.

- UAV Selection as a System

From the 40 identified characteristics, 13 were identified that either has a direct influence on the UAV selection decision or that influences or are influenced by any of the system components or elements thereof. These characteristics and the components that influence one another within the UAV selection process are illustrated in Figure 10. The key variables identified for ultimately making the decision to select a UAV or drone model are those characteristics or components of the system that directly influence the main decision variable, the UAV selection variable. The payload selection variable is indicated below to illustrate how the UAV selection and payload selection processes relate and connect to one another. Due to the system being very user dependent, the influence that the user has on some of the variables is not illustrated visually but described when referring to a specific variable(s). The variables that affect the primary variables (those variables that directly influence the main decision variables) are described as the secondary variables, as they don't have a direct influence on the UAV selection variable, but rather affect another variable that possibly directly affects the main variable.

The variables and their influence (primary or secondary) on selecting a drone model are discussed. One of the first decisions to be made by a user is what *type of drone* is preferred, thus selecting either a multi-rotor or a fixed-wing drone. Selecting a type of drone instantly influences the *take-off and landing ability* of the drone. A multi-rotor possesses a vertical take-off and landing (VTOL) ability, whereas most fixed-wing drones are hand-launched or with a catapult. Only a few fixed-wing drones contain a VTOL ability. These two variables directly influence the main variable, as preferences regarding these drones limit the selection of available aircraft models. Likewise, selecting a UAV instantly defines the type of drone, take-off and landing ability, as well as the safety feature included.

Similarly, the *safety features* embedded in the drone control system or the drone itself, also affect the selection of a UAV. The safety features preferences are heavily influenced by the *topography* of the area where the farm of choice is located. This is due to the user possibly requiring specific safety features when operating the aircraft on the farm. If an aircraft does not contain the safety features deemed important by the user the aircraft should be disregarded as part of the selection.

The topography of the area also affects both the type of UAV selected as well as the take-off and landing ability preferred for the drone. The topography affects the type of UAV selected, as each type of UAV is more suited for a specific topography. A fixed-wing drone is more suited for larger, flat areas to be monitored, whereas a multi-rotor drone is more versatile, and can operate easily in more mountainous areas as well. Similarly, the take-off and landing ability preferred is reliant on the area topography. A drone equipped with VTOL abilities can be operated in any location, even in confined areas or between trees, etc. Drones without VTOL abilities might require more open space to take off and especially land. In areas where open spaces might be restricted, the user might opt for an aircraft with VTOL abilities.

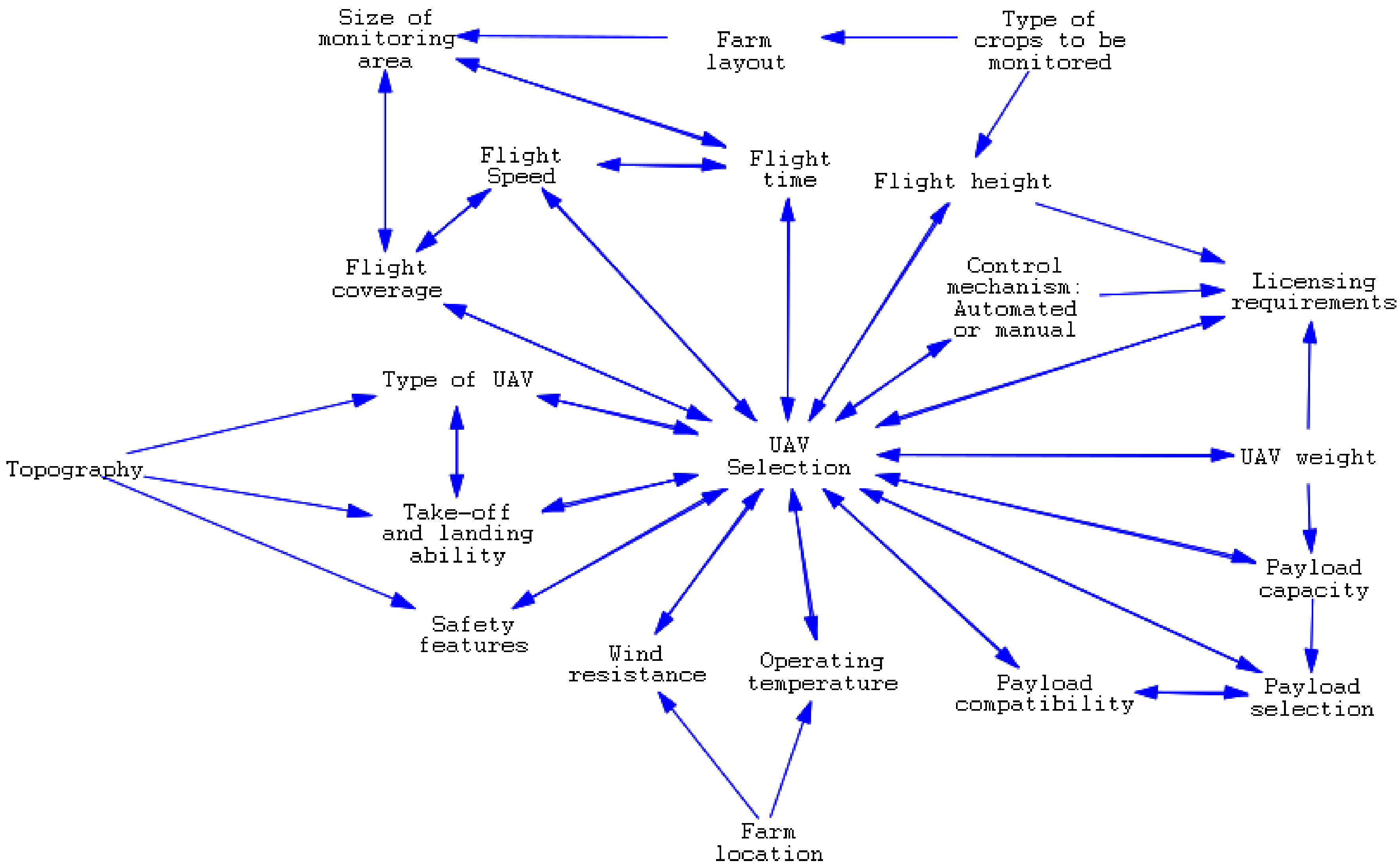

Figure 10 UAV Selection as a System

The next primary variables that influence the selection of a UAV are the aircraft's *wind resistance* ability and the ideal *operating temperatures* of the aircraft. These two variables are directly influenced by the *geographic location of the farm.* A geographic location is associated with certain weather patterns and occurrences common to that area. Therefore, the location of the farm can have an effect on the requirements pertaining to the aircraft's wind resistance and ideal temperatures in which it can operate. These variables only play a very important role in UAV selection in extreme cases. For instance, if the area in which the farm is located is subject to extremely strong winds for almost the entire year, or in areas where the temperatures are either extremely high or extremely low. In most farming areas, such extreme weather occurrences are uncommon, and in the case where the weather might be unsuitable for a drone to operate in, the flight schedule might only be delayed for a few days. In all other 'normal' circumstances, the wind resistance of the aircraft might affect the decision made as it can be regarded as an additional safety measure. Drones with a higher wind resistance have the ability to better withstand strong winds or gusts and can safely navigate home, while other aircrafts might be swept up by unexpected strong winds and lose connection with the GCS.

The size of the farm, more specifically the *size of the monitoring area*, affects the flight time and coverage required. The size of the monitoring area can either be defined by the user, thus the user defines the size of the area to be monitored in a single flight, or be defined based on the drone model selected for the system, or influenced and defined by the layout of the farm and the size of the crop fields to be monitored. A monitoring area can thus be defined by a number of different factors, or through a combination of these factors. The *farm layout* variable directly affects the monitoring area size in the case where the farm is laid out in such a way that each crop field should be defined as a single monitoring area. In this case, each field will be monitored with a single drone flight (if the size of the field is less than the drone's coverage) and to monitor the entire farm, a number of single flights will be performed. The farm layout also affects the monitoring area in cases where multiple crop fields (preferably of the same crop) are positioned next to, or close to one another. In this case, fields can be combined into a single monitoring area, thus decreasing the number of flights required to monitor the entire farm, if the selected drone can cover the defined monitoring areas in a single flight. Thus, the size of the monitoring area influences the *flight coverage* and *flight time* required from the selected drone. The flight coverage and time requirements directly influence the UAV model selected by the user. Conversely, if a drone is selected, the flight coverage and flight time are predetermined for that drone. Thus, the time and coverage variables influence the size of the monitoring area to be defined. In simpler words, if a drone can only fly for 20 minutes, the monitoring area should be defined in such a way that the area aimed to be covered in that flight would take less than 20 minutes. Similarly, monitoring areas can be combined to allow for a larger area to be monitored than originally planned. The speed at which the drone flies while monitoring is also a factor of concern, as the determined *flight speed* can have an effect on the area covered. For instance, an increased flight speed can lead to a larger area coverage in the same timeframe as a lower speed flight. However, an increased flight speed may have an effect on the flight time, as the higher operating speed may cause a faster decrease in battery life, thus decreasing the flight time of the aircraft. An increased flight speed can increase flight coverage, while at the same time decrease the flight time, due to limited battery life. This trade-off should be considered carefully, as a change in flight speed, can lead to the area covered and flight time cancelling each other out. In essence, an increased flight speed may allow for a larger area coverage, but it comes at a cost of decreased flight time. Not all drones allow for an adjustment to flight speed, thus the selection of a UAV model could be a limiting factor on the flight speed variable. Similarly, the selection of a specified flight speed or the ability to alter these speeds could influence the selection of a UAV model.

The farm layout has an effect on the monitoring area size, as discussed above. But in a similar way, the *types of crops* that are to be monitored can have an effect on the layout of the farm for monitoring purposes. This is due to different crop types being planted in different fields and typically fields with the same type of crop are located close to one another, if possible. The layout of the crop fields in relation to one another can influence how the monitoring area is defined. The types of crops to be monitored also impacts the height requirement for the flight. This, however, is only applicable for drones without a predefined cruising height or altitude. Generally, all autonomously operated drone systems fly at a predefined altitude, whereas an aircraft that is manually controlled can fly at any height above the ground. Each different type of crop grows to a different height, thus the cruising height of the drone should be adjusted accordingly, if necessary. The *flight height* or cruising altitude, influences the licensing requirements for both the aircraft and the operator. The maximum flight height of an aircraft, usually height above ground level, is restricted according to the classification of the aircraft. Almost all aircraft classes can fly up to 400 feet above ground level with the Class 4B drone as the only exception. The required flight height influences the UAV selection variable as an aircraft with a specific flight height ability might be selected if necessary. Similarly, once a UAV is selected, the flight height variable becomes a constant, due to the fact that the maximum flight height and possibly the cruising altitude is predetermined, depending on the specific drone.

The other variables that influence the *licensing requirements* are the UAV selected, the weight of the aircraft and the control mechanism of the aircraft. These four variables, including the flight height, ultimately determine the class of the aircraft. Combined with the specified use for the drone (commercial, corporate, non-profit or private), the legislative and licensing requirements are clearly defined. Along with these variables, the specific aircraft model selected affects the licensing requirements if the aircraft is selected before referring to the licensing and legislative requirements. In another sense, if the licensing requirements are limited or defined before selecting a drone model (which is highly unlikely), the licensing requirements variable affects the UAV selection variable. The *weight* of the aircraft or more specifically the Maximum Take-Off Mass (MTOM) has an influence on the licensing prerequisites or requirements. The MTOM is the maximum weight of the aircraft with all payloads and other accessories attached. Thus, the weight of the aircraft affects the available capacity for a payload.

The *payload capacity* can only be influenced by drones with a swappable payload feature or drones that external payloads can be attached to. If weight limitations are defined, then the UAV weight variable influences the UAV selection variable, however, if there are no weight restrictions, the aircraft weight variable holds no influence over the UAV selection variable. In such a case, the UAV would be selected and from that selection, the UAV weight variable is defined as a constant value that only aids in classifying the aircraft for licensing purposes and calculating the available payload capacity. The weight capacity for the payload is determined by deducting the aircraft weight from the MTOM of the aircraft if the payload capacity is not specified separately. Some UAVs specify the dimensions of the payload bay, should an external or additional payload be attached. The payload capacity directly influences the *payload selection* as only payloads that would adhere to the weight and size requirements can be selected to be used in conjunction with the drone. Similarly, only payloads that are compatible with the selected drone model can be selected for use. Thus, the selection of a UAV model limits the payloads to select from, due to not all drones being compatible with all payloads and vice versa. Conversely, when selecting a specific payload, the selection of drones is also limited.

The final variable that influences the licensing requirements to operate a specific drone is the *control mechanism* of the specific aircraft. The control mechanism relates to how the aircraft is controlled, either through remote controls, or manual controls, or the aircraft contains an automated control function. Drones with an automated flight option, allow the user to plan the flight, and then only initiating the flight, leaving the aircraft to perform the flight as planned. Specific regulations and legislation apply to such aircrafts. Manually controlled aircrafts are more common, and the licensing regulations are more clearly noted for these operations. The choice of control mechanism, is solely due to user preference and the selection of a type of mechanism, limits the availability of drones within that category. The selection of a control mechanism, thus influences the selection of a UAV model. In the same manner, if a UAV model is selected without reference to the control mechanism, the variable becomes a constant, as each drone model is built with a set method of control.

An original assumption is made that each characteristic, influences the selection of a UAV model equally, in order to illustrate the UAV selection as a system. However, this does not assist the system user in making the decision regarding a UAV model.

- Identification of Important Characteristics

In order to identify those characteristic(s) that carry the most importance in the UAV model decision, the technical specifications of the selected drones are reviewed. For each drone model mentioned in Table 17, the technical specifications were reviewed to determine if information pertaining to the selected characteristics, those illustrated in Figure 10, are available. This analysis is performed to determine the frequency of availability of information regarding a specific characteristic, among the UAV models selected for analysis. This step allows the researcher to determine what information is most frequently included within the technical specifications of the selected UAVs. Table 22 lists the drone models considered for analysis as rows, and the characteristics as columns.

The information included in Table 22 is based on the available technical specifications for each UAV model identified in the analysis. If the technical specifications of a UAV model include information pertaining to a specific characteristic, a tick-mark is allocated to that block, so as to correspond to the aircraft model and characteristic under consideration. In total 31 different drone models were reviewed and the frequency of each characteristic is indicated at the bottom of the table. From these totals, it is easy to determine which characteristic(s) are more often mentioned or specified within the technical specifications of UAV models. Table 20 ranks the characteristics from the highest to the lowest frequency.

Table 20 Characteristics Ranked in Descending Order of Frequency

Rank	Characteristic	Frequency
1	Flight time	30
2	MOTM/ Weight	29
3	Flight speed	29
4	Take-off & landing preferences	28
5	Payload compatibility	25
6	Wind resistance	22
7	Control mechanism	19
8	Operating temperature	17
9	Payload capacity	15
10	Safety features	15
11	Flight height	12
12	Flight coverage	12

From the above ranking, the characteristics that are most commonly specified are the flight time, weight of the aircraft, flight speed, take-off and landing preferences and payload compatibility. After the characteristics were ranked in descending frequency of availability of information, each characteristic is reviewed within the UAV selection system, illustrated in Figure 10. For each characteristic, the relationship(s) to and from, thus both inbound and outbound, from the characteristic is noted. The number of arrows, both inbound and outbound, for each characteristic is counted. The number of arrows signifies the number of associations between each specific characteristic and other characteristics that are influenced or influence the characteristic under investigation. A single arrow marks a single association or relationship created to or from the characteristic under investigation. The total number of interactions for each individual characteristic is denoted in Table 21.

