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A UAV-Based Close Monitoring of the Vegetation for Precision Agriculture Purposes

Thesis Advisor:

Dr. Tahraoui Sofiane

Dr. Azmedroub Boussad

By:

Mr. Miloua Mokhtar

Mr. Mebarek Bilel Abdelmadjid

Presented in Front of the Committee Members:

Pr. **Benblidia Nadjia**	*Professor*	*President*
Dr. **Choutri Kheireddine**	*MCB*	*Examiner*

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Abstract

This thesis investigates drone-based remote sensing in vegetation monitoring and the potential of artificial intelligence in plant disease detection. The study encompasses the assembly of a quadcopter unmanned aerial vehicle, the selection of suitable sensors for precise vegetation monitoring, and the development of a platform that integrates satellite imagery for vegetation analysis. The results highlight the effectiveness of drones in vegetation monitoring and the significance of AI-supported disease detection that could be integrated to the developed aerial surveying system. The research provides valuable insights for enhancing agricultural practices and disease management strategies, underscoring the importance of advancing sensor technologies and data analysis techniques in this domain.

Résumé

Cette thèse examine la télédétection par drones dans le suivi de la végétation et le potentiel de l'intelligence artificielle dans la détection des maladies des plantes. L'étude englobe l'assemblage d'un véhicule aérien sans pilote de type quadricoptère, la sélection de capteurs adaptés pour un suivi précis de la végétation, et le développement d'une plateforme intégrant des images satellite pour une analyse de la végétation. Les résultats mettent en évidence l'efficacité des drones dans le suivi de la végétation et l'importance de la détection des maladies soutenue par l'intelligence artificielle, qui pourrait être intégrée au système de relevé aérien développé. Cette recherche offre des perspectives précieuses pour améliorer les pratiques agricoles et les stratégies de gestion des maladies, soulignant l'importance de l'avancement des technologies de capteurs et des techniques d'analyse des données dans ce domaine.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
API	Application Programming Language
CAN	Controller Area Network
CIR	Color Infrared
CNN	Convolutional Neural Networks
DN	Digital Numbers
EM	Electromagnetic
ESC	Electronic Speed Controller
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
I2C	Inter-Integrated Circuit
INS	Inertial Navigation System
IoT	Internet of Things
LAI	Leaf Area Index
LiDAR	Light Detection and Ranging
ML	Machine Learning
NDRE	Normalized Difference Red Edge
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NIR	Near Infra-red
PAg	Precision Agriculture
RE	Red Edge
RC	Radio Controller
RGB	Red Green Blue
RPM	Revolutions Per Minute
RSSI	Receiver Signal Strength Indicator
RTL	Return to Launch

SAR	Synthetic Aperture Radar
UART	Universal Asynchronous Receiver-Transmitter
UAS	Unmanned Aerial System
UAV	Unmanned Aerial Vehicle
VI	Vegetation Indices

INTRODUCTION

Agricultural production plays a vital role in sustaining human society by supplying essential needs such as food, fuel, and fiber. However, in the current century, agriculture encounters the demanding task of ensuring an adequate supply and high-quality food to support the ever-growing population of nearly 8 billion people [1], while limited resources necessitate the need for efficient resource utilization, which is particularly crucial in areas such as food production and soil management.

To face this problem modern agriculture is often relying on the expanded utilization of digital technology for monitoring and managing the diverse activities that occur on a farm. This approach commonly referred to as "smart farming”.

The emergence of “smart farming”, which represents the current agricultural revolution in information technology, commenced its development during the 1980s. Subsequently, commercial availability of these technologies started to unfold in the early 1990s [2].

“Smart farming” Also known as digital agriculture is an innovative approach that leverages advanced technologies to optimize agricultural practices. It involves the integration of various technologies, such as remote sensing (RS), Internet of Things (IoT), artificial intelligence (AI), data analytics, and automation, to enable precise and efficient management of farming operations. Typically, smart farming encompasses the practices of acquiring, analyzing, and evaluating data, along with employing precision application technologies. While the terms "smart farming" and "precision agriculture (PAg)" are occasionally used interchangeably, it is important to clarify that precision agriculture is actually a subset or sub-category within the broader concept of smart farming [1, 3].

By utilizing real-time data and insights, smart farming aims to enhance productivity, reduce resource waste, minimize environmental impact, and improve overall farm profitability. It allows farmers to make data-driven decisions, tailor interventions, and maximize crop yields while minimizing inputs such as water, fertilizers, and pesticides.

Technological advancements in smart farming offer solutions to the challenges faced by farmers using various ways such as:

a) Data-driven Decision-making: Smart farming enables farmers to collect and analyze a vast amount of data, including soil conditions, weather patterns, crop health, and pest infestations. This data-driven approach helps farmers gain actionable insights into their operations, leading to informed decision-making regarding irrigation scheduling, crop protection measures, and nutrient management [1, 3].

b) Precision Application of Inputs: Technologies like GPS[1], GIS[2] and RS[3] allow farmers to precisely apply inputs, such as fertilizers and pesticides, only where and when needed. This reduces wastage, minimizes environmental impact, and optimizes resource utilization, resulting in cost savings and improved sustainability [1, 3].

c) Remote Monitoring and Automation: IoT sensors and connected devices enable real-time monitoring of various parameters, including soil moisture, temperature, and crop health. This remote monitoring allows us to detect issues early, such as disease outbreaks or water stress, and take immediate corrective actions [1, 3].

d) Predictive Analytics and Machine Learning: Advanced data analytics techniques, including predictive modeling and machine learning algorithms, can analyze historical and real-time data to predict crop performance, disease outbreaks, or yield potential. This helps farmers anticipate and mitigate risks and optimize resource allocation [1, 3].

By embracing these technological advancements, farmers can overcome various challenges such as unpredictable weather patterns, resource constraints, labor shortages, and market fluctuations empowering them to achieve higher productivity, economic profitability, and environmental sustainability, making agriculture more efficient and resilient. Ultimately contributing to worldwide food and nutrition security.

[1] GPS: Global Positioning System is an accurate worldwide navigational and surveying facility based on the reception of signals from an array of orbiting satellites.

[2] GIS: A geographic information system is a computer system for capturing, storing, checking, and displaying data related to positions on Earth's surface.

[3] RS: the scanning of the earth by satellite or high-flying aircraft in order to obtain information or data.

1. 1 Problem statement and objectives

The global food crisis has revealed the vulnerabilities of Algerian agriculture. The nostalgic image of Algeria as the "breadbasket of Europe" is far from the truth and the substantial food bill serves as a stark reminder of the current reality. Algeria remains heavily reliant on international markets, ranking among the top ten countries in terms of cereal imports. This dependence extends to other agricultural products like powdered milk, oils, sugar, and coffee, etc. To alleviate this situation, it is crucial for Algeria to find ways to export its own agricultural produce and achieve a better-balanced agricultural trade [4].

Algerian agriculture still relies heavily on traditional farming methods. Traditional farming practices, passed down through generations, continue to dominate the agricultural landscape. Many farmers employ manual labor, basic tools, and rudimentary techniques in their cultivation processes. Additionally, there is a limited adoption of modern agricultural technologies and practices, such as mechanization, precision farming, and advanced irrigation systems. This reliance on traditional methods hinders the efficiency, productivity, and sustainability of the agricultural sector in Algeria. .

As based on the analysis provided in India clearly demonstrates that the average income of modern farmers significantly surpasses that of traditional farmers [6]. The yearly earnings of modern farmers are 17.36 times higher than the yearly earnings of traditional Indian farmers [6]. Likewise, the income per acre for modern farmers is 13.88 times greater than that of traditional farmers [6]. Also big American companies like Monsanto and DuPont are currently leveraging Big Data to enhance crop yields. As early as 2014, Monsanto envisioned that providing farmers with data-driven insights from field observations would result in a significant reduction in input expenses and an annual yield increase of 20 million USD [5].

The financial well-being of a nation greatly depends on the income of its residents and its agricultural field, and a significant portion of the population derives their livelihood from agriculture or related agricultural businesses [8].

The implementation of Precision Agriculture is needed to achieve its intended objectives, continuous monitoring of the crop plantation is necessary, particularly during the growth season. By constantly monitoring the plantation and obtaining information from plant images, farmers can gain insights into the health of the plants and take necessary and in-time actions to address any issues as water stress or plant diseases and prevent potential losses [6, 7].

Various imaging technologies, including satellites, mobile phones, and Unmanned Aerial Vehicles (UAVs), are employed to capture a range of images using both active and passive sensors operating across different regions of the electromagnetic (EM) wave spectrum, from microwave to ultraviolet [6, 7]. These images possess distinct spatial, spectral, radiometric, and temporal resolutions, allowing for differential utilization of the sensors [6-8].

In order to overcome the limitations of satellite and mobile phone methods and acquire images in near real-time with the desired resolution, the utilization of Unmanned Aerial Vehicles was suggested [6, 9, 10].

To collect precise field data UAVs are recognized as the most effective and efficient approach [6, 11]. The integration of aerospace engineering and sensor technology has significantly reduced the cost of implementing UAVs in agriculture, leading to their widespread adoption [6, 12, 13].

UAVs employ cameras to capture images and sensors to gather data, facilitating the monitoring process, disease detection and supporting on time decision-making on the farm [6].

1. 2 Main Objective

This thesis falls with the "Startup Master" initiative to provide solutions for the problems stated above; the main objective of this thesis is to comprehensively explore drone-based vegetation health monitoring and develop a solution for vegetation disease detection. It aims to address the challenges faced by farmers in detecting and managing plant diseases and highlights the advantages of using drones in smart farming. The thesis also examines the state of the art in drone-based remote sensing and explores relevant technologies used in smart farming.

Furthermore, it focuses on the assembly of a quadcopter UAV and the selection of suitable sensors for precision agriculture. Additionally, it involves the creation of a desktop application for mission planning and a platform that integrates satellite technology for agricultural monitoring.

1. 3 Thesis chapters outlining

The thesis consists of several chapters that together provide a comprehensive exploration of the topic of drone-based smart farming and disease detection.

CHAPTER 1 examines the state of the art in drone-based disease detection in smart farming and the relative technologies used.

CHAPTER 2 focuses on the assembly of a quadcopter UAV and the selection of suitable sensors for precision agriculture. It discusses the assembly process, calibration procedures, and modifications made to enhance the capabilities of the system. The chapter also explores various sensors, determining the most suitable one for disease detection.

CHAPTER 3 presents an integrated solution that combines a desktop application and a website to facilitate efficient and effective crop monitoring and mission planning. It covers the functionalities of the desktop application, the analytics provided by the website, and the disease detection capabilities.

CHAPTER 4 provides the results of the mission planning with the desktop application and the generated maps from the drone surveys.

CHAPTER 1. REMOTE SENSING FOR AGRICULTURAL APPLICATIONS

1. 1 What is remote sensing

Remote sensing and geospatial techniques play a crucial role in gathering and analyzing data, enabling the identification of variations in crop and soil properties within the field [14].

Remote sensing refers to the measurement of parameters from a distance rather than through direct contact. While it commonly involves the measurement of optical signals, it is not limited to that alone. Remote sensing technologies encompass radar-based remote sensing, visible and infrared spectroscopy, LiDAR (Light Detection and Ranging), and multispectral and hyperspectral imaging. Each of these technologies operates within a specific region of the EM and has its own specifications for target characterization.

All the mentioned remote sensing technologies have made significant contributions to the advancement of PAg. Synthetic aperture radar (SAR), a specific radar technology, utilizes various wavelengths in the radar spectrum to detect surface features and small-scale structures. SAR can penetrate vegetation and soil by using longer wavelengths like the L-band or P-band, which allows for the detection of underground features and moisture content.

Visible/infrared spectroscopy and hyperspectral imaging are widely used in the analysis of vegetation in PAg. These techniques enable the rapid analysis of crops and vegetation, and when combined with machine learning, they yield satisfactory classification results.

To overcome the limitations of crops monitoring using traditional strategies, these remote sensing techniques are employed. For example, the near infrared (NIR) operates within the electromagnetic spectrum with wavelengths ranging from 800 to 2500 nanometers and offers high-throughput capabilities for quality control in agricultural products. It has been applied in various agricultural sectors, including parameter measurement, differentiation of wheat cultivars, and detection of fungal infection.

The integration of NIR with imaging techniques like multispectral and hyperspectral imaging enhances the analysis capabilities, facilitating quality control in crops such as fruits and the assessment of their ripeness and sweetness.

Additionally, remote sensing technologies have significantly enhanced precision agriculture by enabling disease detection, vegetation analysis, and quality control in agricultural products.

Sensing can be defined simply as the measurement of something from a distance rather than in direct contact. Although it typically refers to the measurement of optical signals, it is not limited to that. In this manuscript, remote sensing is discussed in the context of measuring visible and NIR radiation using a modified RGB camera. In this case, it is more accurate to refer to this topic as remote imaging since the data obtained represents a "picture" of the analyzed object [15].

In remote sensing, we measure the radiation reflected by surface targets in order to characterize them. The collected data is then aggregated and represented as discrete images or a pixel grid with two spatial dimensions (X and Y). In the case of multispectral remote sensing, each resolution cell (pixel) contains multidimensional data (λi) consisting of multiple bands or layers captured by the sensor. This data enables us to obtain spectral information for each pixel, facilitating qualitative and quantitative analyses.

Figure 1.1 illustrates a pixelated representation of an image, where a 3-band image is depicted as an array of pixels [16].

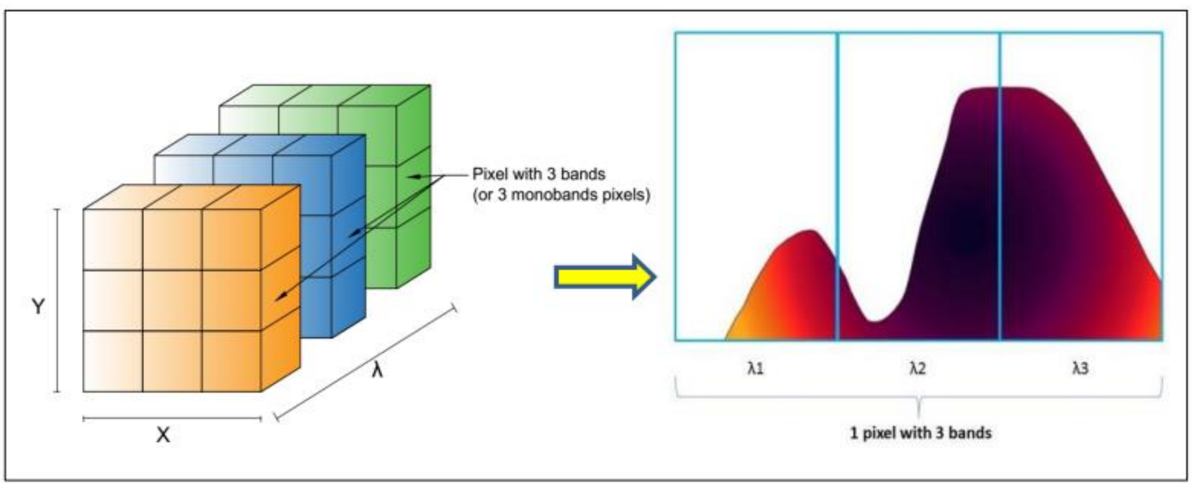

Figure 1.1 illustrates a pixelated representation of an image, where a 3-band image is depicted as an array of pixels [15].

Each pixel in the image contains reflectance information for three distinct monoband channels. Since the monoband pixels are discrete representations of radiation, which inherently has a continuous nature, the process of discretization typically involves averaging the values within the boundaries of each band.

The categorization of cameras in remote sensing is based on their number of channels, also known as spectral resolution. Researchers differentiate between multispectral sensors, which have a limited number of channels, and hyperspectral sensors, which possess hundreds of channels. An example of a multispectral sensor is the RGB camera, which consists of three channels that capture reflected radiation in the red, green, and blue wavelengths, respectively [15].

Remote sensing relies on the principle that various chemical compounds exhibit distinct reactions to radiation by either transmitting, absorbing, or reflecting a portion of the incoming radiation. This behavior leads to the selective absorption of specific wavelengths, known as absorption bands, by different materials or components.

As a result, each material possesses a unique pattern or "spectral signature" across the EM spectrum (refer to Figure 1.2). Consequently, by measuring the reflected radiation from an object and analyzing its spectral signature, it becomes possible to differentiate and identify various materials or components [15].

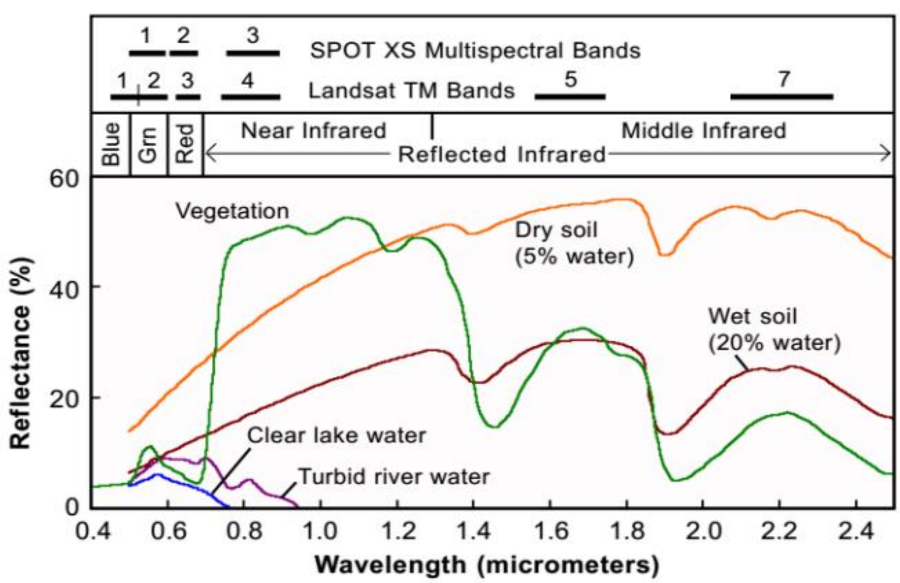

Figure 1.2 Example of spectral signature of different materials [15].

1. 2 Satellite based remote sensing

Satellite-based remote sensing is a conventional approach for obtaining remotely sensed data [14]. Satellite imagery has been utilized since the 1970s to extract agricultural information [2, 16]. However, the freely available images typically have a spatial resolution of 30 m or lower, which is considered too coarse for many applications [14]. The initial satellite, Landsat 1, captured data in four spectral bands (red, green, and two infrared bands) at a spatial resolution of 80 m, with a revisit frequency of 18 days [16].

Additionally, since satellites are positioned between ~480 to ~ 900 kilometers above the Earth's surface, there exists a substantial expanse of atmosphere between the satellite sensor and the Earth's surface. Consequently, interferences arising from weather conditions are frequently encountered in satellite imaging (refer to Figure 1.3) [15].

Nevertheless, certain commercial satellites offer sub-meter resolution satellite imagery, with spatial resolutions of less than 1 m for panchromatic and over 1 m for multispectral data, for specific locations and times at a cost. However, these high-resolution commercial satellite images are often infrequent in availability [14, 17].

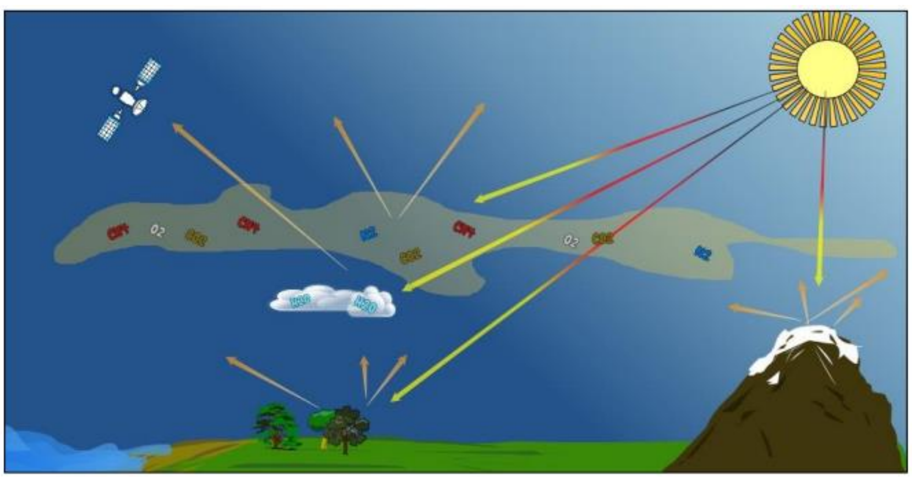

Figure 1.3 Example of atmosphere effects in radiation. Incoming radiation from sun (red-yellow arrows) are reflected unequally [16]

Satellites like QuickBird (~480 km of altitude) and RapidEye (~630 km), offering improved capabilities such as shorter revisit times ranging from one to three days, finer spatial pixel resolutions below 1 m, and a greater number of spectral bands. However, acquiring and processing data from these satellites can be complex and expensive.

Since 2017, the availability of data from Sentinel 2 has provided a cost-effective and more accurate option for assessing vegetation and nutrient status, offering a spatial resolution of 10 m and 13 potentially relevant spectral bands [2, 18], but this is still objectively low on field imaging resolution and disease detection .

Table 1.1 Sentinel-2 (S-2) (786 km) spectral band characteristics [19].

Spectral Bands	**Wavelength (nm)**	**Spatial Resolution (m)**
Band 1 (Aerosol)	443	60
Band 2 (Blue)	490	10
Band 3 (Green)	560	10
Band 4 (Red)	665	10
Band 5 (Vegetation Red-Age)	705	20
Band 6 (Vegetation Red-Age)	740	20
Band 7 (Vegetation Red-Age)	783	20
Band 8 (NIR)	842	10
Band 8A (Vegetation Red-Age)	865	20
Band 9 (NIR)	945	60
Band 10 (MIR)	1375	60
Band 11 (MIR)	1610	20
Band 12 (MIR)	2190	20

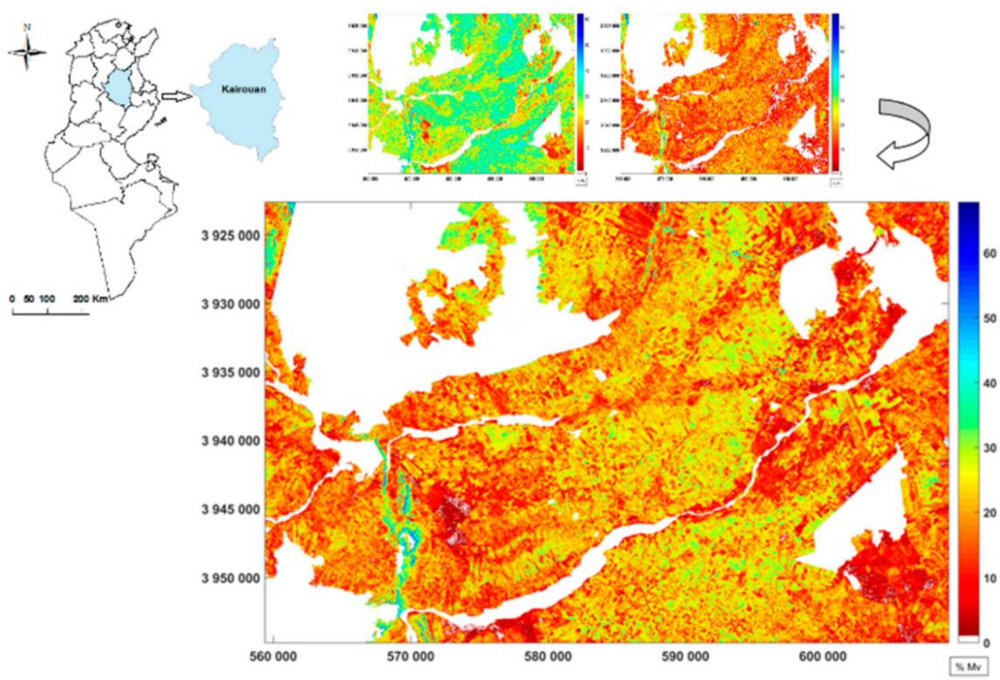

Figure 1.4 Soil moisture map over the Kairouan Plain, derived from the combined use of Sentinel-1 and Sentinal-2 data, with the upper maps representing 01/12/2017 (in the left) and 20/09/2017 (in the right) [20].

In Figure 1.4, a soil moisture map of Kairouan Plain from September 14, 2017, is depicted. The white-colored area on the map represents urban areas, water bodies, and certain reliefs that have been masked. The upper right corner of the figure displays two distinct cases of soil moisture. The first case, represented by green colors, corresponds to a wet date (January 12, 2017), while the second case, represented by red colors, corresponds to a dry date (September 20, 2017) [19].

Utilizing high-resolution satellite imagery proves advantageous in examining fluctuations discrepancies in crop and soil conditions. Nevertheless, challenges related to the accessibility, high cost and expenses associated with obtaining such imagery at the desired spatial and temporal resolution indicate the necessity for an alternative approach [14, 20], especially when considering the impact of cloud cover.

One potential solution is the utilization of small unmanned aerial systems (UAS) in operational Precision Agriculture [14, 17], images captured by low altitude remote sensing platforms such as small UAVs or small crewed aircraft present an alternative solution. UAVs have the advantage of low operational costs and can capture data with very high spatial resolution and the desired temporal frequency [14, 20].

1. 3 UAV based remote sensing

In recent years, significant progress has been observed in the development of Unmanned Aerial Vehicles, with advancements in miniaturization, improvements in components such as GNSS[4] and INS[5] systems, and the availability of lightweight sensors [21, 22]. This technological evolution has positioned UAVs as a valuable platform for collecting data in agricultural applications, bridging the gap between remote sensing and terrestrial techniques.

Utilizing UAVs provides a favorable compromise between the broad coverage achievable with remote platforms like satellites and aircraft, and the accuracy of terrestrial data, while also offering advantages in terms of time-consumption and survey costs [21].

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[4] GNSS: Global Navigation Satellite System refers to a constellation of satellites providing signals from space that transmit positioning and timing data.

[5] INS: Inertial navigation system is an electronic system that uses sensors that can detect & measure the change in an object's motion.

Figure 2.4 illustrates a comparison of different survey systems, correlating the area of interest's extent with the spatial resolution of acquired images [21, 23].