Table 21 Characteristics Ranked in Descending Order of Number of Associations

Rank	Characteristic	Number of Association
1	Flight time	6
2	Flight speed	6
3	Flight coverage	6
4	Take-off & landing preferences	5
5	Payload compatibility	4
6	MOTM/ Weight	4
7	Flight height	4
8	Payload capacity	4
9	Wind resistance	3
10	Operating temperature	3
11	Control mechanism	3
12	Safety features	3

In accordance with the number of interactions per characteristic, the flight time, speed and coverage characteristics prove to be the most important characteristics. However, these results do not coincide completely with the first analysis, based on the availability of information. Thus, the two analyses are combined to provide a more thorough conclusion. Table 23 ranks the characteristics in ascending order according to the combined impact of the frequency and interactions for each individual characteristic. The frequency and number of interactions are multiplied with one another, to calculate the combined weight or level of importance.

Table 22 UAV Models and Corresponding Characteristics

UAV Model	Flight time	Flight coverage	Flight Speed	MTOM / Weight	Payload capacity	Wind resistance	Operating temperature	Flight height	Control mechanism	Take-off & landing preferences	Safety features	Payload compatibility
DJI:												
Matrice 300RTK	✓		✓	✓	✓	✓	✓		✓	✓	✓	✓
P4 Multispectral	✓		✓	✓	✓		✓		✓	✓	✓	✓
P4 RTK	✓		✓	✓		✓	✓		✓	✓	✓	✓
Phantom 4 Pro	✓		✓	✓		✓	✓		✓	✓		✓
Phantom 4 Pro V2	✓		✓	✓		✓	✓		✓	✓		✓
Matrice 30 Series	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
American Robotics:												
Scout drone									✓			
PrecisionHawk:												
BFD 1400-SE8	✓		✓		✓				✓	✓		✓
DJI Matrice 200 V2	✓		✓	✓	✓					✓	✓	
DJI P4 Advanced	✓		✓	✓		✓	✓		✓	✓	✓	✓
Lancaster 5	✓	✓	✓	✓	✓		✓	✓				
Sensefly:												
eBee X	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
eBee AG	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
Sentera:												
Sentera PHX	✓		✓	✓		✓		✓		✓		
DJI Mavic 3	✓		✓	✓		✓	✓		✓	✓	✓	✓
Novadem U130	✓		✓	✓	✓	✓			✓	✓		✓
Trimble UX5	✓	✓	✓	✓		✓		✓		✓	✓	✓
Bramor ppX	✓	✓		✓	✓	✓		✓	✓	✓		✓
Atmos 8	✓		✓	✓	✓							
Penguin B	✓		✓	✓	✓					✓		✓

UAV Model	Flight time	Flight coverage	Flight Speed	MTOM / Weight	Payload capacity	Wind resistance	Operating temperature	Flight height	Control mechanism	Take-off & landing preferences	Safety features	Payload compatibility
Penguin BE	✓		✓	✓	✓					✓		✓
AgEagle RX-60	✓	✓	✓	✓		✓	✓		✓	✓		
AgBot	✓		✓	✓						✓		✓
WingtraOne GEN II	✓		✓	✓	✓	✓	✓		✓	✓	✓	✓
Atmos Marlyn	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓
Delair:												
UX11 Ag	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓
UX5-HP	✓	✓	✓	✓		✓		✓	✓	✓	✓	✓
DT 26E LiDAR	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓
DT 26E Open Payload	✓		✓	✓		✓	✓			✓		✓
DT18 HD	✓	✓	✓	✓		✓		✓		✓	✓	✓
DT18 AG	✓	✓	✓	✓		✓		✓		✓		✓
Total	**30**	**11**	**29**	**29**	**15**	**22**	**17**	**12**	**19**	**28**	**15**	**25**

Table 23 Combined Ranking of UAV Characteristic Importance

Rank	**Characteristic**	**Frequency**	**Interactions**	**Total**
1	Flight time	30	6	180
2	Flight Speed	29	6	174
3	Take-off & landing preferences	28	5	140
4	MTOM or Weight	29	4	116
5	Payload compatibility	25	4	100
6	Flight coverage	12	6	72
7	Wind resistance	22	3	66
8	Payload capacity	15	4	60
9	Control mechanism	19	3	57
10	Operating temperature	17	3	51
11	Flight height or operating altitude	12	4	48
12	Safety features	15	3	45

From Table 23 the most important UAV characteristics to consider, based on information availability and characteristic influence combined are: flight time; flight speed; take-off and landing preferences; MOTM of aircraft weight and; payload compatibility. An assumption can thus be made that these characteristics should be specified or selected by the user, ahead of the other listed characteristics and consequently defining each characteristic in descending order down the list. However, it still remains the users' decision as to what characteristic he deems most important. As most characteristics influence one or more characteristics, a decision regarding a single characteristic will limit the availability of options to select from regarding other characteristics. Those characteristics that directly influence the drone selection variable, limit the drone models to select from once an individual characteristic is defined or specified. The list of available UAVs to choose from can then further be refined once more characteristics are defined by the user. This process can be iterated until a suitable aircraft model is identified, or the list of available models refined to such a point that the user can make an easy decision. The user is however not bound to define certain characteristics ahead of others should the user not deem that characteristic more important that the characteristics listed after it.

- UAV Selection Process

The selection or decision process of a specific UAV model is an iterative process that relies on the unique requirements and needs of the system user. The descending order in which the characteristics are ranked above is thus only a suggestion for a case where the user does not have specific preferences or needs for the system. Figure 11 visually illustrates the process that can be followed by the user to select a suitable UAV model. The first step of the process is to review and define the users' needs and requirements for the system as a whole. Thereafter, the system components (i.e. the farm size and layout, crop types, the topography of the area and the geographic location of the farm) are specified. An assumption is made that these components remain rather constant (to a certain extent) within the system. Only some of these components can possibly change, for instance, the type of crops planted can differ from one planting season to the next, or the layout of the farm and the crop fields can be changed between planting seasons. The user needs and requirements and the system components are evaluated to ensure that it aligns with the overall system goals. If these two groups don't coincide, the user needs and requirements should be re-evaluated. After re-evaluation, the user can proceed to the next steps indicated in the process.

This step enables the user to define each UAV characteristic, in a descending order based on the level of importance given to each characteristic. From the analysis above, the user should first define the flight time, then the flight speed, followed by the aircraft weight, payload compatibility and so forth. The process is designed in such a manner that a single characteristic is defined, and then the available UAV models are filtered based on the defined characteristic. This step iterates until all of the required UAV characteristics are defined or the refined list of UAV models adheres to the previously specified requirements. If the final refined list of UAVs does not adhere to all of the requirements, the process is reviewed from the first step and followed again. Once the list of appropriate UAVs is established, the user should decide whether a suitable UAV model can be selected from the list. If the user is not satisfied with the pre-selected list of UAV models, the process of defining characteristics should be reviewed and repeated until a more desirable result is obtained. If the user is satisfied with the UAVs to select from, the selection process must be continued to select the most suitable UAV model.

The UAV selection process illustrated above is a suggestion of the process that should be followed by the user. The user is however free to adapt the process to suit his demands. For instance, the user can list the characteristics in any order of preferences, should he deem some characteristics more important than others that specifically don't coincide with the results from the importance ranking conducted earlier.

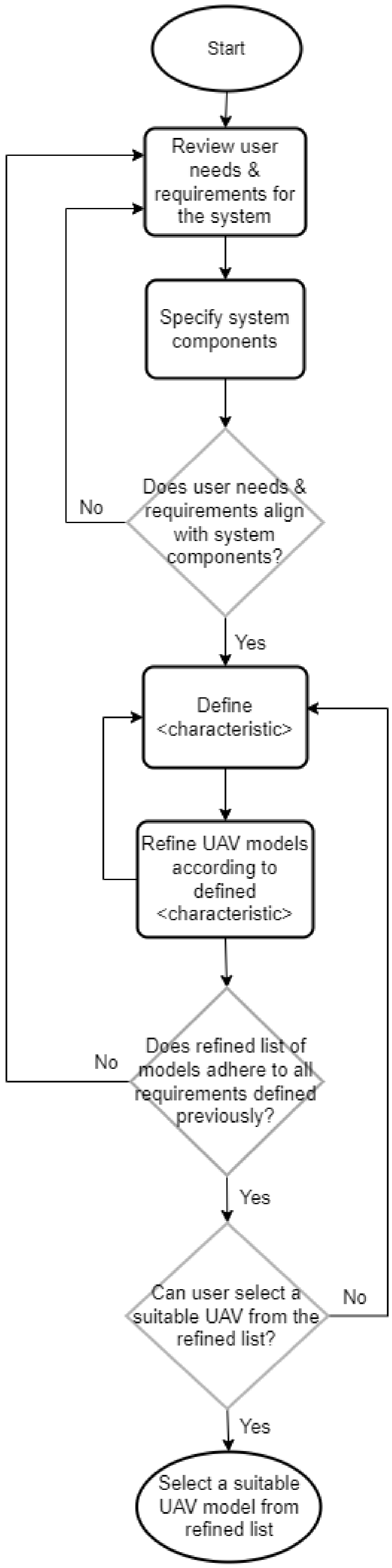

Figure 11 UAV Selection Process

ii) Payload Selection

The second component to be selected as part of the crop monitoring system is the payload. In this case, the payload refers to the camera or sensor, or combination thereof, attached to a drone that captures the crop data. Most cameras attached to drones only capture visual images or videos, however other types of sensors have been developed, including but not limited to: Multispectral, Hyperspectral, Visible Light (RGB) and Thermal sensors. Each sensor type delivers a different output from the captured data or can be used in different calculations related to crop health.

The selection of a suitable sensor relies heavily on the *drone model selected*. This is due to most aircrafts being manufactured with an already attached camera or sensor that cannot be removed and/or swapped easily. In the case where the drone specifications and requirements have preference over the requirements for the payload, the user will typically select the drone before selecting a payload, if the payload can be selected for that specific drone and is not attached to the drone. Some drones contain a swappable payload or open payload feature. A swappable payload allows the user to easily switch between different payloads (if necessary) for the same drone. This feature allows the user to select a payload from a range of payloads compatible with that specific aircraft model, thus expanding the user's selection. An open payload allows the user to attach or insert any payload given that it adheres to the dimensions and specifications of the payload bay of the aircraft. In some cases, an external payload (a camera or sensor developed by a different company than the drone manufacturer) is used by multiple drone manufacturers. In this case, if the user were to select a specific payload before selecting an aircraft, the payload selected limits the UAV models available for selection. If the drone model is selected before selecting a sensor, the available *payload capacity* and *payload compatibility* (only applicable for swappable or interchangeable payload features) are determined by the selected aircraft. The payload capacity and/or compatibility can therefore also limit the selection of payloads available for a specific drone model. Alternatively, if a payload is selected before a UAV model, the selected payload limits the available aircraft models to choose from. Due to a relationship already existing between the payload compatibility, payload selection and UAV selection variables, the selected payload does not directly affect the available payload compatibility and compatibility. This is due to the existing relationship between the UAV selection and the available payload specifications for that particular UAV.

The *system user* heavily influences the selection of a specific payload, by defining the specific *goals of the system* or the *outputs desired* from the system. The user can define the type of output(s) required from the system as what data type to be captured (visual or other) or the post-processing calculations required. This decision affects the type of payload selected as part of the system, as the selected payload should be able to deliver the required output. The system user is indicated in this system due to the important role that he plays in defining the goals and outputs required from the system. Similar to the UAV selection system, the system user component has an effect on the whole system and some variables within the system. Along with the user-defined goals and desired system outputs, the selected payload affects the *selection of post-processing software* solutions. The selection of software is discussed in the next subsection. Each sensor delivers data or images to a predefined *accuracy* or Ground Sampling Distance (GSD). The GSD is influenced by the UAV model and the cruising altitude (flight height) of the UAV as well as the sensor type and designed accuracy. The accuracy level preferred or required by the user can thus influence the selection of the specific payload. Similarly, payloads can deliver a predefined *coverage* of the area being monitored. The coverage offered by a payload differs from the flight coverage due to the overlapping of captured images to create an orthomosaic of the monitored area.

Figure 12 illustrates the variables that affect the payload selection variable.

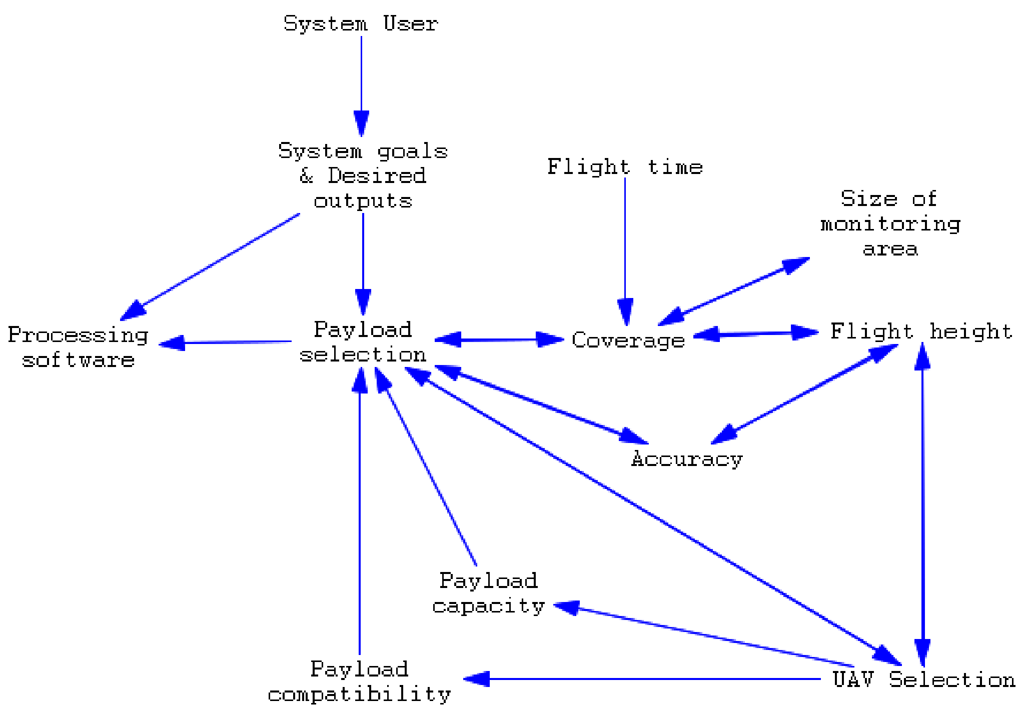

Figure 12 Payload Selection as a System

- Payload Identification

Similar to UAVs, the number of options for sensors or cameras to be attached to a drone is endless. Thus only applicable models are considered and presented as part of the analysis. The specific sensor models identified are those models attached to or compatible with the drone models considered for the analysis. These drone models are listed in Table 17. From the technical specifications or information provided by the drone manufacturers, the sensor or camera attached to the drone, or listed as a payload option is identified. The comprehensive list of payloads for the identified drones is shown in Table 24. The model name (if available), type of payload (camera, type of sensor) and the file or data output produced by each payload is described ("AgBot for Precision Agriculture," ; "AgEagle," 2022; Atmos UAV, 2021; C-Astral Aerospace, 2022; Delair; Delair; Delair, 2017, 2018, 2020; DJI, 2020a, 2020b, 2021a, 2021b, 2022a, 2022b, 2022c; Factory, 2022; MicaSense, 2020a, 2020b; "Novadem," 2022; "Precision Hawk," 2022; SenseFly, 2022; Sentera; Sentera; Sentera; Sentera; Trimble, 2015; Wingtra).

Table 24 Payloads Identified for each UAV Model

UAV Model	**Payload Attached/Compatible with**	**Type of Payload**	**File or Data Output**
DJI:			
Matrice 300RTK	Supports multiple payload configurations.		
P4 Multispectral	Attached camera	Multispectral, with RGB	JPEG images TIFF images
P4 RTK	1-Inch CMOS sensor (attached)	Wide angle image sensor (camera)	4K videos (MOV or MP4 format) 20MP photos
Phantom 4 Pro	1-Inch CMOS sensor (attached)	Wide angle image sensor (camera)	4K videos (MOV or MP4 format) 20MP photos
Phantom 4 Pro V2	1-Inch CMOS sensor (attached)	Wide angle image sensor (camera)	4K videos (MOV or MP4 format) 20MP photos
Matrice 30 Series	Attached zoom and wide angle camera. M30T: Long-wave infrared thermal camera (additional)	Image sensor (camera) M30T: Thermal sensor	Aerial photos M30T: Thermal images
American Robotics:			
Scout drone	No payload information available		
PrecisionHawk:			
BFD 1400-SE8	Large payload capacity (11kg), no other information provided.		
DJI Matrice 200 V2	Zenmuse Z30	Image sensor (camera)	JPEG images MOV, MP4 videos
	Zenmuse X5S	Image sensor (camera)	DNG, JPEG, DNG + JPEG Images RAW, ProRes, MOV, MP4 videos
Sensefly:			
eBee X	S.O.D.A.	Image sensor with RGB	JPEG, DNG + JPEG images
	S.O.D.A. 3D	Image sensor with RGB	nadir and oblique images, JPEG, DNG + JPEG images
	Duet T	Thermal and RGB sensor	Thermal: R-JPEG images RGB: JPEG images
	Aeria X	Image sensor with RGB	JPEG, DNG + JPEG images

UAV Model	Payload Attached/Compatible with	Type of Payload	File or Data Output
	Duet M Parrot Sequoia + MicaSense RedEdge-MX	RGB (S.O.D.A.) and Multispectral (Parrot Sequoia+) combination Multispectral + RGB sensor Multispectral sensor	JPEG, TIFF Four-band multispectral JPEG, TIFF four-band multispectral TIFF, five-band multispectral
eBee AG	Duet M	*See eBee X	*See eBee X
Sentera: Sentera PHX DJI Phantom 4 Pro DJI Mavic 3	 6X 6X Thermal Double 4K Specialised Sensors Single Double 4K Hasselblad L2D-20c camera ½-inch CMOS camera sensor	 RGB + Multispectral RGB + Multispectral + Thermal NDVI/NDRE (multispectral sensor) Analytics (RGB sensor) Ag+ (RGB + Multispectral sensor) Multispectral Weed Mapper (RGB sensor) RGB + Multispectral *See Sentera PHX Photos and videos Photos and videos	 JPEG, TIFF, RAW Five-band multispectral JPEG, TIFF, RAW four-band multispectral JPEG, TIFF, RAW, Four-band multispectral, NDVI, NDRE, Terrain elevation JPEG, TIFF, RAW NDVI, Terrain elevation JPEG, TIFF, RAW four-band multispectral, NDVI, RGB, Terrain elevation JPEG, TIFF, RAW five-band multispectral, NDVI, NDRE, Terrain elevation JPEG, TIFF, RAW RGB, Terrain elevation JPEG, TIFF NDVI, NDRE *See Sentera PHX JPEG, DNG (RAW), MP4, MOV JPEG, MP4, MOV
Novadem U130	Embedded Sensors	HD video and still image camera	
Trimble UX5	Attached camera	24MP mirrorless camera with	

UAV Model	Payload Attached/Compatible with	Type of Payload	File or Data Output
		custom 15mm lens.	
Bramor ppX	Attached camera	24.2MP RGB Sensor	
Atmos 8	No specific payload information provided		
Penguin B Penguin BE	Universal Payload mount Universal Payload mount		
Lancaster 5	No specific payload information provided		
AgEagle RX-60	Attached sensor	Crop health NDVI Sensor	
AgBot	Attached camera	Multispectral sensor/filters	Five-band multispectral
WingtraOne GEN II	Sony RX1R II Sony a6100 (nadir and oblique) MicaSense RedEdge-MX MicaSense Altum	RGB nadir RGB nadir and oblique Multispectral Multispectral and thermal	 Five-band multispectral Five-band multispectral + Thermal
Atmos Marlyn	Sony RX1R II Sony A7C MicaSense RedEdge-MX MicaSense Altum	*See WingtraOne RGB image sensor *See WingtraOne *See WingtraOne	*See WingtraOne *See WingtraOne *See WingtraOne
Delair: UX11 Ag UX5-HP DT 26E LiDAR DT 26E Open Payload DT18 HD DT18 AG	 MicaSense RedEdge-MX Attached sensor RIEGL miniVUX-1DL Open payload: any payload can be attached/inserted if it adheres to given dimensions Attached Sensor MicaSense RedEdge-MX	 *See WingtraOne Mirrorless 36MP camera with 15, 25 or 35mm lens LiDar sensor; Industrial grade RGB sensor Photogrammetry Photogrammetry *See WingtraOne	 *See WingtraOne Raw data LiDAR data RGB data *See WingtraOne

The payloads are further grouped into the types or payloads, indicated in Table 25. Three categories are created, Image sensors/cameras (including RGB sensors), multispectral sensors and thermal images. Payloads containing a combination of the sensors in the different categories are listed more than once, in each category that it can be grouped into. Payloads attached to drones, that are not listed with a unique model name are listed under the drone model in Table 25.

Table 25 Categorised Payloads

Image Sensors or Cameras (including RGB)	**Multispectral Sensors**	**Thermal Sensors**
DJI P4 RTK	Sensefly Duet M	DJI M30T
DJI Phantom 4 Pro	Parrot Sequoia +	Sensefly Duet T
DJI Phantom 4 Pro V2	MicaSense RedEdge-MX	Sentera 6X Thermal
DJI M30	Sentera 6X	MicaSense Altum
Zenmuse 30	Sentera 6X Thermal	
Zenmuse X5S	Sentera Double 4K NDVI/NDRE	
Sensefly S.O.D.A.	Sentera Double 4K Ag+	
Sensefly S.O.D.A. 3D	Sentera Double 4K Weed Mapper	
Sensefly Duet T	AgEagle RX-60	
Sensefly Aeria X	AgBot	
Sensefly Duet M	MicaSense Altum	
Parrot Sequoia +		
Sentera 6X		
6 Sentera X Thermal		
Sentera Double 4K Analytics		
Sentera Double 4K Ag+		
Sentera Double 4K Weed Mapper		
Hasselblad L2D-20c		
DJI Mavic 3 ½-inch CMOS		
Novadem U130		
Trimble UX5		
Bramor ppX		
Sony RX1R II		
Sony a6100 (nadir and oblique)		
Sony A7C		
Deliar UX5-HP drone		
RIEGL miniVUX-1DL		
Delair DT18 HD		

Due to the vast amount of sensors available in the market, only those sensors attached to, or compatible with the drone models identified earlier are used for analysis. The above list of sensors is thus not an exhaustive list of available sensors, as the list of UAV models would also grow as more suitable sensors/cameras are identified and vice versa.

- Selection Process

Similar to the previous selection processes, a recommendation of the process steps to follow to select a suitable payload is developed. The payload selection process is illustrated in Figure 13. The first step in the recommended process is for the user to define his goals and desired outputs from the system. The goals and outputs for the system serve as the main requirements when selecting a payload, as the selected payload should be able to deliver what the user wants from the system. Secondly, it should be determined whether a UAV model has been selected prior to selecting a payload. If a UAV model has been selected, the available payloads are limited to those compatible with the specific drone model. Thus, the compatible payloads should be reviewed first, before the rest of the process can be performed. Once the payloads are reviewed, or in the case where a UAV model has not been selected, the next step is to define the characteristics and requirements relating specifically to the payload. The characteristics to be defined are those identified earlier and illustrated in Figure 12. Once the characteristics are defined and the requirements for the payload specified, the available payloads should be refined according to the requirements and characteristics. In the case where a UAV model has been selected prior to selecting a payload, the list of payloads has already been refined based on their compatibility with the selected UAV. The already refined list is then further refined to address the characteristics and requirements of the payload. From the refined list of payloads, the user should be able to easily select the most suitable payload option for the system.

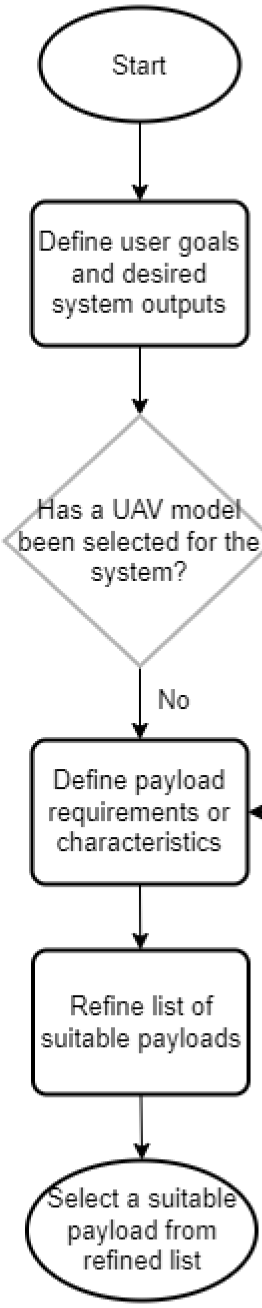

Figure 13 Payload Selection Process

iii) Software Selection

As mentioned above, some GCSs, typically those included in a full-stack COTS solution, include the post-flight processing software as part of the control systems, whereas other systems require third-party software to be used. For a system where third-party software is to be used, a range of factors should be taken into account when selecting the software tool. An assumption is made that for the purpose of this study, the post-flight processing or photogrammetry software solution(s), does not form part of the GCS software accompanying the UAV. An important consideration for selecting post-flight processing software is the *file format* of the data captured by the payload attached to the monitoring UAS. The data will vary depending on the type of payload used and can range from aerial images, and multispectral images, to NIR data or images. The data produced as output from the UAS serves as input to the processing software. The data outputs from the UAS is directly dependent on the *payload* used within the monitoring system. Thus selecting a specific payload affects the data produced as an output to the system. And through selecting a specific payload, the choice of *drones* is affected. These dependencies are bi-directional as selecting a single software tool affects the input data file format. These input files affect the camera or sensor selected as payload and it can be assumed that a certain type of camera or sensor produces a certain type of file output. Selecting a camera based on the file format affects the availability of drones to choose from.

Another aspect to be taken into account is the *desired output(s)* and *results* required by the user. This variable is defined as the *system goals* and *desired outputs* defined or required by the *system user* along with the *requirements* specified by the user. This will affect the software program selected, should the specific program adheres to the users' requirements or not. A user requirement that can potentially have a big impact on selecting a software tool is the budget available for purchasing a software tool or the license thereof. The user directly influences the *format* or desired style of *results* and *conclusions* to be produced by the software. This means that should the user, for instance, require images indicating the calculated NDVI or other VI's for a specific area, a software solution with the ability to produce such results should be selected. These dependencies are illustrated in Figure 14.

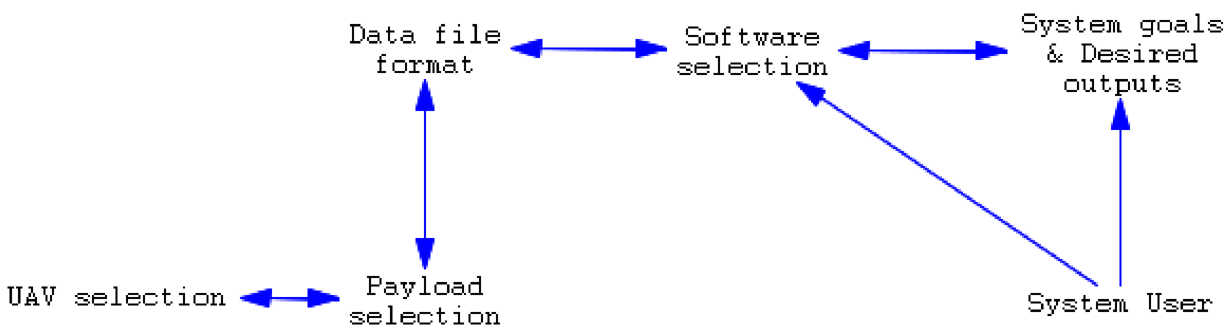

Figure 14 Software Selection as a System

In combination with the software selection system, a user can follow a predetermined selection process to simplify the decision process.

- Software Selection Process

Selecting a suitable software solution from the countless alternatives can be illustrated through a recommended selection process. Similar to the previous selection processes, this process starts by defining the user goals and desired system outputs. These conditions should correspond to the previously defined goals and outputs in general. The conditions can differ with regard to the specifics of the goals and outputs produced by the software solution selected. The next step of the process is to determine whether a payload has already been selected for the system in one of the previous processes. If a payload has already been selected for the system, the output files or data types for the selected payload are reviewed. The available software tools are then refined based on their compatibility with the output files produced by the selected payload. Finally, the refined list of compatible software tools is further refined based on the users' requirements for the system, where after a suitable software tool is selected by the user. In the case where a payload has not been selected for the system in any of the previous processes, the available or possibly suitable payload alternatives are evaluated with regard to the data or file outputs generated by the alternatives. After evaluating the payload alternatives, software tools compatible with the different file/data inputs are determined and grouped together. The software tools are further refined based on the users' specific requirements, where after a suitable software tool can be selected. Ideally, the selected software tool should allow for standard data or file input types that the majority of payloads produce as outputs, so as to not limit the available payload alternatives.

The process as described above is visually illustrated in Figure 15. This process flow map only serves as a recommendation for the user to follow, to make an easier, yet informed decision regarding a suitable software solution.