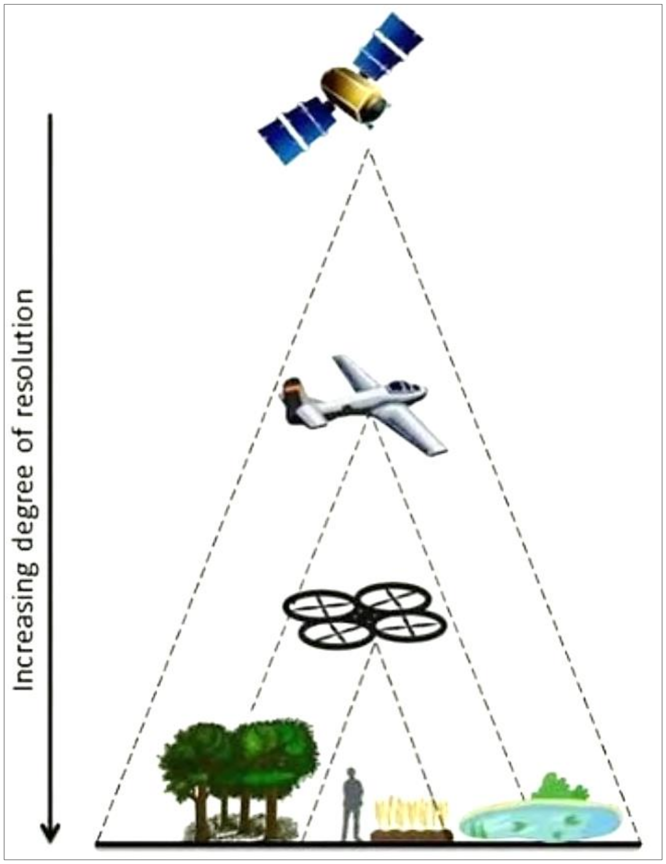


Figure 1.5 Earth observation involves the utilization of remote sensing technologies such as satellites and aerial sensors, combined with manual observations conducted on the ground [24].

Table 1.2 Limitations of satellite data vs drone-based sensing [14].

Sub-meter resolution commercial satellite image	**Drone-based high-resolution image**
Cloud cover and atmospheric dust particles create a bottleneck on image acquisition for some frequencies band such as optical RS.	Low flight height makes a limited effect of cloud cover
Real-time image acquisition and processing are not possible and usually takes some days delay	Images can be obtained and processed in a few hours, depending on the size of the farm
Images captured at some fixed time of day depending on the frequency of revolution of the satellite.	Images can be captured at the desired time of day

Table 1.2 Continuation

Maximum available Panchromatic geometrical resolution is 30 cm, while Multispectral resolution would be 1.2 m	Sub-cm spatial resolution can be achieved as per requirement
Minimum area map which can be ordered is 25 km^2 or more. If only natural color map required, then 10 km^2.	The map can be generated for a small and medium area which would be much cheaper than satellite imaging
Optical images are generally taken from zenith	Images at a different angle can be taken, which will help in getting architectural information of canopies

Therefore, unlike satellites and airplanes, UAVs possess higher resolution capabilities, compensating for smaller coverage areas and making them an ideal platform for identifying within-field variations in agriculture.

Unmanned aerial vehicles offer the capability to incorporate diverse sensors that prove valuable in examining crop-related parameters. Multiple existing literatures demonstrates that drones can be equipped with optical sensors such as RGB, multispectral, hyperspectral, and thermal sensors, enabling the identification of water stress and other forms of stress in crops . LiDAR sensors, when integrated with drones, facilitate the estimation of canopy height and structure, which contributes to the estimation of crop biomass.

Moreover, when utilizing UAV interferometric or tomographic acquisition, it is advantageous to employ multiple acquisitions simultaneously at a low cost. This approach helps to avoid temporal decorrelation, which can have a detrimental impact on the tomographic/interferometric product. By utilizing multiple acquisitions simultaneously, the issue of decorrelation between targets and the subsequent challenge of co-registration can be effectively mitigated. In addition to collecting digital data, drones have been employed for aerobiological sampling over agricultural fields to detect pest infestations at an early stage. Furthermore, drones can be utilized to implement corrective measures in farms, such as targeted pesticide spraying in areas experiencing stress [14].

Table 1.3 Provides an overview of the various sensors used on drones to monitor different crop characteristics [14].

Type	**Weight in KG**	**Types of sensors which can be mounted on the drone**	**Area coverage capacity of the drone**
Nano	>0,25	Area coverage capacity of the drone Nano Less than 0.25 This has not been used in agriculture till now as sensors are usually of more weight and cannot be lifted by nano drones	NA
Micro	0,25< Weight <2	Small RGB, lighter multispectral camera, and small LiDAR sensor can be mounted on this drone	Can cover up to 4-5 acre of ground area depending on the height of flight. Flight height is generally kept lower than 100 meters
Small	2< Weight < 25	High-resolution RGB camera, multispectral camera, LiDAR sensor, a lightweight hyperspectral imager, microwave sensor, and small thermal imager can be mounted on the drone	Can cover up to 10- 20 acre of ground area depending on the height of flight
Medium	25 < Weight < 150	Bigger high-resolution RGB camera, multispectral camera, LiDAR sensor, medium weight hyperspectral imager, microwave sensor, and the thermal camera can be mounted on the drone. It can also be used for spraying of pesticides	Can cover up to 100 acres of ground area depending on the height of flight. Flight height is generally higher than 50 meters
Large	Weight > 150	Bigger and heavyweight cameras and sensors can be mounted on the drone. It can be used for spraying of pesticides	Can cover more than 100 acres of ground area. Flight height is generally higher than 100 meters

The utilization of UAVs has revolutionized agricultural surveys by enabling information collection from an aerial perspective.

1. 4 Types of UAV Applications in Precision Agriculture

Recently, UAV technologies have demonstrated their effectiveness in various Precision Agriculture applications. These applications encompass targeted herbicide applications, identification of water deficiencies, detection of diseases, and more. By utilizing data obtained from UAVs, valuable insights can be gained to address detected issues and optimize crop harvesting through yield estimation. The literature highlights several prevalent applications of UAVs in Precision Agriculture, which include the following main uses [23]:

• Weed mapping and management [23, 25, 26].

• Vegetation growth monitoring and yield estimation [23, 27-29].

• Vegetation health monitoring and diseases detection [23, 30, 31].

• Irrigation management [23, 24, 32].

• Crops spraying [23, 33, 34] and others

- **Weed mapping and management:**

Weed mapping stands out as one of the prominent applications of UAVs in Precision Agriculture. Weeds, unwanted plants that proliferate within agricultural crops, pose various challenges. They compete with the cultivated plants for essential resources such as water and space, leading to reduced crop yields and hindered growth. Furthermore, weeds can cause complications during the harvesting process. Traditional weed management approaches in conventional farming involve uniformly spraying herbicides across the entire field, without considering weed-free areas. However, excessive herbicide usage can contribute to the development of herbicide-resistant weeds and negatively impact crop growth and yield.

UAVs can take pictures and collect data from the entire field, which can then be used to create a detailed map showing where chemicals are needed for weed control: some areas require more chemicals, some require less, and some should not be treated at all [23].

Ana I. De Castro et al. (2018) conducted an experiment that highlights the importance of high spatial resolution for automated weed mapping during the early stages of crop growth. This level of resolution shown in figure 2.5 can be achieved effectively using a UAV [35].

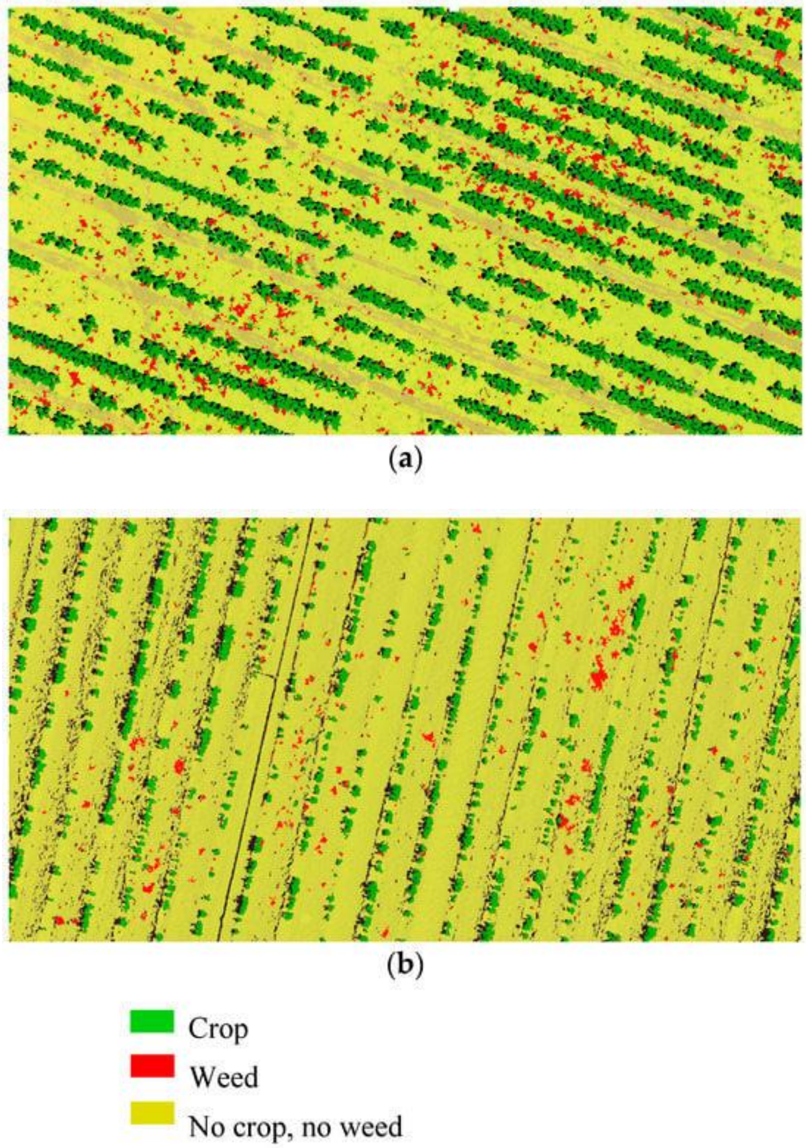


Figure 1.6 Classified image by applying the auto-trained Random Forest classifier Object Based Image Analysis (RF-OBIA) algorithm to UAV images at 30 m flight altitude: (a) sunflower field; (b) cotton field [35].

- **Monitoring the growth of the vegetation and providing yield estimation:**

The lack of ways to monitor crop growth and weather conditions makes it difficult to increase agricultural productivity. However, using UAVs to collect information and visualize crops can help overcome this obstacle. Recent studies have focused on monitoring biomass (the amount of plant material) and nitrogen levels in crops, as well as estimating yield. By measuring biomass and nitrogen, farmers can determine if additional fertilizer is needed. UAVs can also create detailed maps of crops in three dimensions and measure various parameters like crop height, spacing between rows and plants, and Leaf Area Index (LAI), which indicates how much leaf surface area is present. With this information, farmers can make informed decisions about crop management, such as nutrient use and timing of harvesting, and identify any potential mistakes in their approach [23].

In a study made by Aijing Feng et al. (2020) the crop information from the UAV imagery data was compared to the yield data [36]. The yield data was georeferenced and matched with the corresponding points on the orthomosaic images shown in Figure 1.7 and plant height map using a method developed in a previous study by Feng, Zhang, et al. (2019) [37].

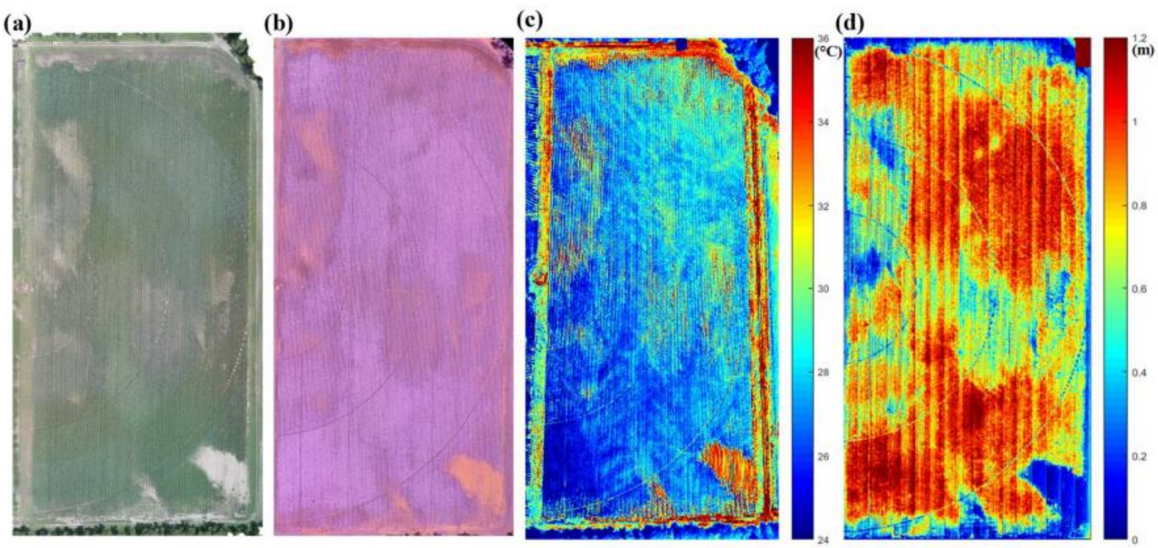


Figure 1.7 Orthomosaic images and plant height map based on data collected on Aug. 12, 2017 (flowering stage). (a) –(c) orthomosaic images acquired from RGB, multispectral, and thermal cameras; and (d) plant height map [36].

Results of the study found that the height and temperature measurements taken by UAVs matched the manual measurements. By analyzing eight different data features, including vegetation indices, canopy cover, plant height, temperature, and a cotton fiber index, it was discovered that plant height during the flowering stage and the cotton fiber index near harvest provided the most accurate predictions of crop yield compared to the other image features.

- **Monitor vegetation health:**

Crop health is crucial for ensuring a good harvest, but diseases can cause significant damage to crops, leading to lower yields and poor quality. Traditionally, experts inspect crops manually, which is time-consuming and limits continuous monitoring. Another approach is to apply pesticides at specific times, but this can be costly and may contaminate groundwater. In

Precision Agriculture, a more targeted approach is taken for disease control. Automated non-destructive detection of crop diseases plays a vital role in decision-making. Diseases bring about changes in the physical and biochemical characteristics of crops, which can be identified through UAV-based data processing. By analyzing crop images, UAVs can detect diseases early on, even before visible signs appear, and map the extent of the infection. This allows farmers to intervene promptly and minimize losses. UAVs are useful in two stages of disease control: first, during the initial infection, where they identify potential infections, and second, during the treatment phase, where UAVs can be used for precise targeted spraying and closely monitor the progress of intervention efforts [23].

- **Crop irrigation management:**

Crop irrigation management is a crucial application of UAV technologies in PAg. With the majority of global water consumption dedicated to crop irrigation, there is a need for precise irrigation techniques. Precision irrigation ensures water is used efficiently by targeting specific areas, timing, and quantities. By detecting areas that require significant irrigation, farmers can save time and water resources while increasing crop productivity and quality. Precision agriculture divides fields into different irrigation zones, enabling precise resource management. UAVs equipped with suitable sensors can identify areas of crops that need more water and produce specialized maps depicting soil characteristics. This supports more efficient irrigation planning for each crop individually [23].

In addition to the common applications mentioned above, UAVs have also been used for soil analysis [20, 38, 39], cotton genotype selection [23, 27], mammal detection [40], and assessment of soil electrical conductivity [41] and others .

1. 5 UAV surveys and data processing techniques

The various tasks involved in a UAV survey are crucial because they can influence the success of the survey and the accuracy of the data collected. The first step is flight planning, which is extremely important as it ensures safe flights and reduces the time and cost associated with post-processing. The flight plan is based on factors such as the size and shape of the area of interest, the characteristics of the sensor, including the focal length and image dimensions, and the required Ground Sample Distance for the application. In agricultural applications, vegetation characteristics can make image matching difficult, so UAV surveys require high levels of overlap, at least 80% along the flight direction and 60% along the cross direction [21]. Nowadays, flight planning is usually done using specialized software like Pix4Dcapture or Mission Planner after inspecting the survey area and defining the project objectives. Once the flight plan has been established, it is uploaded onto the UAV and the flight is executed autonomously using the GNSS and IMU systems on-board. However, during the actual survey, factors such as weather cannot be controlled or planned for. Although flights can be conducted under moderate rain or wind conditions, the most critical factor that can impact the survey is sunlight. It is important to maintain uniform illumination conditions throughout the acquisition phase to prevent any irregularities in the images. It is recommended to carry out surveys during midday, when the sun is at its highest point, to minimize shadows on the ground and reduce the Bidirectional Reflectance Distribution Function effect [21, 42].

Before data acquisition, it is necessary to calibrate the sensors in order to improve the quality of the data and reduce distortions in the images, both geometric and radiometric. Geometric corrections are made using Ground Control Points, which are panels with known geographic coordinates that are visible to the on-board sensor. These panels are used for georeferencing and camera self-calibration during data processing, and they ensure high overlap among images acquired by multi-lens sensors. Radiometric corrections are also necessary, especially when using CIR, multi/hyper-spectral, or thermal sensors. Calibration targets, such as white or gray panels with known spectral characteristics, are used to normalize collected images in relation to illumination conditions and sensor performance. These calibration panels convert pixel values expressed as DN into real reflectance values. Radiometric corrections are particularly useful in agricultural applications for comparing data collected at different times or producing index maps [21, 43].

Using specialized sensors, UAVs can gather information about different aspects of the cultivated field. However, there is currently no set way or established techniques to analyze and visualize the acquired information. The following image processing methods are commonly used to analyze UAV imagery for Precision Agriculture purposes [23]:

- **Photogrammetry/interferometry techniques:**

Photogrammetry involves accurately reconstructing a scene or object from multiple overlapping pictures. These techniques establish the geometric relationships between the images and the object, resulting in 3D models. To create these models, at least two overlapping images of the same scene or object are needed from different viewpoints. Photogrammetry is used to extract three-dimensional digital surface or terrain models and orthophotos. UAVs, with their low-altitude data acquisition, allow for higher spatial resolution in constructing 3D models compared to other remote sensing technologies [23, 44]. However, collecting multiple overlapping images is necessary to cover the entire field. These models provide valuable information about the 3D characteristics of crops, such as vegetation height and density, which can be utilized in applications relying on RGB imagery.

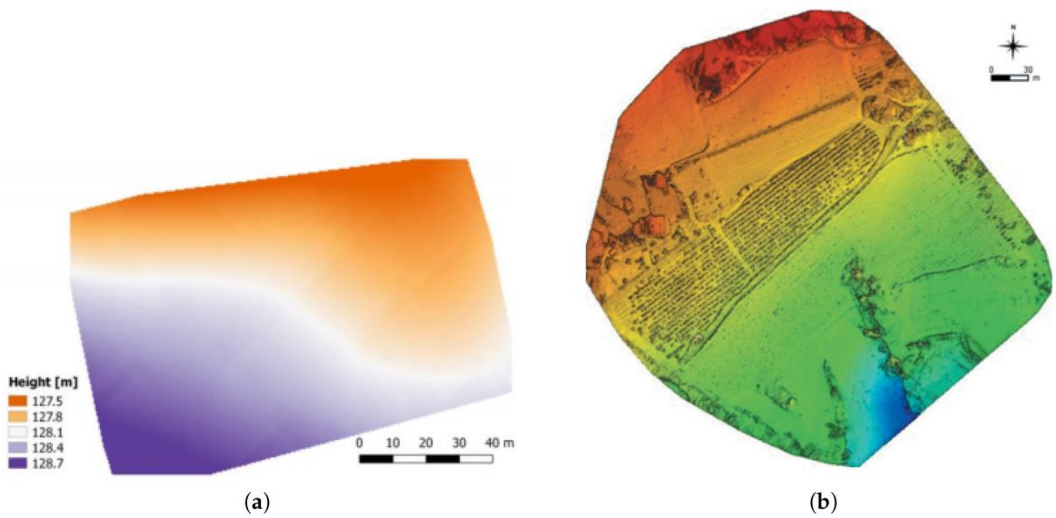


Figure 1.8 (a) A Digital Terrain Model; and (b) a Digital Surface Model [45].

The Digital Terrain Model represents the elevation of the Earth's surface without considering artificial or natural objects in the field. On the other hand, the Digital Surface Model includes the elevation of both the bare Earth and any existing objects captured by the remote sensing system. These models can be used to extract 3D information or create orthomosaics of the crops. An orthophoto is a geometrically corrected aerial photograph that provides accurate measurements and contains the 3D characteristics of the crops [23, 44].

- **Machine learning:**

Machine Learning (ML) and Data Mining are widely used in Precision Agriculture with UAVs. ML helps extract knowledge from the collected data for various vegetation parameters. Regression methods estimate vegetation indices and their correlations with features like nitrogen and biomass [23]. Classification methods are used for weed mapping and disease detection, with Artificial Neural Networks and Random Forest algorithm being popular choices [12, 35]. These methods analyze RGB colors, intensity, and spectral information. They can achieve high accuracy, with Convolutional Neural Networks (CNN) being effective for object detection in large datasets [23, 44].

- **Vegetation indices:**

Vegetation Indices (VIs) are widely used in Precision Agriculture for monitoring crop growth and health. They are mathematical transformations of EM radiation absorption and scattering by vegetation. VIs provide valuable information about vegetation properties such as biomass, nitrogen status, and overall health. Simple VIs that combine RGB and spectral bands like NIR and Red Edge (RE) improve the detection of green and healthy vegetation. Different environments require specific VIs due to their unique characteristics. By combining reflections from different bands, VIs reduce noise from external factors and enhance vegetation detection. For example, VIs based on red and NIR channels increase contrast between vegetation and soil, enabling the elimination of disturbances that affect both zones similarly [23]. Most used VIs in Table 1.4:

Table 1.4 Most used Vegetation indices [23].

Vegetation Index	Abbreviation	Index
Vegetation Indices derived from multispectral information		
Ratio Vegetation Index	RVI	$\frac{NIR}{R}$
Normalized Difference Vegetation Index	NDVI	$\frac{NIR - R}{NIR + R}$
Normalized Difference Red Edge Index	NDRI	$\frac{NIR - RE}{NIR + RE}$
Green Normalized Difference Vegetation Index	GNDVI	$\frac{NIR - G}{NIR + G}$
RGB-based Vegetation Indices		
Excess Greenness Index	ExG	$2G - R - B$
Normalized Difference Index	NDI	$\frac{G - R}{G + R}$

1. 6 Research Focused on UAV Agricultural Applications

There exists multiple research studies on this field of applications some of which we can mention are:

Early research by Nebiker et al. (2008) demonstrated the feasibility of mounting multispectral sensors on UAVs [21, 46], leading to subsequent studies exploring various applications. Notably, studies have focused on in-field weed mapping, vegetation growth monitoring, yield estimation, crop water stress analysis, and optimization of irrigation management [21-23] For instance; De Castro et al. (2018) developed an algorithm based on machine learning techniques to map weeds in sunflowers and cotton fields using high-resolution UAV imagery [35]. De Castro and colleagues (2018) utilized high-resolution UAV imagery to create a weed mapping algorithm using machine learning techniques.

Similarly, Stroppiana et al. (2018) employed an automated procedure to detect weeds in rice fields using UAV data during the early stages of the growing season [47]. Nebiker et al. (2016) investigated the potential of lightweight sensor-equipped UAV surveys for predicting crop yield in rape and barley, revealing a strong correlation between vegetation indices derived from UAV images and reference yield measurements [48].

Stroppiana et al. (2019) employed UAV data to estimate maize vegetation density at the onset of the growing season in Northern Italy [49]. In a study by Hoffmann et al. (2016), crop water stress maps were generated from RGB and thermal UAV imagery captured at different stages of the season in spring barley fields located in Western Denmark [50]. Caruso et al. (2019) conducted experiments on olive orchards, both irrigated and rainfed, using UAV images to estimate tree height, canopy diameter, and canopy volume [51]. Lastly, Quebrajo et al. (2018) emphasized the importance of site-specific irrigation strategies by evaluating the water status of sugar beet plants using thermal data acquired through UAV surveys [24].

The key strength of UAV surveys lies in their ability to rapidly and extensively capture various types of information through versatile sensor deployment, offering a non-invasive approach with a high level of detail capable of detecting within-field variations [21].

1. 7 Advantages of using UAVs in Agriculture and Limitations in Algeria

Using UAVs in agriculture in Algeria offers several advantages. Firstly, they can cover difficult areas with limited internet and GPS signals, making it easier for farmers in mountainous regions like Tizi Ouzou blidéen atlas, or medea to monitor their crops. Additionally, UAVs can operate in various weather conditions and gather valuable data, surpassing the limitations of satellites and airborne platforms. However, there are limitations to consider. The processing of high-resolution images in photogrammetry can be time-consuming, and the cost of sensing hardware and software is often expensive. Therefore, farmers need to carefully choose the appropriate software and hardware based on their specific needs and financial capabilities [44].

In Algeria, the use of drones is currently limited to certain individuals, institutes, and research centers. However, there is optimism and ambition for the widespread adoption of this technology to modernize and facilitate various agriculture applications, ultimately making them more efficient and profitable [44]. The Algerian government has been actively promoting agricultural improvement and food security through national programs. The progress of production and irrigated areas in recent years is presented in Table 1.5 and Table 1.6.

Table 1.5 Evolution of irrigated areas in Algeria from 2000 to 2017 [52].

2000/2001	2002/2003	2004/2005	2007/2008	2010/2011	2012/2013	2015/2016	2016/2017
350 000	644 978	793 334	905 293	981 736	1 053 523	1 260 508	1 301 231

Table 1.6 Evolution of agricultural production (in tons) [52].

Products	1995-1999	2011-2015	Growth %
Cereals	2 590 044	4 196 602	62
Dried vegetables	44 338	88 008	98
Vegetables	2 113 454	11 321 378	436
Potato	1 078 757	4 436 260	311
Grapes	203 600	509 827	150
Olives	217 100	547 984	152
Citrus	432 650	1 202 486	178
Dates	365 600	857 441	135
Milk	1 583 500	3 700 000	134

1. 8 Advancements in Smart Farming: Leveraging IoT and AI for Agricultural Transformation

Smart farming, is revolutionizing traditional farming practices by integrating cutting-edge technologies such as the IoT and AI. These technologies enable farmers to monitor and manage their crops, livestock, and agricultural processes more efficiently, resulting in improved productivity, sustainability, and resource optimization. In this section, we discuss the role of IoT and AI in smart agriculture and highlight their potential benefits and applications.