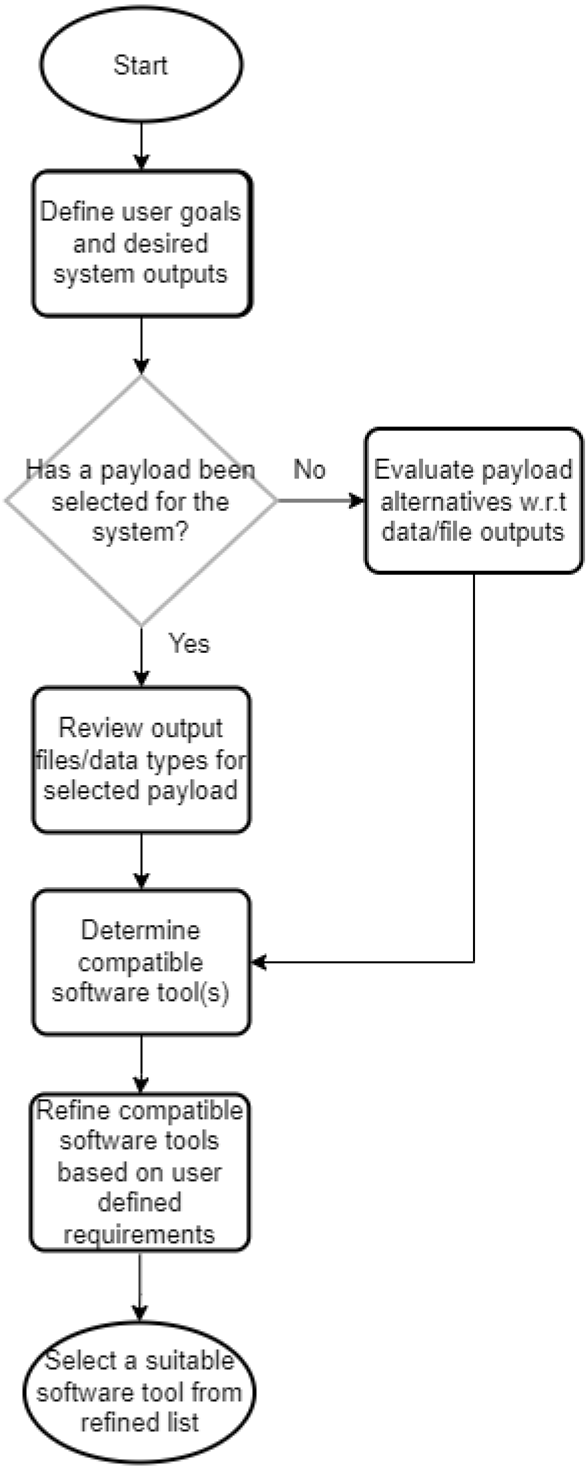

Figure 15 Software Selection Process

- Software Identification

Various software tools have been identified through reviewing the technical specifications of the UAV models identified as part of the analysis. All of the software tools mentioned in the specifications were reviewed and analysed to identify only those software tools suitable for agricultural purposes, and more specifically the tools that can be used to process imagery and data for crop monitoring purposes ("3D Survey," ; Agisoft; "Alteia," ; "Drone Deploy," ; "ENVI Crop Science," ; "ESRI ArcGIS," ; "ESRI ArcGIS Drone2Map," ; "Measure Ground Control," ; "Menci Software," ; "Pix4D fields," ; "Precision Analytics," ; "Sentera FieldAgent," ; "Simactive," ; "Skippy Scout," ; "Trimble Inpho UASMaster,"). Any solution outputs relating to measuring crop health or aiding in determining the health of crops were included in the selection. In addition, software tools that can create orthomosaics or orthophotos from the captured data were also included, as a visual representation of a crop field also carries significant value. When reviewing the suitable software tools, the most important information considered is the outputs or products produced by the software as well as the data file or input type compatibility of the software tool. Table 26 presents a refined list of the software tools available, that specialises in agricultural applications, or can be used for agricultural applications.

Table 26 Software Tools Available

Software Tool	**Outputs/Products**	**Data File Input Compatibility**
Pix4D Fields	Digital maps: - Orthomosaic - Vegetation Indices maps - Zonation maps - Prescription maps - Field boundaries - Digital Surface Models	- RGB: JPEG - Multispectral: TIFF or JPEG - Pre-processed maps: geoTIFF orthomosaic or VI's - Field Boundaries: geoJSON, KML or Shapefile - Geotagged images: JPEG, TIFF
DroneDeploy	Field edge mapping Stand counts Advanced crop health analysis Vegetation Indices Digital Elevation models	Geotagged aerial data: JPG format
Sentera FieldAgent	Crop health Canopy cover Flowering Height and Lodging Stand and Tassel Count Weed detection Exports PDF file of selected information	
Skippy Scout	Scout field maps Disease identification Monitor problem areas	Any image or map from any source, does not specify file type.
Trimble Inpho UASMaster	Photogrammetry workflows	Can process data from almost every UAS vendor, no vendor or file types specified.
Esri ArcGIS Drone2Map	Multispectral analysis Crop status Orthomosaics Digital surface and terrain models Multiple VIs: NDVI; SAVI; GNDVI; Red-Edge NDVI	 Can visualise natural-colour, thermal infrared and multispectral datasets. Supports most main multispectral cameras.
PrecisionAnalytics	Multiple VIs: NDVI; ENDVI; VARI; NDRE; SAVI	RGB, 3-Band Multispectral and Thermal data from:

Software Tool	**Outputs/Products**	**Data File Input Compatibility**
	Growth trends Plant counts and sizes Plant stress identifiers	- DJI sensors - Parrot Sequoia - MicaSense: Red Edge M/MX; Altum
Alteia	Crop characteristics Weed maps	Visual drone data: - RGB - Multispectral - Hyperspectral - LiDAR Field boundaries
Simactive	Digital surface models Digital terrain models Orthomosaics 3D models Calibrated reflectance maps Index maps (NDVI)	Any UAV platform All cameras and sensors Infrared and multispectral imagery
Agisoft Metashape	Multichannel Orthomosaic Vegetation indices	RGB NIR Thermal Multispectral images
3D Survey	Orthophotos Surface models Contour maps	Compatible with any drone and any camera. Nothing mentioned about sensors.
Menci	Orthophotos Orthomosaic Digital surface models	Any drone images: TIF, JPG format
Measure Ground Control	Integrates with Pix4D Orthomosaic Multispectral reflectance map Digital surface and terrain models	
ENVI Crop Science	Integrates with Esri's ArcGIS platform. Crop health information	Spectral and Spatial imagery

iv) Integrated Solution to Design Own System

From the design and development of the three separate decisions that form part of the main solution to design your own system, an integrated solution is created. This solution combines the three decisions to be made within the main decision path. These decisions include the selection of a UAV model, payload and suitable processing software. Each of these decisions was individually evaluated and modelled as a system, to illustrate the different factors and variables that influence these decisions respectively. As mentioned previously, and that became apparent in the analysis of each decision, the main components that influence these decisions are the user; the physical farm characteristics and; licensing and legislation requirements. The user influences the decisions through multiple sub-variables identified earlier in this Chapter. In some of the decision systems, the system user is indicated as a variable, whereas in other systems, one of the sub-variables of the system user is used. In the cases where the sub-variables are used, it illustrates the importance of that variable on the other variables within that decision system. The physical farm characteristics are also divided into their sub-variables when included in the decision systems, as the different sub-variables have distinct influences on the other variables within the system.

Due to the three main decision variables directly influencing each other, the UAV selection and payload selection influence each other bi-directionally, while the payload selection directly influences the selection of a suitable software tool. The three separate decision systems are combined into a single system, to illustrate the collective effect of the variables on one another and on the three decision variables. The integrated system is illustrated in Figure 16. Some of the variables were identified in more than one of the sub-decision systems, for instance, the system user influences all three of the decisions, namely UAV, payload and software selection. Similarly, the system goals and desired outputs specified by the user have an influence on both the payload and software selection decisions. The other variables that share direct influences are the payload compatibility and capacity variables, which both affect and are affected by, the payload and UAV selection variables. Other variables influence one of the decision variables directly, but indirectly influences one of the other variables, thus through influencing another variable that influences the decision variable. These variables have a secondary influence on the decision variables and are depicted in Figure 16.

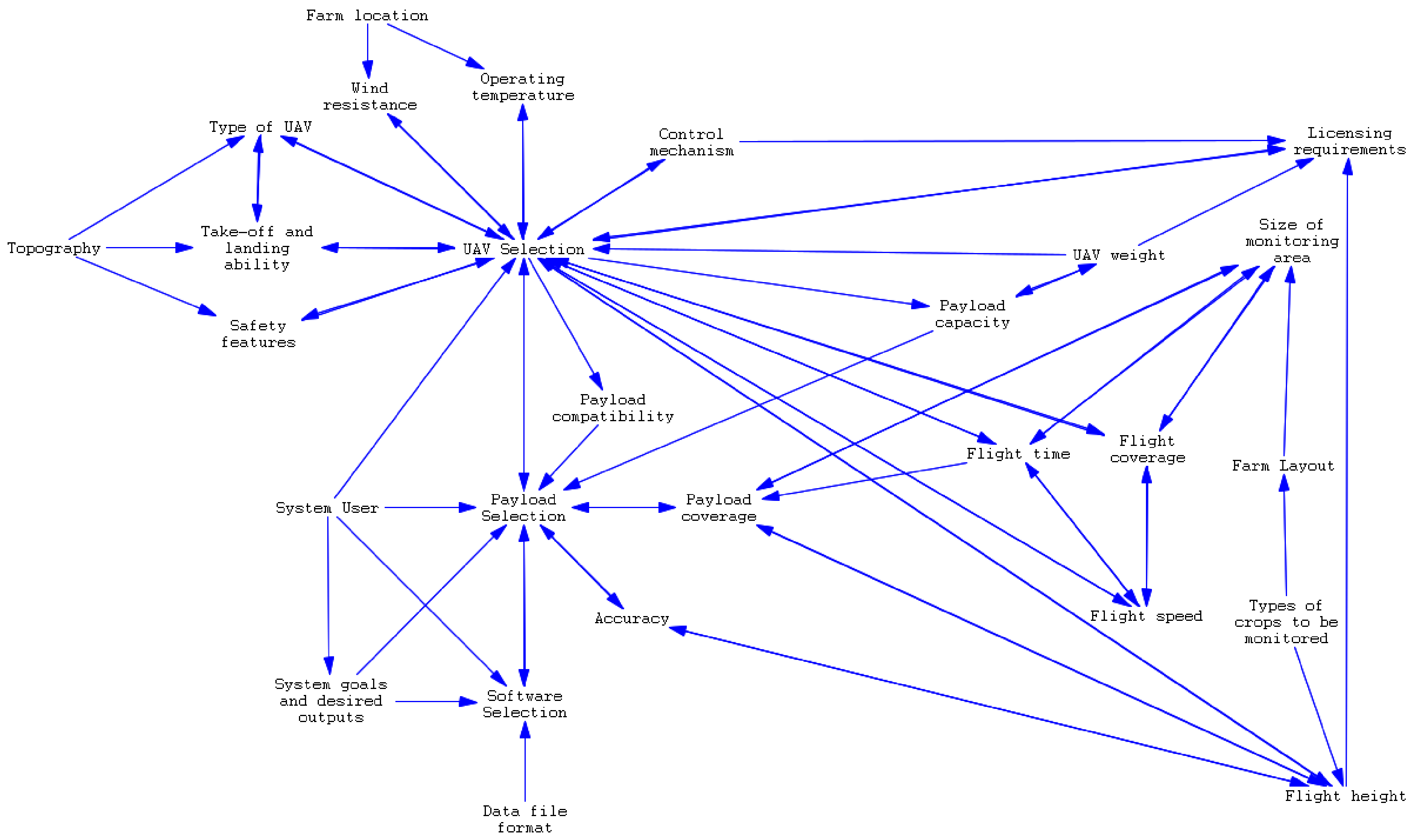

Figure 16 Design Your Own System Illustrated as an Integrated System

- Integrated Solution Design Process

Accompanying the integrated solution system, a process diagram has been developed to combine the three separate sub-decisions to be made when designing your own solution. This process starts by reviewing the users' needs and system requirements along with defining the goals and desired outputs for the system. This step is a combination of the first steps indicated in the various sub-decision processes. When user preferences have been reviewed, the system components (especially the farm characteristics) are specified. After the specification of these components, the user is referred to either the UAV selection or the payload selection process. Depending on the users' preferences, the order in which these processes are followed is influenced. If the user places more emphasis on the UAV model and its specifications, the user will refer to the UAV selection process before referring to the payload selection process. Alternatively, if the user is more peculiar regarding the specifications of the payload, the user will refer to the payload selection process and then to the UAV selection process. This is a consequence of the strong influence these two items have on one another and selecting one greatly influences the selection of the other. After referring to either the UAV selection or payload selection process, the other process should be referred to and performed consequently. Following the selection of a suitable UAV and payload, the software selection process is referred to. The software selection process makes provision for a case where a payload is not yet selected. If this is the case, the software selection process can be completed, followed by the payload selection process. Upon completion of the three sub-decisions to design your own system, the compatibility of the hardware and software components should be evaluated. If all of the components are able to effectively integrate and work together, the system should be evaluated against the initial preferences specified by the user. Upon user satisfaction, the selected system can be purchased and implemented by the user. The complete integrated selection process is illustrated in Figure 17.

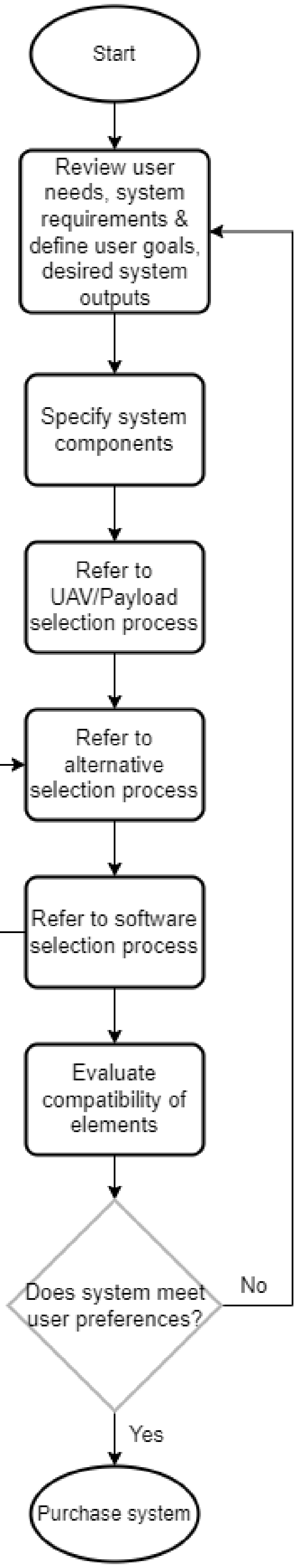

Figure 17 Integrated Solution Selection Process to Design Own System

4.2.2.2 Purchase Full-Stack Solution

If a user opts to acquire a full-stack or COTS solution instead of designing the entire solution and selecting each individual component within the system, the selection process is that of the COTS solution itself. The terms full-stack solution and COTS solution is used interchangeably, referring to the same solution type. A full-stack or COTS solution contains all of the necessary hardware and software within a single solution package. Usually, a full-stack solution, designed for agricultural purposes specifically, contains the UAV, payload or payload options to select from, DCS and additional spare parts and/or maintenance plans or extended warranty periods. Each COTS solution is however different, especially with regard to the included components and/or software. For this analysis, an assumption is made that the post-flight processing software solution is not included in the COTS solution. Selecting a suitable and appropriate COTS solution, as with the other main decisions to be made within the system, can be influenced by a number of factors within and outside the system's boundaries. The selection of a suitable COTS solution and the variables that affect this decision is illustrated in Figure 18. Similar to the UAV selection system, the system user has a strong influence over the entire system, thus the users' influence is not illustrated visually, but rather explained when referring to a specific variable.

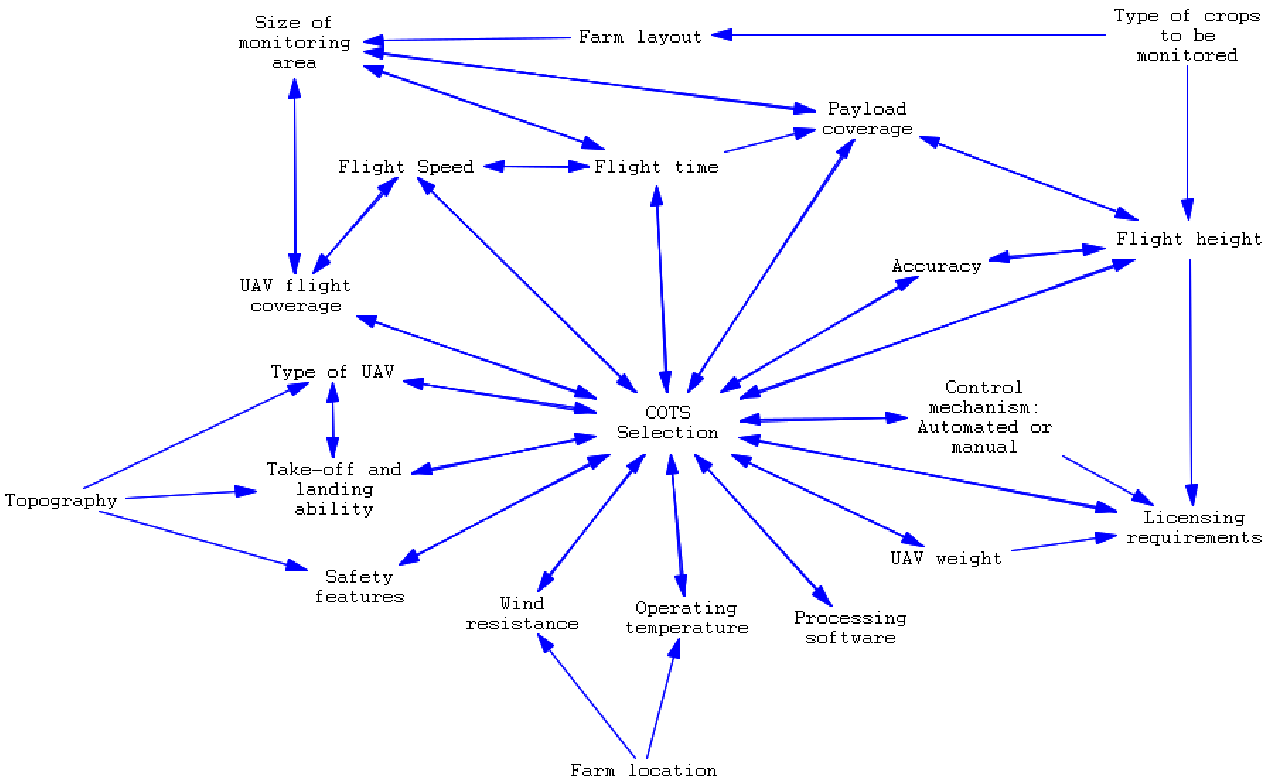

Figure 18 COTS Solution Selection as a System

The main elements of the COTS solution are the UAV and attached payload, thus the variables that influence the selection of the combination of the two are deemed most significant. As the UAV and payload are the main elements of the solution, the two separate elements are combined into a single element, defined as the *COTS selection variable.* The variables that influence the selection of a UAV model and the corresponding payload respectively, that are defined in the previous subsections and systems, are merged to form a single system for the selection of a COTS solution. The payload selection system joins the UAV selection system to form the COTS selection system. The variables that are shared or the effects slightly adapted include: flight height, accuracy, payload coverage, UAV flight coverage, flight time and the size of the monitoring area. Thus, the other variables that directly influence the selection of a UAV model and a payload, respectively, remain constant from the previously defined selection systems. The *flight coverage* variable is specified as the *UAV flight coverage* variable, to distinguish between the flight coverage of the aircraft and the payload respectively. The size of the *monitoring area, flight time* and *flight height* affects the *payload coverage* and is affected by the variable. Similar to how the defined or required monitoring area size affects the flight coverage required, it can have an effect on the required payload coverage. Alternatively, if the payload coverage is constant, the size of the monitoring area needs to be adapted to suit the available coverage. The payload coverage variable directly influences the selection of a COTS solution and is directly influenced by the selection of a COTS solution. The predefined or required *flight time* of the UAV has an influence on the area captured by the payload. A longer flight time allows for a larger area coverage, whereas a shorter flight time leads to a smaller area coverage. Similarly, the *flight height* can also influence the area captured by the payload. This dependency however also relies on the *accuracy* of the data captured or required by the respective payload. Selecting a COTS solution defines the accuracy obtainable by the particular payload. Conversely, if the user defines the required accuracy for the payload, the selection of a COTS solution will be influenced, thus only including suitable payloads.

As mentioned previously, the post-flight processing software does not form part of the COTS solution. Therefore, the software selection sub-decision that forms part of the decision system to design your own solution, is utilised to assist the user in selecting a suitable software solution. This sub-decision is explained and illustrated, along with the recommended software selection process, in sub-section 4.2.2.1 Design of Own System.

- Full-Stack Solution Selection Process

Selecting an appropriate full-stack or COTS solution as part of a crop monitoring system follows a process very similar to the process of selecting a UAV model. As the COTS solution contains a UAV and corresponding payload, the characteristics or variables referred to in the process map are those illustrated in Figure 18. In the UAV selection process, the characteristics of a UAV are ranked in order of importance, to enable the user to more easily define the most important variables ahead of other variables. Due to the COTS solutions containing not only the UAV model, other characteristics relating to the payload may also be deemed more important by the user. The payload selection on the other hand has been expressed as being very user-dependent, where the user is required to define the goals and desired outputs of the system in order to select a suitable payload that can conform to it. The outputs from the system are however still dependent on the post-flight processing software selected, but the data output from the payload affects the selection of a suitable software tool. The COTS solution selection process thus allows the user to specify the goals and desired outputs from the system, before defining any other characteristics or variables related to the UAV model or the payload. In the same step, the users' needs and requirements for the system as a whole is reviewed to ensure they correspond with the goals and outputs sought.

After the user defines his various elements, the system components (the farm characteristics, licensing requirements, etc.) are specified. If the user-defined elements or specifications align with the system components, the process continues to where each characteristic (UAV characteristics and payload characteristics) are defined individually, where after the available COTS solutions are refined based on the defined characteristic. These two steps repeat themselves until all of the necessary characteristics have been defined and the user is able to determine the most suitable solution. From the final refined list of suitable solutions, the user can establish whether the solutions adhere to the most important requirements of the system. If the user is satisfied, a solution is selected from the refined list of solutions. If the user is not satisfied that the possible solutions adhere to the important system requirements, the entire process should repeat itself, thus the user should start by reviewing the requirements and system needs and redefine the goals and system outputs. The process is very repetitive and mainly based on the user and what he requires or wants from the system. In addition, the process should be considered as a recommendation to select an appropriate full-stack solution. The recommended process to select a suitable COTS solution is depicted in Figure 20.

Once the user has selected an appropriate COTS solution, the user is directed to the software selection process described in the previous sub-section. A minor adjustment should be made within the software selection process. Instead of determining whether a payload has already been selected, it should be rephrased to determine whether a COTS solution has been selected. Due to the step of referring to the software selection process succeeding the step where a suitable solution is selected, it becomes redundant to determine whether a solution has been selected in the software selection process step. This step should be disregarded if a full-stack solution is chosen, nonetheless, the user needs to review the output files or data types produced by the selected full-stack solution. An adapted software selection process is illustrated in Figure 19.

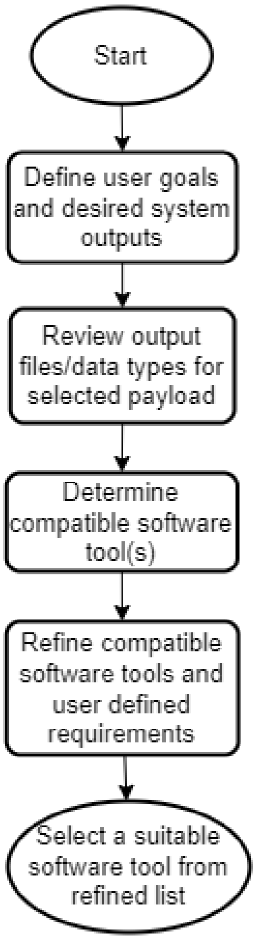

Figure 19 Adapted Software Selection Process

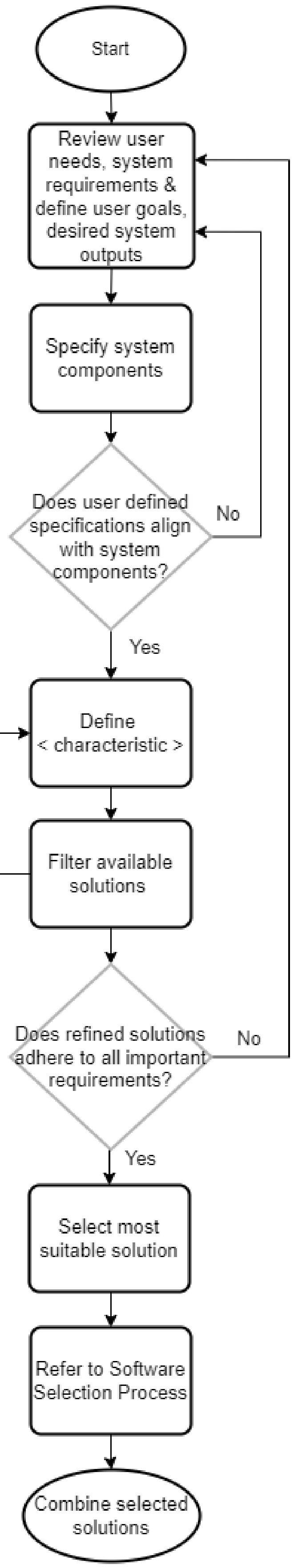

Figure 20 Full-Stack Solution Selection Process

- Full-Stack Solution Identification

From the list of UAV models identified for the analysis in the previous sub-section, those models that provide a full-stack solution as an alternative have been identified. The identified UAV models, can typically be acquired individually and not part of a COTS solution, however, the option does exist should the user wish to purchase the complete solution. Table 27 lists the identified COTS solutions, along with the drone model and payload model included in the solution (Delair; Delair, 2017, 2018, 2020; DJI, 2021a, 2021b; SenseFly, 2021a; Trimble, 2015). Note, this is not a comprehensive list of all of the available full-stack solutions designed for agricultural purposes, only those that can easily be identified based on the previous analyses.

Table 27 Available COTS Solutions for Identified UAV Models

COTS Solution	**UAV Model**	**Payload Model**
eBee Ag solution	eBee Ag	Duet M: RGB and 4-band multispectral
DJI P4 Multispectral Agriculture solution	DJI P4 Multispectral	RGB and multispectral combination camera
DJI P4 Pro V2 solution	DJI P4 Pro V2	1-inch 20MP CMOS sensor (RGB camera)
DJI P4 RTK solution	DJI P4 RTK	1-inch 20MP CMOS sensor (RGB camera)
Trimble UX5 solution	UX5 HP	36MP full-frame sensor camera, combination between NIR and RGB sensor system.
Delair UX11 Ag solution	UX11 Ag	MicaSense RedEdge-MX: RGB and multispectral
Delair UX5 HP solution	UX5	36MP full-frame camera, RGB sensor
Delair DT26E LiDAR solution	DT26E LiDAR	21MP RGB sensor
Delair DT18 HD solution	DT18 HD	21MP RGB sensor
Delair DT18 Ag	DT18 Ag	MicaSense RedEdge-MX: RGB and multispectral

4.3 Solution Categorisation

In addition to the system of solution introduced in the previous sub-sections, a categorisation of possible solutions is developed. This categorisation includes different output selections based on the various categories created relating to the solution type, farm characteristics and UAV characteristics. No categories are created for the selection of payload solutions due to a lack of the necessary information regarding each identified payload. In the previous sub-section, the identified payloads are already grouped according to the type of payload. For the purpose of this summary categorisation, the initial grouping of the payloads is sufficient. For each individual category identified, the appropriate or most suitable solution is identified. The categories and corresponding solutions are identified and elaborated on in the sub-sections to follow.

4.3.1 3PSP Solution

The service provider solution was created for those users who do not want to own their own hardware and software components, but rather only make use of the services provided by a registered service provider. Table 9 identified the available service providers based in South Africa, along with the services provided by each company, the type of outputs produced, the crop types specialised in and where the company is based and what areas are serviced by that company. From this table, three categories are created to further group the service provider solutions. These categories include the output type produced, the geographic location of the company and the crop type specialisations. Each of these categories is further elaborated on in the following sections.

4.3.1.1 Output Type

The outputs produced by each service provider, if the information is available, were identified in Table 9. The types of outputs are grouped into five main output types, indicated in Table 28 for each output type, the service provider(s) that can deliver that specific output are listed. Not all service providers stated their output types, thus only those who disclosed the required information are included.

Table 28 Service Providers Grouped Based on Output Types

Multispectral Thermal Imagery, VI's	**Visual (RGB), Orthomosaics**	**2D/3D maps, Digital Elevation Models**	**Real-time data and information**	**Statistical Analyses**
Aerobotics	Integrated Aerial Systems	Epic Air	Integrated Aerial Systems	Agri Sense International
Integrated Aerial Systems	Epic Air	Specialised agricultural services	Epic Air	
Epic Air	FlyUAVI			
Rocketfarm	Agri Sense International			

Multispectral Thermal Imagery, VI's	Visual (RGB), Orthomosaics	2D/3D maps, Digital Elevation Models	Real-time data and information	Statistical Analyses
FlyUAVI				
Specialised agricultural services				
Southern Mapping				
Agri Sense International				

4.3.1.2 Geographic Locations

Similar to the grouping according to the types of outputs produced, the service providers are grouped according to the geographic locations, where the company is based and what areas they service. Most of the service providers service the whole of South Africa while being based in a major city or province. Some of the service providers extend their services to countries outside of SA, these are all grouped into the 'Other Countries' category. The identified categories with the service providers within each of the categories are indicated in Table 29.

Table 29 Service Provider Grouped According to Service or Base Locations

Whole of South Africa	Johannesburg, Pretoria Region	Kwa-Zulu Natal	Cape Town	Other Countries
Agri Sense International	Southern Mapping	Agri Sense International	Epic Air	Agri Sense International
Southern Mapping	The Awareness Company	DG Geomatics	Integrated Aerial Systems	Southern Mapping
The Awareness Company	FlyUAVI	Specialised agricultural services	Aerobotics	Rocketfarm
UVSSA	UVSSA			Integrated Aerial Systems
Rocketfarm	Rocketfarm			Aerobotics
DG Geomatics				
Integrated Aerial Systems				

A user based in Pretoria can select any service provider that best suit their needs that fall within the categories 'Johannesburg, Pretoria Region' and 'Whole of South Africa.' A similar observation can be made for a user based in any location unless the user is not situated in SA. In that case, the user should individually review each service provider that operates in other countries to identify those most suitable.