1.8.1 The Internet of Things in Smart Farming

IoT plays a pivotal role in smart farming by connecting physical objects, sensors, and devices to collect and exchange data. In agricultural settings, IoT devices can be deployed throughout the farm, collecting real-time information on various parameters such as soil moisture, temperature, humidity, crop health, and livestock behavior. These IoT devices transmit data to a centralized system or cloud platform, where it is processed and analyzed.

1.8.2 IoT sensors and applications in agriculture:

Some of the application of IoT can be mentioned such as Greenhouse automation: IoT sensors provide real-time information on lighting, temperature, soil condition, and humidity, allowing automated adjustments; Climate monitoring: IoT weather stations collect environmental data to map climate conditions, aiding in precision farming.

Figure 1.9 Agriculture IoT weather station [53].

Crop management: IoT devices placed in the field monitor crop-specific data such as temperature, precipitation, and overall crop health.

Precision farming: IoT sensors collect data on lighting, temperature, soil condition, humidity, CO_2 levels, and pest infections, enabling precise resource allocation and improved crop yield.

Predictive analytics: IoT data combined with analytics tools enable farmers to make predictions about crop harvesting time, disease risks, and yield volume.

Agricultural drones: Drones equipped with sensors collect agricultural data and perform tasks such as planting, pest control, and crop monitoring [52].

Figure 1.10 Pesticides spraying drone in action [53].

End-to-end farm management systems: These systems providing remote farm monitoring, analytics, and reporting features. FarmLogs and Cropio are examples of farm productivity management systems [52].

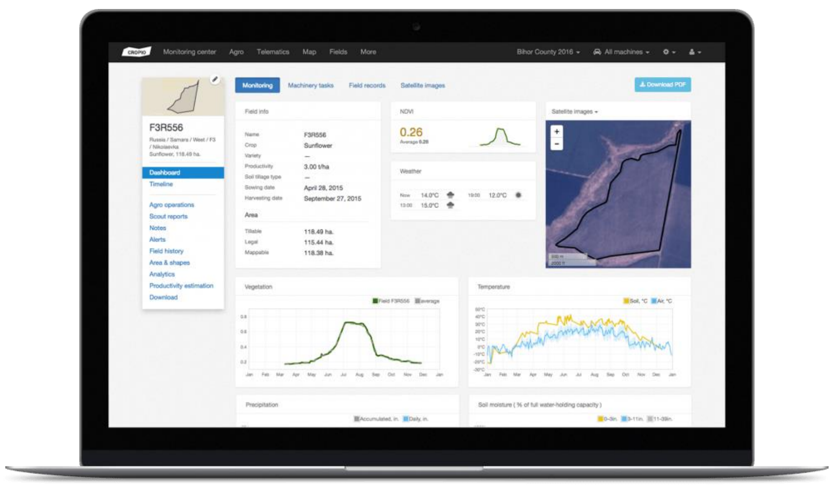


Figure 1.11 Cropio’s field management Dashboard [53].

These IoT applications in agriculture offer improved efficiency, data-driven decision-making, and enhanced productivity [53].

1.8.3 Artificial Intelligence in Smart Farming

AI algorithms and machine learning techniques are applied to the vast amounts of data collected through IoT devices in smart farming. By analyzing historical and real-time data, AI can extract valuable insights, make predictions, and automate decision-making processes, leading to more informed and efficient agricultural practices.

1.8.4 Benefits and Applications of AI in Smart Farming

1. Crop Disease Detection and Diagnosis: AI algorithms can analyze images of plants and identify diseases or nutrient deficiencies accurately. This enables early intervention and targeted treatment, reducing crop losses and the need for excessive pesticide use.

2. Yield Prediction and Optimization: AI models can analyze various data inputs, including weather patterns, soil conditions, and historical yield data, to predict crop yields. This information helps farmers optimize resource allocation, manage market demand, and plan harvest schedules effectively.

3. Robotic Automation: AI-powered robots and drones can perform tasks such as seeding, spraying, and harvesting autonomously. These robots can navigate fields, identify and remove weeds, and gather data for precision farming techniques.

4. Decision Support Systems: AI-based decision support systems provide real-time recommendations to farmers regarding optimal planting times, irrigation schedules, and crop rotation strategies. This helps farmers make data-driven decisions and achieve better outcomes.

1. 9 Conclusion

In conclusion, we showed that UAV-derived data as well as the integration of IoT and AI technologies in smart farming holds tremendous potential to transform traditional agricultural practices. Using close range UAV data collecting and harnessing the power of IoT devices to collect real-time data and leveraging AI algorithms to analyze and interpret this data, farmers can optimize their operations, reduce costs, enhance productivity, and contribute to sustainable agriculture.

By synthesizing the literature in this chapter, we have gained a comprehensive understanding of the capabilities and limitations of remote sensing techniques in agriculture. The insights gathered will serve as a solid foundation for the subsequent chapters, where we will further explore specific methodologies and advancements in UAV-based remote sensing, data processing, IoT and AI integration.

CHAPTER 2. UAV HARDWARE CHOICE AND ASSEMBLY

2. 1 Introduction

UAVs used in agriculture for vegetation monitoring can vary in size, shape, flight time, height, speed, and payload capacity. Operators tend to focus on mini and micro UAVs that weigh less than 25 kg [21]. Two primary categories of vehicles exist within this weight class: fixed-wing and multi-rotor. Both have distinct characteristics, advantages, and uses. However, the choice between fixed-wing and multi-rotor vehicles depends on factors such as the area's dimension and orography, desired image resolution, and available space for take-off and landing.

In this chapter, our specific focus lies in the assembly of a quadcopter drone for our esteemed research project. We shall delve into the rationale behind our choice of a multi-rotor aerial vehicle over a fixed-wing aircraft. This decision shall be made following a thorough discussion of the two primary categories of UAVs within this weight class, namely fixed-wing and multi-rotor vehicles.

Additionally, we explore the essential components of the drone system, providing detailed insights into the functionality and contributions of each element to the quadcopter's overall performance. We cover significant aspects including the frame, motors, electronic speed controllers (ESCs), and other relevant components. Detailed technical data, dimensions, and illustrations are provided throughout to enhance comprehension of component selection and integration.

Finally, we will explore different sensors commonly used in precision agriculture and discuss the sensor we have chosen for our application. By examining these sensors, we aim to highlight their functions and applications in farming. Furthermore, we will provide an in-depth analysis of our selected sensor, explaining how it aligns with our research goals.

2. 2 UAV Technologies: Implementation and Assembly

2.2.1 Fixed-wing

Fixed-wing UAVs (Figure 2.1.d) have wings and are ideal for surveying large areas ranging from 1 to 10 km^2. They provide ground-level imagery with a resolution in the order of decimeters and require about ten square meters of open space for take-off and landing [21]. These unmanned aerial vehicles necessitate comprehensive training in order to operate them effectively.

They are capable of maintaining a vertical balance in the air for multiple hours. However, they lack the ability to move backward, hover, or rotate, making them unsuitable tasks like aerial photography [54].

2.2.2 Multi-rotor

In contrast to fixed-wing, multi-rotor (Figure 2.1) vehicles are better suited for covering smaller areas between 0.01 and 1 km^2. They can acquire data with a resolution in the order of centimeters and do not require additional space for vertical take-off and landing. Generally, multi-rotor vehicles are preferred in PAg applications due to their slower flight speed, ease of operation, and maneuverability [21]. Multi-rotor UAVs come in various configurations, including tri-copters, quad-copters, hexa-copters, or octo-copters [54].

Both fixed-wing and multi-rotor UAVs require the same main components to ensure safe flights, including but not limited to:

- Ground Control Station: a computer on the ground that can communicate with and monitor the UAV.
- Remote Control: flight control systems that manage the UAV's flight operations.
- GNSS system: an on-board GNSS receiver to define the UAV's flight route.
- IMU systems: an Inertial Measurement Unit that comprises accelerometers and gyroscopes to maneuver the UAV.
- Safety systems: other miniaturized on-board sensors that help the UAV maintain a safe and minimal distance from obstacles during flights.
- Payload: equipment used for data acquisition.

Various technical solutions are available on the market for both fixed-wing and multi-rotor UAVs, including products from major commercial labels and self-made options. Table 2.1 and Figure 2.1 displays some examples of UAVs that represent both fixed-wing and multi-rotor vehicles.

Table 2.1 Commercially available drones.

Type	UAV	Related Studies
8 rotors	Mikrokopter Okto XL	[55, 56]
	DJI Spreading Wings S1000	[57-59]
	Aerialtronics Altura AT8	[60]
	Tarot 680	[61]
6 rotors	EM6-800	[62]
	DJI M600	[63]
	Hexacopter P-Y6	[64]
	Mikrokopter Hexa-II	[65]
4 rotors	Parrot AR.Drone 2.0	[66]
	Parrot Anafi	[66]
	DJI Matrice 210	[67]
	DJI Phantom Series	[67-71]
Fixed wing	Quantum Systems Trinity F90+	[72]
	eBee SQ	[73]
	Tuffwing Mapper	[74, 75]

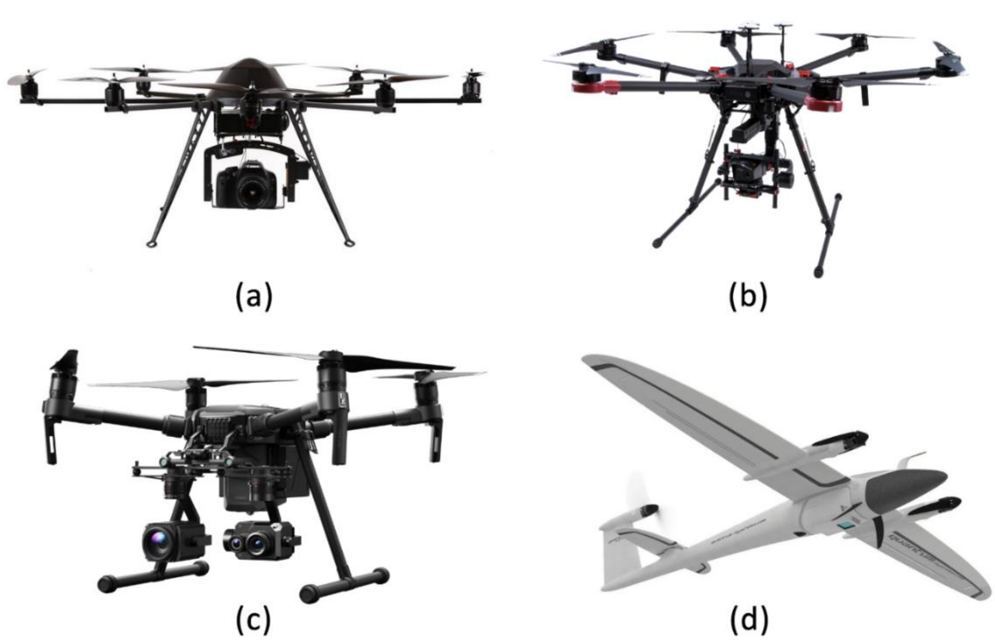


Figure 2.1 Commercial drones used for precision agriculture purposes. (a) Octa-rotor Mikrokopter Okto XL, (b) Hexa-rotor DJI M600, (c) Quad-rotor DJI Matrice 210, and (d) Quantum Systems Trinity F90+.

2.2.3 Assembly of a Quadcopter Drone

Incorporating a drone into our thesis project was essential to achieve our research goals. Considering the unavailability of one at hand and the high cost of purchasing a commercial drone, we opted to undertake the assembly of our own drone.

After careful consideration, we made the decision to construct a multi-rotor aerial vehicle for our study instead of a fixed-wing aircraft. This choice was primarily driven by the availability of the necessary parts and the comparatively lower complexity involved. Moreover, the multi-rotor's suitability for surveying tasks was another key factor in our decision. Unlike fixed-wing drones that require covering larger areas, the multi-rotor's maneuverability allows for efficient surveying in smaller, confined spaces. Additionally, they offer the advantage of requiring less space for takeoff and landing. This advantage further supported our choice to utilize a multi-rotor for our study.

Specifically opting for the quadcopter design. This choice was driven by several factors, including its versatility, stability, and maneuverability. The design offers precise control and agility, making it well suited for our intended purposes. By selecting this type of copter configuration, we aim to leverage its advantages in terms of stability, ease of control, and adaptability for various tasks in our study.

2.2.4 Main components of the drone system

In this section, we will take a closer look at the main components that make up our drone system. We will delve into the details of the frame, motors, propellers, electronic speed controllers, flight controller, radio-controller and power system, providing a comprehensive understanding of how each of these elements contributes to the overall functionality and performance of the quadcoter.

- **Frame**

Drone frames are the structural foundation of the aerial vehicle, influencing its performance and capabilities. Choosing the right frame ensures stability, durability, and optimal integration of various components, making it a critical consideration in drone assembling.

We selected the frame for our drone based on its size, payload capacity and commercial availability, the X-shaped quadcopter frame emerged as the most widely accessible option. Specifically, we opted for a frame design inspired by DJI's flame wheel F450 airframe. Figure 2.2 displays the design and dimensions of this frame.

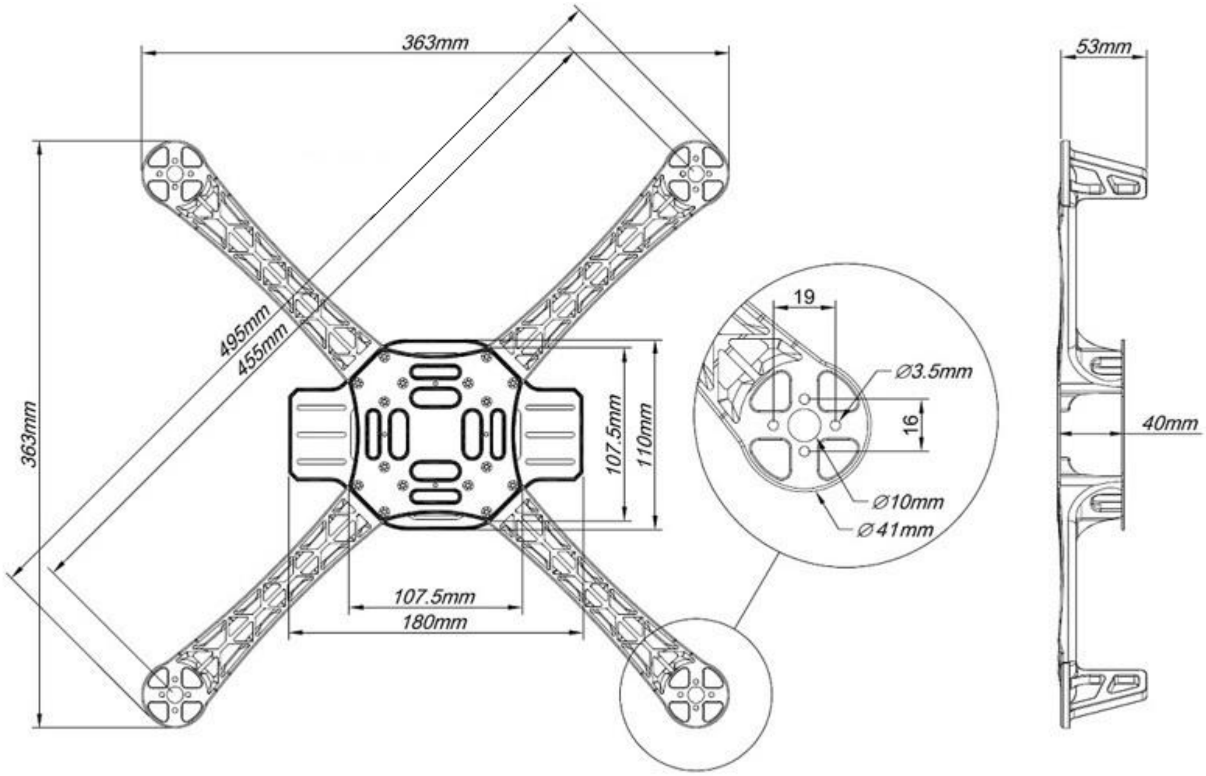


Figure 2.2 Dimensions of a DJI Flame Wheel F450.

- **Motors**

In order to choose the appropriate motors for our drone, it is essential to have an estimate of the overall weight of the quadcopter. This calculation involves taking into account the combined weight of all the components.

Next, we delve into the key parameters of the motors, as these factors heavily influence the motor selection process. By evaluating these parameters, we can make informed decisions about the most suitable motors for our specific requirements.

- Thrust to Weight Ratio:

In every type of multi-rotor, it is crucial to ensure that the motors we use in our drone can generate approximately 50% more thrust than the actual weight of the drone. This extra thrust is essential for the drone to respond effectively to our control inputs and facilitate a smooth take-off [76, 77]. Moreover, it is important for our drone motors to maintain stability and reliable functionality even in slightly windy conditions. By having a high thrust-to-weight ratio, the drone will possess enhanced agility and acceleration. However, it is important to note that this increased agility may also make the drone more challenging to control [76].

Finding the right balance between thrust, weight, and control is key to achieving optimal performance and maneuverability for our drone.

- KV Ratings:

The KV rating serves as a critical parameter for the motor. It refers to the rotational speed, measured in revolutions per minute (RPM), that the motor can generate per volt of input power [77].

Once the propeller is attached to the motor, the RPM tends to decrease due to air resistance. Motors with higher KV ratings spin the propeller at a faster rate and have the capability to draw more current. As a result, we commonly observe the use of larger propellers with low KV motors, while smaller and lighter propellers are better suited for high KV motors [76, 77].

If a larger propeller is paired with a high KV motor, it will require greater torque to spin at a faster rate. While attempting to generate the necessary torque, the motor will draw more current and generate excessive heat. This overheating can potentially cause damage to the motor. Therefore, it is important to consider the appropriate combination of propeller size and motor KV rating to ensure optimal performance and prevent overheating issues [76, 77].

- Motor Size:

Typically, brushless motors are classified using a four-digit numbering system. For instance, let us consider a motor with the name "2212". In this case, the first two digits indicate the diameter of the stator in millimeters, while the last two digits represent the stator height, also measured in millimeters. Essentially, a wider and taller motor has the capability to generate more torque.

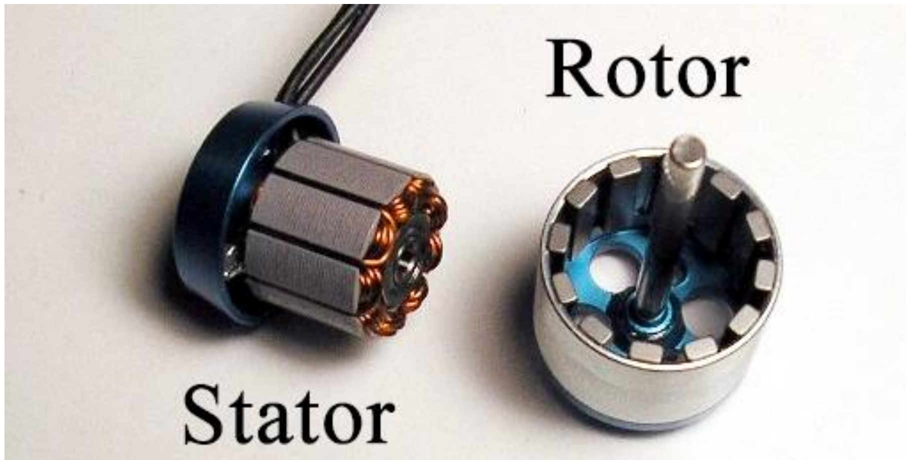


Figure 2.3 REX 220 FLYWARE Rotor and Stator [78].

The choice of motor size is directly influenced by the size of the frame. There is a dependency between the frame size, propeller size, and the motor size and KV rating. The frame size determines the maximum propeller size that can be used, which, in turn, limits the appropriate motor size and KV rating [76]. The table below provides some guidance on motor size selection. In this context, the frame size refers to the wheelbase, which indicates the distance between motors.

Table 2.2 Combinations of frames, propellers and motors.

Frame size	Propeller size	Motor size	KV rating
180 mm – 200 mm	4 inch	1806 - 2204	2600KV+
210 mm – 240 mm	5 inch	2204 - 2206	2300KV – 2700KV
250 mm – 320 mm	6 inch	2204 - 2208	2000KV – 2300KV
330 mm – 350 mm	7-8 inch	2208 - 2212	1500KV – 1600KV
450 mm – 500 mm	9-10 inch	2212 -2216	800KV – 1000KV

Taking into consideration the size of our frame and performing calculations to determine the required motor pulling capacity, we have concluded that the A2212-1000KV brushless motor is the suitable choice. The specific characteristics of this motor are depicted below.

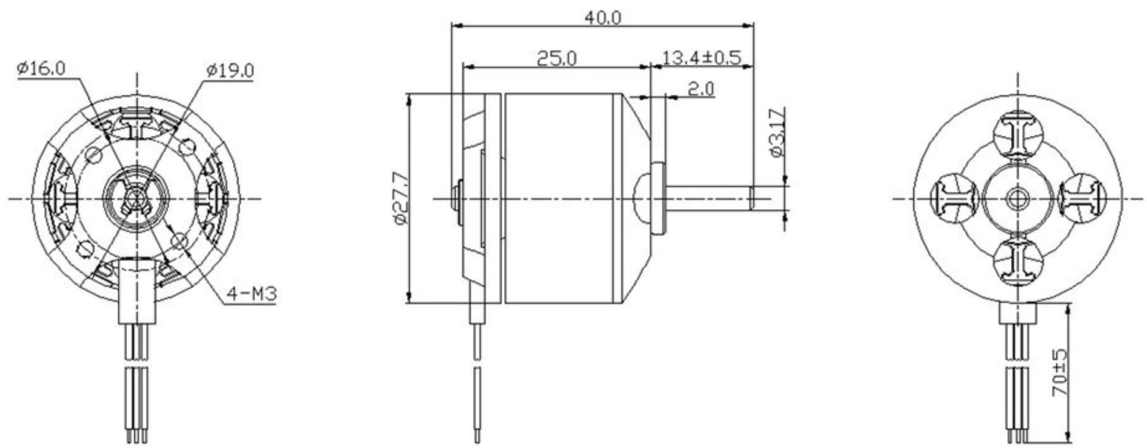


Figure 2.4 A2212 brushless motor outline drawing.

Table 2.3 A2212 brushless motor Technical data [79].

KV	1000 rpm/V
Number of battery cells	2S – 4S
Max efficiency[6]	80%
Max efficiency current[7]	4 – 10 A (>75%)
No load current	0,5 A
Pull	885 g
Resistance	0,090 ohms
Max current	13 A for 60 seconds
Max watts	150 W
Weight	52,7 g
Size	28 mm dia × 28 mm bell length
Shaft diameter	3,2 mm
Poles	14

[6] Efficiency refers to how effectively a motor converts electrical power into mechanical power without excessive energy losses.

[7] Max efficiency current represents the maximum current that the motor can handle continuously without exceeding its thermal limits and risking damage or reduced efficiency.

- **Propellers**

It is important to select propellers that are compatible with the drone's motor specifications and the overall design goals. Choosing the right propellers, helps optimize performance, efficiency, and stability during flight. Beginning with the drone frame, we consider its size to determine the suitable propeller size for our drone. The weight and dimensions of the propeller play a crucial role in determining the lifting thrust and flying speed of the drone.

After referring to the Table 2.2, we have identified the 1045 propellers (Figure 2.5) as the appropriate choice for both the frame and motors. The specifications for the propellers are as follows: the pitch[8] is 4.5 inches, the weight is 14 grams, the shaft diameter is 6 mm, and the total length is 10 inches (254 mm).

Figure 2.5 Clockwise and counter clockwise 1045 propellers.

- **Electronic speed controllers**

Electronic Speed Controllers are devices used in drones to regulate the speed of electric motors. They have an essential role in controlling the rotation speed of the motors, which directly affects the drone's thrust and overall performance.

ESCs receive signals from the flight controller or transmitter and convert them into precise electrical pulses that determine the motor's speed. By adjusting the timing and duration of these pulses, ESCs regulate the power sent to the motors, enabling precise control of the drone's movements, including acceleration, deceleration, and changes in direction.

[8] The term "pitch" refers to the theoretical distance a propeller would travel in one complete revolution in an ideal medium. It represents the forward movement of the propeller per revolution and is usually measured in inches. A higher pitch indicates a greater forward movement per revolution, while a lower pitch signifies less forward movement.

ESCs are vital components in drone systems, making it essential to select the appropriate ones for our specific drone configuration. To determine the suitable ESCs, we need to consider the maximum current that our motors will draw during operation.

According to Table 2.3 in the technical data of the A2212 motor, the maximum current specified is 13 A. Therefore, the suitable ESCs for our setup would be those with a current capacity of 20 A or higher. After conducting market research, we have identified the EMAX 30A ESCs (Figure 2.6) as commercially available options that align with our requirements. These ESCs are well suited for our quadcopter configuration.

Figure 2.6 EMAX 30A ESC.

- **Flight Controller**

The flight controller acts as an indispensable cornerstone for the safe and efficient operation of drones. By seamlessly integrating sensor data, executing complex algorithms, and providing advanced flight features, it ensures stable flight characteristics, precise control, and an elevated piloting experience.

Selecting the right board depends on the physical restraints of the vehicle, features desired, and the applications that we want to run. After considering these factors [80]:

- Sensor Redundancy[9]: Many controllers incorporate multiple integrated IMUs for increased redundancy and fault tolerance.

[9] Sensor redundancy refers to the use of multiple sensors that provide similar or overlapping measurements or data in a system or application. By employing redundant sensors, the system can compare the readings from multiple sensors and identify any inconsistencies or discrepancies. If one sensor fails or provides erroneous data, the redundant sensors can help detect the issue and ensure the continued operation of the system.

- Servo/Motor Outputs: The number of available servo/motor outputs is an important consideration, as it determines the capability to control and operate various actuators and peripherals on the drone.
- UARTs: UART[10] ports serve as essential interfaces for connecting telemetry radios, GPS modules, companion computers, and other devices, enabling seamless communication and data exchange.
- External Buses[11]: External buses like I2C[12] and CAN[13] provide versatile connectivity options for attaching a wide range of devices to the autopilot system. This includes airspeed sensors, LED controllers, and other compatible peripherals.
- Analog I/O: Some controllers offer analog input/output options, allowing the integration of features such as receiver signal strength (RSSI) measurement, battery voltage/current monitoring, and support for other analog sensors.
- Integrated Features: Certain controllers come with integrated features such as an on-screen display (OSD) for real-time flight information and built-in battery monitoring sensors to ensure accurate power management.
- Size: The physical size of the autopilot is a crucial consideration, particularly for smaller vehicles with limited space. Compact autopilot designs are desirable to ensure proper installation and optimal utilization of available space.
- Expense: Controller prices vary depending on the set of features and capabilities they offer. While basic options can be cheap, more advanced controllers with enhanced functionalities may have higher price ranges.