4.3.1.3 Crop Type Specialisations

Some of the service-providing companies specify the types of crops that they specialise in, while others do not provide any information regarding crop types. An assumption can be made that those companies who do not specify specific crop types, can perform their services regardless of the type of crop produced by the user. The companies that do however specify which crop type they specialise in, are categorised according to the crop categories that they service. The crop categories are defined in accordance with the crop classifications defined in by the Food and Agriculture Organisation of the United Nations (*World Programme for the Census of Agriculture 2020*, 2015). The service providers that provided crop information are grouped according to the crop categories and shown in Table 30.

Table 30 Service Providers Grouped based on Crop Categories

Crop Categories	**Service Providers**		
Cereal crops	DG Geomatics	Rocketfarm	
Vegetables and melons	Rocketfarm		
Fruits and nuts	Rocketfarm	DG Geomatics	Aerobotics
Oilseed crops	Aerobotics	Rocketfarm	
Root/tuber crops	Rocketfarm		
Leguminous crops	Rocketfarm		
Sugar crops	Rocketfarm		
Other crops	Rocketfarm		

4.3.2 Farm Characteristics

Solutions can further be grouped into categories stemming from the physical farm characteristics defined. These categories are created for the topographic characteristics of the area, the type of crops planted and the size of the farm or monitoring areas. Since some of these characteristics are constant and cannot be changed, the different solutions for these categories are identified. The solutions are defined by selecting a UAV model(s) best suited for that category. For instance, the topographic characteristics of the farming area cannot be changed, thus solutions for the topographic categories are recommended. The types of crops planted, and the size of the monitoring areas can however be changed from one planting season to the next. To accommodate for these possible changes multiple categories are defined with approximations (where necessary) within each main category. The categories and recommended solutions are further elaborated on in the following sub-sections.

4.3.2.1 Topographic Characteristics

The topographic characteristics of the area where the farm is located can have an effect on the type of UAV selected as part of the monitoring system. This influence is defined and explained in previous sections. Thus, the topographic form of the farm or fields can be grouped into either flat or mountainous areas. For crop fields situated in an overarching flat area, a fixed-wing drone is typically recommended, whereas, for crop fields situated in more hilly or mountainous areas, a multi-rotor aircraft is typically recommended. The classification of UAV models (those identified for analysis) according to the topography of the farm, is indicated in Table 31.

Table 31 Classification of UAV Models According to Topography and type of UAV

Flat Areas (Fixed-Wing UAVs)	**Mountainous or Hilly Areas (Multi-Rotor UAVs)**
Lancaster 5	DJI Matrice 300RTK
eBee X	DJI P4 Multispectral
eBee AG	DJI P4 RTK
Sentera PHX	DJI Phantom 4 Pro
Trimble UX5	DJI Phantom 4 Pro V2
Bramor ppX	DJI Matrice 30 Series
Atmos 8	BFD 1400-SE8
Penguin B	DJI Matrice 200 V2
Penguin BE	DJI P4 Advanced
AgEagle RX-60	DJI Mavic 3
WingtraOne GEN II	Novadem U130
Atmos Marlyn	AgBot
Delair UX11 Ag	
Delair UX5-HP	
Delair DT 26E LiDAR	
Delair DT 26E Open Payload	
Delair DT18 HD	
Delair DT18 AG	

4.3.2.2 Crop Type and Height Categorisation

Crop types are classified according to the Indicative Crop Classification (ICC 1.0) developed by the Food and Agriculture Organisation of the United Nations included as an annexure in the *World Programme for the Census of Agriculture 2020* 2015). The complete crop classification is included in Appendix B. Crops are grouped into categories based on three factors, namely: product type; crop genus or species; and temporary or permanent crops. The main categories of crop types include the following: Cereal crops; Vegetables and melons; Fruit and nuts; Oilseed crops and oleaginous fruits; Root/tuber crops; Stimulant, spice or aromatic crops; Leguminous crops; Sugar crops; and other crops.

The crop types are further refined to only include those crop types that are produced in South Africa. A comprehensive list and/or classification of crops produced in South Africa could not be identified, thus other resources were utilised to identify the main crop types produced within South Africa. The list was developed through the combination of information provided by Statistics SA, the Department of agriculture, land reform and rural development and articles published by SouthAfrica.co.za (*Census of Commercial Agriculture 2017*, 2020; "Crop Farming in South Africa," ; "Plant Production," 2022). The final list of crops produced in SA, grouped according to the categories specified above, is denoted in Table 32.

Crops are further categorised based on an estimate of the height to which the crop grows, thus how tall a single plant grows. This information, along with the flight heights of the UAV models, allows for a categorisation of UAV solutions based on plant height approximations. Crops are grouped into three size categories: small, medium and large, or tree crops. Small crops are those crops that grow to a height of less than 1m, typically your vegetables, melons and legumes. Some of these crops included in the category can grow beyond the 1m threshold, however, those crops are categorised as small crops based on the type of crop. The crop types categorised in the small crop category, along with an approximation of the average height to which each crop grows, are displayed in Table 33.

Table 32 Classification of Crops Produced in South Africa

1. Cereal Crops	**3. Fruits and Nuts**	**4. Oilseed Crops and Oleaginous Fruits**
Wheat	Avocados	Soya Beans
Maize	Bananas	Groundnuts
Barley	Mangoes, Guava	Rapeseed
Oats	Papaya	Sunflower
Lucerne	Pineapples	Olives
Buckwheat	Grapefruit And Pomelo	**5. Root/Tuber Crops**
Quinoa	Lemons And Limes	Potatoes
2. Vegetables and Melons	Oranges	Sweet Potatoes
Asparagus	Tangerines, Mandarins, etc.	Cassava
Cabbages	Grapes	**6. Sugar Crops**
Lettuce	Strawberries	Sugar Cane
Chicory	Apples	Sweet Sorghum
Cucumbers	Peaches and Nectarines	**7. Stimulant, Spice or Aromatic Crops**
Tomatoes	Pears and Quinches	Coffee
Watermelons	Plums	Tea
Carrots	Pecan	Ginger
Turnips	Macadamia	**8. Leguminous Crops**
Garlic	Litchi	Chick Peas
Onions	Almonds	Cow Peas
Leeks	Pistachio	Lentils
Bell Pepper	Walnuts	Lupins
Beetroot	Blueberries	Peas
Celery	Raspberries	Pigeon Peas
Chives	Cherries	Green Beans
Eggplants	Dates	**9. Other**
Pumpkin, Squash, etc.	Figs	Tobacco
Cauliflowers And Broccoli	Gooseberries	Cotton
Spinach		
Cantaloupes		

Table 33 Small Crop Types and Average Height

Crop type	Average Height (m)
Asparagus	1,5
Cabbages	0,3
Lettuce	0,65
Cucumbers	0,6
Tomatoes	1,05
Watermelons	0,5
Carrots	0,3
Turnips	0,325
Garlic	0,6
Onions	0,5
Leeks	0,75
Bell pepper	1
Beetroot	0,5
Celery	0,35
Chives	0,35
Eggplants	0,9
Pumpkin, squash, etc.	0,5
Cauliflowers and broccoli	0,53
Spinach	0,25
Cantaloupes	0,42
Strawberries	0,3
Soya beans	0,7
Groundnuts	0,5
Rapeseed	0,3
Ginger	1
Chickpeas	0,5
Cow peas	0,6
Lentils	0,3
Lupins	0,85
Peas	1,5
Green beans	2,1

The second size category defined is that of medium-sized crops, those crop types that usually grow above 1 meter, up until a height of 3 meters. This category corresponds to the types of crops that are typically planted in large fields. Some crops exceed the upper height bound, but these crops are grouped into the medium crop size category based on the planting habits of that crop type in a commercial farming environment. An approximate value for the average height of each crop categorised in this category is indicated in Table 34.

Table 34 Medium Crops and Average Height

Crop Type	Average Height (m)
Wheat	1,2
Maize	3
Barley	0,9
Oats	1,5
Lucerne	0,6
Buckwheat	0,9
Quinoa	1,2
Chicory	1,25
Sunflower	2,25
Potatoes	1
Sweet potatoes	1
Cassava	2,4
Tea	1,83
Pigeon peas	2,25
Sugar cane	4,25
Sweet sorghum	2,25
Tobacco	1,5
Cotton	1,5

The final category contains the remaining crops, growing to a height beyond three meters. This category mainly consists of tree or bush-like crops, typically planted in an orchard. Some smaller crops are included in this category due to a correspondence between the crop categorisations. The crops included in the category along with an approximation of the average height to which each crop grows are denoted in Table 35.

Table 35 Tall Crops and Corresponding Height

Crop Type	Average Height (m)
Avocados	12,2
Bananas	5
Mangoes, guava	12
Papaya	7,5
Pineapples	1,35
Grapefruit and pomelo	7,62
Lemons and limes	6
Oranges	9,5
Tangerines, mandarins, etc.	3,75
Grapes	1,25
Apples	5
Peaches and nectarines	9
Pears and quinces	9,8

Crop Type	Average Height (m)
Plums	5,5
Pecan	20
Macadamia	20
Litchi	19,5
Almonds	6
Pistachio	8
Walnuts	25
Blueberries	2,7
Raspberries	1,8
Cherries	4,5
Dates	23
Figs	6,75
Gooseberries	1,8
Olives	7,5
Coffee	12,5

The height approximations for the different crop types are significant when combined with the flight height(s) specified for the UAV models included in the analysis. The flight heights are defined as the altitude or height above ground level (AGL), at which the aircraft collects data. Only those UAV models that explicitly state the flight height as a technical specification are evaluated. Some UAV models can fly at different set heights based on the area coverage to be obtained during a single flight. These aircrafts are listed in each relevant flight height category. The height categories are defined based on the provided flight heights and define the maximum height, in meters above ground level, at which the aircraft can fly while collecting data. The UAV models are grouped according to these maximum flight heights in Table 36.

Table 36 Maximum Flight Height of UAV Models

Maximum Flight Height (m AGL)	**UAV Models**					
60	Lancaster 5	AgBot	Delair UX5-HP			
80	Trimble UX5	Delair UX11 Ag	Delair DT 26E LiDAR	Delair DT18 HD	Delair DT18 AG	
100	Trimble UX5					
120	Sensefly eBee X	Sensefly eBee AG	Sentera PHX	Delair UX11 Ag	Delair UX5-HP	Delair DT 26E LiDAR

Maximum Flight Height (m AGL)	**UAV Models**					
150	Trimble UX5	Delair DT18 HD	Delair DT18 AG			
200	Trimble UX5	Bramor ppX				
300	Trimble UX5	Lancaster 5				
500	Trimble UX5	Delair UX11 Ag				
700	Trimble UX5	Delair DT18 HD	Delair DT18 AG			
800	Delair UX5-HP	Bramor ppX				

The UAV flight heights and crop heights identified indicate that the UAVs that fly at the lowest height (60m AGL) are still significantly higher than the tallest crop height. Essentially, the user can select any UAV model, irrespective of the height of the crops. A trade-off however occurs between the flight height and the area coverage and possibly the accuracy of the data captured by the camera/sensor. A larger flight height allows the aircraft to cover a larger area, whereas a lower flight height, significantly reduces the total area coverage.

4.3.2.3 Farm Size and Flight Coverage

The size of the crop fields on a specific farm is typically a constant value, it can however change from one planting season to the next. For the purpose of this analysis, the size of the crop fields is regarded as constant values. Multiple fields, especially if the same crop is planted on these fields, can be combined into a single monitoring area. In other cases, a single field is defined as a single monitoring area. The size of the monitoring area can either be defined by the user as the area to be monitored within a single flight or by the area that can be monitored in a single flight as specified by the UAV model. For this analysis, an approximation of the maximum hectares that can be monitored by a specific UAV model is considered. Only the UAV models that defined the area coverage within the technical specifications are included. The UAV models are categorised according to the estimated maximum area coverage (in hectares). This classification is indicated in Table 37.

Table 37 UAV Models Categorised according to Maximum Area Coverage

Maximum Area Coverage (ha)	**Drones**	
2	Bramor ppX	
32	Bramor ppX	
52	Delair UX5-HP	
90	Delair UX11-Ag	Delair DT18 Ag
120	Delair UX5-HP	Lancaster 5
150	Delair UX11-Ag	Atmos Marlyn
160	AgEagle RX-60	Sensefly eBee Ag
180	Delair DT18 HD	
200	Sensefly eBee Ag	
210	Delair DT18 Ag	
220	Sensefly eBee X	
360	Delair DT18 HD	
500	Sensefly eBee X	
600	Delair UX11-Ag	
780	Delair UX5-HP	
1150	Delair DT18 Ag	
1900	Trimble UX5	Delair DT18 HD
9700	Delair DT26E LiDar	

The system user can refer to the above table to determine which UAV model is most suitable for the size of his crop fields or monitoring areas. As mentioned previously, a trade-off exists between the flight height and the area coverage. Some of the UAV models are listed in more than one category as a result of this trade-off.

4.3.3 UAV Characteristics

Feasible solutions can be categorised based on the inherent characteristics that define the operation of a UAV. Categories are created according to the most important technical input and functional output characteristics presented by the analysed UAV models. These characteristics are selected based on their ability to alter the operation of the system or affect the solutions delivered by the system. The UAV characteristics used to create the necessary categories include flight time, flight speed, flight coverage, and flight height, control mechanism, operating temperatures, wind resistance and take-off and landing preferences. The flight height and coverage categories have already been introduced in previous sub-sections as part of the farm size and crop type categories, respectively. The remaining categories are introduced and explained in the sub-sections to follow.

4.3.3.1 Flight Time

The flight time characteristic is one of the most common specifications provided by drone manufacturing companies. The estimated flight times range from anything between 20 minutes to more than 20 hours per single flight. Fixed-wing drones usually have a longer flight time compared to that of multi-rotor drones. Each UAV model (identified earlier) is analysed and the information pertaining to the flight times is recorded. The models are then grouped into flight time ranges, for instance, all of the aircrafts that can fly for approximately 30 minutes per flight, are grouped together. These aircrafts can thus fly for any duration between 0 and 30 minutes, per single flight. The UAV models are categorised according to their flight time ranges in Table 38.

Table 38 UAV Models Categorised based on Flight Times

Flight Time Range (min)	**UAV Models**				
0-20	Novadem U130				
0-30	DJI P4 Multispectral	DJI P4 Advanced	DJI P4 RTK	DJI Phantom 4 Pro & V2	AgBot
0-35	Delair UX5-HP				
0-40	DJI Matrice 30 Series	DJI Matrice 200 V2			
0-45	DJI Matrice 300RTK	Lancaster 5	DJI Mavic 3		
0-50	Trimble UX5	Atmos Marlyn	Delair UX11 Ag		
0-55	Sensefly eBee AG				
0-60	BFD 1400-SE8	Sentera PHX	AgEagle RX-60	WingtraOne GEN II	
0-90	Sensefly eBee X				
0-100	Atmos 8				
0-110	Penguin BE	Delair DT 26E LiDAR			
0-120	Delair DT18 HD	Delair DT18 AG			
0-135	Delair DT 26E Open Payload				
0-210	Bramor ppX				
0-1200	Penguin B				

4.3.3.2 Flight Speed

The speed at which an aircraft flies while collecting data is recorded as the flight speed or the cruising speed of the aircraft. The speed at which the aircraft fly, vary over time depending on the operation being performed by the aircraft. For instance, the ascent or descent speed will differ from the speed at which the actual monitoring is performed. The flight speed characteristic is also one of the most commonly specified characteristics among UAV models. For most models a single cruising or hovering speed is defined, however, some models can be flown at different flight settings resulting in multiple hovering speeds. These UAV models are categorised in all of the applicable categories. Table 39 indicates the UAV models grouped according to the approximate maximum cruising speed (in km/h).

4.3.3.3 Control Mechanism

The control mechanism of the aircraft refers to the way in which the aircraft is controlled. Most UAVs are flown and controlled by a remote control system connecting the aircraft to GCS. Other UAVs operate completely autonomously, by pre-defining the flight route and then utilising GPS information and possible waypoints to perform the programmed flight. UAV models can thus be distinguished based solely on how they are controlled, autonomously or by remote control. In rare instances, the aircraft can contain a remote control function in conjunction with the autonomous flight control function. These aircrafts can usually be stopped in the middle of a pre-programmed flight and then further manually control the aircraft for the duration of the flight. The identified UAV models are classified according to the control mechanism indicated for those aircrafts. This classification is indicated in Table 41.

Table 39 UAV Models grouped by Flight Speeds

Maximum Cruising Speed (km/h)							
20	**40**	**50**	**55**	**60**	**70**	**80**	**110**
DJI Mavic 3	Novadem U130	DJI P4 Multispectral	Delair UX11 Ag	DJI P4 Advanced	DJI Phantom 4 Pro	DJI Matrice 30 Series	AgEagle RX-60
		DJI P4 RTK	Delair DT 26E LiDAR	DJI P4 Multispectral	DJI Phantom 4 Pro V2	DJI Matrice 300RTK	eBee X
		DJI Phantom 4 Pro	Sentera PHX	DJI P4 RTK	BFD 1400-SE8	DJI Matrice 200 V2	eBee AG
		DJI Phantom 4 Pro V2	DJI Mavic 3	DJI Phantom 4 Pro	DJI P4 Advanced	Trimble UX5	
		DJI P4 Advanced		DJI Phantom 4 Pro V2	DJI Mavic 3	Penguin B	
				DJI Matrice 200 V2		Penguin BE	
				Lancaster 5		Delair UX5-HP	
				AgBot			
				WingtraOne GEN II			
				Delair DT 26E Open Payload			
				Delair DT18 HD			
				Delair DT18 AG			

Table 40 UAV Models grouped according to Operating Temperature Range

Operating Temperature Range (°C)						
-20 to 50	**-20 to 45**	**-15 to 40**	**-10 to 40**	**-10 to 35**	**0 to 40**	**0 to 76,7**
Matrice 300RTK	UX11 Ag	DT 26E LiDAR	DJI Mavic 3	Atmos Marlyn	DJI P4 Advanced	AgEagle RX-60
Matrice 30 Series		DT 26E Open Payload	WingtraOne GEN II		P4 Multispectral	
		eBee X			P4 RTK	
		eBee AG			Phantom 4 Pro	
					Phantom 4 Pro V2	
					Lancaster 5	

Table 41 UAV Models grouped based on Control Mechanism

Remote Controlled	**Autonomous**	**Combination**
DJI Matrice 300RTK	WingtraOne GEN II	WingtraOne GEN II
DJI P4 Multispectral	Atmos Marlyn	
DJI P4 RTK	Bramor ppX	
DJI Phantom 4 Pro	Sensefly eBee X	
DJI Phantom 4 Pro V2	Sensefly eBee AG	
DJI Matrice 30 Series	Scout drone	
BFD 1400-SE8		
DJI Matrice 200 V2		
DJI P4 Advanced		
DJI Mavic 3		
Novadem U130		
Trimble UX5		
Atmos 8		
AgEagle RX-60		
Delair UX11 Ag		
Delair UX5-HP		

4.3.3.4 Operating Temperature and Wind Resistance

The characteristics pertaining to the desired operating environment for a UAV model include the temperature range in which the aircraft can operate effectively as well as the maximum wind speeds the aircraft can withstand. UAV models are grouped based on the temperature ranges in which the aircrafts are designed to operate in Table 40. The temperature range categories created can overlap with one another, but they are grouped separately to ensure that UAV models limited to a specific temperature range are also included.

Additionally, UAV models are grouped into categories pertaining to the maximum wind speeds (measured in kilometres per hour) that the aircraft can withstand. These speeds are generally listed as the wind resistance factor within the technical specifications of the UAV models. The wind resistance categories, and the aircrafts grouped into each category, are shown in Table 42. Combined, these classifications allow a user to easily select an aircraft suited for the climatic conditions of the area where the farm is located.

Table 42 UAV Models grouped based on Maximum Wind Resistance Speeds

Maximum Wind Speed Resistance (km/h)				
36	**45**	**50**	**55**	**65**
DJI P4 RTK	DJI Matrice 200 V2	Delair UX11 Ag	DJI Matrice 300RTK	Trimble UX5
DJI Phantom 4 Pro	Sensefly eBee X	Delair DT18 HD	DJI Matrice 30 Series	AgEagle RX-60
DJI Phantom 4 Pro V2	Sensefly eBee AG	Delair DT18 AG	Bramor ppX	WingtraOne GEN II
DJI P4 Advanced	Sentera PHX		Atmos Marlyn	
Novadem U130	DJI Mavic 3		Delair UX5-HP	
Delair DT 26E LiDAR				
Delair DT 26E Open Payload				

4.3.3.5 Take-off and Landing Mechanisms

The final categorisation of the UAV model solutions distinguishes the aircrafts based on the take-off and landing mechanisms of each drone. Typically, multi-rotor drones take-off and land vertically, whereas fixed-wing drones are hand launched and usually land on their belly in the field. A fixed-wing drone thus takes up a larger amount of space to take off and then land again after finishing the flight. Some fixed-wing drones, however are designed with a vertical take-off and landing mechanism, thus eliminating the large area requirement. The take-off and landing mechanisms are therefore of importance for crop fields with limited space to initiate and end a flight. The UAV models are grouped first according to their means of take-off and then according to how they perform the landing. For take-off, three categories are created: vertical, hand-launched and catapult launched. For landing, four categories are created namely: vertical, belly landing, automatic landing and para landing. Automatic landing includes those aircrafts that perform the landing operation automatically. Only the aircraft models that specifically indicated that they perform an automatic landing, are included in this category, however, a number of other aircrafts possibly also perform an automatic landing operation. Para landing refers to landing the aircraft through the use of an automatically initiated parachute, designed specifically for the aircraft. The categorisation of the UAV models according to their take-off and landing abilities is indicated in Table 43.

Table 43 UAV Take-off and Landing Mechanisms

Take-off Mechanisms			
Vertical	**Hand-Launch**	**Catapult**	
DJI Matrice 300 RTK	Sensefly eBee X	Delair UX5-HP	
DJI P4 Multispectral	Sensefly eBee AG	Delair DT 26E LiDAR	
DJI P4 RTK	Sentera PHX	Delair DT 26E Open Payload	
DJI Phantom 4 Pro	Delair UX11 Ag	Penguin B	
DJI Phantom 4 Pro V2	Delair DT18 HD	Penguin BE	
DJI Matrice 30 Series	Delair DT18 AG	AgEagle RX-60	
BFD 1400-SE8		Trimble UX5	
DJI Matrice 200 V2		Bramor ppX	
DJI P4 Advanced			
DJI Mavic 3			
Novadem U130			
AgBot			
WingtraOne GEN II			
Atmos Marlyn			
Landing Mechanisms			
Vertical	**Belly Landing**	**Automatic Landing**	**Para landing**
DJI Matrice 300RTK	Sensefly eBee X	Sentera PHX	Bramor ppX
DJI P4 Multispectral	Sensefly eBee AG	AgEagle RX-60	
DJI P4 RTK	Trimble UX5		
DJI Phantom 4 Pro	Delair UX11 Ag		
DJI Phantom 4 Pro V2	Delair UX5-HP		
DJI Matrice 30 Series	Delair DT 26E LiDAR		
BFD 1400-SE8	Delair DT 26E Open Payload		
DJI Matrice 200 V2	Delair DT18 HD		
DJI P4 Advanced	Delair DT18 AG		
DJI Mavic 3			
Novadem U130			
AgBot			
WingtraOne GEN II			
Atmos Marlyn			

4.4 UAV Selection Illustration

A theoretical scenario is created: a semi-commercial farm, situated in a mountainous area cultivates sorghum in summer (from November) and wheat and rye in late summer (from February or March). The total size of the farm is approximately 575 hectares, while the total crop field amount to 120 hectares. The rest of the farm is used for grazing purposes. If the user aims to purchase and design the entire system, the following recommendations are made.

Based on the topography of the area, mountainous, a multi-rotor UAV is suggested, when referring to Table 31. Multi-rotor aircrafts are synonymous with vertical take-off and landing abilities, however, it is suggested for mountainous areas to utilise an aircraft that doesn't require a lot of space to take-off and land. Table 43 categorises aircrafts according to the take-off and landing abilities. The available aircrafts can thus be reduced to multi-rotor aircrafts with a vertical take-off and landing ability. Since only multi-rotor drones are considered the fixed-wing aircrafts with a vertical landing and take-off ability are disregarded. The crop types does not limit the user to a specific category of UAVs as they are medium sized crops (cereal and sugar crops).

The total size of the crop fields amount to 120 hectares. If the user wishes to monitor all the crop fields in a single flight, only aircrafts with a greater area coverage (larger than 120ha) according to Table 37 can be considered. Since the UAV models included in Table 37 are only those aircrafts that provide area coverage information, the aircrafts previously categorised based on the topography and crop types, are excluded from this categorisation. The refined list of aircrafts are indicated in Table 44. The aircrafts can further be grouped based on their listed flight times, as most of the multi-rotor aircrafts only provide flight time information and not area coverage information. Here the user can select a flight time suited for his needs, keeping in mind that a longer flight time corresponds with a larger area coverage. Table 44 includes the flight durations for each of the aircrafts, however, it still remains the preference of the user to select a suitable aircraft.

Table 44 Refined List of UAV Models Considered for Theoretical Scenario

UAV model	**Flight Time (min)**
DJI Matrice 300RTK	0-45
DJI P4 Multispectral	0-30
DJI P4 RTK	0-30
DJI Phantom 4 Pro	0-30

UAV model	Flight Time (min)
DJI Phantom 4 Pro V2	0-30
DJI Matrice 30 Series	0-40
BFD 1400-SE8	0-60
DJI Matrice 200 V2	0-40
DJI P4 Advanced	0-30
DJI Mavic 3	0-45
Novadem U130	No information
AgBot	0-30

As the Eastern Cape is known for low temperatures, the list of aircrafts can further be refined based on the operating temperature ranges of the aircrafts. Based on Table 40, aircrafts that can operate below 0 degrees Celsius are selected. Included in Table 45 are those aircrafts that operate between 0 and 40 degrees Celsius. These aircrafts are included due to the seasons in which the crops are planted, makes provision for these aircrafts.

Table 45 Further Refined List of UAVs

UAV model	Flight Time (min)	Operating Temperature Range (°C)
DJI Matrice 300RTK	0-45	-20 to 50
DJI P4 Multispectral	0-30	0 to 40
DJI P4 RTK	0-30	0 to 40
DJI Phantom 4 Pro	0-30	0 to 40
DJI Phantom 4 Pro V2	0-30	0 to 40
DJI Matrice 30 Series	0-40	-20 to 50
DJI P4 Advanced	0-30	0 to 40
DJI Mavic 3	0-45	-10 to 40

The aircrafts mentioned above is a good starting point for the system user to select a suitable UAV. In order to further refine the options, additional information is required, especially regarding the system user's preferences. This information is not available due to the demonstration being based on a theoretical scenario. However, in practice a more thorough selection will occur once all of the important variables have been clearly defined. Once a UAV model is selected, the user can continue to select a suitable payload and software solution. These selection processes are not illustrated due to the lack of information available for this selection.

Chapter 5: Conclusion and Recommendations

5.1 Conclusion

The need for an integrated system of solution for the diagnosis of crop health using machine learning controlled UAVs has been identified. The need presented an opportunity to review the literature to determine whether such a system (1) exists and (2) is a feasible alternative to traditional or more modern methods of crop monitoring. This project presented multiple research questions to be addressed to ensure the success of the project. In addition to these research questions, specific objectives were identified to be met throughout the duration of the project.

In order to gain a thorough understanding of the field of literature and the solution domain, a review was conducted on the most basic terms and research areas regarded as important to the project. This includes precision agriculture, remote sensing, UAVs, and crop monitoring methods. In addition to these topics, literature was consulted to determine different solution alternatives. The selected solution alternative, to design an integrated system of solution for crop monitoring using UAVs, was selected as it aligned with the project aim, research objectives and research questions. Research methodologies were consulted to provide a structured project approach aimed at addressing the project objectives. A case study research approach is selected to allow the researcher to evaluate existing cases and literature throughout the duration of the project. An integrates system of solution framework provides a graphical representation of how research objectives are met throughout the selected research methodology.

The basic system and the components that are included in the system were identified and those component characteristics that can influence the design of the system have been identified. Three main solution paths are identified based on the users' preference for owning the hardware and software components. The solution paths are further broken down into the main decisions to be made within each of the solution paths. These decisions are modelled as systems, clearly indicating the variables and factors that can have an effect on the decision variable. A recommendation of steps to be followed by the system user for each main decision is also presented. Finally, a categorisation of the possible solutions is presented, to allow a user to more refined solution suggestion based on specific categories.

5.2 Research Findings

Upon analysis and the design of the decision support system of solution for a UAV crop monitoring system, it was concluded that the main decisions within the framework can be classified as complex systems. These decision systems, allow for the integration of multiple variables in the system, illustrating the complexity of these systems. It can thus be inferred that a UAV-based crop monitoring system is a complex system. The complexity of the system, along with the high variability of the system components, hinder the creation of a single best solution to fit most circumstances. For each system user and their unique circumstances, a suggested solution can however be created. Designing the suggested best solution is however an intricate process, that can be simplified using the designed solution processes presented in the research. These processes are however only recommendations of the steps to be performed to select the various components within the crop monitoring system.

Upon analysis of the available literature, no solution system that takes all of the identified variables and components into consideration, has been identified. A system of solution to aid in decision-making has been designed based on the literature available on general UAV crop monitoring operations. The two primary solution paths identified, using a service provider or purchasing a system, were identified based on the users' preferences to own a system or not. Following this division, available literature revealed the main components of a UAV-based crop monitoring system. Decision sub-systems were then identified based on the main hardware and software components included within a crop monitoring UAS. The solutions developed in the category where the user purchases the system evolved from the commercially available hardware and software options to be included in the system and the corresponding technical specifications, not from literature. Multiple literature sources were however consulted to identify some of these hardware or software options to be included as part of the solutions. The solution options analysed and presented for the 3PSP solution path were identified as those service providers operating within South Africa. No previous analysis of existing service providers, not limited to South Africa, has been identified.