[10] UART (Universal Asynchronous Receiver-Transmitter) is a hardware communication protocol commonly used for serial communication between electronic devices. It facilitates the transmission and reception of asynchronous data, allowing devices to exchange information bit by bit.

[11] External Buses are communication pathways that allow multiple devices to connect and exchange data within a system.

[12] I2C (Inter-Integrated Circuit) is a serial communication protocol that enables communication between integrated circuits (ICs) using a master-slave architecture. It is commonly used for short-range communication within electronic systems.

[13] CAN (Controller Area Network) is a robust and widely used serial communication protocol primarily designed for automotive and industrial applications. It enables communication between devices or nodes in a network without a central computer controlling the communication.

We have determined that the most suitable flight controller for our quadcopter is the Pixhawk autopilot.

Table 2.4 Pixhawk Specifications [81].

Processor	Sensors	Power	Interfaces	Dimensions
-32-bit ARM Cortex M4 core with FPU[14] -168 Mhz/256 KB RAM/2 MB Flash -32-bit failsafe co-processor	-MPU6000 as main accel and gyro -ST Micro 16-bit gyroscope -ST Micro 14-bit accelerometer/compass (magnetometer) -MEAS barometer	-Ideal diode controller with automatic failover -Servo rail high-power (7 V) and high-current ready -All peripheral outputs over-current protected, all inputs ESD[15] protected	-5x UART serial ports, 1 high-power capable, 2 with HW flow control -Spektrum DSM[16]/DSM2/DSM-X Satellite input -Futaba S.BUS[17] input -PPM[18] sum signal -RSSI input -I2C, SPI[19], 2x CAN, USB -3.3V and 6.6V ADC inputs	-Weight 38 g -Width 50 mm -Height 15.5 mm -Length 81.5 mm

[14] FPU (floating-point unit) is a part of a computer system specially designed to carry out operations on floating-point numbers. Typical operations are addition, subtraction, multiplication, division, and square root.

[15] ESD is a sudden discharge of static electricity that can occur when two objects with different electric potentials come into contact or close proximity.

[16] DSM (Digital Spectrum Modulation) is a digital communication protocol developed by Spektrum to provide reliable and robust radio control signals. DSM2 and DSM-X are subsequent versions of the protocol that introduce further enhancements.

[17] S.Bus (Serial Bus) is a digital communication protocol developed by Futaba. It is primarily used for transmitting control signals between a receiver and servos or other control devices in remote-controlled systems, particularly in RC aircraft and drones. It operates as a serial communication protocol that allows for the transmission of multiple channels of control data over a single wire.

[18] PPM (Pulse Position Modulation) is a digital communication protocol used in remote-controlled systems for transmitting control signals from a transmitter to a receiver. It is a method of encoding control information into a single pulse train.

[19] SPI (Serial Peripheral Interface) is a synchronous serial communication protocol commonly used for short-distance data transfer between microcontrollers, sensors, memory devices, and other peripherals in embedded systems. It allows devices to communicate with each other using a master-slave architecture.

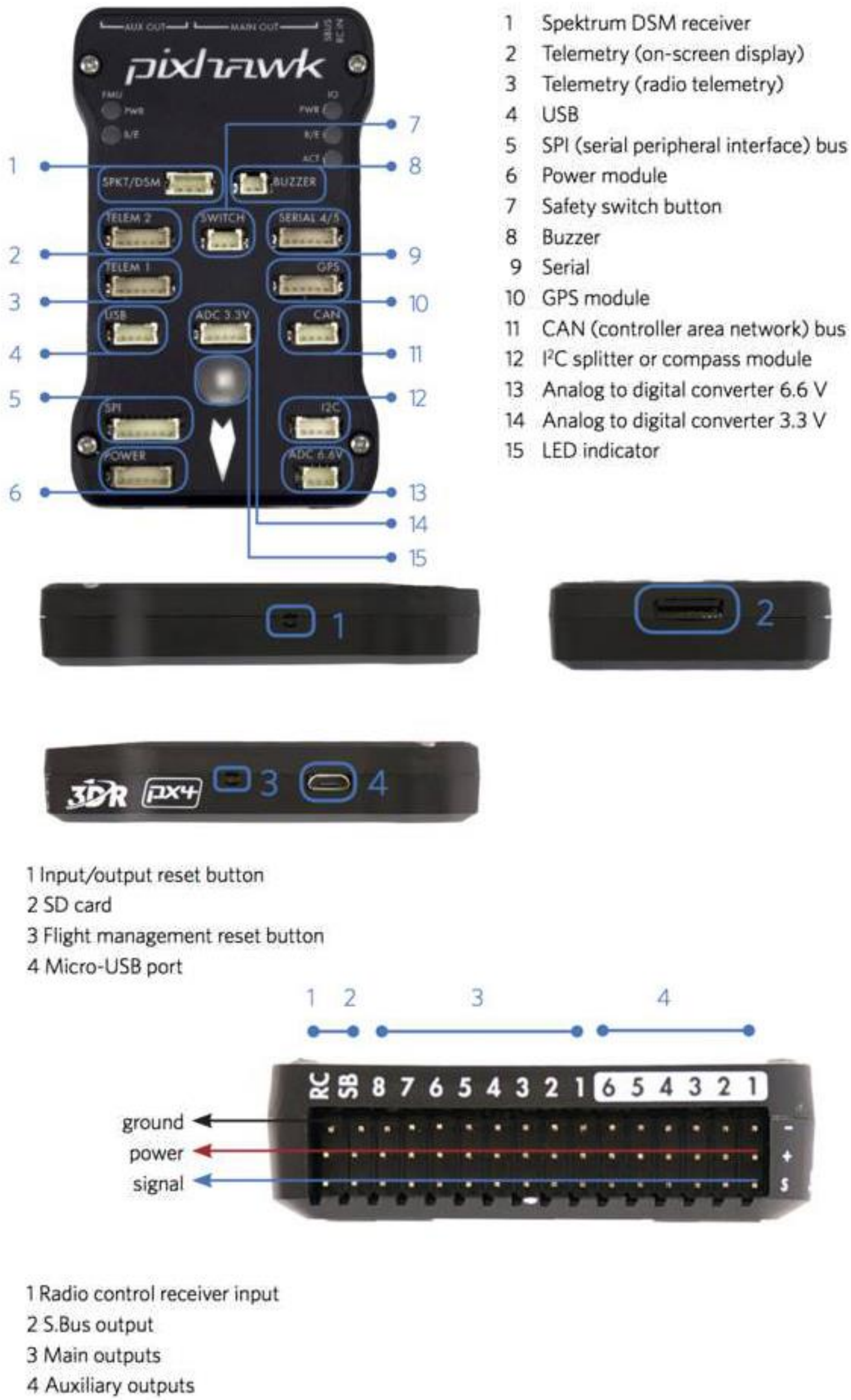


Figure 2.7 Pixhawk connector assignments [81].

- **Radio-controller**

A radio controller (RC), also known as a transmitter, is a handheld device used to remotely control and pilot a drone. It wirelessly communicates with the drone through a receiver unit installed on the aircraft. The radio controller allows the pilot to send commands and inputs to control the drone's movement, such as adjusting throttle, steering, and activating various flight modes. It typically consists of joysticks, switches, buttons, and knobs that provide precise control over the drone's flight and other functionalities.

For piloting our quadcopter, any 8-channel RC would be suitable. In our case, we used the Radiolink T8FB with the R8EF Receiver, which was readily available to us.

Figure 2.8 Radiolink T8FB with the R8EF Receiver.

- **Power system**

To ensure the proper operation of the Pixhawk flight controller, ESCs, motors, and other components, the inclusion of a power module is essential. This power module, which is included with the Pixhawk package, is connected to the flight controller itself, the drone's battery, and the power distribution board of the frame. The power distribution board efficiently distributes power to the various components of the drone, allowing for their proper functioning.

Furthermore, to provide power to the aerial vehicle, a battery is essential. Considering all the components involved, a 3 cell battery is required. Fortunately, CDTA[20] supplied us with a

[20] Centre de Développement des Technologies Avancées

suitable battery (Figure 2.9) for our drone. The supplied battery is a 3-cell LiPo with a capacity of 3300 mAh and a discharge rate of 35.

Figure 2.9 Hobbypower Power Module V1.0 and a 3S LiPo battery 3300 mAh 35C.

- **GPS Module**

The successful execution of outdoor autonomous missions relies heavily on the integration of a GPS module with the flight controller. Therefore, it is imperative that we attach a suitable GPS module to the Pixhawk flight controller. Fortunately, the Pixhawk package includes an M8N GPS module (Figure 2.10) ensuring the availability of reliable positioning and navigation capabilities for our drone during autonomous operations.

- **Telemetry module**

The Pixhawk comes bundled with a 433 MHz telemetry module, providing us with the capability to remotely control the drone and receive information with a ground control station. This telemetry module serves as a communication link, allowing us to maintain real-time situational awareness and exercise precise command over the drone's operations from a remote location.

Figure 2.10 433 MHz telemetry module and GPS module.

2.2.5 Quadcopter assembly

The assembly process for our drone involved carefully connecting and integrating various components to ensure proper functionality. We started by attaching the frame components, including the arms and central body, following the manufacturer's instructions (Figure 2.11). Next, we mounted the motors onto the arms and securely fastened them. The ESCs were connected to the motors, and the wiring was organized and secured to prevent any interference or loose connections (Figure 2.12).

After completing the mechanical assembly, our next step was to install the flight controller. We began by mounting the vibration-dampening mount to minimize any unwanted vibrations. Then, we securely attached the Pixhawk flight controller to the frame, ensuring it was properly positioned and aligned.

With the flight controller in place, we precisely connected the necessary wires to establish crucial connections. We carefully connected the power wires, ensuring a secure and reliable power supply to the flight controller. Additionally, we made the required signal wire connections between the flight controller, ESCs, GPS module, telemetry module and receiver (Figure 2.13).

This carful wiring process allowed for effective communication and control between the different components of the drone system. By ensuring the proper installation and connection of the flight controller, we established a solid foundation for the subsequent calibration and software configurations.

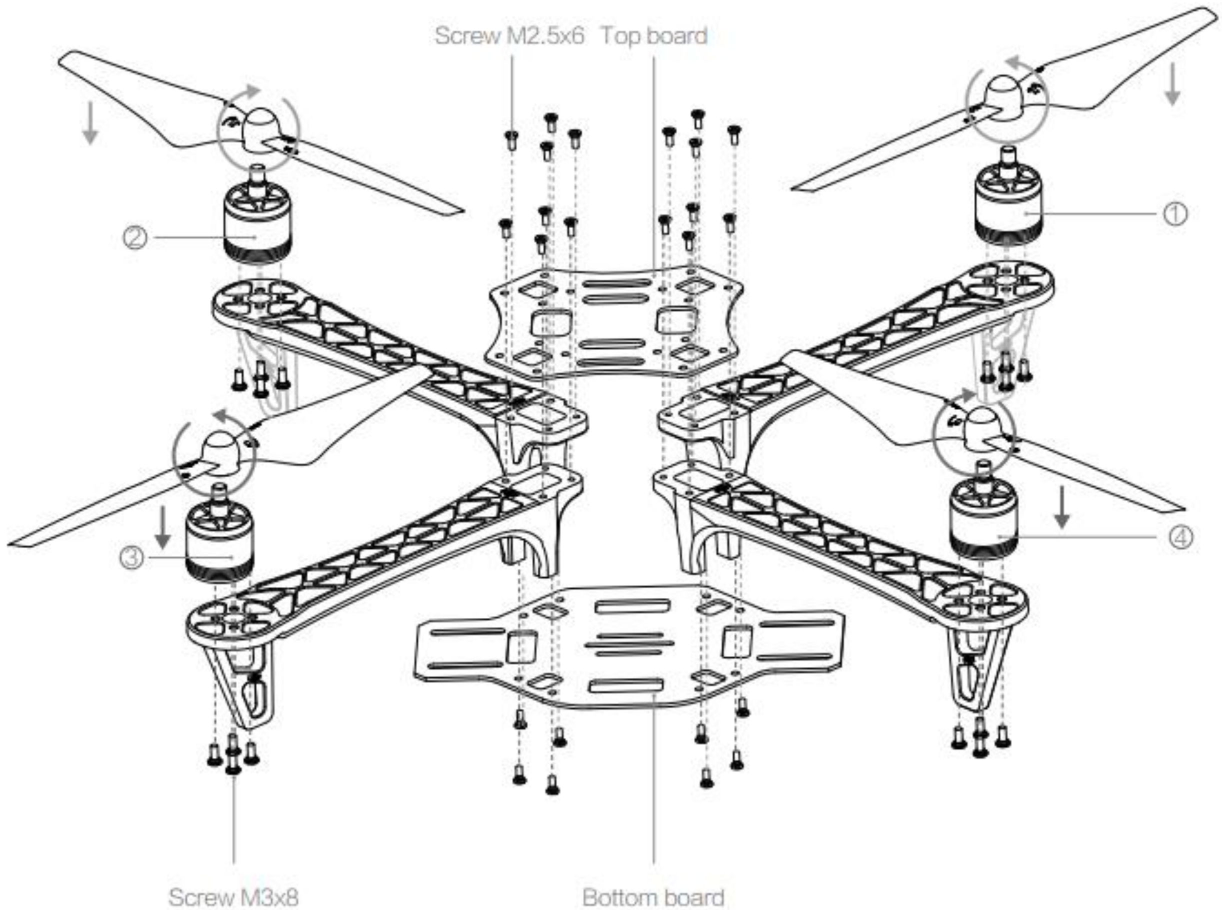


Figure 2.11 Mounting the frame and motors [82].

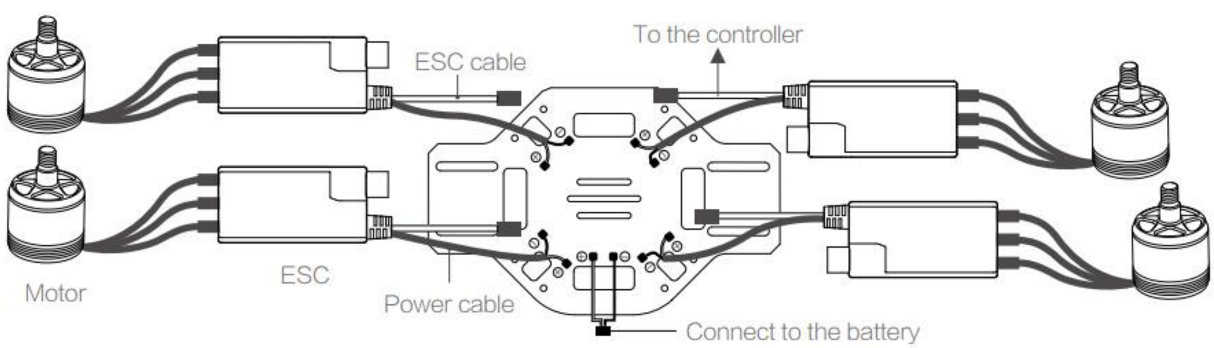


Figure 2.12 Wiring the ESCs and motors [82].

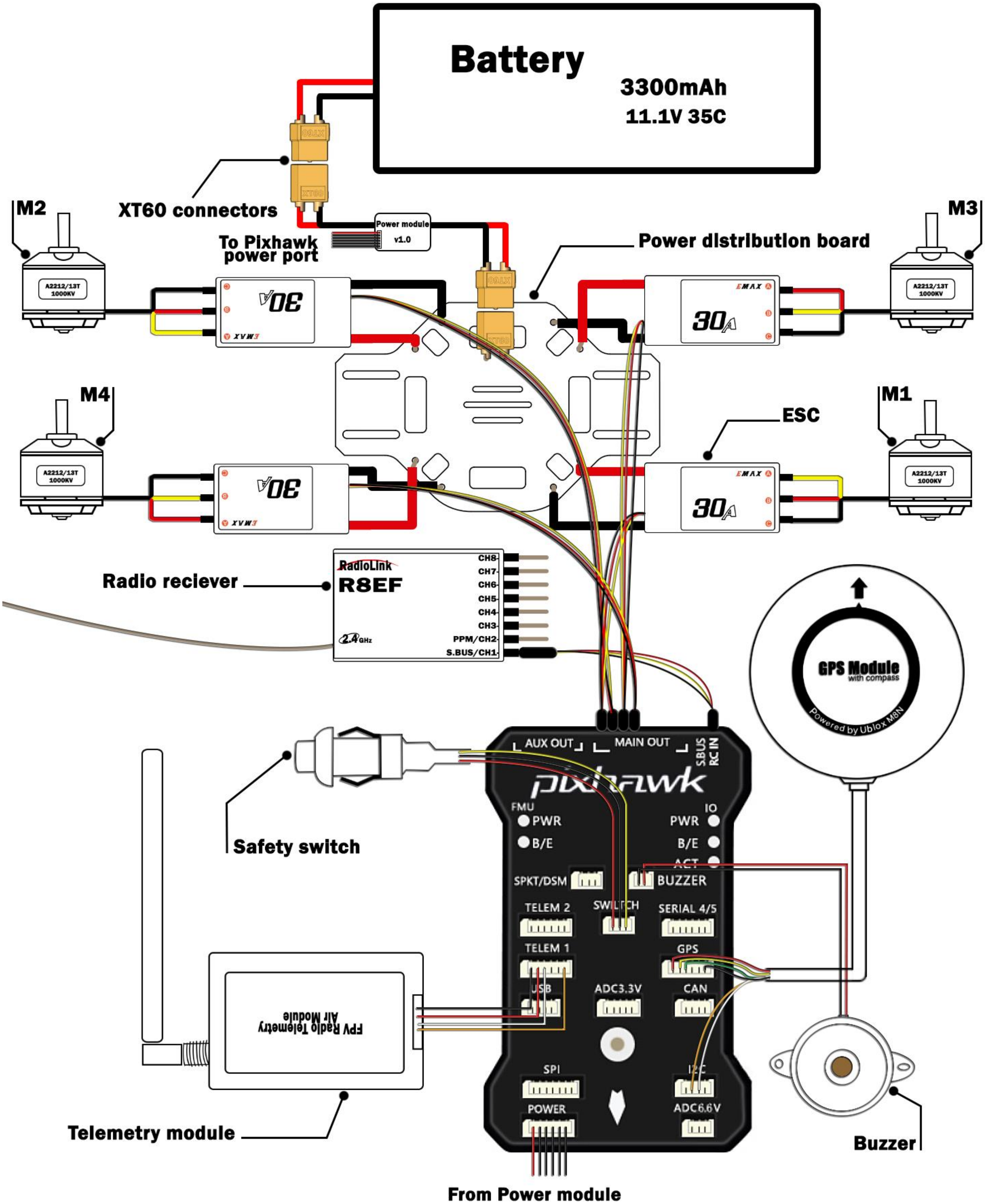


Figure 2.13 Wiring diagram of our quadcopter.

2.2.6 Quadcopter calibration

The Pixhawk flight controller represents an independent hardware project that offers us the flexibility to study and customize its functionalities. It is accompanied by the ArduPilot firmware, an open-source project that empowers us to develop and deploy autonomous unmanned aerial vehicles. This firmware encompasses a wide range of features and tools suitable for diverse vehicle types and applications. Among these tools is the Mission Planner software, which facilitates firmware updates, control of the vehicle and autopilot calibration, ensuring precise and reliable performance of the system. By exploiting these resources, we are empowered to explore and enhance the capabilities of our drone in accordance with our specific requirements.

In this section, we will explore the calibration process of our drone. It is of utmost importance to diligently follow each step without skipping any, as we encountered numerous issues when we overlooked certain calibration procedures.

- **Frame Type**

First, we wire the Pixhawk with an USB cable to a computre with Mission Planner, Afterward, we click on the "Connect" button within the Mission Planner interface to establish a connection with the flight controller, as depicted in Figure 3.14.

Figure 2.14 Connecting the Pixhawk wih Mission Planner.

Within the Mission Planner software, there is a dedicated tab called "Setup" that provides a comprehensive and essential step-by-step guide for performing hardware calibration. We initiate the process by going to “Mandatory Hardware” selecting “Frame Type”, then choosing the "X" shaped copte configuration.

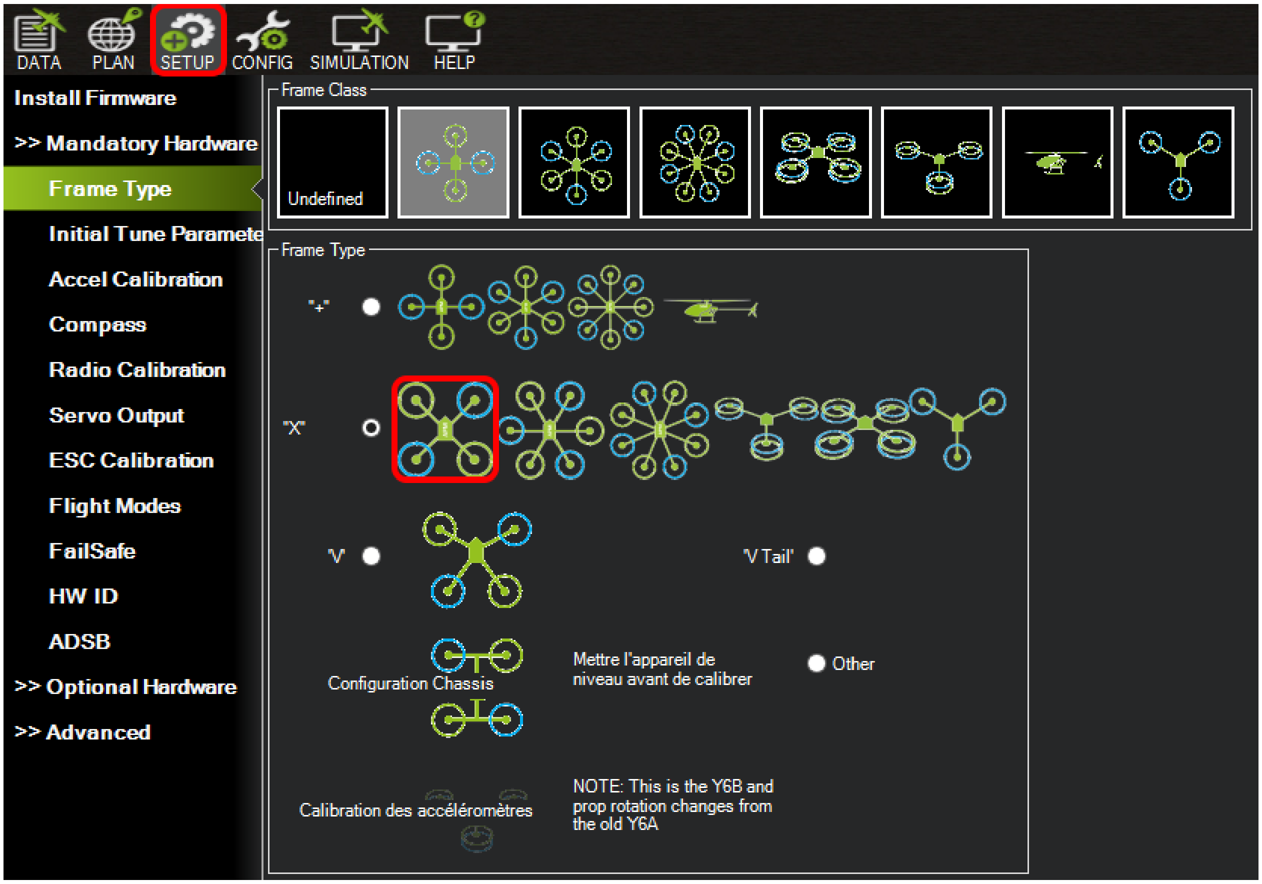


Figure 2.15 Selecting frame type.

- **Accelerometer Calibration**

Following that, we move on to calibrating the accelerometer by navigating to the "Accel Calibration" option and initiating the calibration process by clicking on "Calibrate Accel" to calibrate the 3-axis as shown in Figure 2.16.

During the calibration process, we are prompted to position the vehicle on each axis. By pressing any key, we indicate that the autopilot is correctly positioned, and then move on to the next orientation.

The calibration positions include: level, right side, left side, nose down, nose up, and upside down as shown in Figure 2.17.

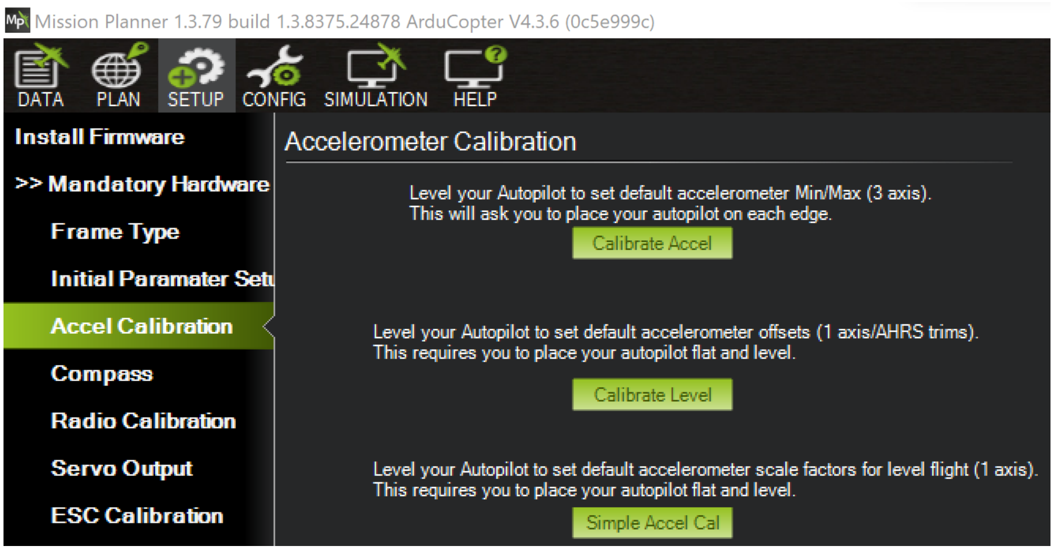


Figure 2.16 Accelerometer calibration.