5.3 Research Objectives Achieved

The research objectives stated in Chapter 1: Introduction were achieved throughout the document, in various chapters, sections or sub-sections. Each of the research objectives is reviewed to establish how they are addressed within the project document.

The first objective defined aims to holistically identify the attributes of drones or UAVs that are relevant to the monitoring of crop health diagnostics. This objective focuses solely on those attributes of UAV aircrafts that are relevant to crop monitoring activities. The basic UAS comprises of the drone and other components to ensure the system operates effectively. The UAS along with these necessary components are identified and briefly explained in Section 4.1.1 Unmanned Aerial System. The main UAS components formed the main decision parts of the system. The UAV selection decision, described in Section 4.2.2.1 Design of Own System, identifies the UAV characteristics of relevance. The characteristics included in the analysis are those characteristics for which information could be freely obtained through the review of the technical specification documents of the UAV models. The characteristics identified are grouped into two categories namely: technical input and functional output characteristics. The characteristics were further refined to identify those characteristics important to the selection of a UAV model for crop monitoring purposes. This refinement and identification are presented in the sub-section Identification of Important Characteristics as a step in developing the UAV selection decision path. Further, UAV solutions were grouped according to the important UAV characteristics in Section 4.3.3 UAV Characteristics In conclusion, research objective one was addressed in the following chapters, sections and subsections:

- Section 4.1.1 Unmanned Aerial System
- Section 4.2.2.1 Design of Own System:
    - UAV Characteristic Identification
    - Identification of Important Characteristics
- Section 4.3.3 UAV Characteristics

The second research objective aimed to analyse the identified attributes of different crop farming systems. This objective is addressed throughout Chapter 4: Solution and Discussion, where all of the different characteristics of the main components of the system are identified. To distinguish between different crop farming systems, the physical characteristics of a farm are included in the analysis. These characteristics are identified in Section 4.1.2 Farm Characteristics.

Specific aircraft models to consider as a solution, based on the categorised farm characteristics are suggested in Section 4.3.2 Farm Characteristics.

In summary, the second research objective was addressed in the following chapters or sections:

- Chapter 4: Solution and Discussion
- Section 4.1.2 Farm Characteristics
- Section 4.3.2 Farm Characteristics

The final research objective relates to the design and development of a comprehensive framework suitable for decision support and evaluation of crops in a farming environment. This objective is addressed in Section

4.2 Integrated System of Solution, where a decision support system of solution was developed. The solution system is divided into the main decisions, which are further elaborated on in the subsections of the above-mentioned section. The main decision paths are defined and described in Sections 4.2.1 Third-Party Service Provider and 4.2.2 Purchase Own System. The third and final research objective is addressed in the following chapters, sections and subsections of the document:

- Section

- 4.2 Integrated System of Solution
    - Section 4.2.1 Third-Party Service Provider
    - Section 4.2.2 Purchase Own System

This sub-section serves as confirmation that each of the defined research objectives was addressed throughout the document. The identified chapters and sections mentioned above, excludes the literature review in Chapter 2: Literature Review, as the literature review serves as the foundation for the solution development part of the project.

5.4 Recommendations and Future Work

The purpose of this research is to provide a system user or potential system user, with a tool to assist him/her in making more informed decisions regarding the design and acquisition of a UAV crop monitoring system. It should be noted that the solutions presented by this study are only recommendations and that the system user should still perform his own research and enquire about certain aspects of the system should he be unsure about a component of the system. Due to the high variability between the solution requirements or specifications presented by a user, no single best solution could be identified and no suitable evaluation methods exist to evaluate the effectiveness of the recommended solution.

Future work includes transforming the created decision support system of solution that is deemed as the basis, into a functioning decision support system to be utilised by system users. Future work could also include performing tests and experiments at existing farms, to evaluate the effectiveness of the solution and gathering data pertaining to each unique solution. The data to be captured can be used to refine the suggested solutions, to enable the system to produce more specific solutions in future. In addition, a complete database with up-to-date information for all of the solution options, including the different hardware and software options such as available UAV models, payload models, software tools etc. can be created in future. This database should be updated regularly to ensure the information included is still applicable and the specific models or versions of software are still available commercially.

Future work could also include a study focusing on the integration of multiple UAVs within a single system. This research can focus on investigating the simultaneous use of more than one aircraft to perform crop monitoring, thus reducing the total time required for monitoring. These systems could be beneficial for extremely large crop fields that usually take an unreasonable amount of time to completely monitor the entire field. Such systems could also be utilised when monitoring tree crops that require a full 360° image of the tree including the sides and the trunk. A final recommendation for future work is to create an interactive tool that allows a user to select the system requirements and inputs and then based on those selections the tool presents the user with solution options designed uniquely for the user. This tool is however dependent on the creation of a comprehensive database mentioned above.

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7.1 Appendix A: Research Timeline

Figure 21 Research Timeline

7.2 Appendix B: Indicative Crop Classification (ICC 1.0)

Group	Class	Subclass	Order	Title	Crop type*
1				Cereals	T
	1.01			Wheat	T
	1.02			Maize	T
	1.03			Rice	T
	1.04			Sorghum	T
	1.05			Barley	T
	1.06			Rye	T
	1.07			Oats	T
	1.08			Millet	T
	1.09			Triticale	T
	1.10			Buckwheat	T
	1.11			Fonio	T
	1.12			Quinoa	T
	1.13			Canary seed	T
	1.14			Mixed cereals	T
	1.90			Other cereals, n.e.c.	T
2				**Vegetables and melons**	T
	2.01			Leafy or stem vegetables	T
		2.01.01		Artichokes	T
		2.01.02		Asparagus	T
		2.01.03		Cabbages	T
		2.01.04		Cauliflower and broccoli	T
		2.01.05		Lettuce	T
		2.01.06		Spinach	T
		2.01.07		Chicory	T
		2.01.90		Other leafy or stem vegetables, n.e.c.	T
	2.02			Fruit-bearing vegetables	T
		2.02.01		Cucumbers	T
		2.02.02		Eggplants (aubergines)	T
		2.02.03		Tomatoes	T
		2.02.04		Pumpkin, squash and gourds	T
		2.02.05		Okra	T
		2.02.90		Other fruit-bearing vegetables, n.e.c.	T
	2.03			Root, bulb or tuberous vegetables	T
		2.03.01		Carrots	T
		2.03.02		Turnips	T
		2.03.03		Garlic	T
		2.03.04		Onions (incl. shallots)	T
		2.03.05		Leeks and other alliaceous vegetables	T
		2.03.90		Other root, bulb, or tuberous vegetables, n.e.c.	T
	2.04			Mushrooms and truffles	T
	2.05			Melons	T
		2.05.01		Watermelons	T
		2.05.02		Cantaloupes and other melons	T
	2.90			Other vegetables n.E.C.	T

Group	Class	Subclass	Order	Title	*Crop type*[*]
3				**Fruit and nuts**	*P*
	3.01			*Tropical and subtropical fruits*	*P*
		3.01.01		*Avocados*	*P*
		3.01.02		*Bananas*	*P*
		3.01.03		*Plantains*	*P*
		3.01.04		*Dates*	*P*
		3.01.05		*Figs*	*P*
		3.01.06		*Mangoes, guavas and mangosteens*	*P*
		3.01.07		*Papayas*	*P*
		3.01.08		*Pineapples*	*P*
		3.01.90		*Other tropical and subtropical fruits, n.e.c.*	*P*
	3.02			*Citrus fruits*	*P*
		3.02.01		*Grapefruit and pomelo*	*P*
		3.02.02		*Lemons and limes*	*P*
		3.02.03		*Oranges*	*P*
		3.02.04		*Tangerines mandarins, clementines*	*P*
		3.02.90		*Other citrus fruits, n.e.c.*	*P*
	3.03			*Grapes*	*P*
	3.04			*Berries*	*P*
		3.04.01		*Currants*	*P*
		3.04.02		*Gooseberries*	*P*
		3.04.03		*Kiwi fruit*	*P*
		3.04.04		*Raspberries*	*P*
		3.04.05		*Strawberries*	*P*
		3.04.06		*Blueberries*	*P*
		3.04.07		*Cranberries*	*P*
		3.04.90		*Other berries, n.e.c*	*P*
	3.05			*Pome fruits and stone fruits*	*P*
		3.05.01		*Apples*	*P*
		3.05.02		*Apricots*	*P*
		3.05.03		*Cherries and sour cherries*	*P*
		3.05.05		*Peaches and nectarines*	*P*
		3.05.06		*Pears and quinces*	*P*
		3.05.08		*Plums and sloes*	*P*
		3.05.90		*Other pome fruits and stone fruits, n.e.c.*	*P*
	3.06			*Nuts*	*P*
		3.06.01		*Almonds*	*P*
		3.06.02		*Cashew nuts*	*P*
		3.06.03		*Chestnuts*	*P*
		3.06.04		*Hazelnuts*	*P*
		3.06.05		*Pistachios*	*P*
		3.06.06		*Walnuts*	*P*
		3.06.07		*Brazil nuts*	*P*
		3.06.08		*Areca nuts*	*P*
		3.06.09		*Cola nuts*	*P*
		3.06.90		*Other nuts, n.e.c.*	*P*
	3.90			*Other fruits, n.e.c.*	*P*

Group	Class	Subclass	Order	Title	Crop type*
4				**Oilseed crops and oleaginous fruits**	
	4.01			*Soya beans*	*T*
	4.02			*Groundnuts*	*T*
	4.03			*Other temporary oilseed crops*	*T*
		4.03.01		*Castor bean*	*T*
		4.03.02		*Linseed*	*T*
		4.03.03		*Mustard*	*T*
		4.03.04		*Niger seed*	*T*
		4.03.05		*Rapeseed*	*T*
		4.03.06		*Safflower*	*T*
		4.03.07		*Sesame*	*T*
		4.03.08		*Sunflower*	*T*
		4.03.09		*Shea tree (shea butter or karite nuts)*	*T*
		4.03.10		*Tung tree*	*T*
		4.03.11		*Jojoba*	*T*
		4.03.12		*Poppy*	*T*
		4.03.13		*Tallow tree*	*T*
		4.03.90		*Other temporary oilseed crops, n.e.c.*	*T*
	4.04			*Permanent oilseed crops*	*P*
		4.04.01		*Coconuts*	*P*
		4.04.02		*Olives*	*P*
		4.04.03		*Oil palms*	*P*
		4.04.90		*Other oleaginous fruits, n.e.c.*	*P*
5				**Root/tuber crops with high starch or inulin content**	*T*
	5.01			*Potatoes*	*T*
	5.02			*Sweet potatoes*	*T*
	5.03			*Cassava*	*T*
	5.04			*Yams*	*T*
	5.05			*Taro*	*T*
	5.06			*Yautia*	*T*
	5.90			*Other roots and tubers, n.e.c.*	*T*
6				**Stimulant, spice and aromatic crops**	
	6.01			*Stimulant crops*	*P*
		6.01.01		*Coffee*	*P*
		6.01.02		*Tea*	*P*
		6.01.03		*Maté*	*P*
		6.01.04		*Cocoa*	*P*
		6.01.05		*Chicory roots*	*P*
		6.01.90		*Other stimulant crops, n.e.c.*	*P*
	6.02			*Spice and aromatic crops*	
		6.02.01		*Temporary spice and aromatic crops*	*T*
			6.02.01.01	*Chillies and peppers (capsicum spp.)*	*T*
			6.02.01.02	*Anise, badian, and fennel*	*T*
			6.02.01.90	*Other temporary spice crops, n.e.c.*	*T*
		6.02.02		*Permanent spice and aromatic crops*	*P*
			6.02.02.01	*Pepper (piper spp.)*	*P*

Group	Class	Subclass	Order	Title	Crop type*
			6.02.02.02	*Nutmeg, mace, cardamoms*	*P*
			6.02.02.03	*Cinnamon (canella)*	*P*
			6.02.02.04	*Cloves*	*P*
			6.02.02.05	*Ginger*	*P*
			6.02.02.06	*Vanilla*	*P*
			6.02.02.07	*Hops*	*P*
			6.02.02.90	*Other permanent spice and aromatic crops, n.e.c.*	*P*
7				**Leguminous crops**	*T*
	7.01			*Beans*	*T*
	7.02			*Broad beans*	*T*
	7.03			*Chickpeas*	*T*
	7.04			*Cowpeas*	*T*
	7.05			*Lentils*	*T*
	7.06			*Lupins*	*T*
	7.07			*Peas*	*T*
	7.08			*Pigeon peas*	*T*
	7.09			*Bambara beans*	*T*
	7.10			*Vetches*	*T*
	7.90			*Leguminous crops, n.e.c.*	*T*
8				**Sugar crops**	**T**
	8.01			*Sugar beet*	*T*
	8.02			*Sugar cane*	*T*
	8.03			*Sweet sorghum*	*T*
	8.90			*Other sugar crops, n.e.c.*	*T*
9				**Other crops**	
	9.01			*Grasses and other fodder crops*	
		9.01.01		*Temporary grass and fodder crops*	*T*
		9.01.02		*Permanent grass and fodder crops*	*P*
	9.02			*Fibre crops*	
		9.02.01		*Temporary fibre crops*	*T*
			9.02.01.01	*Cotton*	*T*
			9.02.01.02	*Jute, kenaf, and other similar crops*	*T*
			9.02.01.04	*Flax*	*T*
			9.02.01.05	*Hemp*	*T*
			9.02.01.90	*Other temporary fibre crops, n.e.c.*	*T*
		9.02.02		*Permanent fibre crops*	*P*
			9.02.02.01	*Ramie*	*P*
			9.02.02.02	*Sisal*	*P*
			9.02.02.90	*Other permanent fibre crops, n.e.c.*	*P*
	9.03			*Medicinal, pesticidal or similar crops*	
		9.03.01		*Temporary medicinal, pesticidal or similar crops*	*T*
			9.03.01.01	*Mint*	*T*
			9.03.01.02	*Basil*	*T*
			9.03.01.90	*Other temporary medicinal, pesticidal or similar crops*	*T*
		9.03.02		*Permanent medicinal, pesticidal or similar crops*	*P*
			9.03.02.01	*Ginseng*	*P*

Group	Class	Subclass	Order	Title	*Crop type*[*]
			9.03.02.02	*Coca*	*P*
			9.03.02.03	*Kava*	*P*
			9.03.02.04	*Guarana*	*P*
			9.03.02.90	*Other permanent medicinal, pesticidal or similar crops*	*P*
	9.04			*Rubber*	*P*
	9.05			*Flower crops*	
		9.05.01		*Temporary flower crops*	*T*
		9.05.02		*Permanent flower crops*	*P*
	9.06			*Tobacco*	*T*
	9.90			*Other crops, n.e.c.*	
		9.90.01		*Other crops, n.e.c. – temporary*	*T*
		9.90.02		*Other crops, n.e.c. – permanent*	*P*

**T = temporary, P = permanent.*