Figure 2.17 Accelerometer and Compass calibration positions for copter [83].

- **Compass calibration**

Following the accelerometer calibration, we proceed to calibrate the compass. It is essential to ensure a 3D GPS fix and be far from any objects that generate metallic or magnetic fields. To initiate the calibration process, we navigate to the "Compass" tab and click on the "Start" button (Figure 2.18).

We elevate the vehicle and rotate it in the air, ensuring that each side (Figure 3.16) faces downward towards the ground for a few seconds, one side at a time. We perform a complete 360-degree rotation, with each turn directed towards a different direction relative to the ground. This process entails six full turns, along with potential additional time and rotations to validate the calibration. If the calibration is unsuccessful, we repeat the calibration process. However, if the calibration is successful, we proceed to reboot the flight controller.

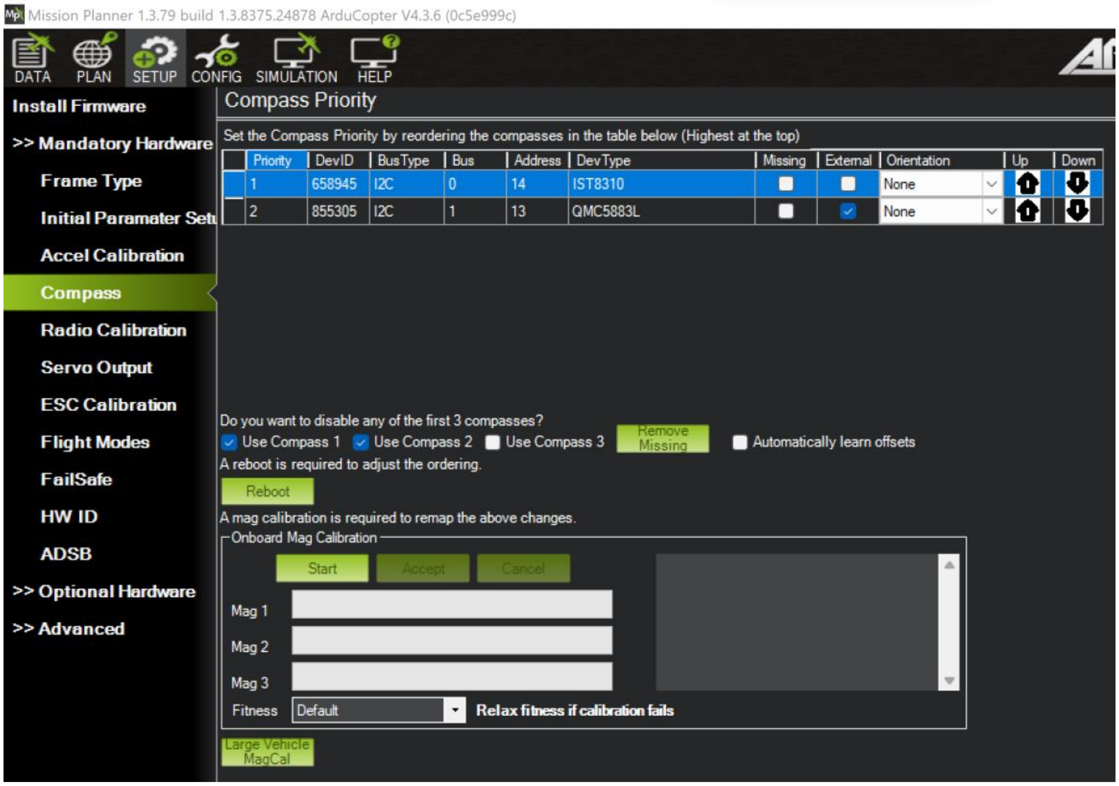


Figure 2.18 Compass calibration.

- **RC calibration**

Next, we calibrate the RC by selecting “Radio Calibration”, we should observe the presence of green bars indicating that the ArduPilot is receiving signals from the Transmitter/Receiver. Then we click “Calibrate Radio” (Figure 2.19).

Then we manipulate the control sticks, knobs, and switches on the transmitter to their extreme positions. This action triggers the appearance of red lines on the calibration bars, indicating the minimum and maximum values recorded so far. Then, we choose the option "Click when Done." A window will pop up, displaying the message "Ensure all your sticks are centered and throttle is down, and click OK to continue." We proceed by moving the throttle to zero and clicking "OK."

Mission Planner will provide a summary of the calibration data, where typical values for minimums are around 1100 and maximums are around 1900.

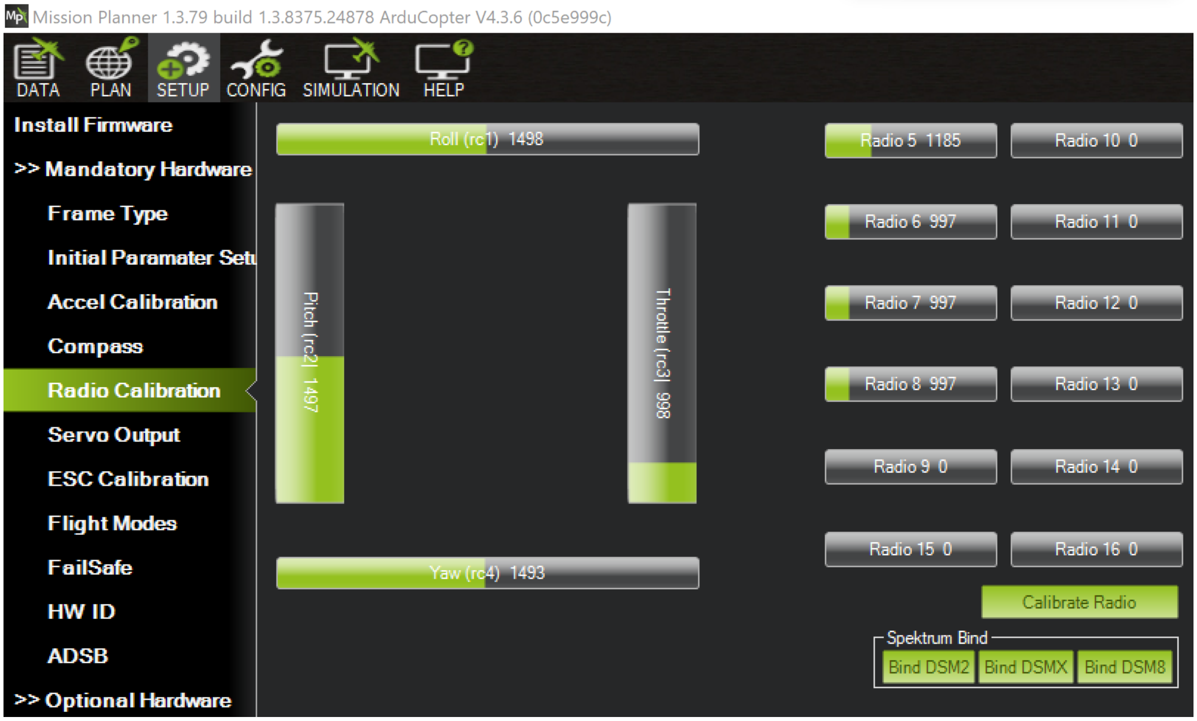


Figure 2.19 RC calibration

- **ESC calibration**

By following the instructions provided in the "ESC Calibration" tab (Figure 2.20), we can effortlessly calibrate all the ESCs.

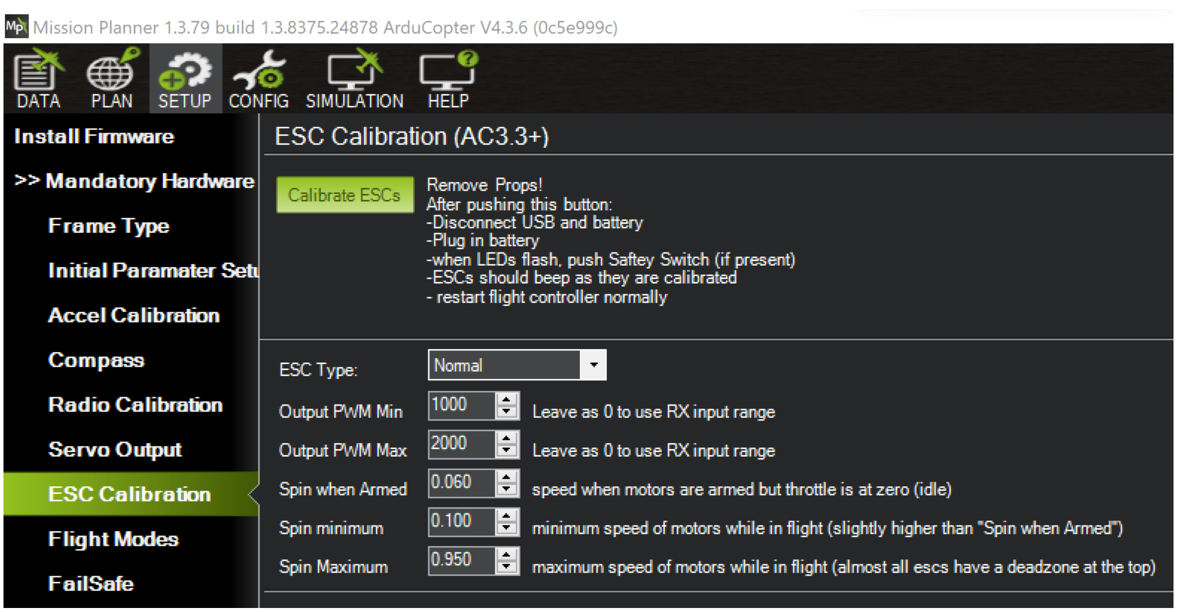


Figure 2.20 ESC calibration.

- **Flight modes**

Prior to completing the calibration process, it is important to configure the flight modes that will be used during our drone surveys. Due to the limited number of available channels in our RC system, directly assigning 6 modes is not possible. However, we can overcome this limitation by modifying the RC's configurations using a mobile application provided by the manufacturer [84]. This allows us to customize the settings and allocate additional flight modes according to our requirements.

Figure 2.21 Mixing RC channels.

To establish a connection, we use Bluetooth to link with the application. Once connected, we navigate to the "PROG.MIX" section, where we have the ability to adjust the channels. In Figure 3.21, the "PROG.MIX1" option is visible. Here, we designate channel 7 as the master "MAS" and channel 5 as the slave "SLA". By modifying the offset values for both the upper "UP" and lower "DOWN" settings, we create a mix between the two channels, enabling us to configure 6 distinct flight modes.

After the configuration, we select the "Flight Modes" tab in Mission Planner and select six distinct flight modes suitable for our specific application then we click on “Save Modes”.

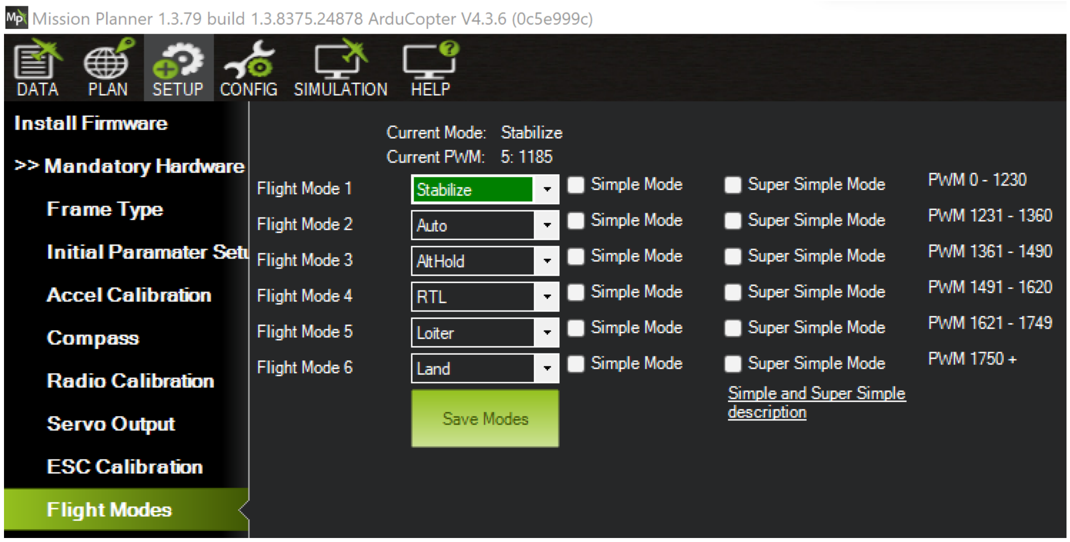
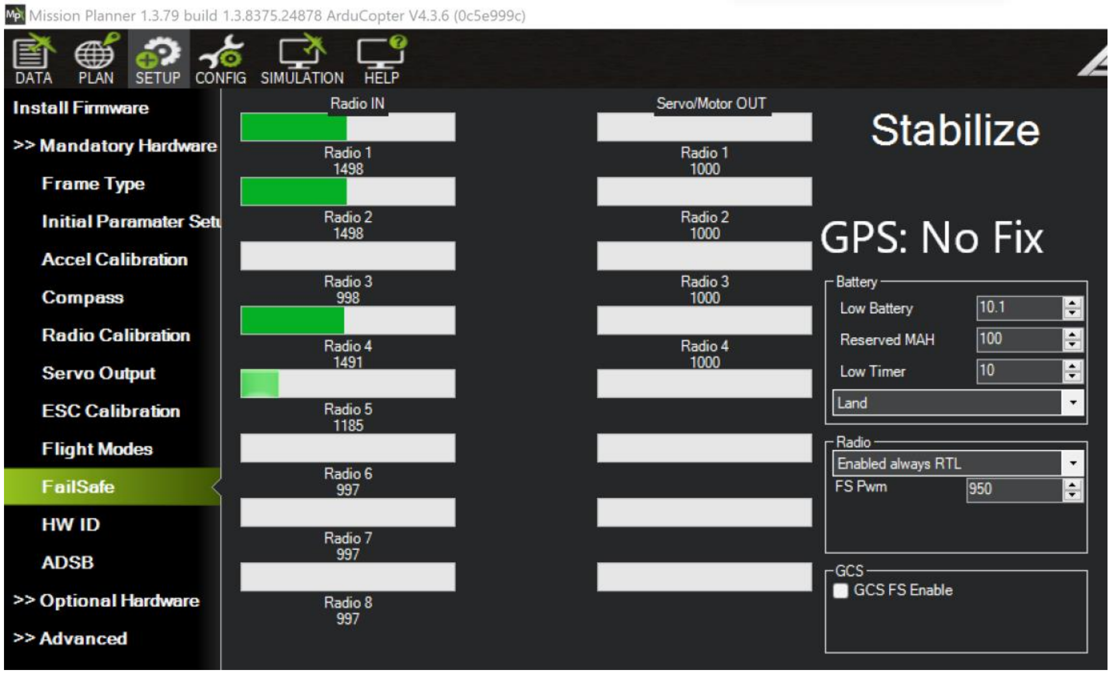


Figure 2.22 Selecting flight modes.

- **Fail safe and battery monitoring**

In this section, we will address the final two configurations required before operating the drone, fail-safe and battery monitoring. The fail-safe (Figure 2.23) configuration is important to ensure that if the battery voltage drops below a certain threshold or the RC signal is lost, the drone will execute a predefined action such as landing, returning to the launch point, or continuing the mission in auto mode. This configuration serves as a safety measure to protect the drone and mitigate potential risks.

Next, we enable the battery monitoring feature by navigating to the "Optional Hardware" tab. Within this tab, we select "Battery Monitor" and choose "Analog Voltage and Current" from the "Monitor" section. In the "Sensor" section, we choose "Other" and for “HR Ver”, we select "The Cube or Pixhawk." This configuration ensures that the system effectively monitors the voltage and current levels of the battery.



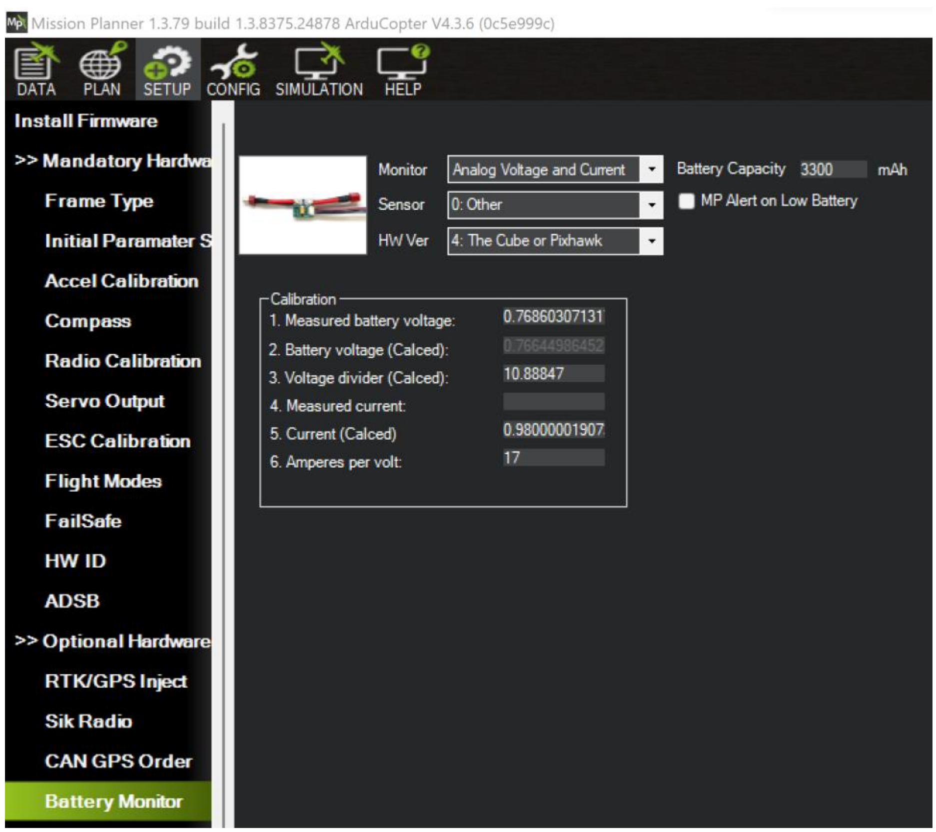


Figure 2.23 Fail safe and battery monitor configurations.

- **Initial flight parameters**

Prior to the initial flight, it is necessary to adjust specific parameters associated with the battery and propeller size. To accomplish this, we navigate to the "Setup" tab and select "Mandatory Hardware," followed by "Initial Tune Parameters." Within this section, we input the propeller size, which in our case is 10 inches, as well as the battery cell count, which are 3. Additionally, we specify the fully charged voltage (4.2 V) and the discharged voltage (3.2 V) for the battery. These configurations ensure the appropriate settings for optimal performance.

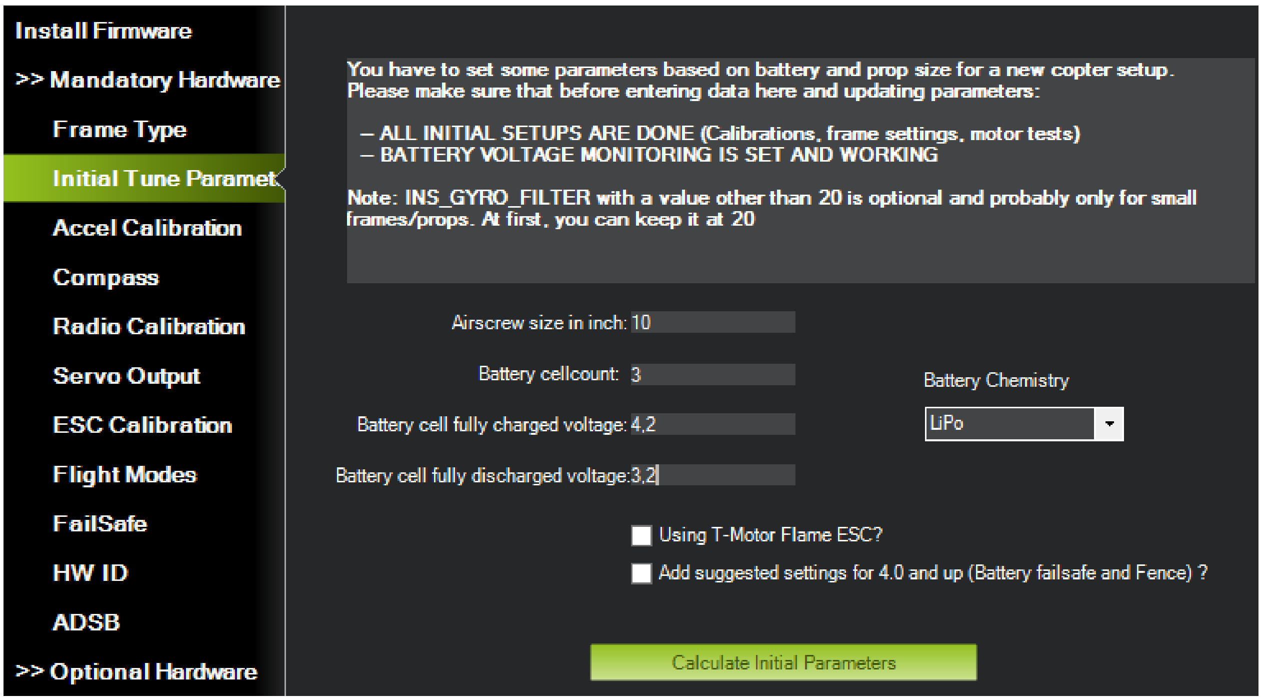
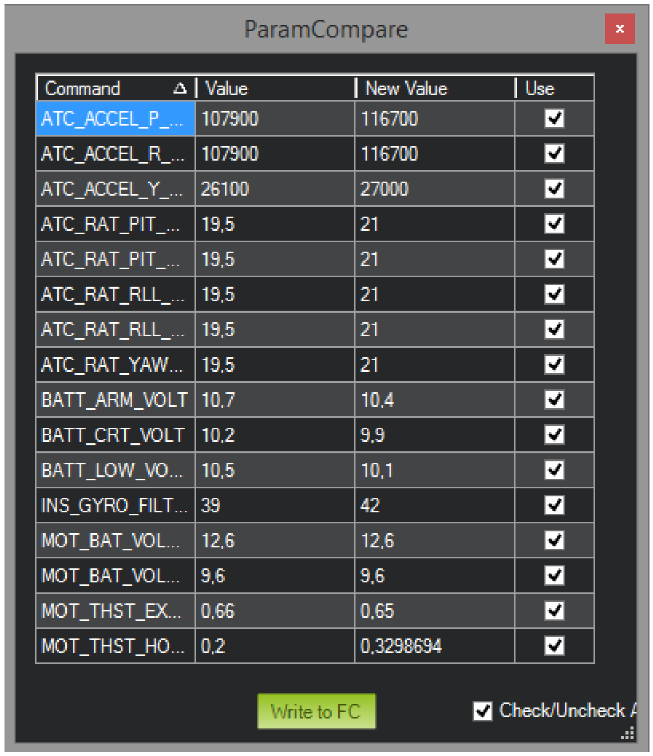


Figure 2.24 Calculating initial tuning parameters.

Next, we proceed to click on "Calculate Initial Parameters," which prompts a window to appear (refer to Figure 3.25). This window displays all the important initial tuning parameters necessary for the first flight. To finalize the calibration process, we click on "Write to FC," ensuring that the calculated parameters are successfully written to the flight controller. With this step completed, the calibration process concludes.



Command	Value	New Value	Use
ATC_ACCEL_P_...	107900	116700	☑
ATC_ACCEL_R_...	107900	116700	☑
ATC_ACCEL_Y_...	26100	27000	☑
ATC_RAT_PIT_...	19,5	21	☑
ATC_RAT_PIT_...	19,5	21	☑
ATC_RAT_RLL_...	19,5	21	☑
ATC_RAT_RLL_...	19,5	21	☑
ATC_RAT_YAW...	19,5	21	☑
BATT_ARM_VOLT	10,7	10,4	☑
BATT_CRT_VOLT	10,2	9,9	☑
BATT_LOW_VO...	10,5	10,1	☑
INS_GYRO_FILT...	39	42	☑
MOT_BAT_VOL...	12,6	12,6	☑
MOT_BAT_VOL...	9,6	9,6	☑
MOT_THST_EX...	0,66	0,65	☑
MOT_THST_HO...	0,2	0,3298694	☑

Figure 2.25 Initial tuning parameters.

2. 3 Sensors

With the integration of specific sensors, UAVs are evolving into robust sensing systems that enhance the capabilities of IoT-based techniques. These sensors play a vital role in capturing high-resolution images [23], enabling the monitoring of various vegetation attributes. Depending on the specific crop parameters that need to be monitored, a range of sensor types can be employed in agricultural UAVs. This allows for a comprehensive assessment of different characteristics of the crops. As technology progresses, sensors are becoming more advanced and affordable [85]. These RS sensors collect specific EM spectrum bands and provide EM radiation measurements at specific wavelengths. There are two types of sensors: active and passive, with active sensors transmitting radiation and passive sensors relying on natural radiation from surfaces [21].

2.3.1 RGB sensors

These sensors function within the visible portion of the EM spectrum, which is also known as light, and their wavelengths fall within the range of 400 to 700 nanometers. The acronym RGB stands for Red-Green-Blue, which refers to the three spectral bands detected by these sensors that are responsible for producing natural color images. In certain RS applications, RGB images are separated into their original channels and either individually utilized or combined into a false color composite to highlight specific features. These sensors capture extremely high-resolution images that are usually easy to process. RGB sensors are primarily used in mapping applications, such as 3D modeling and biomass estimation [21, 43, 55]. However, their use in agriculture is often limited because certain vegetation parameters cannot be evaluated within the visible spectrum but instead require longer wavelengths, such as NIR or RE [23]. Figure 2.26 illustrate some examples of RGB cameras.

2.3.2 Color InfraRed sensors

Color InfraRed (CIR) sensors are capable of detecting near infrared wavelengths, which typically range from 700 to 1000 nm. Within the EM spectrum, the NIR region exhibits the highest peak of vegetation reflectance, making these sensors widely utilized in PAg applications. CIR cameras (illustrated in Figure 2.26) are essentially modified RGB cameras, in which the infrared filter is removed and replaced with a filter for one of the RGB channels, usually the blue channel. In agriculture, CIR sensors are frequently used to derive vegetation properties and are often used in combination with RGB sensors [21].

2.3.3 Multispectral and Hyperspectral sensors

Multispectral sensors are complex systems with multiple lenses that are capable of capturing images across several EM bands at the same time. These sensors commonly consist of four to ten different lenses and can acquire spectral bands beyond the standard R,G,B, and NIR channels. One such band is the RE channel, which covers wavelengths around 700 nm between red and near-infrared. The development of multispectral sensors has significantly increased in recent years, and there are now various typologies available on the market, differing in the number and types of bands, weight, and price. Researchers and farmers alike have shown increased interest in multispectral sensors due to their high potential for PAg applications, particularly for monitoring vegetation vigor's spatial variability. However, processing the acquired images is complex, and various calibration and correction procedures are necessary to obtain reliable information from multispectral sensor data [21].

Hyperspectral sensors, in contrast to multispectral sensors, capture numerous and narrower spectral bands. These sensors typically capture hundreds of bands in narrow bandwidth, providing more detailed information on crops and soils and enabling more precise analysis. However, the price of hyperspectral sensors is still too high, which limits their diffusion in PAg. Additionally, the complexity of data processing increases along with the number of bands [21]. Table 2.5 depict commonly used multispectral sensors and hyperspectral sensors.

2.3.4 Thermal sensors

Thermal sensors, are a specialized type of cameras capable of detecting variations in surface temperature. These sensors can capture radiation emitted by objects within the range of 8000 to 14000 nm in the EM spectrum, which is known as the TIR (thermal infrared) wavelengths. Planck's Law states that the emitted radiation is directly proportional to the temperature of objects, allowing thermal sensors to measure surface temperature. In PAg applications, these sensors are commonly utilized for monitoring vegetation water stress, frequently in conjunction with other sensors [21, 56].

2.3.5 LiDAR sensors

LiDAR sensors, unlike the sensors discussed previously, are active sensors that use lasers to measure distances from targets. They are capable of producing georeferenced 3D point clouds of surfaces and can reconstruct both plants and ground below in vegetated areas. While LiDAR sensors are commonly used in forestry applications, they are also used in agriculture for monitoring vegetation growth and estimating biomass. However, the cost of LiDAR sensors suitable for UAV platforms is still high, and they are not yet widely adopted in the agricultural sector [21, 43, 86].

Table 2.5 Commonly used sensors in PAg

Sensor Type	Brand	Characteristics
RGB	Canon Powershot SX540 Sony Nex-7/ILCE Ricoh GR3 Sony α7r	20.3 MP 442 g 24.2 MP 416 g 16.9 MP 257 g 36.4 MP 407 g
Multi/Hyperspectral	MicaSense RedEdge MCA camera	R G B Red Edge NIR 1280 × 960 230 g 4, 6, 12 bands (user-selectable) 1280 × 1024 497 g (per camera)

Table 2.5 Continuation

Multi/Hyperspectral	Mini MCA Micro MCA Parrot Sequoia InGaAs	4, 6, 12 bands (user-selectable) 1280 × 1024 600, 700, 1300 g 4, 6, 12 bands (user-selectable) 1280 × 1024 497, 530, 1000 g R G Red Edge NIR 2 MP 72 g (Includes 16 Mp RGB Camera) Infrared 640 × 512
CIR	MAPIR Survey3 Tetracam ADC lite Tetracam ADC micro	R G NIR 4,000 x 3,000 pixels 76 g R G NIR 2048 × 1536 pixels 200 g R G NIR 2048 × 1536 pixels 90 g
Thermal	DJI Zenmuse XT Xenics Bobcat 640 GigE SWIR/vSWIR Thermoteknix MicroCAM Integrator	640 × 512 7.5–13.5 µm Weight: 270 g 640 × 512 500–1700 µm 285 g 384 × 288 17 µm 60 g
LiDAR	Velodyne VLP-16 LeddarTech VU8	range: 100 m FOV: 360 deg Horizontal ± 15° Vert Accuracy: 3 cm 830 g range: 185 m FOV: 16 deg Horizontal 0.3 deg Vertical Accuracy: ±5 cm 110,3 g

Figure 2.26 RGB sensor (a) Sony α7r, CIR sensor (b) MAPIR Survey3, Multispectral (c) Parrot Sequoia, Thermal sensor (d) DJI Zenmuse XT and LiDAR (e) LeddarTech VU8.

2. 4 Sensor Selection and Integration

2.4.1 Sensor selection

Due to the limitations imposed by the UAV's payload capacity, the sensors used must adhere to specific requirements, including high precision, lightweight design, low power consumption, and compact size [87]. In our particular application focused on vegetation monitoring, it is essential to choose a sensor specifically designed for this purpose. The suitable sensors for our needs are multi/hyperspectral and CIR sensors. However, due to the challenge of finding available multispectral sensors, we have opted to use a CIR sensor in combination with an RGB sensor.

As mentioned in the CIR sensor section, these sensors are modified RGB cameras capable of capturing IR. Therefore, we obtained a webcam and performed the necessary modifications to transform it into a CIR sensor. Additionally, we connected the modified webcam and an RGB sensor to a Raspberry Pi computer and developed a program that enables the webcam to capture images during UAV missions.

2.4.2 Sensor integration

The integration of sensors into our drone system involves careful consideration of several aspects, including physical placement, wiring, and data acquisition. Each of these components have an important role in ensuring the seamless operation and effective utilization of the sensors. We will discuss each aspect in more detail.

- **Physical Placement:**

Determining the optimal physical placement of sensors on the quadcopter is essential to achieve accurate and reliable data collection. Factors such as sensor type, purpose, weight, and balance need to be taken into account. In our case, the webcam and RGB sensors are mounted on stabilized platforms, oriented to face the ground. This configuration minimizes vibrations and ensures a steady imagery capture during drone operations.

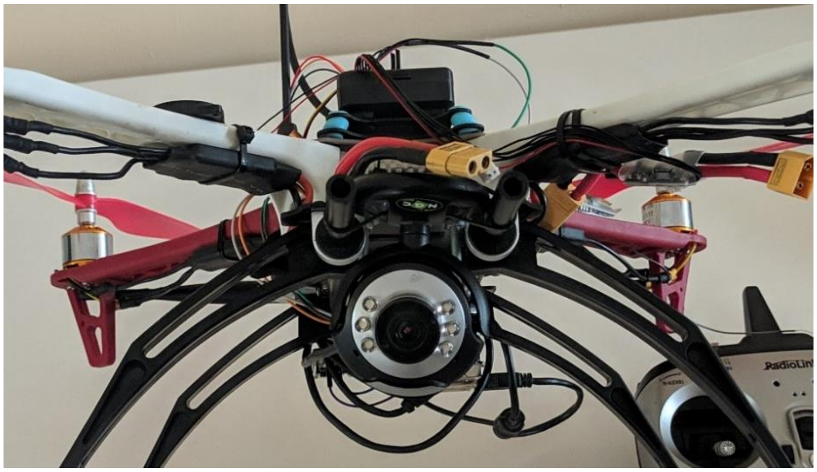


Figure 2.27 Webcam mounting on the drone.

- **Wiring:**

Proper wiring is essential for sensor integration, as it ensures reliable communication between the sensors, Raspberry Pi and the Pixhawk. The wiring is securely connected and routed to avoid any potential damage or interference during flight. The diagram below provides a visual representation of the payload wiring.

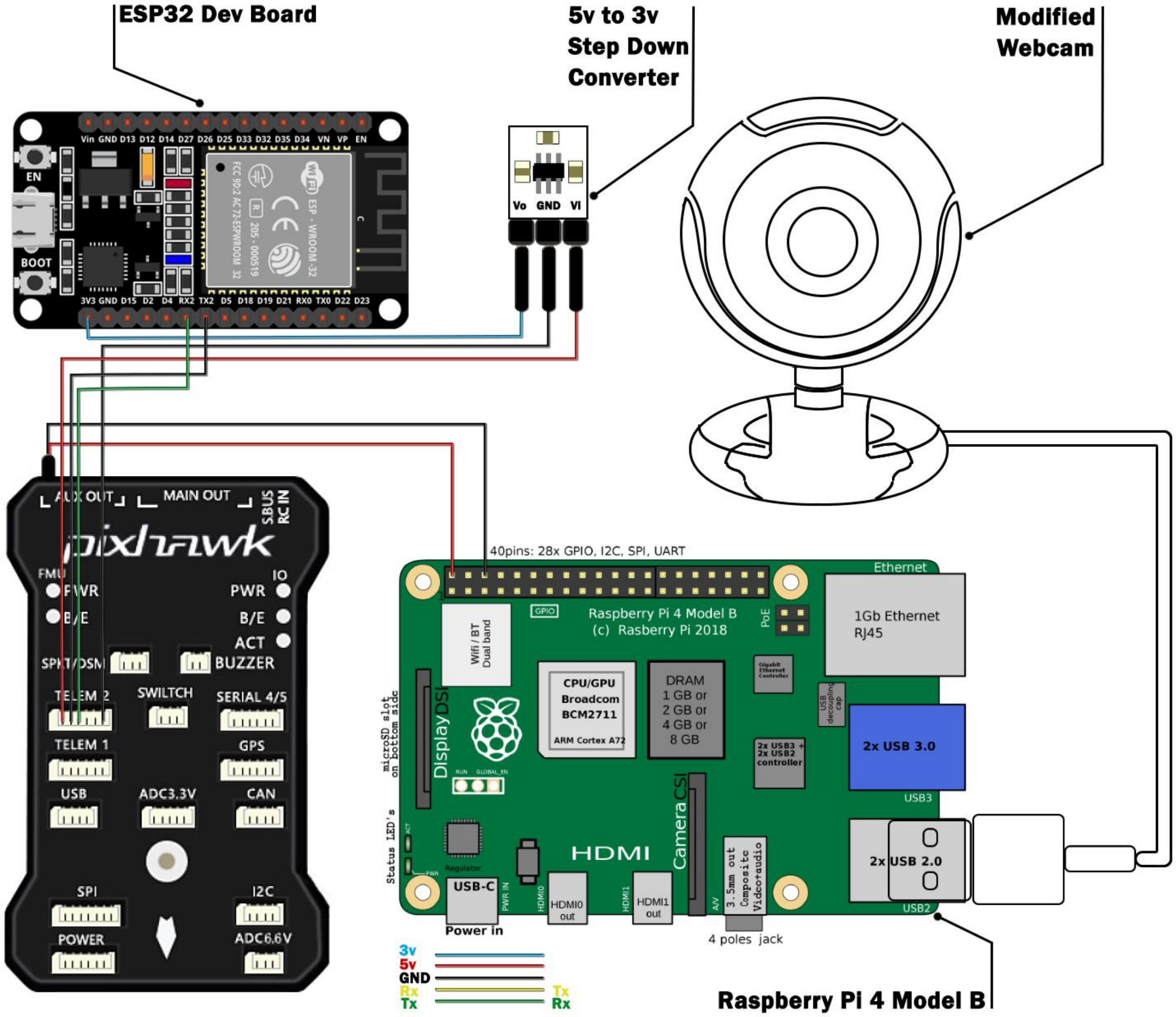


Figure 2.28 Payload wiring diagram.

The diagram illustrates the wiring of the ESP32[21] development board with 5 volts to 3 volts step down converter, which is connected to the flight controller through the second telemetry port. We installed a firmware on the ESP32 board called DroneBridge [88] that enables software utilizing the **MAVLink**[22] protocol to establish a wireless connection with the Pixhawk. This board serves as a bridge, facilitating communication between the Pixhawk and the Raspberry Pi computer.

[21] ESP32 is a system-on-a-chip (SoC) microcontroller developed by Espressif Systems. It is widely used in various Internet of Things (IoT) applications and projects due to its versatility, performance, and built-in features.

[22] The MAVLink (Micro Air Vehicle Link) protocol is a lightweight communication protocol designed for unmanned systems and robotics. It is widely used in the field of UAVs and autonomous vehicles to facilitate communication between onboard systems, ground control stations, and other devices.

- **Data acquisition:**

Data acquisition involves capturing and processing information from the integrated sensors. This step we utilized the Raspberry Pi to manage sensor inputs and perform initial data processing tasks. The acquired data is then stored onboard in an SD card and later on transmitted to a ground station for further analysis.

Throughout the integration process, we ensured that the drone's overall design and payload capacity were compatible with the integrated sensors and associated wiring, without compromising flight stability, endurance, or safety. Rigorous testing and calibration procedures were conducted to validate accuracy, address any potential interference issues, and optimize the performance of the sensors.

2.4.3 Sensor modification

Due to the unavailability and high cost of commercial multispectral sensors, we explored alternative options for vegetation monitoring. After conducting extensive research, we discovered that modifying RGB cameras could be a viable and cost-effective solution [89]. With a webcam readily available, we performed modifications by removing the infrared-blocking filter from the camera, and adding a red filter. This filters out the blue light as shown in Figure 2.29, and measures infrared light in its place.

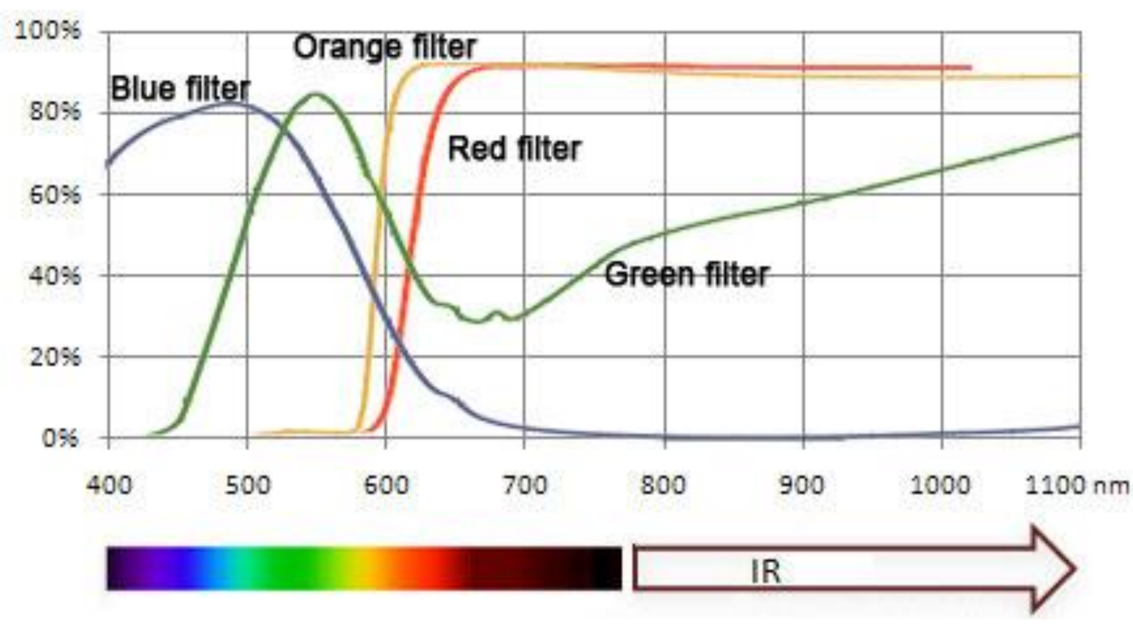


Figure 2.29 Transmission of some color filters.

Following that, we proceeded to attach a plastic red filter to the webcam lens, enabling us to capture wavelengths in both infrared and red spectra. This modification effectively transformed the webcam into a CIR sensor making it suitable for our vegetation monitoring purposes. To validate its functionality, we conducted tests using a heat-emitting object as a sample (Figure 2.31).

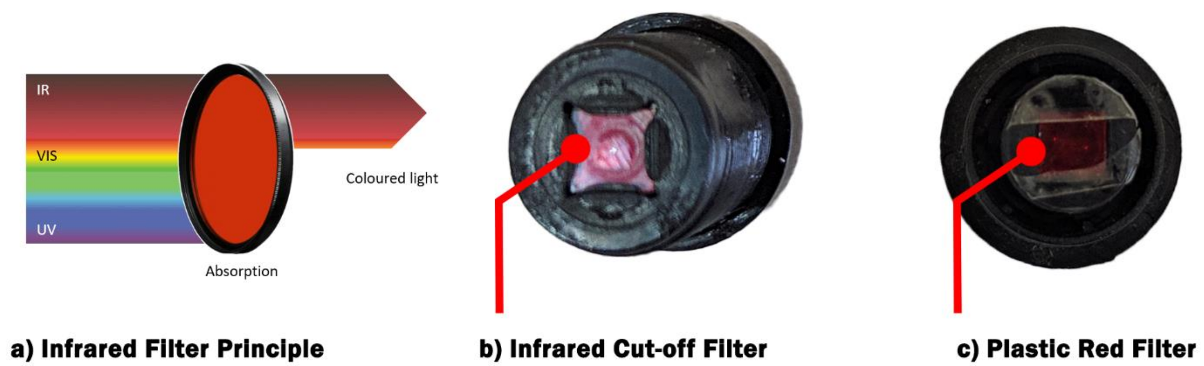


Figure 2.30 Webcam lens with an IR filter and the modified lens with a red filter.

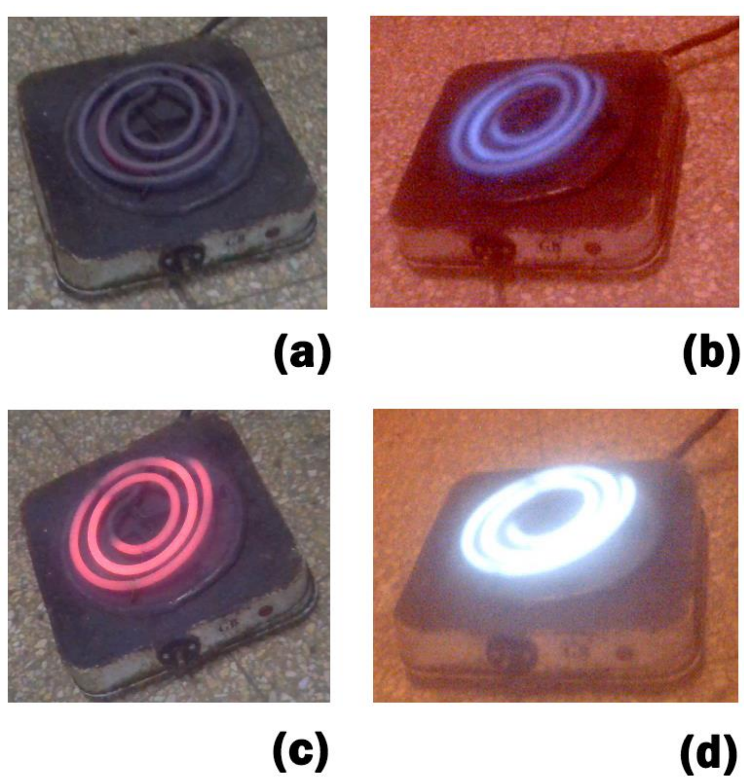


Figure 2.31 Comparison of Radiation Captured by Different Cameras.

Figure 2.31 illustrates the comparison of infrared radiation captured by different cameras: a regular RGB camera (a) and (c), and a modified RGB camera (b) and (d). In (a), the emitted light appears dim, while in (b), the infrared radiation becomes clearly visible. Notably, in (d), the infrared radiation becomes even more pronounced as the heat intensity increases.

2. 5 Conclusion

In this chapter, our focus was on the selection and assembly of a quadcopter UAV, where we discussed the reasoning behind our choices and explored the key components such as the frame, motors, and flight controller. We provided comprehensive diagrams and step-by-step instructions for the assembly process, followed by the calibration procedures to achieve optimal performance

Furthermore, we explored the different sensors commonly used in precision agriculture, including RGB, multispectral, and thermal sensors. Through careful evaluation, we determined the most suitable sensor for our vegetation monitoring application. Additionally, we highlighted the modifications we made to the webcam to enable the capture of NIR images, enhancing the capabilities of our system for vegetation analysis and health assessment.

By combining the expertise in UAV assembly, sensor selection, and modifications, our research project aims to provide a robust and effective solution for disease detection and vegetation monitoring in precision agriculture.

The upcoming chapter will cover the development of a desktop application dedicated to mission planning for the quadcopter and a website designed for crop monitoring and disease detection.

CHAPTER 3. SOFTWARE AND WEBSITE DEVLOPMENT

3. 1 Introduction

The integration of technology in agriculture has revolutionized the way we approach crop monitoring and management. With the advent of unmanned aerial vehicles and advancements in remote sensing, farmers and agricultural researchers now have access to powerful tools for precision farming. This chapter presents a comprehensive solution that combines a desktop application and a website to facilitate efficient and effective crop monitoring and mission planning for drones.

The desktop application, developed using the **PyQt5** [90], which is a Python binding for the Qt framework, a popular and powerful cross-platform toolkit for building graphical user interfaces (GUIs) and **PyMavlink** [91] a Python implementation of the MAVLink protocol, providing a set of tools and libraries for working with MAVLink messages, serves as a mission planner for drones. It provides a user-friendly interface that enables users to plan and customize missions, ensuring optimal coverage and data collection for crop monitoring. By leveraging the functionalities of PyQt5 and PyMavlink, the application enables seamless communication with the drone and allows for real-time adjustments during the mission.

Complementing the desktop application, the website serves as a robust crop monitoring software, offering advanced analytics and insights. Leveraging the **Google Earth Engine API**[23] [92], the website harnesses the power of Landsat 8 and Sentinel 2 satellite imagery to calculate essential vegetation indices such as Normalized Difference Vegetation Index and Normalized Difference Water Index (NDWI). These indices serve as indicators of plant health and water stress, respectively, aiding farmers in making informed decisions about irrigation and fertilizer application.

Furthermore, the website incorporates the **OpenWeatherMap API**[24] [93], providing real-time weather data that enhances the accuracy of crop monitoring and management. Farmers can

[23] The Google Earth Engine API (Application Programming Interface) is a powerful cloud-based platform and set of tools provided by Google for analyzing and processing geospatial data at scale.

[24] The OpenWeatherMap API is a service that provides access to weather data and forecast information through a web-based API. It allows developers to retrieve weather data programmatically and integrate it into their applications, websites, or services.

leverage this information to anticipate potential challenges, such as drought or excessive rainfall, and adjust their agricultural practices accordingly.

One significant feature of the website is its ability to detect and classify potato leaf diseases. By utilizing a deep learning model based on **ResNet 18**[25] architecture [94], the system can accurately identify and categorize the health status of potato leaves. This capability allows farmers to quickly detect diseases such as early blight and late blight, enabling timely intervention and effective disease management.

The backend[26] of the website is built on the **Django**[27] framework [95], ensuring robustness, security, and scalability. Meanwhile, the frontend[28] is developed using **Next.js 13**[29] [96], providing a smooth and responsive user experience.

Overall, this chapter presents an integrated solution that combines a desktop application for mission planning and a website for comprehensive crop monitoring and disease detection. By leveraging remote sensing, machine learning, and advanced APIs, this system equips farmers and agricultural researchers with the necessary tools to make data-driven decisions, optimize crop management practices, and enhance agricultural productivity.

[25] ResNet-18 (Residual Network-18) is a CNN architecture that was introduced as part of the ResNet family by Microsoft Research in 2015.

[26] The website backend refers to the server-side components of a website or web application. It encompasses the technologies, programming languages, and infrastructure that handle the processing, storage, and retrieval of data, as well as the logic and functionality that drive the website's operations.

[27] Django is a high-level web framework written in Python that simplifies the process of building web applications.

[28] The frontend refers to the client-side portion of a web application or website that users interact with directly.

[29] Next.js is a popular open-source React framework for building server-rendered, static, and hybrid web applications.

3. 2 Desktop Application and Drone Integration

The integration between the desktop application[30] and the drone is a critical aspect of this thesis work. As seen in the previous chapter the drone utilized in this study is equipped with a Raspberry Pi 4 and an ESP module, enabling seamless communication and control between the desktop application and the drone.

To establish communication (see Figure 3.1) the desktop application employs Socket[31] technology to connect with the Raspberry Pi. Socket provides a persistent connection, allowing real-time data exchange between the desktop application and the drone. This communication channel enables the transmission of mission plans, commands, and receives mission data from the drone after the flight.

The Raspberry Pi, acting as an intermediary, facilitates the communication between the desktop application and the drone using the Pymavlink library. Pymavlink serves as a robust interface for sending and receiving MAVLink messages between the Raspberry Pi and the drone. By leveraging the capabilities of Pymavlink, the desktop application can command the drone to perform various actions, such as takeoff, landing, waypoint navigation, and return to launch (RTL).

During a mission, the desktop application coordinates the drone's actions based on the planned mission points. As the drone reaches the first mission point, the Raspberry Pi initiates the onboard camera and starts capturing images at a regular interval of 1 second. This functionality enables the collection of aerial imagery for further analysis and crop monitoring purposes.

Upon reaching the last mission point, the Raspberry Pi concludes the image capture by closing the camera. Subsequently, the drone initiates the RTL command, safely navigating back to its takeoff location. This automated process ensures efficient data collection and a safe return of the drone.

[30] You can check the source code for the desktop application following this link: https://github.com/oppenheimer3/PFE_IAB_TELECOM

[31] Socket is a communication protocol that provides full-duplex communication channels over a single TCP (Transmission Control Protocol) connection. It enables real-time, bidirectional communication between a client and a server, allowing data to be transmitted and received simultaneously.

To track the drone's progress and monitor its real-time telemetry data, the desktop application (Figure 3.2) establishes a connection with the drone using the telemetry module. This telemetry connection enables the desktop application to receive live updates on the drone's position, altitude, speed, battery status, and other vital parameters. This tracking functionality enhances situational awareness and provides users with valuable information during the drone's flight.

By integrating the desktop application with the drone's Raspberry Pi and ESP module, this thesis work enables seamless communication, control, and monitoring of the drone's mission. The combination of Socket communication, Pymavlink, onboard camera control, and telemetry facilitates efficient and reliable data collection, ensuring precise and accurate crop monitoring capabilities.

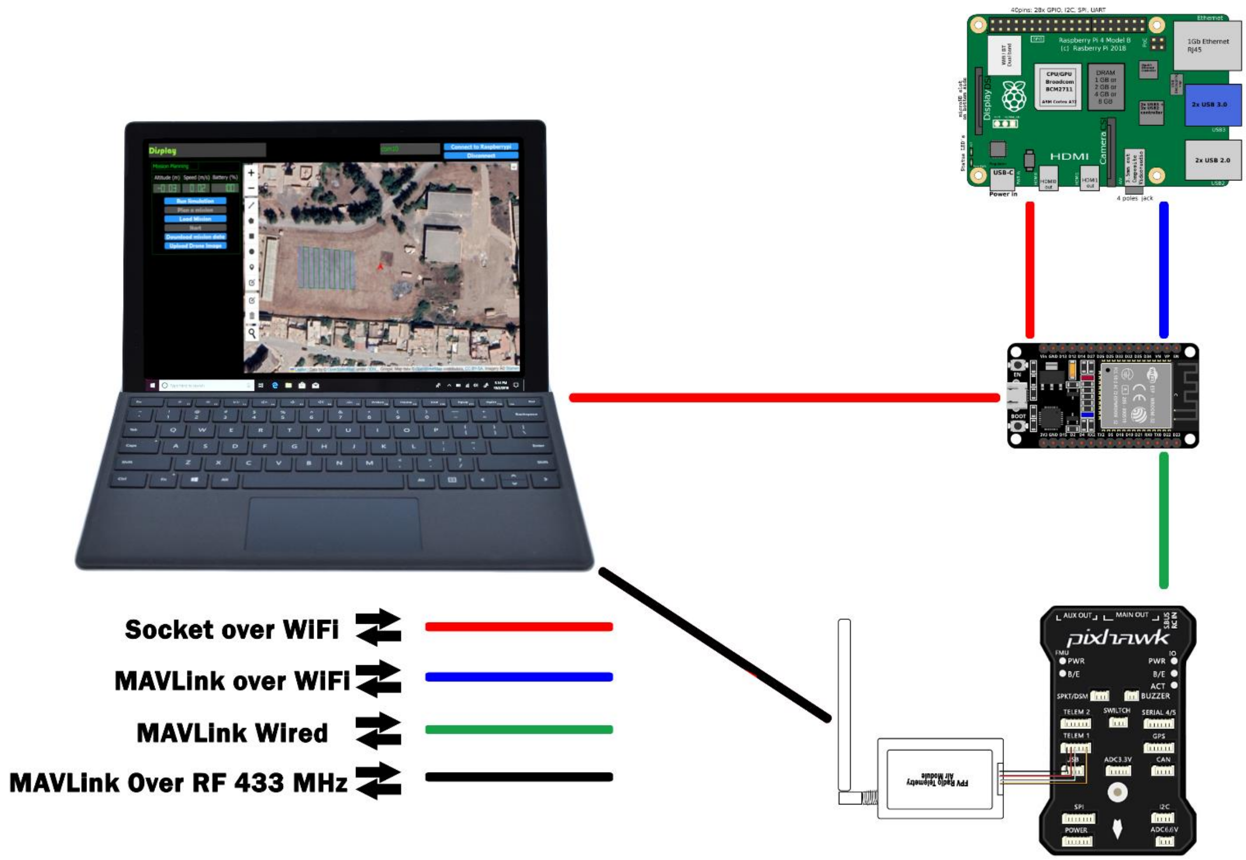


Figure 3.1 Communication Diagram.

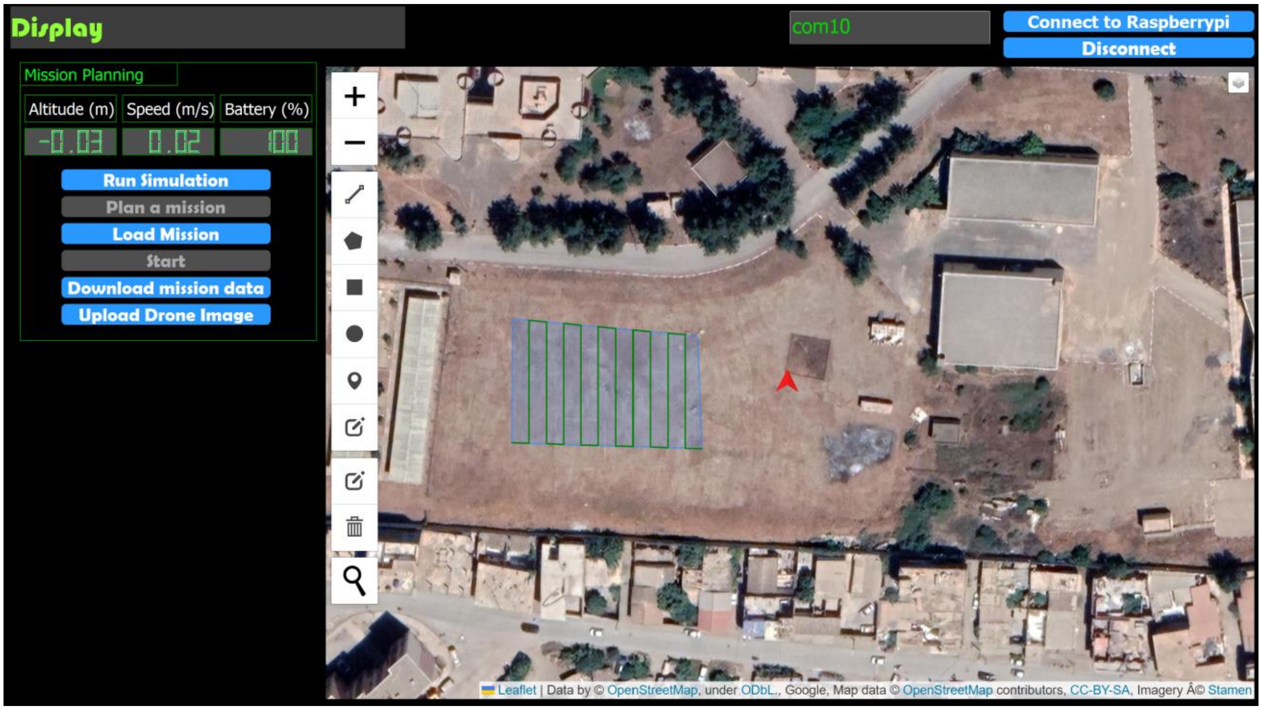


Figure 3.2 Desktop application.

3. 3 Website Purpose, Features, and Functionality

The development of the website is a significant component of this thesis work, serving as a comprehensive platform for crop monitoring and disease detection. The website is built using the Django framework for the backend, providing a robust and scalable foundation for data management and processing.

The website leverages various APIs and technologies to enhance its functionality. The Google Earth Engine API is utilized to access and process satellite imagery from Landsat 8 and Sentinel 2, enabling the calculation of essential vegetation indices such as NDVI and NDWI. These indices serve as key indicators of crop health and water stress, allowing farmers and agricultural researchers to make informed decisions regarding irrigation and fertilization.

In addition, the website integrates the OpenWeatherMap API, providing real-time weather data that enhances the accuracy of crop monitoring. By incorporating weather information into the analysis, users can better understand environmental factors influencing crop growth and adjust their management practices accordingly.

A significant feature of the website is its ability to detect and classify potato leaf diseases. This functionality is achieved by employing a deep learning model based on the ResNet 18 architecture. Users can upload images of potato leaves, and the website employs the trained model to accurately detect and classify diseases such as early blight and late blight. This capability enables timely intervention and effective disease management, contributing to improved crop yield and quality.

To facilitate efficient data storage and retrieval, the website integrates with a PostgreSQL database [97]. PostgreSQL is a reliable and scalable relational database management system, ensuring optimal data management for crop monitoring, weather information, and disease detection results.

Furthermore, the website's frontend is developed using Next.js 13, a powerful React framework. This choice of frontend technology enhances the user experience, providing a responsive and interactive interface for accessing and analyzing agricultural data. Next.js 13 enables server-side rendering, optimizing the website's performance and ensuring smooth navigation for users.

The combination of the Django backend, APIs, PostgreSQL database, and the Next.js 13 frontend forms a robust ecosystem that empowers users to effectively monitor crops, assess their health, and detect diseases. The website serves as a central platform for accessing and analyzing agricultural data, providing valuable insights to farmers and agricultural researchers.

By integrating diverse technologies and APIs, including Next.js 13, this thesis work presents a comprehensive website that enables efficient crop monitoring, accurate disease detection, and informed decision-making in agriculture. The seamless integration of these components contributes to the overall effectiveness and usability of the website, empowering users to optimize their agricultural practices and enhance productivity.

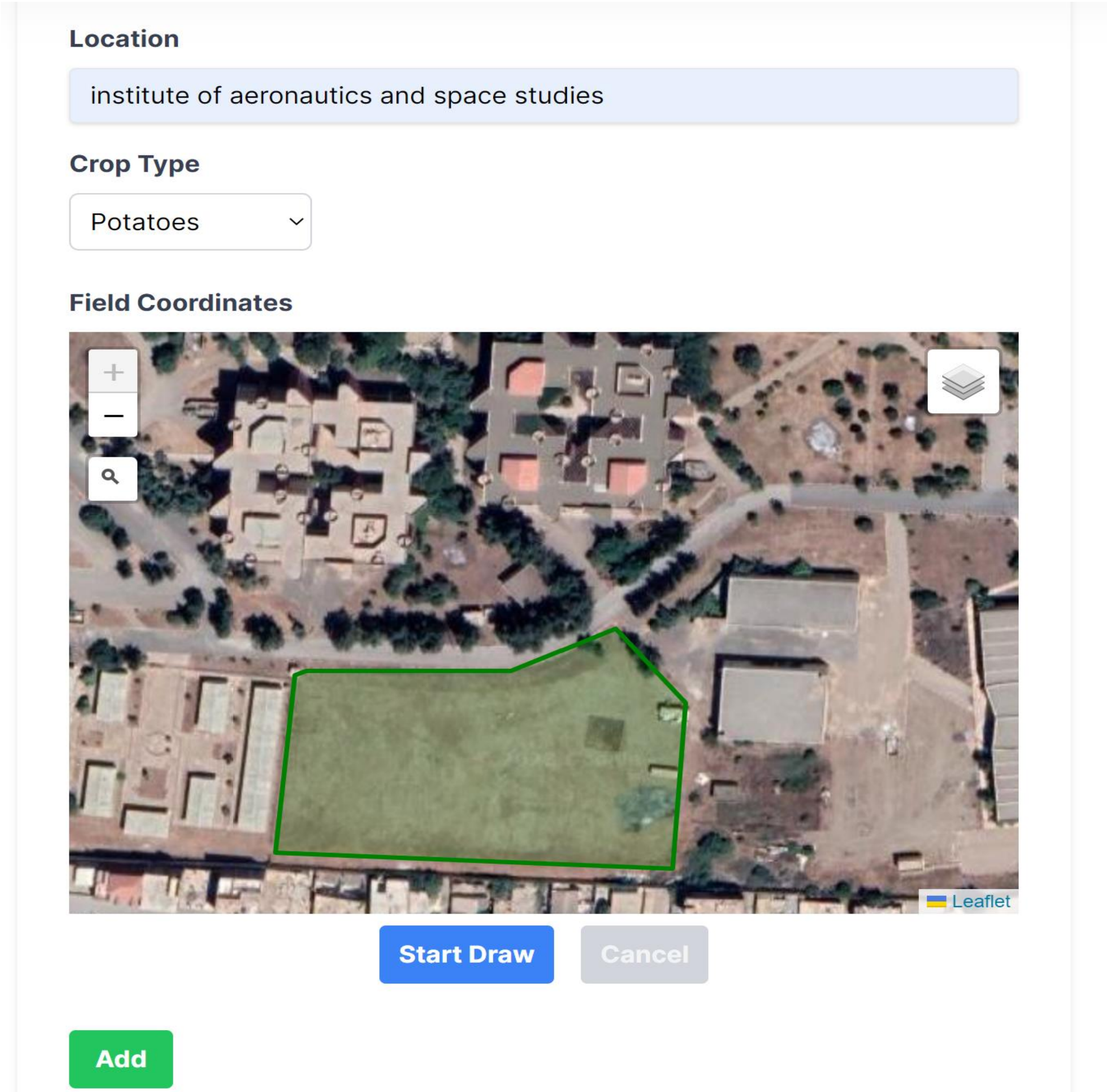


Figure 3.3 Selecting an Area of Interest.

The website allows you to conveniently choose an area of interest (AOI) and the crop type, facilitating the monitoring of any field.

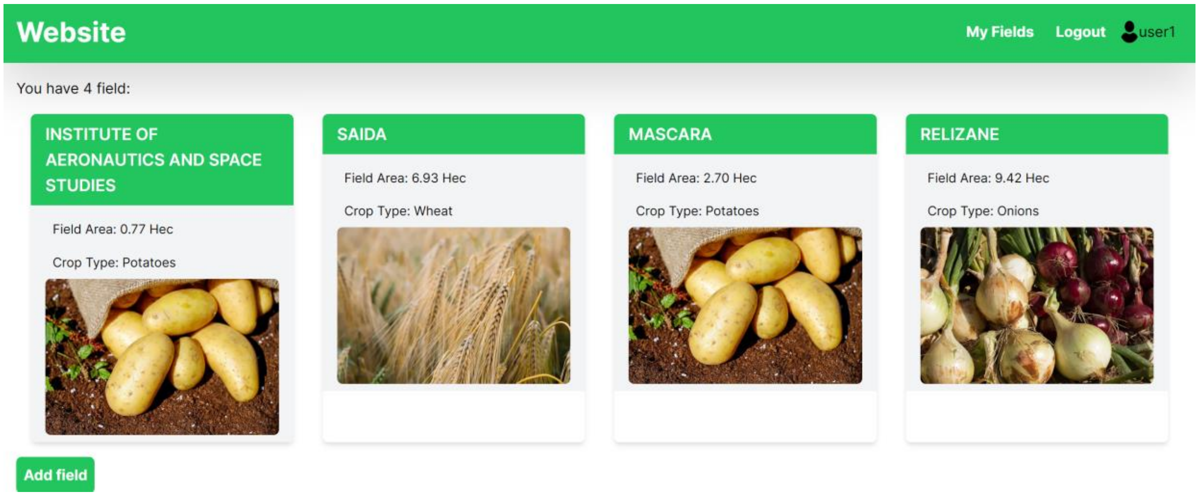


Figure 3.4 Log of different fields.

Logs to help organize and categorize agricultural fields, making it easier to manage and retrieve specific information about individual fields or groups of fields. This organization can include details such as crop type, field boundaries, farmer information, and relevant metadata.

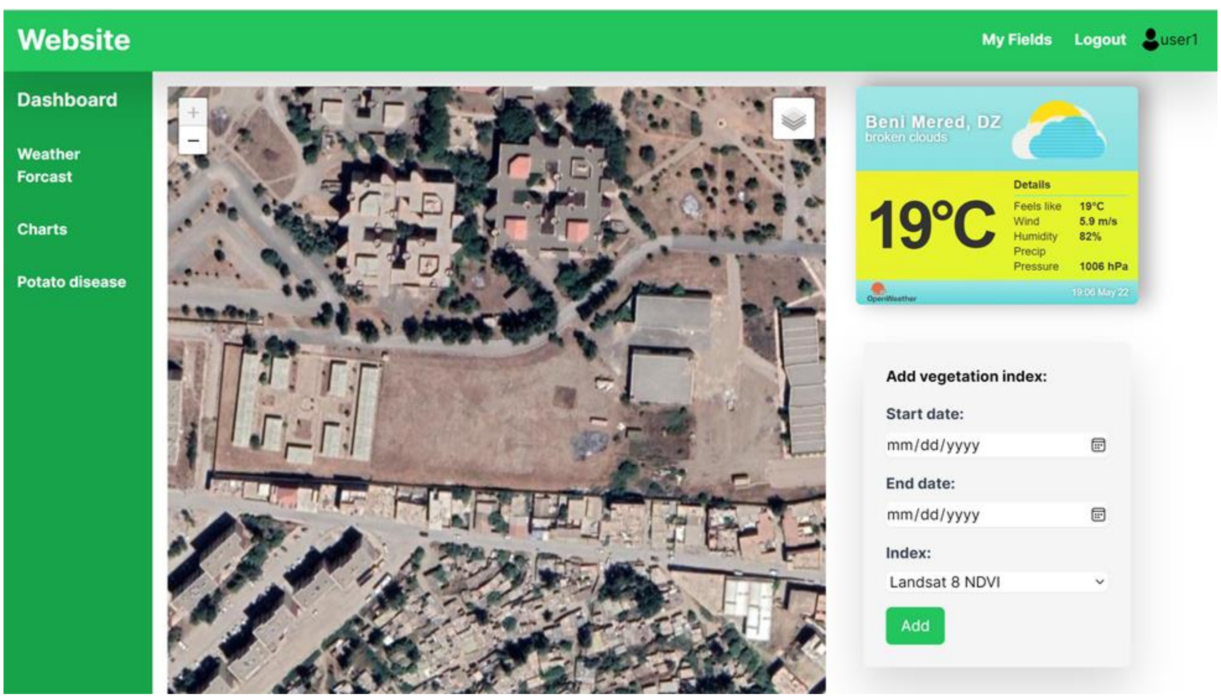


Figure 3.5 Website Dashboard.

The dashboard features the weather API and a dedicated section where you can easily select the desired date to view the NDVI or NDWI data.

Figure 3.6 illustration of the NDVI within the AOI and the average NDVI value for the AOI.

The dashboard also provides the average NDVI which serves as a reliable indicator of the overall health and vigor of the vegetation present in that field

3. 4 Potato Leaf Disease Detection Algorithm

The potato leaf disease detection algorithm developed in this thesis is an essential tool in automatically identifying and classifying potato leaf diseases. Leveraging a deep learning model based on the ResNet 18 architecture which is built with PyTorch[32] deep learning framework [98], the algorithm accurately detects and categorizes diseases such as early blight and late blight from uploaded leaf images.

To train the model, a diverse dataset of potato leaf images was collected from Kaggle[33] [99, 100]. This dataset includes labeled samples of healthy leaves, as well as leaves infected with early blight and late blight. The ResNet 18 model was trained on this dataset using transfer learning techniques, fine-tuning it to learn disease-specific features.

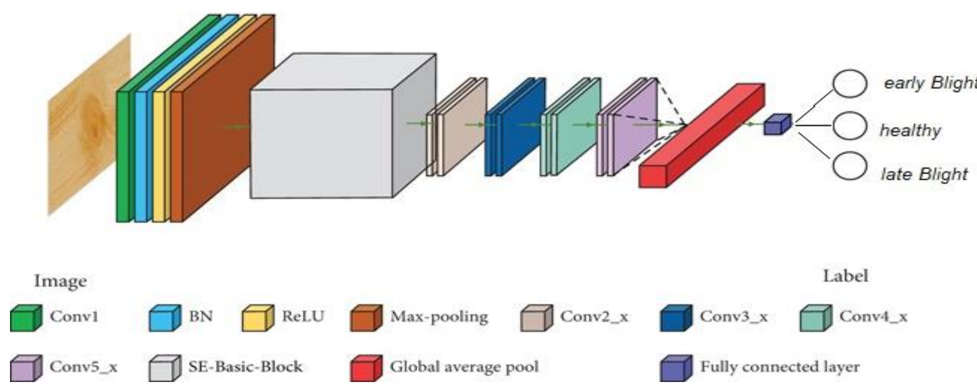


Figure 3.7 Model Architecture.

After training, the model was evaluated using a separate validation set to assess its performance in terms of loss and accuracy metrics. The evaluation ensures that the model can effectively detect and classify potato leaf diseases.

[32] PyTorch is an open-source deep learning framework that provides a flexible and efficient platform for developing and training neural networks.

[33] Kaggle is an online community and platform that hosts data science and machine learning competitions, provides datasets, and offers a collaborative environment for data scientists, researchers, and practitioners.

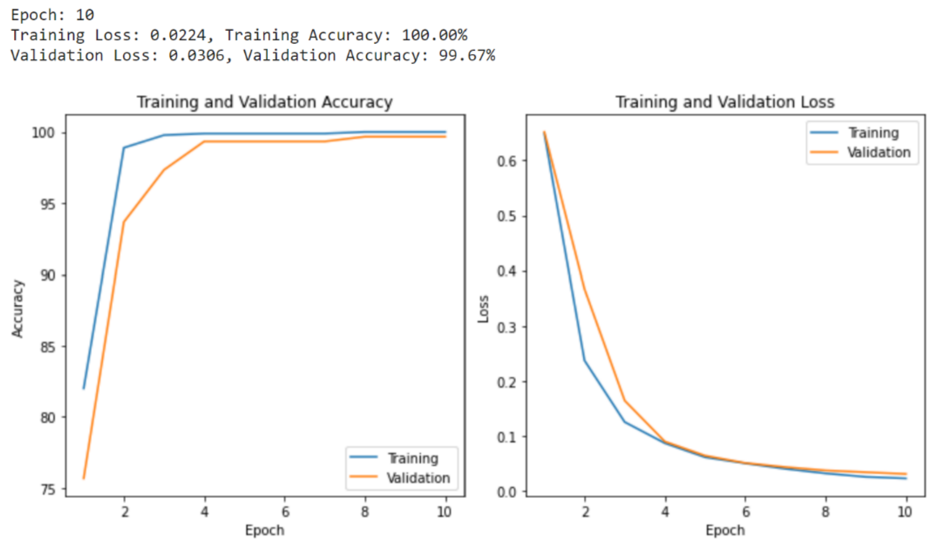


Figure 3.8 Training and validation metrics.

Once the model was trained and evaluated, it was integrated into the website's backend infrastructure. Users can upload potato leaf images through the website, and the deployed model analyzes these images to provide disease detection and classification results. The algorithm enables timely intervention and effective disease management, contributing to improved crop health and productivity.

The utilization of the Kaggle dataset, along with the ResNet 18 architecture, empowers the potato leaf disease detection algorithm to automate the identification and classification of potato leaf diseases accurately. This algorithm provides farmers and agricultural researchers with an efficient and reliable tool for disease monitoring and management.

Continuous refinement and updates to the algorithm can be achieved by incorporating additional labeled data and fine-tuning the model as new information becomes available. The potato leaf disease detection algorithm, integrated into the website, serves as a valuable asset for enhancing crop health and optimizing agricultural practices.

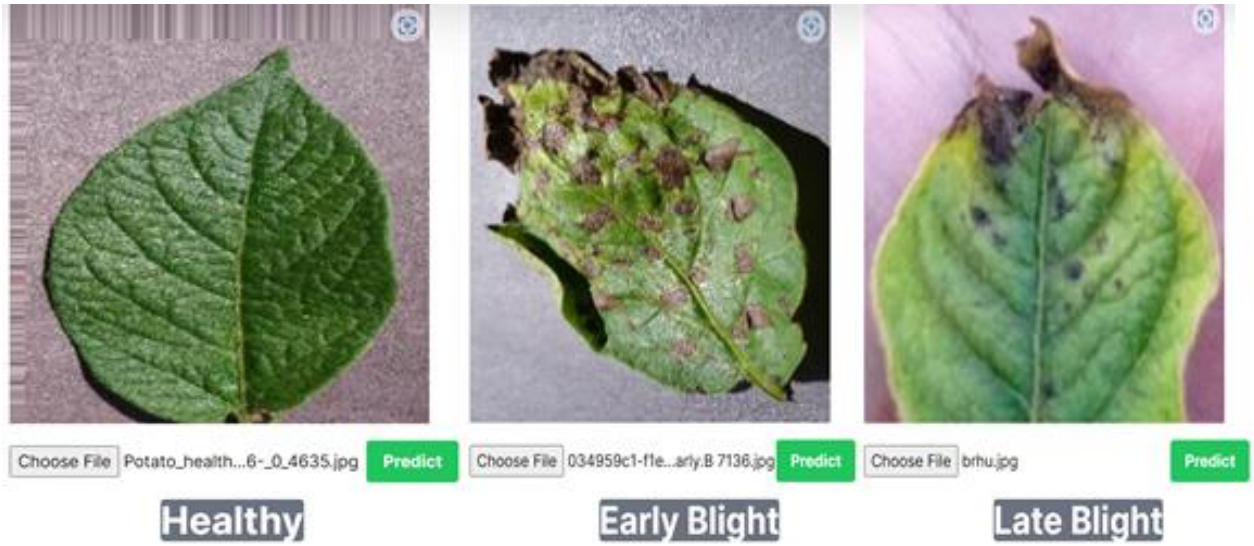


Figure 3.9 Potato disease detection tool identifying disease type.

With the understanding that AI plays a significant role in plant disease detection, drones equipped with high-resolution RGB sensors can be employed to create comprehensive plant datasets. By capturing detailed imagery of plants and employing AI algorithms, it is possible to analyze the data and identify signs of diseases accurately.

3. 5 Conclusion

The comprehensive solution presented in this chapter combines a desktop application and a website to facilitate efficient and effective crop monitoring and mission planning for drones. The desktop application, developed using PyQt5 and PyMavlink, serves as a user-friendly mission planner for drones. It allows users to plan and customize missions, ensuring optimal coverage and data collection for crop monitoring. The seamless communication with the drone and real-time adjustments during the mission enhance the efficiency and effectiveness of data collection.

Complementing the desktop application, the website acts as a robust crop monitoring software, providing advanced analytics and insights. Leveraging the power of Landsat 8 and Sentinel 2 satellite imagery through the Google Earth Engine API, the website calculates essential vegetation indices like NDVI and NDWI. These indices serve as indicators of plant health and water stress, aiding farmers in making informed decisions about irrigation and fertilizer application.

The website also incorporates real-time weather data from the OpenWeatherMap API, enhancing the accuracy of crop monitoring and management. By anticipating potential challenges, farmers can adjust their practices accordingly, mitigating the impact of adverse weather conditions.

A significant feature of the website is its ability to detect and classify potato leaf diseases. Utilizing a deep learning model based on the ResNet 18 architecture, the system accurately identifies and categorizes the health status of potato leaves. This capability enables farmers to detect diseases such as early blight and late blight promptly, facilitating timely intervention and effective disease management.

Built on the Django framework for the backend and Next.js 13 for the frontend, the website ensures robustness, security, and scalability. The user experience is smooth and responsive, providing an intuitive platform for farmers and agricultural researchers to access valuable insights and data.

In the next chapter, we delve into the analysis and presentation of the results derived from the drone surveys conducted using the modified webcam. This chapter focuses on the mission planning and the outcomes of our data collection efforts and provides a comprehensive understanding of the findings obtained.

CHAPTER 4. RESULTS AND DISCUSSION

4. 1 Introduction

The preceding chapters of this thesis have presented a comprehensive exploration of drone based remote sensing for agricultural purposes. In CHAPTER 1 we delved into the theoretical framework and methodology employed to investigate UAV based monitoring of the vegetation. Building upon this foundation, the purpose of this chapter is to present and analyze the findings obtained through our drone surveys and data collection with the modified RGB sensor to capture red and infrared wavelengths spectrum. By presenting these results, we aim to address the research questions and contribute to the existing body of knowledge in the field of drone based remote sensing

In this chapter, we will provide a detailed account of the data collected, the analysis techniques employed, and the resulting outcomes. The findings will be presented in a clear and structured manner to facilitate understanding and interpretation. Furthermore, we will discuss the implications and significance of these results, considering their alignment with the research objectives and their potential impact on agriculture.

4. 2 UAV surveys

Due to limitations on flying the drone outside of our institute, we made the decision to select an area within our university campus that contains vegetation for our drone survey. This allowed us to comply with the regulations and restrictions while still conducting valuable research in an accessible and controlled environment.

By choosing a specific area within the university that encompasses vegetation, we were able to gather data and insights related to the agricultural aspects present on campus. Although the scale may be smaller compared to larger agricultural areas, this localized study provided us with an opportunity to examine and understand the dynamics of vegetation within the university setting.

The selection of this area within our university for the drone survey offered several advantages. It facilitated convenient access and allowed us to closely monitor and study the vegetation in a well-defined space. Additionally, it provided a controlled environment where factors such as environmental conditions and maintenance practices could be closely observed and documented.

Despite the limited scope, the findings and analysis from this selected area within the university campus can still contribute to our understanding of drone-based remote sensing applications in agriculture. It highlights the potential of utilizing drones for vegetation monitoring, even within restricted areas, and provides insights that can be further applied to larger agricultural contexts.

The area selected (Figure 4.1) within the university is located near the Institute of Aeronautics and Space Studies, it consists of natural vegetation, such as flowers and weeds, which give it its distinctive features.

Figure 4.1 Selected AOI location and size for the drone survey.

As mentioned in CHAPTER 1 the characteristics of vegetation can make it challenging to match images, so during UAV surveys, it is necessary to have a high level of overlap, we planned the quadcopter flight and made an overlapping of 70%. This required calculating the appropriate flight height to achieve the desired overlap.

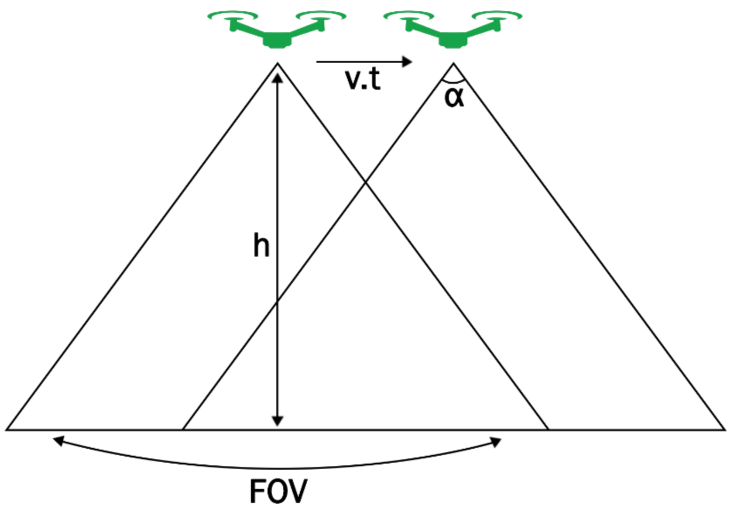


Figure 4.2 Photographic overlap.

$$v.t = 30\% \times FOV \rightarrow FOV = \frac{v.t}{30\%}$$

$$\tan\frac{\alpha}{2} = \frac{FOV}{2 \times h} \rightarrow h = \frac{FOV}{2 \times \tan\frac{\alpha}{2}}$$

$$h = \frac{v.t}{30\% \times 2 \times \tan\frac{\alpha}{2}} \rightarrow h = \frac{v.t}{0.6 \times \tan\frac{\alpha}{2}}$$

With a fixed drone speed of 5 m/s and the known angle of view of our CIR sensor $\alpha = 33.4°$, we determined the required flight height as follows:

$$h = \frac{5 \times 1}{0.6 \times \tan\frac{33.4}{2}} = 27.77\ m$$

Then using the desktop application, we created a flight plan and uploaded the mission to the flight controller (Figure 4.3).

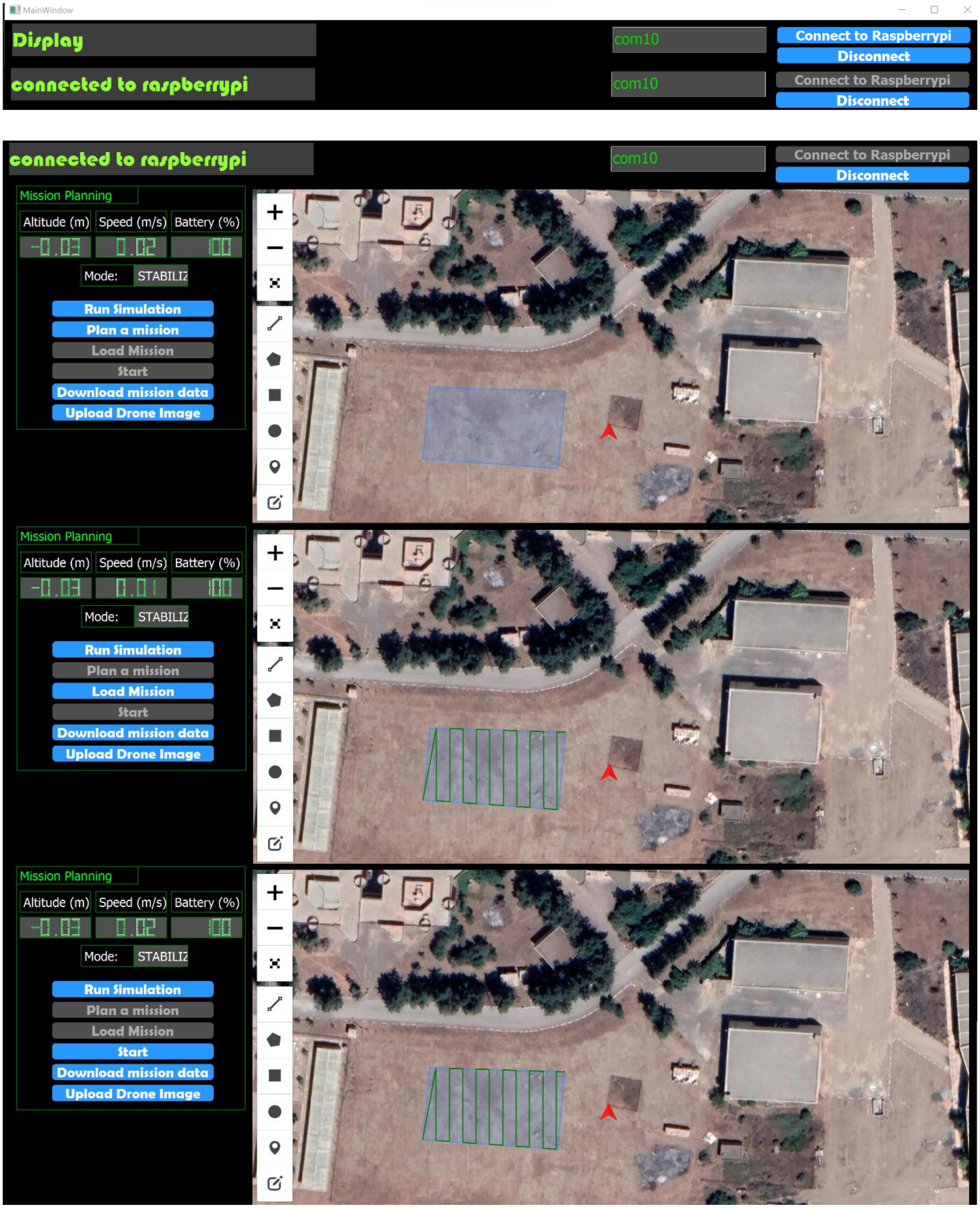


Figure 4.3 Connecting to Raspberry Pi and planning the mission with our desktop application.

Initially, we established a connection to our quadcopter using the telemetry module and subsequently connected it to the Raspberry Pi. To plan our mission, we utilized a polygon to outline the desired flight path. Following that, we uploaded the mission to the Pixhawk flight controller and finally started the flight.

Figure 4.4 Our quadcoter surveying the AOI 30 m high and performing an RTL.

4. 3 Data processing and analysis

After we acquired the images from the drone survey, we connected to the Raspberry Pi and downloaded the data for processing and analysis.

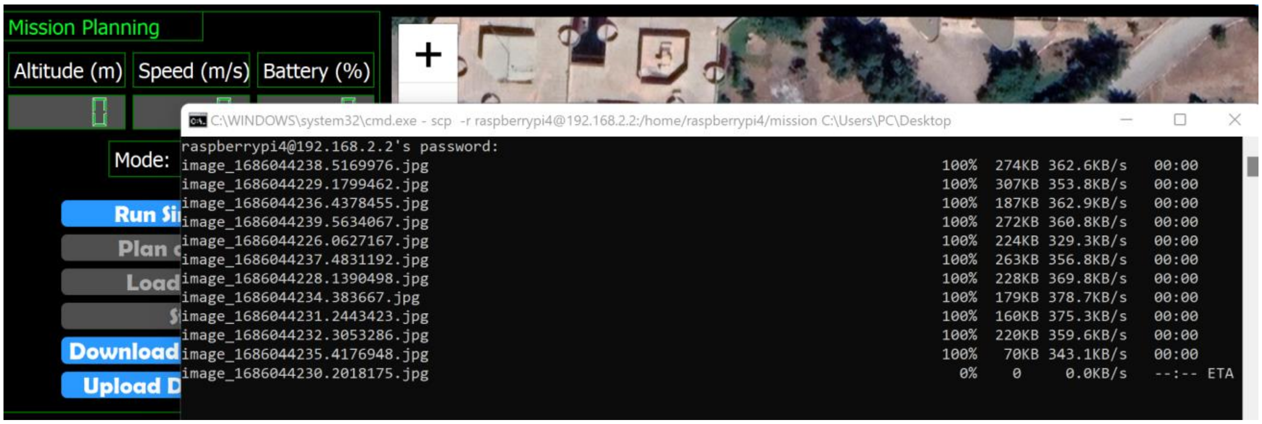


Figure 4.5 Downloading the data from the Raspberry Pi.

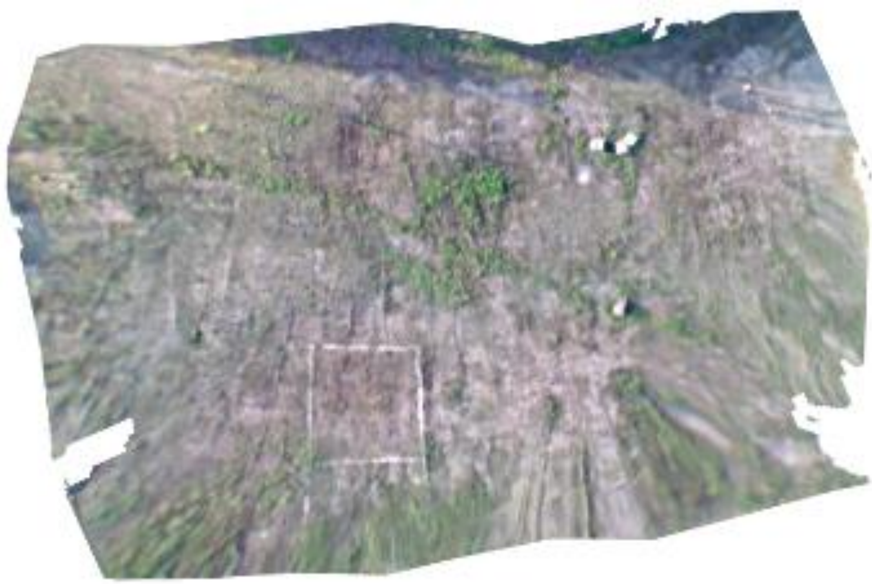
The images were captured on 04/06/2023 using both the CIR and RGB sensors. Prior to calculating the NDVI from the images, it was necessary to generate a map. This was achieved by using an open-source software called OpenDroneMap [101], which allowed us to stitch the images together and create a comprehensive maps as shown in Figure 4.6.

However, the stitching of the RGB images was not as successful as that of the CIR sensor due to its lower resolution and bad placement on the quadcopter. Although, we can distinguish different land cover types such as soil, vegetation and concrete, therefore we used the RGB map as a ground truth to offer initial insights into the accuracy of the NDVI map.

After generating the maps, using a python code we calculated the NDVI (Figure 4.7) using the formula from Table 1.4:

$$\frac{NIR - R}{NIR + R}$$

(a)



(b)

Figure 4.6 AOI Mapped with (a) CIR sensor and (b) RGB sensor.

Figure 4.6 shows a noticeable contrast in the vegetation, but it is difficult to determine whether the vegetation is healthy or unhealthy based on the image alone. On the other hand, the RGB map, allows us to easily differentiate between vegetation and soil, but it does not provide information about the density or health of the vegetation.

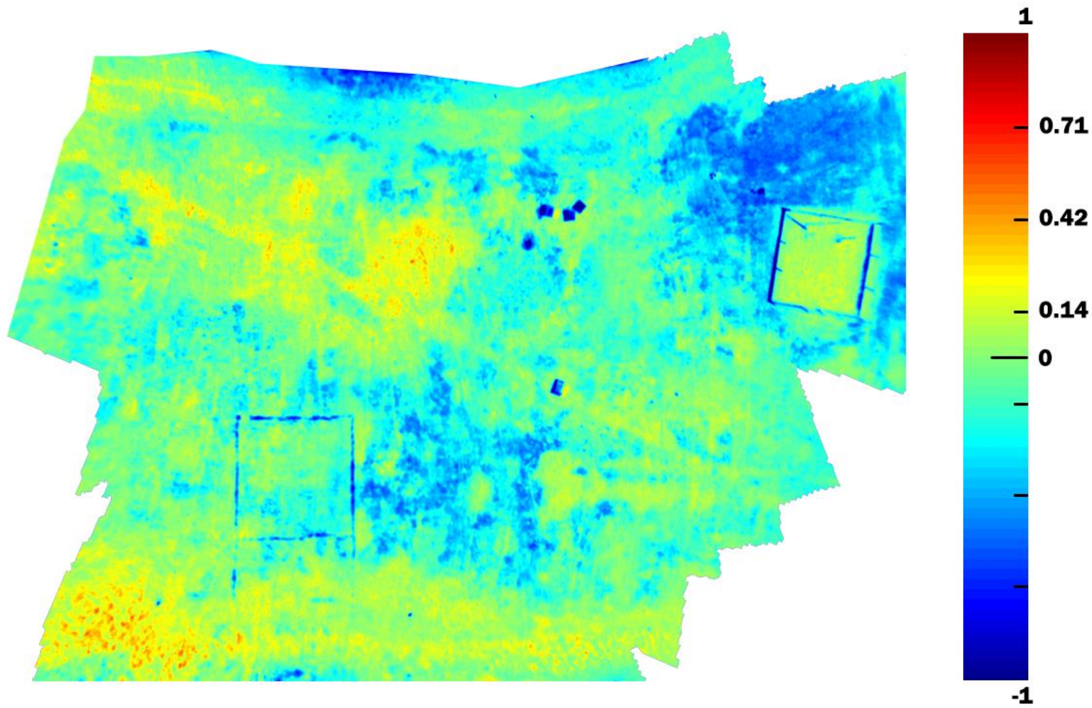


Figure 4.7 NDVI map of the AOI.

Figure 4.7 presents an insightful color palette that enables a comprehensive analysis of the map. Within the range from -1 to 0, the absence of near infrared reflectance suggests the presence of areas characterized by bare soil and concrete. As we progress along the range from 0 to 1, there is a gradual increase in the intensity of near infrared reflectance. Higher values within this range indicate a higher level of reflectance, which in turn signifies the health and density of plants. This unique aspect of the map sets it apart from both the CIR and RGB maps, as it offers us the opportunity to discern the density of vegetation and make assessments regarding its overall health. For some crops, too dense or too sparse of an area could mean issues with the yield. By examining the variations in near infrared reflectance, we can gain valuable insights into the state and vitality of the vegetation.

Regarding the identification of potato leaf diseases, we conducted some photography and analysis using our algorithm, and the outcomes were highly promising. This application serves as our foundation for disease identification, and our future plans involve expanding its scope to encompass a broader spectrum of diseases. Our ultimate goal is to establish comprehensive databases for each disease, enabling us to offer farmers accurate diagnoses and effective remedies. Through this program, we aspire to empower farmers by equipping them with the necessary resources to tackle various agricultural challenges effectively.

4. 4 Discussion

In discussing the results of this thesis, it is important to acknowledge certain limitations that may have affected the accuracy and precision of our findings. One significant limitation was the relatively low resolution of the RGB and CIR sensors used in our study. The lower resolution of these sensors can lead to reduced spatial detail and potentially impact the accuracy of our vegetation health assessments.

Another limitation was the inaccessibility to more advanced multispectral sensors and calibration targets, which are known to provide higher accuracy and reliability in vegetation monitoring. The absence of these resources may have introduced some level of uncertainty and reduced the overall precision of our measurements.

Despite these limitations, the findings of our study remain significant. We were able to demonstrate the potential of AI-assisted plant disease detection highlighting the value of incorporating AI algorithms in identifying and classifying plant diseases, which can be a crucial step in effective disease management strategies.

It is worth noting that the limitations identified in this study serve as opportunities for future research and improvement. Future studies could focus on utilizing higher-resolution sensors and exploring the integration of multispectral data to enhance the accuracy and reliability of vegetation monitoring. Additionally, efforts to improve the accessibility of calibration targets and advanced sensor technologies would contribute to more precise and robust data collection in the field.

CONLUSION

The main objective of this study was to extensively explore the use of drones for monitoring vegetation health and develop a solution for detecting plant diseases. It addressed the challenges faced by farmers in disease detection and management while emphasizing the benefits of employing drones in smart farming. The thesis investigated the current state of drone-based remote sensing and examines relevant technologies utilized in smart farming practices. Additionally, it focused on building a quadcopter UAV, selecting suitable sensors for precision agriculture, developing a desktop application for mission planning, and integrating satellite technology for agricultural monitoring.

The main findings of this master's thesis demonstrate the effectiveness of artificial intelligence in identifying and classifying potato diseases, which can be extended to identifying plant diseases in general. These findings will contribute to the development of a drone-based remote sensing dataset specifically for plant disease detection, utilizing high-resolution RGB sensors. Furthermore, the use of drone-based remote sensing with CIR sensors enables effective monitoring of vegetation, providing valuable insights for taking appropriate actions to address and resolve issues in a timely manner.

The significance of this study is rooted in its potential to revolutionize agricultural practices in Algeria through the integration of AI, drones, and satellite-based remote sensing. By embracing these cutting-edge technologies, farmers in Algeria can harness timely disease detection, targeted interventions, and optimized crop management strategies. This thesis not only adds to the existing body of knowledge in the field but also provides practical insights that can pave the way for the development of innovative solutions in plant disease detection and vegetation monitoring. As a result, this research holds the promise of transforming agricultural practices in Algeria, empowering farmers with advanced tools and techniques to enhance productivity, sustainability, and overall agricultural outcomes.

Moving forward, further research and collaboration between academia, industry, and farmers are essential to refine and expand upon the findings presented in this thesis. Continued advancements in AI, remote sensing technologies, and data analysis techniques hold the promise of driving sustainable agricultural practices, improving crop yields, and ensuring food security.

BUSINESS MODEL CANVAS - *BMC*

Project holders:	Supervisors:	Project code:
1- Miloua Mokhtar 2- Mebarek Bilel Adelmadjid 3- Meskine Hocine	S- Tahraoui Sofiane CO-S- Azmedroub Boussad	05_17_3284

Start-up project: **A UAV-based close range monitoring of the vegetation for precision agriculture purposes.**

Key Partners:	Key Activities:	Value Propositions:	Customer Relationships:	Customer Segments:
Agricultural tech companies Drone manufacturers/suppliers Government agencies	Drone monitoring operations Fields mapping Collecting and analyzing agricultural data Collaboration with key partners **Key Resources:** Drones equipment and sensors Software for services providing Human resources Access to agricultural land and customers	Increased crop yield and quality Reduced costs Improved operational efficiency	Ongoing support Specific farming needs Feedback and input **Channels:** Partnerships Company website Online marketing Demonstrations at agricultural events	Farmers Private agribusinesses Large national farms Agricultural insurance

Cost Structure:	Revenue Streams:
Costs of drone equipment, sensors, and software Salaries for personnel Costs of marketing Research and development costs for improving technology and data analysis methods	Service contracts for ongoing monitoring and maintenance One-time service fees for customers Revenue sharing partnerships with agricultural technology companies

With our project, we aim to be a pioneering startup based in Algeria that specializes in providing precision agriculture services through the utilization of advanced drone technology, satellite imagery, and AI analytics and IoT technologies. Beginning with this application and with the goal of developing numerous additional apps in this sector, our ambition is to empower farmers and revolutionize the agricultural industry. We want to do this by providing new tools and important insights to aid in informed decision-making.

The target market for our project includes farmers, government-owned farms, agribusinesses, and agricultural insurance companies. We are driven by our vision of making precision agriculture accessible to all stakeholders. We believe that by harnessing the power of drones, satellites, AI and IoT, we can help farmers overcome the challenges they face, enhance their productivity, and contribute to a more sustainable agricultural ecosystem.

In our country, the availability of comprehensive precision agriculture services is currently limited. Recognizing this gap, we are passionate about introducing cutting-edge technology to transform the way farming is practiced. By leveraging our expertise in drone development, web development, and drone application design, we are well-positioned to pioneer advancements in the precision agriculture sector.

We understand the unique challenges faced by farmers, such as limited land availability, water scarcity, and the need to address crop diseases and nutrient deficiencies. By providing them with accurate and timely insights derived from drone and satellite data, we aim to empower them with the knowledge necessary to optimize their agricultural practices, make informed decisions, and achieve higher crop yields while reducing their environmental footprint.

While precision agriculture has gained traction in other parts of the world, its adoption in Algeria is still in its early stages. This represents a significant growth opportunity for our project, as we aim to be at the forefront of transforming the agricultural landscape and establishing ourselves as the leading provider of precision agriculture services.

As we continue to develop our platform and expand our service offerings, we are dedicated to fostering strategic partnerships with industry stakeholders, agricultural organizations, and governmental bodies to drive awareness and adoption of precision agriculture practices.

Marketing and Commercialization Strategy:

In order to successfully enter the market, we have developed a comprehensive marketing and commercialization strategy. Our primary objective is to raise awareness about the significant advantages of precision agriculture and position our startup as the leading provider of advanced and customized solutions in the industry. To achieve this, we will employ various strategic approaches and tactics that will enable us to effectively reach and engage our target audience.

- Digital Marketing:

We will use digital marketing to create a strong online presence and attract our target customers. This includes implementing search engine optimization (SEO) techniques to improve our website's visibility, running targeted online advertising campaigns, and utilizing social media platforms to engage with farmers, agricultural businesses, and industry influencers. Through engaging content, informative blog posts, and visually appealing visuals, we will communicate the benefits and value of our precision agriculture services.

- Content Creation:

We recognize the importance of providing valuable and educational content to our audience. We will develop high-quality content such as blog articles, case studies, and video tutorials that highlight the benefits and applications of precision agriculture. By sharing our expertise and insights, we aim to position ourselves as thought leaders in the industry and build trust with potential customers.

- Industry Events:

We will actively participate in relevant industry events, conferences, and exhibitions to showcase our services and establish connections with key stakeholders. These events provide valuable opportunities to network with farmers, agricultural professionals, government officials, and potential partners. By presenting our innovative solutions and demonstrating their effectiveness, we will solidify our position as a reputable and trusted provider in the precision agriculture sector.

- Partnerships:

Collaborating with agricultural organizations, research institutions, and industry influencers will be a key aspect of our marketing strategy. By forming strategic partnerships, we can tap into existing networks, gain credibility, and access a wider audience. We will explore opportunities for joint marketing initiatives, co-branded content, and knowledge sharing to mutually benefit both parties and enhance our market reach.

Through these marketing and commercialization strategies, we aim to create a strong brand presence, generate leads, and ultimately drive customer acquisition. By effectively communicating the unique value proposition of our precision agriculture services, we will position ourselves as the go-to provider for farmers seeking advanced and tailored solutions to optimize their crop yields, reduce resource usage, and mitigate risks.

- **Service Offering:**
- Drone Surveys and Imaging:

We will offer drone surveys equipped with high-resolution cameras and sensors. These surveys capture detailed aerial imagery of crop fields, providing farmers with valuable information about crop health, nutrient deficiencies, pest infestations, and irrigation needs.

The leveraged experienced in this project ensure precise flight paths and data collection, delivering accurate and reliable results.

- Satellite Imagery and Data Analysis:

Our platform provides access to satellite imagery. By subscribing to our satellite services, users can select their area of interest and access detailed satellite images at regular intervals.

Currently we process the satellite data to generate valuable indices such as Normalized Difference Vegetation Index and Normalized Difference Water Index. The indices help farmers monitor vegetation health, water stress, and optimize irrigation practices.

- Disease Detection and Crop Monitoring:

In our platform, we currently offer potato leaf disease detection as a key service. However, we are continuously expanding our range of AI-based plant disease detection. Our dashboard provides crop monitoring via Sentinel 2 and Landsat.

- Data Analytics and Insights:

In the near future, we aim to employ sophisticated AI algorithms and data analytics techniques to process the collected drone and satellite data. Our platform will generate comprehensive reports and actionable insights that empower farmers to optimize their agricultural practices.

- Consulting and Support:

We understand that adopting precision agriculture solutions can be a learning curve for many farmers. We will create a team of experts who will provides personalized consulting and support services to guide farmers through the implementation and utilization of our services.

- **Revenue streams**

We have identified several revenue streams that we plan to implement, including:

- Subscription revenue:

Clients have the option to subscribe to our platform and gain access to a wide range of services, including satellite-based crop monitoring, disease detection tools, and actionable insights. We will offer flexible subscription plans, allowing clients to choose between monthly or yearly payment options based on their needs and preferences.

- Service revenue:

Clients can easily reach out to us through our user-friendly website or other online channels to request our drone survey services. We provide flexible options to accommodate their specific requirements. They can choose between prolonged contracts for ongoing projects or opt for a one-time fee arrangement for individual surveys. Our goal is to cater to their needs and provide them with the most convenient and efficient service experience possible.

- Advertising Revenue:

Income generated from displaying advertisements on our platform or through partnerships with advertisers.

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